Effects of IT-enabled Monitoring on Labor Contracting in Online Platforms: Evidence from a Natural Experiment

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Abstract

Two-sided platforms are typically plagued with asymmetric information, limiting market efficiency. Situated in the context of the increasingly popular online platforms for labor contracting (herein referred to as "online labor markets"), this paper investigates whether the implementation of an IT-enabled monitoring system mitigates moral hazard in online platforms and the consequences thereof. Our identification hinges on a natural experiment at *Freelancer* when it introduced an IT-enabled monitoring system with enhanced offline tracking features in August 2015. Based on a unique dataset including 17,827 fixed-price projects and 8,563 time-based projects matched on observable characteristics, we employ a difference-in-differences (DID) approach to identify the treatment effect of the monitoring system implementation on various outcomes from both the employer (demand) side and the contractor (demand) side, including employer contractor choice, platform entry barrier and employer surplus. We found that the implementation of the monitoring system lowers the employers' preference for high-reputation bidders in time-based projects, and thus reduces the reputation premiums and partially lowers the entry barrier for contractors who have not yet established a reputation on the platform. Specifically, using fixed-price projects as the baseline, on average, the implementation of the monitoring system increased the number of bids by 17.4% (primarily from bidders with no prior experience on the platform) and increased employer surplus in time-based projects by 21.5%. Our results testify the partial substitution relationship between reputation systems and monitoring systems, and suggest that IT-enabled monitoring systems have a significant effect on alleviating moral hazards, reducing agency costs, and intensifying supply-side platform competition.

Keywords: platforms, online labor market, moral hazard, monitoring systems, reputation systems, entry barrier, contract type

1. Introduction

By developing unique digital infrastructures that tap into underused physical and human resources, the platform economy is transforming business processes and individual activities (Choudary et al. 2016). Online labor markets, two-sided platforms that connect employers with freelance contractors, are at the forefront of this phenomenon. Over the past decade, online labor markets have experienced tremendous growth. As a prominent example, by December 2015, about 17 million registered users have completed over 9 million projects posted in *Freelancer*, one of the major online labor markets.

Despite the tremendous growth, online labor markets are plagued with agency problems – moral hazard and adverse selection – due to the asymmetric information between employers and contractors (Horton 2015), amplified by spatial and temporal separations (Hong et al. 2015). On the one hand, compared with the traditional employment relationship, monitoring and control mechanisms to ensure work performance (Srivastava and Teo 2012) in online labor markets are weaker and more indirect (Horton and Golden 2015). Exploiting this limitation, opportunistic contractors may exhibit moral hazard behavior by misrepresenting or over-reporting their effort. On the other hand, due to the lack of a viable screening mechanism on the contractors, online labor markets are subject to adverse selection, wherein employers could not separate high quality contractors from low quality ones (Lin et al. 2016).

To mitigate information asymmetry, major online platforms have developed reputation systems that allow buyers (or employers) to share experiences of sellers (or contractors) (Dellarocas 2006; Moreno and Terwiesch 2014). Contrary to the prediction that information asymmetry will inevitably lead to market failures (Diamond 1976), online platforms from auction sites such as *eBay* and *Taobao*, to online labor markets such as *Freelancer* and *Upwork*, have experienced substantial growth thanks to their robust reputation systems that have effectively prevented them from deteriorating into markets of 'lemons' (Bockstedt and Goh 2011; Dellarocas 2005, 2006; Ba and Pavlou 2002). The information sharing among employers enabled by reputation systems allows employers to screen for capable and trustworthy contractors who are willing to expend commensurate effort for the projects, thus mitigating both adverse selection and moral hazard. Given that adverse selection arises in online labor markets because contractors have private information about their capabilities, information sharing among employers lowers the likelihood that contractors could misrepresent their capability to win contracts. In addition, by enabling employers to share information on contractors, reputation systems serve as a sanctioning device that deters contractors' shirking behavior when employers could not observe contractors' actual effort (Banker and Hwang 2008). The differentiating role of reputation systems can be witnessed in price premiums and higher winning probabilities enjoyed by reputable contractors in online platforms (Ba and Pavlou 2002; Moreno and Terwiesch 2014). One unintended consequence of reputation systems, however, is that they create an entry barrier for qualified contractors who have not yet established a reputation in a particular platform (Pallais 2014).

Another strategy used by employers to address the moral hazard problem is through contract design. Two contract forms are available in online labor markets: time-based contracts and fixed-price contracts. In time-based contracts, compensation is determined based on hourly wages set in the contracts and the amount of hours the contractors have spent after the contract is written (Mani et al. 2012). While time-based contracts provide a stronger incentive to achieve better project performance (Dey et al. 2010; Mani et al. 2012), they are more susceptible to moral hazard problems. In fixed-price contracts, compensation is based on project outcome, such that contractors receive payment only when they successfully complete the project (Mani et al. 2012). Therefore, fixed-price contracts have the potential to mitigate moral hazard. However, fixed-price contracts typically involve high contracting costs and suffer from a lack of flexibility in accommodating changing requirements, leading to high ex post costs of maladaptation and renegotiation (Benaroch et al. 2016). Taken together, fixed-price contracts are limited in their efficacy in fully resolving information asymmetry.

With the advance in information technology and network bandwidth, a new mechanism to mitigate moral hazard – online monitoring – has gained popularity among online platforms (Agrawal et al. 2013). Specifically, with the use of a suite of IT-enabled monitoring technologies, employers have access to the random screenshots of the contractors' working progress, and even keystroke recordings from the automatically archived log files, which serve as the first-hand information about the contractors' effort and help to alleviate moral hazard.

While a significant amount of research effort has been afforded to the design, evaluation, and optimization of reputation systems, few studies have considered the role of monitoring, particularly its interactions with reputation systems and implications for competition in online platforms. Specifically, we consider the following three research questions:

- *Does IT-enabled monitoring substitute for reputation systems such that it reduces employers' preference for bidders with high-reputation? What type of information from reputation systems is substituted by monitoring?*
- *Does IT-enabled monitoring reduce entry barrier for contractors in online labor markets, thus intensifying competition between contractors?*
- *Does IT-enabled monitoring reduce contract price and increase employer surplus?*

To address the above research questions, our analyses leverage a natural experiment when *Freelancer* embedded an IT-enabled monitoring system with enhanced offline tracking features into its application on August 2nd, 2015. This natural experiment offers us an ideal research design to identify the effect of IT-enabled monitoring systems in online platforms. Our econometric identification hinges on the fact that monitoring only affects time-based projects but not fixed-price projects, which allows us to use time-based projects as the treatment group and fixed-price projects as the control group. Using a large dataset including 201,408 projects posted on *Freelancer*, we first performed propensity score matching to balance the fixed-price projects and time-based projects, so that they are comparable in terms of any observable characteristic. We then use a difference-in-differences (DID) approach to identify the treatment effect of the implementation of monitoring systems on employer contractor choice, platform supply-side competition and employer surplus. Our analyses suggest that after the implementation of the IT-enabled monitoring systems, employers place less emphasis on the reputation component that signals contractors' effort, and thus pay a lower reputation premium. Further, using fixed-price projects as the baseline, on average, the monitoring system implementation increases number of bids in time-based projects by 17.4% (primarily from bidders with no prior experience on the platform), indicating lowered entry barrier. And finally, the employer surplus in time-based projects significantly increases by 21.5%.

Our study differentiates from prior literature on monitoring mechanisms on three fronts. First, most prior studies focus on the performance effect of monitoring in offline contexts (Duflo et al. 2012; Hubbard 2000; Pierce et al 2015; Staats et al. 2016), whereas this study focuses on its impact on demand-side (employer) preference and supply-side (contractor) competition in online platforms. Second, our study advances prior literature on the relationship between monitoring systems and reputation systems in online platforms (Demiroglu and James 2010; Diamond 1991; Lin et al. 2016). Recent studies found that in an online labor market with a monitoring system, high reputation cannot significantly increase the prospect of being awarded time-based projects (Lin et al. 2016). We advance this literature by uncovering the partial substitutive relationship between monitoring systems and reputation systems in shaping employer preference. Third, numerous studies have attested to the positive role of reputation systems in addressing information asymmetry (Dellarocas 2005, 2006; Kokkodis and Ipeirotis 2015; Moreno and Terwiesch 2014; Pallais 2014; Yoganarasimhan 2013), this study considered the unintended consequence of reputation systems in creating an entry barrier for contractors who has not established a reputation on a particular platform, finding that implementation of an IT-enabled monitoring system can partially reduce such entry barriers.

2. Literature Review

2.1. Platform Economy and Online Labor Markets

Platform-based businesses are thriving in today's economy (Anderson et al. 2013; Choudary et al. 2016; Eisenmann et al. 2006, 2011; Van Alstyne et al. 2016). Numerous new business models have been developed based on platform paradigm, ranging from platforms that enable transaction of physical products (e.g., *eBay*, *Taobao*, *Amazon Marketplace*), outsourcing of services (e.g., *Upwork*, *Freelancer*) and local tasks (e.g., *TaskRabbit*, *PostMates*), to sharing of car rides (e.g., *Uber*, *Lyft*) and temporary lodging (e.g, *AirBnB*, *CouchSurfing*). Due to asymmetric information between the two sides of the platform, one major theme in research on platform research is to tackle the agency problems with reputation systems (e.g., Brown and Morgan 2006; Dellarocas 2005, 2006; Duflo et al. 2013; Kokkodis and Ipeirotis 2015; Zacharia et al. 2000). Studies show that reputation systems improve disclosure and serve as sanctioning devices that deter the "agents" from shirking (Bockstedt and Goh 2011; Dellarocas 2005, 2006; Moreno and Terwiesch 2014; Pavlou and Dimoka 2006).

The research context of this study, online labor markets, are web-based two-sided platforms that facilitate the contracting of labor services around the globe (Hong et al. 2016; Lin et al. 2016). In recent years, online labor markets have grown dramatically. It is reported that 25 percentage of jobs in the US are offshored (Blinder and Kruger 2013), with a substantial amount delegated through online labor markets[1]. Because of spatial and temporal separations between employers and contractors, information asymmetry persists in such platforms, as contractors' qualities are difficult to observe and their actual effort levels are difficult to monitor. Therefore, similar to many other online platforms, agency problems are prevalent in online labor markets, making it a major theme in the literature on online labor markets.

Two forms of agency problems exist on online labor markets. First, there is adverse selection. Adverse selection is driven by the asymmetric 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 review history of contractors, based on ratings supplied by their past employers. A number of studies consider on the effect of reputation on employers' contractor choice. They found that reputation scores posted by previous employers can help contractors get significantly better employment (Pallais 2014). With a better reputation, contractors can obtain price premiums (Bajari and Hortacsu 2004), receive more employment opportunities, and are less likely to exit the platform (Moreno and Terwiesch 2014). Reputation in online labor markets is also shown to be transferrable, such that the previous ratings in related tasks can also indicate contractors' category-

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

specific quality in other similar projects (Kokkodis and Ipeirotis 2015). In summary, a great number of studies suggest that the reputation system helps to address the adverse selection problem.

Second, once a contractor is awarded the contract, the moral hazard problem follows. Moral hazard occurs when a contractor opportunistically lowers his or her effort level to maximize his own utility, to the detriment of the employer (Eisenhardt 1989). Moral hazard is caused by the employers' inability to monitor the contractor's actual effort level and the misalignment between the employer's and contractor's interests. Online labor markets are prime examples of platforms subject to the moral hazard problems due to the spatial and temporal separation of the employers (principals) and contractors (agents). In order to mitigate moral hazard in online labor markets, a stream of research finds that reputation systems provide pre-contractual screening (Banker and Hwang 2008; Yoganarasimhan 2013), and serve as a sanctioning device to the deter the shirking behavior (Dellarocas 2006; Moreno and Terwiesch 2014).

2.2. Monitoring and Reputation

Like reputation systems, monitoring systems can also mitigate moral hazard. Prior studies have analyzed the performance effect of monitoring, primarily in offline employment contexts (Duflo et al. 2012; Hubbard 2000; Pierce et al. 2015; Staats et al. 2016). Monitoring systems provide a means for the principals (employers) to obtain information on the actions of agents (contractors), thus mitigating information asymmetry (Zhao 2008). In online labor markets, monitoring enables the employers to check the project progress effortlessly and learn about the contractors' effort level by directly observing the monitoring records (Lin et al. 2016). The effectiveness of monitoring in increasing the contractors' effort and subsequently leading to better performance has been repeated shown in multiple offline employment contexts, such as, the trucking industry (Hubbard 2000), schools (Duflo et al. 2012), restaurants (Pierce et al. 2015), and hospitals (Staats et al. 2016).

Reputation systems, on the other hand, provide signals of contractors' future performance based on their past performance as evaluated by previous employers (Banker and Hwang 2008). Ample literature suggests that the monitoring system can also mitigate moral hazard problems (Drago 1991; Duflo et al.

2012; Hubbard 2000; Pierce et al. 2015). Notably, closely related to this study, prior literature (Lin et al. 2016) indicates that the effectiveness of reputation depends on contract type, such that time-based contracts benefit less from reputation systems.

However, most prior studies analyze monitoring systems and reputation systems separately, without considering how they interact with each other in mitigating information asymmetry and whether they are substitutes or complements to each other (Demiroglu and James 2010; Diamond 1991). A key contribution of this study is that we recognize that monitoring systems and reputation systems mitigate information asymmetry through different mechanisms. By their nature, monitoring systems are effective in addressing moral hazards but much less effective in addressing adverse selection, while reputation systems are more effective in addressing adverse selection. As a result, monitoring systems may substitute reputation systems in mitigating moral hazards.

2.3. Contract Type

Two prevalent contract types dominate online labor markets, namely, fixed-price contracts and time-based contracts[2] (Banerjee and Duflo 2000). Fixed-price contracts are outcome-driven, whereby the agent gets a fixed payment according to the amount of output (Chen and Bharadwaj 2009; Mani et al. 2012). On the other hand, time-based contracts, also known as cost-plus contracts, require that the payment is calculated based on the agent's efforts and time in the work process (Clemons and Chen 2011; Mani et al. 2012). From the perspective of transaction cost economics, the decision of contract type depends on the tradeoff between potential renegotiation costs of fixed-price contracts and the cost-efficiency losses of time-based contracts (Susarla and Krishnan 2014). In comparison, 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); whereas, time-based contracts entail higher ex-post monitoring and auditing costs (Bajari and Tadelis 2001; Dey et al. 2010; Susarla and Krishnan 2014).

[2] In Banerjee and Duflo's paper (2000) the counterpart of fixed-price contracts are termed "time and materials contracts." Since the costs are measured by the agent's efforts and time in the projects, time and materials contracts are herein refer to "time-based contracts" in online labor platforms.

In terms of incentive alignment, for fixed price contracts, contractors are contracted for the final outcome of the projects, which provides sufficient motivations for them to spend efforts and time on the projects with efficiency. Thus, both adverse selection and moral hazard problems in the "buy" choice are less severe (Fama 1991). However, for time-based contracts, contractors' payments are based on the amount of time they have spent on the projects. Contractors might engage in misrepresentation of their capability as well opportunistic "shirking" behavior, especially when their capability and efforts could not be observed (Zhao 2008). Therefore, both adverse selection and moral hazard problems usually are more severe than in the fixed price contracts. Meanwhile, a time-based contract could provide more flexibility and yield 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-based contracts as these are the only two contract type options in major online labor markets.

3. Hypotheses Development

In this section, we propose three hypotheses. First, we propose a substitution effect between monitoring systems and reputation systems in online platforms. Second, we propose the role of monitoring systems in lowering entry-barriers for contractors and intensifying market competition. Finally, we propose the effect of monitoring systems in reducing employers' willingness to pay reputation premium and, correspondingly, increasing employers' surplus.

3.1. Substitution between Monitoring and Reputation

Monitoring systems and reputation systems alleviate moral hazard problems via different mechanisms. On the one hand, monitoring systems convert contractors' private information about their actual effort into procedural tractable records that an employer could observe (Lin et al. 2016). As such, they lower the probability of "shirking" going unnoticed, and in turn increase contractors' effort (Drago 1991). On the other hand, reputation systems facilitate pre-contractual screening of contractors (Banker and Hwang 2008; Pavlou and Dimoka 2006). They also serve as a sanctioning mechanism by imposing a potential penalty on shirking behavior by reducing probability of landing contracts in the future (Dellarocas 2006; Moreno and Terwiesch 2014).

Given that monitoring systems enable employers to directly observe contractors' effort, we argue that they diminish employers' reliance on reputation systems to deter shirking behavior. Without monitoring systems, employers have to rely on contractors' past reputation to extrapolate the expected effort level of contractors for the focal project (Kokkodis and Ipeirotis 2015). However, the extrapolation could be inaccurate for a number of reasons. First, reputation is based on reporting of previous employers. As a contractor's true effort level is not observed, the reporting could be inaccurate (Pallais 2014). Second, even if the reporting of past experience were accurate, past effort level does not guarantee future effort level on a particular project. A contractor might be overstretched by engaging in multiple projects, or could become more strategic or opportunistic over time with experience. With IT-enabled monitoring systems, employers can verify a contractor's actual level of effort based on directly observed monitoring records and, if needed, condition employment based on observed level of effort. In sum, monitoring systems allow a more direct and precise observation of contactor effort than what can be inferred from a reputation system, and as such, they, at least partially, substitute reputation systems.

Second, monitoring systems reduce cost uncertainty. Monitoring systems allow employers to observe contractors' current performance and progress, thereby facilitating meaningful interactions between employers and contractors. Without monitoring systems, employers prefer contractors with high-reputation not only because of their higher expected effort, but also because of lower cost uncertainty (variance) (Mani et al. 2012). Since reputable contractors are expected to be more experienced and more capable, they are less likely to cause budget overrun in time-based projects. With monitoring systems, employers are informed in real time about contractors' performance (e.g. the timely update of project progress, the whole workflow, the contractors' work habits). They can improve contractors' performance by providing feedback based on the automatically archived log files. Therefore, irrespective of the contractors' reputation, employers can reduce cost uncertainty by monitoring contractor performance, which reduces the disparities between the high-reputation contractors and low-reputation contractors. In summary, monitoring systems lower employers' concerns about the contractors' shirking behavior and cost uncertainty, and thus substitute for the signaling effect of reputation systems. Therefore, we propose:

H1: *After the implementation of an IT-enabled monitoring system, employers will place less emphasis on contractors' reputation for time-based projects.*

3.2. Monitoring, Entry Barrier and Contractor Competition

Now we consider the effect of IT-enabled monitoring systems on the contractor (supply) side. Before the implementation of monitoring systems, employers rely on reputation systems to mitigate moral hazard, especially for time-based contracts. Knowing employer's concerns and preference, novice contractors avoid bidding on time-based contracts as their likelihood of success will be slim. Consequently, time-based contracts are dominated by contractors with a good reputation (Pallais 2014). After the implementation of IT-enabled monitoring systems, employers can observe contractors' effort from the procedural track records rather than rely on reputation systems. Therefore, the barrier to entry due to accumulated reputation prominently drops (Demiroglu and James 2010) and novice contractors are more likely to bid for those time-based contracts. Therefore, we propose:

H2a: *After the implementation of an IT-enabled monitoring system, more bidders will compete in time-based projects.*

Monitoring systems not only increase the number of low experience bidders, but also entice employers to hire more low experience bidders. This is consistent with the logic of the substitution relationship between monitoring systems and reputations we explained earlier, and the subsequent change in employer preference. As the difference between the contractors with little platform experience and those with extensive experience narrows, employers are more likely to hire low experience contractors. Prior to the implementation of monitoring systems, reputation serves as an important signal that facilitates the differentiation of contractors (Brynjolfsson et al. 2004; Pallais 2014). With the monitoring systems implemented that allows direct observation of contractors' effort, the signaling value of reputation decreases. We thus expect that monitoring systems will intensify supply-side competition by attracting a large number of low experience contractors. Therefore, we propose:

H2b: *After the implementation of an IT-enabled monitoring system, there will be a higher percentage of contractors with no platform experience in time-based projects, conditional on number of contractors bidding for the projects.*

3.3. Monitoring, Reputation Premium and Employer Surplus

As we mentioned earlier, without monitoring systems, reputation serves as an important signal to facilitate the differentiation of contractors (Brynjolfsson et al. 2004; Pallais 2014). With monitoring systems, the signaling value of reputation decreases as employers gain a more effective tool to mitigate moral hazard. Given the substitution effect between monitoring systems and reputation, employers will be less willing to pay the price premiums for reputation. Allgulin and Ellingsen (2002) support this argument, wherein authors found that when the monitoring system is precise, efficient and low-cost, 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 can only be paid at his corresponding reservation wage. Similarly, 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), also lends support to our argument. Therefore, after the implementation of IT-enabled monitoring systems, it is less likely for employers to pay price premiums for time-based projects. Accordingly, as employers no longer need to pay as high reputation premiums to overcome the moral hazard problems, we expect that the employer could reap a higher surplus after a platform implements a monitoring system. Therefore, we propose:

H3a: *After the implementation of an IT-enabled monitoring system, employers are less willing to pay a price premium for time-based projects.*

H3b: *After the implementation of an IT-enabled monitoring system, employers will reap a higher surplus.*

4. Research Context

4.1. Data Source

Our data is obtained from www.freelancer.com (*Freelancer*), one of the largest online labor market platforms. In *Freelancer*, an employer can post a project with 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 (Figure 1-a). If the unit of the project budget is dollars per hour, it means that the employer will write a time-based contract and then the contractor will get paid for his or her hourly work (Figure 1-b).

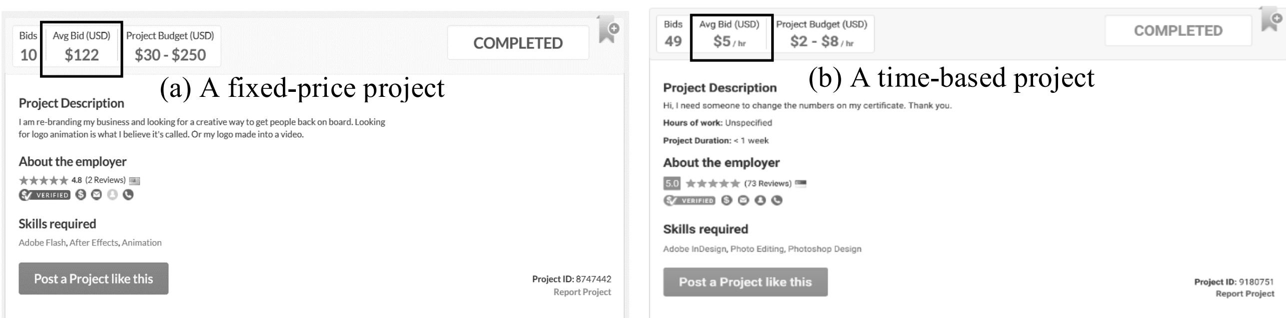

Figure 1. Screenshots of the Webpages of a Fixed-price Project vs a Time-based Project

Typically, a project is open for bidding for a week and any contractor who is interested can bid to win the project. At the end of the bidding period, the employer review bidders' basic information, such as their nationality, skills, self-introduction, bid amount, average hourly wage, etc. Moreover, *Freelancer* also provides bidders' previous project experience and their former employers' ratings and comments. Additionally, filtering tools are also available and enable the employer to sort bidders according to the number of reviews, average rating, etc. Once the employer finds the bidder who satisfies his or her minimum requirements, the employer could award that contractor the contract which includes detailed project requirements, contract price, and project schedule.

4.2. Sample and Variables

We obtained a unique archival dataset from *Freelancer* that includes 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, to reduce possible selection bias and the relationship between various pretreatment covariates and the contract choice, we matched fixed-price and time-based projects (Ho et al. 2007) based on distributions of important covariates suggested by the previous literature (Table 1) using propensity score matching (PSM). Our final sample includes 17,827 fixed-price projects and 8,563 time-based 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, contract type, number of bidders and average bid price, winning contractor and so on); 2) contractor-level information (i.e. ratings, the amount of reviews, average hourly wage, etc).

Table 1. Definitions and Summary Statistics of Project-level Variables

Variable	**Variable definition**	Mean	SD	Min	Max
Budget_min	The minimum of project budget set by the employer	93.46	933.14	2.00	75000.00
Budget_max	The maximum of project budget set by the employer	262.34	2181.88	2.00	150000.00
Bid_min	The minimum of bid prices for each project	112.08	997.66	2.00	75000.00
Bid_max	The maximum of bid prices for each project	618.99	13822.15	2.00	1666666.00
Time-based	A dummy variable(0,1), =1 if the project is a hourly project; =0 if the project is a fixed-price project	0.32	0.47	0.00	1.00
Bid_count	Total number of bids received by the project	13.22	16.87	1.00	196.00
Bid_avg	Average bid price for each project	216.41	2352.63	2.00	208463.00
Paid_amount	Amount of dollars paid by the employers after the project was completed	240.99	1659.12	1.00	135000.00
Project_title_length	Number of characters in the project title	5.18	3.12	1.00	43.00
Project_desc_length	Number of characters in the project review posted by the employer after the project has ended	14.44	5.35	1.00	27.00
NDA	A dummy variable(0,1), =1 if the employer and the	0.00	0.06	0.00	1.00

	bidder have assigned a NDA contract to protect the employer's right				
Featured	A dummy variable(0,1), =1 if the project is a featured project	0.01	0.08	0.00	1.00
Nonpublic	A dummy variable(0,1), =1 if the project is an non-public project	0.01	0.11	0.00	1.00
Fulltime	A dummy variable(0,1), =1 if the project is an fulltime project	0.00	0.01	0.00	1.00
Language_en	A dummy variable(0,1), =1 if the project is described in English	0.96	0.20	0.00	1.00
Currency_us	A dummy variable(0,1), =1 if the project budget is measured in dollars (the currency of US)	0.78	0.42	0.00	1.00
Software	A dummy variable(0,1), =1 if this is a software project	0.24	0.43	0.00	1.00
Design	A dummy variable(0,1), =1 if this is a design project	0.07	0.26	0.00	1.00
Writing	A dummy variable(0,1), =1 if this is a writing project	0.20	0.40	0.00	1.00
Marketing	A dummy variable(0,1), =1 if this is a marketing project	0.07	0.25	0.00	1.00
Data_entry	A dummy variable(0,1), =1 if this is a data-entry project	0.05	0.22	0.00	1.00
Translation	A dummy variable(0,1), =1 if this is a translation project	0.05	0.22	0.00	1.00

Notes: The estimation results remain identical if we delete 1% or 5% outliers based on the key variables.

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
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
Completion_rate	Percentage of awarded projects which were successfully completed	0.87	0.21	0.02	1.00
User_norating	A dummy variable(0,1), =1 if the contractor doesn't have any reviews written by employer(s)	0.85	0.36	0.00	1.00
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
Local_freelancer	A dummy variable(0,1), =1 if the contractor works for offline jobs nearby	0.003	0.06	0.00	1.00
Preferred_freelancer	A dummy variable(0,1), =1 if the contractor gets a special Preferred *Freelancer* Badge because their workmanship and customer service abilities	0.03	0.18	0.00	1.00

5. Research Methodology

5.1. Identification: A Quasi-Natural Experiment

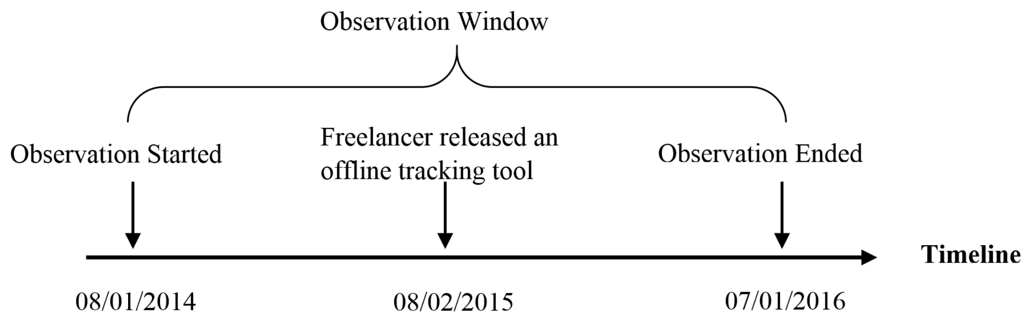

Figure 2. A Timeline of Our Observation Window

As mentioned before, information asymmetry problem particularly plagues time-based projects. Because the risk of a time-based project is mainly allocated to the principal (the employer), there is a tradeoff between monitoring costs and the uncertainty or risk of the outcome for the employer (Mani et al. 2012). On August 2nd, 2015, *Freelancer* released an offline tracking tool[3]. Such an IT artifact serves as a control tool that allows employers to effortlessly monitor the freelancers. Specifically, this monitoring system randomly takes screenshots every ten minutes, and tracks the amount of minutes the contractor has spent. Therefore, it can effectively 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 the 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 time-based projects. Taken together, this monitoring system alleviates the concerns about losing track of the progress for time-based projects and effectively lowers monitoring costs. The tool better serves the interests of the employers of time-based projects, because there are higher ex-post monitoring costs and risk in time-based contracts (Bajari and Tadelis

[3] https://www.freelancer.com/community/articles/offline-tracking-now-available

2001; Dey et al. 2010; Susarla et al. 2009; Susarla and Krishnan 2014) and such risk is mainly allocated to employers. More importantly, since the monitoring system is mandatory for time-based contractors, it is reasonable to assume that employers adjust their hiring preferences accordingly. Therefore, given the more essential need for effective monitoring tools and the higher likelihood of a strategic adjustment for employers of time-based projects, the monitoring system should have an effect on time-based projects but not fixed-price projects. Therefore, we use fixed-price projects as the control group and examine the effect of the IT-enabled monitoring system on time-based projects relatively to fixed-price projects.

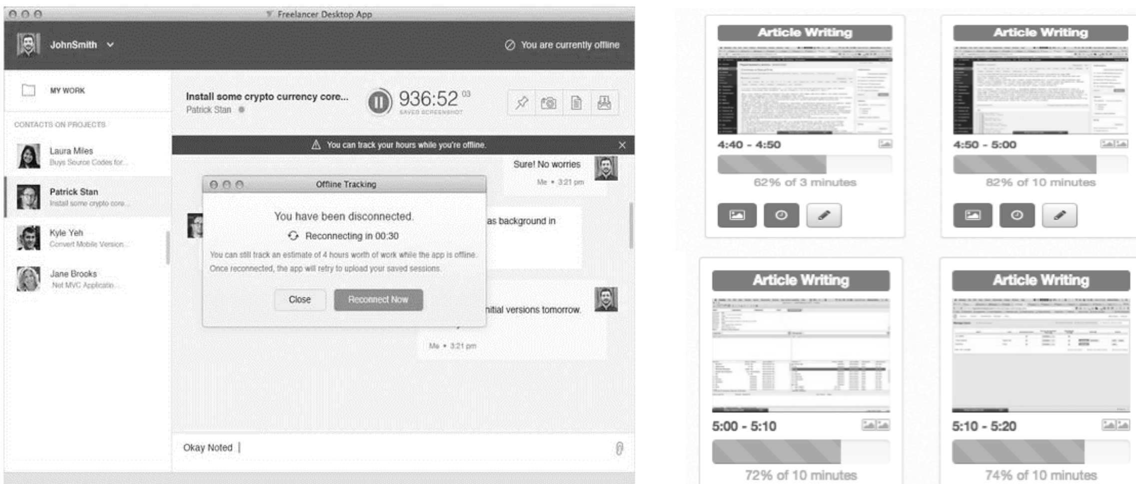

Figure 3. A Screenshot of the *Freelancer* Application with the Enhanced Tracking Feature

5.2. Econometric Analyses

5.2.1. Propensity Score Matching (PSM)

In order to satisfy the common support requirement and reduce the potential heterogeneity across time-based projects and fixed-price projects, we deploy the propensity score matching method to generate a more comparable sample (Hong et al. 2015; Lin et al. 2016; Xu et al. 2016; Xue et al. 2010). First, according to the previous literature (Banerjee and Duflo 2000; Gopal and Sivaramakrishnan 2008; Lin et al. 2016; Roels et al. 2010), we identify project characteristics and employer characteristics which might correlate with the contract type (Table 3). Then we predict the propensity score and match the fixed-price projects with time-based projects. Furthermore, we also compare the distribution of propensity score and a balance check of all the observed covariates (Xu et al. 2016). As Table 4 shows, the matching process has dramatically reduced the bias and the means of covariates are not significantly different after the matching process. Our final sample includes 17,827 fixed-price projects and 8,563 time-based projects.

Table 3. Pretreatment Covariates Used to Adjust for Potential Selection Bias

Covariates	Variable	Variable Description
Task complexity, risk of project (Gopal and Sivaramakrishnan 2008)	Project type dummies	Dummy variables for various project categories, including software, design, marketing, data-entry, etc.
To what extent outcome is sensitive to agent's or principal's effort (Roels et al. 2010)	NDA dummy	A dummy variable(0,1), =1 if the employer and the bidder have assigned a NDA contract to protect the employer's right
Project Title Length (Lin et al. 2016)	Project_title_length	Number of characters in the project title
Project Description Length (Lin et al. 2016)	Project_desc_length	Number of characters in the project description
Project Size (Lin et al. 2016)	Paid_amount	The amount of dollars paid by the employers after the project was completed
External environment (Banerjee and Duflo 2000)	Project_submit_month	The month dummy, which is used to control all the changes in economic cycles, platform policy, labor supply, and so on
Client Level of Knowledge(Lin et al. 2016)	Employer_tenure_month; Employer_overall_rating	Employer's tenure at *Freelancer* measured in months, which is also a proxy of employers' experience and relevant knowledge

Table 4. Balance Check for Propensity Score Matching[4]

Variable	Sample	Mean		%bias	% reduced	t-test	
		Treated	Control		|bias|	t	p>|t|
Project_desc_length	Unmatched	14.300	14.81	-9.600		-7.940	0.000
	Matched	14.300	14.23	1.200	87.30	0.800	0.424
Title_length	Unmatched	5.181	5.202	-0.700		-0.580	0.561
	Matched	5.181	5.152	0.900	-32.20	0.630	0.527
NDA	Unmatched	0.003	0.005	-3.000		-2.290	0.022
	Matched	0.003	0.004	-2.000	31.40	-1.420	0.156
Nonpublic	Unmatched	0.014	0.013	1.000		0.850	0.397
	Matched	0.014	0.014	0.100	85.80	0.100	0.924
Software	Unmatched	0.235	0.265	-7.000		-5.660	0.000
	Matched	0.235	0.238	-0.600	91.30	-0.420	0.678
Design	Unmatched	0.065	0.084	-7.300		-5.860	0.000
	Matched	0.065	0.064	0.100	98.90	0.060	0.952
Writing	Unmatched	0.205	0.198	1.800		1.450	0.146

[4] We match fixed-price projects with time-based projects by using the Nearest Neighbor (4) matching method.

	Matched	0.205	0.200	1.100	36.40	0.750	0.451
Marketing	Unmatched	0.071	0.065	2.600		2.130	0.033
	Matched	0.071	0.069	0.800	69.20	0.520	0.600
Data-entry	Unmatched	0.053	0.050	1.100		0.920	0.356
	Matched	0.053	0.052	0.200	83.20	0.120	0.901
Translation	Unmatched	0.051	0.049	0.900		0.740	0.462
	Matched	0.051	0.049	1.000	-16.10	0.700	0.485
Employer_tenure_month	Unmatched	39.570	38.820	2.700		2.120	0.034
	Matched	39.570	39.240	1.200	55.70	0.800	0.423
Employer_overall_rating	Unmatched	4.886	4.885	0.200		0.150	0.878
	Matched	4.886	4.881	0.800	-347.7	0.570	0.571

Notes: a. Results of Nearest Neighbor (4) Matching Method are presented. We also conducted robustness checks with other matching algorithms in the additional analysis section. The result is qualitatively consistent. b. All t-tests of various month dummies are not significant. Results of month dummy variables are suppressed for brevity.

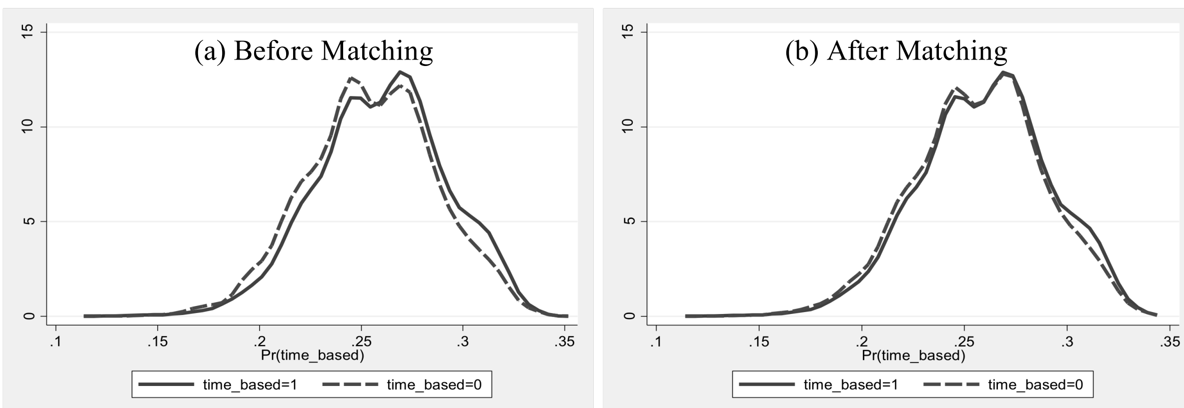

Figure 4. Distribution of Propensity Scores for Time-based Projects and Fixed-price Projects

5.2.2. Estimating Employer Preference

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.

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

where X_{ij} represents 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 and employer characteristics, such as project budget, the length of title, the employer's tenure measured in months, etc. B_j means the bidders' related characteristics, such as bidders' ratings, whether he or she is from a developed country and so on[5]. 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 (Heckman and Snyder 1997; Lin et al. 2016) 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.

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

$$U_{ij} = \alpha Price\_Premium_{ij} \times After_i \times Time\_based_i + \beta Bidder\_Rating_j \times After_i \times Time\_based_i$$
$$+\gamma P_i + \delta Controls + \varepsilon_{ij} \tag{3}$$

where α is a 4×1 matrix of coefficient estimates and each row corresponds to one of the following four groups: 1) $After = 0, Time\_based = 0$; 2) $After = 1, Time\_based = 0$; 3) $After = 0$, $Time\_based = 1$; 4) $After = 1, Time\_based = 1$. We will discuss coefficient β in the next section.

5.2.3. Principal Component Analysis for Dimension Reduction

Freelancer has a multi-dimensional reputation system during our observational period, which presents multiple indicators prominently shown when the cursor is on the contractor profile. As high correlations were observed among some rating dimensions, we first employed the Principal Component Analysis (PCA) for dimension reduction, which generated two principal components by using 1 as the cutoff for eigenvalues, as shown in Table 5. The first component (PC1) comprises dimensions of ratings entered by the employers after the transaction, which largely indicate a contractor's capability. The second component (PC2) is contractors' project completion rate, which was computed by the system based on the percentage of projects completed for all contracted projects. This component largely indicates a contractor's effort at work because project incompletion is typically due to insufficient effort. Therefore,

[5] Based on our review data, a contractor's average rating is almost constant during our observational period. Therefore, we didn't treat the contractor rating as a time-variant variable here. We will include the time-variant contractor ratings into the model in future research.

we label PC1 as "Quality of Contractor" and PC2 as "Effort at Work". This label assignment was confirmed by interviewing a number of *Freelancer* employers on how they perceive the reputation signals of contractors. We report the item loadings and Eigenvalues/variance explained in Table 5 and Table 6, respectively. Note that there are two more reputation signals (on-budget and on-time) that form a third component, however, the eigenvalue was only 0.72, way below a common threshold of 1. Therefore, we did not retain that component.

Table 5. Item Loadings of Three Principal Components

Variable	Eigenvectors	
	1	2
Quality	0.45	–0.01
Communication	0.44	–0.01
Expertise	0.45	–0.02
Professionalism	0.45	–0.01
Hire-again rating	0.45	–0.01
Completion Rate	0.03	1.00

Table 6. Eigenvalues and Variance Explained by Two Principal Components

Name	Component	Eigenvalue	Difference	Proportion Of variance explained	Cumulative variance explained
Quality of Contractor	1	4.57	3.57	0.76	0.76
Effort at Work	2	1.00	0.82	0.17	0.93

One direct implication of this dimension reduction analyses is that the coefficient β in the Equation (3) is a 4×2 matrix of coefficient estimates. Each of row represents the coefficient estimates of two components for each group. Additionally, as suggested by the previous literature (Lin et al. 2016), in order to control for the unobserved heterogeneity among contractors in different projects, we limit our analysis to projects wherein contractors have also bided for other type of projects (dual-typed bidders) during the observation period.

5.2.4. Difference-in-Difference Models

To evaluate Hypothesis 3b, we create a unit-free employer surplus measure, Employer_Surplus, which denotes 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.

We also construct a price premium measure evaluated at the awarded bid price, $Award\_BidPrice\_Premium_i$, to assess the price premiums achieved by contractors. If we find $Award\_BidPrice\_Premium_i$ increases after the implementation of monitoring systems, then on average, the price premium obtained by the contractor side is higher than before.

$$Employer\_Surplus_i = \frac{Budget\_Max_i - Award\_BidPrice_i}{Budget\_Max_i} \tag{4}$$[6]

$$Award\_BidPrice\_Premium_i = \frac{(Award\_BidPrice_i - Bid\_Min_i)}{Bid\_Min_i} \tag{5}$$

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. 2004):

$$Bid\_Count_i = \alpha + \beta_1 After_i + \beta_2 Time\_based_i + \beta_3\, After_i \times Time\_based_i + v_i + \varepsilon_i \tag{6}$$

$$Award\_BidPrice\_Premium_i = \alpha + \beta_1 After_i + \beta_2 Time\_based_i + \beta_3\, After_i \times Time\_based_i + v_i + \varepsilon_i \tag{7}$$

$$Employer\_Surplus_i = \alpha + \beta_1 After_i + \beta_2 Time\_based_i + \beta_3\, After_i \times Time\_based_i + v_i + \varepsilon_i \tag{8}$$

In the models, the dependent variable is the total number of bids for each project i, Bid_Count_i. $After_i$ is the dummy variable indicating whether the project is posted after August 2nd, 2015.[7] The

[6] Based on the summary statistics of our sample, the mean of awarded price is 160.65 dollars. However, the mean of the maximum of bids among our sample is 618.99 dollars, which implies the maximum of bids is not reasonable proxy for employer's willingness-to-pay (WTP). Moreover, we found that there are 35.35% projects whose awarded prices are equal to the maximums of budgets. Hence, we believe that the maximums of budget is a more reasonable measure than the maximum of bid prices.

[7] The IT-enabled monitoring system has been introduced since August 2nd, 2015. Since this monitoring system is imperative for all the time-based contractors and usually there is a time lag between project submission date and award date, we consider the $After_i$ of those projects posted after August 2nd is equal to 1. We also tried to label $After_i$ 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.

contract type is indicated by $Time\_based_i$, which equals to 1 if the project is an time-based project and 0 if it employs fixed-price contract. The interaction term between $After_i$ and $Time\_based_i$ (β_3) thus identifies the effect of the implementation of the IT-enabled monitoring system on time-based projects relative to fixed-price projects. To control for the heterogeneity of projects, we also add other project characteristics and employer characteristics (v_i) into the DID model and ε denotes the error term.

5.3. Empirical Results

5.3.1. Employer Preference Estimation

Based on the result of the linear fixed-effects model with a DID set up (Table 7),[8] 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 7 attested, for fixed-price projects, the employer preference shows minor increase (from 0.009 to 0.012), however, for time-based projects, the employer 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 time-based projects.

To further check our argument that IT-enabled monitoring substitutes for reputation signals about effort at work, we also test whether the change in $\beta_{Quality\_of\_contractor}$, $\beta_{Effort\_at\_work}$ and $\beta_{Price\_Premium}$ for time-based projects before and after the implementation of monitoring systems are statistically significant, respectively.

[8] The result of Conditional Logit Model is highly consistent with the estimation result of the linear Fixed-Effects models. As we mentioned, we opt for the linear model for straightforward interpretation of interaction effects.

Table 8 shows that the change in $\beta_{Quality\_of\_contractor}$ is not significant. However, $\beta_{Effort\_at\_work}$ significantly decreased (F(1, 25379)=4.26, p-value= 0.039) when monitoring systems were implemented. In line with this, the magnitude of $\beta_{Price\_Premium}$ also significantly increased (F(1, 25379)= 4.96, p-value=0.026). Overall, the findings suggest that there exists a substitution effect between the monitoring system and the reputation system, and employers of time-based projects become more sensitive to bidding price after the implementation of the monitoring system.

Table 7. Estimation Results of the Fixed-Effects Model

Variable	Sub-group	Project_awarded
Quality_of_contractor	Fixed_price, Before	0.002***(0.000)
	Fixed_price, After	0.002***(0.001)
	Time_based, Before	0.002***(0.000)
	Time_based, After	0.002***(0.001)
Effort_at_work	Fixed_price, Before	0.009***(0.001)
	Fixed_price, After	0.012***(0.001)
	Time_based, Before	0.013***(0.002)
	Time_based, After	0.008***(0.002)
Price_premium	Fixed_price, Before	–0.007***(0.001)
	Fixed_price, After	–0.003***(0.001)
	Time_based, Before	–0.002** (0.001)
	Time_based, 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
R-square overall		0.154

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 time-based 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.

Table 8. Tests for the Change in Coefficients of Attributes

Null Hypothesis	F Statistic	Prob>F
$\beta(Quality, Time\_based, before) = \beta(Quality, Time\_based, after)$	0.07	0.797
$\beta(Effort, Time\_based, before) = \beta(Effort, Time\_based, after)$	4.26	0.039
$\beta(Price\_premium, Time\_based, before) = \beta(Price\_premium, Time\_based, after)$	4.96	0.026

Although the linear model helps to ensure consistency of the estimation results and provides a meaningful interpretation of coefficients for the interaction terms (Greenwood and Agarwal 2015), linear probability models are subject to heteroscedasticity and sometimes generate predicted probability outside the range of [0,1] (Horrace and Oaxaca 2006). We took two approaches to address the potential limitation. First, we evaluate the significance level based on the robust standard errors. Second, following Horrance and Oaxaca (2006) and Greenwood and Agarwal (2015), we check the range of predicted probabilities. The result shows that 99.98% of our observations fall within the interval of [0,1], which suggests that the invalid predicted probability is not a big concern for our preference estimation model.

5.3.2. Bidding Behavior and Entry Barrier

As employers become less willing to pay high price premiums to reputable bidders, we expect that the time-based project market will be see lower entry barriers, more competitive and attracts more bids. According to the result in Column (1) of Table 9, 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. Hence, this result alleviates our concerns about a weak control group[9]. This increase in Bid_Count might result from multiple reasons, such as increase in 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

[9] The positive coefficient of "After" rules out the alternative explanation that the observed increase in number of bidders in time-based projects might come from the less number of bids for fixed-price projects.

system was available, the increase in Bid_Count in time-based projects is larger than that of fixed-price projects. The finding that the interaction term is 0.160 implies that the number of bids increases 17.4%.[10] Therefore, H2a is supported.

In order to further assess the argument that monitoring systems reduce entry barrier for low-reputation bidders for time-based projects, we compare the number of low-reputation bidders awarded with time-based contracts before and after the implementation of the IT enabled monitoring system. We create a binary variable, "norating", which denotes whether the contractor has received any employer-entered reviews before (Lin et al. 2016). Then we use the percentage of contractors (Perc_norating) who haven't accumulated any reputation records from employers (Lin et al. 2016), as a proxy of the entry barrier in terms of reputation. Assuming that contractors and employers are rational, we expect not only a higher percentage of low-reputable contractors (those contractors with no reviews) submitting their bids for time-based contracts, but also a higher probability for low-reputable contractors to win time-based contracts. Furthermore, we also control for project characteristics which are likely to correlate with contractors' bids, such as project budget, the employers' ratings and tenure, etc. As the estimation result in Table 9 shows, the partial coefficient between the Time_based dummy and the percentage of bidders with no ratings is only 0.008 before *Freelancer* implemented the monitoring system. But, ceteris paribus, the partial coefficient increases to 0.028, after the implementation of monitoring systems. This increase implies that other things equal, the percentage of contractors with no ratings increases more in time-based projects than fixed-price projects. Specifically, based on the result of marginal effect estimates, it increases 9.1%. The fact that relatively more participation of inexperienced contractors validates our argument that the implementation of monitoring systems lowers the entry-barrier for time-based projects (the treatment group). Therefore, H2b is also supported. Overall, our result regarding the number of bids

[10] Based on the estimation results in Column (2) of Table 9, before the implementation of monitoring systems, the partial correlation between Time_based dummy and Log_bid_count 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% Since o.16 is close to zero, we omit the ½*Var($\hat{\beta}$) in the calculation (Halvorsen and Palmquist 1980; Zhang and Zhu 2011).

and the percentage of bidders without ratings is consistent with our hypothesis that monitoring systems will attract more contractors by lowering the entry barrier.

Table 9. Estimation Results of the DID Models

Model	(1)	(2)
Dependent Variable	Log_bid_count	Perc_norating
After	0.088*** (0.021)	0.015*** (0.003)
Time_based	−0.023 (0.023)	0.008** (0.004)
Time_based * After	0.160*** (0.032)	0.020*** (0.005)
Log_paid_amount	−0.026*** (0.007)	−0.010*** (0.001)
Log_bid_count		0.092*** (0.001)
Log_budget_max	0.155*** (0.009)	0.001 (0.001)
Language_en	0.291*** (0.030)	−0.013** (0.005)
Log_title_length	0.118*** (0.014)	0.018*** (0.002)
Log_preview_desc_length	0.326*** (0.013)	0.010*** (0.002)
Log_employer_overall_rating	0.004 (0.013)	−0.000 (0.002)
Log_employer_reviews_count	−0.027*** (0.006)	−0.000 (0.001)
Log_employer_tenure_month	0.033*** (0.012)	0.005** (0.002)
Employer_developed	0.084*** (0.017)	−0.059*** (0.003)
Intercept	−1.233*** (0.068)	0.049*** (0.011)
N	26,390	26,390
Adj R-squared	0.460	0.446

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. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

5.3.3 Price Premiums and Employer Surplus

Given the more bids for time-based projects, according to the Column (1) of Table 10, we find that the interaction term in the Equation (7) is significantly negative, which suggests that on average employers paid lower price premiums to the awarded contractors. Based on the marginal effect of the interaction term at the mean values of all the covariates, the price premiums paid by employers of time-based projects decline 30.1%. Hence, Hypothesis 3a is also supported. In line with this declining trend of price premiums, the interaction term in the Equation (8) is significant and positive. 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%. On the whole, results of all the three DID models lend support to Hypothesis 2a, Hypothesis 2b, Hypothesis 3a and 3b.

Table 10. Estimation Results of the DID Models about Price Premium and Employer Surplus

Model	(1)	(2)
Dependent Variable	Price_premium	Employer_surplus
Time_based	–0.333***(0.028)	0.277***(0.012)
After	0.112***(0.031)	–0.017* (0.009)
Time_based *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.

5.4. Robustness Checks

5.4.1. Alternative Matching Methods

In order to balance the distribution of observed characteristics across the treatment and control group, we conduct the Propensity Score Matching to generate the matched sample. However, to verify the stability of our results, we employ multiple matching algorithms to rerun the DID models for price premiums evaluated at the awarded bid prices, number of bids, bidders with no ratings, and employer surplus. The results of One-to-one Matching, Kernel Matching, Radius Matching process are consistent with our main results (Table 11). Therefore, our results are robust to multiple matching specifications.

Table 11. Estimates of ATT of the Number of Bids

Model	(1)	(2)	(3)	(4)
Dependent Variable	Perc_norating	Log_bid_count	Price_premium	Employer_surplus
One-to-one Matching, with replacement	0.016* (0.009)	0.098***(0.034)	−0.229***(0.053)	0.037** (0.017)
Radius Matching, caliper(0.10)	0.022***(0.005)	0.130***(0.023)	−0.135***(0.028)	0.028** (0.012)
Kernel Matching, caliper(0.10)	0.022***(0.005)	0.126***(0.023)	−0.137***(0.028)	0.028** (0.012)

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

5.4.2. Alternative Explanations

Even though we found that employer surplus of time-based projects increases after the implementation of online monitoring systems, it is possible that this is driven by factors other than the change of employer preference. An alternative explanation is that contractors require lower hourly salaries than they did before. In order to assess the possibility of 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 change in the employer surplus of time-based projects with respect to the average bid prices is not significant. However, the incremental employer surplus of time-based 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 lower bids.

Table 12 DID Estimations of the Impact of the IT-enabled Monitoring System on Employer Surplus

Model	(1)	(2)	(3)	(4)
Dependent Variable	Employer_surplus corresponding to _Bid_Avg	Employer_surplus corresponding to _Award_BidPrice	Employer_surplus corresponding to _Bid_Avg_New	Employer_surplus corresponding to _Award_BidPrice
Time_Based	–2.706(3.231)	0.277***(0.012)	0.531***(0.024)	0.446***(0.021)
After	0.260(0.171)	–0.017* (0.009)	–0.005 (0.016)	–0.014 (0.013)
Time_Based *After	2.121(2.230)	0.030** (0.015)	0.025 (0.022)	0.040* (0.023)
Log_paid_amount	1.389(1.435)	–0.127***(0.005)	–0.118***(0.009)	–0.183***(0.008)
Log_bid_count	0.232(0.255)	0.048***(0.004)	0.001 (0.008)	0.037***(0.007)

Log_budget_max	–0.799(0.969)	0.193***(0.006)	0.235***(0.008)	0.278***(0.009)
Log_title_length	–1.224(1.210)	0.012* (0.007)	–0.007 (0.008)	0.011 (0.009)
Log_project_desc_length	–1.471(1.394)	0.012** (0.006)	–0.020** (0.010)	0.030** (0.015)
Log_employer_overall_rating		0.006 (0.004)	–0.006 (0.007)	0.005 (0.006)
Log_employer_reviews_count		–0.012***(0.003)	0.005 (0.005)	–0.013***(0.004)
Log_employer_tenure_month		0.007 (0.006)	0.015 (0.011)	0.011 (0.008)
Employer_developed		0.031***(0.009)	0.063***(0.012)	0.074***(0.013)
Intercept	3.094(3.636)	–0.364***(0.030)	–0.560***(0.055)	–0.578***(0.064)
N	26390	26390	17319	17319
Adj R-squared	0.000	0.160	0.093	0.161

Notes:
a. In Model (1), the employer surplus is calculated with respect to the original average bid price, Bid_Avg. Bid_avg= sum(Bid_Price)/ Bid_Count. Model (2) uses the awarded bid price to calculate the employer surplus, which is the sample as our main result. The result of Model (1) and (2) are computed based on the whole matched sample. b. Because the average bid price is disproportionately influenced by the maximum of bid prices, we create a new measure of the average bid price by ruling out the maximum and the minimum of bid prices if the number of bidders is greater than two, Bid_Avg_New. Bid_Avg_New = [sum(Bid_Price) – Bid_Max – Bid_Min]/(Bid_Count -2). In Model (4), we still use the awarded bid price to calculate the employer surplus. Since this new measure requires that the number of bids is greater than two, we limit our sample to those projects with more than two bids. Therefore, 9071 projects are dropped because their number of bids is less or equal to two. c. Dummy variables for various project categories, such as software, design, marketing, data-entry, are included. The results of these dummies are suppressed for brevity. d. 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. e. Robust standard errors are reported in parentheses. f. * p<0.1, ** p<0.05, *** p<0.01.

6. General Discussion

In this research, we report evidence that shows the implementation of IT-enabled monitoring systems can lower entry barriers to online labor platforms, reduce employers' preference for high reputation contractors, drive supply-side competition and increase employer surplus. Our estimation results are based on a quasi-natural experiment design with fixed-price projects as the control group and time-based projects as the treatment group. First, the employer preference estimation analysis suggests that after the implementation of an IT-enabled monitoring system, while there is no change in preference for reputation that signals contractor capability for both fixed-price and time-based projects, employers care less about reputation that signals contractor effort for time-based projects (but not fixed-price projects). Second, the results from our DID estimations show that the introduction of the IT-enabled monitoring system intensifies supply-side platform competition by lowering the entry barrier, as it attracts more (inexperienced) contractors to bid for time-based projects. Further, employers are less willing to pay for reputation premiums, and thus enjoy a higher surplus. This finding suggests that there exists a partial substitutive relationship between the monitoring system and the reputation system.

Our study contributes to several streams of IS research. First, it 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 platform. Unlike the previous literature mainly examining the effect of monitoring systems in a firm setting (Gopal and Koka 2010; Pierce et al. 2015), we analyze the impact of monitoring systems on a two-sided online labor platform. Such an advantage enables us to identify unique aspects of online platforms and holistically study the effect of IT-enabled monitoring systems on various outcomes in online labor platforms. Second, our study extends the previous research on the effect of reputation systems in digital platforms (Ba and Pavlou 2002; Bockstedt and Goh 2011; Dellarocas 2005, 2006; Moreno and Terwiesch 2014). According to the previous literature on reputation systems, reputation acts as a signal of contractors' future performance (Banker and Hwang 2008), and motivates the contractor to spend more effort (Horton and Golden 2015). However, our result suggests that its effect can be substituted by IT-enabled monitoring, which alleviates the moral hazard problem by efficiently providing more precise information about contractors' effort (Agrawal et al. 2014; Pierce et al. 2015). This suggests 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 the moral hazard problems and improving agents' productivity (Duflo et al. 2012). In this study, we show that, by partially substituting for reputation systems, IT-enabled monitoring systems help reduce agency costs by lowering entry barrier for contractors who has no prior experience on a focal platform, reducing reputation premiums, intensifying supply-side competition and increasing employer surplus. Therefore, our finding suggests the possible role of IT-enabled monitoring in overcoming a limitation of reputation systems that has hitherto been ignored in the IS literature: they create entry barriers for qualified contractors who have not established reputation in a particular platform.

Our research also provides important managerial implications on 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, monitoring systems are also found to be highly effective in improving agents' performance (Duflo et al. 2012; Hubbard 2000; Pierce et al. 2015). However, our study suggests that there exists a partial substitutional relationship between these mechanisms. Hence, our study deepens our understanding of the optimal design of online labor platforms (Hong et al. 2015) by emphasizing the potential interaction effect between the reputation systems and monitoring systems.

We acknowledge a number of limitations of this research, which opens up avenues for future research. First, we note that due to data limitation, employers' actual usage of records from monitoring systems is not available. However, given this is mandatory for contractors, it does not appear to be a serious concern. Further, considering that only some employers actually use the IT-enabled monitoring system, our estimated effects of the IT-enabled monitoring system tend to be on the conservative side. Second, 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 project final performance. Finally, our study was conducted in the context of online labor market and our finding could be limited in generalizability to other online platforms. Although moral hazard is a universal issue in online platforms, the IT artifact examined in this study – an offline tracking tool – may not be applicable to platforms that focus on transactions of physical products, such as eBay. Further research should explore the effects of other monitoring systems that are suitable for other online platforms.

7. Concluding Remark

Using a large scale data set from one of the major platforms that facilitate labor contracting, we utilize propensity score matching in tandem with a quasi-natural experimental difference-in-difference analysis to identify and quantify the effects of implementing an IT-enabled monitoring system. Our results demonstrate a partial substitution between monitoring systems and reputation systems, and further suggest the role of implementing a monitoring system in lowering entry barrier for contractors with no prior reputation and thus driving supply-side competition. Overall, our results provide support for the effectiveness of IT-enabled monitoring in addressing moral hazard issues in online labor markets, and carry important implications for the design of two-sided platforms.

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