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

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May 2011

PRELIMINARY REVISION

Abstract

Communications technology enables labor services' offshoring through remote hiring. This paper demonstrates how independent outsourcing agencies reveal worker quality and facilitate hiring in online markets for remote work. Over one third of the workers employed on oDesk.com, a large online labor market, are affiliated with one of many small outsourcing agencies. Affiliation signals that a worker is relatively high-quality and preempts public learning about affiliates' quality on the job, allowing inexperienced affiliates to earn high initial wages. Once the quality of workers has been revealed through experience, low-quality workers, most of whom are non-affiliates, are selected out of the market. This selection effect leads to a rapid reduction in the agency wage premium for experienced workers. While agencies appear to help form teams for large projects, the full set of findings cannot be explained by the presence of complementarity between worker productivity and agency affiliation. Affiliates in the same agency share offline ties, suggesting that an agency has a pre-existing advantage in determining worker quality. By conveying this information and reducing employers' costs of quality verification, agencies increase total output in the market.

*This paper was presented at the 2010 NBER Summer Institute under the title "Information and Labor Market Intermediaries in Online Search and Hiring."

†Email: cstanton@stanford.edu, cmt2122@columbia.edu. This research was funded in part by the Ewing Marion Kauffman Foundation. The contents of this publication are solely the responsibility of Christopher Stanton and Catherine Thomas. Stanton thanks the Kauffman Foundation for generous support for "Entrepreneurship Through Online Outsourcing." We are grateful to Gary Swart, Anand Hattiangadi, Josh Breinlinger, Dmitry Diskin, and Sean Kane at oDesk for their ongoing help with this project. We thank Tim Bresnahan, Boğaçhan Çelen, Liran Einav, Marina Halac, Caroline Hoxby, Bruce Kogut, Eddie Lazear, Ben Lockwood, Kathryn Shaw, and Ali Yurukoglu for helpful discussions.

1 Introduction

Recent advances in communications technology have created new ways for firms to hire workers and new means of labor services delivery. The ability to hire workers from anywhere in the world has been described as the basis for the "next industrial revolution" (Blinder, 2006).[1] In his 2001 paper "Wiring the Labor Market", Autor predicted that new labor market intermediaries would emerge to facilitate electronic service delivery. One possible intermediation role is to provide employers with information about distant workers. Another possible function is to provide services that are complementary to remote-worker quality, such as assisting workers directly, providing physical capital or training, or enabling teamwork. Intermediaries are now widely observed in markets for remote work. Studying their activities clarifies the nature of trade frictions between workers and employers in different locations and offers insight into how intermediaries facilitate gains from this type of trade.

This paper investigates the role of intermediaries within oDesk.com, one of the largest online markets for remote labor services. Launched in 2005, oDesk provides a platform for remote interaction between potential employers and workers, managing the contracting and work delivery processes, and allowing employers to monitor worker output.[2] Around one third of the workers employed through oDesk are affiliated with independent intermediary organizations known as outsourcing agencies. A typical outsourcing agency is located in a low-wage country. Most agencies have between five and ten members with similar backgrounds who work on similar tasks. Potential employers observe a worker's agency affiliation and an agency-level feedback score that is common to all agency members. While employers interact directly with the worker rather than with the head of the agency—who is usually, himself, a successful oDesk worker—the agency head collects a share of all affiliates' wages.[3]

Using very detailed administrative-level data obtained from oDesk.com on workers' wages, project results, project-management practices, and firms' hiring decisions, this study asks how

[1] An estimated 25 percent of all U.S. jobs are potentially "offshorable" (Blinder and Krueger, 2009), either within or across firm boundaries. Much of this is due to the possibility of remote work and electronic product delivery.

[2] The typical job posted on oDesk is about 75 hours long and has a value of about $500. The site now processes over $100 million in arm's length contracts per year; the majority of these transactions spans international borders and, hence, constitutes both labor services outsourcing and offshoring.

[3] oDesk collects 10 percent of all workers' revenues earned on the site in fees. The agency head collects a worker-agency specific share of each agency affiliate's revenues. As discussed in the following section, a worker's agency status is constant over the course of his or her oDesk career.

intermediated exchange between the buyers and suppliers of remote labor services provides greater gains from trade than direct exchange (Spulber, 1999). Do outsourcing agencies facilitate hiring through information provision and/or increase productivity directly through providing complementary services?

The empirical approach to distinguishing between agencies' proposed information transmission and productivity-increasing roles is based on the observation that the value of any information conveyed to employers by agency affiliation is greater when other observable information about worker quality is relatively limited. oDesk is a public learning environment (Farber and Gibbons, 1996; Altonji and Pierret, 2001; Lange, 2007), in that employers on the site post feedback about workers' past projects. This implies that less public information is available for inexperienced workers who have yet to receive feedback on the site. Thus, the value of the information provided by agency affiliation is likely to be greatest for inexperienced workers. In contrast, if agency affiliation serves to increase worker productivity directly, this effect is more likely to be present throughout affiliates' oDesk careers.[4]

The results suggest that agencies provide important information about worker quality. Agency affiliates have higher initial wages than non-affiliates but, for those workers who find additional work on the site, the difference between the wages earned by affiliates and non-affiliates dissipates. Compared to affiliates' wages, non-affiliates' wages are more responsive to posted feedback—the new information that arrives in the market.[5] These facts are consistent with the idea that agency affiliation is correlated with worker productivity and that agencies facilitate hiring by screening workers.

Under this interpretation, affiliation conveys to potential employers that workers are of high relative quality, so that employers are willing to pay affiliates higher initial wages. Once information about worker quality is revealed via publicly observed feedback measures, employers re-hire only high- quality workers and are unwilling to pay a premium to hire affiliated rather than non-affiliated workers with the same measured quality from past work. Non-affiliates revealed to be high-quality

[4]In particular, there is no clear reason why the productivity effect of agency affiliation should diminish over time. Bidwell and Fernandez-Mateo (2010) document that the intermediation premium increases over time in staffing agencies that learn about workers and employers, and improve match quality over time.

[5]The empirical approach relies on the assumption that hourly wage rates are correlated with the expected value to the employer of hiring a given worker. Appendix 1 motivates this assumption as an empirical prediction of a model of agencies in a public learning environment with overlapping generations of workers.

experience faster wage growth than affiliates because good feedback leads to larger changes in employers' expectations of worker quality. Hence, an agency's ability to screen the quality of inexperienced workers (and offer affiliation only to high-quality workers) preempts the selection on quality in the marketplace that takes place after feedback has been publicly revealed.

Analysis of affiliates' and non-affiliates' probability of transitioning to a second job reveals that the aggregate agency wage premium declines for experienced workers due to differential selection. The average quality of inexperienced affiliates appears to be higher than that of inexperienced non-affiliates on the first job; employers report project success more frequently for affiliate workers, and affiliates have a greater likelihood of being hired for a second job. However, a large part of the difference in the probability of being re-hired for a second job is due to affiliates' superior feedback scores on the first job. A good feedback score is associated with a significantly higher increase in the probability of being re-hired for non-affiliate workers than for affiliate workers, particularly for high-skill tasks like programming. This corroborates the hypothesis that feedback revealed on the job is more informative for non-affiliates.

The data do not support the most plausible reasons for the presence of a time-varying relationship between worker productivity and agency affiliation. In particular, the data appear inconsistent with the possibility that non-affiliates' productivity increases more on the first job. Affiliates tend to have first jobs that last longer, providing greater opportunity for on-the-job learning for this group of workers. In addition, affiliates tend to have less prior work experience than non-affiliates—suggesting that, in a setting where the rate of productivity gains is declining with experience, affiliates' productivity would likely increase more on any given job.

Another possible reason for a time-varying association between worker productivity and agency affiliation is that an agency provides different complementary activities to its affiliates at different stages in their careers. The most plausible explanation of this kind relates to the prevalence of team-based projects changing over an agency affiliates' career. As the nature of offshore work has shifted from simple tasks such as data entry to more-complex tasks such as programming, the ability to communicate, monitor, and work in teams may be critical to accommodate large projects.[6] The data contain information on which workers are simultaneously billing time on the same project for

[6]Teams of workers arise endogenously in many other settings, often because team production is more effective than individuals working alone (Wuchty et al., 2007), and outsourcing agencies may help enable teamwork.

the same employer, identifying when teamwork is most likely to occur. While affiliates often work in teams with members of the same agency, wages for agency-affiliated workers are not related to whether the worker is operating in teams or performing an individual assignment. Nonetheless, data on when non-affiliates are matched in teams reveals that non-affiliates have smaller wage increases when moving to a team-based job from an individual job compared to non-affiliates who do not move to teams. Thus, team efficacy may be lower for non-affiliates, consistent with the view that agencies enable greater teamwork complementarities among agency team members. However, changes in the propensity to work on teams for affiliates and non-affiliates between jobs for any given worker cannot explain why the average agency premium diminishes with experience on the site.

Analysis of firms' hiring choices provides further evidence consistent with the view of agencies as information providers. An unusual feature of the dataset is that it contains many details about the hiring process. Modeling a hire as a discrete choice from a set of workers with observable characteristics sheds some light on the marginal value to the employer of different worker characteristics. Narrowing the focus to openings in highly-skilled programming categories demonstrates that employers in this job category attribute positive value to agency affiliation primarily when the agency affiliate is inexperienced—that is, when no work history is available to the employer. The incremental value associated with agency affiliation for inexperienced workers is similar in magnitude when the employer is hiring for a team-based or for an individual project.

Consistent with the view that agency affiliation enables employers to distinguish worker quality is the fact that agencies are particularly common where the information about worker quality from other observable characteristics is especially incomplete. Specifically, agencies are more common in low-wage countries and least common in the United States. The majority of employers are located in the United States, and it is likely that other observable characteristics about U.S. workers, such as the name of the undergraduate institution attended, convey more information about inexperienced workers' quality than does analogous information about workers in a different country. Agencies are also concentrated in job categories that require advanced and specific skills—such as programming—where it is likely that employers find it most difficult to assess worker quality from observable characteristics.

A necessary condition for agencies' information-transmission role is that they have a comparative advantage in determining inexperienced workers' quality. An examination of how agencies are organized offers some insight into the nature of this advantage. Affiliates within the same agency are likely to know each other offline; they are often located in the same city, and many attended the same educational institutions. Agency affiliates are also likely to be specialists in the same job category. The pre-existing knowledge contained in local ties and specialization in an area of expertise appears to allow agencies to determine worker quality and screen accordingly. Outsourcing agencies perform a similar role to that of the experts described in Biglaiser (1993) and the certification intermediaries described in Lizzeri (1999), except that, in this case, intermediaries have already incurred the fixed costs of acquiring expertise and of learning seller quality.[7]

Despite the fact that affiliation is valuable primarily at the start of any one worker's career, outsourcing agencies are likely having a large impact on the efficiency of the oDesk marketplace. In public learning environments (such as in the environment described in Tervio (2009), which resembles many features of the oDesk environment), revealing employee quality is analogous to providing employees with transferable skills (Becker, 1962). Inefficiency arises from the fact that each employer bears all the costs associated with revealing inexperienced workers' quality but gains only a fraction of the benefit. Hence, too few inexperienced workers are employed in the market. Pallais (2010) uses experimental data to demonstrate that this is, indeed, the case for data entry jobs in the oDesk market.

The data offer evidence that agencies serve to increase the value of transactions on the site. On the intensive margin, the average quality of an employed worker on his first job is higher. Furthermore, while 60 percent of non-affiliates that are hired once go on to be hired for more than one job, compared to 74 percent of affiliates (consistent with the prediction that affiliates are revealed to be higher quality on average), only 8 percent of all non-affiliates have their quality revealed by being hired once, whereas 35 percent of affiliates are employed at least once. This

[7] Unlike in Spence (1973), the structure of these intermediaries does not require 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. Other studies of online labor markets discuss different methods by which information is credibly shared. Bagues and Labini (2009) show how mandatory disclosure of quality-relevant worker information affects worker outcomes such as unemployment duration, wages, and job satisfaction. Several recent papers focus on how new technologies facilitate employee search—via online job boards, for example (Kuhn and Skuterud, 2004; Nakamura et al., 2009; Stevenson, 2009).

suggests agencies also serve to increase the value of transactions on the extensive margin—the information they provide is a public good and leads to an increased supply of known high-quality workers in the market.

The findings have broader implications for remote work and offshoring. By demonstrating that agencies provide information about supplier quality, the results confirm that incomplete information about quality hinders the number of remote transactions and, hence, the rate at which the gains from offshore trade are realized. The results also highlight the continued relevance of traditional labor-market ties—such as offline social and educational networks—in facilitating online work.

What do these findings imply for services' offshoring and the growth of intermediation? The size of any one agency's offline network appears to limit the size of the online agency (since its screening advantage relies on offline network ties), and there are significant barriers to entry by new agencies. This is because for new agencies to be successful, the agency head needs to have established that he is a high-quality worker—something that is hard for an inexperienced non-affiliate to accomplish. Constraints on the growth rate of this particular type of intermediary suggest agencies cannot easily expand to meet rapidly growing demand for their certification services. One implication, then, is that incomplete information may continue to impede the rate at which labor services move 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 employer hiring decisions. Section 6 concludes.

2 The oDesk.com Marketplace

2.1 Background

Launched in 2005, oDesk.com has grown to become one of the largest of several online marketplaces for remote work. A firm that wants to hire a remote worker can create an account on oDesk.com, post a project description, and view potential job applicants located around the world. There are a variety of job tasks posted on the site, falling into three broad categories. First, there are tasks requiring specialized skills, where the output may only be verified at the end of a project. These tasks include database design, software development, and web programming (the largest job category). Second, there is highly-skilled, but easy-to-monitor work such as website design. Employers hiring in web design can typically observe output after each webpage is complete. Finally, there are low-skilled tasks such as data entry. Employers post the expected duration of work in their job advertisements, and typical jobs last from several weeks to multiple months.[8]

The employer observes a large amount of information about each applicant, including education and work experience outside oDesk. For workers with experience on the oDesk site, a verifiable job history is available, including a revenue-weighted feedback score (out of five) from past jobs. Detailed comments about performance are also available.[9] For the subset of workers—both experienced and inexperienced—that are affiliated with an agency, their affiliation is observable on their profile page, along with an agency-level feedback score out of five. The agency feedback score is the revenue-weighted feedback score for all jobs started for any worker who was ever affiliated with the agency.

Figure 1 provides an example worker profile containing the information the employer observes when evaluating a job applicant.[10] This profile is for one of the most prolific workers on oDesk: Evgeny M. Evgeny is located in Omsk, Russia and is a programmer and software developer. Since joining the market in 2007, he has earned over $400,000 in wages for work he has completed through oDesk. The top right corner of Figure 1 shows that Evgeny has outstanding feedback from past jobs (nearly 5 out of 5).

On the bottom right-hand side of Evgeny's profile, employers can observe that he is affiliated with the outsourcing agency qcode. The qcode brand and feedback score are observable on Evgeny's profile. In fact, Evgeny heads qcode, a 17-member outsourcing agency that he started. Evgeny collects a share of the revenues generated by other members of the qcode agency.

Many features of qcode's organization appear typical of the other agencies operating on oDesk.

[8] We are unable to determine whether workers and firms use other platforms in addition to oDesk. Competitor sites in the same market appear to be imperfect substitutes. These other sites have varied fee arrangements, ranging from combinations of upfront payments pre-match to escrow fees for payment-upon-delivery contracts. Because other sites do not offer monitoring systems, most competitors' job postings are dominated by payment-upon-delivery (i.e., fixed-fee) contracts.

[9] The feedback environment resembles eBay's, in that stars are prominently displayed on the worker's profile. Potential employers can also choose to view any detailed feedback left by prior employers.

[10] Most potential employers also choose to interview candidates to gather more information. The data contain timestamps for when interviews occur, but there is no information about what is learned.

For example, all workers affiliated with qcode are located in Omsk, Russia, and most affiliates attended the same university. The typical agency is a small collection of workers, often from the same city, where workers appear likely to know each other through shared offline affiliations.

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 agency members are in the modal city for their respective agency affiliates. In addition, many agency members attended the same schools. 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 job category, even when the type of work is finely categorized. For example, over 90 percent of agency members with work experience have had at least one job in the modal job category of their agency, out of the nine broad categories on oDesk. Over 80 percent of experienced agency members have had at least one job in the modal job category for the agency, out of the 76 more-narrowly-defined job categories.

2.2 Worker-level Summary Statistics

Between August 1, 2008 and December 28, 2009, nearly 125,000 workers signed up with oDesk. Ten percent of these new workers were affiliated with an outsourcing agency.[11] However, agency affiliates made up 33 percent of workers who are hired for at least one job in the sample. Table 1 presents some summary information about the prevalence of agency affiliates in the data overall; within the three most frequently observed job categories; and then within the four most prevalent worker countries. While only eight percent of non-affiliates find a job on the site, 35 percent of affiliates are employed at least once. This pattern is replicated within job category and within country. 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.

The additional rows in each panel of Table 1 summarize the worker-level characteristics that employers can observe. Columns 1 and 2 show that, across all hired workers, non-affiliates are

[11] Agency affiliation is, in practice, fixed for the duration of an oDesk career. Workers wishing to leave an agency must create new worker profiles, losing all previous feedback and work history.

likely to have better English language skills (87 percent compared to 82 percent), are more likely to report at least having an undergraduate degree (40 percent compared to 35 percent), and are more likely to have taken at least one of the skills certification tests administered by oDesk (78 percent compared to 59 percent). On average, non-affiliate workers in the sample appear to have a higher level of observable competence than affiliate workers. This also tends to be true within job category, and within country.[12]

The final rows in each panel of Table 1 detail the log hourly wages earned by each group of workers on their first job. Columns 1 and 2 of Panel A show that affiliates receive significantly higher hourly wages on their first job. The average hourly wage (in levels) on a first job for non-affiliates is around \$4.85, whereas affiliates earn \$8.08, on average. In India, Russia, the Philippines and the U.S., affiliates earn significantly higher first hourly wages. Affiliates hired in Data Entry and Web Design jobs, but not those first employed in Web Programming, earn higher wages. However, Figure 3 takes worker locations into account and shows that, within most countries, the distribution of affiliate first wages in Web Programming has a higher mean and smaller variance than the distribution of non-affiliate first wages. The one country shown in the figure where this is not true is the United States.

The data in Table 1 and Figure 3 suggest that affiliates are paid more on their first job, despite the fact that key observable characteristics (education, language skill, oDesk tests) might suggest that they are lower-quality than non-affiliate workers located in the same country and working in the same job category.

2.3 Framework Motivating the Empirical Approach

The summary statistics in Table 1 present something of a puzzle. Agency-affiliated workers appear less skilled, but employers are more likely to hire inexperienced affiliates than inexperienced non-affiliates. Employers are also willing to pay affiliates higher hourly wages.

The investigation in this paper is also guided by four further empirical facts about observed features of the marketplace in general: (1) Inexperienced workers—particularly those who are non-

[12] Appendix Table 1 reproduces these summary statistics for all workers who bid for at least one job since August 1, 2008. Among all applicants, not just those who successfully find work, agency affiliates tend to appear more highly skilled.

affiliated—have difficulty finding employment (as shown in Table 1); (2) a small portion of all workers (such as Evgeny M.) are employed for many jobs and earn high wages; (3) publicly available feedback scores are strongly correlated with the probability that a worker is hired and with the wages for experienced workers; and (4) many firms post jobs but do not hire on the site. These facts closely mirror the equilibrium of a public-learning environment set out in Tervio (2009), which demonstrates market failure in the discovery of talent. In this model, too few inexperienced workers are employed since talent discovery (analogous to posting feedback in oDesk) is a public good, but superstars (analogous to oDesk workers like Evgeny M.) are earning high wages and are always employed. In this equilibrium, wages reflect expected quality, and novice workers are paid their reservation wage, but wages cannot adjust enough to overcome the inefficiency of incomplete information.

Appendix 1 shows that agencies can be introduced into a simple version of Tervio's model to derive predictions consistent with a screening role. In the model, agencies can screen the quality of connected workers. Workers with agency affiliation are positively selected, resulting in higher average quality among affiliates compared to non-affiliates. Employers understand the positive selection into agencies, and the agency brand results in higher initial wages for agency members in their first job. The first job for all workers is like an audition, and the market learns about worker ability after the fact. This means that the best non-affiliates catch up over time in response to good feedback.

The following empirical predictions are consistent with a perfect Bayesian equilibrium of this model: (1) higher initial wages for agency affiliates; and (2) larger wage changes for non-affiliates in response to good feedback. If agencies were providing better workers because of teamwork or complementarities, the agency advantage would persist over time. These intuitive predictions guide the empirical approach in the following sections.

3 Empirical Analysis of Hourly Wages

3.1 Initial agency affiliate wage premium

As described above, the data in Table 1 (and Figure 3 for Web Programming) reveal that agency affiliates earn higher initial wages, on average, compared to non-affiliates. But affiliates also differ from non-affiliates along other observable dimensions. In this section, the Oaxaca-Blinder method (Oaxaca, 1973; Blinder, 1973; Fortin et al. 2010) is used to decompose the log of the first hourly wage into a component due to differences in observable characteristics other than agency affiliation and an "unexplained" component that is associated with agency affiliation. The log wage of worker i on the first job, w_{i1}, is:

$$w_{i1} = \beta_{1N} + A_i\beta_{1A} + X_i\beta_{2N} + A_iX_i\beta_{2A} + t + \varepsilon_i \tag{1}$$

where A_i is equal to 1 if worker i is an agency affiliate and equal to zero otherwise, X_i are individual worker characteristics, and t is a calendar time effect. The subscripts N and A indicate that the coefficients correspond to non-affiliates and affiliates, respectively. The separate constant for agency affiliates captures baseline differences in outcomes between affiliates and non-affiliates on the first job. The empirical approach is to estimate how much of the difference in outcomes between affiliates and non-affiliates is due to measurable differences in characteristics; the remainder is attributed to the agency and other factors correlated with agency affiliation but absent from the data. This decomposition provides results relative to a baseline group. The natural baseline for evaluating the impact of agencies is to hold affiliates' characteristics constant but to "weight" those characteristics as if they were evaluated for non-affiliates. This allows an examination of how much of the wage gap remains unexplained.

The procedure is as follows: First, partition the sample of workers by agency status. Second, separately regress w_{i1} on X_i (including a constant) and t for agency members and non-members. This procedure provides estimates of $\beta_A = (\beta_{1A}, \beta_{2A})$ and $\beta_N = (\beta_{1N}, \beta_{2N})$. The difference in the average w_{i1} between members and non-members attributable to differences in observable characteristics is measured as $(X_A - X_N)\,\beta_N$, where X_A and X_N are the mean values of each column of X_i for affiliates and non-affiliates, respectively (including the different constants). The difference in initial wages attributable to agency affiliation is given by $(\beta_A - \beta_N)\,X_A$. This term captures the fact that employers appear to value the same characteristics differently for affiliates and non-affiliates.[13]

The results from this log wage decomposition are presented in Panel A of Table 2. Column 1 of

[13] Characteristics include all measurable resume characteristics that can be easily quantified, test scores observed in workers' profiles, and any work history from prior fixed price jobs.

this panel shows that affiliates' average log wages are 1.913 compared to 1.611 for non-affiliates on the first hourly job. The first column includes job category and country fixed effects. The agency premium is 47.7 percent of the log wage difference.

The Oaxaca-Blinder decomposition depends on the choice of omitted category when indicator variables are included among the observable characteristics (Fortin et al. 2010). The remaining columns of Table 2 Panel A restrict the sample to binary categories, alleviating concern over the excluded category. These columns include new agency affiliates and non-affiliates from India and Russia (two countries where agencies are particularly prevalent) whose first jobs are in Data Entry, Web Design, and Web Programming. Column 2 shows that, for Data Entry, the log wage gap is $.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 absent the agency. 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.[14] While this analysis is descriptive, the results suggest that agency affiliation is associated with higher initial wages within narrowly defined skill groups.

The data also contain records indicating whether agency affiliates are hired by employers who are simultaneously employing workers from the same agency. It is possible that the shared agency affiliation facilitates easy team formation, and hence is associated with the observed agency wage premium. In addition, the data record whether an employer has hired members of the same agency in the past. If an agency has prior experience working with a given employer, it could increase the value to that employer of the next employee from the same agency. For example, the employer could be willing to pay higher hourly rates to affiliates because the agency possesses employer-specific information that either allows it to match affiliates to particular openings, or to share production-relevant information with subsequent affiliate employees. These are two possible ways in which agency-affiliation directly increases the value of a worker to a given employer.

The sample of employed agency affiliates is divided into three groups: those for whom their

[14] Decompositions using the first bid as the dependent variable produce similar findings. See Appendix Table 1 for these results.

first employer (1) has never employed another worker from the same agency, (2) has previously employed another worker from the same agency, and (3) has employed another worker from the same agency within a 30 day window of the worker's hire date. Approximately 43 percent of the sample of agency workers fall into categories 2 or 3.

The goal is to determine if the agency premium is particularly large for affiliates falling into the second or third group because these hires offer the greatest opportunity for affiliation to increase the value of the worker directly.

Panel B of Table 2 reproduces the Oaxaca-Blinder wage decomposition with a restricted sample. The sample excludes all agency affiliated workers in groups 2 and 3 (those whose first employer has never hired another worker from the same agency and does not hire another agency worker within 30 days). The average initial log hourly wage for these agency workers is 1.764, which is smaller than the wage for all agency affiliates. 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 the other observable characteristics of these affiliates 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. Affiliates in the restricted sample are paid slightly lower first wages than the average across all affiliates initially employed in Web Programming, but 180.3 percent of the observed wage difference compared to non-affiliates can be attributed to agency affiliation rather than differences in other observed characteristics.

The estimates imply that affiliates on team-based projects or those who match with employers experienced with the agency have higher wages than the remaining agency workers. However, there is much across-agency variation in wages and worker characteristics. It may be that only the best agencies work in teams. Table 3 analyses across- and within-agency variation in initial wages for employed affiliates. Across agencies, team work is associated with a wage premium. Within agencies, workers who are matched to team based projects do not earn higher wages.

Panel A of Table 3 provides results from regressing the initial log wage on variables indicating whether the employer falls into the second or third category described above, as well as an indicator that the employer falls into both categories. The variable "teamwork" indicates that the employer is employing another agency member at the time of this 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 the "teamwork" variable is significantly associated with initial affiliate wages. Those affiliates who are hired by an employer who is currently employing another agency member are paid higher initial hourly wages. In contrast, prior shared experience between the employer and agency does not appear to play any role in explaining higher initial affiliate wages.

However, Panel B of Table 3 reveals that the premium associated with teamwork in agencies is due to the fact that agencies where affiliates tend to work in teams also tend to earn higher wages. This panel includes agency fixed effects in the regression described above. Within-agency, there is no premium associated with being employed on a team for the first job compared to being the only agency worker employed by the employer. There continues to be no association between the extent of prior agency-employer interaction and the agency premium.

This section reveals that agency affiliates are paid more on their first jobs, controlling for differences in other observable characteristics. While the results for team work and prior agency-employer interaction do not explain the entire wage premium, it is the case that agency affiliates in teams are paid more (mostly because of higher wages for agencies that often work in teams). In addition, other unobserved factors may be correlated with agency affiliation that are particularly valuable to employers. An analysis within-person is necessary to assess the impact of information and team work while holding constant a workers's fixed effect.

3.2 Using data from career trajectories to evaluate how the agency premium evolves

The data contain the oDesk careers of individual workers, including experienced workers who received their first job prior to the beginning of the sample on August 1, 2008.[15] A comparison of new workers and experienced workers from earlier cohorts suggests that agency affiliates in the cross section of experienced workers (with more than three jobs on the site who are hired in the Fall of 2009) do not earn higher wages than non-affiliates. Table 4 presents summary information about

[15] August 1, 2008 is the first date included in the sample because of a database change around this time that actively recorded agency affiliations.

these workers. 36 percent of workers in this sample are affiliated with an agency and, for workers in Web Programming, 45 percent are agency affiliates. For Data Entry and Web Programming, there is no significant difference in the hourly wages received between affiliates and non-affiliates. For Web Design, non-affiliates actually receive slightly (but significantly) higher hourly wages than affiliates. For Web Design and Web Programming, there is generally no significant difference in other observable characteristics for affiliates and non-affiliates. One notable fact is that the feedback score for these groups of workers does not differ by affiliation status for most job categories.

The absence of a wage premium for experienced affiliates suggests that agency affiliation is most valuable at the start of a worker's career. Analyzing the relationship between affiliation status, job characteristics, wage growth, and future employment offers insight about whether the diminishing relative agency premium can be attributed to (1) larger gains in productivity over the course of the career for workers who are not affiliated with an agency, (2) differential selection into subsequent jobs for agency affiliates and non-affiliates, changing the composition of workers in the market, or both. The analysis begins by examining wage growth rates in response to feedback, hours between jobs, and changes in team composition. Re-employment rates after the first job will be analyzed in the subsequent section.

A test of whether new information affects wage growth differently for affiliates and non-affiliates is a crucial component of the empirical strategy. The top panel of Figure 4 provides non-parametric evidence. The wage change between jobs is separately regressed on feedback on the first job for agency affiliates and non-affiliates using a local polynomial procedure. The graphical results suggest non-affiliates' wages are more responsive to feedback toward the top of the feedback distribution. The bottom panel of Figure 4 shows that feedback is highly skewed. The modal feedback score is 5 out of 5.

For all workers who were employed for at least two jobs, the rate of wage change can be estimated as:

$$
\begin{aligned}
w_{i2} - w_{i1} \;=\;& \delta_0 + A_i \delta_{A,0} + Feedback \delta_{Feedback} + A_i * Feedback \delta_{A,Feedback} + Team \delta_{Team} + \\
& A_i * Team \delta_{A,Team} + WithinAgencyTeam \delta_{AgencyTeam} + HoursWorked \delta_{Hours} \\
& + A_i * HoursWorked \delta_{A,Hours} + YrsExperience \delta_{Experience} \\
& + A_i * YrsExperience \delta_{A,Experience} + C_i + t_2 + JobControls + \varepsilon_{it}
\end{aligned} \quad (2)
$$

where A_i continues to indicate whether worker i is agency-affiliated and C_i is a cohort fixed effect, included to control for different transition rates to second jobs for more recently arriving cohorts. Monthly dummies, t_2, for the month the second job begins control for possible aggregate changes in the market over time. The C_i includes cohort effects, and $JobsControls$ include differences in the expected duration of each job. The equation also contains: an indicator if the worker has not received feedback before the second job, interacted with agency membership, an indicator if years of work experience is missing, interacted with agency experience, and job controls, containing differences in dummy variables for the expected duration of a project.

Table 8 Panel A contains calculations using estimates of equation (2) to compare wage growth for affiliates and non-affiliates. Again, the result is that wages are much more responsive to additional feedback for non-members. Using a feedback score of 4.5 on the first job as the baseline for comparison, the log wage change for non-affiliates is 0.17 compared to a change of 0.09 for affiliates (Column 1). This implies non-members with even decent feedback catch up quickly. Moderately good feedback closes 38.3 percent of the initial wage gap due to agency affiliation. Using the wage gap estimates from Table 3, positive feedback closes 26.7 percent of the wage gap in Data Entry, 54.6 percent of the initial wage gap in Web Design, and 27.6 percent of the gap in Web Programming.[16]

Because these results come from a within-person specification, any unobserved time invariant component is differenced out. However, any omitted variable that is changing between jobs may explain the differential responses to feedback. The two most plausible omitted variables are different rates of change in underlying (observed to the market) productivity and the changing composition of teams. All specifications proxy for differences in underlying productivity changes with flexible

[16] These calculations use the restricted sample of workers in India and Russia.

controls for the hours worked on the first job, hours interacted with agency status, the number of prior years of work experience, and years of prior work experience interacted with agency status. All specifications also contain proxies for differences in task characteristics, including changes in the expected duration of each job. Different rates of productivity changes between jobs do not explain the differential responsiveness of wages to new information (as shown in Appendix Table 4).

Panel B of Table 8 accounts for differences in team work between jobs. These specifications include indicators for general team changes and team changes within an agency. A team based job is defined as any job that employs another person as recorded in the hourly time billing system on the same project within 30 days of a worker's date of hire. An agency team based job is classified in the same way, including only workers within the same agency. 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 incorporates differences in work practices and the effect of potential agency complementarity.

Team changes have very little effect on wage changes for agency affiliated workers. Importantly, the magnitude of the effect of feedback on wage differences changes little after accounting for team work. In no column is the impact of team based work statistically greater than zero for agency workers. This is consistent with the within-versus-across agency evidence that the best agency workers may be matched to team based projects, but team based work is not a cause of the agency wage premium.

For non-affiliate workers, however, team based projects may be problematic. Under the assumption that workers' pay is proportional to their marginal product of output, non-affiliates' wages are negatively related to team work. This suggests that agencies may facilitate productive teams compared to groups of non-affiliates.

4 Evidence from First Job Outcomes and Survival Probabilities

The previous section establishes that non-affiliates who are employed for more than one job experience higher wage growth than affiliates who also find additional jobs. Under the hypothesis that affiliation conveys that a worker is of relatively high quality, but that this information is subsequently revealed on the job for the best non-affiliates, non-affiliates on the first job are of lower average quality, with a higher variance in quality, compared to similar affiliates. The average probability of being re-employed on the site is thus predicted to be higher for affiliates. In logic similar to the wage dynamics analysis, the difference in the probability of re-employment between affiliates and non-affiliates is predicted to decline with feedback. This section examines these predictions.

4.1 First Job Outcomes

The data elicited from employers allow a direct test of whether affiliates perform better on their initial jobs. The first piece of analysis repeats the Oaxaca-Blinder decomposition with project outcome measures as the dependent variable.[17]

These results are given in Table 6 Panel A. The dependent variable is an indicator for whether the employer reported the job was successful. Agency affiliates' first projects are, on average, more successful than non-affiliates' projects, as predicted. 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. Across job categories in India and Russia, 64.2 percent of agency affiliates' projects are successful in Web Programming, versus 56.9 percent of non-affiliates' projects. Of this difference, 62.5 percent is attributable to agency affiliation.

The second dependent variable is the log 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 expected project duration is included as a control, so variation in the length of time worked is likely to reflect employer satisfaction with the work performed up to the termination of the employment spell.[18] The data in Panel B of the table reveal that agency affiliates have much longer first jobs. The overall difference in log hours worked is 0.684 (3.658 - 2.973), of which 53.1% cannot be explained

[17]The procedure is modified slightly to account for differences in expected job difficulty that may be correlated with agency status. To do this, attributes of each job opening X_i 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 opening description).

[18]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.

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 in the difference in project duration in Web Programming jobs (at 100.2 percent).

Table 7 explores the possibility that the greater success on the first job enjoyed by affiliates is associated with teamwork or prior agency-affiliation interaction. It repeats the analysis in Table 3 with the measure of success on the first job as the dependent variable rather than the first hourly wage. Panel A of the table reveals that agency affiliates working in teams on their first jobs are more likely to be successful, particularly in Web Programming in India and Russia. Overall, teamwork is associated with an increased probability of success of 6 percent (7 percent for Web Programming in India and Russia). However, as for the first hourly wage analysis, including agency fixed effects reveals that the higher success rate associated with teamwork is because members of more successful agencies work in teams. There is no significant difference in the success rate of affiliates working alone and working in teams in these agencies. (For Data Entry, affiliates working in teams are actually less likely to be successful than affiliates from the same agency working alone). As in the hourly wage analysis, prior agency-employer interaction is not related to the success rate, either across or within agencies.

The evidence in this table confirms the prediction that agency affiliates are more likely to be successful, that is, are higher quality, than non-affiliates employed for at least one job. This difference cannot be attributed to the increased likelihood of teamwork (measured by the employer simultaneously employing at least one other agency member) within agencies or by prior agency-employer interaction.

4.2 Probability of finding a second job

In order for the information revealed on the job to be more informative about non-affiliate quality, inducing a greater proportion of non-affiliates to be selected out of the market, the probability of being re-employed must be related to agency status.

The data follow individual workers over their entire oDesk careers to date. There are two possible explanations related to the probability of re-hire consistent with differential wage growth—either the lowest quality non-affiliates or the highest quality affiliates are being selected out of the market.

Table 8 presents a linear probability model where the dependent variable is equal to 1 if the worker is employed for a second job. The independent variables include an indicator for agency affiliation and a set of controls for the characteristics of the first job. Also included are worker-cohort fixed effects to control for differences in re-employment probabilities depending on when workers joined the site, along with worker country fixed effects. Column 1 includes job category fixed effects. The first row of Panel A shows the estimated coefficient for agency affiliation. Affiliates are significantly more likely to be employed for a second job. Columns 2 to 4 show this is particularly true for Data Entry and Web Programming jobs. In the latter case, affiliates are 10% more likely to be hired a second time.

A large part of agency affiliates' subsequent hiring success is due to their performance on the first job. In the following equation, the dependent variable is equal to 1 if worker i is hired for a second job on the site:

$$\begin{aligned} 1_i(ObserveSecondJob) &= \phi_0 + A_i\phi_{A,0} + Feedback_{i1}\phi_{Feedback} + A_i * Feedback_{i1}\phi_{A,Feedback} \\ &\quad + X_i\phi_X + A_i * X_i\phi_{A,X} + t + \varepsilon_i. \end{aligned} \tag{3}$$

Including the interaction of the feedback score on the first job and the variable indicating agency affiliation in this equation, $A_i * Feedback_{i1}$, permits flexible estimation of whether the information revealed from prior jobs has a differential impact on agency members' future career prospects. This is accomplished by testing whether the coefficient $\phi_{A,Feedback}$ is significantly different from zero. The coefficient on agency status indicates whether agency members persist in finding additional jobs after controlling for the results on the first job. Estimating a pooled model, combining affiliates and non-affiliates into a single sample, tests the restrictions $\phi_{Feedback} > 0$ and $\phi_{A,Feedback} < 0$.

Panel A presents the difference between agency affiliates and non-affiliates' probabilities of finding subsequent work without controlling for project results. Panel B presents the results when including the worker's feedback score on the first job as an independent variable, as well as the interaction of affiliation status and feedback score. These results are consistent with the hypothesis that workers receiving the best feedback scores remain in the market. The results for Web Programming are particularly interesting. An affiliate receiving a feedback score of 5 out of 5 increases the probability of being re-hired by $(5 \times (.04 - .02) - 1 \times .04 + .15) = 21$ percentage points compared to a non-affiliate receiving a score of 1 out of 5. A non-affiliate receiving a score of 5 out of 5 is 16 percent more likely than a non-affiliate receiving 1 out of 5 to be rehired. That is, a feedback score of 5 out of 5 closes more than half of the difference in the probability of being hired for a second job between affiliates and non-affiliates in Web Programming. The negative significant coefficient on the interaction of affiliation and feedback in this job category suggests that the feedback score received on the first job contains more information for non-affiliates than for affiliates, and that this information is used to select out the lowest performing non-affiliates.

Table 9 repeats the analysis of whether variation across or within agencies in affiliate outcomes is associated with team work or prior agency-employer interaction. The dependent variable is equal to 1 if the worker is hired for a second job. Similar to the findings for initial wages and first job success, affiliates working in agency teams on their first job are more likely to find a second job. However, this can mostly be attributed to the fact that agencies where affiliates are employed in teams are more likely to be rehired, whether the affiliate works on a team on his first job or not.

Because not all agency-affiliates continue working on oDesk after the first job, it is possible that only relatively low-quality agency members appear in the data as having a second job because, for example, high quality agency affiliates leave the market. More information is available about the quality of agency workers before the first job and, hence, initial wage rates among agents could be expected to be positively correlated with quality. The data reveal whether the agency affiliates who transition to a second job are those initially employed at a wage that is lower than the average initial wage for all new affiliates.

The left y-axis of Figure 5 gives the estimated probability that members and non-members 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 members and non-members find a second job does not appear to differ as a function of the wage on the first job. The figure does reveal some differences at the tails of the distribution of initial wages, however the density plots in Figure 5 (right y-axis) show that there are very few observations driving these outliers.

A formal test of whether worker characteristics that are observable at the time of the first hire, including the first wage, differentially affect the probability of observing second jobs for affiliates and non-affiliates, is done in the following linear probability estimation:

$$\begin{aligned} 1_i(ObserveSecondJob) &= \gamma_0 + A_i\gamma_{A,0} + \log Wage_{i1}\gamma_w + A_i * \log Wage_{i1}\gamma_{A,w} \\ &\quad + X_i\gamma_X + A_i * X_i\gamma_{A,X} + \varepsilon_i. \end{aligned}$$

where the X_i include all observable characteristics from the resume, job characteristics, and cohort dummies. The null hypothesis is that there is no differential selection into being employed for a second job based on initial wages or worker characteristics, or $\gamma_{A,W} = 0$ and $\gamma_{A,X} = 0$ for the subset of $\gamma_{A,X}$ on worker's observables. Appendix Table 4 presents these results for the linear probability model, and the results suggest differential selection on observables is not a problem. These results offer reassurance that, whereas initial wage appears to adjust to variation in worker characteristics that are observable from before the first job, the selection into subsequent jobs, for both members and non-members, is unrelated to initially observable characteristics once initial wages are controlled for.

5 Evidence from Firm Hiring Choices

Oyer and Schaefer (2010) emphasize that studies of employer hiring are relatively limited compared to studies of employee outcomes. The oDesk data enable a test of whether agency affiliation is associated with the relative likelihood of being hired and, by implication, associated with the value employers expect to gain from hiring a worker in this market. Under the hypothesis that agency affiliation signals that a worker is high quality, but that this information is revealed on-the-job, employers should be willing to pay higher wages to inexperienced agency affiliates than to inexperienced non-affiliates; among experienced workers, employers attribute no additional value to agency affiliation.

5.1 Conditional Logit Choice Model

To measure whether observed employer behavior is consistent with the hypothesis that agencies facilitate hiring by reducing incomplete information about inexperience affiliate workers, a conditional logit procedure can be used to model the probability an employer posting an hourly job hires an applicant as a function of the applicant's characteristics. The employer also has the ability to make no hire. 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 buyers know workers offline or from prior assignments.

Indexing job openings—rather than workers—with the subscript i, the firm that posts job opening i chooses one alternative j from the choices set J_i, where the size of the choice set varies across openings. Alternative $j = 0$ allows the firm to leave the market without hiring. The employer's payoff from choosing a given applicant is: $U_{ij} = \alpha + z_j\beta + \varepsilon_{ij}$ for $j > 0$, where z_j 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_{ij} is assumed to follow a type I extreme value distribution. The worker characteristics included in z_j are: an agency affiliation dummy, an indicator if the worker has been hired for exactly one job (revealing their quality), an indicator if the worker has been hired for at least two jobs (revealing that the worker is likely to be high quality), and interaction terms for each worker experience variable with agency affiliation. The model is estimated using two different definitions of agency affiliation. A worker's agency is defined as "established" if agency workers have, in total, been employed for four or more jobs. A worker is affiliated with a "well-established agency" if their agency members have collectively worked on at least 34 jobs in total.[19] Under the hypothesized role of agencies, the estimated coefficient on agency affiliation should be positive and the estimated coefficients on the interaction terms should be negative. Specifically, the sum of the estimated coefficients on the agency indicator variable and the interaction of the agency indicator variable with the variable indicating that it is publicly know that a worker is high quality is predicted to be insignificantly different from zero.

Table 10 presents the conditional logit results.[20] In each specification, there is a positive and

[19] These cutoffs correspond to the median and 90th percentile of the jobs-per-agency distribution.

[20] The likelihood function is then given by $L = \prod_i P_0^{y_{i0}} P_1^{y_{i1}} P_2^{y_{i2}} ... P_{J_i}^{y_{iJ_i}}$. The y_{ij} is a $((J_i + 1) \times 1)$ vector indicating

significant coefficient on the variable indicating that a worker has been employed for at least two jobs. This suggests workers with at least two prior jobs are valued more highly by employers, all else equal, consistent with the market selecting to rehire only high quality workers. The estimated coefficients on the wage rate bid are negative and significant, revealing that firms prefer to pay lower wages. Turning to the main coefficients of interest, the results in Columns 1 and 2 show that affiliation with an agency is positively valued by an employer, all else equal, and that affiliation with a well-established agency is particularly valuable. The estimated coefficients on the interaction of the indicators of agency affiliation and prior experience are negative and significant. This suggests that the increased probability of hire associated with being an agency member is partially offset when agency members have prior work experience (the comparison group is experienced non-members).

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 teams or because agencies provide information. The potential for complementarities arising from teamwork facilitated by agency affiliation are likely to be greater if the employer is searching for multiple workers. While the agency premium is greater for inexperienced workers affiliated with an agency for which the employer is hiring for multiple openings, the negative interaction between revealed quality and affiliation is also larger in magnitude for this group of employers (-1.284 in Column 3 compared to 0.971 in Column 4). These findings are consistent with the hypothesis that affiliates from agencies that engage in team work are better quality than affiliates from other agencies (as shown in the across-agency analysis in Tables 3, 7 and 9), but that the additional information provided by agency affiliation about worker quality is less useful once these affiliates' quality is revealed on-the-job.

the alternative chosen in opening i. The probability each alternative j is chosen is given by $P_j = \frac{1}{\sum\limits_{k \in J_i} e^{z_{ik}\beta - z_{ij}\beta}}$. The log likelihood is then $\ln L = \sum\limits_i \sum\limits_{j \in J_i} y_{ij} \ln P_j$. From the definition of P_j, it is clear that the probability an alternative j is chosen is generated by pairwise comparisons between the alternative j and alternatives $-j$. The constant α is identified from likelihood components involving $e^{z_{i0}\beta - z_{ij}\beta}$ or $e^{z_{ij}\beta - z_{i0}\beta}$. 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.

5.2 Addressing potential choice set endogeneity

The association between agency affiliation and the propensity to make 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. Under this possibility, applicants (and, in particular, affiliate applicants) might tailor their behavior to employer characteristics. If workers expect that a given employer is more likely to 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, bid rates are associated with an increased likelihood of hiring, as previously mentioned. However, a given worker's bid rate on different jobs should be unrelated to whether a hire is eventually made if that worker is unable to anticipate which jobs these are. 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 members or non-members, suggesting neither group tailors their bid 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 buyers are most likely to hire. This motivates an investigation of whether candidates are 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 to the opening within the first nine hours after the opening becomes visible. The results (shown in Appendix Table 6) suggest employers who are inundated with early applications are actually less likely to hire.

Taken together, the lack of significant association between worker actions (both for affiliates and non-affiliates) and ex post buyer hiring decisions support 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 can be interpreted as measures of the incremental employer payoffs associated with hiring workers with specific characteristics. The findings related to firm choices, hence, 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.

6 Conclusion

Incomplete information in supplier markets is a trade friction that limits the potential efficiency of task offshoring. This paper presents evidence that new types of organizations have sprung up to intermediate the relationship between employers and the suppliers of labor services by providing information about worker quality. Outsourcing agencies in the oDesk.com market appear to credibly signal that agency affiliates are higher-quality than non-affiliates.[21] Since information about worker quality is also revealed on the job in this market, the information conveyed by agency affiliation is most valuable for inexperienced workers.

The oDesk marketplace resembles the equilibrium outcome described in Tervio (2009), where, because the information about worker quality revealed on the job is a public good, an inefficiently low number of inexperienced workers are hired. Outsourcing agencies in oDesk.com reduce this inefficiency by preempting the public learning process. Employers appear willing to pay higher wages to inexperienced affiliates than to inexperienced non-affiliates because they believe affiliates are high quality, even though prior feedback on worker quality is unavailable for either group. The data on outcomes from the first job reveal that affiliates are, indeed, higher-quality on average. Affiliates are also more likely to be re-hired on the site, but non-affiliates with high feedback scores on the first job are almost as likely as affiliates to transition to a second job. The results suggest that feedback scores are, hence, more informative for non-affiliates. Evidence from firms' hiring choices confirms these findings.

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), there is limited evidence that the outsourcing agencies studied here provide complementary services that directly increase the productivity level, or rate of productivity growth, of affiliated workers. One of the leading theories for how agencies could help increase the value of affiliates to employers is through facilitating teamwork among agency affiliates. Although employers often hire workers

[21] According to oDesk.com senior management, the infrastructure built to accommodate agencies within the oDesk market was not designed for this purpose. Rather, it originated in an attempt to increase the number of workers on the site by creating incentives for existing workers to encourage new workers to sign up.

from the same agency, and workers in these agencies are typically paid higher initial wages, the agency premium in these cases is more strongly associated with an agency fixed effect than with a teamwork effect within agency. There is also limited evidence that agencies provide complementary services only at the start of affiliates' oDesk careers, or that affiliates experience less productivity growth on the job.

This study also relates to the empirical literature on incomplete information in online consumer product markets, in which the product being sold is analogous to the labor services provide by an oDesk worker.[22] Lewis (2010) 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. In their work on the loan market Prosper.com, Freedman and Jin (2008) find that borrower affiliation with a social network is not associated with borrower quality. They suggest that this is due to characteristics of the market design, which limit incentives for group founders to grant membership only to good-quality borrowers.[23] In the oDesk setting, an agency head has a strong incentive to maintain the average feedback score (and, hence, member quality) within the agency, not only because this affects his own future earnings, but also because he collects a fraction of the revenues earned by all other members.

The fact that members of the same agency tend to share many observable characteristics and appear to know each other offline likely facilitates screening.[24] Putting these facts together leads to the conclusion that offline social ties among groups of remote workers are the source of complementarity between agencies and employees on oDesk.com. The information embodied in social ties allows agencies to discern worker quality, to affiliate only high- quality workers, and to credibly signal that affiliation is correlated with worker quality. This reduces the inefficiencies associated with public quality revelation on the site. However, it also suggests there are limits to agency

[22]Resnick and Zeckhauser (2002),Bajari and Hortacsu (2004), and Houser and Wooders (2006) discuss the economics of Internet auctions and summarize the empirical evidence on the relationship between seller feedback and price. Because individual feedback is highly correlated with future earnings, oDesk workers appear to face strong incentives to refrain from moral hazard, and do not require a relatively long-lived intermediary to create this incentive (as is the case in Biglaiser and Friedman, 1994).

[23]Interestingly, Freedman and Jin (2008) find that borrowers affiliated with groups defined by tangible connections, such as alumni of the same school, do perform better. They attribute this to increased incentives for social monitoring within these groups.

[24]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.

size related to the size of each agency head's personal offline network. The mechanisms outlined also suggest limits to the number of potential new agencies. Since affiliation is fixed throughout a worker's career, new agencies can only be formed by good-quality non-affiliates who are fortunate enough to be hired and, hence, given the opportunity to have their quality revealed.

The analysis of this new market for remote services provides evidence that intermediaries can serve to reduce inefficiencies resulting from incomplete information. The intermediaries studied in this paper are especially prevalent in low-wage countries and in job categories for which it is harder to verify quality—in other words, precisely where information about quality is particularly incomplete. The means by which agencies facilitate hiring in the oDesk market—experienced, high-quality workers' ability to screen inexperienced workers' quality, among their pre-existing offline ties—also restrict the extent to which agencies can fully resolve information incompleteness. This is because there appear to be limits to the size of any one agency, as well as limits to the number of new agencies. Overall, then, incomplete information about provider quality is likely to hinder the rate at which jobs that are technically offshorable (as measured in Blinder and Krueger, 2009) are, in fact, offshored.

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Appendix 1: A Framework illustrating the role of Agencies

This appendix presents a simple game to illustrate how agencies can serve to credibly signal that inexperienced agency-affiliates are high quality—the primary agency function present in the data.[25] The model is in discrete time with an information structure similar to Tervio (2009), where worker quality is revealed on the job. New generations of workers enter the labor market in each period and compete with existing workers to find jobs. In what follows, there are two worker quality levels—low and high quality. The equilibrium predictions from the model are robust to assuming there is a distribution of worker quality, where the agency affiliates workers above a quality threshold, so that the distribution of worker quality among affiliates is the truncated-below distribution of non-affiliate worker types in the data. The following subsections describe the game and characterize a steady-state perfect Bayesian equilibrium which resembles observed outcomes in the data.

A1.1 Game Structure

There are three types of players: workers, employers (firms or buyers), and an agency.[26]

Workers. Worker quality (productivity) is given by θ, which is unknown to both workers and employers upon entering 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 $H > L$. E workers arrive in the oDesk market in each period. An exogenous fraction of arriving workers, S, is connected to the agency. The worker's objective is to maximize lifetime earnings. Each worker can be employed for a maximum of two periods, and has a per-period outside option w_0, which is normalized to zero.[27] Quality, θ, is publicly revealed after the first employment spell. All potential employers observe output on every completed job.

Employers. There are N employers (firms) that hire a single worker in each period.[28] Each

[25] If agencies serve to increase worker productivity directly, affiliates are predicted to be paid more on the first job. Depending on the nature of the complementarities between affiliation and worker productivity, the agency premium might persist over time, or might decrease or increase. 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 for why it might diminish over time.

[26] Including only one agency mirrors the hypothesis that any one agency has a local monopoly and is unable to screen workers connected to any other agency.

[27] Because workers don't know their type prior to the first employment spell, the initial outside option is independent of worker quality.

[28] While job heterogeneity is an important feature of the oDesk environment, this section analyzes a representative employment relationship to provide intuition. The empirical work in sections 3, 4, and 5 controls for observable firm

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

Agency. The agency owns a screening technology that can determine the quality of the fraction of connected inexperienced workers arriving in the market, S.[29] In what follows, it is assumed that S is small enough, relative to N, that the total number of (experienced and inexperienced) agency-affiliated workers in the market in each period is less than the number of hiring firms. The agency chooses whether to offer affiliation to each screened inexperienced worker. Workers offered agency affiliation choose whether to accept the offer or join the pool of non-member new workers. Agency membership lasts throughout the worker's career.[30] The agency collects an endogenously determined fraction $(1 - \beta)$ of each agency member'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 each post a single job opening. (2) E new workers enter the marketplace, S of these new workers are screened by the agency. The agency offers affiliation to a subset of screened workers. (3) Workers offered agency affiliation choose whether to affiliate under the revenue sharing agreement defined by the contract β. (4) The N firms in the market hire one of: an experienced worker in the second period of their working life, a new agency-affiliated worker, or a worker from the pool of available inexperienced workers. The wage paid to a known high-quality worker is w_H, the wage paid to an agency affiliate is w_A, and the wage paid to an inexperienced worker drawn from the pool is $w_{\overline{\theta}}$. If wages are paid to known type L workers, these wages are w_L. Each worker offered a job decides whether or not to accept. (5) Production takes place, wages are paid to the workers, the agency collects its revenues, and the quality of all newly-employed workers is revealed.

and job characteristics. Reflecting the oDesk environment, it is assumed that the number of employers, N, is small relative to E, which determines the number of workers available for employment in each period.

[29] S is assumed to be exogenous since the boundaries of an agency are often determined by offline networks. Offline interaction confers the ability to screen.

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

A1.2 A Perfect Bayesian Equilibrium

There is a perfect Bayesian equilibrium to this game with the following features: (1) The agency only accepts screenable workers with type $\theta = H$. (2) Screenable $\theta = L$ type workers exit the market without finding work. (3) Workers wage bids are such that $w_{\bar{\theta}} < w_L \geq w_0$ and $w_{\bar{\theta}} < w_A = w_H$.[31] In this equilibrium, workers unconnected to the agency are indifferent between entering oDesk and working off the platform. Employers are indifferent between hiring a worker known to be high quality, hiring an inexperienced agency member, and drawing from the pool of unknown workers. Employers strictly prefer to hire unknown workers rather than type L workers. High quality screened workers are indifferent between affiliating with the agency and remaining independent.

In this equilibrium, inexperienced non-members pay for information revelation: unscreened workers are willing to accept wages below their reservation wage, $w_{\bar{\theta}} < w_0$, because with probability h they will receive w_H in the second period of their career. Wages equilibrate such that employers are indifferent between hiring a known H type, hiring a novice agency affiliated worker, and hiring a novice unscreened worker.

The agency contract takes a portion of affiliates' wages. If a worker is screenable, an H type screened worker learns he is high quality and will receive w_H in the second period of his working life. If a screened worker does not join the agency, he would be willing to accept a wage $w_{\bar{\theta}} - \varepsilon < w_0$ in the first period of his working life, where $\varepsilon > 0$. This implies that screened H type workers are hired in the first period with probability 1, with or without the agency. The agency contract takes this into account, and makes the worker indifferent between receiving lifetime income $w_{\bar{\theta}} + w_H$ and receiving $\beta\left(w_A + w_H\right)$. Given employer beliefs, the value of the stream of future revenues from never allowing an L type worker into the agency is greater than the maximum deviation payoff for an agency.[32]

A more detailed description of the equilibrium follows:

[31] We impose the following assumptions on the relative magnitudes of model parameters: (1) $H - \frac{(1-h)}{(1+h)}(H-L) \geq c$. (2) $E > \frac{N-2hS}{1+h}$. (3) $N > h + 2hS$.

[32] As long as the agency has a sufficiently high discount rate.

Equilibrium Strategies and Beliefs

Workers. Unscreened workers have expected career earnings equal to their outside wage. Employment in the first period of their working life reveals their type. If they are high quality, they receive w_H in the second period of their working life. This means $w_{\overline{\theta}}$ solves $w_{\overline{\theta}} + hw_H = 2w_0 = 0$, so $w_{\overline{\theta}} < w_0 = 0$.[33]

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, screened workers who know their type could signal to firms that they are high quality, guaranteeing employment and receiving a wage of w_H in the next period. A screened H type 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 his lifetime earnings on joining the agency are $2\beta w_H$. The agency sets β so that screened H type workers are indifferent between affiliating and signaling their quality with a low wage bid in the first period: $2\beta w_H = w_{\overline{\theta}} - \varepsilon + w_H$ with $\varepsilon \to 0$. Indifferent workers offered affiliation choose to affiliate with the agency.

Because 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 be below w_0. Similarly, inexperienced screened workers who learn they are low quality when they are not offered agency affiliation drop out of the market. Because no screenable workers join the unknown pool, the distribution of worker quality in the pool mirrors the overall workforce, and the expected quality of a draw from the pool is: $\overline{\theta} = (1-h)L + hH$.

Employers. Each employer believes that an agency affiliated worker is high quality with probability 1. If a firm ever observes a low quality agency worker, it believes all agency workers are high quality with probability 0.

The number of firms N exceeds the number of known high quality workers in the market, including new agency members; the wage for each worker type makes firms indifferent between hiring a known H type at wage w_H and drawing from the pool at the wage $w_{\overline{\theta}}$. The size of the

[33] The "break even" condition for new non-screenable workers is: $p(w_{\overline{\theta}} + hw_H) = 0$, where p is the probability a new worker is drawn from the pool. In this equilibrium, wages adjust so that the term in parentheses is equal to zero whatever the number of workers in the pool and hence the probability a given worker in the pool is employed. This means p, and hence E, are only determined by $E > D$.

inexperienced worker pool is sufficiently large such that $w_{\overline{\theta}}$ makes an inexperienced worker in the labor pool indifferent between taking the job offer and remaining unemployed in the first period of his life. It is assumed that the firm makes non-negative profits in expectation when drawing from the pool. The equilibrium wage of known high quality workers, w_H, is set such that $\pi_H = \pi_{\overline{\theta}}$, or, $H - c - w_H = \overline{\theta} - c - w_{\overline{\theta}}$. The agency wage is $w_A = w_H$.

Agency. The agency believes that as long as all agency members in the past have been high quality, then $w_A = w_H$ for each employed agency member. The agency screens S new workers and offers affiliation only to the H types, under a contract where the agency collects $(1-\beta)$ of affiliates' wages. In expectation, there are hS workers who join an agency each period.

Payoffs and Deviations

Workers. New agency affiliates are hired with probability 1 in each period. They receive lifetime payoffs equal to $2\beta w_A = 2\beta w_H$. There are no profitable deviations for these workers in either period of their working lives, since bidding a higher wage means unemployment.

Payoffs for unaffiliated high quality workers are $p(w_{\overline{\theta}} + w_H) > 0$, and $p(w_{\overline{\theta}} + 0) < 0$ for an unaffiliated low quality worker. It is never profitable for an unscreened inexperienced worker to deviate by bidding a wage $w' \neq w_{\overline{\theta}}$. Bidding a wage below $w_{\overline{\theta}}$ implies negative expected lifetime payoffs (below w_0). Bidding a wage above $w_{\overline{\theta}}$ means the worker is not hired, so the lifetime payoff is 0.

Firms. The condition that firms are indifferent between hiring from the pool and hiring a known high quality worker or new agency member, together with the zero expected lifetime payoff of unscreened workers, gives: $w_H = \frac{(1-h)}{(1+h)}(H-L)$, and $w_{\overline{\theta}} = -h\frac{(1-h)}{(1+h)}(H-L)$. The expected payoff for each firm is: $\pi = H - c - \frac{(1-h)}{(1+h)}(H-L)$. Because wages for known high types and inexperienced agency members are decreasing in the proportion of high types in the population, h, firm profits are increasing in the proportion of high types in the population.

Agency. Since there are $2hS$ agency members employed in the market, agency revenues in each period are: $R_A = 2hS(1-\beta)w_H > 0$.[34] Given the employers' beliefs, the agency's maximal payoff from deviating and letting L types into the agency is $2hS(1-\beta)w_H + (1-h)Sw_H$. The agency can

[34]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 $\epsilon = \frac{\varepsilon}{2w_H}$.

take $w_H - w_0$ of an L type's wages. This payment would occur in a single period because employers would then believe agency candidates are high quality with probability 0. Recall $\beta = \frac{w_{\bar{0}}+w_H}{2w_H}$; this is the maximal agency contract subject to the H type worker's participation constraint. The agency will not deviate for any discount rate δ satisfying

$$\frac{2hS\left(1-\beta\right)w_H}{1-\delta} \geq 2hS\left(1-\beta\right)w_H + \left(1-h\right)Sw_H. \tag{4}$$

A1.3 Efficiency Implications

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.[35] A fraction of firms employ known high quality workers or new agency members, 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 workers known to be high quality remaining in the labor force from the previous period, and less the number of new agency members. 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:

$$Y = NH - \left(\frac{1-h}{1+h}\right)\left(N-2hS\right)\left(H-L\right) - Nc. \tag{5}$$

Setting $S = 0$ in equation 5 denotes net output in an economy with no agency. Comparative statics with respect to S provide efficiency implications. The first derivative of equation 5 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.[36]

[35] It is assumed that there are no additional fixed costs associated with agency screening. This is reasonable if the ability to screen is associated with pre-existing social connections.

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

A1.4 Empirical Predictions

This equilibrium provides the theoretical grounding for the predictions related to worker histories that are observed in the data. The first set of predictions relates to the first job. Since agency members are expected to be higher quality than unscreened workers on average, agency members are predicted to receive higher initial wages than non-members (shown empirically in Section 3.1). Agency members' first projects are also more likely to be successful (shown in Section 4.1). In addition, agency members are predicted to be hired immediately, whereas non-agency members 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 members 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 hence 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 workers are high quality in equilibrium, all are rehired. Finally, agency affiliates are predicted to experience no wage growth but those unscreened workers who are rehired experience wage growth of $(w_H - w_{\overline{\theta}})$ between their first and second job. This is due to a selection effect and an employer learning effect. The L type non-members leave the market, whereas the H type non-members 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 agencies credibly signal that affiliates are high quality, has an prediction of the described equilibrium 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.[37] Each additional application is treated as a different "search" spell, and unsuccessful

[37] The data include a single spell of initial job search for each worker, so it is not possible to use multiple spells to

applications are censored. This yields a setup incorporating time varying covariates for each worker. As in the wage analysis, including specifications that limit the sample to relatively homogenous workers in just a few job categories helps mitigate concerns that unobserved composition differences stemming from job categories or countries affect relative differences in delay in finding work across agency members and non-members.

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. The table also shows that higher hourly bids are associated with longer job search durations.[38]

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.

[38] 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.

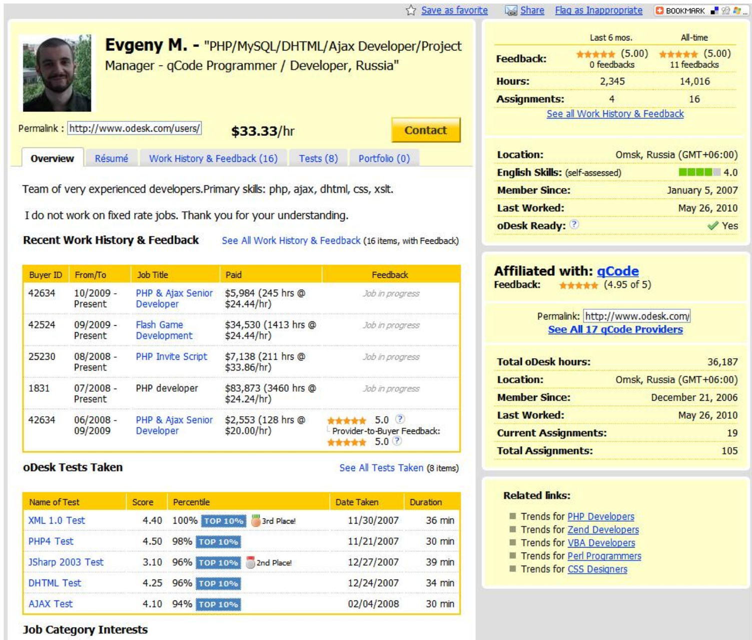

Figure 1: An example worker profile. The feedback score is in the top right corner, and the agency brand appears as "qcode". The work history on recent jobs is instantly visible in the middle of the screen.

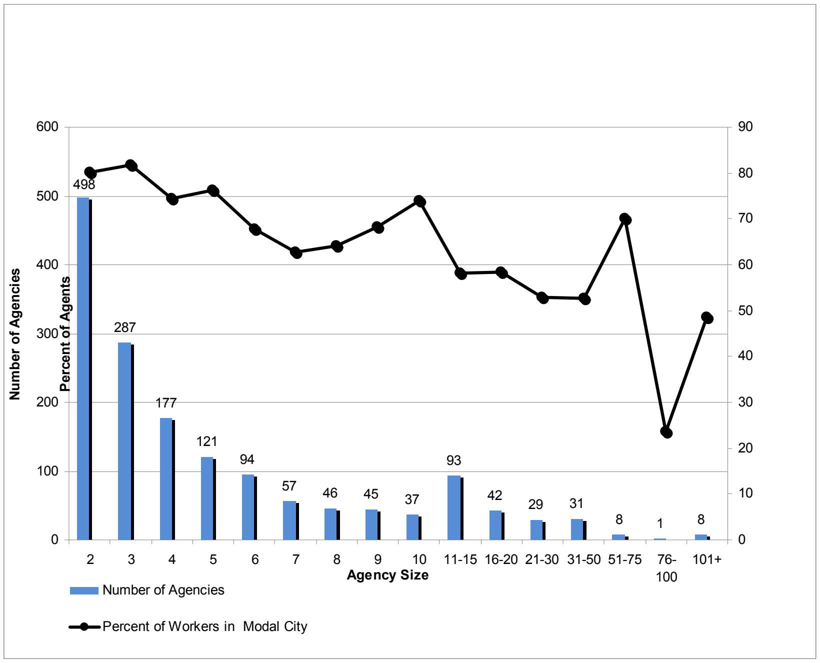

Figure 2: The number of agencies (by size) and the concentration of workers in the agency's modal city. The modal city measure under estimates geographic concentration because of different city spellings and the lack of accounting for suburbs and nearby towns.

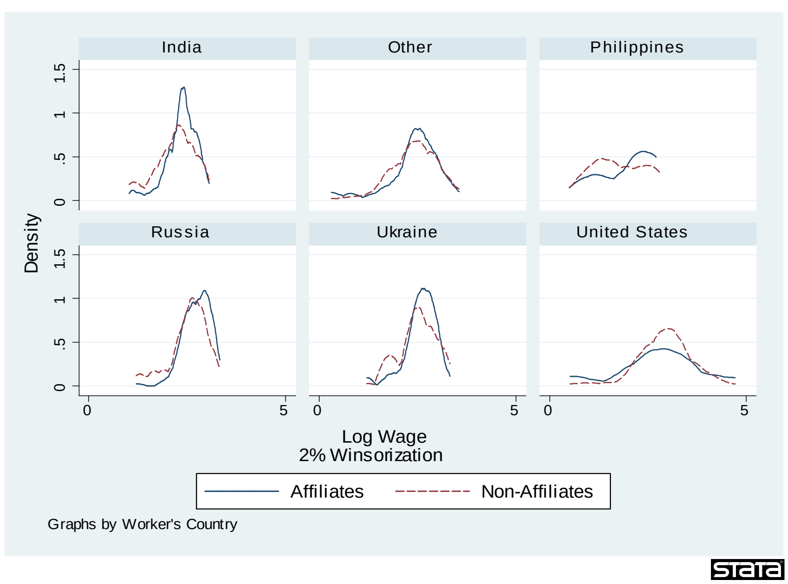

Figure 3: Density of log wages on the first job in Web Programming, split by country. Wages are winsorized at the 2% level by country.

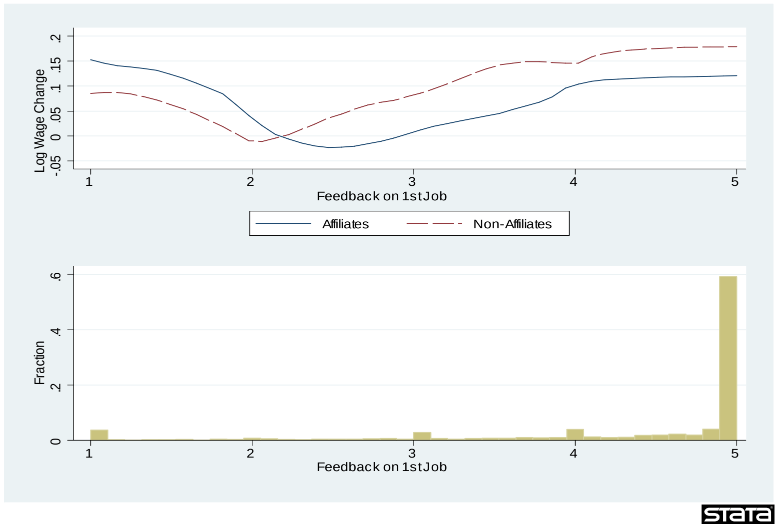

Figure 4: The top panel provides the relationship between log wage changes and feedback on the first job. Workers without feedback on the first job are excluded. The figures are constructed from Kernel-weighted local polynomial smoothed estimates. The bottom panel is a histogram of feedback scores on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

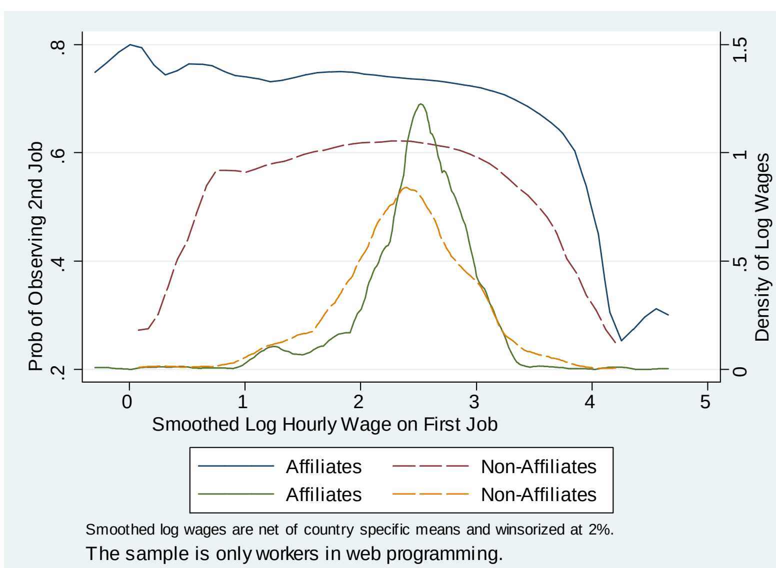

Figure 5: The left y-axis gives the estimated probability of survivorship as a function of the wage on the first job. The right y-axis gives the density of wages. Log wages on the x-axis are net of country-specific fixed effects from a first-stage regression. These wages are then winsorized at the 2% level by country.

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	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	0.4	0.35**	0.41	0.39	0.37	0.32	0.36	0.32**
Taken 1 or More Tests Indicator	0.78	0.59**	0.82	0.66**	0.77	0.60**	0.70	0.55**
Log Hourly Wage	1.61	1.91**	0.29	0.31	2.09	2.23**	2.42	2.41
Standard Deviation of 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	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 1 or More Tests Indicator	0.66	0.51**	0.70	0.60**	0.89	0.81**	0.77	0.68**
Log Hourly Wage	1.62	2.03**	2.53	2.72**	0.71	0.90**	2.19	2.34**
Standard Deviation of 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). Workers whose first bid occurs prior to August 1, 2008 are excluded. Asterisks ** indicate that t-tests reject equality of the means between the non-affiliates and corresponding affiliates values at the 5% level. For the standard deviation, 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 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 joining the site after August 1, 2008)				
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	1.94	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 Table 3 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 the first hourly hire and first hourly bid, respectively. Workers whose first bid occurs prior to August 1, 2008 are excluded. 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 covariates 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. 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 Wage Regressions for Affiliate 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								
Team Work	0.10***	0.10***	0.03	0.05	0.08	0.06	0.06	0.09**
	(0.024)	(0.024)	(0.103)	(0.110)	(0.058)	(0.083)	(0.039)	(0.041)
Number of Prior Hires for Agency-Employer Pair		0.00		0.00		-0.04		0.00
		(0.001)		(0.004)		(0.027)		(0.004)
Interaction of Team Work and Prior Agency-Employer Hires		-0.00		-0.01		0.02		-0.01*
		(0.001)		(0.006)		(0.031)		(0.005)
Number of Workers	4179	4179	298	298	479	479	1223	1223
R-squared	0.623	0.624	0.471	0.472	0.291	0.303	0.261	0.269
Panel B. Regressions with Agency Fixed Effects								
Team Work	0.03	0.03	0.15	0.15	-0.06	-0.07	-0.05	-0.03
	(0.021)	(0.022)	(0.115)	(0.121)	(0.079)	(0.101)	(0.031)	(0.033)
Number of Prior Hires for Agency-Employer Pair		-0.00		0.02		-0.01		-0.00
		(0.001)		(0.024)		(0.028)		(0.005)
Interaction of Team Work and Prior Agency-Employer Hires		-0.00		-0.02		0.01		0.00
		(0.001)		(0.026)		(0.030)		(0.005)
Number of Workers	4179	4179	298	298	479	479	1223	1223
R-squared	0.908	0.909	0.938	0.939	0.873	0.874	0.888	0.891

Notes: Standard errors in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a unique worker on the first hourly hire. Workers whose first bid occurs prior to August 1, 2008 are excluded. Only agency affiliates are included in the sample. The dependent variable is the log hourly wage. In the panel A, regressions are across agency. Team work 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. "Interaction" captures the combined effect of agency-employer firm relationship longevity and team work. In panel B, fixed effects for each agency are included. All columns contain the same controls as the original wage decomposition shown in Table 2.

Table 4: Summary Statistics for Experienced Workers

	Non-Affilliates	Affiliates	Non-Affilliates	Affiliates	Non-Affilliates	Affiliates
	Data Entry		Web Design		Web Programming	
Log Hourly Rate	1.00	0.90	2.30	2.42**	2.51	2.53
	(0.67)	(0.87)	(0.59)	(0.44)	(0.5)	(0.39)
Good English Skills Dummy	0.99	0.98	0.97	0.96	0.93	0.96
	(0.12)	(0.16)	(0.18)	(0.19)	(0.25)	(0.2)
BA Degree or Higher	0.92	1.00**	0.90	0.90	0.94	0.94
	(0.27)	(0.00)	(0.31)	(0.3)	(0.24)	(0.24)
Number of Total Hires	18.21	16.76	22.26	18.44	19.07	16.6
	(20.33)	(17.98)	(25.88)	(15.17)	(21.33)	(14.68)
Feedback Score	4.77	4.56**	4.66	4.66	4.66	4.63
	(0.33)	(0.61)	(0.46)	(0.46)	(0.47)	(0.48)
Number of Workers	211	41	277	159	335	270

Notes: The sample is experienced workers with three or more total hires and non-zero feedback who are hired for subsequent jobs. 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.

Table 5: Wage Change between First and Second Jobs, Estimated Linear Combinations of 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, 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: 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 2 or more hourly jobs. Workers whose first bid occurs prior to August 1, 2008 are excluded. Data cleaning involved dropping workers whose wages decline by more than 70% because these workers are likely paid off the platform (disintermediation). This affects 67 observations. 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.

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 the first hourly hire. Workers with bids prior to August 1, 2008 are excluded. 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) only include workers in India and Russia. A dummy variable for India is included Columns (2)-(4).

Table 7: Success on First Job Regressions for Affiliate 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								
Team Work	0.06***	0.06***	0.05	0.02	0.04	0.09	0.07**	0.07**
	(0.017)	(0.017)	(0.073)	(0.077)	(0.056)	(0.071)	(0.032)	(0.034)
Number of Prior Hires for Agency-Employer Pair		-0.00		-0.01		0.02		0.01
		(0.001)		(0.007)		(0.014)		(0.005)
Interaction of Team Work and Prior Agency-Employer Hires		0.00		0.01		-0.02		-0.00
		(0.001)		(0.008)		(0.017)		(0.005)
Number of Workers	3717	3717	280	280	425	425	1069	1069
R-squared	0.077	0.077	0.191	0.199	0.143	0.147	0.087	0.091
Panel B. Regressions with Agency Fixed Effects								
Team Work	0.03	0.03	-0.26*	-0.28*	0.00	0.02	0.04	0.05
	(0.023)	(0.024)	(0.136)	(0.145)	(0.105)	(0.142)	(0.046)	(0.050)
Number of Prior Hires for Agency-Employer Pair		0.00		0.00		0.04		0.01
		(0.001)		(0.030)		(0.040)		(0.006)
Interaction of Team Work and Prior Agency-Employer Hires		-0.00		0.01		-0.02		-0.01
		(0.001)		(0.033)		(0.044)		(0.007)
Number of Workers	3717	3717	280	280	425	425	1069	1069
R-squared	0.539	0.539	0.799	0.804	0.777	0.781	0.597	0.600

Notes: Standard errors in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a unique worker on the first hourly hire. Workers whose first bid occurs prior to August 1, 2008 are excluded. Only agency affiliates are included in the sample. 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. Team work 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. "Interaction" captures the combined effect of agency-employer firm relationship longevity and team work. In panel B, fixed effects for each agency are included. All columns contain the same controls as the original wage decomposition table 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 as a Function of Project Results

	All Categories (1)	Data Entry (2)	Web Design (3)	Web Programming (4)
Panel A. Estimates without first job output measures				
Agency Affiliate Indicator	0.12***	0.23***	0.00	0.10***
	(0.010)	(0.032)	(0.036)	(0.022)
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	0.147	0.232	0.195	0.190
Panel B. Estimates including first job feedback measures				
Agency Affiliate Indicator	0.12***	0.26***	-0.00	0.15***
	(0.017)	(0.062)	(0.060)	(0.037)
Feedback on First Job	0.02***	0.02***	0.02**	0.04***
	(0.002)	(0.007)	(0.011)	(0.007)
Agency Affiliate x Feedback on First Job	0.00	0.01	0.00	-0.02*
	(0.004)	(0.020)	(0.015)	(0.009)
Observations	12794	1252	892	2206
R-squared	0.156	0.246	0.206	0.214

Notes: Standard errors in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a unique worker on the first hourly hire. Workers whose first bid occurs prior to August 1, 2008 are excluded. 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 has job category dummies. Columns (2) through (4) restrict the sample by job category.

Table 9: Probability of Finding a Second Job for Affiliate 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								
Team Work	0.03**	0.04***	0.21***	0.20***	-0.03	-0.03	0.02	0.02
	(0.014)	(0.014)	(0.046)	(0.047)	(0.049)	(0.059)	(0.026)	(0.027)
Number of Prior Hires for Agency-Employer Pair		-0.00		-0.00		-0.02*		0.00
		(0.001)		(0.006)		(0.013)		(0.004)
Interaction of Team Work and Prior Agency-Employer Hires		-0.00**		-0.00		0.01		-0.00
		(0.001)		(0.008)		(0.016)		(0.004)
Number of Workers	4179	4179	298	298	479	479	1223	1223
R-squared	0.141	0.148	0.287	0.302	0.153	0.163	0.157	0.157
Panel B. Regressions with Agency Fixed Effects								
Team Work	-0.01	-0.00	0.08	0.09	-0.00	0.06	0.00	0.00
	(0.018)	(0.018)	(0.070)	(0.074)	(0.080)	(0.105)	(0.035)	(0.038)
Number of Prior Hires for Agency-Employer Pair		-0.00*		0.02		0.01		0.00
		(0.001)		(0.016)		(0.027)		(0.005)
Interaction of Team Work and Prior Agency-Employer Hires		0.00		-0.01		-0.02		-0.00
		(0.001)		(0.017)		(0.029)		(0.005)
Number of Workers	4179	4179	298	298	479	479	1223	1223
R-squared	0.591	0.594	0.843	0.849	0.797	0.798	0.652	0.652

Notes: Standard errors in parentheses, and *** p<0.01, ** p<0.05, * p<0.1. An observation is a unique worker on the first hourly hire. Workers whose first bid occurs prior to August 1, 2008 are excluded. Only agency members are included in the sample. 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. Team work 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. "Interaction" captures the combined effect of agency-employer firm relationship longevity and team work. In panel B, fixed effects for each agency are included. All columns contain the same controls as the original wage decomposition table 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

	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 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 August 1, 2008 and November 1, 2009 in Web Programming. Job openings where the employer initiates some contacts 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 4 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 other workers.

Appendix Table 1: Summary Statistics for Workers' First Bids

	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 Bidding	112782	12019	25757	1152	8784	1912	7041	2735
Good English Skills Indicator	0.55	0.8**	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). Workers whose first bid occurs prior to August 1, 2008 are excluded. Asterisks ** in the Affiliate column indicate that t-tests reject equality of the means between the Non-Affiliates and corresponding Affiliates values at the 5% level. For the standard deviation, 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

Generates Linear Combinations 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: 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 2 or more hourly jobs. Workers whose first bid occurs prior to August 1, 2008 are excluded. Data cleaning involved dropping workers whose wages decline by more than 70% because these workers are likely paid off the platform (disintermediation). This affects 67 observations. 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) are 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 Transitions

	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 2 or more hourly jobs. Workers whose first bid occurs prior to August 1, 2008 are excluded. Data cleaning involved dropping workers whose wages decline by more than 70% because these workers are likely paid off the platform (disintermediation). This affects 67 observations. 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 allows 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 (1)	Data Entry (2)	Web Design (3)	Web Programming (4)
Main Effects				
Log Hourly Wage	-0.02***	0.00	-0.02	-0.00
	(0.007)	(0.018)	(0.029)	(0.021)
Good English Skills Dummy	0.21***	0.16***	0.18*	0.14***
	(0.016)	(0.036)	(0.090)	(0.037)
BA Degree or Higher	0.00	0.05**	0.05	0.01
	(0.011)	(0.018)	(0.044)	(0.041)
Pre oDesk Years Experience	-0.00	-0.00	0.00	0.00
	(0.001)	(0.005)	(0.006)	(0.004)
Agency Affiliate Interactions				
Log Hourly Wage	-0.02	0.00	0.02	-0.05
	(0.012)	(0.028)	(0.055)	(0.029)
Good English Skills Dummy	-0.03	0.01	0.02	-0.01
	(0.025)	(0.037)	(0.140)	(0.031)
BA Degree or Higher	-0.02	-0.08**	-0.06	0.04
	(0.020)	(0.038)	(0.052)	(0.058)
Pre oDesk Years Experience	0.01	0.02***	-0.01	-0.01
	(0.027)	(0.005)	(0.010)	(0.007)
Observations	12794	1252	892	2206
R-squared	0.16	0.264	0.24	0.204

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. Workers whose first bid occurs prior to August 1, 2008 are excluded. 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 specification contain main effects and agency interactions for all right hand side variables except country fixed effects (not reported). No interactions are statistically significant if they are not reported.

Appendix Table 5: Log Wage Regressions Measuring Strategic Bidding

	Pooled		Agency Members		Non-Members	
	(1)	(2)	(3)	(4)	(5)	(6)
Employer Hires Someone	-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 August 1, 2008 and November 1, 2009 in Web Programming. Job openings where the employer initiates some contacts 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

	All Applications	Agency Affiliate Applications	Non-Affiliate Applications
	(1)	(2)	(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 9 hours after a job application 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. We use this sample because we noticed some strange 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 (1)	Data Entry India and Russia Only (2)	Web Design India and Russia Only (3)	Web Programming India and Russia Only (4)
Log Hourly Rate	0.53***	0.62***	0.62***	0.63***
	(0.008)	(0.023)	(0.023)	(0.023)
Agency Affiliate Indicator	1.30***	1.47***	1.49***	1.44***
	(0.059)	(0.099)	(0.100)	(0.093)
Bid Number	1.01***	1.01***	1.01***	1.01***
	(0.000)	(0.001)	(0.001)	(0.001)
Number of Fixed Price Hires	1.24***	1.29***	1.29***	1.29***
	(0.013)	(0.026)	(0.026)	(0.025)
Worker is from India		0.69	0.84	0.24***
		(0.692)	(0.247)	(0.030)
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. Workers whose first bid occurs prior to August 1, 2008 are excluded. All columns include skill and experience controls similar to the Oaxaca-Blinder specifications. Column (1) includes country and job category indicators.