Christopher Stanton and Catherine Thomas

Landing the first job: the value of intermediaries in online hiring

Article (Accepted version) (Refereed)

Original citation:
Stanton, Christopher and Thomas, Catherine (2016) Landing the first job: the value of intermediaries in online hiring. Review of Economic Studies, 83 (2). pp. 810-854. ISSN 0034-6527
DOI: 10.1093/restud/rdv042

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

Christopher Stanton, London School of Economics

Catherine Thomas, London School of Economics†

October 2014

Abstract

Online markets for remote labor services allow workers and firms to contract with each other directly. Despite this, intermediaries—called outsourcing agencies—have emerged in these markets. This paper shows that agencies signal to employers that inexperienced workers are high quality. Workers affiliated with an agency have substantially higher job-finding probabilities and wages at the beginning of their careers compared to similar workers without an agency affiliation. This advantage declines after high-quality non-affiliated workers receive good public feedback scores. The results indicate that intermediaries have arisen endogenously to permit a more efficient allocation of workers to jobs.

Keywords: Labor market intermediation, offshoring, incomplete information.

JEL codes: F16, J30, D02, O30.

*We are grateful to Gary Swart, Anand Hattiangadi, Josh Breinlinger, Dmitry Diskin, and Sean Kane at oDesk for their help with this project. We thank Tim Bresnahan, Boğaçhan Çelen, Stephen Chaudoin, Pascal Courty, Liran Einav, Alex Hirsch, Marina Halac, John Horton, Caroline Hoxby, Amit Khandelwal, Bruce Kogut, Eddie Lazear, Claire Lim, Ben Lockwood, Luis Rayo, Jonah Rockoff, Nathan Seegert, Kathryn Shaw, Adam Szeidl, Ali Yurukoglu and numerous seminar participants for helpful comments and discussions.

†Email: C.Stanton@lse.ac.uk; c.m.thomas@lse.ac.uk. This research was funded in part by the Ewing Marion Kauffman Foundation. The contents of this paper are solely the responsibility of Christopher Stanton and Catherine Thomas. Stanton thanks the Kauffman Foundation for generous support for "Entrepreneurship Through Online Outsourcing."

1 Introduction

Online hiring markets allow employers to view ratings of workers' historical performance, but new workers entering these markets do not have feedback or other verified performance data. In the absence of prior experience, workers may not know their quality, or know how to communicate it to potential employers in different countries. This paper presents evidence that organizations called outsourcing agencies have sprung up within these markets to intermediate between workers and employers by providing information about inexperienced worker quality.

The largest online labor market, oDesk.com, which is the setting studied in this paper, was designed explicitly for firms to contract directly with workers, eliminating the need to send work abroad through specialist IT-services firms.[1] To the surprise of oDesk's management, more than 1,100 small autonomous intermediary organizations called outsourcing agencies entered the oDesk market within its first few years. Outsourcing agencies operate within the oDesk platform, but contracting, monitoring, and work direction still take place between employers and individual workers.

Prior to the emergence of online outsourcing markets like oDesk, Autor 2001(a) predicted that online labor markets would require new types of intermediaries to perform two roles: first, to reduce information frictions and, second, to increase the productivity of remote workers. The main finding in this paper is that intermediary agencies perform the first of these roles: they reduce information frictions in the market by screening workers and communicating the results to employers. Under an assumption that workers and firms have symmetric information conditional on observed worker characteristics, the agencies in the market are estimated to have improved matching efficiency by about 11 percent during the sample period.[2] Their role in increasing worker productivity directly appears limited.

A brief description of oDesk and the structure of agencies provides context for the analysis. The hiring process begins when an employer posts a job opening, looking to hire a single worker. Workers provide hourly wage offers in their job applications, and the employer evaluates these offers alongside resume profiles when deciding which applicant, if any, to hire. After a job ends, the employer is asked to leave public feedback for the worker, and this feedback automatically enters the worker's profile if payment for the job is accepted. Figure 1 provides a sample worker profile. The top right corner of Figure 1 shows that Evgeny M., the example worker, has excellent feedback from past jobs—scoring 5 out of 5.

[1] Blinder and Kruger (2009) estimate that 25 percent of U.S. jobs are potentially "offshorable," in part because work can be delivered electronically. On oDesk, the market studied in this paper, over 80 percent of transactions span country borders and constitute international services trade. As of 2013, there were over 100,000 employers and 140,000 workers actively billing in each quarter (Agrawal, Horton, Lacetera and Lyons, 2014).

[2] The market inefficiency caused by lack of information about novice workers has been identified in a hiring experiment in Pallais (2014). Her finding, along with the analysis of workers' careers in this paper, suggests that inexperienced workers do not have credible alternative means to signal to employers that they are high quality.

The bottom right-hand side of Evgeny's profile shows that he is one of 17 workers affiliated with one of the agencies called *qCode*. Along with affiliation status, employers also observe the revenue-weighted feedback score for all current and past agency members in an agency affiliate's profile. For *qCode*, the agency-level feedback is 4.95 out of 5. Agencies are typically founded by workers with past success on oDesk, and agency founders then bring additional inexperienced workers into the market as affiliates of their agency. Around 30 percent of non-U.S. oDesk workers are affiliated with one of the agencies operating in the market. With 17 affiliates, the agency *qCode* is larger than the mean agency operating on oDesk, but in many other respects, its organization appears representative. For example, affiliates of most agencies know each other offline and share similar backgrounds. Almost all workers affiliated with *qCode* are located in the same city; attended the same local university in Siberia; and, as the agency name suggests, specialize in technical job tasks.

All contracts between workers and firms are spot contracts, allowing both parties to renegotiate or cancel the arrangement at any time. In contrast, agencies maintain longer relationships with affiliates, and over 97 percent of agency relationships last for a worker's entire oDesk career. Agencies are able to retain workers, in part, because they have the option to remove all feedback from a worker's profile that is received while the worker is affiliated with the agency. oDesk introduced this feature of the contracting structure at the request of early agency heads who wanted incentives to bring affiliates onto the platform. A worker, hence, may lose his individual reputation if he leaves the agency. However, all feedback received by agency affiliates is permanently included in the aggregate agency feedback score. In exchange for affiliation, agency heads collect a fraction of workers' earnings.

The hypothesis that agencies provide information about worker quality is evaluated using the equilibrium predictions from an employer learning model that adapts Tervio's (2009) analysis of on-the-job talent discovery to allow an agency to preempt information revelation. In the model, some workers are exogenously screenable by an agency head, and in equilibrium, agency affiliation is only offered to high-quality screenable workers. The agency is long-lived and its reputation is valuable, so employers believe agency affiliation conveys that workers are high-quality relative to non-affiliates. As a result, inexperienced affiliates are predicted to have an early advantage over inexperienced non-affiliates when public information about inexperienced workers is sparse. As employers learn about workers after information is revealed on-the-job, the affiliate advantage is then expected to decline for affiliates when compared to experienced workers who receive good feedback scores.[3]

In evaluating the prediction about inexperienced workers, Oaxaca-Blinder decompositions (Oaxaca,

[3] The empirical analysis of the model is in the spirit of Lange (2007), Farber and Gibbons (1996) and Altonji and Pierret (2001).

1973; Blinder, 1973; Fortin et al., 2011) and an entropy balancing reweighting technique (Hainmueller 2012) are used to show that inexperienced affiliates are at least 75 percent more likely to find any work; they find jobs after less search time and effort; and they earn initial hourly wages that are 20 percent higher than observably similar non-affiliates. An event study that examines the behavior of a subset of workers who switch into agency affiliation is then used to show that the estimated effect of affiliation is likely to be causal. The effect of affiliation is recovered by using time-stamped data on job applications and the appearance of the agency brand in a worker's profile. Workers' wage offers increase significantly and instantaneously when the agency brand appears in the electronic resume. The probability of finding a job also increases despite the wage offer increase.

Consistent with the information-provision agency role, affiliates' and non-affiliates' subsequent careers respond differently to the arrival of good feedback from early jobs, suggesting that good on-the-job feedback changes employers' beliefs more for non-affiliates than for affiliates. In regressions with worker fixed effects, the initial affiliate wage advantage declines among workers with similar feedback scores. Experienced non-affiliates with good feedback see a 10-percent hourly wage increase, compared to a 3-percent increase for experienced affiliates. Employers tend not to hire experienced workers with bad feedback, and the lowest-quality workers are selected out of the market. For experienced workers that remain in the market, wages converge for affiliates and non-affiliates with similar feedback scores and characteristics.

Further tying this together, agencies are most prevalent in job categories where obtaining information about worker quality is relatively difficult. For example, agency affiliates concentrate in technical job categories. These jobs involve programming, or other tasks, where determining worker quality may require the actual delivery of an entire completed project. In contrast, non-technical jobs tend to involve easily-monitored tasks like data entry or personal assistant work. Around 70 percent of all the agencies observed in the data specialize in technical work. Forty-nine percent of the new workers coming into the market in technical job categories are agency affiliates, whereas only 18 percent of new workers in non-technical categories are affiliated with an agency. Each of these pieces of evidence is consistent with the hypothesis that agency affiliation is most valuable when there is limited public information about worker quality.

The data also permit an assessment of Autor's second hypothesis concerning the provision of direct production benefits by intermediaries. For example, agency heads may provide translation services or training that increase worker productivity on the job. Under this role, the agency advantage is predicted to be heterogeneous and to depend on affiliated workers' skills. There is no detectable heterogeneity consistent with the implications of this role.[4]

[4] There is empirical evidence suggesting that market intermediaries perform varied functions in other markets. Some literature suggests that intermediaries exist in international trade to reduce the fixed costs associated with market entry or

There is, however, some evidence that affiliates staffed on team projects receive better feedback scores when other team members are affiliated with the same agency, consistent with the possibility that agencies may help to coordinate teams of specialized workers (Becker and Murphy, 1992). Nonetheless, team coordination alone does not explain the majority of the evidence about agencies: agency affiliates staffed on individual projects earn higher wages than those on team-based projects; the share of affiliates staffed on agency team-based projects is too small to account for the early-career agency benefits or for the wage and employment dynamics over workers' careers; and team based work is more frequent in non-technical work than in technical work, but agencies are much more prevalent in technical tasks.

The existence of agencies as information providers requires that agency heads are able to capture some of the returns from screening workers. Two institutional features of the oDesk marketplace allow for this. First, the ability to remove affiliates' feedback allows agency heads to have long-term contracts with workers. This allows them to capture a return from screening potential affiliates. In contrast, when only spot contracts are available, employers invest too little in determining inexperienced workers' quality because the return accrues to workers, as documented by Pallais (2014). The inability to capture the long-term value of investment in information is the same reason that firms may be reluctant to invest in providing general skills training (Becker, 1962) unless they have monopsony power or private information that allows them to capture the return (Acemoglu and Pischke; 1998, 1999).

Second, the public nature of agency-level feedback makes it likely that any attempt to degrade affiliate quality will be detected by all employers. This likely limits agency heads' incentives to allow low-quality affiliates into the agency and makes the information conveyed by affiliation credible to employers. Empirically, new affiliates' wages and feedback are very stable as the agency grows, but if bad feedback does arrive, it significantly increases the likelihood that the individual agency in question ceases to bring on new affiliates.

Relative to alternative possible screening arrangements, agencies are also likely to have a cost advantage. The data reveal that members of an agency are likely to know each other offline. Due to shared educational or professional experience, a potential affiliate's quality or fit with online work is likely to be known in advance by the agency head.[5] This setting shows that hiring and investment do not have to be done jointly

searching for trading partners (Ahn et al., 2011, among others). In the largest online labor market platforms, these activities are performed by the platform itself, and employers contract directly with both agency-affiliated and non-agency-affiliated workers. In this respect, they also differ from the temporary staffing agencies described in Autor (2001b), and in Bidwell and Fernandez-Mateo (2010), which also provide matching functions. Recent papers on trade in goods markets study the information provision by intermediary organizations. Feenstra and Hanson (2004) view wholesalers as certification intermediaries that arise because of incomplete information about product quality. The dynamics of bilateral trading relationships have also been shown to reflect the fact that partner types are initially unknown (Antras and Foley, 2014; Araujo et al., 2012). Formal or informal institutional arrangements may also mitigate trade frictions by reducing trading-partners' incentives to engage in opportunistic behavior (Milgrom et al., 1990; Greif, 1993).

[5] Although affiliates share offline ties, it is unlikely that the first-order effect of these ties is to reduce moral hazard by

to achieve efficiency gains. This also suggests, however, that the scope of any one agency that relies on offline networks is likely to have a limited ability to increase trade in these markets, in part, because the size of offline networks constrains the extent to which an agency can grow.

By examining the reasons for the entrance of intermediaries, this paper sheds light on the potential barriers to trade in labor services and the extent to which these barriers can be overcome (Spulber, 1999). The main implication is that while there are information frictions in these markets, endogenously arising market organizations may mitigate the extent to which information frictions reduce trade. This paper complements the findings in Pallais (2014) by showing that agencies have emerged to reduce the problem of the inefficient allocation of talent to job openings. The total gains from the presence of intermediaries in the marketplace appear substantial when considering firms' willingness to pay for agency affiliates. Affiliates comprise 32 percent of the inexperienced workers hired, and they earn 50-percent more over their careers than observably similar non-affiliates.

The paper proceeds as follows: Section 2 describes the empirical setting for the paper. Section 3 presents a simple model to illustrate the agency information-provision role. Section 4 includes the empirical analysis that provides evidence this agency role. Section 5 discusses alternative possible intermediation roles and the implications of the results for online labor markets and more general settings. Section 6 concludes.

2 The Setting

oDesk is a spot market for remote work that was established in 2005. It has grown to become the largest global online labor market.[6] Agrawal, Horton, Lacetera, and Lyons (2014) document that as of early 2013, the total wage bill on oDesk was around $95 million per quarter and was growing rapidly. Over 90 percent of the wage bill comes from employers in high income countries while workers in low income countries receive about 75 percent of the total wages paid.[7] This paper uses proprietary transactions data from oDesk, and this section describes how a transaction comes takes place and is recorded in the data.

increasing the social costs of shirking. Employed workers face strong individual reputational incentives within the oDesk market to refrain from shirking, as feedback scores are the single most important factor associated with ongoing employment and earnings in the market. The role of social ties among members of these organizations, therefore, appears to differ from the role played by social ties in other settings, such as the rotating savings and credit associations (Roscas) studied in Besley et al. (1993).

[6] Many features of oDesk described in the introduction, like the posting of feedback and the visibility of job histories, are shared by other online labor markets. The main feature distinguishing oDesk from other similar markets is that payments to workers for legitimate hours billed are guaranteed. This guarantee arises because oDesk provides proprietary monitoring and productivity software that allows employers to remotely view a contractor's computer; employers then have the ability to dispute pay. oDesk handles all wage payments and retains ten percent of each transaction.

[7] Only a small fraction of employers in high income countries are likely to have migrated from the countries staffing jobs. As Ghani, Kerr, and Stanton (2014) report, less than five percent of American employers in the oDesk database have ethnic Indian last names even though 28 percent of all jobs originating from the United States are staffed in India.

When posting a new job, an employer fills out a description of the task, the skills required, and the expected project duration.[8] Employers classify their posting into one of several unique job categories, and these tasks broadly fall into two types of work: technical and non-technical. Technical jobs require specialized skills, and for many technical projects, the output is a website, a software application, or a specialized deliverable that can be verified to work only toward the end of an entire project. In contrast, non-technical jobs often involve work that is easy-to-monitor at any point.[9] About half of all job postings during the sample involve technical jobs, but the share of non-technical job posts increased as oDesk began marketing for administrative support related tasks.

On the worker side, job seekers fill out resume profiles that employers can browse through and that appear along with an hourly wage offer in a job application. These profiles typically include a biographical sketch, a description of the worker's education, skills, and experience, and the job category of desired work. Workers can also take tests online to demonstrate competence in individual subject areas. The tests range from English language and writing skills to web development knowledge to the ability to use tools for database administration. Workers have the option to conceal test scores or to post them publicly. There is no verification process that reveals the number of times a given test has been taken or that the worker in question actually took the test him or herself. After a hire is made, an indication that the worker has been hired is immediately entered into the worker's online resume. Feedback from the job arrives after a project ends and this feedback is automatically affixed to the worker's profile if any payments are accepted. After a worker gains experience, the profile page contains data on wages, hours, and feedback from prior jobs.

When oDesk was founded, all workers entered the market without agency affiliation. As the market matured, agencies began to enter, and oDesk accommodated this entry by displaying agency affiliation and the agency feedback score within a worker's profile. It is important to note that affiliation is a characteristic that appears on a worker's resume profile, as shown in Figure 1, but does not alter the job application, hiring, or work processes. Through oDesk's monitoring system, the employer observes exactly which individual employee does the work, whether or not the worker is agency affiliated.

The modal agency contains a small number of workers, often from the same region or city. Conversations with oDesk's management emphasized that agency affiliates tend to know each other offline and that affiliates tend to have similar backgrounds. In exchange for affiliation, a share of affiliates' wages are transferred to the agency. This transfer is not observed in the data because it happens outside of oDesk,

[8] Employers can also choose whether to specify hourly-paying or fixed-price contracts. During the sample period considered here, hourly-paying contracts were more prevalent. Fixed-price contracts tended to involve small budgets and were concentrated in non-technical job categories.

[9] 69 percent of technical jobs are posted in the web development category followed by the next largest category, software development, at 17 percent. Around 56 percent of non-technical tasks are posted in the administrative support category which includes data entry, web research, and virtual personal assistance tasks.

but oDesk's internal research about agencies suggests that, on average, agency heads collect around five to six percent of affiliates' wages.[10]

As mentioned in the introduction, the agency head has ownership rights over an affiliated worker's individual feedback as part of the affiliation process. For workers who wish to leave an agency, the agency head has the right to scrub the worker's individual feedback score. However, the feedback of any worker who does work under an agency brand is permanently attached to the agency's collective reputation.

3 Motivating Framework

This section introduces worker certification by an agency into a simple version of Tervio's (2009) model of a labor market in which ability is revealed on-the-job. It provides testable predictions about how the effect of certification on job-finding probabilities and wages varies over workers' careers.

Players. There are three categories of participants in the market: workers, firms, and an agency.[11] Workers live two periods and enter the market in overlapping generations, while the agency and firms are infinitely lived. At the end of each period, E old workers exit the market. When the next period begins, they are replaced by E new workers resulting in a a total of $2E$ potential workers during any period. Workers' per-period outside wages are normalized to zero. Each worker's permanent quality, θ, takes one of two values, High (H) or Low (L), but upon entry into the market, a worker does not know her particular value of θ. She knows only that $\theta = H$ with probability h, and $\theta = L$ with probability $1 - h$. Individual realizations of θ are revealed through on-the-job experience after a worker is employed, and once a worker's θ is revealed, it becomes public information. Workers' types are also indexed by a second dimension, s, which indicates whether or not a worker is "screenable" by the agency. This takes one of two values: 0 (not-screenable) or 1 (screenable). Types θ and s are distributed independently.

The agency is infinitely lived and may offer "affiliation" to each worker in exchange for a fee from that worker. The fee may be a lump-sum paid in advance, a lump-sum spread across periods, or an ad-valorem percentage of affiliates' earnings. Affiliation is simply a public signal associated with an individual worker that is observed by all players. On its own, affiliation has no productive value. Workers offered agency affiliation choose whether to accept the offer. The agency is relevant in the market because it it can observe the quality type θ of a screenable worker before that worker has on-the-job experience. The

[10]oDesk does not collect data on the contract between agencies and agency-affiliated workers, and all payments between agency affiliates and agency heads happen offline. Qualitative details about these contracts come from discussions between agency heads and oDesk staff. Conversations with oDesk's management and John Horton, oDesk's former staff economist, suggested that the agency share of a worker's wages tends to fall as the worker gains experience.

[11]Including only one agency in the model mirrors the fact that agencies appear to have a local monopoly in their ability to screen connected workers.

parameter a denotes the exogenously determined share of workers that are screenable by the agency. The agency is assumed to be somewhat patient, and it maximizes the stream of discounted payoffs from the fees that it collects from affiliates.

In each period there are N identical firms that can hire, at most, one worker. If a firm hires a worker of type θ, it produces gross output θ and must pay the worker the contracted wage. If a firm does not hire it produces zero. Firms are able to observe the following about workers: when the worker entered the market, any historical output and, hence, quality information, and whether the worker is affiliated with an agency. Whether a worker is screenable by the agency, and the outcome of any screening, are not observable to firms. Firms are assumed to maximize per period profits, equal to the value of output less the wage paid to the employed worker.

Contracts. Firms and workers are restricted to one-period spot employment contracts that pay a fixed wage. The set of possible contracts between the agency and individual workers is a bit more detailed. In each period that the worker is affiliated, the contract between an agency and an individual affiliate specifies a fee, β_t, to be paid to the agency, where $t \in \{1, 2\}$ refers to the period of the worker's life. The worker or the agency can unilaterally dissolve affiliation at the beginning of any period. The agency contract also specifies ownership rights to a worker's public feedback history. For workers with past work experience under an affiliation agreement, the agency contract contains an option to remove the public record of feedback for workers who opt to leave affiliation.

Timing. The timing within each period is as follows:

1. E new workers enter the marketplace to join the E existing workers starting the second period of their lives.

2. The agency screens workers. The agency offers affiliation to a subset of the $2E$ workers under the fee-schedule defined by the contract β_t. Workers offered agency affiliation choose whether to affiliate and pay the agency any contracted fee.

3. As a reduced form way to specify how the market clears, it is assumed that the N firms submit demand schedules to a market-clearing authority. Firms can condition these schedules on workers' wage offers and three dimensions of observable worker characteristics: quality, H, L, or U, where U signifies an inexperienced worker whose quality is unknown; A or N, signifying whether the workers is an affiliate or non-affiliate; and $t \in \{1, 2\}$, for the period of a worker's life. These schedules are preference rankings, and firms also rank a preference for not hiring. [12]

4. Each worker submits a wage offer to the market-clearing authority.

5. The market clearing authority selects a firm at random and then assigns the firm the best available worker given the demand schedule. In the event of ties, workers with known high quality are assigned first, followed by agency affiliates, followed by workers of unknown type, followed by workers with known low quality. This is repeated until all firms have been assigned a worker.

6. Production takes place and the quality of all newly-employed workers is revealed.

7. E workers exit the marketplace.

3.1 Equilibrium

Perfect Bayesian Equilibrium without Intermediation. Setting $a = 0$, such that there are no screenable workers, establishes a benchmark without the agency. Equilibrium firm-worker matches and wages are derived using a condition similar to that in Tervio (2009), such that jobs are scarce relative to workers, but known high quality workers are scarce relative to jobs. This condition is that the number of job openings is larger than the number of known high quality workers and is smaller than the number of new workers plus the number of known high quality workers. Precise mathematical details are provided in the appendix.

In steady state, only two classes of workers are hired. All experienced workers revealed to be high quality from prior experience are hired in the second period of their lives; the remaining workers matched to jobs are inexperienced. Observed wages are relatively high for workers with job experience, reflecting the positive selection of high types over time, while wages are lower for inexperienced workers, reflecting uncertainty about their types. Because workers in the second period of their lives are revealed high types, they experience wage growth. Workers revealed to be low types earn their outside wage of zero in the second period and are not re-employed.

To pin down the exact difference in wages by experience, the assumption made about the number of firms and the fraction of workers of each type implies that equilibrium wages make firms indifferent between hiring known high types at wage w^H and hiring an unknown worker at wage w^U. Because workers

[12] As an example, a firm could submit a preference ranking of:

$$\max\left(H - w_{H2},\ H - w_{A1},\ H - w_{AH2},\ L - w_{AL2},\ H - w_{AU2},\ L - w_{L2},\ hH + (1-h)\,L - w_{U1},\ hH + (1-h)\,L - w_{U2},\ 0\right)$$

where H, L, h, and l are constants and $w_{H2}, w_{A1}, w_{AH2}, w_{AL2}, w_{AU2}, w_{L2}, w_{U1}, w_{U2}$ are, respectively, the wages of a known high type in the second period, an agency affiliate in the first period, an agency affiliate revealed to be a high type in the second period, an agency affiliate revealed to be a low type in the second period, an agency affiliate in the second period with no revealed type, a known low type in the second period, an unknown type in the first period, and an unknown type in the second period.

are abundant relative to firms, the equilibrium wage for workers of unknown quality, w^U, is determined by the expected lifetime indifference condition for these workers: $(w^U + hw^H) = 0$. Upon finding a job and gaining one period of experience, with probability h, the worker receives w^H in period two. Workers not selected in the first period of their lives are passed-over in favor of new workers who are willing to accept low wages for the chance to earn higher subsequent wages. This means that revealed low types and unknown-type workers in the second period of their lives are never hired in this equilibrium. This gives $w^U = -hw^H$. Equilibrium wages for high types are determined by a system of two equations for workers' and firms' indifference conditions, respectively: $w^U = -hw^H$ and $hH + (1-h)L - w^U = H - w^H$, yielding $w^H = \frac{(1-h)}{(1+h)}(H-L)$ and $w^U = -h\frac{(1-h)}{(1+h)}(H-L)$. Workers who find employment in both periods of their lives experience a wage increase from w^U to w^H.

Total output with no agency equals the number of high types times their quality plus the number of unkown types times their expected quality. In steady-state, total output is:

$$Y = \left(\frac{2hH + (1-h)L}{(1+h)}\right)N.$$

In Tervio (2009), inefficiency in the market equilibrium comes about because mediocre experienced workers crowd out inexperienced new workers. In contrast, with just two types, the market allocation here is constrained efficient given the information available to workers and firms. When there is an alternative organization like an agency that allows for screening and certification prior to information revelation on-the-job, this allocation can be improved. The efficiency gains from the presence of agencies are split between the agency and screenable, high-quality workers.

Perfect Bayesian Equilibrium with Agency Intermediation. Letting $a > 0$ enables the agency to screen a subset of workers. To illustrate differences in the dynamics of careers between agency affiliates and non-affiliates, we focus on an equilibrium under conditions that guarantee that some non-affiliates are hired. Precise mathematical details are provided again provided in the appendix.

There is a constrained-efficient perfect Bayesian equilibrium in which the agency offers affiliation to screened high type workers inexperienced workers the market under the contract β_t, derived below. The agency does not offer affiliation to screened low types or to unscreened workers. Workers offered affiliation accept and remain affiliates for both periods of their lifetimes. On the equilibrium path, firms believe that agency affiliates are high types with probability one.

In steady state, the following workers are matched to jobs: all agency affiliates in the first period of their lives; all agency affiliates in the second period of their lives; all known high types in the second period of their lives; some unscreened workers of unknown types in the first period of their lives. No other workers are hired in equilibrium.

Equilibrium wages for agency affiliates in both periods of their lives, w^A, equal the wages of experienced workers revealed to be high types. That is, $w^H = w^A > 0 > w^U$. Wages are w^U for those non-affiliates who find jobs as inexperienced workers. If a non-affiliate is revealed to be a high-type, wages change from w^U to w^H, while wages for agency affiliates are constant in both periods.[13,14]

This equilibrium generates several empirical predictions for worker-level outcomes.

1. Affiliates are more likely to be hired at the start of their career than non-affiliates; affiliates submit higher initial wage offers and earn higher initial wages than non-affiliates who find employment.

2. Among workers who find jobs, affiliates are more likely to be re-employed than non-affiliates; those non-affiliates who are re-employed experience higher wage growth than re-employed affiliates, closing the initial wage gap.

The contract between affiliates and the agency is not uniquely determined across time periods. In equilibrium, the best the agency can do is extract the difference between w^U and w^H from an affiliate, but the payment can happen across periods or in a single lump-sum. The reason that the agency cannot do better is that, by offering affiliation to the worker, the agency allows the worker to infer that he is a high-type. The worker can then use this informational advantage outside of affiliation by offering a wage slightly below w^U, guaranteeing employment while inexperienced, and earning a high wage with certainty in the second period. Specifying that the agency takes all revenue as a lump-sum prior to any hiring means that there is no distortion or incentive for workers to leave the agency in the second period. In this case, $\beta_1 = (1 + h)\, w^H$, with $\beta_2 = 0$.[15]

The agency increases output in every period because its presence increases the share of employed high types. The equilibrium number of known high types and expected high types through affiliation is given by $E_{HA} = 2ahE + h(N - E_{HA})$, where $2ahE$ is the total number of affiliates in the market, and $h(N - E_{HA})$ is

[13] Because of the assumptions governing the number of firms relative to the number of known high types and agency affiliates, equilibrium wages are determined by the same system of equations for indifference conditions as in the equilibrium without the agency. Screened workers who are not offered agency affiliation offer zero wages because the failure to be offered affiliation means that these workers infer they are low-types. There is thus no upside from having their type revealed. Unscreened workers with unknown types in the first period of their lives offer the same wages as in the equilibrium without an agency.

[14] Other models of employer-employee matching with incomplete information offer different testable predictions that are not present here. For example, Lockwood (1991) allows firms to test potential workers for quality and hire only productive workers. As a consequence, unemployment duration is a signal of low quality. The equilibrium level of testing in the economy can be inefficient. In the model presented here, unemployment duration does not provide information directly, although non-affiliates tend to be lower-quality and are also less likely to become employed. In another example, Chiappori et al. (1999) model wage dynamics with learning about workers in the presence of wage rigidity, where recent wage growth provides some information about worker type. In the model in this paper, with only two worker types, the mechanism is simpler–once employed for one period, a worker's type is fully revealed.

[15] This gives total per-period agency revenues of $ahE(1 - h)(H - L)$.

the number of employed unknown types in the previous period revealed to be high-quality and who remain in the market in the second period of their lives. Total output in each period is:

$$Y = \left(\frac{2hH + (1-h)L}{1+h}\right) N + \frac{(1-h)2ahE(H-L)}{1+h}.^{16}$$

The increase in output when $a > 0$, compared to when $a = 0$ and there is no agency, is given by the second term in this equation, $\frac{(1-h)2ahE(H-L)}{1+h} > 0$. This term is increasing in the share of entering workers screenable by the agency, a, as well as in the difference in output between high- and low-type workers, $(H - L)$.

Assuming the agency is sufficiently patient, the agency never deviates from the equilibrium, and the quality of affiliated workers is independent of agency size. The beliefs required for this equilibrium are reasonable: if there has never been a defection by the agency, firms believe all agency affiliates are high types with probability one, separating inexperienced affiliated workers from other inexperienced workers. If a deviation ever occurs and firms detect that the agency has let in a worker who is revealed to be a low type, the firms permanently believe that all future affiliates are high types with probability h, the population-level probability that a worker is high-quality. If this occurs, affiliation offers no benefits to individual workers, and the number of new or future agency affiliates falls to zero. This equilibrium agency behavior suggests the following empirical prediction:

3. Agencies do not allow low-quality workers into the agency. If an agency affiliate receives poor feedback, it increases the likelihood that the agency in question never has new affiliates join.

The three predictions are evaluated in the remainder of the paper.

4 Empirical Analysis

4.1 The Data

Proprietary data to evaluate these predictions were obtained directly from the oDesk production databases. Although oDesk began operations in 2005, the data used here cover the period August 1, 2008 through December 28, 2009. Earlier data are not incorporated because changes to the database that records agency affiliation meant that it was not possible to track agency records prior to this period.[17] There are 1,126

[16] This is calculated by simplifying $E_{HA}H + (N - E_{HA})(hH + (1-h)L)$ where $E_{HA} = \frac{h}{1+h}(N + 2aE)$.

[17] A separate database query contains the extended employment histories up to the later date of 8/14/2010. This data is referred to in the paper as the extended sample.

separate agencies with at least one new non-U.S. affiliate active between August 1, 2008 and December 28, 2009 and 872, or 77 percent, of these agencies have complete observable histories because they were founded after oDesk implemented its detailed tracking system for agency affiliation. Table 1 presents summary statistics about these organizations. An average of 3.25 unique workers per agency are employed during the 16-month period covered. The smallest agency contains just one worker and the largest contains 76 employed workers. On average, during the 16 months of data, 2.87 new affiliates for whom it is possible to track the entirety of a worker's career as an affiliate are employed per agency.

While the majority of employers are located in the United States, agencies are most prominent in developing countries. It is rare to observe affiliation in the U.S., which hosts only one percent of the agencies in the sample. India or Pakistan is the modal country for 52 percent of agencies, followed by the Philippines at 14 percent and Russia or the Ukraine at 11 percent. The affiliates of a given agency also tend to be concentrated in the same country, consistent with the hypothesis that agency affiliates appear to know the agency head from non-oDesk interactions. Taking the mean across agencies, 98 percent of employed affiliates are located in the modal country of their respective agencies.

Agency affiliates are similarly concentrated by type of work, with an average of 84 percent of hires in the modal technical or non-technical classification for the agency in question. Most agencies concentrate in technical tasks, as 69 percent of all agencies have modal jobs in technical categories. The concentration by country and type of work are related–agencies specializing in technical work are disproportionately prevalent in India or Pakistan.

Table 2 presents summary statistics where workers are the unit of analysis. In the main sample, there are 83,029 workers located outside of the U.S. who created a resume profile and applied for at least one job during the sample period.[18] Thirteen percent, or 10,751, of these new workers were affiliated with an outsourcing agency on their first job application. Affiliation is again relatively prevalent among new oDesk workers in India and Russia compared to workers in the Philippines. Mirroring the concentration of agencies in technical job categories, relative to non-affiliates, affiliates are far more likely to be technical workers. 68 percent of new affiliates apply for technical work while just 34 percent of new non-affiliates apply for technical jobs.[19]

The remaining rows in the first two columns of Table 2 provide summary measures detailing how non-

[18]Restricting the sample to exclude US workers retains 79 percent of all jobs for inexperienced workers. Of the 2,663 U.S. workers who were hired, only 159 were agency affiliates. This paper focuses on contracts that span international borders and so the analysis concentrates on non-U.S. workers. The main results are generally unchanged if workers from the U.S. are included in the analysis after accounting for heterogeneity across country. Online Appendix Table 1 presents some summary statistics including workers from the U.S.

[19]While $10,751$ workers are agency affiliates at the time of their first job application, $1,433$ workers apply for jobs as non-affiliates and then join an agency. This group of workers' job-application behavior is analyzed in detail later in the paper.

affiliates and affiliates differ on a subset of the observable characteristics used in the empirical analysis. The full list and definition of the observable worker characteristics that are used subsequently is given in Appendix Table 1. New affiliates are more likely to have a bachelors or higher degree than new non-affiliates and are also more likely to have good English language skills. They are marginally less likely to have taken at least one of the skills tests that oDesk provides. Importantly, affiliates make significantly higher initial hourly wage offers. The average initial log hourly wage offer of a non-affiliate is 1.94, compared to an initial affiliate log hourly wage offer of 2.15. Online Appendix Table 2 details information about the distribution of test scores for different tests, and the differences between affiliates and non-affiliates.

4.2 Affiliation and Earnings

Agency affiliates earn significantly more than non-affiliates over their careers. The final three rows of Table 2 compare total earnings between the groups. The affiliates earned an average of $\$1,787$ between the date that they first applied for a job and August 14, 2010, the last date in the extended sample. The $72,278$ non-affiliates in the sample earned an average of \$387 over the same period, less than one quarter of affiliates' earnings.

It is possible that a portion of this \$1,400 gap in mean earnings between affiliates and non-affiliates is due to differences in observable characteristics that potential employers value. The Oaxaca-Blinder method is used to decompose the gap into: (a) a portion of the mean difference between affiliates and non-affiliates that can be attributed to a detailed set of observable resume and job characteristics and entry cohort fixed effects; and (b) an unexplained portion that can be attributed to agency affiliation. The model for outcome y_i (here, total earnings for worker i) is given by a linear regression $y_i = X_i\beta_N + \varepsilon_i$ for a non-affiliate and by $y_i = X_i\beta_A + \varepsilon_i$ for an affiliate. The subscripts N and A indicate that the coefficients correspond to non-affiliates and affiliates, respectively. The vector X_i contains a constant term along with individual worker characteristics from the resume profile, including test scores.[20] Fixed effects for workers' countries are included to capture differences in outside opportunities; job category fixed effects are included to capture differences in the market price of individual skills; and cohort effects, corresponding to the calendar month of the first job application, capture differences in career horizons and macroeconomic fluctuations in market conditions.

The gap in average outcomes between affiliates and non-affiliates due to differences in observable characteristics is measured as $\left(\bar{X}_A - \bar{X}_N\right)\beta_N$. $\bar{X}_A$ and $\bar{X}_N$ are the mean characteristics for each group. Holding

[20] The resume characteristics consist of dummies for levels of educational attainment, prior years of work experience, prior programming experience, the oDesk test scores that are observed in workers' profiles, measures of English language ability, and any observable work history on small fixed-price contracts. These variables are described in Appendix Table 1.

observable characteristics for both groups constant, taking the difference in means, and "weighting" this difference in characteristics by β_N provides an estimate of the mean difference in outcomes attributed to differences in observable characteristics other than affiliation status.[21] The remaining difference in outcomes, $\bar{X}_A(\beta_A - \beta_N)$, captures that employers value the same observable characteristics differently in affiliates and non-affiliates. This latter component is due to agency affiliation or to other factors correlated with agency affiliation but excluded from X_i. The presence of a constant term in X_i captures the mean difference in the outcome across groups, but the specification does not restrict differences due to affiliation to be captured in the estimated constant terms. The weights on education, English language ability, prior labor-market experience, or any other characteristic may differ for an affiliate versus a non-affiliate.

With these quantities in hand, the premium from affiliation is

$$\text{Premium} = \frac{Y_{Base} + \bar{X}_A(\beta_A - \beta_N)}{Y_{Base}} \tag{1}$$

where Y_{Base} is a baseline outcome and the numerator is the baseline plus the effect of affiliation due to affiliation itself. Several values are possible for the baseline outcome. For example, the premium relative to the group of non-affiliates uses $\bar{X}_N\beta_N$ as the baseline outcome.

In the decomposition, only 30 percent of the $1,400 earnings gap is explained by the detailed set of observable resume and job characteristics data, X_i, while 70 percent is attributed to agency affiliation or factors unobserved by the econometrician but correlated with agency affiliation. Using this estimate to calculate an earnings premium from affiliation suggests that the effect of affiliation on workers' career earnings is substantial: new affiliates earn a premium over the wages of non-affiliates that is equivalent to 251 percent of a non-affiliate's average earnings.

Columns 3 and 4 of Table 2 analyze career outcomes for workers who are employed for at least one job. Restricting the sample to workers that are hired, the pattern with respect to observable characteristics is reversed: in this subsample, non-affiliates have higher levels of observable skills. Among this subset of workers, affiliates' earnings advantage narrows: they earn twice as much as non-affiliates in the raw data, the share of the earnings gap that can be attributed to affiliation also falls to 50 percent, and the affiliation premium for career earnings, relative to the non-affiliate earnings baseline, drops to 40 percent.

The analysis in Columns 5 and 6 further restricts the sample to workers who have been hired more than once. Among these workers, levels of observable skills increase slightly for both affiliates and non-affiliates, and non-affiliates continue to have higher average skills levels. For these workers, the affiliation earnings

[21] Oaxaca and Ransom (1999) show that the share of the outcome attributed to agency affiliation in this decomposition is invariant with respect to the omitted dummy variable.

premium falls to 26 percent.[22]

The comparison of Columns 1 and 2, with Columns 3 and 4, and then with Columns 5 and 6, suggests that the career earnings affiliation premium is, in large part, due to outcomes at the start of workers' careers. As will be shown, it arises primarily on the extensive margin of "landing the first job." For the workers who are employed for several jobs, the affiliation earnings premium is substantially diminished.

4.3 Early Career Advantages

4.3.1 The First Job

Table 3 examines whether the outcomes from the start of workers' careers are consistent with the first set of model predictions: inexperienced agency affiliates are more likely to find jobs while earning higher wages and better feedback upon employment. Entropy balancing estimates are presented in the table as well as Oaxaca-Blinder decompositions. This technique provides an alternative to the Oaxaca-Blinder decomposition that reweights observations of affiliates and non-affiliates to balance the moments of the distributions of observable characteristics between the two groups (Hainmueller, 2012). The procedure takes the distribution of affiliate characteristics as given and then finds weights for each non-affiliate such that the weighted distribution of non-affiliate characteristics matches the distribution of affiliate characteristics as closely as possible. Weighted regression with an affiliation dummy then provides an estimate of the affiliation effect for workers with characteristics that match the characteristics of the affiliate distribution. Because the regression is weighted to reflect the distribution of affiliate characteristics, the reported constant is the expected counterfactual outcome for affiliates in the absence of affiliation. The affiliation premium from equation (1) is calculated relative to this base for the entropy balancing estimates. These estimates also allow an assessment of the sensitivity of the Oaxaca-Blinder estimates when the dependent variable is binary and there are multiple categories of fixed effects.

The first column of Table 3 shows that 27 percent of the 10,751 affiliates in the sample find at least one job, compared to only ten percent of non-affiliates. In Oaxaca-Blinder decompositions, observable characteristics, while correlated with employment outcomes, explain only 27.6 percent of the mean difference in the probability of finding a job. The remaining 72.4 percent can be attributed to agency affiliation. This implies that affiliates are 121 percent more likely to find a job than the non-affiliate baseline. Under the reweighting estimate, affiliates are 75 percent more likely to find a job relative to the counterfactual of being in the pool of non-affiliates.

Columns 2 and 3 examine the elapsed time and the number of applications made prior to the first hire

[22] This is calculated for workers' earnings after the second job, excluding their earnings on the first job.

for workers that find at least one job. At the median for affiliates, five days elapse between the first job application and the first hire, with a median of three job applications. The corresponding figures for non-affiliates are thirteen days and ten job applications. To examine these differences in more detail, Figure 2 expands the sample to consider all job seekers, and separately plots the empirical cumulative job-finding hazard for affiliates and non-affiliates as a function of the number of job applications submitted. It is clear that affiliates find their first jobs with less search time elapsed. The pattern is similar when controlling for observable differences that may be correlated with agency affiliation and allowing for censored spells of job search in Cox and Weibull models, as shown in Appendix Table 2. A model that does not account for information frictions or heterogeneity across workers would predict the exact opposite of these results—that search durations increase with wage offers. However, affiliates submit higher wage offers and are also more likely to land jobs. Consistent with the model's predictions, an affiliate's initial unemployment spell is much shorter than a similar non-affiliate's.

Column 4 of Table 3 examines differences in log hourly wages on the first job for workers who are hired at least once. Consistent with the empirical predictions of the model, affiliates receive higher initial hourly wages. Because the dependent variable is in logarithms, the estimate of the average effect of affiliation in levels is around 20 percent.

With regard to differences in job outcomes, Column 5 shows that affiliates' first jobs last around 60-percent longer in terms of hours worked. Employers are asked the expected duration of the project and the expected hours of work per week, and these are included as controls in the analysis.[23] This result shows that, within projects of a given expected duration, employers are willing to continue the employment of inexperienced affiliates for a longer time. Employers do not exercise the option to terminate affiliates' contracts early.

Column 6 examines employers' assessments of whether a completed project was a success. This measure is collected from an internal survey and is not shared with the public or the worker. The sample excludes ongoing projects, and, among completed jobs, 62 percent of affiliates' first projects are considered successful, compared to 57 percent of non-affiliates' first projects. The estimate of the affiliation effect is ten percent in the Oaxaca-Blinder decomposition and 12 percent in the entropy balancing estimates. That is, on average, affiliates are more likely than observably similar non-affiliates to be successful on their first projects.

The final two columns in Table 3 present an analysis in which the dependent variable indicates whether the feedback score received on the first job exceeds 4.5 on a 5-point scale. In both Columns 7 and 8,

[23] For ongoing jobs, the hours worked are recorded at the end of the sample period. The groupings for expected duration are: less than one week; less than one month; 1 to 3 months; 3 to 6 months; and ongoing or more than 6 months. There are three groupings for expected hours per week: full-time (40 hours), between 20-40 hours, and less than 20 hours. Each specification in Columns 2 to 8 contains controls for hours per week $\times$ expected duration.

ongoing projects are excluded. When workers do not receive feedback, the dependent variable in Column 7 is coded as a zero, whereas the sample in Column 8 is restricted to those workers who receive a feedback score.[24] Sixty-nine percent of affiliates who received feedback obtained a score of at least 4.5, compared to 68 percent of non-affiliates. The estimates suggest that affiliates receive feedback that is about 2.7 to four percent higher after accounting for differences in observable characteristics.

Panels B and C present the same results for the subset of workers with initial job applications in technical and non-technical categories, respectively. Column 1 shows that affiliates in technical work are more likely to be hired at least once than non-affiliates, relative to the same outcomes in non-technical work. Under the Oaxaca-Blinder decomposition, the estimated agency affiliation premium is larger in technical work, although the reweighting estimates of the premium are similar in both technical and non-technical work. The difference in some other first-job outcomes—most notably, the speed of hire and the number of applications prior to initial hire—between inexperienced affiliates and non-affiliates, both with and without controlling for the differences attributable to observable characteristics, is greater among technical workers. These results are shown in Columns 2 and 3.

Column 4 of Panels B and C show that the percentage difference in initial wages for affiliates and non-affiliates is larger in non-technical jobs, but the difference in levels is largest in technical jobs. The findings for first job duration, presented in Column 5, are similar across technical and non-technical workers. In Column 6, the estimated magnitudes of the agency effect on job success—which is one key measure of worker quality—are far larger for technical than non-technical work. From the Oaxaca-Blinder decomposition, the agency effect in technical work is around 14 percent, compared to only four percent in non-technical job categories. For the feedback measures, shown in Columns 7 and 8, there is a positive agency effect in technical work, but, for non-technical categories, non-affiliates are actually more likely than affiliates to receive good feedback.

These results are broadly consistent with the predictions about wages, job-finding probabilities, and job outcomes early in workers' careers, particularly for workers employed in technical work where skill assessment may be difficult. The next section assesses whether the early career advantage, as estimated here, is likely to be caused by agency affiliation.

[24]There are two main reasons why the success and feedback measures may be missing. The first is that the job is ongoing, and the second is that the job is finished but the employer chose not to submit this information. While the former reason is likely to be correlated with good on-the-job performance, the latter is likely to be correlated with poor worker performance. Rather than infer information from the fact that these measures are missing for some workers, the analysis concentrates on the subset of workers with available performance data. Subsequent analysis accounts for employer non-response to these questions.

4.3.2 Switchers' Wages and Employment Probabilities Both Increase

While the estimates account for an extensive set of observable worker characteristics, it is possible that affiliation is correlated with an omitted characteristic about workers that is observed and valued by employers. Most agency affiliates are brought onto oDesk by the agency head and do not apply for jobs without observable agency affiliation in their profiles. However, there are $1,433$ workers who switch into agency affiliation while searching for their first job but after applying for some jobs as non-affiliates. This enables the use of event studies to estimate the information-provision effect of agency affiliation on wage offers.

Because workers apply for many jobs, often over a short time interval, the estimated agency-affiliation effect on wage offers is identified using only a small window around the appearance of the agency brand in a workers' resume profile. The estimating equation is:

$$\log Wage\ Offer_{it} = \alpha_i + \beta_1 \left(Affiliate_{it}\right) + \beta_2 AppNumber_{it} + \beta_3 f\left(TimeFromFirstApp_{it}\right) + \varepsilon_{it}, \quad (2)$$

where α_i are worker fixed effects and β_1 measures the effect of the appearance of the agency brand on workers' wage offers. Controls for the application number and the function $f\left(TimeFromFirstApp_{it}\right)$, a cubic polynomial capturing the elapsed time since a worker first began applying for jobs, capture potential trends in wage offers and the intensity of application behavior.

Table 4 presents the results from estimating equation 2 using various time windows around the switch into agency affiliation. Out of the $1,433$ switchers, there are $1,381$ workers with job applications in a four-day window around a switch into agency affiliation. This gives about 6.2 applications per worker, enough to separately identify a worker's fixed effect and pre-affiliation wage offer behavior from the agency-affiliation effect. The baseline estimate in Column 1 shows that agency affiliation is associated with an 8.6-percent increase in the wage at which an inexperienced worker offers to work. Column 2 contains a falsification test using this same sample. A randomly generated placebo agency switching date was generated for each worker in the pre-switch period and was included as a "false indicator" that the worker switched into the agency as of this time. If agency switchers' wage offers followed a positive trend not picked up by the controls for time and application number, then the placebo date should capture reflect the possibility that the response happens before the arrival of the agency brand in the workers' profile. The estimated coefficient on the placebo is small and is not statistically significant. The specification in Column 3 includes both the placebo switching indicator and the indicator for the actual appearance of the agency brand. The estimate of the agency effect is almost identical to the estimate in Column 1, without the placebo.[25] These results suggest that the effect of agency affiliation on inexperienced workers' wage offers is nearly instantaneous. Workers who join agencies appear to apply for jobs as if they understand the increased probability of employment as affiliates, even at higher wage offers.

Other event studies are also possible. Estimates from the public revelation of test scores do not have the same positive effects, making it unlikely that the estimates of the effect of affiliation are driven by the simple act of adding details to workers' online resumes.[26]

It is possible to use these estimates to assess bounds on the causal effect of affiliation on wages in terms of the initial premium. The agency wage-offer premium for agency switchers is 11.5 percent in a Oaxaca-Blinder decomposition.[27] With these results in hand, suppose that this estimate of 11.5 percent is itself composed of the true affiliation effect plus a component due to model misspecification or omitted variables observable to employers. Using the smallest and largest estimates from Table 4, agency affiliation itself is responsible for between $(.0724/.115) = 63$ percent and $(.0868/.115) = 75$ percent of the affiliation wage-offer premium. Thus, after accounting for worker fixed effects over a short time window, a large fraction of the original effect attributed to agency affiliation appears to be due to the presence of the agency brand itself. Under an assumption that the ratio of the true affiliation effect due to misspecification or an omitted variable in the wage offer data is the same for the initial wages paid to hired workers, the affiliation effect itself is responsible for between 63 and 75 percent of the 23.1 percent agency first-job wage premium—or 14.5 to 17.3 percent.

Does a demand shift for inexperienced affiliates cause part of the increase in wage offers for switchers, or is the effect driven by the incidence of agency fees? It is possible that wage offers after switching simply reflect pass-through of the agency share of newly affiliated workers' wages just as a tax on goods increases the price of those goods. A standard incidence analysis, holding underlying demand and other costs fixed, predicts that quantities would fall as prices rise. If, on the other hand, job-finding probabilities increase

[25]These findings are robust to also including job-category fixed effects (Columns 4 and 5), and to using a three-day rather than a four-day window (Column 6). Column 7 includes job-category fixed effects and a two-day window.

[26]Appendix Table 3 presents these estimates for the most popular tests. The public revelation of test scores does not significantly increase non-affiliates' wage offers either overall or for workers disclosing scores above the 90th percentile of the test score distribution. When point estimates are statistically different from zero for non-affiliates, they are negative. Interactions for agency affiliates at or above the 90th percentile are positive for scores on technical tests, but they are not significant. The signs of interactions for affiliation are mixed when considering non-technical tests. Although the results for non-affiliates are small in magnitude and imprecisely estimated across specifications, one interpretation of negative point estimates that is consistent with the information structure in the theoretical motivation is that non-affiliates may learn their position in the distribution as a result of taking tests, inducing them to reduce their wage offers to capture the future return from the increased likelihood of good feedback.

[27]For this calculation, the parameters β_A and β_N are estimated using the entire set of inexperienced non-affiliates' and affiliates' job appplications. Because the set of switchers into affiliation may be non-random, the affiliation premium is calculated using the characteristics for the switchers, $\bar{X}_{Switchers}$, against the non-affiliate baseline. This is the larger of the possible estimates of the raw premium, making the portion of the premium due to the event study a conservative estimate.

after the switch to agency affiliation, a demand shift is likely responsible for at least a part of the increase in wages offered.

Job finding hazards are estimated for the subset of agency switchers and non-affiliates to assess the extent to which demand shifts for switchers into agencies. Table 5 presents the results. Compared to non-affiliates, agency switchers are estimated to find jobs with 35-percent fewer job applications after joining agencies relative to the non-affiliate baseline in Cox proportional hazard models (Column 1), and 22-percent fewer job applications in Weibull models (Column 3).[28] Finally, because the modal switcher moves into agency affiliation at the 15th job application, the job search behavior sample is restricted to those workers with 15 applications or more prior to finding the first job or to censoring. The results remain similar. Workers who switch into affiliation find work more quickly than do workers who remain non-affiliates, suggesting that demand increases for workers when the agency brand appears along with their resume.

4.4 Subsequent Wages and Employment Probabilities are Most Responsive to Feedback for Non-affiliates

Affiliates' increased probability of being hired, together with their higher wages on the first job, are consistent with the model's first set of equilibrium predictions. The second set of predictions are that the wages of high-quality non-affiliates increase to the level of high-quality affiliates after on-the-job quality revelation, while low-quality workers leave the market entirely.

Table 6 provides initial evidence that, for workers who remain in the market after the first job, the ongoing agency affiliation earnings premium is much diminished. The first column presents the hourly wage increases between the first and subsequent jobs for non-affiliates who are hired for at least two, at least three, and at least four jobs, respectively. The second column presents the same information for affiliates. Non-affiliates' wages increase by an average of 14.7 percent between jobs one and two. For affiliates, the hourly wage increases by an average of only 5.7 percent. Between jobs two and three, both non-affiliates and affiliates see a positive change in their log hourly wage, but, for both groups, the growth is smaller between jobs two and three than between jobs one and two. Non-affiliates experience wage growth of 12.7 percent while affiliates' wages grow by 3.7 percent.

The penultimate row of Table 6 summarizes average hourly wage growth for non-affiliates and affiliates between their first and fourth jobs for workers employed for at least four jobs in the data. The wages of surviving non-affiliates grow by 33.3 percent overall, while affiliates' wages grow by 13.6 percent between

[28] When including controls for the actual wage offer, results are even more extreme (Columns 2 and 4), but these specifications that control for worker "price" do not map directly into shifts in demand.

the first and the fourth job.[29] In general, the steeper wage gradient for non-affiliates suggests that there is wage convergence. That wages grow but with declining increments is consistent with standard models of Bayesian learning about workers (see Lange 2007). Larger wage growth for non-affiliates suggests that employers may be updating their beliefs differentially about affiliates and non-affiliates. The remainder of this section examines these career dynamics.

On average, around 68 percent of workers are re-hired after their first job. Whether there are differences in re-employment probabilities between affiliates and non-affiliates, as well as these probabilities' responsiveness to good feedback, is estimated using the following linear model:

$$\begin{aligned} 1\left(SecondJob_i\right) &= \alpha + \beta_1 Affiliate_i + \beta_2 GoodFeedback_i + \beta_3 Affiliate_i \times GoodFeedback_i \\ &\quad + \beta_4 NoFeedback_i + \beta_5 Affiliate_i \times NoFeedback_i + X_i\beta_6 + \alpha_t + \varepsilon_i. \end{aligned} \tag{3}$$

The sample is workers who land their first job between 8/1/2008 and 12/28/2009, and the dependent variable is an indicator that a second job is observed prior to 8/14/2010. The results are shown in the first four columns of Table 7. All specifications contain monthly time fixed effects, α_t, so the estimates are within entering cohort. The regression contains indicators for a good feedback score and for zero feedback, with a baseline of bad feedback (a score less than or equal to 4.5). Thus, β_2 is the marginal effect of a good feedback score relative to a bad feedback score on the probability of re-hire for non-affiliates. For affiliates, this marginal effect is $\beta_2 + \beta_3$, as the effect of feedback is allowed to differ for affiliates and non-affiliates through the interaction term. The matrix X_i contains observable characteristics about workers and jobs.

Consistent with the equilibrium predictions of the model, the coefficient on the agency-affiliation indicator is positive and significant, ranging from 0.056 to 0.081 depending on the specification and controls. By the end of the first job, employers have information about the quality of all workers who have received a feedback score. Having good feedback is positively and significantly associated with re-hire, overall and in both technical and non-technical job categories. This is consistent with the equilibrium in the model where revealed low-quality workers who receive bad feedback exit the market. For non-affiliates who receive a feedback score, good feedback increases the mean probability of finding a second job by 18 to 19 percentage points. For affiliates, the increase in the probability of re-hire associated with a good feedback score is significantly smaller—around four or five percentage points below the estimate for non-affiliates. This significant difference exists only for workers whose first jobs were in a technical job category. Column

[29] The relative wage growth trajectory for affiliates in technical jobs is much flatter than the relative growth for affiliates in non-technical jobs. Affiliates in technical jobs see total wage growth between the first and fourth jobs of less than nine percent. In contrast, affiliates in non-technical jobs see hourly wage growth between the first and fourth jobs of 22.5 percent.

3 shows that the increase in the probability of re-hire associated with a good feedback score is six-percent lower for affiliates in technical work. For non-technical workers, there is no significant difference in the responsiveness to good feedback of the probability of re-hire for affiliates and non-affiliates.

The remaining columns of Table 7 examine the relationship between wages on subsequent jobs, feedback scores and affiliation status. This analysis includes all workers in the original sample who were hired for at least two jobs in the longer sample extending to 8/14/2010, resulting in nearly 55,000 observations of workers on distinct jobs. These last four columns of the table report results from the regression:

$$\begin{aligned} \log Wage_{it} &= \alpha_i + \beta_1 Exper_{it} + \beta_2 Exper_{it} \times Affiliate_i + \beta_3 GoodFb_{it} \times Exper_{it} + \\ &\quad \beta_4 Affiliate_i \times GoodFb_{it} \times Exper_{it} + \beta_5 NoFb_{it} \times Exper_{it} + \beta_6 Affiliate_i \times NoFb_{it} \times Exper_{it} \\ &\quad + \beta_7 JobNumber_{it} + \beta_8 Affiliate \times JobNumber_{it} + X_{it}\beta_9 + \varepsilon_{it}. \end{aligned} \tag{4}$$

Worker fixed effects, α_i, capture differences in initial wages for workers with no feedback or experience. The variable $Exper_{it}$ is an indicator that the worker is experienced and eligible to have previous feedback. The effect of experience is allowed to differ for affiliates and non-affiliates through the parameter β_2. The regression also contains indicators that experienced workers have good feedback ($GoodFb_{it}$) or no feedback ($NoFb_{it}$), along with interactions for affiliation status. For experienced workers, the indicators for good feedback or zero feedback capture differences from a baseline of a bad feedback score after gaining experience. Gaining experience adds a one-time discrete shift in wages, while $JobNumber_{it}$, the number of previous hires, and an affiliate interaction, allow wages to evolve along different paths for affiliates and non-affiliates. The matrix X_{it} contains fixed effects for job category and calendar time.

Similar to the results on selection into re-hiring, affiliates' wages are less responsive than non-affiliates' wages to a good feedback score. Column 6, the most general specification, shows that a good feedback score is associated with an hourly wage increase of 10.4 percent for non-affiliates but of only 3.4 percent for affiliates.[30]

These findings offer further evidence that employers' expectations about worker quality change most for non-affiliates with good feedback. This is consistent with the belief-updating process in the theoretical framework that generates wage convergence. Having earned good feedback, a non-affiliate is able to be re-hired and also receives a rapidly increasing hourly wage. For affiliates, a public signal that he or she is high-quality is not associated with as large an increase in the probability of re-hire or with as large a wage-feedback response. Good feedback on early jobs, thus, allows non-affiliates to catch up with affiliates.

[30] The 3.4-percent increase is the sum of the estimated coefficient for good feedback (0.104) and the estimated coefficient for the interaction between good feedback and the affiliation indicator variable (−0.070).

To underscore this convergence, Table 8 presents summary statistics on wages and resume characteristics for experienced non-U.S. oDesk workers who have had three or more previous jobs with at least one feedback score at the time of measurement. The sample consists of $9,489$ unique non-affiliates and $2,640$ unique affiliates.[31] The first row of the table shows that the difference between the group average log hourly wages, net of job category and time fixed effects, is much smaller than the difference for inexperienced workers. The numbers in Columns 1 and 2 give the average deviation from the workers' typical hourly wage in a given job category and month for non-affiliates and affiliates, respectively. While the residual log hourly rate is statistically different between the two groups, the magnitude of the gap is $(-0.014 + 0.035)$, which, at 0.041, is much smaller than the original gap of 0.231 for inexperienced workers estimated from Oaxaca-Blinder decompositions in Column 4 of Table 3. It is also worth noting that the raw mean feedback score for non-affiliates is slightly higher than the raw mean feedback score for affiliates. Over time, it appears that, for the best non-affiliates, wages and feedback converge with those of affiliates.

4.5 Agency Dynamics

4.5.1 Agency Evolution and Survival

An implication of the agency role described in the model is that, in equilibrium, the agency benefits from its ability to screen only if it can maintain its reputation. It does this by offering affiliation only to high-quality screenable workers. It is possible that agency heads may be tempted to deviate from this strategy if the supply of new, high quality, screenable workers declines or nears exhaustion. Table 9 assesses whether affiliate quality changes with the size of the agency.

The results suggest that the quality of workers is very stable as agencies grow. The first three columns of the table include the 1,126 agencies active during the time period spanned by the data, and the last three columns include only the 872 agencies for which the complete agency history is observed. Panel A presents the results of regressions of log hourly wages on measures of agency size. In Panel B, the dependent variable is an indicator for a good feedback score (a score of at least 4.5 out of 5). The regressors of interest are the number of workers previously hired under the agency brand and its square. Agency fixed effects are included in all specifications, as are the detailed worker-level controls given in Appendix Table 1. The estimated coefficients make it clear that the hourly wage and feedback score of the most recently affiliated worker do not vary as an agency grows. The coefficients on agency size and the square of agency size are very small relative to the mean, and are statistically insignificant. This is true both for technical jobs

[31] This analysis includes all workers who applied for their first job before August 1, 2008, not just the inexperienced workers with job applications beginning after this date.

(Columns 2 and 5) and non-technical jobs (Columns 3 and 6), and for the whole sample of agencies as well as for the agencies whose entire histories are observed in the data.

Panel C in Table 9 examines how an agency evolves as a function of the feedback received for the most recently affiliated agency member. The results in Panel C come from a Cox model in which failure is defined as the most recently affiliated member being the last new agency affiliate observed in the data. This variable is informative about whether or not an agency is growing. If no further new affiliates are observed in the data, the agency is viewed as failing.[32]

The results suggest that an agency is significantly less likely to grow in size when the most recent affiliate has received bad feedback, the baseline category. The hazard ratio of 0.831 in Column 1 on the indicator for having received good feedback, is significantly less than one, indicating that an agency is less likely to fail when the last affiliate receives good feedback. The coefficient on missing feedback is less than one, but insignificantly so, revealing that the probability of agency failure after missing feedback is not significantly different from the probability of agency failure after bad feedback. From Columns 2, 3, 5 and 6 of Table 9, recent bad or missing feedback significantly increases the likelihood of agency failure, but this relationship is only present for agencies whose modal job category is technical rather than non-technical work. In agencies specializing in non-technical work, a bad feedback score for the most recently affiliated worker does not significantly affect the probability that an agency continues.

Overall, the results in Table 9 reveal that agencies are very stable; wages and feedback remain the same as an agency gets larger. While it seems plausible that each agency faces an increasing incentive to affiliate workers that are of lower-than-agency-average quality because the marginal affiliate's impact on agency reputation is decreasing in agency size, there is little evidence of this in the data. This motivates the model's equilibrium assumption that firm beliefs are such that observing a low-quality affiliate discredits the relevant agency's reputation entirely, and this assumption is particularly appropriate for technical work.[33]

4.5.2 Attrition from agencies is rare

The probability of finding work after the first job is positively related to feedback. Do agencies retain workers with good feedback? Table 10 establishes that very few workers remain on the site after having

[32]It is not possible to evaluate agency failure using the job prospects of existing experienced affiliates, as these workers have public individual feedback scores and the agency plays a small role in their ongoing career prospects.

[33]These findings are similar to the insights about the dynamics of seller reputation in other online markets. For example, Cabral and Hortacsu (2010) study the dynamics of seller reputation on eBay and show that buyers react to information about a seller's information and that seller's actions reflect reputation considerations. Specifically, sellers are more likely to exit after receiving bad feedback. Section 4 of Bar-Isaac and Tadelis (2008) surveys the growing literature on the dynamics of intermediary reputation.

left an agency. The sample of workers included in this analysis is all agency affiliates who are hired at least once. The vast majority of affiliates remain affiliated with the same agency for their entire oDesk career. There are some workers leave agencies but continue on oDesk as non-affiliates, but this group is small: only 2.5 percent of affiliates on the first job and only 1.5 percent of affiliates in technical jobs. Of the small amount of attrition from agencies that does occur, the majority happens in non-technical jobs, where 5.2 percent of affiliates work as a non-affiliate after have worked with an agency. In regressions where the dependent variable is an indicator that the affiliate in question eventually leaves the agency, the table reveals that affiliates who leave an agency are not observably different than affiliates who remain, except for the possibility that those who leave earn slightly lower wages on the first job. However, this result appears to be driven by heterogeneity across agencies and does not hold in specifications with agency fixed effects. This offers some support for the model's assumption that contracts adjust to keep even the best workers affiliated with the agency over time.

5 Alternative Intermediation Functions and Discussion

5.1 Direct Benefits and Team Production

The results, so far, are consistent with the hypothesis that agencies provide information about inexperienced worker quality. This section asks if there is also evidence of an intermediation role that increases worker productivity directly (Autor, 2001a). For example, agencies could be providing translation services for workers with poor English language skills or training for less-educated or less-skilled workers. The maintained assumption here is that agencies provide a uniform signal of quality for all affiliates, or no signal of quality for all affiliates. In this case, under the hypothesized alternative role of direct agency benefits to productivity, agency affiliation might be expected to have a heterogeneous effect among workers with differing skills. For example, if agencies benefit workers with poor language skills, then the relationship between productivity measures or wages and the good English skills dummy is expected to be less pronounced for affiliates relative to non-affiliates. Using the Oaxaca-Blinder regressions, if agencies benefit workers with poor English skills, $(\hat{\beta}_A^{GoodEnglishSkills} - \hat{\beta}_N^{GoodEnglishSkills})$, is predicted to be negative.

If there is no evidence of heterogeneous effects, then agencies may not be providing direct productive benefits. The results in Table 11 show that agency job-finding, wage, and productivity advantages are indeed relatively uniform across workers with different observable characteristics. Estimated coefficients and robust standard errors from a pooled version of the Oaxaca-Blinder models are reported. In the pooled model, non-affiliates serve as the baseline, with coefficient estimates reported in the first of each successive pair of columns. Every covariate entering the model also has an affiliate interaction, reported in the second of each pair of columns. The relevant test is whether the affiliation interaction differs from the non-affiliate baseline. The first four covariates are of interest for assessing whether agency effects are heterogeneous across affiliates.

The results for wages, shown in Columns 5 and 6, are most interesting. For workers with a bachelor's or higher degree, the estimated interaction term for affiliation is small, positive, and statistically insignificant in the model for log wages. While non-affiliates appear less likely to report having a bachelor's or higher degree, the wage premium for educated workers relative to less-educated workers does not differ under agency affiliation.

Given that the workers in the sample are located outside of the United States, heterogeneity in the agency effect on wages for employed workers with varying English skills may be likely. However, this is not the case. In the log wage model, the agency interaction is negative, and the standard error is larger than the point estimate. The agency interaction is not significantly different from the baseline for non-affiliates in any specification. While non-affiliates report having good English skills more frequently, the difference between the group means is small (87 percent compared to 79 percent, as shown in Table 2, Columns 3 and 4). Overall, it does not appear that agencies provide a benefit based on translation or other language services.

These results, combined with the remaining estimates corresponding to years of prior experience and an indicator for having taken skills tests, lead to the conclusion that the magnitude of the agency wage premium is unrelated to affiliates' skill levels. It is not possible to detect the provision of direct benefits that increase affiliates' on-the-job productivity. This casts doubt on the alternative hypothesis that affiliation directly causes workers to be more productive.

For several other dependent variables related to first jobs—notably, days of job search and number of applications prior to initial hire— the affiliate interaction suggests that the agency premium is, if anything, greater for affiliates with higher levels of observable skills. Relative to affiliates with poor English skills, those with good English skills have shorter searches and make fewer applications prior to initial hire, relative to the difference that English skills makes in these outcomes for non-affiliates. In general, there are no heterogeneous agency interactions that suggest that affiliation has a particularly large effect on the outcomes of relatively less skilled affiliates.[34,35]

[34]The regressions in Table 11 also include detailed interactions for individual categories of tests and test scores. No interactions are statistically different from zero for detailed test score measures when the log wage, days of job search, number of job applications prior to employment, or the length of the first job is the dependent variable. Interactions for database administration are statistically significant when success or feedback scores are the dependent variable, but no other test score interactions are statistically different from zero in these specifications.

[35]If the signaling value of affiliation is complementary with workers' skills, rather than uniform across all affiliates, then this

An additional potential agency role is the potential that they facilitate hiring groups of workers. Whether a worker is on a team-based job is a job characteristic that can be included as an observable characteristic in the Oaxaca-Blinder decomposition, revealing whether variation in teamwork affects wages, job finding probabilities, and project outcomes. A team-based job is defined as one in which the worker is hired by an employer who has also hired another oDesk worker within a seven-day window around the worker's application date. Around 60 percent of the jobs on oDesk are classified as team-based jobs. An agency-team-based job is defined as one in which an employer hires more than one agency affiliate within a seven-day window. Around one third of affiliates' first jobs involve agency teams.[36,37]

An additional consideration is whether the ability to form teams of agency affiliates has any additional positive effect for agency affiliates. Lyons (2014) finds that homogeneous teams achieve better outcomes in an experiment in the oDesk setting, and affiliates of the same agency tend to be relatively homogeneous—sharing many observable characteristics. It is therefore possible that agencies facilitate team production. Around 22 percent of the affiliate sample involves workers on team-based jobs without another team member from the same agency.

Nonetheless, these patterns in team organization provide enough variation to identify the effect of agency teams separately from individual workers' participation on general team-based projects. The sixth row of coefficients in Table 11 shows that there is some evidence for an agency-team effect. Wages for affiliates on agency teams are higher by 11.4 percent; job-finding speeds increase; projects last longer; and feedback is superior for agency-team-based projects. The estimates suggest that agency affiliates are generally better at working on teams than non-affiliates, and working with members of the same agency appears to generate advantages.

From the detailed estimates, it is possible to decompose the estimated agency premium from Table 3 into two portions: one due to agency-team production; and a residual portion that is orthogonal to the agency-team estimate by including additional controls in the Oaxaca-Blinder decompositions. This is done by treating teamwork and agency teamwork as part of the "explained" component of the wage/outcome gap due to agency affiliation. The bottom two rows of Table 11 present the results of decompositions that include both an indicator for being employed on a team job, and an indicator for being employed on

exercise is more problematic. In this case, it is possible that workers with low skills receive the additional production benefit from affiliation and workers with high skills receive the complementary signaling benefit. The net result would be a bias toward finding a common agency effect. Agencies prevalence in technical jobs does not provide evidence for complementarity, as all specifications contain job category fixed effects.

[36] These measures may overstate the incidence of team production for workers because there is no guarantee that workers who are hired jointly in a short time span actually perform work together.

[37] When splitting the sample into technical and non-technical jobs, 51.4 percent of non-affiliates' technical jobs are classified as team-based jobs, 51.2 percent of affiliates' technical jobs are team-based, and 33.1 percent of affiliates' technical jobs are agency-team based jobs. In non-technical categories, 71.8 percent of non-affiliates' jobs are team-based, while 68.2 percent of affiliates' jobs are team-based and 32.8 percent of affiliates' jobs are agency-team based.

a team with members of the same agency. The row labeled "Agency Premium Accounting For Teams" includes decomposition results that treat $\left(\beta_A^{Team} - \beta_N^{Team}\right) \bar{X}_A^{Team}$ and $\left(\beta_A^{Agency-Team} - 0\right) \bar{X}_A^{Agency-Team}$ as part of the agency premium. In contrast, the row labeled "Premium Removing Agency Teams" removes $\beta_A^{Agency-Team} \bar{X}_A^{Agency-Team}$ and $\left(\beta_A^{Team} - \beta_N^{Team}\right) \bar{X}_A^{Team}$ from the calculation of the agency premium. With this latter calculation, the reported agency premium after removing differences in agency team production assumes that the removal of agency teams would result in individual work. These assumptions lead to larger estimates of the effect of team production (and smaller estimates of the agency premium) relative to assumptions that agency affiliates would form teams with other workers.

Overall, the results are mixed, but a significant premium for job-finding probabilities, wages, hours worked, and success still exists after any team composition effect from the agency premium. Affiliates working individually find jobs about 11 to 13 percent faster than non-affiliates, earn wages that are about 15 percent higher, work on projects that involve 30 percent more hours; and have success reported about 6 percent more frequently. However, agency teamwork explains most of the observed feedback advantage between affiliates and non-affiliates, so there is some evidence that team production may enhance agency affiliates' output quality.

Whether the advantages of team production are causal requires an analysis over workers' careers. Adding measures of team production to the models in equations (3) and (4), agency teamwork is found to have little influence in explaining the documented variation over the careers of affiliates and non-affiliates. Columns 1 through 4 in Table 12 revisit the analysis in Table 7, allowing for differences in teamwork and in agency-based teamwork. The sample is workers on their first job, and the dependent variable is an indicator that a worker finds a second job. The point estimates on the agency-affiliate indicator in each of the first four columns is positive and significant, and the estimates are similar in magnitude to the estimates that did not account for team production (Table 7, Columns 1 to 4). It is important to note that, when detailed controls are included, the parameter estimates on the feedback measures and the affiliate-feedback interactions are also similar to the estimates given in Table 7. The finding that affiliates' re-employment probability is less reponsive to feedback than the equivalent probability for non-affiliates remains particularly strong in technical work. Affiliates on technical agency teams are slightly more likely to find subsequent jobs, but the main effect of agency affiliation is around six times larger than the effect of agency-team production.

Columns 5 to 8 of Table 12 revisit the panel analysis of wages over workers' careers presented in Columns 5 to 8 of Table 7. These specifications all include worker fixed effects, allowing for the identification of the effect of various measures of teamwork using only variation within worker. The estimates in Column 6 indicate that being on a team-based job is associated with lower wages for non-affiliates, but the effect is mitigated for affiliates working in teams. In addition, there is no positive effect on wages for affiliates who work on affiliate teams. All other estimates are very similar to the comparable specifications in Columns 5 to 8 of Table 7, including those in which the effect of teamwork is allowed to vary over time. In addition, the estimates of the effect of feedback are nearly identical when allowing for differential trends by team-based job status, suggesting that compositional changes in team production over workers' careers are unlikely to explain the documented convergence in wages between affiliates and non-affiliates.

5.2 Implications for Online Labor Market Organization

How much do intermediaries matter? A back-of-the-envelope calculation suggests that the total gain from agencies' presence in this market is substantial. Thirty-two percent of the inexperienced workers who find work are affiliates. Assuming that, in the absence of agencies, affiliates would be unable to communicate their superior, unobserved quality to employers, the employment outcomes for non-affiliates serve as a baseline for how the market would operate in the absence of agencies. An adjustment is required, however, because Table 2 suggests that a portion of the earnings difference is due to agency affiliates having differentially valued observable characteristics. Thus, average earnings per worker in the absence of affiliation are estimated as: $Earnings_N S_N + (Earnings_N + \Delta Earnings_{A,N} \times (1-0.50))\, S_A$, where $Earnings_i$ is the mean earnings for group $i = N$ (for non-affiliates) or A (for affiliates); S_i is the share of each group; $\Delta Earnings_{A,N}$ is the earnings gap between affiliates and non-affiliates; and $(1-0.50)$ is the portion of the gap attributable to differences in characteristics (not due to agency affiliation).

Using this number offers an estimate of revenues per worker in the absence of intermediaries in the market because it assumes that employers will select workers who resemble affiliates, based on their observed characteristics, at the same rate that affiliates currently land the first job. Thus, the calculation ignores the extensive margin where agency affiliation helps workers to land the first job, while assuming that the same number of hires are made.[38] Taking the difference between the actual per-worker transaction volume and this calculation suggests that, in the absence of agencies, average earnings per worker would have been about \$3,779, compared to \$4,211 in the presence of agencies. Therefore, under these assumptions, agencies increase allocative efficiency by about 11.4 percent.

The finding that inexperienced affiliates are, on average, higher-quality workers than inexperienced

[38] It is likely that the equilibrium number of hires is also larger when agencies provide information about worker quality. For simplicity, the model in Section 3 assumes that all firms make hires with and without the agency. Pallais (2014) allows for information to affect the extensive margin of the number of hires. Using experimental data, she finds that the number of hires increases with information about worker quality.

affiliates raises the question of how agencies screen for quality and why all workers don't join agencies. The answer is likely to be that the boundaries of existing social networks limit the size of any single agency. Affiliates of the same agency are frequently located in the same city and have similar skills, often having attended classes together at the same educational institutions and, in general, are very likely to know each other personally. This suggests that agencies are able to screen worker quality and offer affiliation only to high-quality workers by using the shared offline social ties that pre-date workers' oDesk registration. It is also possible that the high-quality workers who start agencies tend to be acquainted only with other high-quality potential workers. In either case, the type of social ties that are known to play a role in traditional labor markets, such as referral systems through "Old Boy Networks" (Saloner, 1985), appear to facilitate screening in this setting.[39] Agencies are performing a role that is similar to that played by the experts described in Biglaiser (1993), the certification intermediaries in Lizzeri (1999) and the temporary help supply firms discussed in Autor (2001b), but without requiring either any costly additional screening or self-selection, as in Spence (1973). In this way, rather than being rendered obsolete by recent developments in communication technology, offline social ties complement online interactions.[40]

5.3 General implications for labor and product markets

oDesk presents an unusually detailed setting for studying the question of market responses to incomplete information because the information that employers have about workers in this market is comparable to that available to researchers. In many relevant ways, the oDesk market resembles other spot markets for labor, such as the general model described in Tervio (2009), where employment of inexperienced workers, who lack verified performance data, is likely to be inefficiently low (Pallais, 2014). Many subsets of labor markets do have public revelation of ability from experience: Actors make films that are public outputs; graphic and web designers produce portfolios of work that are shared with clients; fund managers have documented performance histories through reporting returns; academics publish papers and have public records of citation counts; chefs have ratings from food critics, etc.

The agency role within the oDesk market raises the question of whether other mechanisms and organizations that reduce incomplete information will arise endogenously within spot labor markets. Agencies

[39] 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. Burks et al. (2013) provide estimates of the productivity effects of referrals.

[40] Several recent related papers study the role of social networks in providing information about online investment quality. Agrawal et al. (2011) suggest that investors sharing personal connections to unsigned music artists are less responsive to others' investment decisions because they have informational advantages about the artist's quality. In their study of the loan market Prosper.com, Freedman and Jin (2010) find that borrower affiliation with a social network is not associated with borrower quality. They propose that this is due to characteristics of the market design, which limit incentives for group founders to grant membership only to good-quality borrowers.

on oDesk are particularly prevalent where information about worker quality is most incomplete, consistent with the hypothesis that they are an endogenous response to this source of market failure. For example, a larger share of workers are affiliated with agencies in countries where the educational institutions are most likely to be unfamiliar to potential employers, of whom the majority are US-based. Affiliation is also relatively prevalent in job categories where worker and, hence, work quality is hardest to assess before and even during the job; that is, in technical rather than non-technical tasks. Other studies of online labor markets discuss different methods by which information can be credibly shared.[41]

There is a growing empirical literature on incomplete information in product markets that identifies how buyers and sellers respond to credible information about product quality. In some cases, institutional features of the market allow sellers to provide information. For example, Lewis (2011) examines the role of voluntary information disclosure in defining explicit contracts between buyers and sellers regarding the quality of used cars sold on eBay Motors. In other cases, the feedback provided by other buyers conveys quality information: Resnick and Zeckhauser (2002) and Bajari and Hortacsu (2004) discuss the economics of internet auctions and summarize the empirical evidence on the relationship between the information contained in seller feedback and price. Jin and Kato (2006) present evidence that feedback can be a credible signal that sellers offer good quality. Luca (2010) shows that restaurant revenues respond more strongly to online restaurant reviews for unbranded restaurants without a national reputation. In general, these papers do not investigate buyers' incentives to leave feedback, or the problem faced by inexperienced sellers with no existing feedback, which is the main question addressed here.

Relatively few empirical papers demonstrate how third parties provide quality-related information, but Sufi (2009) and Tang (1999) show that, in the market for financial services, third-party rating agencies impact firm's access to bank loans, which has real effects on firms' investment policies. As is the case for intermediaries on oDesk, these effects are larger when other information about loan quality is limited. The contribution of this paper to the broader literature is to highlight the institutional features that have proven to be sufficient for third-party organizations to emerge to provide information: In oDesk, agencies appear able to screen inexperienced worker quality without incuring additional costs, but the key features that allow them to extract surplus from doing so are the publicly-revealed agency-level feedback together with the long-term contracting arrangement that is possible between agencies and workers, but not between workers and employers.

[41] See Horton (2010) for a discussion of the features of online labor markets. Bagues and Labini (2009) show how mandatory disclosure of quality-relevant worker information affects worker outcomes, such as unemployment duration, wages, and job satisfaction.

6 Conclusion

This paper presents evidence that intermediary organizations called outsourcing agencies have arisen within online labor markets to provide information about worker quality that is valuable to employers. Affiliation with one of the many small independent outsourcing agencies on oDesk.com is strongly positively correlated with success on the site—affiliates' lifetime earnings are around three and a half times higher than the earnings of non-affiliates who have similar observable skills and characteristics. The results reveal that the source of this advantage is that agencies credibly signal that inexperienced agency affiliates are relatively high quality, reducing information frictions in the market. Agencies protect their own reputations by continuing to affiliate only high quality workers.

This agency-affiliation premium is consistent with an information-provision role because it originates during the early stages of workers' careers, when information about worker quality is particularly incomplete. In addition, agency affiliation is concentrated in settings where information is likely to be most valuable: in technical jobs and for workers in overseas countries where it is hardest for potential employers to verify worker quality from observable charateristics. Among experienced workers, there is little-to-no ongoing agency-affiliation premium. Good feedback received by workers on their early jobs appears to substitute for the information contained in agency affiliation. Non-affiliates' likelihood of being re-employed, and their subsequent hourly wages, are more responsive to the feedback scores received on the job than for affiliates, implying that more information is contained in good feedback scores for non-affiliated workers.

An important implication of the findings is that agencies have a large positive impact on the volume of trade by increasing the number of high-quality workers in the market. By demonstrating how intermediaries have arisen to perform this information-provision role, the findings suggest that organizations that overcome incomplete information frictions can have a large effect on the allocative efficiency of labor-offshoring markets, despite the large amount of digital information that is available to trading partners.

References

[1] Acemoglu, Daron, and Jörn-Steffen Pischke. 1998. Why Do Firms Train? Theory and Evidence. *The Quarterly Journal of Economics*, 113(1), 79-119.

[2] Acemoglu, Daron, and Jörn-Steffen Pischke. 1999. Beyond Becker: training in imperfect labour markets. *The Economic Journa*l, 109(453), 112-142.

[3] Agrawal, Ajay, Christian Catalini and Avi Goldfarb. 2011. "Friends, Family, and the Flat World: The Geography of Crowdfunding." NBER Working Paper No.16820.

[4] Agrawal, Ajay, John Horton, Elizabeth Lyons and Nicola Lacetera. 2014. "Digitization of Information and the Market for Contract Labor' Forthcoming in Goldfarb, A., Greenstein, S. and Tucker, C (Eds) Economics of Digitization: An Agenda. National Bureau of Economic Research.

[5] Altonji, Joseph, and Charles Pierret. 2001. "Employer Learning and Statistical Discrimination." *The Quarterly Journal of Economics*, 116(1), 313-350.

[6] Ahn, Jae-Bin, Amit Khandelwal and Shang-Jin Wei. 2011. "The role of intermediaries in facilitating trade," *Journal of International Economics*, 84(1), 73-85.

[7] Antras, Pol and C. Fritz Foley. 2014. "Poultry in Motion: A Study of International Trade Finance Practices." *Journal of Political Economy*, forthcoming.

[8] Araujo, Luis, Giordano Mion and Emanuel Ornelas. 2012. "Institutions and Export Dynamics." CEPR Working Paper No.8809.

Autor, David. 2001a. "Wiring the Labor Market." *Journal of Economic Perspectives*, 15(1), 25-40.

[9] Autor, David. 2001b. "Why Do Temporary Help Firms Provide Free General Skills Training?" *The Quarterly Journal of Economics*, 116(4), 1409-1448.

[10] Bagues, Manuel. and M. Sylos Labini. 2009. "Do on-line labor intermediaries matter? The impact of AlmaLaurea on the university-to-work transition." in *Studies of Labor Market Intermediation*, Autor, D.,(ed), University of Chicago Press.

[11] Bajari, Patrick and Ali Hortaçsu. 2004. "Economic Insights from Internet Auctions." *Journal of Economic Literature*, 42(2), 457-486.

[12] Bar-Isaac, Heski, and Steven Tadelis. 2008. textitSeller reputation. Now Publishers Inc.

Becker, Gary. 1962. "Investment in Human Capital: A Theoretical Analysis." *Journal of Political Economy*, 70(5), 9-49.

[13] Becker, Gary, and Kevin Murphy. 1992. "The Division of Labor, Coordination Costs, and Knowledge." *The Quarterly Journal of Economics*, 107(4), 1137-1160.

[14] Besley, Timothy, Stephen Coate and Glenn Loury. 1993. "The Economics of Rotating Savings and Credit Associations." *American Economic Review,* 83(4), 792-810.

[15] Bidwell, Matthew, and Isabel Fernandez-Mateo. 2010. "Relationship Duration and Returns to Brokerage in the Staffing Sector." *Organization Science*, 21(6), 1141-1158.

[16] Biglaiser, Gary. 1993. "Middlemen as Experts." *The RAND Journal of Economics*, 24(2), 212-223.

[17] Blinder, Alan. 1973. "Wage Discrimination: Reduced Form and Structural Estimates." *The Journal of Human Resources*, 8(4), 436-455.

[18] Burks, Stephen, Bo Cowgill, Mitchell Hoffman, and Michael Gene Housman. 2013. "The Facts about Referrals: Toward an Understanding of Employee Referral Networks" Working Paper.

[19] Blinder, Alan, and Alan Krueger. 2009. "Alternative Measures of Offshorability: A Survey Approach." *Journal of Labor Economics*, forthcoming.

[20] Cabral, Luis, and Ali Hortacsu. 2010. "The dynamics of seller reputation: Evidence from ebay*." *The Journal of Industrial Economics*, 58.1, 54-78.

[21] Casella, Alessandra, and Nobuyuki Hanaki. 2006. "Why Personal Ties Cannot Be Bought." *American Economic Review*, 96(2), 261-264.

[22] Casella, Alessandra, and Nobuyuki Hanaki. 2008. "Information channels in labor markets. On the resilience of referral hiring." *Journal of Economic Behavior & Organization*, 66(3-4), 492-513.

[23] Chiappori, Pierre-Andre, Bernard Salanie, and Julie Valentin. 1999. Early starters versus late beginners. *Journal of Political Economy*, 107(4), 731-760.

[24] Farber, Henry and Robert Gibbons. 1996. "Learning and Wage Dynamics." *The Quarterly Journal of Economics,* 111(4), 1007-1047.

[25] Feenstra, Robert and Gordon Hanson. 2004. "Intermediaries in Entrepot Trade: Hong Kong Re-Exports of Chinese Goods," *Journal of Economics and Management Strategy*, 13(1), 3-25.

[26] Freedman, Seth and Ginger Zhe Jin. 2010. "Do Social Networks Solve Information Problems for Peer-to-Peer Lending? Evidence from Prosper.com." *NET Institute Working Paper No. 08-43.*

[27] Fortin, Nicole, Thomas Lemieux, and Sergio Firpo. 2011. "Decomposition Methods in Economics." *Handbook of Labor Economics,* 4(1), 1-102.

[28] Ghani, Ejaz, William Kerr, and Christopher Stanton. 2014. "Diasporas and Outsourcing: Evidence from oDesk and India." *Management Science,* 60(7), 1677-1697.

[29] Greif, Avner. 1993. "Contract Enforceability and Economic Institutions in Early Trade: The Maghribi Traders' Coalition," *American Economic Review*, 83(3), 525-548.

[30] Hainmueller, Jens. 2012. Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. Political Analysis, 20, 25-46.

[31] Horton, John. 2010. "Online Labor Markets." Working Paper.

[32] Jin, Ginger and Andrew Kato. 2006. "Price, Quality and Reputation: Evidence from An Online Field Experiment." The RAND Journal of Economics, 37(4), 983-1005.

[33] Lange, Fabian. 2007. "The Speed of Employer Learning." *Journal of Labor Economics,* 25(1), 1-35.

[34] Lewis, Gregory. 2011. "Asymmetric Information, Adverse Selection and Online Disclosure: The Case of eBay Motors." *American Economic Review*, 101(4), 1535-1546.

[35] Lizzeri, Alessandro. 1999. "Information Revelation and Certification Intermediaries." *The RAND Journal of Economics*, 30(2), 214-231.

[36] Lockwood, Ben. 1991. "Information Externalities in the Labour Market and the Duration of Unemployment." *The Review of Economic Studies*, 58(4), 733-753.

[37] Luca, Michael. 2010. "Reviews, Reputation, and Revenues: The Case of Yelp.com." Harvard Business School Working Paper No.13-042.

[38] Lyons, Elizabeth. 2014. "Team Production in International Labor Markets: Experimental Evidence from the Field." Working paper.

[39] Milgrom, Paul, Douglass North and Barry Weingast. 1990. "The role of institutions in the revival of trade: The law merchant, private judges, and the champagne fairs," *Economics and Politics*, 2(1), 1-23.

[40] Montgomery, James. 1991. "Social Networks and Labor Market Outcomes: Toward an Economic Analysis." *American Economic Review*, 81, 1408-1418.

[41] Oaxaca, Ronald. 1973. "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review*, 14(3), 693-709.

[42] Oaxaca, Ronald and Michael Ransom. 1999. "Identification in Detailed Wage Decompositions." *The Review of Economics and Statistics*, 81(1), 154-157.

[43] Pallais, Amanda. 2014. "Inefficient Hiring in Entry-Level Labor Markets." *American Economic Review*, forthcoming.

[44] Resnick, Paul and Richard Zeckhauser. 2002. "Trust Among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System." *The Economics of the Internet and E-Commerce.* Michael R. Baye, editor. Volume 11 of Advances in Applied Microeconomics. Amsterdam, Elsevier Science, 127-157.

[45] Saloner, Garth. 1985. "Old Boy Networks as Screening Mechanisms." *Journal of Labor Economics*, 3(3), 255-267.

[46] Spence, Michael. 1973. "Job Market Signaling." *The Quarterly Journal of Economics*, 87(3), 355-374.

[47] Spulber, Daniel. 1999. "*Market microstructure: Intermediaries and the theory of the firm.*" Cambridge: Cambridge University Press.

[48] Sufi, Amir. 2009. The real effects of debt certification: Evidence from the introduction of bank loan ratings. *Review of Financial Studies*, 22(4), 1659-1691.

[49] Tang, Tony. T. 2009. Information asymmetry and firms' credit market access: Evidence from Moody's credit rating format refinement. *Journal of Financial Economics*, 93(2), 325-351.

[50] Tervio, Marko. 2009. Superstars and Mediocrities: Market Failure in the Discovery of Talent. *The Review of Economic Studies*, 76(2), 829-850.

Appendix 1: Proofs

The model presented in Section 3 describes two perfect Bayesian equilibria: first, an equilibrium in the case of no agency and, second, an equlibrium in the case where the agency can screen a share of new workers. This appendix offers a proof that the second proposed equilibrium is a perfect Bayesian equilibrium. The proof for the first equilibrium follows as a special case by setting the share of screenable workers, a, to zero.[42]

We focus on conditions that guarantee some workers without agency affiliation are hired; this allows a contrast between workers' careers under affiliation and non-affiliation. The condition is that the number of job openings, N, is larger than the number of known high quality workers and the number of agency affiliates. We also posit that the number of openings is smaller than the number of new workers plus the number of high quality workers and agency affiliates (who are high quality in equilibrium).

After applying a law of large numbers, let E_{HA} denote the (non-stochastic) number of revealed high quality workers and agency affiliates in the market. With probability h, each of the E new workers who enter the market is high quality. Given that all agency affiliates and revealed high quality workers are hired in equilibrium, $N - E_{HA}$ non-affiliates with unknown types are hired. This gives the steady-state condition $E_{HA} = h(N - E_{HA}) + 2ahE$ where $h(N - E_{HA})$ is the number of high types after revelation of ability on the job and $2ahE$ is the number of agency affiliates. This yields $E_{HA} = \frac{h}{1+h}(N + 2aE)$. The condition $E_{HA} < N < E_{HA} + (1 - a)\,E$ corresponds to the case considered.

Strategies: We first formally define each player's equilibrium strategy and beliefs, and then we show that there is no profitable deviation for any player. Given the market clearing process outlined in the main text, a strategy for the firm is a function that maps observable worker characteristics and wage offers to a hiring ranking. Subscripts are used to denote a particular value specific to workers of type each type along 3 dimensions, ijt. When used for the firm's strategies, these subscripts denote how a particular type of worker is distinguished in the firm's ranking. When used for a worker's wage offer strategy, it denotes a strategy conditional on the information that has been revealed.

Let i be the worker's agency affiliation, $i \in \{A, N\}$, revealed type from past work, $j \in \{H, L, U\}$ (where U indicates the worker's type has not been revealed), and $t \in \{1, 2\}$ indicating the period of the worker's

[42] It is certainly possible to construct other equilibria of the model. For example, there is another equilibrium in which all market participants believe the agency only affiliates high quality workers in even periods. In odd periods, new affiliates are random. The equilibrium described in the text is one reasonable equilibrium among the set of equilibria that maximize allocative efficiency. The differences in wage and career dynamics between affiliates and non-affiliates are robust among the set of constrained efficient equilibria. .

life. The equilibrium strategy for each firm is then a ranking function:

$$\max\left(X_{ijt} - w_{ijt} \text{ for all } ijt, 0\right)$$

where, without loss because of the discrete nature of types, each X_{ijt} is a type-specific constant that the firm submits for each observable type of worker and w_{ijt} is the wage offer submitted by the worker. The zero allows the firm the option to not hire. All firms equilibrium rankings set $X_{AH2} = X_{AU1} = X_{AU2} = X_{NH2} = H$ (note X_{AH1}, X_{AL1}, X_{NH1}, X_{NL1} are not possible, as a worker in the first period does not have a type revealed from work experience). Further, $X_{AL2} = X_{NL2} = L$, and $X_{NU1} = X_{NU2} = hH + (1-h)L$. The market clearing authority then evaluates these rankings and uses the relevant constants X_{ijt} less the wage offered for each worker to evaluate which worker a randomly drawn firm prefers to hire. This continues until no firms remain.

A strategy for each worker is a mapping from type and the history of play to a wage offer in each period and a mapping from the history of play and an agency contract-offer to an affiliation acceptance decision (accept affiliation or reject). For all workers, equilibrium wage offers are

$$\begin{aligned} w^A &= w_{NH2} = w^H := \frac{(1-h)}{(1+h)}(H-L) \\ w_{AL2} &= w_{NL2} = w_{NU2} = 0 \\ w_{NU1} &= -h\frac{(1-h)}{(1+h)}(H-L) = w^U := -hw^H. \end{aligned}$$

Here w^A is used for shorthand for the wage of all agency affiliates, as $w_{AU1} = w_{AH2} = w_{AU2}$.[43] If no past agency affiliate has been revealed to be a low type, each worker's affiliation strategy is to accept the contract at $t = 1$ iff $\beta_1 + \beta_2 \leq (1+h)\, w^H$. For workers at $t = 2$ and $j = H$ or L, affiliation is accepted iff $\beta_2 \leq 0$. For workers at $t = 2$ and $j = U$, affiliation is accepted iff $\beta_2 \leq w^H$.

The agency's strategy is a mapping from the history of play, a worker's screenability, s, a worker's type, θ, and the period in a worker's life t to a contract offer (β_1, β_2) for workers at $t = 1$ and β_2 for workers at $t = 2$ that stipulates a lump-sum payment to the agency at the beginning of the period. For workers who have $s = 1$, θ is known by the agency even when they have no past work experience. For workers who have $s = 0$, θ is unknown by the agency unless the worker has past experience.

[43] Note that wages with superscriptes denote equilibrium wages, that may be earned by several types of workers. Wages with subscripts (ijt) denote the wages paid to a worker of type (ijt).

The agency's contract strategy is:

$$
\begin{aligned}
(\beta_1, \beta_2) &= \left((1+h)\, w^H, 0\right) && \text{for workers with } \theta = H, s = 1, t = 1 \\
(\beta_1, \beta_2) &= (\Upsilon, 0) && \text{for workers with } \theta = L, s = 1, t = 1 \\
(\beta_1, \beta_2) &= ((1-h)\,\Upsilon, 0) && \text{for workers with } \theta = U, s = 0, t = 1 \\
\beta_2 &= 0 && \text{for workers with } \theta = H, s \in \{0,1\}, t = 2 \\
\beta_2 &= \Upsilon && \text{for workers with } \theta = L, s \in \{0,1\}, t = 2 \\
\beta_2 &= (1-h)\,\Upsilon && \text{for workers with } \theta = U, s \in \{0,1\}, t = 2
\end{aligned}
$$

where Υ is the present discounted value of agency revenues from following the equilibrium strategy and ever allowing a low quality worker into the agency.

Beliefs: On the equilibrium path, agency affiliates are always revealed to be high quality after being hired. If, over the history of past play, there has never been an agency affiliate that is a revealed low quality worker on the job, all players believe that inexperienced agency affiliates are high quality with probability 1. Off the equilibrium, if there is ever a low quality worker observed as an agency affiliate, all players believe that inexperienced agency affiliates are high types with probability h. Beliefs about experienced workers equal the type that is revealed through the job. All of these beliefs are consistent with Bayes' rule.

There are no profitable deviations: Given these strategies and beliefs for workers and firms, firms are indifferent between matching with a known high-quality worker at $t = 2$, an affiliate at $t = 1$, an affiliate at $t = 2$, or an inexperienced non-affiliate at $t = 1$. If the firm is matched with a high quality worker or an affiliate, the firm earns $H - w^H = \frac{2hH+(1-h)L}{(1+h)} > 0$. If matched with an inexperienced non-affiliate of unknown type at $t = 1$, the firm earns $hH + (1-h)\,L + hw^H = \frac{2hH+(1-h)L}{(1+h)} > 0$. If matched with a known L type worker, the firm gets L. If matched with an unknown and inexperienced worker, the firm gets $hH + (1-h)\,L$. It is clear that the firm prefers to be matched with an unknown type at $t = 2$ relative to a revealed L type.

All firms prefer matching with affiliates, known high types, or inexperienced unknown workers at $t = 1$ to matching with unknown types at $t = 2$ because $\frac{2hH+(1-h)L}{(1+h)} > hH + (1-h)\,L$. This also implies that the firm prefers the matches as a result of the equilibrium to matching with a low type. By the previous inequality, any deviation that weakly increases the probability of matching with any other type of worker makes the firm worse off and weakly reduces the firm's payoffs: the firm does not set wages or realized output, and the ranking only influences the allocation of matches. Each firm can do no better than the equilibrium matches given workers' wage offers. In fact, the equilibrium rankings are simply the firm's profit function, and maximize profits by definition.

Now consider potential deviations by workers. If an affiliate or a known high quality worker submits a wage higher than w^H, matching occurs with probability 0 and payoffs fall from w^H to 0. Because the agency fee is collected before matching occurs, affiliates cannot avoid the fee by submitting a wage that results in no match. Alternatively, a deviation to a wage lower than w^H does not change the probability of matching, but results in payoffs lower than w^H. Non-affiliates at $t = 1$ are exactly indifferent between their wage offer and foregoing employment by raising their wage offer. This is because w_{NU1} comes from the lifetime zero-profit condition for non-affiliates. Any increase in the wage offer results in never being hired. A reduction in wages below w_{NU1} results in employment with probability 1, but expected lifetime earnings are negative with a wage cut.

Workers' decisions to accept affiliation are also optimal. All workers with $s = 0$ or $s = 1$ and $\theta = L$ turn down the agency contract. The agency demands more fees than the lifetime earnings for these workers, resulting in negative lifetime payoffs relative to remaining unaffiliated. Workers offered the agency contract $(\beta_1, \beta_2) = (1 + h, 0)$ infer that they are high quality and accept the contract. This contract makes the worker exactly indifferent between affiliation and working as a non-affiliate with wage offers $\left(w_{NU1} = -hw^H - \varepsilon, w_{NH2} = w^H\right)$.

Lifetime earnings for the worker under non-affiliation are $(1 - h)\, w^H$. Total wages for the worker under affiliation are $2w^H$, and the agency collects $(1 + h)\, w^H$, such that worker receives $2w^H - (1 + h)\, w^H$, which equals the payment under non-affiliation. The agency has no incentive to deviate from this strategy by construction. The equilibrium contract makes the agency indifferent between continuing on and collecting payments from the future stream of affiliates and allowing a non-affiliate into the agency. However, no non-affiliate will be willing to pay the future stream of discounted payments to the agency under reasonable discount rates. In addition, the contract for screenable high quality workers is optimal, as any other contract either results in the worker no selecting affiliation or leaves money on the table.

Figure 1

A sample worker profile. The individual feedback score is in the top right corner, and the agency name appears as *"qCode"*, along with the agency-level feedback score. The work history on recent jobs is visible in the middle of the screen.

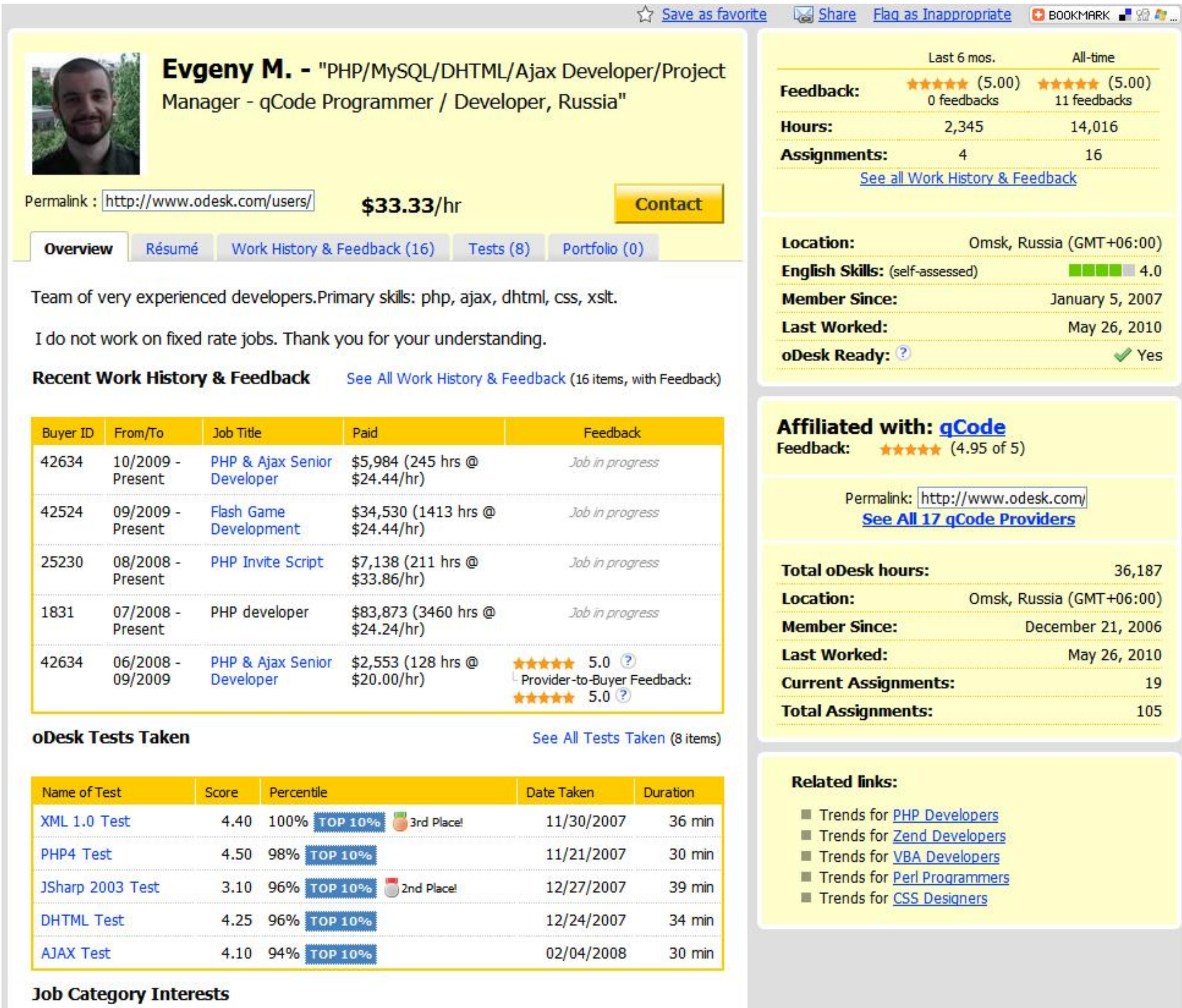

Figure 2: The Share of Affiliates and Non-Affiliates employed at least once by the number of applications made prior to first hire.

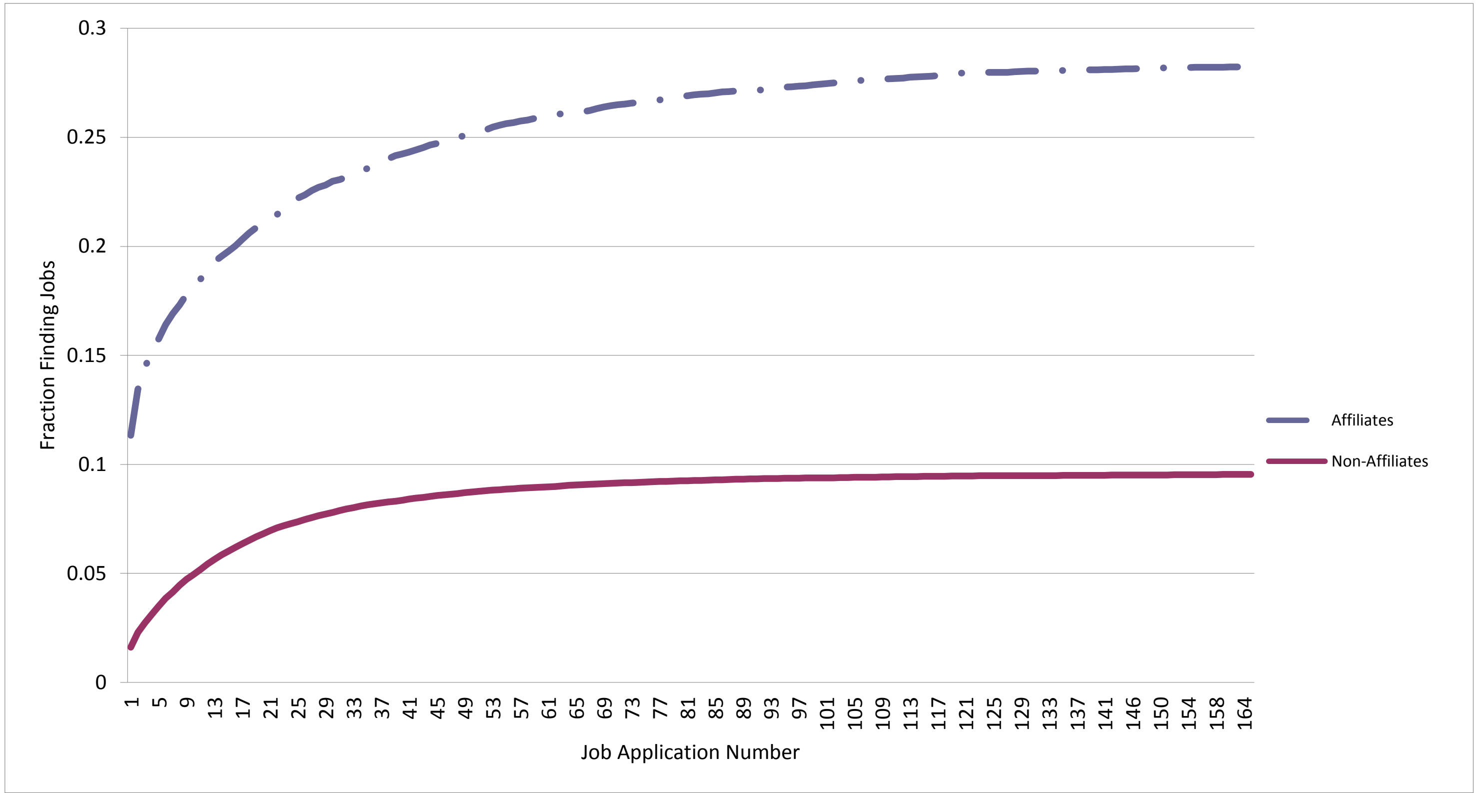

Table 1: Summary Statistics with Outsourcing Agencies as the Unit of Analysis.

	Mean	Std Dev.	Min	Max
	(1)	(2)	(3)	(4)
Complete agency history is observed (Agencies established after 8/1/2008)	0.77	0.42	0	1
Number of unique workers hired in the data while under agency identifier	3.25	5.49	1	76
Number of inexperienced workers first hired in the data while under agency identifier	2.87	5.03	1	65
Modal worker country for the agency is:				
The U.S.	0.01	0.09	0.00	1
India or Pakistan	0.52	0.50	0.00	1
Russia or Ukraine	0.11	0.32	0.00	1
The Philippines	0.14	0.35	0.00	1
Share of hires from the agency's modal country	0.98	0.11	0.32	1
Share of hires in modal technical or non-technical classification	0.84	0.28	0.50	1
Modal job is technical	0.69	0.46	0.00	1
Number of agencies	1126			

Notes: The sample involves outsourcing agencies with a newly hired worker between 8/1/2008 and 12/28/2009. Some agencies exist prior to this time. Agencies that do not have new affiliates during the sample period are excluded from these calculations. In later analysis that focuses on agencies over time, an extended sample is used. Technical jobs are those listed under Web Development, Software Development, Networking and Info Systems, 3D Modeling and CAD, Engineering and Technical Design, or Search Engine Optimization. Non-technical jobs are those listed under Administrative Support, Business Services, Customer Services, Sales and Marketing, and Writing and Translation. Some agencies have zero recorded hours of work; this is because some projects are initiated towards the end of the sample, but billing begins only after the sample period ends. For ongoing projects, total hours are recorded as of the end of the sample.

Table 2: Summary Statistics with Workers as the Unit of Analysis.

	All Applicants for Hourly Jobs		Workers Hired Once or More		Workers Hired Twice or More	
	Non-Affiliates	Affiliates	Non-Affiliates	Affiliates	Non-Affiliates	Affiliates
	(1)	(2)	(3)	(4)	(5)	(6)
Number of workers with first applications between 8/1/2008 and 12/28/2009, including workers in the U.S.	112,943	12,276	9,376	3,390	6,319	2,524
Number of these workers outside the U.S. (main sample)	72,278	10,751	6,872	3,231	4,611	2,253
Share of Affiliates and of Non-Affiliates in:						
India/Pakistan	0.27	0.54	0.02	0.55	0.25	0.55
Russia/Ukraine	0.03	0.08	0.06	0.13	0.06	0.12
The Philippines	0.35	0.11	0.38	0.11	0.40	0.11
Technical Jobs	0.34	0.68	0.38	0.73	0.37	0.72
Non-Technical Jobs	0.66	0.32	0.62	0.27	0.63	0.28
Mean Characteristics by Group:						
Log Hourly Wage on First Job (First Application in Columns 1-2)	1.94	2.15	1.37	2.03	1.29	1.99
Bachelors Degree or Higher, Indicator	0.25	0.30	0.42	0.33	0.45	0.35
Good English Skills, Indicator	0.54	0.78	0.87	0.79	0.92	0.85
Skills Tests Taken, Indicator	0.39	0.37	0.72	0.50	0.78	0.55
Years of Prior Experience	5.33	3.94	5.48	4.08	5.42	4.08
Mean Career Earnings Through 8/14/2010 [a], $	387	1,787	3,348	6,045	3,700	5,850
Earnings Gap Due to Affiliation from Oaxaca-Blinder Decomposition	70%		50%		44.2%	
Affiliation Earnings Premium Over Average Non-Affiliate Earnings	251.4%		40.4%		25.7%	

Notes: The sample consists of workers with first job application dates on oDesk between 8/1/2008 and 12/28/2009. The sample in Columns 1 and 2 is oDesk workers on their first hourly-paying job application, while Columns 3-6 restrict the sample to those workers who are hired for at least one, or at least two, hourly jobs. The proportion of affiliates and non-affiliates joining oDesk over time is relatively constant during the sample period. For the calculations in Columns 1 and 2, workers are assigned to affiliation status as-of their first application. For the calculations in Columns 3-6, workers are assigned to agency affiliation status based on whether they are affiliated as of their first hourly-paying job, regardless of whether workers switch into agency affiliation between the first job application and the first employment spell. Prior to finding a first job, there are 1,433 workers who first apply for jobs as non-affiliates and then switch into agency affiliation. Of these, 408 find jobs. There are 101 workers who begin as affiliates and then switch to non-affiliation. Of these, 15 find jobs. There are 106 workers who begin as non-affiliates, switch into affiliation, and then switch back out of affiliation. Of these, 22 find jobs. Two-sample t-tests with unequal variances all reject equality of the means between non-affiliates and affiliates at the 1% level. The Oaxaca-Blinder decomposition includes monthly time fixed effects, job category fixed effects, the worker's pre-odesk years of experience, scores on oDesk skills tests as detailed in Appendix Table 1, revenue from fixed-price contracts before the first hourly job, the number of hires on fixed-price jobs, and dummy variables for worker education levels, English skills, programming experience, and country. The agency affiliation premium is defined as the mean percentage increase or decrease in an outcome for agency affiliates relative to non-affiliates net of differences explained by observable characteristics.

[a] Total Earnings for workers in Columns 5 and 6 are calculated for jobs after the first job.

Table 3: Estimates of Affiliate Job-Finding Probability, Wage, and Productivity Differences on the First Job

Dependent Variable:	Indicator for Being Hired At Least Once	Log 1 + Elapsed Days of Job Search	Log Applications Prior to Initial Hire	Log Hourly Wage	Log 1 + Hours Worked	Success Reported by Employer	Good Feedback (Greater than 4.5)	Good Feedback (Given Feedback Provided)
Sample:	Job Applicants	Workers on First Job						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Job Categories								
Summary Data:								
Number of Affiliates	10,751	3,231	3,231	3,231	3,231	2,822	2,822	2,424
Number of Non-Affiliates	72,278	6,872	6,872	6,872	6,872	6,046	6,046	5,144
Mean of Dependent Variable: Affiliates	0.27	1.97	1.61	2.03	3.74	0.62	0.59	0.69
Mean of Dependent Variable: Non-Affiliates	0.10	2.46	2.12	1.37	3.15	0.58	0.58	0.68
Mean Difference Between Affiliates and Non-Affiliates	0.17	-0.48	-0.51	0.66	0.59	0.04	0.01	0.01
Estimates:								
Oaxaca-Blinder Estimate of Gap % Due to Affiliation	72.4%	49.1%	37.6%	34.9%	57.0%	135.0%	12.2%	265.5%
Entropy Balancing Estimate of Affiliation Effect	0.114	-0.202	-0.172	0.193	0.288	0.068	0.006	0.027
	(0.005)	(0.055)	-0.0450	(0.024)	(0.052)	(0.015)	(0.015)	(0.016)
Entropy Balancing Estimate of Constant	0.152	2.175	1.779	1.836	3.448	0.554	0.584	0.660
Agency Affiliation Premium from OB Decomposition	120.9%	-23.8%	-19.3%	23.1%	33.6%	10.0%	0.2%	2.7%
Agency Affiliation Premium from Re-weighting	75.0%	-20.2%	-17.2%	19.3%	28.8%	12.2%	1.1%	4.1%
Panel B: Workers with Initial Applications or Jobs in Technical Job Categories								
Summary Data:								
Number of Affiliates	7,259	2,359	2,359	2,359	2,359	2,035	2,035	1,734
Number of Non-Affiliates	24,561	2,606	2,606	2,606	2,606	2,254	2,254	1,988
Mean of Dependent Variable: Affiliates	0.29	1.82	1.42	2.34	3.91	0.64	0.60	0.71
Mean of Dependent Variable: Non-Affiliates	0.11	2.41	1.86	2.09	3.37	0.60	0.62	0.70
Mean Difference Between Affiliates and Non-Affiliates	0.19	-0.59	-0.44	0.25	0.54	0.04	-0.02	0.01
Estimates:								
Oaxaca-Blinder Estimate of % Due to Agency Affiliation	70.4%	47.2%	52.1%	73.0%	62.2%	196.9%	-15.1%	430.1%
Entropy Balancing Estimate of Affiliation Effect	0.124	-0.241	-0.200	0.173	0.305	0.086	0.005	0.041
	(0.007)	(0.073)	(0.057)	(0.024)	(0.067)	(0.020)	(0.020)	(0.020)
Entropy Balancing Estimate of Constant	0.171	2.063	1.624	2.168	3.606	0.555	0.597	0.665
Agency Affiliation Premium from OB Decomposition	123.0%	-27.6%	-22.9%	18.3%	33.8%	13.8%	0.4%	4.3%
Agency Affiliation Premium from Re-weighting	72.5%	-24.1%	-20.0%	17.3%	30.5%	15.5%	0.8%	6.1%

Table 3, Contd.: Estimates of Affiliate Job-Finding Probability, Wage, and Productivity Differences on the First Job.

Dependent Variable:	Indicator for Being Hired At Least Once	Log 1 + Elapsed Days of Job Search	Log Applications Prior to Initial Hire	Log Hourly Wage	Log 1 + Hours Worked	Success Reported by Employer	Good Feedback (Greater than 4.5)	Good Feedback (Given Feedback Provided)
Sample:	Job Applicants	Workers on First Job						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Panel C: Workers with Initial Applications or Jobs in Non Technical Jobs						
Summary Data:								
Number of Affiliates	3,493	872	872	872	872	787	787	690
Number of Non-Affiliates	47,716	4,266	4,266	4,266	4,266	3,792	3,792	3,156
Mean of Dependent Variable: Affiliates	0.21	2.38	2.11	1.18	3.26	0.57	0.56	0.64
Mean of Dependent Variable: Non-Affiliates	0.10	2.49	2.28	0.93	3.01	0.57	0.56	0.67
Mean Difference Between Affiliates and Non-Affiliates	0.11	-0.11	-0.17	0.26	0.25	0.01	0.00	-0.03
Estimates:								
Oaxaca-Blinder Estimate of % Due to Agency Affiliation	78.1%	36.9%	35.9%	91.9%	99.0%	437.7%	198.0%	46.6%
Entropy Balancing Estimate of Affiliation Effect	0.088	-0.033	-0.058	0.230	0.234	0.008	0.005	-0.021
	(0.008)	(0.083)	(0.069)	-0.0450	(0.075)	(0.023)	(0.023)	(0.024)
Entropy Balancing Estimate of Constant	0.121	2.417	2.160	0.954	3.029	0.562	0.555	0.661
Agency Affiliation Premium from OB Decomposition	91.0%	-3.9%	-6.2%	23.7%	24.7%	3.9%	1.4%	-2.0%
Agency Affiliation Premium from Re-weighting	72.7%	-3.3%	-5.8%	23.0%	23.4%	1.4%	0.9%	-3.2%

Notes: The table presents mean differences between affiliates and non-affiliates for the dependent variables in each column heading. Oaxaca-Blinder decomposition and entropy balancing re-weighting estimates of affiliation effects are presented below the summary statistics. The entropy balancing reweighting procedure picks a set of weights to make the first moments of the marginal distributions of affiliate and non-affiliate characteristics as close as possible. The reported results are from weighted regressions of the dependent variable on an agency affiliation indicator using these balancing weights (see Hainmuller 2012 for details). The reported standard error is the survey-weights adjusted standard error. For both the Oaxaca-Blinder and entropy balancing estimates, the following controls are included: the set of controls for worker characteristics and job category, month, and worker country fixed effects as specified in Table 2, plus a full set of project duration and weekly expected hours interactions, and the number of alpha-numeric characters in the job opening description. Month dummies account for differences in cohorts, including right-censoring propensities for ongoing jobs. The agency affiliation premium is again defined as the mean percentage increase or decrease in an outcome for agency affiliates relative to non-affiliates net of differences explained by observable characteristics. For the Oaxaca-Blinder decompositions, the premium is calculated relative to the set of non-affiliates. For the re-weighting estimates, the premium is relative to a baseline of non-affiliates who have the same distribution of characteristics as the set of affiliates. In the Oaxaca-Blinder calculations, when the dependent variable is in logarithms, the agency affiliation premium is interpreted as a premium in levels, and is the estimated portion of the outcome gap due to agency affiliation that is unexplained by differences in characteristics. For the re-weighting premium, when the dependent variable is in logarithms, the premium is the point estimate from the weighted regression. When the dependent variable is in levels, the premium in Oaxaca-Blinder decompositions is the estimated portion of the outcome gap due to agency affiliation divided by the mean of the dependent variable for non-affiliates. For the re-weighting premium when the dependent variable is in levels, the premium is the point estimate for agency affiliation divided by the constant term. An observation in Column 1 is a unique worker who applies for at least one hourly job between 8/1/2008 and 12/28/2009. The dependent variable in Column 1 is an indicator for whether the worker is hired for at least one job. An observation in the remaining columns is a unique worker on the first hourly job during the same time period; there are 4,929 unique employers in this sample. In Columns 6 to 8, differing numbers of observations reflect that jobs may be ongoing as of 12/28/2009. In Column 7, the dependent variable is coded as zero when a job has been completed but the employer does not leave feedback. Column 8 drops observations where the employer does not leave feedback.

Table 4: The Effect of Agency Affiliation on Log Hourly Wage Offers for Agency Switchers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Indicator for Joining Affiliation	0.0858***		0.0868**	0.0724**	0.0766**	0.0821***	0.0786**
	(0.030)		(0.034)	(0.029)	(0.032)	(0.032)	(0.035)
Indicator Turned On at Placebo Date		0.0322	-0.0019		-0.0083		
		(0.023)	(0.027)		(0.025)		
Window in Days Before and After Affiliation Switch	4	4	4	4	4	3	2
Job Category Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Number of workers	1,381	1,381	1,381	1,381	1,381	1,360	1,336
Observations	8,604	8,604	8,604	8,604	8,604	7,460	6,266
R-squared	0.869	0.869	0.869	0.879	0.879	0.884	0.889
Oaxaca-Blinder Wage Offer Premium for Switchers	11.5%	11.5%	11.5%	11.5%	11.5%	11.5%	11.5%

Notes: Robust standard errors clustered by worker in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The sample is workers who join oDesk as non-affiliates who switch their affiliation status by joining an agency prior to their first date of employment. Columns 1 to 5 use a four-day window around the date that the worker changes affiliation status. Columns 6 and 7 use three and two day windows, respectively. All specifications include controls for the job application number, a cubic polynomial measuring the elapsed time since the worker's first job application, and worker fixed effects. The variable Post-Affiliation is an indicator that the worker has switched into an agency, meaning that the worker's profile has an affiliate identification. The placebo date in the job application history is generated as a false Post-Affiliation indicator prior to the actual switch time-stamp. For each bid after the first bid in the time window, a 20 percent probability is assigned that all future bids are classified as Post-Affiliation, and this process stops once the Placebo Indicator is turned on or the worker makes a switch to agency affiliation. The placebo indicator is always turned on after affiliation. The Oaxaca-Blinder wage offer premium for switchers is calculated by recovering the coefficients of the Oaxaca-Blinder decomposition using the log of the wage offer as the dependent variable in a sample of switchers and non-affiliates. With these coefficients, the premium for agency switchers is calculated using the characteristics of the set of switchers in the sample. The reported estimates are calculated using the same method for log wage premiums reported in Table 3.

Table 5: Job Finding Hazards and Agency Switchers

	Hazard Relative to Job Applications				Hazard Relative to Job Applications. Time at Risk Begins at Application Number 15	
	Cox	Cox	Weibull	Weibull	Cox	Weibull
	(1)	(2)	(3)	(4)	(5)	(6)
Agency Affiliate Indicator	1.349***	1.423***	1.218***	1.287***	1.262***	1.215***
	(0.0608)	(0.0596)	(0.0645)	(0.0619)	(0.0696)	(0.0738)
Log Hourly Wage Bid		0.589***		0.589***		
		(0.0168)		(0.0167)		
Has BA or higher degree	0.951*	0.961	0.923***	0.932**	0.942	0.923*
	(0.0296)	(0.0305)	(0.0306)	(0.0312)	(0.0441)	(0.0458)
Has Good English Skills	1.786***	1.826***	1.627***	1.652***	1.818***	1.786***
	(0.0379)	(0.0387)	(0.0387)	(0.0392)	(0.0816)	(0.0830)
Taken a Skills Test	1.018	0.97	0.99	0.932	1.083	1.088
	(0.0872)	(0.0859)	(0.0887)	(0.0882)	(0.125)	(0.128)
Years of Prior Labor Market Experience	0.994**	0.999	0.992**	0.998	0.994	0.993
	(0.00350)	(0.00354)	(0.00365)	(0.00368)	(0.00505)	(0.00526)
Years of Prior Experience Missing	0.966	0.988	0.975	0.999	0.95	0.946
	(0.0360)	(0.0371)	(0.0378)	(0.0384)	(0.0545)	(0.0572)
Log of Weibull Shape Parameter			0.0418***	0.0228***		-0.0226*
			(0.00784)	(0.00790)		(0.0134)
Number of Observations	589,397	589,397	589,397	589,397	228,055	228,055
Log Likelihood	-66,253	-65,400	-21,359	-20,515	-21,868	-6,963
Number of Workers	72,275	72,275	72,275	72,275	9,832	9,832
Number of Hires	7,236	7,236	7,236	7,236	2,798	2,798

Notes: Exponentiated coefficients reported. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The sample only includes those workers who enter oDesk as non-affiliates; three original non-affiliates are excluded because of an issue with the recorded time of job applications. The agency affiliate indicator is set equal to one after a worker has joined an agency. The indicator is switched to zero if the worker subsequently leaves the agency. Columns 5 and 6 restrict the sample to only those workers at risk after the 15th job application, the median number of applications prior to a worker switching affiliation status. Cox models use Breslow methods for ties.

Table 6: Summary Statistics on Wage Changes between Jobs

	All Jobs		Technical		Non-Technical	
	Non-Affiliates	Affiliates	Non-Affiliates	Affiliates	Non-Affiliates	Affiliates
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Log Wage Change Between:						
Jobs 1 and 2	0.147	0.057	0.099	0.029	0.195	0.111
Number of workers reaching job 2	*4666*	*2274*	*2317*	*1477*	*2349*	*797*
Jobs 1 and 2	0.142	0.058	0.095	0.032	0.190	0.106
Jobs 2 and 3	0.127	0.037	0.108	0.032	0.144	0.046
Jobs 1 and 3	0.270	0.094	0.203	0.064	0.334	0.151
Number of workers reaching job 3	*3674*	*1749*	*1831*	*1143*	*1843*	*606*
Jobs 1 and 2	0.137	0.055	0.087	0.024	0.185	0.113
Jobs 2 and 3	0.126	0.036	0.113	0.033	0.139	0.041
Jobs 3 and 4	0.070	0.045	0.067	0.031	0.072	0.070
Jobs 1 and 3	0.263	0.091	0.200	0.057	0.323	0.154
Jobs 1 and 4	0.333	0.136	0.267	0.088	0.396	0.225
Number of workers reaching job 4	*3070*	*1418*	*1489*	*923*	*1581*	*495*

Notes: The sample consists of workers in the sample in Table 3, Column 2 who go onto future jobs. Wage changes are calculated using the initial contracted wage on each employment spell. All differences between affiliates and non-affiliates are significant at the 1% level except for the change between jobs 3 and 4, which is significant at the 10% level for all jobs, at the 5% level for technical jobs, and is not significant for non-technical jobs. Numbers of observations occasionally differ across tables depending on whether workers are required to have started billing hours or recording revenue at the end of the sample.

Table 7: Non-Affiliates' Future Employment and Wages Respond Most to Feedback

Dependent Variable	Indicator for Finding a Second Job				Log Wage			
Sample	Workers on first job				Unbalanced panel of workers with 2+ total jobs			
Subsample by job type	All	All	Tech	Non Tech	All	All	Tech	Non Tech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agency affiliate indicator	0.056***	0.081***	0.067***	0.087***				
	(0.012)	(0.012)	(0.022)	(0.022)				
Good feedback indicator (Experienced workers in cols 5-8)	0.191***	0.179***	0.189***	0.169***	0.109***	0.104***	0.077***	0.123***
	(0.009)	(0.008)	(0.014)	(0.016)	(0.010)	(0.009)	(0.012)	(0.015)
Affiliate x Good feedback score	-0.043***	-0.045***	-0.062**	-0.017	-0.082***	-0.070***	-0.045**	-0.079***
	(0.013)	(0.016)	(0.025)	(0.038)	(0.015)	(0.014)	(0.018)	(0.027)
Zero feedback indicator (Experienced workers in cols 5-8)	0.074**	0.073***	0.018	0.098***	-0.019	-0.012	-0.057	0.002
	(0.030)	(0.027)	(0.027)	(0.023)	(0.026)	(0.025)	(0.042)	(0.035)
Affiliate x Zero feedback	-0.037	-0.02	0.025	-0.016	0.024	0.014	0.058	-0.020
	(0.031)	(0.029)	(0.031)	(0.076)	(0.038)	(0.038)	(0.057)	(0.064)
Experienced worker indicator					0.172***	0.175***	0.152***	0.196***
					(0.010)	(0.010)	(0.013)	(0.017)
Affiliate x Experienced worker					-0.207***	-0.172***	-0.162***	-0.154***
					(0.015)	(0.015)	(0.019)	(0.029)
Number of jobs						0.016***	0.016***	0.014***
						(0.002)	(0.001)	(0.002)
Affiliate x Number of jobs						-0.005***	-0.005***	-0.002
						(0.001)	(0.002)	(0.003)
Detailed Controls	No	Yes	Yes	Yes	No	No	No	No
Mean of Dependent Variable	0.687	0.687	0.674	0.701	1.72	1.72	1.93	1.42
Number of Observations	10,103	10,103	4,965	5,138	54,846	54,846	31,832	23,014
R-squared	0.066	0.136	0.151	0.154	0.865	0.869	0.865	0.885

Notes: *** p<0.01, ** p<0.05, * p<0.1. Columns 1-4 present the results of linear probability models with robust standard errors clustered by country in parentheses. The dependent variable is a dummy variable set equal to one if a second hourly job is observed prior to August 14, 2010. An observation in these models is a unique worker on his or her first hourly job. All specifications in Columns 1-4 have monthly time dummies, job category fixed effects, and worker country fixed effects. The specifications with detailed controls contain the controls in the Oaxaca-Blinder decomposition of Table 3, Column 4. Columns 5-8 present the results of fixed effects regressions with standard errors clustered by worker in parentheses. The dependent variable is the log hourly wage recorded at the beginning of the contract. The sample includes all workers who enter oDesk between 8/1/2008 and 12/28/2009 with two or more jobs prior to 8/14/2010. Agency affiliation is calculated as-of the first job. All specifications in Columns 5-8 include worker fixed effects, job category fixed effects and monthly time dummies.

Table 8: Summary Statistics for Experienced Workers

	All Job Categories		Technical Jobs		Non-Technical Jobs	
	Non-Affiliates	Affiliates	Non-Affiliates	Affiliates	Non-Affiliates	Affiliates
Residual Log Hourly Rate	-0.014	0.035***	-0.0170	0.033***	-0.0090	0.044***
Good English Skills Dummy	0.946	0.944	0.939	0.943*	0.957	0.948***
BA Degree or Higher	0.321	0.336***	0.322	0.34***	0.32	0.321
Number of Prior Hires	22.78	17.94***	21.47	17.65***	25.04	19.16***
Feedback Score	4.59	4.55***	4.58	4.55***	4.61	4.56***
Number of Jobs	65,763	27,110	41,765	21,997	23,981	5,064
Number of Experienced Workers	9,489	2,640	6,389	2,235	3,100	405

Notes: Asterisks indicate that two-sample t-tests with unequal variances reject equality of the means for the non-affiliates' and affiliates' at the 1-percent, ***, 5-percent, **, and 10-percent, *, level. The sample contains workers with three or more total hires and non-zero feedback who are hired for the third or more job before 12/28/2009. In this sample there is no restriction that a workers' first job application occurred after 8/1/2008. The number of total hires multiplied by the number of experienced workers does not equal the number of jobs because a worker's first three jobs or jobs prior to 8/1/2008 are not included in the sample. Because some workers are employed in both technical and non-technical jobs, the number of experienced workers in technical and non-technical categories is based on a classification of workers into their modal job type.

Table 9: Analysis of Agencies Over Time

Subsample by agency history	All			Only Agency with Complete Histories 8/1/2008)	(Established After	
Subsample by agency modal job type	All	Tech	Non Tech	All	Tech	Non Tech
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent variable is the log of the hourly wage for new agency affiliates on their first hourly job. Regressions contain fixed effects for each agency id and controls as detailed in the notes.						
Unique Workers Hired Previously Under Agency Id	-0.0043	-0.0021	0.0071	0.0025	0.0122	0.0036
	(0.0066)	(0.0064)	(0.0345)	(0.0165)	(0.0161)	(0.0349)
Workers Hired Squared	0.0001	0.0001	-0.0013	-0.0001	-0.0002	-0.0012
	(0.0001)	(0.0001)	(0.0012)	(0.0004)	(0.0004)	(0.0012)
Mean of Dependent Variable	2.03	2.35	1	1.79	2.25	0.96
Number of Observations	3,231	2,433	712	1,918	1,211	637
R-squared	0.897	0.806	0.896	0.925	0.896	0.898
Panel B: Dependent Variable is an indicator for a good feedback score for new agency affiliates on their first hourly job. Regressions contain fixed effects for each agency id and controls as detailed in the notes. Missing feedback scores are excluded.						
Unique Workers Hired Previously Under Agency Id	-0.0037	-0.0041	0.0038	0.0035	0.0027	0.0073
	(0.0074)	(0.008)	(0.0304)	(0.0131)	(0.0152)	(0.0319)
Workers Hired Squared	0.0001	0.0001	0.0004	0	0	0.0004
	(0.0002)	(0.0002)	(0.0011)	(0.0003)	(0.0003)	(0.0012)
Mean of Dependent Variable	0.69	0.71	0.62	0.69	0.73	0.63
Number of Observations	2,424	1,795	565	1,512	956	504
R-squared	0.546	0.499	0.724	0.639	0.624	0.736
Panel C: Dependent variable is an indicator that the observed affiliate is the last affiliate under the agency id. Exponentiated coefficients of Cox proportional hazards models with detailed job category and time fixed effects are reported.						
Good Feedback for Worker	0.831***	0.827**	0.86	0.824***	0.817**	0.852
	(0.056)	(0.071)	(0.088)	(0.060)	(0.077)	(0.091)
No Feedback for Worker	0.906	0.912	0.853	0.919	0.931	0.875
	(0.067)	(0.084)	(0.102)	(0.072)	(0.095)	(0.104)
Number of Observations	4,938	3,861	1,077	2,826	1,849	977
Number of Agencies	1,126	791	826	868	562	306
Number of Exits	830	564	653	675	432	243

Notes: *** p<0.01, ** p<0.05, * p<0.1. The number of previous unique workers hired under the agency id is calculated as of the time of hire for the worker in question, but the calculation begins for workers hired after August 1, 2008. For agencies in existence prior to August 1, 2008, it is not possible to calculate the number of unique workers prior to this date, so the number of unique agency affiliates begins when it is possible to begin tracking affiliation in the job application database. Columns 4-6 restrict the sample to agencies established after 8/1/2008. These agencies have complete histories. The specifications in Panels A and B contain agency fixed effects, detailed job category fixed effects, month fixed effects and the same controls for worker characteristics as the Oaxaca-Blinder decompositions in Table 3, Column 4. In Panel C, the dependent variable is an indicator that the worker is the last affiliate. The sample in Panel C is extended beyond the main sample period to better allow classification of agency exit. An exit is classified as never observing a new worker after the worker in question and August 14, 2010. Agencies with final workers observed after January 14, 2010 are treated as censored, with no exit time recorded. Panel C contains calendar time fixed effects and job category fixed effects, with robust standard errors in parentheses.

Table 10: Analysis of Attrition from Agencies As a Function of First Job Performance and Characteristics

Sample	All Jobs		Affiliates with First Jobs in Technical Categories		Affiliates with First Jobs in Non-Technical Categories	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Hourly Wage	-0.012**	-0.005	-0.016***	-0.004	-0.007	0.000
	(0.005)	(0.007)	(0.006)	(0.004)	(0.010)	(0.017)
Good Feedack for Worker Indicator	0.006	0.005	-0.000	0.002	0.017	0.035
	(0.007)	(0.006)	(0.006)	(0.006)	(0.019)	(0.022)
No Feedback for Worker Indicator	0.001	0.005	-0.000	-0.002	-0.007	0.036
	(0.007)	(0.007)	(0.007)	(0.005)	(0.021)	(0.032)
Worker with BA or Higher Degree	-0.002	0.008	0.001	0.006	-0.012	0.022
	(0.008)	(0.010)	(0.007)	(0.007)	(0.025)	(0.031)
Worker with Good English Skills	-0.003	0.002	-0.005	0.005	0.005	-0.000
	(0.006)	(0.005)	(0.006)	(0.006)	(0.014)	(0.020)
Taken a Test	0.008	-0.003	0.003	-0.006	0.010	-0.043
	(0.010)	(0.010)	(0.011)	(0.008)	(0.030)	(0.038)
Agency Fixed Effects	No	Yes	No	Yes	No	Yes
Mean of DV	0.025	0.025	0.015	0.015	0.052	0.052
Number of Observations	3,231	3,231	2,359	2,359	872	872
R-squared	0.135	0.757	0.147	0.821	0.154	0.804

Notes: The dependent variable is an indicator that the worker formally leaves the agency of record on the first job any time after the first hire. Job category, month of first job, and country fixed effects are included in all specifications. The log hourly wage and feedback scores are measured from each worker's first hire. The other worker characteristics included are the same as those in the Oaxaca-Blinder wage decompositions in Table 3.

Table 11: Detailed Decomposition from Pooled Regressions to Assess Heterogeneous Agency Benefits

Dependent Variable	Log 1 + Elapsed Days of Job Search		Log Applications Prior to Initial Hire		Log Hourly Wage		Log 1 + Hours Worked		Success Reported by Employer		Good Feedback (Greater than 4.5)		Good Feedback (Non-Missing Feedback Sub-Sample)	
	Non-Affiliate Baseline	Affiliate Interaction	Non-Affiliate Baseline	Affiliate Interaction	Non-Affiliate Baseline	Affiliate Interaction	Non-Affiliate Baseline	Affiliate Interaction	Non-Affiliate Baseline	Affiliate Interaction	Non-Affiliate Baseline	Affiliate Interaction	Non-Affiliate Baseline	Affiliate Interaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Affiliate Characteristics:														
Has BA or higher degree	0.393***	-0.137*	0.121***	-0.022	-0.012	0.019	0.023	-0.005	-0.001	0.008	-0.006	0.023	0.008	0.008
	(0.0416)	(0.0789)	(0.0247)	(0.0503)	(0.0196)	(0.0313)	(0.0470)	(0.0808)	(0.0145)	(0.0270)	(0.0148)	(0.0273)	(0.0150)	(0.0277)
Has Good English Skills	0.501***	-0.243***	0.459***	-0.119**	0.009	-0.001	-0.075	0.039	0.0704**	-0.0551*	0.021	0.020	0.017	0.034
	(0.0606)	(0.0915)	(0.0375)	(0.0554)	(0.0285)	(0.0408)	(0.0727)	(0.104)	(0.0216)	(0.0330)	(0.0216)	(0.0332)	(0.0223)	(0.0337)
Years of Prior Labor Market Experience	0.008	0.008	0.00611**	0.013	0.00941***	-0.002	0.007	-0.011	0.00337*	0.001	-0.002	0.006	-0.002	0.005
	(0.0050)	(0.0117)	(0.00302)	(0.00785)	(0.00257)	(0.00535)	(0.00655)	(0.0137)	(0.00183)	(0.00446)	(0.00190)	(0.00442)	(0.00194)	(0.00443)
Taken a Skills Test	0.434***	0.003	0.372***	-0.087	0.038	0.023	-0.192**	0.214*	-0.034	0.037	-0.015	0.029	0.005	-0.010
	(0.0739)	(0.125)	(0.0455)	(0.0817)	(0.0327)	(0.0487)	(0.0812)	(0.126)	(0.0256)	(0.0420)	(0.0261)	(0.0423)	(0.0264)	(0.0432)
Indicators for Team Production:														
Indicator for Team-Based Job	0.029	-0.022	0.0565**	0.029	-0.239***	0.114**	-0.0847*	-0.243**	-0.0694***	0.0724**	0.0415**	-0.0512*	0.0291**	-0.0715**
	(0.0390)	(0.0820)	(0.0237)	(0.0531)	(0.0184)	(0.0340)	(0.0453)	(0.0868)	(0.0140)	(0.0283)	(0.0143)	(0.0288)	(0.0147)	(0.0297)
Indicator for Affiliate on an Agency Team		-0.319***		-0.265***		0.106**		0.327***		-0.002		0.109***		0.152***
		(0.0762)		(0.0498)		(0.0315)		(0.0794)		(0.0258)		(0.0257)		(0.0258)
% of Workers in Team-Based Jobs	64.1%	55.8%	64.1%	55.8%	64.1%	55.8%	64.1%	55.8%	65.9%	56.3%	65.9%	56.3%	66.3%	56.5%
% of Affiliates on an Agency-Based Team	0.0%	33.0%	0.0%	33.0%	0.0%	33.0%	0.0%	33.0%	0.0%	32.8%	0.0%	32.8%	0.0%	32.1%
Agency Premium Accounting For Teams	-23.7%		-19.1%		22.7%		33.1%		9.9%		0.5%		2.8%	
Premium Removing Agency Teams	-12.4%		-11.3%		15.4%		30.3%		5.9%		-2.8%		-1.0%	
Number of Non-Affiliates and Affiliates	6,872	3,231	6,872	3,231	6,872	3,231	6,872	3,231	6,046	2,822	6,046	2,822	5,144	2,424

Notes: Robust standard errors in parentheses. Estimates are derived from a pooled regression with a full set of interactions for agency affiliates. Team-Based Jobs are defined based on an employer hiring within a 7-day window around a worker's hiring date. Agency teams are defined similarly for workers of the same agency. The "Agency Premium Removing Agency Teams From Premium" calculation is conducted by taking the "Unexplained" difference in the Oaxaca-Blinder decomposition and then subtracting both the sum of the coefficient on agency teams times the percentage of workers on agency teams and the difference in the affiliate and non-affiliate coefficient on team-based jobs times the adjusted mean percentage of affiliates on agency teams as detailed in the text. This calculation assumes that agency team-based jobs would revert to being individual jobs rather than team-based with workers from outside of the agency at approximately the same rate at which team based jobs are observed in the data for agency affiliates. When splitting the sample into technical and non-technical jobs, 51.4% of non-affiliates' technical jobs are classified as team-based jobs, 51.2% of affiliates' technical jobs are team-based, and 33.1% of affiliates' technical jobs are agency-team based jobs. In non-technical categories, 71.8% of non-affiliates' jobs are team-based, while 68.2% of affiliates' jobs are team-based and 32.8% of affiliates' jobs are agency-team based.

Table 12: Teamwork Explains A Small Fraction of the Over-Career Variation in the Affiliation Premium

Dependent Variable	Indicator for Finding a Second Job				Log Wage			
Sample	Workers on first job				Unbalanced panel of workers with 2+ total jobs			
Subsample	All	All	Tech	Non Tech	All	All	Tech	Non Tech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agency affiliate indicator	0.0701***	0.103***	0.0784***	0.103***				
	(0.0136)	(0.0155)	(0.0202)	(0.0275)				
Good feedback indicator (Experienced workers in cols 5-8)	0.169***	0.179***	0.190***	0.169***	0.102***	0.102***	0.076***	0.122***
	(0.0161)	(0.00767)	(0.0142)	(0.0161)	(0.009)	(0.009)	(0.012)	(0.015)
Affiliate x Good feedback score	-0.0171	-0.0444***	-0.0589**	-0.0198	-0.071***	-0.070***	-0.045***	-0.079***
	(0.0378)	(0.0163)	(0.0251)	(0.0359)	(0.014)	(0.014)	(0.017)	(0.026)
Zero feedback indicator (Experienced workers in cols 5-8)	0.0982***	0.0727***	0.0159	0.0989***	-0.011	-0.011	-0.058	0.003
	(0.0225)	(0.0267)	(0.0271)	(0.0219)	(0.025)	(0.025)	(0.042)	(0.035)
Affiliate x Zero feedback	-0.0164	-0.0207	0.0283	-0.0196	0.013	0.014	0.061	-0.019
	(0.0756)	(0.0304)	(0.0293)	(0.0737)	(0.038)	(0.038)	(0.056)	(0.064)
Indicator for Team-based Job	-0.0148	-0.00162	-0.0240	0.0133	-0.063***	-0.083***	-0.061***	-0.098***
	(0.0139)	(0.0129)	(0.0296)	(0.0158)	(0.005)	(0.008)	(0.011)	(0.013)
Affiliate x Indicator for Team-based Job	-0.00613	-0.0412**	-0.0241	-0.0301	0.041***	0.041***	0.021	0.038
	(0.0169)	(0.0166)	(0.0346)	(0.0404)	(0.009)	(0.014)	(0.017)	(0.028)
Indicator for Affiliate on an Agency Team	-0.0512***	0.00721	-0.00306	0.0236	-0.028***	-0.003	-0.004	0.018
	(0.0178)	(0.0176)	(0.0241)	(0.0241)	(0.010)	(0.013)	(0.016)	(0.028)
Experienced worker indicator					0.172***	0.172***	0.150***	0.192***
					(0.010)	(0.010)	(0.013)	(0.017)
Affiliate x Experienced worker					-0.170***	-0.172***	-0.162***	-0.154***
					(0.015)	(0.015)	(0.019)	(0.029)
Number of jobs					0.015***	0.014***	0.015***	0.012***
					(0.001)	(0.001)	(0.001)	(0.002)
Affiliate x Number of jobs					-0.005***	-0.004**	-0.004**	-0.001
					(0.001)	(0.001)	(0.002)	(0.003)
Trend x Indicator for Team Job						0.002***	0.002*	0.002**
						(0.001)	(0.001)	(0.001)
Affiliate x Trend x Indicator for Team Job						0.001	0.002	0.001
						(0.001)	(0.002)	(0.002)
Affiliate x Trend x Indicator for Agency Team Job						-0.003***	-0.004***	-0.003
						(0.001)	(0.001)	(0.003)
Detailed Controls	No	Yes	Yes	Yes	No	No	No	No
Mean of Dependent Variable	0.687	0.687	0.674	0.701	1.72	1.72	1.93	1.42
Number of Observations	10,103	10,103	4,965	5,138	54,846	54,846	31,832	23,014
R-squared	0.067	0.137	0.153	0.154	0.870	0.870	0.866	0.886

Notes: ***p<0.01, **p<0.05, *p<0.1. All specifications parallel Table 7 but add the indicated measures for team-based jobs. Team-based jobs are defined based on an employer hiring another worker within a 7-day window around a worker's hiring date. Agency teams are defined similarly for workers of the same agency.

Appendix Table 1: Variable Definitions and Measurement

Measure Name	Description	Time of Measurement
	Job Characteristics	
Detailed Job Category	The category chosen by the employer when posting a job. The most common job category is Web Development, followed by Administrative Support. Specifications with job category fixed effects contain dummy variables for each of the 10 main job categories.	At time of job posting.
Technical Job	An indicator that the job is listed under categories Web Development, Software Development, Networking and Info Systems, 3D Modeling and CAD, Engineering and Technical Design, or Search Engine Optimization. Non-technical jobs (indicated with a zero) include Administrative Support, Business Services, Customer Services, Sales and Marketing, and Writing and Translation.	At time of job posting.
Expected Duration and Hours Per Week	Interactions of the employer's posted estimate of the expected duration in calendar time (5 categories) that the job will require and the required hours of work per week (3 categories).	At time of job posting.
Characters in Job Post	The number of alpha-numeric characters returned in a SQL query of the job description.	At time of job posting.
Team-Based Job	An indicator that an employer hires another worker within a 7-day window around a worker's hire date.	At time of hire.
Agency-Team Job	An indicator that an employer hires another worker from the same agency within a 7-day window around an agency affiliated worker's hire date.	At time of hire.
	Worker Resume Characteristics	
Agency Affiliate	The worker's affiliation status.	Data collected at end of sample period from a database table that records dates of switches if status was changed. If a worker never has a recorded status change in the database table, then agency affiliation is taken from the job application transaction data. Each piece of analysis makes clear how affiliation status changes are treated.
English Ability	Self-reported English proficiency on a 5 point scale. Workers reporting English ability greater than or equal to 4 are classified as having "good English skills."	End of sample period.
Years of Experience	Years of labor market experience prior to joining oDesk. In specifications with controls for worker characteristics, years of experience enters linearly and a dummy variable is included for those workers who do not report the measure.	End of sample period, adjusted for oDesk start date.
Education	Self-reported educational credentials, with structured selections for common degrees. Specifications with controls for worker characteristics include a dummy variable for reporting a bachelors degree equivalent or higher.	End of sample period.
Test Scores	Records of publicly available scores on over 300 different skills tests. In specifications with controls for worker characteristics, tests are grouped into categories defined by oDesk corresponding to the underlying skill group, with the maximum score in the group and an indicator for the presence of at least one public test for each test category. The most frequently observed tests are in English language skills, followed by office skills, followed by programming skills.	Data collected at end of sample period from a database table that records dates of test results. Test scores were calculated retrospectively to reflect only information observable at the time of a workers' first hire or first application.

Appendix Table 1, Contd.: Variable Definitions and Measurement

Measure Name	Description	Time of Measurement
	<u>Worker Resume Characteristics, continued.</u>	
Country	Worker's country.	End of sample period.
Revenue and Number of Hires on Fixed Price Projects	The worker's past revenue and number of hires on fixed price contracts. In specifications with controls for worker characteristics, both measures enter linearly. Fixed price jobs are less frequently posted and filled during the sample period, and they have much lower average wage bills than hourly jobs.	At time of job application or hire.
Number of Hires on Hourly Projects	The worker's past number of hires on hourly contracts. See notes on individual specifications when this measure is used.	At time of job application or hire.
Current Feedback Score	The feedback score as a potential employer would see it. Includes feedback from fixed price and hourly projects. In models for workers' initial hourly jobs, any feedback from prior fixed price jobs enters linearly. See notes on individual specifications for other uses of this measure.	Data collected at end of sample period from a database table that records dates of feedback updates. For the empirical work, feedback scores were reverse-engineered using the oDesk revenue-weighting scheme to reflect the information observable to employers at the time of the job application or hire.
	<u>Worker and Job Outcomes</u>	
Hourly Bid and Hourly Rate	The workers' hourly bid when applying for a project and hourly rate of pay received upon successfully receiving the job. On contracts with rate changes, the first hourly rate with billing is used.	At time of job application or hire.
Total Hours Worked	The number of hours recorded in the oDesk billing system.	End of sample period. This is the final number of hours if a contract has been completed or the number as-of the end of the sample for ongoing contracts.
Good Feedback Score	Indicator that the feedback score left for the worker was greater than 4.5 out of 5.	After job ends.
Project Success	Indicator that the employer reported the job was completed successfully on a post-project survey.	After job ends.

Appendix Table 2: Duration of Job Search Prior to Finding the First Hourly-Paying Job

	Hazard Relative to Time (Scale is Days of Search)				Hazard Relative to Job Applications			
	Cox	Cox	Weibull	Weibull	Cox	Cox	Weibull	Weibull
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agency Affiliate Indicator	2.12***	2.039***	2.124***	2.051***	1.59***	1.618***	1.481***	1.57***
	(0.056)	(0.055)	(0.057)	(0.057)	(0.045)	(0.045)	(0.044)	(0.045)
Log Hourly Wage Bid		0.682***		0.685***		0.658***		0.651***
		(0.008)		(0.009)		(0.008)		(0.009)
Has BA or higher degree	0.828***	0.839***	0.827***	0.827***	0.94***	0.963***	0.916***	0.95***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.024)	(0.024)	(0.024)	(0.025)
Has Good English Skills	1.843***	1.939***	1.734***	1.81***	1.476***	1.547***	1.316***	1.33***
	(0.055)	(0.062)	(0.052)	(0.059)	(0.045)	(0.049)	(0.042)	(0.043)
Taken a Skills Test	1.211***	1.295***	1.159***	1.245***	1.139***	1.194***	1.111***	1.133***
	(0.048)	(0.052)	(0.047)	(0.051)	(0.047)	(0.05)	(0.048)	(0.05)
Years of Prior Labor Market Experience	0.999	0.999	0.999	0.999	0.995	0.999	0.992	0.997
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Years of Prior Experience Missing	0.978	0.967	0.989	0.974	0.979	0.988	0.972	1.002
	(0.03)	(0.03)	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)
Log of Weibull Shape Parameter			-0.887***	-0.948***			-0.128***	-0.03***
			(0.007)	(0.01)			(0.007)	(0.009)
Number of Observations	764,215	764,215	764,215	764,215	764,535	764,535	764,535	764,535
Log Likelihood	-100,689	-99,598	-40,964	-39,906	-96,459	-95,677	-31,267	-30,276

Notes: Exponentiated coefficients reported. Robust standard errors in parentheses. There are 10,103 workers who find jobs out of the total sample of job applicants, with characteristics reported in Columns 1 and 2 of Table 2. In this analysis, the agency affiliate indicator is fixed over the worker's career. Workers who find their first job as affiliates or non-affiliates are classified as such for the duration of their job search. Otherwise, the worker's affiliation is calculated as of the time of the first bid. Table 5 separately considers job-finding hazards for those workers who switch into agencies. 408 of the workers in this sample are classified as affiliates after entering oDesk as non-affiliates because they find jobs as affiliates. 22 workers are classified as non-affiliates because after entering oDesk as affiliates, they find jobs as non-affiliates. Cox models use Breslow methods for ties.

Appendix Table 3: The Effect of Revealing a Test Score on Wage Offers

Test:	PHP 5	html	Email Etiquette	English Spelling	General English	MS Office
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Non-affiilate test takers with job applications within a 4-day window of score revelation					
After Score Revealed	-0.0471	0.0630	-0.0908***	-0.0541**	-0.00904	-0.00667
	(0.0490)	(0.0408)	(0.0288)	(0.0233)	(0.0241)	(0.0266)
Observations	1,489	2,007	7,428	9,891	15,648	9,858
R-squared	0.851	0.874	0.704	0.727	0.780	0.704
	Panel B: Pooled sample of affiliate and non-affiliate test takers with job applications in a 4-day window of revealing a score above the 90th percentile of the distribution					
After Score in the 90th Percentile Revealed	-0.0540	-0.00764	-0.127**	-0.00101	-0.0218	0.00135
	(0.0572)	(0.0454)	(0.0543)	(0.0863)	(0.280)	(0.0435)
Affiliate x Score in the 90th Percentile	0.0564	0.0785	-0.0287	-0.199*	-0.113	0.114
	(0.0747)	(0.0551)	(0.0736)	(0.105)	(0.224)	(0.0865)
Observations	591	326	883	762	283	1,855
R-squared	0.847	0.933	0.823	0.733	0.941	0.702

Notes: Robust standard errors clustered by worker in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The sample in Panel A is non-affiliates who have job applications within a 4 day window of the revelation of a test score. The sample in Panel B includes agency affiliates and non-affiliates who reveal a test score above the 90th percentile of the distribution. The dependent variable in all regressions is the log wage offer in a job application. All specifications include controls for the job application number, a cubic polynomial measuring the elapsed time since the worker's first job application, worker fixed effects and job category fixed effects.

Online Appendix Table 1: Summary Statistics for Workers, including U.S. workers

	All Applicants for Hourly Jobs		Workers Hired Once or More		Workers Hired Twice or More	
	Non-Affiliates	Affiliates	Non-Affiliates	Affiliates	Non-Affiliates	Affiliates
	(1)	(2)	(3)	(4)	(5)	(6)
Number of workers with first applications between 8/1/2008 and 12/28/2009, including workers in the U.S.	112,943	12,276	9,376	3,390	6,697	2,628
Share of Affiliates and of Non-Affiliates in:						
Technical Jobs	0.28	0.66	0.34	0.72	0.34	0.72
Non-Technical Jobs	0.72	0.34	0.66	0.28	0.66	0.28
India/Pakistan	0.17	0.48	0.18	0.52	0.20	0.53
Russia/Ukraine	0.02	0.07	0.05	0.12	0.05	0.11
The Philippines	0.22	0.09	0.10	0.28	0.31	0.11
United States	0.36	0.12	0.27	0.05	0.22	0.04
Mean Characteristics by Group:						
Log Hourly Wage on First Job (First Application in Columns 1-2)	2.19	2.26	1.58	2.05	1.50	2.02
Bachelors Degree or Higher, Indicator	0.23	0.30	0.40	0.33	0.42	0.34
Good English Skills, Indicator	0.55	0.80	0.87	0.80	0.91	0.83
Skills Tests Taken, Indicator	0.39	0.36	0.71	0.50	0.76	0.54
Years of Prior Experience	6.69	4.32	6.45	4.24		
Mean Career Earnings Through 8/14/2010 [a], $	320	1,642	3,245	6,095	3,512	5,515
Earnings Gap Due to Affiliation from Oaxaca-Blinder Decompositioı	68%		47%		33.8%	
Affiliation Earnings Premium	2.81		0.42		0.19	

Notes: See notes for Table 2 in the text.

[a] Total Earnings for workers in Columns 5 and 6 are calculated for jobs after the first job.

Online Appendix Table 2: Summary Statistics about Tests. The Unit of Analysis is a Worker on the First Job.

Category of Skills Test	Non-Affiliates: Number of Workers With Public Tests	Non-Affiliates: Mean of Maximum Score in Category	Non-Affiliates: Standard Deviation	Affiliates: Number of Workers With Public Tests	Affiliates: Mean of Maximum Score in Category	Affiliates: Standard Deviation
	(1)	(2)	(3)	(4)	(5)	(6)
Administrative and Basic Computer Use	3195	75.24	21.56	590	75.52	21.70
Programming	552	75.51	20.23	355	77.58	19.84
Web Development	1091	72.99	20.74	774	76.60	20.43
English	3746	51.91	26.65	689	46.17	26.18
Databases	339	76.04	18.57	219	78.66	17.25
Design	1343	67.03	23.73	712	74.30	22.53

Notes: The sample consists of workers on the first hire corresponding to Table 3. Counts of the number of workers with public tests give the number of workers with at least one public test score in each category of skills tests. For each of these workers, the maximum score in the category is used in the analysis, and the mean and standard deviations are taken across workers.