Effects of IT-enabled Monitoring Systems in Online Labor Markets

Completed Research Paper

Chen Liang
Arizona State University
Tempe, Arizona, US
chen.liang.4@asu.edu

Yili Hong
Arizona State University
Tempe, Arizona, US
hong@asu.edu

Bin Gu
Arizona State University
Tempe, Arizona, US
bin.gu@asu.edu

Abstract

This paper investigates how IT-enabled monitoring systems mitigate moral hazard in an online labor market and their effect on market competition. We exploit a quasi-experiment at Freelancer when it introduced enhanced offline tracking features in 2015. Using a large dataset including 17,827 fixed-price projects and 8,563 hourly projects, we use a difference-in-differences (DID) approach to identify the treatment effect of the implementation of IT-enabled monitoring systems on employer contractor choice, employer surplus and market competition. We found that the IT-enabled monitoring system lowers the employers' preference for high-reputable bidders, and thus reduces the reputation premiums. Meanwhile, comparing the trend of fixed-price projects, the implementation of the monitoring systems increased the number of bids by 17.4% and increased employer surplus in hourly projects by 21.5%. Our result suggests that IT-enabled monitoring systems have a significant effect on alleviating moral hazards, reducing agency costs, and facilitating market competition.

Keywords: monitoring systems, moral hazard problems, reputation systems, online labor market, market competition, IT policy and management, contract choice

Introduction

Information technology has a profound effect on firm boundaries (Bresnahan, et al. 2002; Dewan and Ren 2011; Hitt 1999). As IT reduces transaction costs, firms increasingly resort to market mechanisms such as outsourcing and offshoring for service procurement. Online labor markets are at the forefront of this phenomenon. In the past few decades, online labor markets have undergone a tremendous growth. For example, by December 2015, there were over 9 million projects posted in Freelancer, one of the most prominent online labor markets, and about 17 million registered users have used the platform to look for job opportunities[1].

Despite the tremendous growth, online labor markets have their limitations due to information asymmetry and agency problems between contractors and employers, amplified by spatial and temporal separations (Hong and Pavlou 2014; Horton 2015). Unlike the traditional temporary employment, monitoring and control mechanisms to ensure work performance (Srivastava and Teo 2012) are weaker and indirect in online labor markets (Horton et al. 2015). Therefore, it's easier for opportunistic contractors to shirk and misrepresent their effort. A common solution to this agency problem is the use of fixed-price contracts, where compensation is outcome-driven. That is, contractors get a fixed payment only when they complete the projects successfully (Mani et al. 2012). Consequently, the dominant strategy for contractors is to complete the projects, which mitigates the moral hazard problems (Fama 1991).

An alternative to fixed-price contracts in online labor markets is hourly contracts, where compensation is determined based on the amount of hours the contractors have spent and the hourly wages set in the contracts (Mani et al. 2012). While hourly contracts provide a stronger incentive for better project performance (Mani et al. 2012) and have better applicability to complex projects (Bajari and Tadelis 2001; Dey et al. 2010) , they also offer the contractors monetary incentives to shirk by over-reporting work hours or lowering their effort levels[2]. Therefore, asymmetric information in online labor markets renders moral hazard problems of hourly projects more prominent (Bajari and Tadelis 2001).

To alleviate moral hazard issues in online labor markets, many online labor platforms started to provide online tracking functionality (Agrawal et al. 2013). For instance, Freelancer released an enhanced tracking feature in its application since August 2nd, 2015. In this study, we analyze how such IT-enabled monitoring tools would influence employers' and contractors' behavior in online labor markets. In particular, we address three research questions: First, do IT-enabled monitoring systems help alleviate moral hazard problems, and thus lower employers' preference for bidders with high-reputation? Second, if IT-enabled monitoring systems indeed change employer preference, how does such a change influence the competition between contractors? Third, given its impact on the market competition, how do IT-enabled monitoring systems affect employer surplus?

We propose a number of hypotheses based on the agency theory and we expect IT-enabled monitoring systems to have a significant effect on alleviating the moral hazard problems in hourly contracts relative to fixed-price contracts. We treat the contractors' bidding and employers' contract rewarding decisions as revealed preferences and analyze how the enhanced monitoring feature affect both the demand and the supply sides of the hourly project market. Our econometric identification hinges on a quasi-natural experiment (release of enhanced offline tracking feature in the Freelancer application), in which we consider hourly projects as the treatment group and fixed-price projects as the control group. With a large dataset including 26,390 projects posted on Freelancer, we use a difference-in-differences (DID) approach to identify the treatment effect of the feature change on employer contract decision, employer surplus, and market competition. Our analysis suggests that after the introduction of the enhanced offline tracking features, employers have less preference for bidders with high-reputation, and thus be less willing to pay the reputation premiums. Further, taking fixed-price projects as the control group, the treatment fosters market competition for hourly projects by increasing the number of bids on hourly contracts by 17.4% and increases the employer surplus in hourly projects by 21.5%.

Our paper makes three key contributions. First, our paper is the first large-scale empirical research to investigate the effect of IT-enabled monitoring systems on employer and contractor choices in online labor markets, which extends prior research on the contract design in labor markets (Chen and Bharadwaj 2009; Clemons and Chen 2011; Fama 1991). Second, this paper contributes to research on reputation systems in online platforms. While previous literature focused on the effect of reputation system on agency problems (Dellarocas 2006; Gopal and Koka 2010; Horton and Golden 2015). Our paper investigated the effect of monitoring systems and its interaction with reputation systems. Specifically, our study showed that there exists a partial substitution relationship between reputation systems and IT-

[1] https://www.freelancer.com/about

[2] http://blog.freelancersunion.org/2014/05/13/hourly-rate-or-project-fee-what-makes-freelancers-more-money/

enabled monitoring systems. Third, numerous studies have attested to the positive role of reputation systems, however, the unintended consequence of reputation systems is that they increase entry barrier for inexperienced contractors who have not established a reputation (Pallais 2014), which is yet to receive research attention. Our study suggests that monitoring systems serve to lower the entry barrier for inexperienced contractors and help to address the "cold-start" problem at online labor markets (Pallais 2014) and provides valuable practical implications. Finally, this study extends our understanding of the design of online labor markets (Hong et al. 2016, Horton 2015), specifically, we extend the understanding of designing IT-enabled monitoring systems to alleviate moral hazard problems, reduce agency costs, and facilitate competition in online labor markets.

This paper proceeds as follows. Section 2 introduces the theoretical background followed by the hypotheses development section. In the empirical analysis part, the data description and empirical models are presented. Finally, we discussed the overall findings, implications, and limitations.

Theoretical Background

Online Labor Market

Online labor markets facilitate the procurement of labor services from all over the world (Hong and Pavlou 2014) by matching employers with contractors (Zheng et al. 2015). During recent years, online labor markets have grown so dramatically that as much as around 25 percentages of workers in the US are hired through online work projects[3]. Because of spatial and temporal separations between employers and contractors, information asymmetry persists in such markets, as contractors' qualities and their actual effort levels are difficult to observe. Therefore, agency problems are prevalent in online labor markets.

One type of agency problems that has attracted attention from both the practice and academic scholars is the adverse selection problem. Adverse selection problems are driven by the asymmetric distribution of information and the difficulties in evaluating the contractors' abilities and skills (Eisenhardt 1989; Horton 2015). In order to address the adverse selection problems, most online labor markets provided the reputation history of contractors by tracking their previous project performance. There is a stream of research investigating the effect of reputation system on alleviating the adverse selection problems and employers' awarding decisions. First, good reputation increases the probability of being awarded. When the contractors are entry-level, the evaluation information posted by previous employers or the platform can significantly help them to get better employment, ceteris paribus (Pallais 2014). Additionally, since the technologies are correlated, the previous ratings in related tasks can also indicate contractors' category-specific quality in other similar projects (Kokkodis and Ipeirotis 2015). Moreover, owing to the good reputation (comments or ratings), contractors can obtain price premiums, get more employment, and have less intention to exit the platform (Moreno and Terwiesch 2014). However, based on an adverse-selection model, Horton found that information driven from public feedbacks tends to inflate because of the bilateral public rating platform design (Horton et al. 2015). Apart from ratings and reviews information, the third-party certification is also one of the optional signaling mechanisms (Goes and Lin 2012). In summary, extant literature suggests that the reputation system and third-party certification system help to address the adverse selection problem.

Once the contractors are awarded, another type of agency problems, the moral hazard problem follows. Moral hazard problems refer to the situation when the contractor has no intention to maximize the employer's utility and opportunistically lowers his or her effort level (Eisenhardt 1989). Such shirking problems are caused by the unobservability of the contractor's actual effort level and the misalignment between the employer's and contractor's interests. Online labor markets are prime examples of markets that are subject to the moral hazard problems due to the spatial and temporal separation of the employers (principals) and contractors (agents) and lack of effective monitoring systems. However, no prior research has examined how the reputation systems and monitoring systems interact to address the moral hazard problems and subsequently influence employers' and contractors' behaviors.

---

[3]http://www.forbes.com/sites/groupthink/2014/10/21/the-next-big-thing-in-e-commerce-online-labor-marketplaces/#5f62eb9c6117

Contract Choice

In the practice of outsourcing, there are two prevalent contract types, namely, fixed-price contracts and time and materials contracts (Banerjee and Duflo 2000). Fixed-price contracts are outcome-driven, and the agent gets a fixed payment according to the billing cycle and the amount of output (Mani et al. 2012). On the other hand, time and materials contracts, also named as cost-plus contracts, require that the payment should be calculated based on the agent's effort and time in the work process (Mani et al. 2012). From the perspective of transaction cost economics, the decision of construal structure depends on the tradeoff between potential renegotiation costs of fixed-price contracts and the cost-efficiency losses of time and materials contracts (Susarla and Krishnan 2014). According to the extant literature, many factors influence the contract choice, such as firm size (Gopal and Sivaramakrishnan 2008), age of firm, trust, reputation (Banerjee and Duflo 2000), task complexity, risk of project (Gopal and Sivaramakrishnan 2008), previous collaboration experience, business familiarity (Gefen et al. 2008), and to what extent outcome is sensitive to the agent's or the principal's efforts (Roels et al. 2010). Compared to time and materials contracts, fixed-price contracts have higher ex-ante costs to collect information and to negotiate the provision, plus higher ex-post maladaptation costs and renegotiation costs (Susarla et al. 2009). However, time and materials contracts usually entail higher ex-post monitoring and auditing costs (Bajari and Tadelis 2001; Dey et al. 2010; Susarla et al. 2009; Susarla and Krishnan 2014).

Some researchers consider the trade-off between two types of contracts as a "make-or-buy" decision (Bajari and Tadelis 2001). The "buy" choice, corresponding to the fixed-price contract, means the external contractor takes all the production costs. Therefore, such a choice is preferred when the task is easy to define. And the "make" choice, corresponding to the time and material contract, indicates that the employer bear all the production costs. Therefore, it is similar to the process of self-production. On the incentive side, for the "buy" choice, contractors are contracted for the final outcome of the projects, which provides sufficient motivations for them to spend effort and time on the projects with efficiency. Thus, the moral hazard problems in the "buy" choice are usually less severe (Fama 1991). However, for a "make" choice, contractors' payments are based on the amount of time they have spent on the projects. Without an effective monitoring system, contractors might engage in the opportunistic "shirking" behavior, especially when their efforts could not be precisely monitored. Therefore, the moral hazard problems usually are more severe than in the "buy" choice. Meanwhile, a "make" choice could have better performance and higher client validation quality than the other if the monitoring and auditing process is effective and efficient (Dey et al. 2010). Apart from these two contract types, there are other optional contract types, including performance-based contracts, profit-sharing contracts (Dey et al. 2010), and hybrid contracts (Banerjee and Duflo 2000). Our paper focuses on the comparison between the fixed-price and time and materials contracts as these are the only two contract type options in most online labor markets (e.g., Freelancer and Upwork).

Monitoring and Reputation

Both the monitoring system and the reputation system could be effective mechanisms to alleviate moral hazard problems. Monitoring is a mean of lowering the information asymmetry by collecting more information on the actions of contractors. Reputation serves as a signal of contractors' future performance based on their performance ratings evaluated by previous employers (Banker and Hwang 2008). Most of the previous literature suggests that both the monitoring system and the reputation system can independently mitigate moral hazard problems (Drago 1991; Duflo et al. 2012; Hubbard 2000; Pierce et al. 2015).

On the one hand, monitoring transforms the individual information about contractors' actual effort into information that the principals could observe. Therefore, it can lower the probability of "shirking" going unnoticed, and thus increase the contractors' effort (Drago 1991). There is a large body of research supporting that, more monitoring increases the contractors' effort and leads to better performance (Duflo et al. 2012; Hubbard 2000; Pierce et al. 2015). On the other hand, reputation links contractors' performance in the present project with the probability of getting hired in the future. Therefore, reputation acts as a stimulus to motivate contractors to spend more effort (Horton and Golden 2015). In order to avoid getting a bad reputation, the contractor will be less likely to shirk, which implies that reputation system plays a role as a sanctioning mechanism (Dellarocas 2006). However, the monitoring system and the reputation system might not work independently, which implies that there might be some unexpected interaction relationship between both mechanisms (Demiroglu and James 2010; Diamond 1991). Because both a well-designed reputation system and a precise monitoring system are effective tools to mitigate moral hazard, the introduction of the IT-enabled monitoring system might lower the employers' reliance on the reputation system, and thus weaken the effect of the reputation system. Therefore, we expect that the monitoring system might partially substitute for the reputation system in reducing contractors' shirking behavior. However, none of the previous IS studies has investigated the interaction relationship between the monitoring system and the reputation system. To sum up, both the monitoring system and the reputation system help to alleviate moral hazard (Dellarocas 2006; Duflo et al. 2012; Horton and Golden 2015; Hubbard 2000; Pierce et al. 2015), but it's still unclear whether they substitute for each other in online labor markets.

Hypotheses Development

Substitution between Monitoring and Reputation

When the risk of moral hazard is high, the employer prefers to choose the contractor with high-reputation, because the reviews and feedbacks from previous employers help to alleviate information asymmetry and serves as a signal of contractor's average effort level (Banker and Hwang 2008). However, when the IT-enabled monitoring system is available, the function of the reputation system might be partially substituted by the monitoring system because monitoring system can lower the need for reputation signals in term of contractors' effort and cost uncertainty. First, because of the asymmetric information about the contractors' effort, employers regard the contractors' reputation as the signals to identify the types of contractors (Kokkodis and Ipeirotis 2015). For example, from the perspective of employers, a contractor with high-reputation usually be thought as an agent with high effort, which implies employers' preference for contractors with high-reputation (Pallais 2014). However, when the IT-enabled monitoring tool is available, the employers can verify the contractors' actual levels of effort and only continue the employment if they find that the contractors' levels of effort are acceptable. Therefore, by using an efficient monitoring system, the employers don't need to emphasize contractors' reputation too much because they have the capability to ensure the awarded contractor's actual effort (Gopal and Koka 2010). Second, monitoring provides better information about the contractors' performance and how to improve it, so that it can help to save time and decrease the cost uncertainty. Before the IT-enabled monitoring tool is introduced, the employers might prefer for contractors with high-reputation not only because of their higher expected effort but also because of the smaller cost uncertainty (variance) (Mani et al. 2012). However, with the help of the IT-enabled monitoring system, employers can have better information about contractors' performance and instruct them to perform more efficiently. Therefore, no matter the contractors have high-reputation or not, the employers can keep the cost uncertainty at a low level by ensuring that contractors are making satisfactory progress. This improvement suggests that the monitoring system reduces the difference between contractors with high-reputation and those with low-reputation in terms of cost uncertainty. All in all, the monitoring systems lower employers' worries in contractors' shirking behavior and high cost uncertainty, and thus substitute for the signal effect of the reputation systems. Therefore, we propose the following hypothesis and employ a revealed-preference-based empirical framework to test it:

H1: After IT-enabled monitoring tool is available, employers of hourly projects will place a less emphasis on worker reputation.

Monitoring and Employer Surplus

In the same vein, because of the partial substitution effect between monitoring systems and reputation, employers will be less willing to pay the price premiums, especially the reputation premiums. From the perspective of the supply side (contractors), reputational contractors tend to milk their reputation by charging the price premiums (Moreno and Terwiesch 2014). However, such price premiums don't guarantee the higher product quality (Jin and Kato 2006). In such cases, reputation helps to foster product differentiation of reputable contractors' service. Meanwhile, from the perspective of the demand side, because of the potential moral hazard problems in the online labor markets, employers are uncertain about the effort level of contractors without the monitoring system. Therefore, employers would pay a price premium to the high-reputation contractors (Fombrun 1996) and even consider the reputation premiums as the cost of overcoming moral hazard (Esfahani 1991). However, since the monitoring system can alleviate the moral hazard problems and partially substitutes for reputation, there is no need for employers of hourly projects to pay such reputation premiums to address moral hazard problems. Moreover, our argument is also supported by Allgulin and Ellingsen's (2002) finding that when the monitoring system is very precise, efficient and cheap, the agent's utility reaches its minimum level and they become less capable of earning rents. When the agent can be monitored perfectly, any effort level can only be paid at his corresponding reservation wage (Allgulin et al. 2002). This argument is also supported by the Efficiency Wage Model, which predicts that more intense monitoring leads to lower wage premiums (Ewing and Payne 1999; Leonard 1987; Shapiro and Stiglitz 1984). Since employers no longer need to pay the reputation premiums to overcome moral hazard, we expect that the employer surplus will be higher after a platform implements a monitoring system. So we propose the following hypotheses:

H2a: After IT-enabled monitoring tool is available, employers of hourly projects will tend to pay a lower price premium[4].

H2b: After IT-enabled monitoring tool is available, employers of hourly projects will enjoy a higher surplus.

Monitoring and Competition

Now considering the effect of IT-enabled monitoring systems on the supply side, we expect that more contractors will be interested in hourly projects because of the lower entry barrier, as the reputable contractor's past reputation on work efforts becomes substitutable. On one hand, the monitoring system lowers the entry barrier by decreasing the need for reputation to mitigate moral hazard problems. Before the monitoring system is available, the reputation acts as an entry barrier for relatively new contractors who have not yet built their reputation on the platform. Consequently, those contractors with good reputation posted by the employers can obtain better employment with a higher rent (Pallais 2014). However, after the release of IT-enabled monitoring systems, employers can obtain direct information about contractors' effort from the real track records instead of past performance, which implies the barrier of entry based on reputation prominently drops (Demiroglu and James 2010). Therefore, inexperienced contractors are more likely to bid for those hourly projects. On the other hand, based on the logic of partial substitution relationship between the monitoring system and reputation we explained earlier, and the subsequent change in employers' preferences, the difference between contractors with little platform experience and experienced contractors is dramatically narrowed. Hence, the additional value due to high-reputation will be greatly removed, and low-reputational contractors' work will serve as a closer substitute for high-reputable contractors' work. In such case, the price elasticity of demand will rise and the market will become more competitive. On the whole, we expect that the monitoring system facilitates competition, and more contractors will enter the more competitive market. Therefore, we formalize the next hypothesis as follows:

H3: After IT-enabled monitoring tool is available, the number of bidders of hourly projects will be higher.

Research Methodology

Date Source

Our data is collected from www.freelancer.com (Freelancer), which is one of the largest online labor market platforms. This year, it was awarded as *2015 Best Employment Website* and *2015 Best*

---

[4] One could argue that the implementation of IT-enabled monitoring tool induces changes in both the supply and demand sides. We employ the two following ways to validate the causal relationship between the observed result and the change in employer surplus. First, we create a new price premium measure with the minimum of bid prices as the baseline to take the potential change in the supply side into consideration. Second, we conduct a falsification test by taking the employer surplus evaluated at the average bid price as the dependent variable in the DID model. If the result regarding a lower price premium and a higher employer surplus is caused by the supply side, we expect that the falsification test should fail. On the whole, both the new price premium measure and falsification test support our hypotheses.

Professional Services Website[5]. In Freelancer, the employer can pose his/her project description, project budget and skills required. By showing the budget of the whole project, the employer indicates that this project adopts a fixed-price contract. If the unit of the project budget is dollars per hour, it implies that the employer will make a time and materials contract and then the contractor will get paid for his or her hourly work.

Typically, a project will open for bidding for a week and any contractor who is interested can bid to win the project. For fixed price projects, the bidders need to post their expected payment and state how long it would take him to fulfill the project; and for hourly projects, the bidders need to post their expected hourly rate. Before the bidding period expires, the employer can review bidders' basic information, such as their nationality, skills, self-introduction, average hourly wage, etc. Moreover, Freelancer also provides bidders' previous project experience and their former employers' ratings and comments. Just like the traditional hiring process, if the employer is interested in some candidates among all the bidders, he/she could chat with them before hiring. Additionally, some filtering tools are also available and enable an employer to sort bidders according to the number of reviews, average rating, etc. Once the employer finds the candidate who satisfies him/her the most and meets his/her minimum requirements, he or she could award that contractor and send out more detailed instructions. We obtained an archived sample dataset from Freelancer including the project information and user information from Aug 1st, 2014 to July 1st, 2016. We follow Lin et al. (2016) to construct our sample. For example, we limited our sample to awarded projects that reflect realistic labor demand without the contamination of resubmitted projects. Further, we matched fixed-price and hourly projects (Ho et al. 2007) based on distributions of important covariates suggested by the previous literature using propensity score matching (PSM). Our final sample includes 17,827 fixed-price projects and 8,563 hourly projects. The descriptive information of our dataset is shown in Table 1 and Table 2.

The dataset includes the following attributes: 1) project-level information (i.e. project description, project budget, type of contracts, number of bidders and average bid price, who was awarded and so on); 2) user-level information (i.e. ratings, the amount of reviews, nationality, average hourly wage, etc.).

Table 1 Definitions and Summary Statistics of Related Variables

Variable	Variable definition	Mean	Sd	Min	Max
Num_Bid	Total number of bids received by the project	13.22	16.87	1	196
Budget_Min	The minimum budget set by the employer	93.46	933.14	2	75000
Budget_Max	The maximum budget set by the employer	262.34	2181.88	2	150000
Employer_Developed	A dummy variable(0,1), =1 if the employer comes from a developed country	0.73	0.45	0	1
Project_title_length	Number of characters in the project title	5.18	3.12	1	43
Desc Length	The length of project description	87.14	86.88	6	2222
Num_Employerreview	Total number of reviews received by employers	47.07	107.54	0	1686
Employer_Rating	Average rating score received by the employer	4.91	0.44	0	5
NDA	A dummy variable(0,1), =1 if the employer and the bidder have assigned a NDA contract to protect the employer's right	0	0.06	0	1
Featured	A dummy variable(0,1), =1 if the project is a featured project	0.01	0.08	0	1

[5] https://en.wikipedia.org/wiki/Freelancer.com

Nonpublic	A dummy variable(0,1), =1 if the project is an non-public project	0.01	0.11	0	1
Fulltime	A dummy variable(0,1), =1 if the project is an fulltime project	0	0.01	0	1
Language_en	A dummy variable(0,1), =1 if the project is described in English	0.96	0.2	0	1
Currency_us	A dummy variable(0,1), =1 if the project budget is measured in dollars (the currency of US)	0.78	0.42	0	1

Table 2. Definitions and Summary Statistics of User-level Variables

Variable	Variable definition	Mean	SD	Min	Max
User_hourly_rate	Hourly rate set by the contractor	7.95	22.70	0.00	1500.00
User_avg_rating	Average overall employer-entered ratings for the contractor	7.56	4.04	0.00	10.00
User_earnings	An earnings proxy provided by *Freelancer*, which increases as projects are completed and paid by the employer in *Freelancer*	0.08	0.48	0.00	8.84
User_tenure_month	Contractor's tenure at *Freelancer* measured in months	34.67	30.91	1.00	201.00
User_belong_company	A dummy variable(0,1), =1 if the contractor was hired by a company before	0.47	0.50	0.00	1.00
User_developed	A dummy variable(0,1), =1 if the contractor comes from a developed country	0.25	0.43	0.00	1.00
Quality	Average quality rating given by all the employers (ranging from 0 to 5)	4.81	0.54	1.00	5.00
Communication	Average communication rating given by all the employers (ranging from 0 to 5)	4.82	0.55	0.00	5.00
Expertise	Average expertise rating given by all the employers (ranging from 0 to 5)	4.80	0.55	0.00	5.00
Professionalism	Average professionalism rating given by all the employers (ranging from 0 to 5)	4.83	0.55	0.00	5.00
Hire-again rating	Average hire-again rating given by all the employers (ranging from 0 to 5)	4.81	0.58	0.00	5.00
Completion_rate	Percentage of awarded projects which were successfully completed	0.87	0.21	0.02	1.00
Overall	Average overall employer-entered ratings for the contractor	4.81	0.52	1.00	5.00
Review_count	Total number of reviews which were written by previous employers	12.40	50.51	1.00	3853.00
Milestone_percentage	A special feature at *Freelancer*, which increases as projects are completed, the controlled payments have been received by the contractors at *Freelancer*	73.28	40.70	0.00	120.00

Identification: A Quasi-Natural Experiment

As mentioned before, the information asymmetry problem has been a serious issue, especially for hourly projects. Because the risk allocation of an hourly project is mainly on the principal (the employer), the tradeoff between monitoring costs and the uncertainty or risk of outcome always troubles the employer (Mani et al. 2012). On August 2nd, 2015, Freelancer released an enhanced tracking feature to help alleviate the monitoring problem. Such an IT artifact serves as a control tool with the potential to allow employers to effortlessly monitor the freelancers. This monitoring system randomly takes screenshots every ten minutes, and tracks the amount of minutes the contractor has been spent. Therefore, it can confidently keep a record of the project process even with an unstable Internet connection, sparing the employers' efforts to keep checking the project process. Considering the spatial and temporal separations between the employer and contractor, such a monitoring system makes it more convenient for the employer to prevent the contractor from shirking and to track the project progress by reducing monitoring costs. The employer could file a dispute regarding the quality of the contractor's work based on the offline tracking logs. Additionally, after the monitoring tool was released, the tool is mandatory for all the contractors who are awarded hourly projects. Taken together, this monitoring system alleviates the concerns about losing track of the progress for hourly projects and effectively lowers monitoring costs. So it might better serve the interests of the employers of hourly projects, because there are higher ex-post monitoring costs and risk in hourly contracts (Bajari and Tadelis 2001; Dey et al. 2010; Susarla et al. 2009; Susarla and Krishnan 2014) and such risk is mainly allocated on employers. More importantly, since the monitoring system is mandatory for hourly contractors, it's reasonable to assume that the employers may adjust their hiring preference accordingly. Therefore, given the more essential need for effective monitoring tools and the higher likelihood of a strategic adjustment for the employers of hourly projects, the monitoring system should have a stronger effect on hourly projects than fixed-price projects. Here, we consider fixed-price projects as the control group and examine the effect of the IT-enabled monitoring system on hourly projects.

Empirical Model and Results

Measures and Models

Linear Probability Model

To estimate employer preference for contractors in terms of their observable characteristics, we formulate a model to compare each contractor's winning probability within each project. Specifically, we estimate the probability of one bidder being awarded as Pr ($bidder_{ij}$=1). Denote U_{ij} for the employer's utility from hiring bidder j for project i.

$$U_{ij} = \alpha X_{ij} + \beta B_j + \gamma P_i + \varepsilon_{ij} \qquad (1)$$

where X_{ij} denotes a set of project-bidder paired characteristics, such as the price premium of each bid. P_i indicates a set of time-invariant project characteristics, such as project budget, the length of description, etc. B_j means the bidders' related characteristics, such as bidders' employer-entered ratings, whether he or she is from a developed country and so on[6]. ε_{ij} is a random error. Based on our aforementioned theoretical background, we extended the latent utility model as follows. This model could be estimated with a linear probability model (Greenwood and Agarwal 2015; Heckman and Snyder 1997) or a logit model (Lin et al. 2016; Liu et al. 2015). Given our interest in interpreting the interaction effects, we opt to use a linear approach for estimation.

$$Price\_Premium_{ij} = \frac{(Bid\_Price_{ij} - Bid\_Min_i)}{Bid\_Min_i} \qquad (2)$$

$$U_{ij} = \alpha Price\_Premium_{ij} \times After \times Hourly + \beta Bidder\_Rating_j \times After \times Hourly$$
$$+ \gamma P_i + \delta Controls + \varepsilon_{ij} \qquad (3)$$

---

[6] Based on our review data, the average rating of each contractor is almost constant during our observational period. Therefore, we didn't treat the contractor rating as a time-variant variable here.

where α is a 4X1 matrix of coefficient estimates and each row is corresponding to one of the following four groups: 1) $After = 0, Hourly = 0$; 2) $After = 1, Hourly = 0$; 3) $After = 0, Hourly = 1$; 4) $After = 1, Hourly = 1$. Since there exist high linear correlations between the bidders' employer-entered ratings of different dimensions, we employed the Principal Component Analysis (PCA) to reduce the dimensions and generated two components representing four kinds of employer-entered ratings for bidders, including 1) PC1: Quality of Contractor; 2) PC2: Effort at Work[7]. Therefore, β is a 4×2 matrix of coefficient estimates. Each of row represents the coefficient estimates of four components for each group.

DID Models

In order to test Hypothesis 2b, we create a relative employer surplus measure Employer_Surplus, which measures the relative percentage of employer surplus with respect to the maximum of the project budget. Here, the employer surplus means the gap between the maximum of project budget and the final awarded bid price. If the price is just equal to the employer's Willingness To Pay (WTP), that is, the maximum of the budget, he or she is indifferent between hiring and not hiring and the employer surplus will be zero.

$$Employer\_Surplus_i = {(Budge\_max_i - \ Award\_BidPrice_i)}/{Budge\_max_i} \quad (4)^8$$

Based on this data set and our research design, we estimated the treatment effect based on the Difference-in-Difference (DID) model (Bertrand et al. 2002):

$$Employer\_Surplus_i = \alpha + \beta_1 After_i + \beta_2 Hourly_i + \beta_3 After_i \times Hourly_i + v_i + \varepsilon \quad (5)$$

$$Num\_Bids_i = \alpha + \beta_1 After_i + \beta_2 Hourly_i + \beta_3 After_i \times Hourly_i + v_i + \varepsilon \quad (6)$$

In the model, the dependent variable is the total number of bids for each project i, Num_Bids_i. $After_i$ is the dummy variable indicating whether the project is posted after August 2nd, 2015[9]. The contract type is indicated by $Hourly_i$, which equals to 1 if the project is an hourly project and 0 if it employs fixed-price contract. The interaction term between $After_i$ and $Hourly_i$ (β_3) thus identifies the heterogeneous effect of the availability of the IT-enabled monitoring system on fixed-price projects and hourly ones. To control for the heterogeneity of projects, we also added other project characteristics and employer characteristics (v_i) into the DID model and ε denotes the error term.

Empirical Result

Employer Preference and Surplus

Based on the result of the Linear Probability model, we find that before and after the IT-enabled monitoring system was implemented, for Quality_of_contractor, the coefficients remain unchanged at remains at 0.002 ($p<0.001$), indicating employers' preference towards this dimension of reputation does not change. Interestingly, we observe a different pattern regarding the coefficients for the other dimension of reputation: Effort_at_work. As Table 3 shows, for fixed-price projects, the employer preference shows minor increase (from 0.009 to 0.012), however, for hourly projects, the employer

---

[7] Quality of work, communication, expertise, professionalism, would hire again rating items are mainly loaded on the Quality of Contractor component. Additionally, the completion rate item is mainly loaded on the Effort at Work component.

8 Based on the summary statistics of our sample, there are 35.35% projects whose awarded prices are equal to the maximums of budgets. Hence, we believe that the maximum of project budget is a reasonable proxy for employer's Willingness To Pay (WTP). Moreover, since the maximum of the project budget is usually higher than the maximums of bid price in our sample, employer surplus with respect to the maximums of budget actually is a more conservative measure than the surplus with respect to the maximums of bids.

[9] The IT-enabled monitoring system has been introduced since August 2nd, 2015. Since this monitoring system is imperative for all the hourly contractors and usually there is a time lag between project submission date and award date, we consider the "After" of those projects posted after August 2nd is equal to 1. We also tried to label "After" as 1 if the projects were posted after September 1st, the result is still highly consistent. Our conclusions remain robust if we adopt different time dummies.

preference shows a relatively large decrease (from 0.013 to 0.008), indicating employers show substantially less preference for high reputation contractors regarding the Effert_at_work dimension. Further, we also check how bid price affects employers before and after the implementation of the monitoring system. Interestingly, we found although employers are less price-sensitive for fixed-price projects (maybe due to temporal effects), they became more price sensitive for hourly projects. We also retested Hypothesis 1 with the Conditional Logit model, and the results are qualitatively the same.

Table 3 Estimation Results of the Linear Probability Model

Variable	Sub-group	Project_awarded
Quality_of_contractor	Fixed_price, Before	0.002***(0.000)
	Fixed_price, After	0.002***(0.001)
	Hourly, Before	0.002***(0.000)
	Hourly, After	0.002***(0.001)
Effort_at_work	Fixed_price, Before	0.009***(0.001)
	Fixed_price, After	0.012***(0.001)
	Hourly, Before	0.013***(0.002)
	Hourly, After	0.008***(0.002)
Price_premium	Fixed_price, Before	−0.007***(0.001)
	Fixed_price, After	−0.003***(0.001)
	Hourly, Before	−0.002** (0.001)
	Hourly, After	−0.005***(0.001)
Log_b_count_rating		0.008***(0.001)
User_developed		0.027***(0.003)
Log_milestone_percentage		−0.009***(0.001)
User_belong_company		0.005***(0.001)
Log_bidder_tenure_month		−0.004***(0.001)
Log_bidder_rank		−0.012***(0.001)
Log_bid_order_rank		0.016***(0.001)
Log_b_hourly_rate		−0.006***(0.001)
Intercept		0.125***(0.007)
N		161,994
Clusters(projects)		25,380
R-square within		0.022
R-square between		0.651

Notes: a. Price premium is defined as Price_premium = (Bid_amount −Bid_min)/Bid_min. b. We limit our sample to those projects which are awarded to only one contractor. Therefore, our sample in the fixed-effect model only includes 26,390-582=25,808 projects. c. The result is based on all the contractors who bided for both the fixed-price and hourly projects (named as "dual-typed contractors") (Lin et al. 2016). Those projects whose winners all bided for one type of projects were dropped from our sample. Therefore, our final sample includes 25,808-428=25,380 projects. d. Results of dummy variables denoting contractor characteristics (whether the contractor gets a special Preferred *Freelancer* Badge, etc.) are suppressed for brevity. e. User_count_rating denotes the number of ratings in projects with similar skills. This number is provided by the *Freelancer* website to help employers to evaluate different bidders' experience in relevant skills. f. Bidder_rank means the bidder's ranking among all the candidates. *Freelancer* automatically sorts all the bidders according to its own ranking algorithm which is mainly based bidders' employer-entered reviews. g. Bid_order_rank denotes the sequence in which the bidders' bids were submitted. h. Robust standard errors are reported in parentheses; g. $p<0.1$, ** $p<0.05$, *** $p<0.01$.

In line with the change in employer preference, based on the marginal effect of the interaction term at the mean values of all the covariates, the price premiums paid by employers of hourly projects decline 30.1%. Additionally, we also find that the interaction term in the Equation (5) is significantly positive, which suggests that on average employers enjoy more surplus in hourly projects than before. Based on the marginal effect of DID model at the mean values, on average, the implementation of monitoring systems (the treatment) increases the employer surplus by 21.5%, which lends support to Hypothesis H2b. On the whole, results of the DID models lend support to Hypothesis 2a and Hypothesis 2b.

Table 4 Differences-in-Differences Estimations of the Impact of the IT-enabled Monitoring System on Employer Surplus

Dependent Variable	Price_premium	Employer_surplus
Hourly	−0.333***(0.028)	0.277***(0.012)
After	0.112***(0.031)	−0.017* (0.009)
Hourly *After	−0.241***(0.043)	0.031** (0.015)
Log_paid_amount	0.166***(0.012)	−0.127***(0.005)
Log_bid_count	0.355***(0.012)	0.048***(0.004)
Log_budget_max	−0.140***(0.015)	0.193***(0.006)
Language_en	0.023 (0.035)	0.004 (0.015)
Log_title_length	−0.025 (0.017)	0.012* (0.007)
Log_preview_desc_length	−0.006 (0.014)	0.012** (0.006)
Log_employer_overall_rating	−0.004 (0.011)	0.006 (0.004)
Log_employer_reviews_count	0.025***(0.007)	−0.012***(0.003)
Log_employer_tenure_month	−0.019 (0.017)	0.007 (0.006)
Employer_developed	−0.082***(0.024)	0.031***(0.009)
Intercept	0.090 (0.077)	−0.364***(0.030)
N	26,390	26,390
Adj R-squared	0.120	0.160

Notes: a. Dummy variables for various project categories, such as software, design, marketing, data-entry, are included. The results of these dummies are suppressed for brevity; b. Results of dummy variables denoting project characteristics (whether a NDA contract is included, whether the project is featured or sealed, whether the project is a fulltime job, whether the currency is dollar, whether the project is written in English) are suppressed for brevity; c. Robust standard errors are reported in parentheses; d. * p<0.1, ** p<0.05, *** p<0.01.

Bidding Behavior

According to the result of DID model, we found that the coefficient of After (β_1) is positive, which means that there are more contractors bidding for fixed-price projects than before. This increase in Num_Bids might result from multiple reasons, such as the popularity of Freelancer, etc. Taking this into consideration, the interaction term (β_3) is still significantly positive, which suggests that after the IT-enabled monitoring system was available, the increase in Num_Bids of hourly projects is larger than that of fixed-price projects. This is consistent with our hypothesis that a more homogenous service market will attract more contractors. The finding that the interaction term is 0.160 implies that the number of bids increases 17.4%[10]. Therefore, Hypothesis 3 is also supported.

Overall, our results of the Conditional Logit model and the DID models support all of our hypotheses.

---

[10] Based on the estimation results in Table 5, before the implementation of monitoring systems, the partial correlation between Hourly dummy and Log_ Num_Bids is -0.023. This partial coefficient becomes 0.137 after the implementation. Since the dependent variable takes the log transformation, we transform the change in the coefficient with the exponential function to obtain the actual increase in the number of bids. Exp(0.160) - 1=17.4%.

Table 5 Differences-in-Differences Estimations of the Impact of the IT-enabled Monitoring System on Num_Bids	
Dependent Variable	Log_ Num_Bids
After	0.088*** (0.021)
Hourly	–0.023 (0.023)
Hourly * After	0.160*** (0.032)
Log_paid_amount	–0.026*** (0.007)
Log_budget_max	0.155*** (0.009)
Language_en	0.291*** (0.030)
Log_title_length	0.118*** (0.014)
Log_preview_desc_length	0.326*** (0.013)
Intercept	–1.233*** (0.068)
N	26,390
Adj R-squared	0.460

Notes: a. Dummy variables for various project categories, such as software, design, marketing, data-entry, are included. The results of these dummies are suppressed for brevity; b. Results of dummy variables denoting project characteristics (whether a NDA contract is included, whether the project is featured or sealed, whether the project is a fulltime job, whether the currency is dollar, whether the project is written in English) are suppressed for brevity; c. Dummy variables for employers' characteristics (the average rating, number of reviews, employer tenure measured in months, whether the employer is from a developed country) are suppressed for brevity; d. Robust standard errors are reported in parentheses; d. * p<0.1 ** p<0.05 *** p<0.01.

Robustness Check

To further validate our hypotheses, we performed several robustness checks. First, we tried to balance the distribution across the treatment and control group with multiple matching methods, and then retested our results with the matched sample. Second, we used an alternative measure of price premiums and reran the DID model. We also tested if employer preference for actual bid prices had changed. Third, we also conducted a falsification check in order to rule out the alternative explanation that the change in awarded bid prices came from lower average bid prices rather than the change of employer preference.

Alternative Matching Methods

In order to balance the distribution of observed characteristics across the treatment and control group, we tried to conduct the Propensity Score Matching and retested the hypotheses with the matched sample. Specifically, we included employers' reputation (employer ratings given by awarded contractors, the number of reviews the employers receive), whether the employer is from a developed country, the number of characters in project description (Lin et al. 2016), project type dummies, the month dummies as the pretreatment covariates to match the hourly projects and fixed-price projects. We estimated the coefficient of the interaction term in the DID model with the use of the One-to-one Matching, Radius Matching, Kernel Matching. All the results are consistent with our main results.

Table 6 Estimates of ATT in the Matched Sample			
Matching algorithms	Price_premium	Employer_surplus	Log_Num_bids
One-to-one Matching, with replacement	–0.229***(0.053)	0.037** (0.017)	0.098***(0.034)
Radius Matching, caliper(0.10)	–0.135***(0.028)	0.028** (0.012)	0.130***(0.023)
Kernel Matching, caliper(0.10)	–0.137***(0.028)	0.028** (0.012)	0.126***(0.023)

Note: * p<0.1, ** p<0.05, *** p<0.01.

Alternative Measurements

In order to retest the Hypothesis 2b, we created an alternative measure of awarded bid prices, Award_BidPrice, which is the ratio of the bid price of the awarded contractor to the maximum of the project budget. If the awarded bid price is just equal to the employer's willingness-to-pay (WTP), that is, the maximum of the budget, he or she is indifferent between hiring and not hiring and Award_BidPrice will be equal to one. In such case, the employer surplus will be zero. In the main result section, we showed that, after the IT-enabled monitoring system was available, employer surplus of hourly projects is higher than it was before. So when we took $Award\_BidPrice\_Perc$ as the dependent variable, we still expected that the interaction term in DID model would be negative. And the result of this robustness check is also consistent with our argument and again supports Hypothesis 2a.

$$Award\_BidPrice\_Perc_i = \frac{Award\_BidPrice_i}{Budget\_Max_i} \qquad (7)$$

In the main result, we included Price_Premium, a standardized price measurement, in the model to test Hypothesis 1. To further check our argument, we also built the model including the actual bid prices (log-transformed) and tested if the result is still consistent. The estimates of the Linear Probability Model including the actual bid prices (log-transformed) suggests that after the monitoring system was available, employers were more sensitive to Bid_Price and no longer put substantial weights on Effort_at_work component of bidders' employer-entered ratings as before. Hence, the result is consistent with our main results.

Falsification Checks and an Alternative Explanation

Even though we found that the employer surplus of hourly projects is higher than it was before, it is possible that this is driven by factors other than employer preference. An alternative explanation is that contractors require lower hourly salaries than they did before. In order to rule out this alternative explanation, we tested if the coefficient of the interaction term in the DID model is still significant by taking the employer surplus evaluated at the average bid price as a dependent variable. According to the estimates of the DID model, after the IT-enabled monitoring system was available, the increase in the employer surplus of hourly projects with respect to the average bid prices is not significantly higher than that of fixed-price projects. However, the incremental employer surplus of hourly projects with respect to awarded bid prices is significantly higher than that of the control group (fixed-price projects), which implies that such a change in employer surplus is mainly because of employers' less willingness to pay price premiums, rather than the lower bid prices. Additionally, in order to validate our argument that the introduction of IT-enabled monitoring system facilitates the market competition by lowering the entry barrier, we also employ a DID model to estimate the impact of the IT-enabled monitoring system on the percentage of contractors (Perc_norating) who haven't accumulated any reputation records from employers (Lin et al. 2016). Our result suggests that after the IT-enabled monitoring system was introduced, Perc_norating of hourly projects is significantly lower than before. Specifically, based on the result of marginal effect estimates, it (Perc_norating) increases 9.1% after the implementation of monitoring systems. On the whole, the fact that there is relatively more participation of inexperienced contractors in hourly projects supports our argument that IT-enabled monitoring system facilitates market competition by lowering entry barrier.

Discussion

Key Findings and Implications

In this research, we show the evidence that the introduction of IT-enabled monitoring systems can lower the employers' preference for contractors with high-reputation, increase employer surplus and facilitate market competition. Our estimation results are based on a quasi-natural experiment design with fixed-price projects as the control group and hourly projects as the treatment group. The results of our DID models and the Linear Probability Model suggest that after the monitoring system was introduced, employers are less willing to pay the premiums for the high reputation in Effort at Work, and thus enjoy a higher surplus. This finding implies that there exists a partial substitution relationship between the monitoring system and the reputation system. Moreover, our results also show that the introduction of IT-enabled monitoring systems facilitates competition by attracting more inexperienced contractors to bid for the projects.

Additionally, our study also contributes to several strands in the online labor market literature. First, our study is the first large-scale empirical research to examine the effect of IT-enabled monitoring systems on both the demand and supply side of an online labor market. Unlike the previous literature mainly examining the effect of monitoring system within a firm (Gopal and Koka 2010) or one location(Pierce et al. 2015), our large dataset can be leveraged to test the influence of the monitoring system on the whole online labor market within a certain platform. Such an advantage enables us to identify the ripple effect of the IT-enabled monitoring system on the market structure. Second, our study extends previous research on the effect of reputation systems in digital platforms. According to the previous literature on reputation systems, reputation acts as a signal of contractors' future performance (Banker and Hwang 2008), and motivates contractors to spend more effort (Horton and Golden 2015). However, our results suggest that its effect can be partially substituted by the IT-enabled monitoring system, which alleviates moral hazard by efficiently providing more precise information about contractors' effort (Agrawal et al. 2014; Pierce et al. 2015). This implies that future research on reputation systems should also take the availability of monitoring systems as a critical contingency factor. Third, this research suggests that the impact of IT-enabled monitoring systems is not limited to mitigating moral hazard problems and improving agents' productivity (Duflo et al. 2012). In this study, we show that the IT-enabled monitoring systems can help to reduce agency costs, raise employer surplus, and facilitate market competition. Therefore, our finding implies that IT artifacts can have a prominent effect on the market structure.

Our study has several important implications. First, this study has implications for the stream of online labor market literature by exploiting a quasi-experiment methodology. Different from the previous literature using the Heckman selection model to address the endogeneity problems (Gopal and Koka 2010), we employ a quasi-experiment and investigate the effect of IT-enabled monitoring system on both the demand and supply sides. The DID model doesn't only have the advantage of controlling for self-selection bias, but also well address the time-series heterogeneity issue (Xue et al. 2011). Therefore, our quasi-natural experiment approach allows us to provide a full picture of the impact of IT-enabled monitoring system on both the demand and supply sides. Second, our research provides some managerial implications to the platform design of online labor markets. There is a large body of research suggesting that the reputation system helps to mitigate moral hazard by acting as both a stimulus for high effort (Horton and Golden 2015) and a sanctioning mechanism (Dellarocas 2006). Meanwhile, the monitoring system is also found to be highly effective in improving agents' performance (Duflo et al. 2012). However, our study suggests that there exists a partial substitution relationship between these mechanisms. Hence, our study deepens our understanding of the optimal design of online labor markets (Hong et al. 2015) by emphasizing the potential interaction effect between the reputation systems and monitoring systems. Finally, our study suggests that monitoring systems lower the entry barrier for inexperienced contractors and help to address the "cold-start" problem at online labor markets (Pallais 2014), which provides valuable practical implications.

Limitations and Further Research

We acknowledge a number of limitations of this research, which opens up avenues for future research. First, we note that complete data on the actual employer monitoring behavior is not available. However, considering there might be only part of the employers adopting the IT-enabled monitoring system, our estimated effect of the IT-enabled monitoring system tend to be conservative. Second, due to data limitations, our research only tested the effect of the IT-enabled monitoring system on the hourly contract market by using the observational data from only one particular crowdsourcing platform. Even though our platform is one of the largest crowdsourcing platforms all over the world, the effect of monitoring systems might still vary as the usefulness and ease-of-use of monitoring systems or platform characteristics change. Further research should retest our hypotheses under the context of other platforms or other monitoring systems. Finally, we only focused on testing the effect of IT-enabled monitoring system on the employer preference and contractors' bidding behaviors. Future research could collect the reviews and ratings data corresponding to these awarded projects in order to explore the effect of the IT-enabled monitoring system on the project final performance.

References

~~Agrawal, A., Horton, J., Lacetera, N., and Lyons, E. 2013. "Digitization and the contract labor market: A research agenda," *National Bureau of Economic Research*.~~

~~Agrawal, A., Lacetera, N., and Lyons, E. 2014. "Does Standardized Information in Online Markets Disproportionately Benefit Job Applicants from Less Developed Countries?,".~~

~~Allgulin, M., and Ellingsen, T. 2002. "Monitoring and pay," *Journal of Labor Economics* (20:2), pp 201-216.~~

~~Bajari, P., and Tadelis, S. 2001. "Incentives versus transaction costs: A theory of procurement contracts," *RAND Journal of Economics* (32:3), pp. 387-407.~~

~~Banerjee A V, Duflo E. 2000. "Reputation effects and the limits of contracting: A study of the Indian software industry", *The Quarterly Journal of Economics* (115:3), pp. 989-1017.~~

~~Banker, R.D. and Hwang, I. (2008) "Importance of Measures of Past Performance: Empirical Evidence on Quality of e-Service Providers," *Contemporary Accounting Research* (25:2), pp. 307-337.~~

~~Bertrand, M., Duflo, E., and Mullainathan, S. 2002. "How much should we trust differences-in-differences estimates?," *National Bureau of Economic Research*.~~

~~Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt. 2002. "Pehnology, Organization, and the Demand for Skilled Labor." *The new relationship: Human capital in the American corporation*, pp.145.~~

Chen2009 Chen, Y., and Bharadwaj, A. 2009. "An empirical analysis of contract structures in IT outsourcing," *Information Systems Research* (20:4), pp. 484-506.

Clemons2011c Clemons, E. K., and Chen, Y. 2011. "Making the decision to contract for cloud services: managing the risk of an extreme form of IT outsourcing," System Sciences (HICSS), the 44th Hawaii International Conference on, IEEE2011, pp. 1-10.

~~Dellarocas, C. 2006. "Reputation mechanisms". *Handbook on Economics and Information Systems*,pp. 629-660.~~

~~Demiroglu, C., and James, C. M. 2010. "The role of private equity group reputation in LBO financing," *Journal of Financial Economics* (96:2), pp. 306-330.~~

Dewan2011 Dewan, Sanjeev, and Fei Ren. 2011. "Information technology and firm boundaries: Impact on firm risk and return performance." *Information Systems Research* (22:2), pp.369-388.

Dey2010 Dey, D., Fan, M., and Zhang, C. 2010. "Design and analysis of contracts for software outsourcing," *Information Systems Research* (21:1), pp. 93-114.

~~Diamond, Douglas W.1989. "Reputation acquisition in debt markets." *The Journal of Political Economy* (97:4), pp. 828-862.~~

~~Diamond, D. W. 1991. "Monitoring and reputation: The choice between bank loans and directly placed debt," *Journal of political Economy* (99:4), pp. 689-721.~~

~~Drago, R. 1991. "Incentives, pay, and performance: a study of Australian employees," *Applied Economics* (23:9), pp. 1433-1446.~~

~~Duflo, E., Hanna, R., and Ryan, S. P. 2012. "Incentives work: Getting teachers to come to school," *The American Economic Review* (102:4), pp. 1241-1278.~~

~~Eisenhardt, K. M. 1989. "Agency theory: An assessment and review," *Academy of management review* (14:1), pp. 57-74.~~

~~Esfahani, H. S. 1991. "Reputation and uncertainty Toward an explanation of quality problems in competitive LDC markets," *Journal of Development Economics* (35:1), pp. 1-32.~~

~~Ewing, B. T., and Payne, J. E. 1999. "The trade-off between supervision and wages: evidence of efficiency wages from the NLSY," *Southern Economic Journal* (66:2), pp. 424-432.~~

~~Fama, E. F. 1991. "Time, salary, and incentive payoffs in labor contracts," *Journal of Labor Economics* (9:1), pp. 25-44.~~

~~Fombrun, C. 1996. *Reputation*, Wiley Online Library.~~

Gefen2008 Gefen, D., Wyss, S., and Lichtenstein, Y. 2008. "Business familiarity as risk mitigation in software development outsourcing contracts," *MIS Quarterly* (32:3), pp. 531-551.

~~Greenwood, B.N. and Agarwal, R. (2015) "Matching platforms and HIV incidence: An empirical investigation of race, gender, and socioeconomic status," *Management Science* (62:8), pp.2281 - 2303.~~

~~Goes, P., and Lin, M. 2012. "Does Information Really'Unravel'? Understanding Factors That Motivate Sellers to Seek Third-Party Certifications in an Online Labor Market," *Understanding Factors That*~~

~~*Motivate Sellers to Seek Third-Party Certifications in an Online Labor Market (November 1, 2012). NET Institute Working Paper:12-02.*~~

Gopal2008 Gopal, A., and Sivaramakrishnan, K. 2008. "Research Note-On Vendor Preferences for Contract Types in Offshore Software Projects: The Case of Fixed Price vs. Time and Materials Contracts," *Information Systems Research* (19:2), pp. 202-220.

~~Gopal, A., and Koka, B. 2010. "The role of contracts on quality and returns to quality in offshore software development outsourcing." *Decision Sciences*, (41:3), pp. 491-516.~~

~~Heckman, J. J., & Snyder Jr, J. M. (1997). "Linear probability models of the demand for attributes with an empirical application to estimating the preferences of legislators". *RAND Journal of Economics*. S142-S189.~~

Hitt1999 Hitt, L. 1999. "Information technology and firm boundaries: Evidence from panel data." *Information Systems Research* (10:2), pp.134-149.

~~Ho, D. E., Imai, K., King, G. and Stuart, E. A. 2007. "Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference," *Political Analysis*. (15:3), pp.199-236.~~

~~Hong, Y. and Pavlou, P. A., 2014. "Is the World Truly 'Flat'? Empirical Evidence from Online Labor Markets," Empirical Evidence from Online Labor Markets. *Fox School of Business Research Paper*, (15-045).~~

Hong2016a Hong, Y., Wang, C. and Pavlou, P. A. 2016. "Comparing Open and Sealed Bid Auctions: Evidence from Online Labor Markets." *Information Systems Research* (27:1), pp.49-69.

~~Horton, J. J. 2015. "Supply Constraints as a Market Friction: Evidence from an Online Labor Market."~~

~~Horton, J. J., and Golden, J. M. 2015. "Reputation Inflation: Evidence from an Online Labor Market."~~

~~Hubbard, T. N. 2000. "The demand for monitoring technologies: the case of trucking," *Quarterly Journal of Economics* (115:2), pp. 533-560.~~

~~Lin, M., Liu, Y., and Viswanathan, S. 2016. "Effectiveness of Reputation in Contracting for Customized Production: Evidence from Online Labor Markets," *Management Science* (forthcoming).~~

Liu2015c Liu, De, et al. 2015. "Friendships in online peer-to-peer lending: Pipes, prisms, and relational herding," *Mis Quarterly* (39:3), pp. 729-742.

~~Jin, G. Z., and Kato, A. 2006. "Price, quality, and reputation: Evidence from an online field experiment," *The RAND Journal of Economics* (37:4), pp. 983-1005.~~

~~Kanat, I., Hong, Y. and Raghu, T. S. 2015. "Surviving and Thriving in the Online Labor Markets: A Geoeconomic Analysis." *Available at SSRN 2701471*.~~

~~Kokkodis, M., and Ipeirotis, P. G. 2015. "Reputation Transferability in Online Labor Markets," *Management Science* (62:6), pp.1687-1706.~~

~~Leonard, J. S. 1987. "Carrots and sticks: Pay, supervision and turnover," National Bureau of Economic Research Cambridge, Mass., USA.~~

Mani2012 Mani, D., Barua, A., and Whinston, A. B. 2012. "An empirical analysis of the contractual and information structures of business process outsourcing relationships," *Information Systems Research* (23:3-part-1), pp. 618-634.

~~Xue, M., Hitt, L. and Chen, P. 2010. "Determinants and outcomes of internet banking adoption." *Management science* (57:2), pp. 291-307.~~

Moreno2014 Moreno, A., and Terwiesch, C. 2014. "Doing business with strangers: Reputation in online service marketplaces," *Information Systems Research* (25:4), pp. 865-886.

~~Pallais, A. 2013. "Inefficient hiring in entry-level labor markets," *The American Economic Review* (104:11), pp. 3565-3599.~~

~~Pierce, L., Snow, D. C., and McAfee, A. 2015. "Cleaning house: The impact of information technology monitoring on employee theft and productivity," *Management Science* (61:10), pp 2299-2319.~~

~~Roels, G., Karmarkar, U. S., and Carr, S. 2010. "Contracting for collaborative services," *Management Science* (56:5), pp. 849-863.~~

~~Shapiro, C., and Stiglitz, J. E. 1984. "Equilibrium unemployment as a worker discipline device," *The American Economic Review* (74:3), pp. 433-444.~~

Srivastava2012 Srivastava, S. C., and Teo, T. S. 2012. "Contract performance in offshore systems development: Role of control mechanisms," *Journal of Management Information Systems* (29:1), pp. 115-158.

Susarla2009 Susarla, A., Barua, A., and Whinston, A. B. 2009. "A transaction cost perspective of the" Software as a Service" business model," *Journal of Management Information Systems* (26:2), pp. 205-240.

~~Susarla, A., and Krishnan, R. 2014. "Contracting in the Shadow of the Future," *Available at SSRN 1975215*.~~

Zheng2015
Zheng, A., Hong, Y. and Pavlou, P., 2015. Value Uncertainty and Buyer Contracting: Evidence from Online Labor Markets. *Proceedings of the International Conference on Information Systems*, Dallas, TX.