# Search, Screening, and Information Provision: Personnel Decisions in an Online Labor Market

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**Abstract**

Marketplaces such as online labor markets are often in a position to provide agents with public certified information to facilitate trade. I examine how employers on oDesk.com, the world's largest online marketplace, use public information in hiring. By experimentally varying employers' access to applicants' past wage rates, I demonstrate that market provided cheap-to-observe signals of quality are used by employers as substitutes for costly search and screening. I show that when employers are searching for someone low skilled then the provision of coarse information from the market is sufficient and employers will not pay a cost to acquire more information. When employers are looking for someone high skilled they will pay fixed screening costs to acquire information beyond what is provided by the platform. If the coarse information is not provided by the marketplace, then even employers looking for unskilled labor will pay to acquire more information. This leads to more matches and hiring quality workers at a lower price. However, the cost savings from identifying and hiring these low cost, but high quality workers does not outweigh the upfront cost of information acquisition.

JEL J01, J30, M50, M51; Personnel Economics, Firm Employment Decisions, Information Acquisition

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# 1 Introduction

Identifying high quality workers is one of the most important problems a firm faces. According to a survey by Silicon Valley Bank, 90 percent of startups believe finding talent is their biggest challenge.[1] In fact, talent acquisition is so important to the strategy of firms like Facebook, that its CEO, Mark Zuckerberg, once remarked that, "Facebook has not once bought a company for the company itself. We buy companies to get excellent people." Traditionally, firms have relied on resumes and costly interviews to ascertain if a worker is a good fit for the firm. Increasingly, firms are turning to "big data" and workplace analytics to cheaply generate insights into candidates' potential productivity.[2] Technology that provides agents with cheap but noisy signals reduces incentives to acquire more precise information and consequently might lead to worse decisions.

Online labor marketplaces such as oDesk.com are playing an increasing role in the hiring process.[3] Online labor marketplaces, even more so than the traditional labor market, seek to harness the power of big data and algorithms to foster efficient matching.[4] These marketplaces are in the position to provide large quantities of standardized and verified information to facilitate hiring. For example, oDesk.com does not allow workers to delete ratings or comments provided by employers after a job is completed. This information is distinct from what workers include in their resumes, and thus, valuable to employers. Despite the general view that more information is better when it comes to bilateral matching with asymmetric information, some research has hypothesized limitations to the social gains of the digitization of the labor market. Autor (2001b), proposes that information about workers' attributes can be usefully grouped into low and high "bandwidth" varieties.[5] Low bandwidth data are objectively verifiable information such as education, credentials, experience, and salaries – the kind of information that is easily provided for employers through online marketplaces. High bandwidth data are attributes such as quality, motivation, and "fit," which are typically hard to verify except through direct interactions such as interviews and repeated contact. Hence, providing employers with large quantities of low bandwidth information does not reduce the problem of gathering high bandwidth information, which may be a more precise signal of applicant quality.

This paper empirically studies how employers shift their hiring strategies in response to an exogenous change, which makes employers unable to observe applicants' past wage rate history. There is reason to belive that this information is valuable to employers and facilitates trade by reducing costs of acquiring information about workers in the marketplace. Despite the general view that more information is better when it comes to bilateral matching with asymmetric information, the equilibrium amount of information an employer has when hiring an applicant may not be monotonically increasing in the public information provided by the marketplace. This because the equilibrium level of information depends both on market provided information as well as information acquired via costly search and screening.

[1] `http://www.svb.com/News/Company-News/Looking-For-a-Job--Try-a-Tech-Startup/`

[2] `https://hbr.org/resources/pdfs/comm/workday/workday_report_oct.pdf`

[3] The major players in this industry were oDesk.com, Elance.com, Freelancer.com, and Thumbtack.com. In December of 2013, oDesk and Elance merged to form oDesk-Elance.com, but maintained separate online platforms until May 2015 when the company changed its name to upwork.com and released one unified platform. My experiment was run post-merger, but solely on the oDesk.com platform.

[4] Horton (2013) looks at the effects of algorithmically recruiting applicants to job openings for employers, and Agrawal et al. (2013b) shows that verified work experience disproportionally helps contractors from less developed countries.

[5] Rees (1966) makes a similar distinction between formal and informal information networks. Formal networks include the state employment services, private fee-charging employment agencies, newspaper advertisements, union hiring halls, and school or college placement bureaus. Informal sources include referrals from employees, other employers, miscellaneous sources, and walk-ins or hiring at the gate.

If there is a fixed cost associated with information acquisition then a substitution from market provided information to costly search and screening could lead to an equilibrium increase in information. As the endogenous level of information provision changes in the marketplace, how will employers shift their hiring strategies? Additionally, how do changes in the chosen hiring strategy affect worker quality and to what extent should firms rely on cheap-to-observe public signals when making hiring decisions? To answer these questions I designed and conducted a field experiment using the online labor marketplace oDesk.com.[6]

The experiment I designed, which is described in detail in section 3.2, altered the information set available to a randomly selected group of employers by hiding all the previous hourly wage rates an applicant agreed to work for on the platform. Past wage rates are particularly useful in the screening process, as they provide a snapshot estimate of the worker's relative marginal product. No matter the competitive market environment, a worker's marginal product must be at least his wage, or no employer would pay that wage. A worker's current or past employer may be better informed about a worker's ability than the overall marketplace, and past wages provide at least a glimpse of what others think a worker's marginal product might be. In conventional labor markets, employers do not directly have access to an applicant's past wages unless the applicant chooses to disclose it. In this paper, I consider an online marketplace where the status quo is, and always has been, for employers to know the complete work history, including wages and earnings, for all applicants to their job. I observe how altering the publicly available set of "low bandwidth" information by removing applicants' past wage rates changed the employer's screening strategy and the result this has on match formation, wage negotiation, and job outcomes.

This paper has five main findings. First I find that when employers are unable to observe applicant's past wage rates they increase their search by viewing more applicants and increase screening by interviewing more applicants more deeply. Employers strategically react to having less information by actively acquiring information through a more costly, but perhaps more precise, source by taking time to ask the applicant more questions and get more information about his quality.

Second, I find that when employers are unable to observe applicants' past wage rates employers are more likely to fill a job posting. This may seem surprising because standard economic theory predicts that as information is removed from an employer they are less able to differentiate between candidates based on quality. However, if there is a fixed cost associated with acquiring information, then a reduction in exogenous information provision does not necessitate a reduction in the equilibrium level of information, because employers substitute for the reduction in market provided information with even more information from costly interviewing.

Third, I show that employers that are unable to observe past wage rates interview and hire cheaper but otherwise equivalent candidates, and are more satisfied with the work output. This selection effect on wages completely dominates a small negotiation effect which increases wages for workers. Hired applicants earn a higher percentage of their original bid. However this small increase in salary is outweighed by employers offering a contract to much cheaper applicants.

Fourth, I provide evidence that although employers hire cheaper workers and are *ex post* more satisfied with the work output when they can not observe past wage rates, employers are not making a mistake by using platform-provided information when available. Using a difference-in-difference approach I show that treated employers that increased their use of costly intensive search during the experimental period reduced their use of costly search once the experiment concluded and they once again could

[6] The online market for labor is already an economically important source of labor supply and demand, and it's estimated to grow substantially in the coming years (Agrawal et al. (2013a)). The Economist (2013) predicted that combined, online labor markets will be worth more than $5 billion by 2018.

observe past wage histories. This finding indicates that when employers have access to coarse but cheap information, it may be optimal for them to use this information to reduce upfront hiring costs. However, employers need to be aware that this upfront cost savings comes at a price, as they will likely pay slightly more for an equivalent worker.

Fifth, I demonstrate that not all employers are affected by the loss of the past wage history signal equally. The treatment disproportionally affects the search and screening behavior of employers that are looking to hire workers with a lower level of experience. This effect is driven by an already comparatively higher use of costly intensive screening by employers that are interested in hiring intermediate and expert contractors. Additionally, while both first time employers as well as established employers are affected by the treatment, the effects are differentially larger for first time employers.

The remainder of the paper proceeds as follows: Section 2 briefly reviews the relavent literature and describes this paper's contributions; section 3 describes empirical context; section 4 presents the empirical findings; section 5 discusses the results; and section 6 concludes.

## 2 Literature Review

One of the central problems in the personnel economics literature on hiring is that that firms and workers cannot costlessly observe all relevant aspects of potential trading partners. This means that search is a common feature of hiring.[7] Traditional economic literature models the labor market as employees searching for wages, which are posted by the hiring firm.[8] Another much smaller branch of literature has focused on the demand side of the market. Barron et al. (1985) and Barron et al. (1989) study employer search by relating the number of applicants or interviews per employment offer and the time spent on recruiting and screening per applicant or per interview to characteristics of the vacancy and the employer. They argue that search along the extensive margin and search along the intensive margin are substitutes. In traditional models of search, a firm (or employee) acquires information simultaneously on the existence of an additional candidate (or job) as well as the value of the match. In fact, hiring procedures in the firm generally consist of two sets of activities. One set involves recruitment of applicants, while the second set involves screening and selection from among these applicants.

In contrast to most of the literature on hiring that takes a search theoretic approach, this paper follows Van Ours and Ridder (1992), which shows that most vacancies are filled by a pool of applicants formed shortly after search. I separate the questions of locating an additional candidate from ascertaining the match quality of a candidate. Thus, the important economic question is, which of the applicants to the job should the firm choose, or should the firm choose none of the available applicants at all.[9] In doing so, I deviate from much of the current literature, and choose to describe the firm's hiring decision as an information acquisition model where a firm must choose how much information to acquire about applicants before choosing whether to hire or to not hire an applicant.[10]

The economic literature on endogenous information acquisition usually assumes that agents acquire information when the value of information exceeds its cost (Arrow (1996); Grossman and Stiglitz (1980)). The information acquisition literature has largely focused on situations where externalities such as the

[7] See Devine and Kiefer (1991) for a detailed summary of the search literature on hiring.

[8] For example, Stigler (1961), Mortensen (1970) and McCall (1970); see Mortensen and Pissarides (1999) for a detailed review of costly applicant search.

[9] Additional support for focusing on selection comes from Van Ours and Ridder (1993) which finds that employers spend far more time on selection than on search.

[10] See figure A.1 which confirms that the applicant pool is generally set before employers begin to message applicants.

public nature of information, or behavioral considerations lead to either an over or under investment in information acquisition.[11]

In contrast to the existing literature, which highlights miss-investment in information, I focus on how the endowment of information to agents alters incentives to acquire more costly information. Building on evidence that the equilibrium level of information acquisition is fundamentally dependent on the market institutions, this paper empirically demonstrates the effects of the market provision of information on employer hiring strategies, including costly search and screening.[12]

The literature on determinants of hiring focuses on how either firm and job attributes or market attributes affect recruiting and screening behavior. Holzer (1996) argues that employers choose among the various recruitment and screening methods on the basis of their relative costs and benefits.[13] Barron et al. (1989) shows that employers tend to screen more applicants for more important positions. My paper is closely related to Barron et al. (1997), which also allows the firm to endogenously acquire information about the match quality of the applicant. Barron found that both applicants and vacancy characteristics strongly influence firms' search both at the intensive and extensive margin. My paper, in contrast, focuses on the effect of market provided information on the firms' information acquisition decision, and the interaction with firm and applicant characteristics.[14]

This paper also contributes to a growing literature that details the impact of screening technology on the quality of hires. While information technology and big data signals seem to suggest "efficiency" to many practitioners and academics, I find evidence that they can get in the way of costly but more informative practices, with fixed costs, like interviewing. Strategies discussed in the literature include the use of job testing, labor market intermediaries, and employee referrals. My paper is similar to Hoffman et al. (2015) in that it investigates the effects of verifiable information on employer hiring. Hoffman found that in addition to reducing costs, verifiable signals such as job testing can solve agency problems in hiring. They also show that applicants hired using on the job testing have longer tenure than those hired through traditional means. My finding, that public verifiable information can reduce incentives to conduct costly search adds an interesting confounding factor to their results, as it makes clear the complete costs of using job testing to solve agency problems.[15]

Finally, the paper seeks to tie hiring strategy directly to firm outcomes by measuring the causal impact of employer's use of public information on costly search and the effect of that costly search on employer satisfaction. Recent theoretical literature in management has highlighted the critical role of individuals in creating and sustaining competitive advantages (Abell et al. (2007); Teece (2007)).[16] Under-

[11] See Kübler and Weizsäcker (2004); Kraemer et al. (2006); Hoffman (2014) as a recent sampling of experimental literature which focuses on behavioral reasons for miss-allocation in information.

[12] Endogenous information acquisition has been used to analyze auctions (e.g., Milgrom and Weber (1982)), voting (e.g., Martinelli (2006); Persico (2004)), and medical patient decision-making (e.g., Kőszegi (2003)), among many other applications.

[13] Holzer (1987) was the first to detail an employer search model in which firms choose hiring procedures as well as reservation productivity levels. Fallick (1992) details how more expensive recruitment methods must provide more applicants and or better ones.

[14] There also exists a more macro focused literature including Burdett and Cunningham (1998) which advocate that the analysis of employers' search would be greatly improved if the market conditions the firm faced at the time of search could be taken into account. Russo et al. (2000) details how tightness of the labor market affects employer recruitment behavior. The procyclicality of on-the-job search is mainly driven by the increase in the availability of better jobs in Pissarides (1994) and Schettkat and für Sozialforschung (1995). Russo et al. (2001), adds to this literature by analyzing changes in recruitment behavior at the individual firm level at different points of the business cycle.

[15] See Autor and Scarborough (2008) for other recent work focusing on the effects of job testing on worker performance. Work by Autor (2001a); Stanton and Thomas (2012); Horton (2013) focuses on labor market intermediaries. Recent empirical work which focus on the effects of employee referrals include Burks et al. (2013); Brown et al. (2012); Pallais and Sands (2013).

[16] Also see Barney (1991); Hall (1993); Reed and DeFillippi (1990); Peteraf and Barney (2003); Coff and Kryscynski (2011).

standing firm-level recruitment and hiring strategies may help explain persistent firm-level conditional differences observed in profitability (Oyer and Schaefer (2011); Blasco and Pertold-Gebicka (2013)). My paper details the importance of costly search which enables an employer to assess applicants high bandwith information and hire cheap, high quality employees.

# 3 Empirical Context

During the past ten years, a number of online labor markets have emerged. In these markets, firms hire workers to perform tasks that can be done remotely, such as computer programming, graphic design, data entry, research, and writing. Online labor markets differ in their scope and focus, but common services provided by the platforms include maintaining job listings, hosting user profile pages, arbitrating disputes, certifying worker skills, and maintaining feedback systems. The experiment reported in this paper was conducted on oDesk, the largest of these online labor markets.

On oDesk, employers write job descriptions, self-categorize the nature of the work, and set required skills for jobs posted to the oDesk website. Workers learn about vacancies via electronic searches or email notifications, and can submit applications to any publicly advertised job on the platform. After a worker submits an application, the employer can interview and hire the worker on the terms proposed by the worker or make a counteroffer, which the worker can accept or reject, and so on.

In the first quarter of 2012, employers spent $78 million on wages through oDesk. The 2011 wage bill was $225 million, representing 90% year-on-year growth from 2010. As of October 2012, more than 495,000 employers and 2.5 million contractors have created profiles, though a considerably smaller fraction are active on the site. Approximately 790,000 job openings were posted in the first half of 2012. See Agrawal et al. (2013a) for additional descriptive statistics on oDesk.

Based on dollars spent, the top skills in the marketplace are technical skills, such as web programming, mobile applications development (e.g., iPhone and Android), and web design. Based on hours worked, the top skills are web programming, data entry, search engine optimization, and web research. The difference in the top skills based on dollars versus hours reflects a fundamental split in the marketplace between technical and non-technical work. There are highly-skilled, highly-paid contractors working in non-technical jobs, yet a stylized fact of the marketplace is that technical work tends to pay better, generating longer-lasting relationships and requiring greater skill.

There has been some research which focuses on the oDesk marketplace. Pallais (2014) shows via a field experiment that past worker experience on oDesk is an excellent predictor of being hired for subsequent work on the platform. Stanton and Thomas (2012) use oDesk data to show that agencies (which act as quasi-firms) help workers find jobs and break into the marketplace. Agrawal et al. (2013b) investigates what factors matter to employers in making selections from an applicant pool, and presents some evidence of statistical discrimination; the paper also supports the view of employers selecting from a more-or-less complete pool of applicants rather than serially screening.

## 3.1 Transacting on oDesk

The process for filling a job opening on oDesk is qualitatively similar to the process in conventional labor markets. First, a would-be employer on oDesk creates a job post and chooses whether to make it public or private. Public jobs can be seen by all workers on the platform, while private jobs only invited applicants can see. Employers choose a job title and describe the nature of the work. Additionally, employers choose a contractual form (hourly or fixed-price), specify what skills the project requires (both by listing skills and by choosing a category from a mutually exclusive list), and specify what kinds of applicants they are looking for in terms of past experience. Employers also estimate how long the project is likely to last. Once the job posting is written, it is reviewed by oDesk and then posted to the marketplace.

Once posted to the marketplace, would-be job applicants can view all the employer-provided job post information. Additionally, oDesk also presents verified attributes of the employer, such as their number of past jobs, average wage rate paid and so on. Applicants are free to apply to any public job posting on the platform. When they apply, they include a bid (which is an hourly wage or a fixed price, depending on contract type) and cover letter. After applying, the applicant immediately appears in the employer's "applicant tracking system" or ATS, with their name, picture, bid, self reported skills, and a few pieces of oDesk-verified information, such as total hours-worked and their average feedback rating from previous projects (if any). Figure 1 shows the default view to an employer of the ATS prior to viewing the detailed information contained in the job application. By default, employers only view applicants for the job who are predicted to be a good fit using oDesk's proprietary machine-learning algorithms. To view a complete list of applicants the employer must click on the "Applicant" tab on the right side of the screen.

Employers can click on an applicant's limited listing to view their full profile, which has that applicant's disaggregated work history, with per-project details on feedback received, hours worked and wage rate earned on all past jobs. As these clicks are recorded by oDesk, they provide an intermediate measure of employer interest beyond hiring. Figure 2 shows an employer's view of an applicant's disaggregated work history after expanding or viewing an application.

Although all job applications start with the worker applying to a job opening, not all of these applications are initiated by the worker. As in conventional labor markets, oDesk employers may choose to actively recruit candidates to apply for their jobs. Upon completing a job posting employers are shown a pool of 10 applicants who report having the skills requested for the posted job. Employers are given the option of inviting some or all of these applicants to apply to the job. Additionally, the employer can search on his own for some skill or attribute they are looking for in candidates. The search tools on oDesk will return lists of workers, and will contain information about that worker's past work history. If they choose, the employer can then "invite" a worker they are interested in. These recruiting invitations are not job offers, but rather invitations to apply to the employer's already-posted job opening.

Only 36% of employers choose to recruit applicants on jobs posted on oDesk. Of employers that choose to recruit, on average 3 out of 4 recruited applicants are recruited from the oDesk provided pool of applicants shown to all employers after posting a job. Of course, these recruited applicants are not required to apply to the job opening—about half do apply. These "recruited" applicants and organic applicants (applicants who are not recruited) both appear in the employer's ATS. Employers are free to evaluate candidates at any time after they post their job.

If the employer hires a candidate via oDesk, oDesk mediates the relationship. If the project is hourly, hours-worked are measured via custom tracking software that workers install on their computers. The tracking software, or "Work Diary," essentially serves as a digital punch clock.

The oDesk marketplace is not the only marketplace for online work (or IT work more generally). As such, one might worry that every job opening on oDesk is simultaneously posted on several other online labor market sites *and* in the traditional market. However, survey evidence suggests that online and offline hiring are only very weak substitutes and that posting of job openings on multiple platforms is relatively rare. For example, Horton (2010) found limited evidence of multiple postings when comparing jobs posted on oDesk and its largest (former) rival, Elance.

### 3.2 Description of the Experiment

In September 2014, oDesk conducted an experiment that altered the information set available to employers by hiding applicant‘s past wage rates. All employers operating on the oDesk platform, both new and experienced, were eligible for the experiment, and were randomized for the duration of the experiment into either a treatment or control group when they posted their first job during the experimental period. Once an employer was assigned to the treatment group, the treatment affected all aspects of the site. Thus, past wage information was completely hidden on worker's profiles both in search results, and when viewing the detailed profile after clicking on an applicant in the ATS. Table 1 shows that randomization was effective and the experimental groups were well balanced.

Figure 3 shows the changes implemented both in search as well as in the employer's ATS for treated employers. When employers click an applicant's limited listing and view their full profile, which has that applicant's disaggregated work history, the information presented to the employers allocated to the treatment group differs from that presented to the set of control employers. Specifically, when viewing the per-project details both the number of hours worked on the job as well as the hourly wage rate earned on any job was removed. Employers allocated to the control group can view both the price, $p$, and applicants worked for as well as the quantity of work preformed, $q$. Employers allocated to the treatment group can only observe the $p * q$ or the total earnings on each job.

When reviewing past work history, which according to a February, 2015 client survey was the second most important piece of information in hiring after the bid amount, employers can only observe the title of the job, the total earnings on the job, and any feedback left (if available) by the past employer. Other than the lack of job specific past wage information, there were no other changes in the user interface or in information available between treated and control employers. Treated employers still know the number of past jobs the applicants worked, the total number of hours on the platform the applicants worked, as well as the applicants' total past earnings. Thus, it is possible for employers to calculate applicants' average past wages, but not applicants current wage rate.

### 3.3 Overview of the Data

Over the course of the experiment, 2948 employers were assigned to the control group and posted a total of 4661 job openings. 2975 employers where assigned to the treatment group and posted 4815 job openings. Table 2 presents summary statistics of the baseline hiring behavior on oDesk.com.[17] Beginning at the top of the hiring funnel and proceeding downwards, it is clear employers narrow down the set of applicants until they arrive at the candidate(s) they wish to hire. On average, 35 applicants apply to each job posting on oDesk. On average 1.3 of these applicants are invited to apply to the job by the employer leaving 33.6 applicants who apply to a job without being invited. I refer to these applicants as organic applicants.[18] On average, employers only view about 7 of the applications submitted to the job by organic applicants. It is here that employers become much more selective, choosing only to send messages to about 2 applicants on average. Employers specifically ask at least one question to about 60% of the applicants they message, or about 1 applicant on average. Finally, in order to conduct "face-to-face" interviews, about half of applicants who are messaged are asked for a Skype ID by the employer. On average, this hiring process leads to about 40% of job openings posted on oDesk being filled.

[17] To show baseline hiring behavior, I show average statistics for the control group of employers.

[18] For the analysis on screening, I look only at the messaging behavior of organic applicants. When an applicant is invited, oDesk automatically begins a message thread between the applicant and the employer. Thus, it becomes difficult to identify invited applicants the employer actually screens.

## 4 Empirical Results

The first question I seek to answer using this experiment is, how do employers shift their hiring strategies to make use of publicly available low bandwith information such as applicants past hourly wage rate? Hiring can conveniently be separated into search and screening. Employers search to identify another posible candidate, and then screen that candidate to identify his quality or fit for the job. Table 3 presents differences in mean search and screening measures across treatment groups.

To measure employer search, I track whether an employer "views" an application by clicking to expand the applicant's application within the applicant tracking system. Treated employers on average view another 0.4 applications from a baseline of 6.7 applications per opening. While this results seems small on a per job basis, there are over one hundred thousand jobs posted per month. On a per month basis, being unable to observe applicants past wages leads employers to considering an additional twenty thousand applicants, who previously were not even in the employers consideration set.

Employers on oDesk acquire information through a costly screening process. This process involves messaging an applicant using the platform provided messaging system, asking the applicant questions, and/or exchanging Skype IDs in order to set up a "face-to-face" meeting with the applicant. The second panel of Table 3 looks at four measures of employer screening or information acquisition behavior: (i) whether an employer "messages" an applicant by formally contacting the applicant for further discussion; (ii) whether an employer "questions" an applicant as evidenced by use of a question mark in a message; (iii) whether an employer "questions" an applicant as evidenced by use of one or more question words: who, what, where, when, why, or how; and (iv) whether an employer "Skypes" an applicant by asking the applicant to exchange Skype IDs. Table 3 shows that employers that are unable to observe applicants' past wage rates increase the number of applicants they question as evidenced by both the number of applicants messaged that include a question mark, as well as the number of applicants messaged that include a question word. Employers ask questions to an additional 0.15 applicants per job opening. The raw differences in mean counts does not report any statistical difference in the number of applicants messaged or the number of applicants asked for Skype IDs. However, taken together, there does seem to be an increase in both the amount of applicants searched through as well a the number of applicants screened when employers lack the information provided from observing the wage rate an employer was previously willing to work for.

Since the four measures of screening magnitude are all rough proxies for information acquisition behavior, I use a principal component analysis to create an aggregate measure of screening behavior. This measure expains 75% of the variation in the 4 measures. Figure 4 shows that the difference in the means between the first principal component is significantly different between employers who could and could not observe applicants' past wage history.

I collected the data from a randomized experiment; therefore the simple correlations reported here can be interpreted as causal relationships. However, to further allay concerns about omitted variables, and to potentially increase precision, in the next sections I estimate the effect of hiding applicants past wages on search and screening in a multivariate regression framework.

### 4.1 Employer Search

Due to the count nature of our outcome variable, I follow, Budish et al. (2015) and show estimates from a quasi-maximum likelihood Poisson model with heteroskedasticity-robust standard errors. The regressions in this section are derived from a version of the following model:

$$\text{VIEWED}_j = \beta_0 + \beta_1 \text{TRT}_j + \text{EMPLOYER COVARIATES}_j + \text{OPENING COVARIATES}_j + \epsilon_j \tag{1}$$

In table 4, the dependent variable is $\text{VIEWED}_j$ which is the number of applicants viewed by the employer on job opening, $j$. $\text{TRT}_j$ is an indicator for treatment assignment of the employer of job opening, $j$. The specification used includes both employer and job opening covariates, which include: job subcategory dummies, the number of prior jobs filled, the employers past spending, the number of applications to the job, the number of recommended applicants to the job, and the average bid by applicants on the job.

Treated employers view 1.07 times the number of applications from a baseline average of 7 applications per opening in the control group.[19] After observing an applicant's application and noticing that wage rate history information which was previously used in ascertaining that applicants quality is missing, employers view additional candidates.

#### 4.1.1 Characteristics of Searched Applicants

In addition to changing the number of applicants employers search for and screen, not being able to observe applicants' past wage history could alter the characteristics of the applicants employers choose to view, message, and hire. According to a 2015 client survey on oDesk.com, the top 3 features, in order of importance, used when making a decision over who to contact and eventually hire are: the applicant's hourly rate, the applicant's feedback rating (specifically does the applicant have "good enough" feedback), the applicant's experience. Thus, I will analyze three main groups of applicant characteristics: wage characteristics, experience characteristics, and feedback characteristics.

When both treatment and control group employers choose to view an application, they can only observe the applicants' basic information. Thus, when deciding to view or not view an application, the information set is identical for both treatment and control employers. Therefore, I do not expect the treatment to have any effect on the characteristics of viewed applicants. It is useful to view table 5 as a placebo test, which confirms balance in the experiment at the time employers choose to view applications.

### 4.2 Employer Screening

The differences in means presented above suggest that removing employers ability to observe applicants past wage rates increase screening. The addition of controls and proper analysis of the data using quasi-maximum likelihood Poisson model with heteroskedasticity-robust standard errors confirms these results and shows a much more robust story. The regressions in this section are derived from a version of the following model:

$$\text{Y}_j = \beta_0 + \beta_1 \text{TRT}_j + \text{EMPLOYER COVARIATES}_j + \text{OPENING COVARIATES}_j + \epsilon_j \tag{2}$$

In column (1) of Table 6, the dependent variable, $\text{Y}_j$, is the number of applicants messaged in job, $j$. Controlling for job opening characteristics as well as employer characteristics, employers in the treatment group message 1.08 times the number of applicants as control employers. The mean number of

[19] the coefficient on TRT from the poisson model is interpreted as a the difference in the logs of expected count of viewed application, thus, we interoperate coefficient as being associated with viewing exp(.069)=1.07 times as many applicants.

applicants messaged per job is 1.7. Thus, employers message an additional 0.14 applicants messaged per job.

In column (2), the dependent variable, $Y_j$, is the number of applicants messaged where Skype IDs are exchanged in job, $j$. Controlling for the number of applicants messaged, job opening characteristics as well as employer characteristics, employers in the treatment group are associated with asking 1.9 times the number of applicants for Skype IDs as control employers. The mean number of applicants per job that the employer attempted to exchange Skype IDs with is only 0.89 applicants. Thus, the increase in applicants Skyped is equivalent to exchanging skype ids with .08 more applicants on average. Per month, this corresponds to employer on oDesk conducting Skype interviews with an additional eight thousand applicants. This is a very large increase in costly information acquisition across the platform.

In column (3) the dependent variable, $Y_j$, is a count of the number of applicants messaged in job, $j$, where at least one message exchanged with the employer contained a question mark.[20] A question mark is taken as evidence of the employer asking the applicant a question, and thus, evidence of seeking additional information about that applicant. Controlling for the number of applicants messaged, treated employers use question marks in 1.15 times as many message-threads as control employers. The mean number of applicants that are asked a question in the control group is 1.18, so an increase of about 15% is equivalent to another 0.2 applicants questioned per job.

In column (4) the dependent variable, $Y_j$, is a count of the number of applicants messaged in job $j$, where at least one message contains at least one of the following question words: who, what, where, when, why, or how. This results confirms that employers are increasing the number of applicants questioned substantially per job. Here, a coefficient on the treatment indicator of .178 means that treated employers use at least one question word in 1.19 times the number of message-threads than control employers per job opening. This corresponds to about 0.2 more applicants questioned per job posting.

Taken all together, these four results in Table 6 provide evidence that removing past wage information does not only cause employers to widen their choice set and contact more applicants, but to also attempt to get more information from the applicants they contact via message.[21]

#### 4.2.1 Characteristics of Screened Applicants

Does altering the information publicly available to employers alter the characteristics of the applicants the employer chooses to message? Again, I compare the observable characteristics of applicants along three main dimensions: their wages, their experience, and their feedback, but now I limit my analysis to only applicants who were messaged by the employer in the top panel and to applicants that were offered a contract in the lower panel.

The top panel of Table 7 indicates that treated employers choose to message applicants with bids that are on average 6% lower than the group of applicants messaged by control employers. These are applicants who clearly value their work product lower as evidenced by a lower profile wage rate and lower historical average accepted wages. There is some slight evidence that employers also seem to message applicants whose have lower work experience as indicated by a 10% reduction in the average dollar amount of previous hourly earnings, and a 15% reduction in fixed price earnings of the applicants messaged. However, this is not due to having worked fewer hours, but having been willing to previously work for a lower wage. These do not seem to be applicants who are newer to the platform or applicants

[20] Using a count of total question marks over all messages sent in a job opening instead of a count of message-threads with question marks gives similar results. I report a count of message-threads to maintain consistency with the specification in column (1) and column (2).

[21] See the appendix for alternative specifications.

with substantially worse work experience. Additionally, messaged applicants again do not differ on their historical feedback scores. These results provide evidence that employers that are unable to use an applicants' past wages as a signal of quality seem to locate a subset of applicants who are substantially cheaper to an employer without being observably worse applicants as measured by market level signals.

On oDesk, an employer need not view and interview an applicant prior to offering a contract. In fact, 21% of contracted applicants were not messaged prior to being offered a contract on a job. In the lower panel of Table 7, I check to see if the same pattern of selection holds for applicants who are offered a contract as for applicants who were messaged. The results illustrate that applicants hired by employers that do not know the applicants' past wages hire applicants who bid 9.5% less. The applicants hired, like those who were interviewed, differ only on one attribute. The wage they demand in return for their services.

### 4.3 Hiring Outcomes

I turn now to analyzing effects of employers substituting from platform provided information to information obtained through costly search and screening on the probability of a posted job being filled, the wage negotiation which occurs after a contract is offered and the employers' *ex post* job satisfaction.

#### 4.3.1 Probability of Hiring

According to a 2013 oDesk client survey, the primary reason for not hiring a worker for an open job posting is that the employer "couldn't identify a contractor with the right skills." An employer will only fill a job when he can adequately identify an applicant who is is a proper match for the position. The treatment unambiguously reduces the number of available signals the employer can use to identify if an applicant has the right skills. However, as an employer's ability to ascertain quality is diminished, his incentives to acquire information are increasing. Employers that are unable to observe past wage information do increase both the number of applicants they view as well as the number of applicants they message and most importantly the number of applicants they acquire additional information. Thus, in equilibrium the effect of hiding past wages may actually increase the employer's ability to ascertain an applicants' quality, and the probability of hiring an applicant for an open job posting. Table 8 shows that the treatment increases the probability of hiring.

The regressions in this section are derived from a version of the following linear model:

$$\text{AnyHired}_j = \beta_0 + \beta_1 \text{Trt}_j + \epsilon_j \tag{3}$$

In column (1) the sample is limited to only the first job posting by each employer after the start of the experiment. Further job postings were dropped from this specification to control for possible, but highly unlikely, employer selection into additional jobs posted to the platform. $\text{AnyHired}_j$ is an indicator for whether the employer made a hire on job, $j$, and $\text{Trt}_j$ is an indicator for treatment assignment on job, $j$. The coefficient on the treatment indicator is positive and highly significant, with the treatment increasing hiring by about 3 percentage points, from a baseline hire rate in the control group of only 40%. This is a percentage increase of 7%, which is extremely high and economically important to a platform that generates revenue by taking a percentage of contractor earnings. Column (2) includes both employer and job opening level covariates and shows that adding covariates has little effect on the outcome of the regression. Column (3) adds job postings that are not an employer's first during the course of the experiment. An indicator variable for the order of the job posting is included and standard errors are clustered at the employer level. Running the fill rate regression on the full sample only slightly reduces the coefficient from 0.029 to 0.026 and increases the precision of the estimates slightly. Adding covariates in column (4) increases precision slightly and has little effect on the magnitude of the coefficients.

Removing a signal of an applicants' relative marginal value does not reduce the employer's ability to identify and hire quality applicants.

#### 4.3.2 Wage Negotiation

A survey by Hall and Krueger (2010) found that only about 30% of workers report there was some bargaining in setting the wage for their current job. The bargaining rate is especially low for blue collar workers (5%) but much higher for knowledge workers (86%). On oDesk, at least 14% of jobs on the platform participate in some type of wage bargaining prior to signing a contract, as evidenced by agreeing to a contract wage that is not equal to the winning applicants' wage bid.[22]

I have already detailed that the increased use of intensive screening to acquire more information about applicants, when employers are unable to observe applicants' past wages, leads to selecting applicants who are willing to work for nearly 10% lower wages. Once and employer has chosen an applicant, hiding that applicants' past wages may alter negotiations over pay with the employer. Table 9 shows that there is a small but positive affect on wages which comes from worker's who are offered contracts making a higher percentage of their bid. Column (1) reports an estimate of the regression:

$$\log(\text{WAGE TO BID RATIO}_{ja}) = \beta_0 + \beta_1 \text{TRT}_{ja} + \epsilon_{ja} \tag{4}$$

Where WAGE TO BID RATIO$_{ja}$ is calculated as the ratio of the wages paid to the winning applicant to the hourly bid submitted by the winning applicant in assignment, $a$, which came from job posting $j$. An assignment is the oDesk specific word for job once both parties have signed the contract. In this model, there is always only one assignment to each job posting, as I limit our analysis to only the first job assignment which is created from a job posting. I subset the data in this way, as negotiation effects on follow up job assignments cannot be directly attributable to hiding of the wage history of applicants for certain employers. Thus, a WAGE TO BID RATIO of 1 means the employer paid the employee exactly the employee's bid amount. WAGE TO BID RATIO below 1 indicates that the employer is paying the employee an amount less than the employee's bid. The coefficient on the treatment indicator is positive and highly significant, with the treatment increasing the wage to bid ratio by about 1.2%, from a baseline ratio of 0.973. Thus, while the overall effect of the treatment is negative due to the large negative selection effect of selecting applicants with lower bids, removing an employer's knowledge over applicants' past wages has a small but significant positive effect on wages due to bargaining.

Figure 5 plots the distribution of wage to bid ratios that are not equal to one for the first contract signed for each treatment and control employer after the start of the experiment. Some employees manage to negotiate wages which are higher than their initial bid amount. Interviews with workers on oDesk reveal, that for top level talent, it is not unheard of to use other offers to attempt to negotiate up the contract wage relative to the bid. Additionally, Figure 5 allows us to conclude that the treatment effect does not appear to be driven by outliers such as bidding only one cent on a job opening.

[22] This is a lower bound estimate, as its possible that there wage negotiation, but the amount settled on was exactly the contractors bid. Getting data on wage negotiation and delving into this phenomenon is beyond the scope of this paper.

#### 4.3.3 Feedback

Employers are hiring cheaper workers, but not workers who appear worse in measurable quality *ex ante*. Thus, employers that do not know past wage rate information tend to get their work completed cheaper than employers that make hiring decisions conditional on applicant's past wage rate history. Although treatment employers do not choose applicants that are *ex ante* of lower quality than those chosen by control employers, the applicants true quality is still unknown. Thus, I turn my attention to determining if applicants hired through the fundamentally different search process caused by removing past wage rate information do a better job completing the job.

Specifically, conditional on an employer leaving feedback on the applicant hired, do treated employers leave worse feedback than control employers? Table 10 shows there is no measurable difference in public feedback left between treatment and control employers, but that employers that could not hire conditional on applicants' past wage rates leave better private feedback on the first job they hired from a job opening. The regressions in this section are derived from a version of the following model:

$$\log(\textsc{Feedback Variable}_{ja}) = \beta_0 + \beta_1 \textsc{Trt}_{ja} + \epsilon_{ja} \mid \textsc{Feedback Left}_{ja} \tag{5}$$

where the sample is limited to only first job openings posted by each employer and only the first of the assignments spawned by that job opening. The reason I limit my analysis to only the first assignment spawned from a job opening, is that including follow-up assignments bias the results as employers are more likely to create a follow up assignment when the worker is of high quality.

In column (1), $\textsc{Feedback Variable}$ is the publicly viewable 1 to 5 star feedback rating that an employer can leave for a worker on assignment $a$ from job opening $j$ after the job is complete, $\textsc{Trt}_{ja}$ is an indicator for treatment assignment of assignment $a$, which came from job posting $j$. The coefficient on the treatment indicator in column (1) is not significant indicating that employers that hire without knowing an applicant's past wage history do no leave better or worse feedback than employers that know this information.

There has been substantial research, including Nosko and Tadelis (2015) and Horton and Golden (2015) that detail the limits of public reputation in platform markets. On oDesk, both employers and workers also have the option of leaving private feedback which is never displayed on the platform. They are told that this feedback will only be used internally by oDesk.

In Column (2) $\textsc{Feedback Variable}$ is equal to a 0-10 rating, which is viewable only to oDesk. The coefficient on the treatment indicator is positive and significant. Employers that were not able to view applicants' past wages when hiring leave feedback that is 5% higher than employers that hired applicants conditional on knowing their past feedback score.

### 4.4 Are Employers making a Mistake?

The evidence presented in the previous sections demonstrates that when employers cannot observe past wage rate history they choose to acquire information about applicants' quality though more costly intensive search. This intensive search allows employers, at an upfront cost, to better identify high quality low cost employees, which can have long term positive effects on firm outcomes. Thus, should employers ignore market provided low bandwidth information and rely on costly screening all the time?

To assess this, I take advantage of the fact that I observe the behavior of treated and control employers after the experiment was concluded, and look for persistent treatment effects. I examine the impact of the treatment on treated employers in the post period using difference-in-difference methodology.

The models presented are quasi-maximum likelihood Poisson regression with heteroskedasticity-robust standard errors:

$$\begin{aligned} \mathrm{Y}_j = \beta_0 + \beta_1 \textsc{Trt}_j + \textsc{Post Period}_j + \textsc{Trt x Post Period}_j + \textsc{Employer Covariates}_j \\ + \textsc{Opening Covariates}_j + \epsilon_j \end{aligned} \quad (6)$$

Where $\mathrm{Y}_j$ is one of the measures of costly intensive search used previously on job $j$. Table 11 shows that employers for which past wages were hidden reduce their use of costly search in the post period. These results are consistent with a story that indicates that when an employer has access to imprecise signals of employer quality he should take advantage of these signals and use them instead of other more costly information acquisition strategies. However, it is extremely important to understand that these results are generated in a market for task based labor where the long run effects of hiring a slightly less skilled employee or an employee at a slightly higher cost are minimized relative to traditional labor markets.

### 4.5 Heterogenous Screening Effects

On oDesk.com,the status quo is for employers to know the complete work history, including wages and earnings, for all applicants. Thus, removing employers' ability to observe past wage rate history might differentially effect those employers who have previously posted jobs on the platform, and are aware of what information is generally provided by the platform. In Table 12, I show results of an interaction model that looks for differential effects for employers that have never previously posted a job on the platform and employers that have posted a job prior to the start of the experiment using a quasi-maximum likelihood Poisson regression with heteroskedasticity-robust standard errors.

$$\begin{aligned} \mathrm{Y}_j = \beta_0 + \beta_1 \textsc{Trt}_j + \textsc{New Employer}_j + \textsc{Trt x New Employer}_j + \textsc{Employer Covariates}_j \\ + \textsc{Opening Covariates}_j + \epsilon \end{aligned} \quad (7)$$

$\mathrm{Y}_j$ is equal to one of the previously used measures of screening. $\textsc{Trt}_j$ is an indicator which is set equal to one when the employer in job, $j$ is treated. $\textsc{New Employer}_j$ is an indicator which is equal to one when the job posting $j$ is that employer's first on the platform, and $\textsc{Trt x New Employer}_j$ is an interaction term which is set equal to one when the employer on job $j$ is treated and job $j$ is his first posting on the platform.

Table 12, shows that being unable to observe past wage history does not seem to differentially affect the number of applicants messaged, but it increases use of intensive screening, such as asking questions or asking for Skype IDs, differentially more for first time employers relative to experienced employers. Focusing on the third column, where the dependent variable is the number of applicants the employer asked a question as measured by use of a question mark, the treatment indicator, $\textsc{Trt}$, has a coefficient of 0.078. Thus, experienced employers that are unable to observe past wage history exchange Skype IDs with about 1.08 times as many applicants than experienced employers that are able to observe past wage history. The coefficient on first time job poster is highly significant and negative indicating that employers that are new to oDesk.com exchange Skype ids with about 0.68 times as many messaged applicants than experienced employers. Finally, the interaction term is positive and significant indicating first time treated employers ask applicants questions on 1.41 times as many interviews than untreated first time employers. The implication is that first time employers use drastically lower amounts of costly intensive screening than experienced employers, and the treatment increases the use of costly intensive search for these first time employers even more than it increases use among experienced workers. This treatment effect for first time employers still does not increase the new employer's use of intensive search to the baseline levels of experienced employers.

There is no one strategy fits all when it comes to screening strategies. Generally, personnel economics assumes there are complementarities between certain firms and certain employees, such that firms should tailor their hiring to attract the employees that generate the most match specific productivity.[23] On oDesk, jobs range from data entry to complicated legal work, and the quality and experience of workers who compete to complete these jobs ranges from novice to professional. When posting a job opening on oDesk, the platform offers employers the opportunity to choose if they would like to see more beginner, intermediate, or expert workers. This expressed preference over contractor type gives insight into how important a high quality worker is to the employer on every job opening. In Table 13, I present the results of an interaction model that looks for differential treatment effects on intensive search by preferred contractor tier using using a quasi-maximum likelihood Poisson regression with heteroskedasticity-robust standard errors:

$$\begin{aligned} \mathrm{Y}_j = \beta_0 + \beta_1 \textsc{Trt}_j + \textsc{Contractor Tier}_j + \textsc{Trt x Contractor Tier}_j + \textsc{Employer Covariates}_j \\ + \textsc{Opening Covariates}_j + \epsilon \end{aligned} \tag{8}$$

The results of Table 13 indicate that the treatment only increases the level of costly intensive screening for employers that are looking for beginner level workers. Employers that cannot observe past wage history and are looking to hire beginner applicants exchange Skype IDs with 1.33 times as many messaged applicants as employers that can observe past wage history and are interested in hiring beginner applicants. The baseline level of intensive search for intermediate and expert level workers is already quite high when compared with the baseline level of intensive search for beginner workers. The treatment effect on the level of intensive search is much lower for employers looking to hire intermediate and experienced workers, and neither treatment effect is significantly different from zero.

### 4.6 Robustness Check

If the employer were to have other high quality signals of applicant type available, such as having previously observed the applicant's productivity, I would expect her to rely on this information and thus, hiding past wage information would have no effect. In addition to posting public jobs on oDesk, if an employer wishes to work with a specific applicant, he is able to create a private job posting. Only applicants expressly invited by the employer may apply to private job postings. In the sample, private job postings have a median number of applicants of 1. As such, the employers usually have a much deeper knowledge of the quality of the applicants to private job postings. Table 14 presents the results of running the main screening regression subsetted to include only private jobs. The coefficients on the $\textsc{Trt}_j$ indicator are not significantly different than zero for all 4 measures of costly screening, demonstrating that there is no treatment effect on screening for private jobs.

## 5 Discussion

I find that when employers on oDesk are unable to observe workers past wage rates, they seek to acquire more information through costly search and screening. This increase in acquired information allows employers to fill more jobs and hire applicants who are cheaper but not worse on other observables. These

[23] The assumption of such a complementarity underlies the large literature on assortive matching in labor markets (see Rosen (1982) and Sattinger (1993)).

employers also report being more satisfied with the work output. However, even after observing that acquiring information through costly search and screening leads to more and better matches, employers return to lower levels of search and screening behavior post experiment.

I show that these results are primarily driven by employers that are looking to hire workers with a lower level of experience. This effect is driven by an already comparatively higher use of costly intensive screening by employers that are interested in hiring intermediate and expert contractors. Additionally, while both first time employers as well as established employers are affected by the treatment, the effects are differentially larger for first time employers.

This pattern of results is constant with a particular story of information acquisition in markets where costly search and screening is available. Specifically, the results indicate that there is a fixed price to acquiring information through search. If the employer is searching for someone low skilled then the provision of coarse information from the market is good enough and the employer not going to pay a fixed cost to acquire more information. If the employer is looking for someone high skilled he may be willing to pay the fixed cost to acquire more information about the applicants. If coarse information is not provided by the marketplace, then even when the employer is looking for someone unskilled he is willing to pay the fixed cost and acquire more information. This leads to the employer to hire a cheaper worker and being *ex post* more satisfied. But is the employer's increased satisfaction enough, that they were previously making a mistake by relying on platform provided information when looking for low skilled workers?

The evidence in this paper suggests that employers who increase their search and screening behavior when they are unable to observe past wage rates decrease their use of costly search and screening when the experiment is completed and they can once again observe workers past wage rates. This result indicates that employers do not make a mistake by relying on platform provided information at least when hiring beginner level workers.

To get a better perspective on why employers that want to hire unskilled workers choose to rely on platform provided information instead of costly screening although they know this we lead to hiring a more expensive worker, we conduct some back of the envelope calculations. n From figure 6, we can clearly see that employers hiring a beginner applicant expect to pay substantially less than those intermediate or advanced applicants. The average job that hires a beginner level contractor costs about $500 compared to about $1700 on jobs that hire an expert level contractor. Based on the finding that employers who cannot observe applicants past wage rates offer contracts to applicants that bid about 9.5% lower, we can estimate that costly screening saves an employer hiring a beginner applicant about $50 on a job in wages. This is compared to about $170 on a job that is interested in hiring an expert level contractor. While estimating the upfront cost of increased search and screening behavior is a bit more difficult, we do know from survey data contained in Figure 7 that 80% of employers spend less than 8 hours on search and screening behavior. While most likely the costs of hiring are not linear, if we figure that a majority of time is spent not on posting or viewing candidates on platform, but on organizing and screening the candidates off platform, it seems very reasonable that employer might prefer to pay an extra $50 in wages and save an hour or two in time upfront.

# 6 Conclusion

I designed a novel experiment that seeks to understand how employers on oDesk.com make use of publicly available, large quantities of standardized and verified information. This information is usually not available to employers in the traditional labor market. When employers do not have the ability to observe an applicant's past wage history, they substitute for this informational loss by exerting costly effort to acquire more information about candidates though interviewing. This strategic reaction to a reduced information environment actually leads employers to be more likely to fill an open job posting, and to hire cheaper candidates. This treatment effect is limited to employers that are looking to hire low expertise workers, as employers that want to hire expert workers already find it optimal to conduct more intensive interviews.

It is important to note the limitations of the analysis in this paper. One very important limitation of my analysis is that all firms in this market are hiring task based labor. Thus, incentives to locate a top notch employee are lower than in the traditional labor market, since both the expected life of an employee and the firing costs are much lower than in the traditional labor market. Additionally, my experiment studies the effects of removing information, not adding information. Firm institutions are extremely important in hiring. For example, some firms recruit every year at a fixed set of colleges regardless of changes in academic rankings. Perhaps, basing hiring decisions on past wage history is as much a function of tradition as optimal information use. If this were the case, we would expect to observe larger treatment effect when compared to adding past wage history information to a market that traditionally did not have this information.

My results are potentially relevant for understanding under what circumstances firms might seek to use online labor marketplaces. Online labor marketplaces can only reduce asymmetric information, when the of signals they provide are useful in matching. For example, if a firm is interested in hiring highly skilled labor, my findings suggest that the market provided signals are of little use. Instead, the firm must rely on costly screening by acquiring information about applicants. This might make an online labor platform a less attractive option for this type of labor, as one of the platform's main advantages, reduced hiring costs, cannot be fully harnessed. My results also suggest that costly screening of applicants by asking questions or conducting Skype interviews is generally associated with experienced employers. Less experienced employers may be relying too heavily on market provided signals, which could reduce the quality of their matches and slow their access to the platform. By removing market provided signals like past wage rate information, the platform may be able to "push" first time users of the platform into relying less on the vague market provided signals and more heavily on costly techniques such as asking questions and conducting skype interviews.

Finally, my results have more general implications about the relationship between course public information and costly private information acquisition. Firms need to consider the effects of providing their hiring agents with vague but informative data especially when long and short term incentives of agents and firms are not completely aligned. Hiring agents may use this data as a substitute for more costly but more precise information accession strategies.

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# A More Details on Transacting on oDesk

Figure A.1 shows the timing of application, interviews and hiring decisions relative to the time the job was posted. Clearly most applications are submitted soon after the job is posted with the probability of an application being posted dropping steadily over time. Interviewing and hiring follow a bimodal distribution. Employers begin interviewing candidates shortly after the job is posted and then make job offers. Those who can not come to an agreement with their first choice applicant then interview some more and make a 2nd round of offers.

When an employer "views" and application by clicking on it, the application is expanded and the first thing shown below the bid information already observable on the unexpanded list of applicants is the applicant's cover letter and the text responses to any questions posed in the job posting. Figure A.2 shows an example of this information. Directly below this is the desegregated "work history" of the applicant which was shown above (in text) in figure 2.

## B Search and Screening

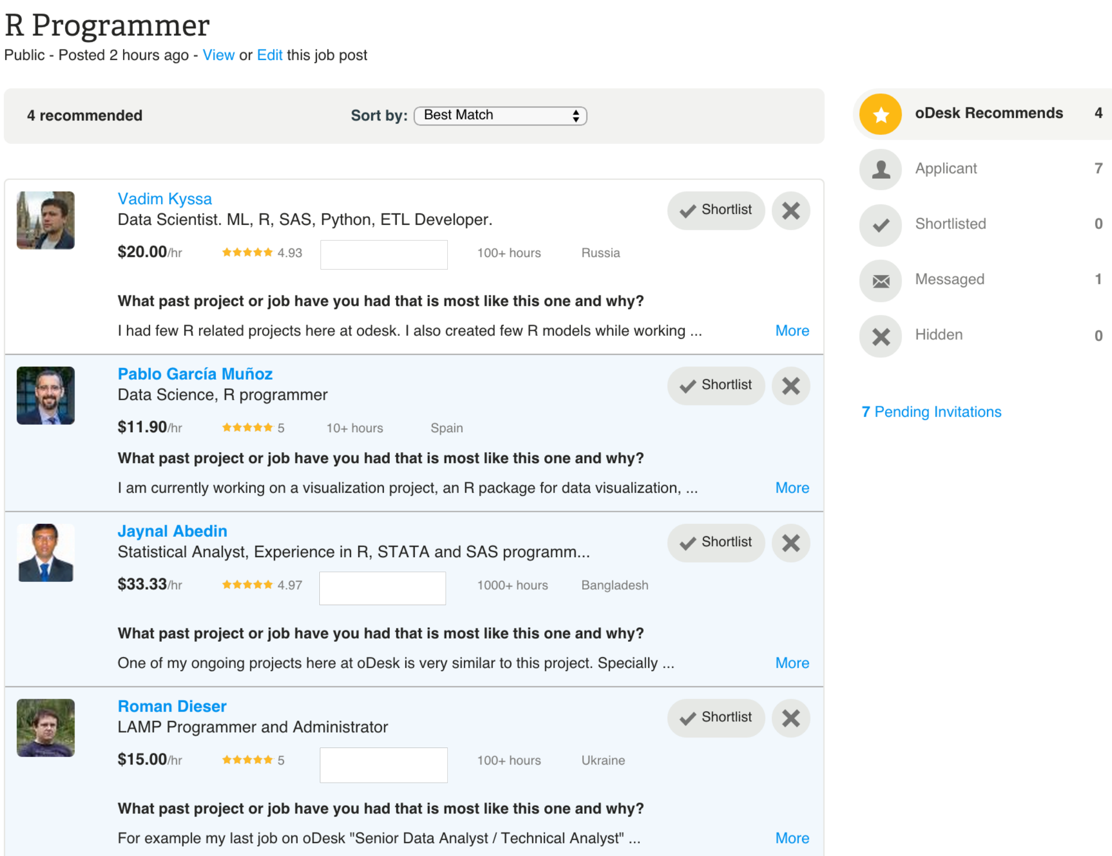
In this section we explore a series of robustness checks and additional specifications related to the effects of hiding past wage rate information on search and screening behavior.

Table A.1 uses a log-linear model to rerun the results provided in Table 4. The quasi-poisson model is the preferred specification as only 37% of jobs skype any applicants, and this model better adjusts for the number of zeros which skew the distribution of the data.

Table A.2 uses our preferred quasi-poisson specification to show that the results on information acquisition are similar regardless of the dependent variable used as a rough proxy for the amount of intensive information acquisition the employer engaged in.

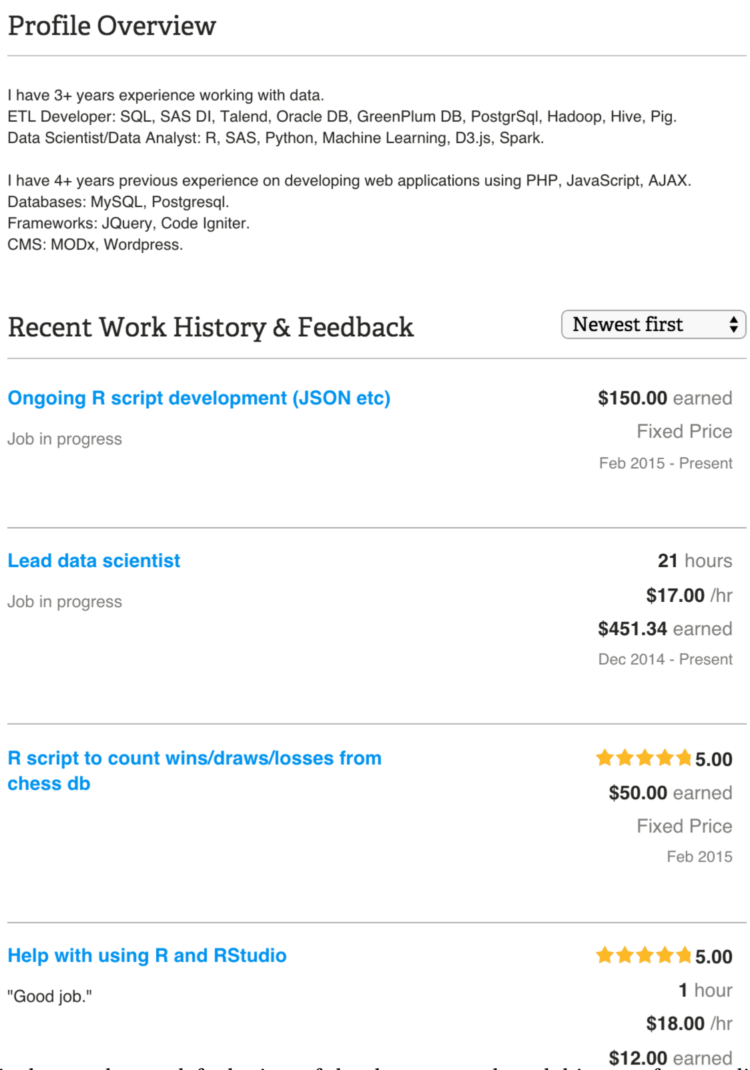
As a further robustness check, Figure A.3 shows that running Figure 6 using a log-linear specification instead of a quasi-poisson regression does not materially effect the direction of the results.

Figure 1: Default View of the Applicant Tracking System (ATS)



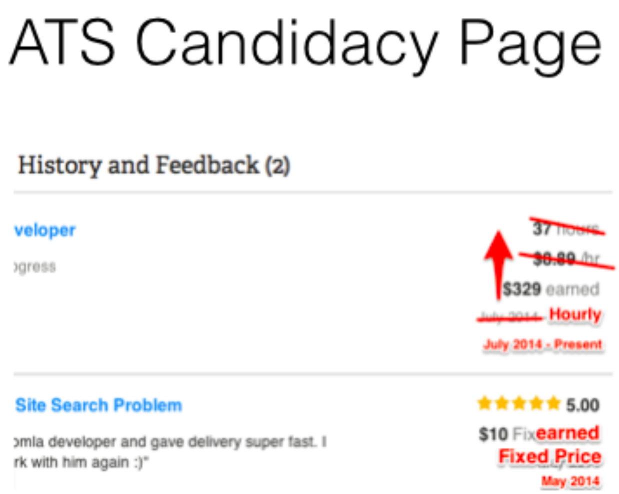

*Note:* This is the default listing of applications as observed by the employer after posing a job and having applicants apply. Only applicants recommended by oDesk's proprietary matching algorithm are displayed by default. Notice there are 7 total applications submitted at the time of the screenshot but only 4 are displayed by default. Employers can directly contact applicants from this page, directly hire applicants from this page, or they can click on a listing to expand it and view the applicants' complete application and work history. At the time of the experiment Job Success Score was not displayed. This feature was added later

Figure 2: Expanded View of Disaggregated Work History



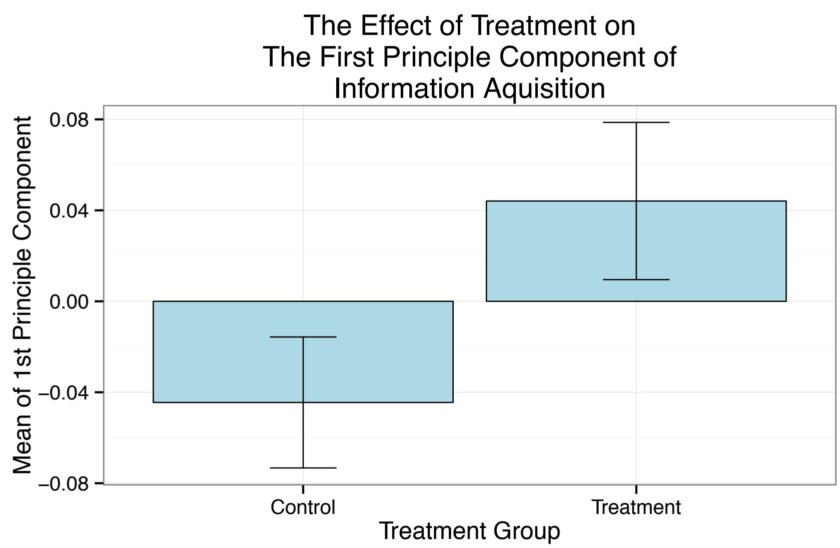

*Note:* This is the employers default view of the desegregated work history of an applicant which is viewable after expanding (viewing) an application. In the treatment group, the 21 hours and \$17.00/hr would be hidden for the "lead data scientist" job. Only the \$451.34 would be observable. The employer also sees an expanded profile (see A.2 in appendix **??**).

Figure 3: Changes to the UI for treated employers.



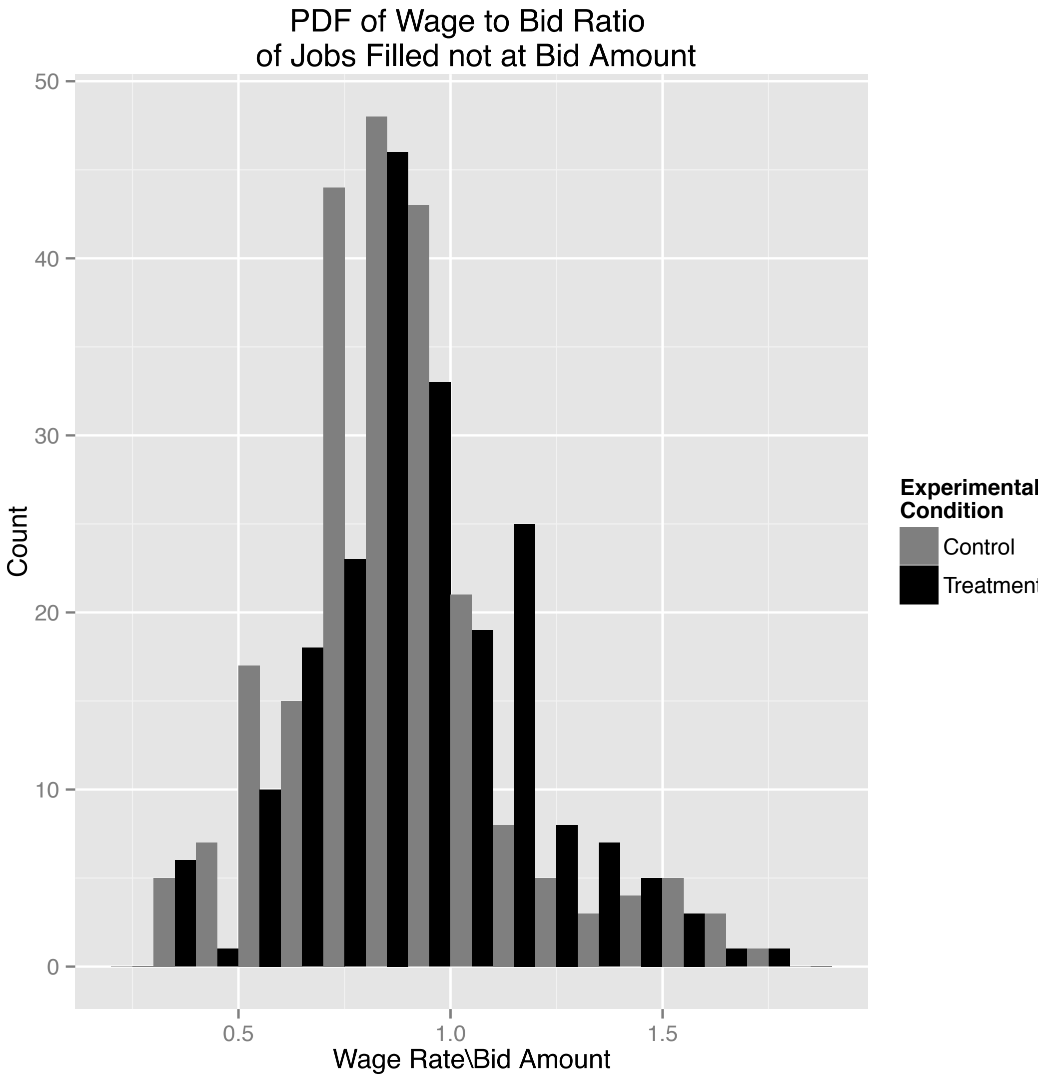

*Note:* This production screen shot details the changes made to workers profile pages. These changes occurred in the applicant tracking system (ATS), which is the flow that controls what employers see after posting a job posting.

Figure 4: First Principle Component of Screening



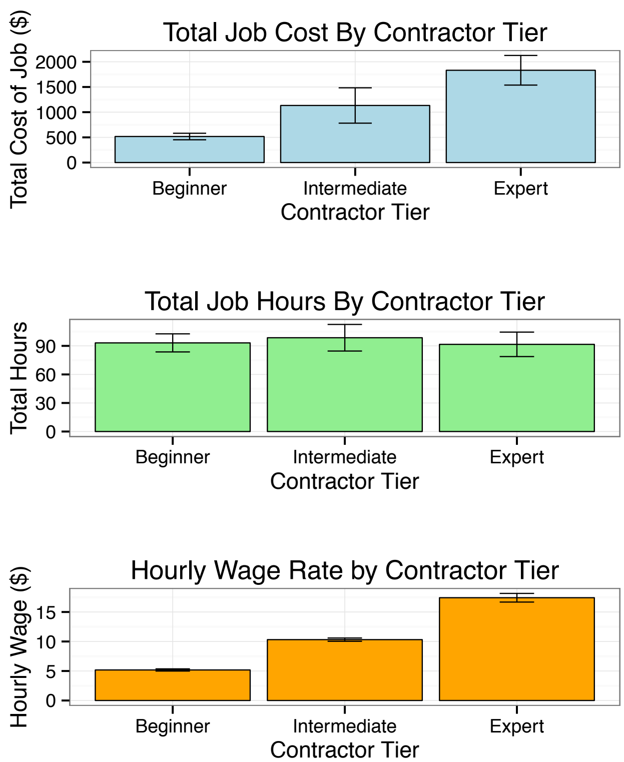

*Note:* The analysis was limited to the first job posting after the start of the experiment which were hourly job postings. The 4 inputs to the principle component analysis are: number of applicants messaged, number of applicants asked a question as indicated by use of a question mark, number of applicants asked a question as indicated by use of a question word, and the number of applicants asked for a skype id.

Figure 5: Distribution of the Non-equal Wage to Bid Ratio by Treatment Group



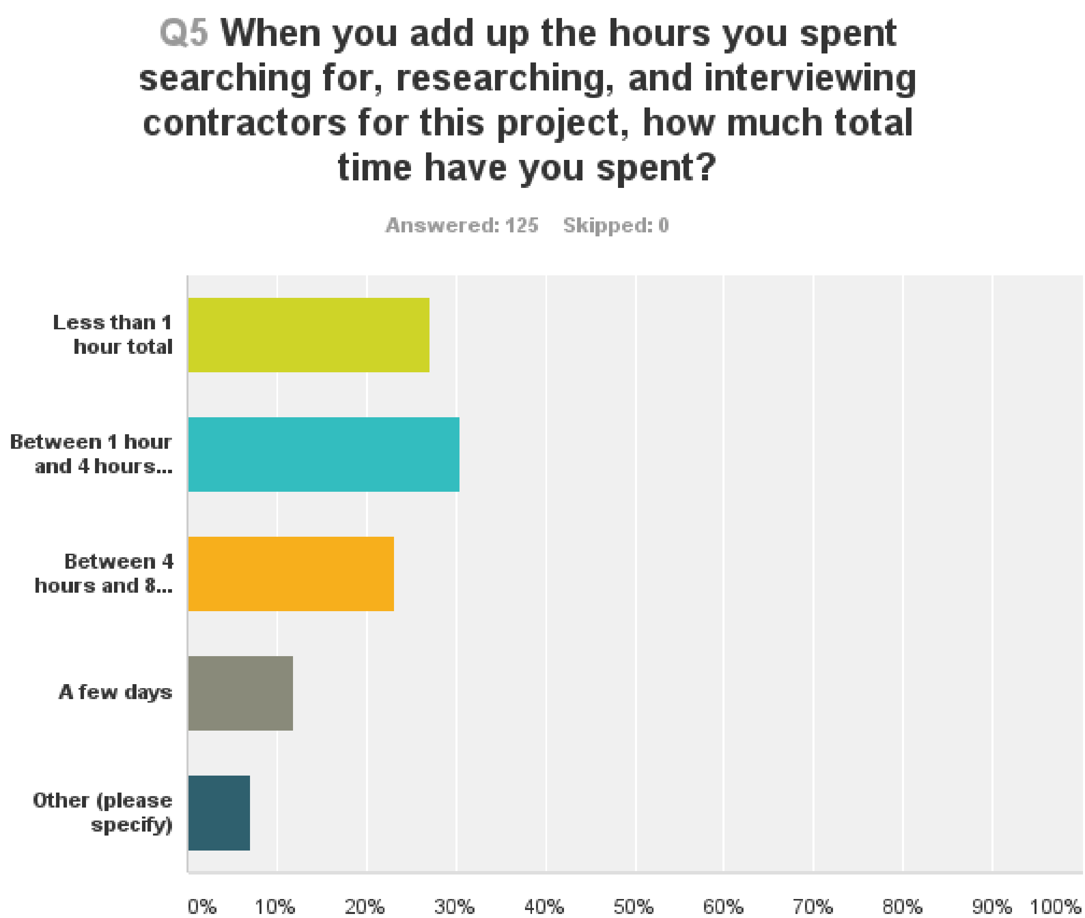

*Note:* This table plots the distributions on Wage-to-Bid ratio for treatment and control jobs. Wage-to-bid ratio is calculated as the ratio of the wages paid to the winning applicant to the hourly bid submitted by the winning applicant in that job. The top and bottom .5% of wage to bid ratios were dropped. All bid to wage ratios equal to one were dropped.

Figure 6: Job Characteristics by Contractor Tier



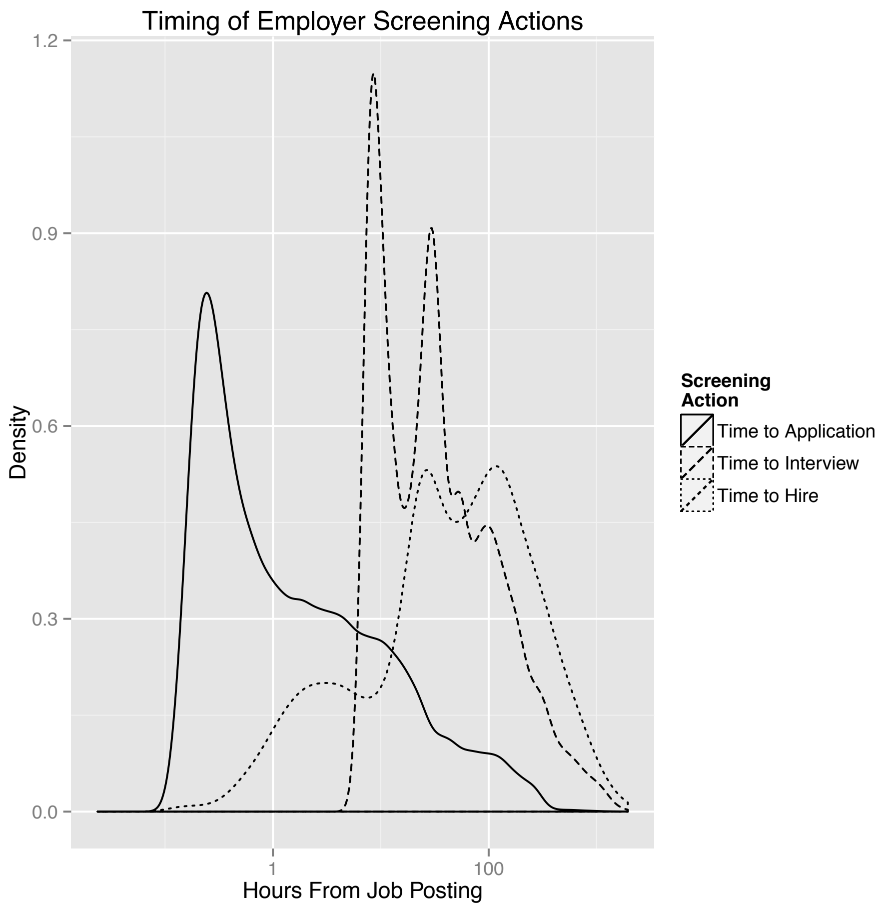

*Note:* This figure is limited to hourly job postings, that filled and billed more than $0.01.

Figure 7: Interviewing Survey



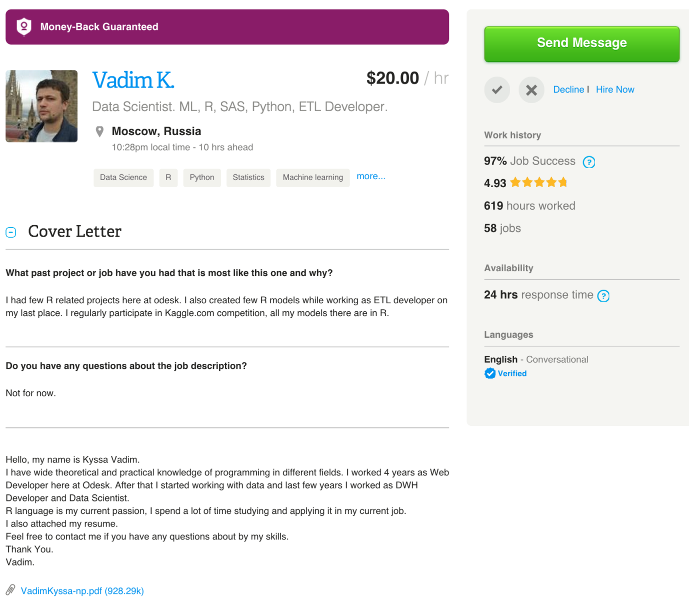

*Note:* This data came from a 2013 oDesk client survey

Figure A.1: PDF of Timing of Screening Behavior




*Note:* This figure is limited to only non-invited applicants to public job postings.

Figure A.2: Expanded View of ATS Application




*Note:* At the time of the experiment Job Success Score was not displayed. Upon expanding an application, the employer also sees an expanded profile See A.2 in appendix **??**.

Table 1: Balance Table of Employer, Job Posting, and Applicant Characteristics

| | Control mean: $\bar{X}_{CTL}$ | Treatment mean: $\bar{X}_{TRT}$ | Difference In Means | p-value | |
|---|---|---|---|---|---|
| *Employer Attributes* | | | | | |
| Prior Job Postings | 23.584 | 24.172 | 0.588 (1.312) | 0.654 | |
| Prior Billed Jobs | 10.767 | 11.415 | 0.648 (0.633) | 0.306 | |
| Prior Spend by Employers | 5880.736 | 6293.257 | 412.521 (483.769) | 0.394 | |
| Num Prior Contractors | 10.966 | 11.888 | 0.921 (0.806) | 0.253 | |
| Avg Feedback Score of Employer | 4.811 | 4.785 | -0.026 (0.016) | 0.097 | † |
| Num of Reviews of Employer | 8.155 | 8.923 | 0.767 (0.721) | 0.287 | |
| *Job Posting Attributes* | | | | | |
| Number non-invited Applicants | 33.618 | 33.474 | -0.144 (1.088) | 0.894 | |
| Avg Best Match Score | 0.355 | 0.358 | 0.003 (0.004) | 0.396 | |
| Avg Bid | 12.768 | 12.605 | -0.163 (0.241) | 0.498 | |
| Prefered Experiance in Hours | 33.816 | 34.233 | 0.416 (3.397) | 0.902 | |
| Estimated Job Duration in Weeks | 17.208 | 16.909 | -0.299 (0.548) | 0.585 | |
| *Applicant Attributes* | | | | | |
| Tenure in Days | 670.913 | 664.847 | -6.066 (5.684) | 0.286 | |
| Hours Worked to Date | 808.262 | 785.033 | -23.229 (19.039) | 0.222 | |
| Num Past Jobs Worked | 17.342 | 17.469 | 0.127 (0.357) | 0.721 | |
| Past Hourly Earnings | 6500.266 | 6213.784 | -286.481 (199.042) | 0.150 | |
| Past Fixed Wage Earnings | 1120.839 | 1092.754 | -28.085 (36.861) | 0.446 | |
| Num Prior Employers | 13.726 | 13.792 | 0.066 (0.263) | 0.802 | |
| Min Feedback Rating | 3.185 | 3.187 | 0.002 (0.013) | 0.871 | |
| Avg Feedback Rating | 4.594 | 4.589 | -0.005 (0.004) | 0.215 | |
| Max Feedback Rating | 4.936 | 4.930 | -0.005 (0.002) | 0.027 | * |
| Wage Bid | 10.500 | 10.337 | -0.164 (0.261) | 0.531 | |
| Profile Wage | 10.609 | 10.408 | -0.201 (0.235) | 0.393 | |
| Min Hr. Wage (6 months) | 7.499 | 7.208 | -0.291 (0.183) | 0.112 | |
| Avg Hr. Wage (6 months) | 9.072 | 8.801 | -0.271 (0.210) | 0.198 | |
| Max Hr. Wage (6 months) | 11.243 | 11.048 | -0.194 (0.253) | 0.442 | |

*Notes:* This table reports means and standard errors across experimental groups of employer, job posting, and applicant characteristics. The Top Panel reports characteristics of employers allocated to treatment and control. The middle panel reports characteristics of job postings by treatment and control groups for the first job posted after allocation to the experiment for each employer. The bottom panel reports characteristics of employers at the time they were allocated to treatment or control groups. The bottom and top 1% by average historical wage were dropped. Reported p-values are the for two-sided t-tests of the null hypothesis of no difference in means across groups. In the bottom panel, standard errors are clustered at the employer level. Significance indicators: $p \leq 0.10$ :† ,$p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

Table 2: Baseline Screening Behavior

| Statistic | N | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|---|
| Number of Applicants | 2,948 | 35.105 | 43.296 | 0 | 22 | 639 |
| Number of Organic Applicants | 2,948 | 33.691 | 43.036 | 0 | 20.5 | 639 |
| Number of Applications Viewed | 2,948 | 7.321 | 9.257 | 0 | 5 | 122 |
| Number of Organic Applicants Messaged | 2,948 | 1.797 | 3.684 | 0 | 1 | 91 |
| Number of Organic Applicants Questioned | 2,948 | 1.121 | 2.050 | 0 | 0 | 36 |
| Number of Organic Applicants Skyped | 2,948 | 0.890 | 1.890 | 0 | 0 | 23 |
| Number of Hires | 2,948 | 0.580 | 1.039 | 0 | 0 | 26 |
| Pct of Jobs Filled | 2,948 | 0.403 | 0.491 | 0 | 0 | 1 |

*Notes:* This table provides baseline (control) statistics of hiring on oDesk. The statistics reported are for first job openings of employers assigned to the control group. Organic Applicants are applicants who were not invited to apply to the job.

Table 3: Search and Screening Behavior

| | Control mean: $\bar{X}_{CTL}$ | Treatment mean: $\bar{X}_{TRT}$ | Difference In Means | p-value | |
|---|---|---|---|---|---|
| *Measures of Search* | | | | | |
| Num. Viewed Applications | 6.671 | 7.122 | 0.451 (0.242) | 0.062 | † |
| *Measures of Screening* | | | | | |
| Num. Messaged Applicants | 1.797 | 1.925 | 0.128 (0.097) | 0.188 | |
| Num. Skyped Applicants | 0.890 | 0.946 | 0.056 (0.057) | 0.322 | |
| Num. Questioned Applicants (Q Word) | 1.121 | 1.271 | 0.150 (0.062) | 0.015 | * |
| Num. Questioned Applicants (Q Mark) | 1.187 | 1.308 | 0.120 (0.060) | 0.046 | * |

*Notes:* This table reports means and standard errors across experimental groups for the number of applicants searched, and intensely screened by treatment and control group. The top panel reports 1 measure of search behavior, and the bottom panel reports 4 measures of screening behavior. Reported p-values are the for two-sided t-tests of the null hypothesis of no difference in means across groups. Significance indicators: $p \leq 0.10$ :† ,$p \leq 0.05$ : $*$, $p \leq 0.01$ : $**$ and $p \leq .001$ : $***$.

Table 4: Effect of Hiding Past Wages on Search

| | *Dependent variable:* |
|---|---|
| | Num Viewed<br>Poisson |
| Hidden Wages Treatment Group (TRT) | 0.069$^{**}$ |
| | (0.034) |
| Constant | 1.773$^{***}$ |
| | (0.134) |
| Opening Level Covariates | Yes |
| Observations | 5,855 |

*Notes:* The sample is restricted to hourly first job posts by an employer. All models include covariates including: category indicators, prior jobs billed by the employer, employers prior spendings on the platform, the number of applications to the job openings, the number of recommended applications to the job opening, and the average applicants bid. Significance indicators: $p \le 0.10 : *$, $.p \le 0.05 : **$ and $p \le .01 : ***$.

Table 5: Characteristics of Viewed Applicants

| | Control mean: $\bar{X}_{CTL}$ | Treatment mean: $\bar{X}_{TRT}$ | Difference In Means | p-value |
|---|---|---|---|---|
| *Viewed Applications* | | | | |
| Bid Amount | 12.585 | 12.345 | -0.240 (0.344) | 0.485 |
| Profile Wage Rate | 12.564 | 12.338 | -0.226 (0.315) | 0.474 |
| Avg 6 Month Wage | 10.624 | 10.228 | -0.396 (0.284) | 0.163 |
| Min 6 Month Wage | 8.660 | 8.271 | -0.388 (0.246) | 0.114 |
| Max 6 Month Wage | 13.241 | 13.031 | -0.210 (0.369) | 0.569 |
| Previous Hours Worked | 899.176 | 932.298 | 33.122 (31.199) | 0.288 |
| Prior Billed Openings | 22.725 | 22.916 | 0.192 (0.663) | 0.772 |
| Previous Hourly Earnings | 8016.728 | 8344.449 | 327.721 (336.873) | 0.331 |
| Previous FP Earnings | 1615.918 | 1565.433 | -50.485 (73.387) | 0.492 |
| Avg Feedback | 4.661 | 4.660 | -0.000 (0.006) | 0.969 |
| Min Feedback | 3.234 | 3.241 | 0.007 (0.021) | 0.747 |
| Max Feedback | 4.960 | 4.959 | -0.001 (0.003) | 0.831 |

*Notes:* This table reports outcome means and standard errors across experimental groups of applicants who are viewed by employers. The treatment group are employers who are unable to observe past wage history information of the applicants. The unit of randomization was employer.The standard error for the difference in means is in parentheses next to the estimate. Reported p-values are the for two-sided t-tests of the null hypothesis of no difference in means across groups. Standard errors are clustered at the employer level. Significance indicators: $p \leq 0.10 : \dagger$ ,$p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

Table 6: Effect of Hiding Past Wages on Information Acquisition

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Number of Apps Messaged | Number of Apps Skyped | Number of Apps with "?" | Number of Apps with Question Words |
| | Poisson | Poisson | Poisson | Poisson |
| | (1) | (2) | (3) | (4) |
| Hidden Wages | | | | |
| Treatment Group (TRT) | 0.085$^{*}$ | 0.088$^{*}$ | 0.144$^{***}$ | 0.178$^{***}$ |
| | (0.051) | (0.050) | (0.042) | (0.044) |
| Constant | 0.607$^{***}$ | −0.666$^{***}$ | −0.001 | −0.044 |
| | (0.176) | (0.238) | (0.175) | (0.187) |
| Opening Level Covariates | Yes | Yes | Yes | Yes |
| Observations | 5,855 | 5,855 | 5,855 | 5,855 |

*Notes:* This table shows the relationship between measures of information acquisition and the treatment. The level of observation is the job posting. Estimates are from quasi-maximum likelihood Poisson models. Heteroskedasticity-robust standard errors are reported. The sample is restricted to hourly first job posts by an employer. The DV in Model (1) is a count of the number of applications that included the word "skype" in a message with the employer. The DV in Model (2) is a count of the number of applications that exchanged messages including a question mark with the employer. The DV in Model (3) is a count of the number of applications that included at least one of the following question words: Who, What, Where, When, Why, or How. All models include covariates: category indicators, prior jobs billed by the employer, employers prior spending on the platform, the number of applications to the job openings, the number of recommended applications to the job opening, the number of applications that exchanged messaged with the employer and the average applicants bid. Significance indicators: $p \leq 0.10 : *$, $.p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table 7: Characteristics of Messaged and Contracted Applicants

| | Control mean: $\bar{X}_{CTL}$ | Treatment mean: $\bar{X}_{TRT}$ | Difference In Means | p-value | |
|---|---|---|---|---|---|
| *Messaged Applicants* | | | | | |
| Bid Amount | 13.964 | 13.119 | -0.845 (0.512) | 0.099 | † |
| Profile Wage Rate | 13.490 | 12.741 | -0.748 (0.443) | 0.091 | † |
| Avg 6 Month Wage | 11.697 | 10.874 | -0.823 (0.405) | 0.042 | * |
| Min 6 Month Wage | 9.375 | 8.677 | -0.698 (0.341) | 0.041 | * |
| Max 6 Month Wage | 14.912 | 13.957 | -0.955 (0.549) | 0.082 | † |
| Previous Hours Worked | 1189.007 | 1167.145 | -21.861 (56.595) | 0.699 | |
| Prior Billed Openings | 30.631 | 29.023 | -1.607 (1.254) | 0.200 | |
| Previous Hourly Earnings | 11607.165 | 10348.016 | -1259.150 (627.746) | 0.045 | * |
| Previous FP Earnings | 2347.145 | 1985.281 | -361.863 (136.299) | 0.008 | ** |
| Avg Feedback | 4.713 | 4.708 | -0.004 (0.008) | 0.620 | |
| Min Feedback | 3.200 | 3.227 | 0.027 (0.035) | 0.441 | |
| Max Feedback | 4.978 | 4.973 | -0.005 (0.004) | 0.181 | |
| *Contracted Applicants* | | | | | |
| Bid Amount | 11.805 | 10.656 | -1.149 (0.642) | 0.073 | † |
| Profile Wage Rate | 12.111 | 11.023 | -1.088 (0.636) | 0.087 | † |
| Avg 6 Month Wage | 10.647 | 8.942 | -1.705 (0.686) | 0.013 | * |
| Min 6 Month Wage | 8.338 | 7.023 | -1.315 (0.507) | 0.009 | ** |
| Max 6 Month Wage | 13.767 | 11.644 | -2.123 (1.062) | 0.046 | * |
| Previous Hours Worked | 1123.247 | 1212.009 | 88.762 (101.144) | 0.380 | |
| Prior Billed Openings | 35.025 | 33.168 | -1.856 (2.235) | 0.406 | |
| Previous Hourly Earnings | 8165.331 | 8298.720 | 133.389 (703.910) | 0.850 | |
| Previous FP Earnings | 1881.266 | 1728.527 | -152.739 (170.449) | 0.370 | |
| Avg Feedback | 4.718 | 4.711 | -0.008 (0.020) | 0.709 | |
| Min Feedback | 3.193 | 3.151 | -0.042 (0.084) | 0.618 | |
| Max Feedback | 4.974 | 4.981 | 0.007 (0.009) | 0.408 | |

*Notes:* This table reports outcome means and standard errors across experimental groups of applicants who are messaged and offered contracts by employers. The treatment group are employers who are unable to observe past wage history information of the applicants. The unit of randomization was employer. The standard error for the difference in means is in parentheses next to the estimate. Reported p-values are the for two-sided t-tests of the null hypothesis of no difference in means across groups. Standard errors are clustered at the employer level. Significance indicators: $p \leq 0.10 : \dagger$ ,$p \leq 0.05 : *$, $p \leq 0.01 : **$ and $p \leq .001 : ***$.

Table 8: Effect of Hiding Past Wages on Job Fill Rate

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | I(Job Filled) | | | |
| | OLS | OLS | OLS | OLS |
| | (1) | (2) | (3) | (4) |
| Hidden Wages Treatment Group (TRT) | 0.029$^{**}$ | 0.027$^{**}$ | 0.026$^{**}$ | 0.023$^{**}$ |
| | (0.013) | (0.013) | (0.012) | (0.011) |
| Constant | 0.403$^{***}$ | 0.392$^{***}$ | 0.404$^{***}$ | 0.384$^{***}$ |
| | (0.009) | (0.061) | (0.009) | (0.055) |
| Job Order Dummy | No | No | Yes | Yes |
| Opening Level Covariates | No | Yes | No | Yes |
| Employer Level Covariates | No | Yes | No | Yes |
| Observations | 5,922 | 5,855 | 9,476 | 8,973 |

*Notes:* The results are limited to hourly job posts. Columns (1) and (2) are limited to first job postings by employers. Columns (3) and (4) use the full sample with standard errors clustered at the employer level. Columns (2) and (4) add covariates including: category indicators, prior jobs billed by the employer, employers prior spendings on the platform, the number of applications to the job openings, the number of recommended applications to the job opening, and the average applicants bid. Significance indicators: $p \leq 0.10 : *$, .$p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table 9: Effect of Treatment on Hired Worker Wage Negotiation

| | *Dependent variable:* |
|---|---|
| | log(Wage to Bid Ratio) |
| Hidden Wages Treatment Group (TRT) | $0.012^{*}$ |
| | (0.006) |
| Constant | $-0.027^{***}$ |
| | (0.005) |
| Observations | 1,500 |

*Notes:* The sample is restricted to assignments originating from an hourly first job post by an employer that hire exactly 1 applicant. The top and bottom .5% of ratios were dropped Significance indicators: $p \le 0.10 : *$, $.p \le 0.05 : **$ and $p \le .01 : ***$.

Table 10: Effect of Treatment on Job Feedback Score

| | *Dependent variable:* | |
|---|---|---|
| | log(Public Feedback) | log(Private Feedback) |
| | (1) | (2) |
| Hidden Wages Treatment Group (TRT) | 0.012 | 0.056* |
| | (0.018) | (0.032) |
| Constant | 1.427*** | 2.180*** |
| | (0.058) | (0.067) |
| Employer Level Covariates | Yes | Yes |
| Observations | 1,042 | 1,212 |

*Notes:* The sample is restricted to assignments originating from an hourly first job post by an employer. The sample includes only public job openings. The sample is further limits the analysis to include only the first job post spawned from each assignment. Covariates included are category indicators, the total value of the job, the total number of hours of the job, the number of prior billed jobs for the employer Significance indicators: $p \leq 0.10 : *$, $.p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table 11: Effect of treatment on Intensive Search
By Exparemental Period

| | *Dependent variable:* | | |
|---|---|---|---|
| | Number of Apps Skyped | Number of Apps with "?" | Number of Apps with Question Words |
| | (1) | (2) | (3) |
| Hidden Wages | | | |
| Treatment Group (TRT) | $0.097^{*}$ | $0.152^{***}$ | $0.143^{***}$ |
| | (0.056) | (0.047) | (0.049) |
| Post Treatment Period | $0.176^{***}$ | $0.094^{*}$ | $0.117^{**}$ |
| | (0.054) | (0.049) | (0.052) |
| TRT x Post Period | $-0.129^{*}$ | $-0.186^{***}$ | $-0.253^{***}$ |
| | (0.074) | (0.067) | (0.073) |
| Constant | $-1.040^{***}$ | 0.172 | 0.164 |
| | (0.213) | (0.147) | (0.157) |
| Opening Level Covariates | Yes | Yes | Yes |
| Observations | 11,767 | 11,767 | 11,767 |

*Notes:* This table shows the relationship between measures of information acquisition and the treatment by experimental period and post period. The level of observation is the job posting. Estimates are from quasi-maximum likelihood Poisson models. Heteroskedasticity-robust standard errors are reported. The DV in Model (1) is a count of the number of applications that included the word "skype" in a message with the employer. The DV in Model (2) is a count of the number of applications that exchanged messages including a question mark with the employer. The DV in Model (3) is a count of the number of applications that included at least one of the following question words: Who, What, Where, When, Why, or How. All models include covariates: category indicators, prior jobs billed by the employer, employers prior spending on the platform, the number of applications to the job openings, the number of recommended applications to the job opening, the number of applications that exchanged messaged with the employer and the average applicants bid. Significance indicators: $p \leq 0.10 : *$, $.p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table 12: Effect of Hiding Past Wages on Information Acquisition
By New and Established Employers

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Number of Apps Messaged | Number of Apps Skyped | Number of Apps with “?” | Number of Apps with Question Words |
| | Poisson | Poisson | Poisson | Poisson |
| | (1) | (2) | (3) | (4) |
| Hidden Wages Treatment Group (TRT) | 0.093* | 0.019 | 0.078* | 0.121*** |
| | (0.053) | (0.054) | (0.044) | (0.046) |
| First Job Posting | −0.010 | −0.512*** | −0.481*** | −0.347*** |
| | (0.118) | (0.145) | (0.120) | (0.116) |
| TRT x First Job Posting | −0.031 | 0.377** | 0.349** | 0.288** |
| | (0.152) | (0.160) | (0.139) | (0.139) |
| Constant | 0.613*** | −0.532** | 0.124 | 0.049 |
| | (0.176) | (0.236) | (0.173) | (0.186) |
| Opening Level Covariates | Yes | Yes | Yes | Yes |
| Observations | 5,855 | 5,855 | 5,855 | 5,855 |

*Notes:* This table shows the relationship between measures of information acquisition and the treatment by new and established employers. The level of observation is the job posting, and the baseline group is beginner level contractors. Estimates are from quasi-maximum likelihood Poisson models. Heteroskedasticity-robust standard errors are reported. The sample is restricted to hourly first job posts by an employer. All models include covariates: category indicators, prior jobs billed by the employer, employers prior spending on the platform, the number of applications to the job openings, the number of recommended applications to the job opening, the number of applications that exchanged messaged with the employer and the average applicants bid. Significance indicators: $p \leq 0.10 : *$, $.p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table 13: Effect of Hiding Past Wages on Information Acquisition
By Requested Contractor Tier

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Number of Apps Messaged | Number of Apps Skyped | Number of Apps with "?" | Number of Apps with Question Words |
| | Poisson | Poisson | Poisson | Poisson |
| | (1) | (2) | (3) | (4) |
| Hidden Wages Treatment Group (TRT) | 0.107 | $0.290^{**}$ | $0.331^{***}$ | $0.372^{***}$ |
| | (0.112) | (0.126) | (0.101) | (0.106) |
| Intermediate Contractor | $-0.183^{**}$ | $0.211^{**}$ | $0.198^{**}$ | $0.174^{**}$ |
| | (0.087) | (0.106) | (0.083) | (0.086) |
| Expert Contractor | −0.030 | 0.203 | 0.143 | 0.133 |
| | (0.109) | (0.136) | (0.104) | (0.114) |
| TRT x Intermediate | 0.025 | $-0.261^{*}$ | $-0.239^{**}$ | $-0.245^{**}$ |
| | (0.127) | (0.142) | (0.113) | (0.118) |
| TRT x Expert | −0.188 | $-0.298^{*}$ | $-0.320^{**}$ | $-0.339^{**}$ |
| | (0.153) | (0.177) | (0.141) | (0.153) |
| Constant | $0.736^{***}$ | $-0.816^{***}$ | −0.127 | −0.160 |
| | (0.188) | (0.255) | (0.197) | (0.211) |
| Opening Level Covariates | Yes | Yes | Yes | Yes |
| Observations | 5,754 | 5,754 | 5,754 | 5,754 |

*Notes:* This table shows the relationship between measures of information acquisition and the treatment by requested contractor tier. The level of observation is the job posting, and the baseline group is beginner level contractors. Estimates are from quasi-maximum likelihood Poisson models. Heteroskedasticity-robust standard errors are reported. The sample is restricted to hourly first job posts by an employer. The DV in Model (1) is a count of the number of applications messaged. The DV in Model (2) is a count of the number of applications that included the word "skype" in a message with the employer. The DV in Model (3) is a count of the number of applications that exchanged messages including a question mark with the employer. All models include covariates: category indicators, prior jobs billed by the employer, employers prior spending on the platform, the number of applications to the job openings, the number of recommended applications to the job opening, the number of applications that exchanged messaged with the employer and the average applicants bid. Significance indicators: $p \leq 0.10 : *$, $.p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table 14: Effect of Hiding Past Wages on Information Acquisition on Private Job Postings

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Number of Apps Messaged | Number of Apps Skyped | Number of Apps with "?" | Number of Apps with Question Words |
| | Poisson | Poisson | Poisson | Poisson |
| | (1) | (2) | (3) | (4) |
| Hidden Wages | | | | |
| Treatment Group (TRT) | −0.186 | −0.227 | −0.224 | −0.218 |
| | (0.241) | (0.259) | (0.216) | (0.240) |
| I(visibility == "private") | | | | 20.015 |
| Constant | −0.750 | $-1.897^{**}$ | −0.427 | $-20.307^{***}$ |
| | (0.521) | (0.783) | (0.741) | (0.888) |
| Opening Level Covariates | Yes | Yes | Yes | Yes |
| Observations | 2,392 | 2,392 | 2,392 | 2,392 |

*Notes:* This table shows the relationship between measures of information acquisition and the treatment. The level of observation is the job posting. Estimates are from quasi-maximum likelihood Poisson models. Heteroskedasticity-robust standard errors are reported. The sample is restricted to hourly first job posts by an employer.The DV in Model (1) is a count of applicants messaged. The DV in Model (2) is a count of the number of applications that included the word "skype" in a message with the employer. The DV in Model (3) is a count of the number of applications that exchanged messages including a question mark with the employer. The DV in Model (4) is a count of the number of applications that included at least one of the following question words: Who, What, Where, When, Why, or How. All models include covariates: category indicators, prior jobs billed by the employer, employers prior spending on the platform, the number of applications to the job openings, the number of recommended applications to the job opening, the number of applications that exchanged messaged with the employer and the average applicants bid. Significance indicators: $p \le 0.10 : *$, .$p \le 0.05 : **$ and $p \le .01 : ***$.

Table A.1: Effect of Hiding Past Wages on Search
Log Linear Models

| | *Dependent variable:* |
|---|---|
| | Num Viewed |
| | OLS |
| Hidden Wages Treatment Group (TRT) | $0.049^{*}$ |
| | (0.026) |
| Constant | $1.430^{***}$ |
| | (0.120) |
| Opening Level Covariates | Yes |
| Observations | 5,855 |

*Notes:* The sample is restricted to hourly first job posts by an employer. All models include covariates including: category indicators, prior jobs billed by the employer, employers prior spendings on the platform, the number of applications to the job openings, the number of recommended applications to the job opening, and the average applicants bid. Significance indicators: $p \leq 0.10 : *$, .$p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table A.2: Effect of Hiding Past Wages on Information Acquisition
Alternate DVs

| | *Dependent variable:* | | |
|---|---|---|---|
| | Total Number of Words | Total Number of Question Marks | Total Number of Question Words |
| | Poisson | Poisson | Poisson |
| | (1) | (2) | (3) |
| Hidden Wages | | | |
| Treatment Group (TRT) | 0.110* | 0.097* | 0.090 |
| | (0.062) | (0.056) | (0.057) |
| Constant | 5.858*** | 1.008*** | 0.998*** |
| | (0.249) | (0.235) | (0.240) |
| Opening Level Covariates | Yes | Yes | Yes |
| Observations | 5,855 | 5,855 | 5,855 |

*Notes:* This table shows the relationship between measures of information acquisition and the treatment. The level of observation is the job posting. Estimates are from quasi-maximum likelihood Poisson models. Heteroskedasticity-robust standard errors are reported. The sample is restricted to hourly first job posts by an employer.The dependent variable in model (1) is the total number of words in messages sent by the employer. The dependent variable in model (2) is the total number of question marks in messages sent by the employer. The dependent variable in model (3) is the total number of question words used in messages sent by the employer. All models include covariates: category indicators, prior jobs billed by the employer, employers prior spending on the platform, the number of applications to the job openings, the number of recommended applications to the job opening, the number of applications that exchanged messaged with the employer and the average applicants bid. Significance indicators: $p \leq 0.10 : *$, $.p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table A.3: Effect of Hiding Past Wages on Information Acquisition
Log Linear Models

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | log1p(Apps Messaged) OLS | log1p(Apps Skyped) OLS | log1p(Apps with "?") OLS | log1p(Question Words) OLS |
| | (1) | (2) | (3) | (4) |
| Hidden Wages | | | | |
| Treatment Group (TRT) | 0.016 | 0.012 | 0.024 | $0.040^{***}$ |
| | (0.020) | (0.025) | (0.015) | (0.015) |
| Constant | $1.255^{***}$ | 0.181 | $0.926^{***}$ | $0.824^{***}$ |
| | (0.096) | (0.144) | (0.073) | (0.075) |
| Opening Level Covariates | Yes | Yes | Yes | Yes |
| Observations | 3,285 | 2,195 | 2,799 | 2,678 |

*Notes:* This table shows the relationship between measures of information acquisition and the treatment. The level of observation is the job posting. Estimates are from quasi-maximum likelihood Poisson models. Heteroskedasticity-robust standard errors are reported. The sample is restricted to hourly first job posts by an employer. The DV in Model (1) is a count of the number of applications that included the word "skype" in a message with the employer. The DV in Model (2) is a count of the number of applications that exchanged messages including a question mark with the employer. The DV in Model (3) is a count of the number of applications that included at least one of the following question words: Who, What, Where, When, Why, or How. All models include covariates: category indicators, prior jobs billed by the employer, employers prior spending on the platform, the number of applications to the job openings, the number of recommended applications to the job opening, the number of applications that exchanged messaged with the employer and the average applicants bid. Significance indicators: $p \leq 0.10 : *$, .$p \leq 0.05 : **$ and $p \leq .01 : ***$.