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Contract Choice, Moral Hazard, and Performance Evaluation: Evidence from Online Labor Markets

Peng Huang
Robert H. Smith School of Business,
University of Maryland
huang@umd.edu

Yifei Wang
Robert H. Smith School of Business,
University of Maryland
ywang269@umd.edu

Abstract

Due to the spatial and temporal separations between clients and freelancers, online labor markets (OLMs) are particularly susceptible to issues related to information asymmetry. Based on the economics of information, we hypothesize that the choice of contract type—i.e., between the fixed-priced (FP) contract and the time-and-materials (TM) contract—has important implications for curbing moral hazard during contract execution, and therefore will influence the client's perceived contractual performance upon project completion. We test the predictions by assembling a dataset of data analytics projects completed by freelancers on Upwork, the largest online freelancing platform. We find that, consistent with our hypothesis, freelancers under a TM contract receive significantly lower performance ratings by their clients on average compared to those under an FP contract. Interestingly, we also find that the level of expertise required for a project moderates the effect of contract choice on client satisfaction; the negative impact of a TM contract is smaller (i.e., less negative) when a project requires intermediate-level or expert-level skills. Our study offers useful insights into an important institutional determinant of contractual performance evaluation, which has profound implications for freelancers' reputations in OLMs.

Keywords: online labor market, contract choice, contractual performance, information asymmetry, moral hazard

1. Introduction

Online labor markets (OLMs) are marketplaces that connect workers with short-term job opportunities in the context of knowledge work. These platforms, such as *Upwork* and *Freelancers.com*, help independent workers, many of whom could not have a traditional job due to personal circumstances, find employments that offer flexible work schedules. Furthermore, OLMs help clients recruit contingent service providers, often with rare skills that are difficult to source in traditional labor markets. In recent years, OLMs brokered labor relationships in a wide range of occupations, giving rise to the gig economy. Statistics reveal that over a third of the US workforce involves in gig work to some extent: more than 57 million workers in the US economy participated in freelancing in 2019, accounting for 35% of all US workers. Moreover, the direct contribution of freelancing to the economy is over $1 trillion, nearly 5% of the U.S. GDP. Recent studies also show that many workers consider OLMs as a substitute source of income for full-time employment because online work shortens the search time between jobs, reducing the duration of unemployment (Borchert et al., 2018; Cantarella & Strozzi, 2021).

Despite the merits of these platforms, more than 60% of OLM projects fail to reach a contract, with the client unable to hire any freelancer (Zheng et al., 2015). Notably, one of the most significant challenges faced by OLMs is the issue of information asymmetry due to the spatial and temporal separation of the client and the worker (Benson et al., 2020; Pelletier & Thomas, 2018). For example, a client on an OLM may be unable to differentiate high-quality freelancers from low-quality ones, and she cannot effectively screen those who bid on her projects, leading to adverse selection. Earlier research has examined several ways of addressing these pre-contractual information asymmetries in the context of OLMs. For example, studies have shown that signaling mechanisms such as reputation (Lin et al., 2018; Moreno & Terwiesch, 2014) and experience in related fields (Agrawal et al., 2015) help mitigate this type of information asymmetry. Despite the progress, this line of literature has mainly focused on the issue of adverse selection, such as the client's decision on which contract type to use (Chen & Bharadwaj, 2009; Yao et al., 2010) or which vendor to hire (Lin et al., 2018). In contrast, much less is known about the role of post-contractual information asymmetry—i.e., moral hazard—in determining the outcomes of a contractual relationship.

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In this work, we aim to bridge this gap and investigate how the contract type used in an OLM project—through its role in curbing moral hazard during contract execution—will influence the client's perceived contractual performance upon project completion. We examine the difference between two contractual formats commonly used in OLMs: the fixed-priced (FP) contract and the time-and-materials (TM) contract. Particularly, building on agency theory and the economics of information (Stiglitz, 2000), we propose that the use of different contract types in an OLM project will influence the likelihood of moral hazard taking place and the cost of monitoring, and therefore will result in differences in the client's perceived contractual performance. We further hypothesize that the relationship is moderated by the level of expertise required for the project, because the degree of contract incompleteness and the difficulty in outcome verification are both increasing with project complexity (Al-Najjar, 1995; Bapna et al., 2010), therefore making moral hazard more difficult to prevent for expert-level projects, regardless of the contract choice.

To test these predictions, we conduct empirical investigations by examining a sample of data analytics projects collected from *Upwork*, each with detailed information on the project characteristics, the freelancer characteristics, the type of contract adopted, the level of expertise required for the project, and the client's evaluation of the contractual performance. To address the potential endogeneity of the choice of contract type, we employ an endogenous treatment regression model in which we use instruments that exogenously shift the contract type choice. As an alternative identification strategy, we further present analyses based on a matched sample in which each observation under a TM contract is matched to one under an FP contract using a propensity score matching method. Consistent with our theorizing, we find that, with everything else being equal, the perceived contractual performance—as measured by client satisfaction—is significantly lower under a TM contract than under an FP contract. Interestingly, the results also show that the negative impact of a TM contract on the client's satisfaction is weaker (i.e., less negative) for intermediate-level or expert-level projects than for entry-level ones. Taken together, these findings deepen our understanding of the relationships between contract choice, moral hazard, and contractual performance evaluation in OLMs, and lead to some important managerial implications.

The findings regarding the relationships between contract choice, moral hazard, and performance evaluation are important because they have far-reaching implications for OLMs. For example, it is well known that clients increasingly rely on OLM reputation systems to screen potential vendors and they are willing to pay a premium for more reputable workers (Moreno & Terwiesch, 2014). However, if the client's rating of contractual performance—which forms the foundation of the freelancers' reputation in OLMs—is determined by institutional factors in addition to freelancer characteristics, clients need to be cognizant of potential biases in the generating process of vendor reputation and use these reputation scores with caution. Furthermore, freelancers who accept jobs under a time-and-material contract also need to anticipate the potential negative impact of the contract choice on their performance ratings, and therefore may preemptively take actions to reduce the client's concerns over moral hazard—such as initiating more frequent and transparent communications with the client to report their work progresses—and be mindful of the client's expectations regarding project timeline and cost.

2. Theory and Hypotheses

We start by drawing on the economics of information (Macho-Stadler & Pérez-Castrillo, 2001) as a unifying theoretical framework to understand how the choice between TM and FP contracts can lead to different implications for moral hazard during project execution, which will, in turn, affect client satisfaction upon the conclusion of the project. Because an OLM is mediated through an online platform, monitoring is particularly difficult compared to employment relationships in an offline, physical environment due to the spatial and temporal separations between clients and freelancers (Liang et al., 2019). Although most OLMs have some monitoring systems that allow a client to keep track of the work progress remotely, the client and the worker typically do not have direct, face-to-face interaction that offers richer nonverbal cues. Under a TM contract, the client bears significant risks because work time is typically self-reported, leaving room for opportunistic behaviors on the part of the freelancer such as inflating the reported work hours (Corts & Singh, 2004; Liang et al., 2019). Facing this issue, the client may have to incur greater monitoring costs to reduce the likelihood of moral hazard. In contrast, under an FP contract, the worker bears a significant part of the project risk because project cost or time overruns could affect the worker's project profitability (Gopal & Koka, 2012; Gopal et al., 2003). Therefore, under an FP contract, the worker has strong incentives to execute the project and manage her progress efficiently, reducing the likelihood of moral hazard. This, in turn, will relieve the burden of monitoring on the part of the client.

Furthermore, due to the complex nature of IT projects, it is often difficult for a client to estimate the amount of effort involved in a project accurately ex-ante (Larsen et al., 2013). Therefore, before contracting, the client often underestimates the complexity of a project, its scope, and its true cost (Conrow & Shishido, 1997). Under an FP contract, the client and the worker may engage in negotiation to adjust the client's expectations if the two parties' estimates over the project budget diverge significantly. Under a TM contract, however, the discrepancy in expectations is less likely to be discovered and corrected ex-ante because the payment terms are based on an hourly rate rather than a lump-sum payment. As a result, longer-than-expected project duration or budget overrun may come as a surprise if the client underestimates the cost initially. Because making adjustments to contract terms in the middle of a project is particularly complex, significant adaptation costs will occur if the client and the worker engage in renegotiation (Bajari & Tadelis, 2001).

Given these differences, we expect that client satisfaction in OLM projects upon project completion will vary between the two contract types. Particularly, because a TM contract is associated with higher monitor costs during project execution and/or higher adaptation costs when a budget overrun occurs, we hypothesize that:

H1. Upon the completion of an OLM project, the client's satisfaction is lower under a TM contract than under an FP contract, with everything else being equal.

In OLMs, jobs are associated with varying degrees of expertise requirement. For example, an entry-level project such as data entry typically requires minimum domain knowledge. The task is usually repetitive and straightforward, and the deliverables are easy to verify. In contrast, an expert-level project may require a complex set of skills and years of professional experience in some specific knowledge domains. We propose that the level of expertise requirement associated with a project moderates the relationship between the contract type and perceived contractual performance. Particularly, we expect that the difference in client satisfaction between an FP contract and a TM contract will be smaller when a project is more complex and requires high-level expertise.

As we argued earlier, in OLMs the client cannot perfectly observe the effort of a worker and moral hazard may arise due to opportunistic freelancer behaviors. Under such conditions, an FP contract is preferred by a client because it has the merit of preventing moral hazard and reducing the need for monitoring. However, the effectiveness of an FP contract in curbing moral hazard during contract execution also depends on the ease with which the project output can be verified against the contract terms (Bapna et al., 2010; Eisenhardt, 1989). When the goal of a project is clearly defined and its outcome is easy to measure, such as for an entry-level task, the use of an FP contract (an outcome-based contract) has a clear advantage over a TM contract (a behavior-based contract) in reducing the likelihood of moral hazard (Baron & Besanko, 1987). Therefore, the use of an FP contract likely results in significantly higher client satisfaction than a TM contract.

However, expert-level projects have two distinct features: 1) it is difficult for the client to completely specify in the contract all the project requirements and all the contingencies that may arise during project execution (Al-Najjar, 1995; Susarla et al., 2010), and 2) the outcome of the project is usually difficult to verify for clients unfamiliar with the knowledge domain (Aubert et al., 2002; Bapna et al., 2010). Under such conditions, moral hazard can still arise even when an FP contract is used, because a freelancer's opportunistic behavior cannot be easily detected by the client. For example, in a project that involves the development of a data processing application, the freelancer may produce a program that meets all the functional requirements but does not scale well for large data sets or breaks down when the number of users increases. The detection of these quality issues often requires sophisticated knowledge and rigorous testing beyond the client's capabilities. Therefore, for an expert-level project, the use of an FP contract is not as effective in dispelling the client's concerns over moral hazard as it is for a project that requires entry-level skills. In other words, both the incompleteness of an FP contract and the difficulty in verifying the project deliverables are increasing in the complexity of the underlying project, therefore creating room for opportunistic behaviors by the freelancer and reducing the effectiveness of an FP contract in curbing moral hazard. As a result, we hypothesize that:

H2. The negative impact of a TM contract on the client's satisfaction will be weaker (i.e., less negative) for expert-level projects than for entry-level projects.

3. Method

3.1. Research Context

We conduct empirical investigations using data collected from *Upwork*, a freelancing platform formerly known as *Elance-oDesk* that resulted from a merger between two companies, *oDesk* and *Elance*, in December 2013. It is currently the largest freelancer marketplace with $1 billion worth of jobs posted annually. It connects businesses with freelancers around the globe in more than 70 job categories, ranging from video editing, graphic design, software development, social media solutions, financial planning to administrative support.

To post jobs on *Upwork*, a client registers an account by providing information such as the company name, website URL, and verification of a payment method. The client can then post a job by either creating her post from scratch or using a template in which many fields are pre-populated with suggestions that *Upwork* has adapted from similar projects. A typical job post includes a job post title, the job category, a job description, screening questions, relevant skills, and the level of expertise required.

An important part of a job post is the way that the client budgets for the project, in which she chooses to pay the freelancer either on an hourly basis or a fixed price. With an hourly project, the professional tracks the time he spends working, and the client is billed weekly. With a fixed-price project, pricing is predetermined and the client either pays all at once or by milestones—i.e., predetermined deadlines that break the project into smaller pieces of work. The funds are deposited into escrow at the beginning of the project and/or each milestone, and then released as the client approves the work by the freelancer.

Once a job is posted, freelancers bid for the project by submitting their cover letters and proposals. For fixed-price projects, freelancers can also propose milestones that divide the payment for a project into predefined pieces with specific goals. For hourly contracts, freelancers may include their hourly rate when submitting a contract proposal. Clients then interview and negotiate with applicants before hiring. During the negotiation, the freelance may choose to update the proposal terms such as the bid or hourly rate before creating a final contract. Once the proposal is accepted and a contract is signed, the freelancer starts working on the project and logs his work time using a virtual monitoring system called 'Work Diary,' which tracks time and records the progress made by the freelancer through a desktop app. Upon project completion, both the client and the freelancer can provide feedback and evaluate the other party on several processes- and outcome-related criteria.

3.2. Data and Variables

We assemble a dataset of projects completed by freelancers with data analytics skills from *Upwork*. As a first step, we identify all independent freelancers who identify themselves as professionals in the domain of data analytics and who reside in the United States, resulting in 1,075 freelancers. We then collect their complete job histories on *Upwork* during the period between January 2014 (which is when the company first started operation as *Upwork* after the merger of *oDesk* and *Elance*) and August 2021. To limit the impact of unobservable, confounding factors of the clients, we restrict the sample to projects posted by independent, non-enterprise clients. We choose data analytics projects as the sample because there are significant variations in project size and the level of expertise involved, and there is a balanced use of the two contract types. The final sample includes 12,388 projects completed by 1,075 freelancers.

Dependent variable. The dependent variable, *client satisfaction*, is measured by the client's overall rating of the project performance on a scale of 1-5 upon project completion. The perceived project performance is calculated as the average of six components: *skills* (i.e., how skillful the worker is), *availability* (i.e., how flexible the freelancer is regarding her availability), *communication* (i.e., the degree of effectiveness of the freelancer's communication), *quality* (i.e., the quality of the deliverables), *deadlines* (i.e., how well the freelancer meets deadlines), and *cooperation* (i.e., how easy it is to cooperate with the freelancer). Each of the six components is rated by the client separately on a 1-5 scale.

Independent variable and moderator variable. The main independent variable of interest is the *contract type* associated with a project. The contract type is selected by the client when a job is posted on *Upwork*, which takes the form of either a TM or an FP contract. Furthermore, we use the *expertise* level of the project (which can be *entry*, *intermediate*, or *expert*) as a moderator variable. The level of *expertise* required for the project is specified by the client in the job posting.

Control variables. We control for various individual-level and project-level characteristics. At the individual level, we measure an individual's *platform experience* at the beginning of the project by calculating the difference (in days) between the project start date and the user's registration date. At the project level, we control for the total amount of *earnings* the worker made from completing the project. Using the information on the starting and ending dates of a project, we calculated the variable *project duration* to account for the length of the project. To capture the degree of skill match between the freelancer's skill set and the project's skill requirement, we calculated the similarity score of the two using well-established text mining techniques. Particularly, in our research context, both the skill requirement of an *Upwork* project and a freelancer's skillset as described in his profile are specified by choosing from a large collection of predefined hashtags (e.g., #DataVisualization, #MachineLearning, etc.), and we compute the *skill match* score between the two sets of hashtags using the Jaccard similarity coefficient (Burtch et al., 2021; Hass, 2017). Because our sample consists of projects in the data analytics domain, most of them involve some computer programming tasks. Therefore, we also control for the primary programming language by extracting the first programming languages specified on the list of skill hashtags associated with each project. The variable *programming language* is coded as a categorical variable that consists of seven different languages. Finally, to control for the client-vendor trust that may have been developed through prior interactions (Corts & Singh, 2004), we create a binary control variable *first-time interaction* that is set to 1 if the freelancer and the client transact for the first time.

Table 1. Summary Statistics

Variable	Unit or Range	Mean	Std. Dev.
client satisfaction	1-5	4.541	0.772
TM contract	binary	0.497	0.500
expertise			
entry	binary	0.521	0.500
intermediate	binary	0.188	0.391
expert	binary	0.291	0.454
skill match	0-1	0.843	0.190
project duration	log of days	2.905	1.703
platform experience	log of days	6.909	1.008
earnings	log of $	6.465	1.845
first-time interaction	binary	0.882	0.322
programming language			
Python	binary	0.367	0.482
R	binary	0.166	0.372
JavaScript	binary	0.095	0.293
Google analytics	binary	0.058	0.234
VBA	binary	0.086	0.281
Tableau	binary	0.041	0.199
SQL	binary	0.134	0.341
AWS	binary	0.052	0.222
same country	binary	0.918	0.274
monitoring system	binary	0.895	0.306

Tables 1 shows the summary statistics of the key variables. In our sample, TM contract type was used in approximately 49.7% of the projects. Our data indicate that on average there is a good match between the project skill requirement and the freelancer's self-reported skillset, with a mean Jaccard similarity coefficient of 84%. In addition, 52% of the projects require entry-level expertise, while intermediate-level and expert-level projects make up 19% and 29% of the sample, respectively. Among these data science and analytics projects, *python* and *R* appear to be the most popular programming languages, accounting for the primary language of 37% and 17% of the sample, respectively.

3.3. Empirical Specification

We start with a two-way (freelancer and year) fixed effects panel data approach to evaluate the hypotheses. Specifically, let Y_{ijt} be the measure of client satisfaction with freelancer *i* for project *j* in year *t*, X_j denote the contract type (with 1 being a TM contract), and E_j denote project *j*'s required expertise level. Let $\boldsymbol{Z}_{ij}$ represent a vector of the time-varying individual- and project-level control variables (such as platform experience, project duration, project earnings, skill match between the freelancer and the project, etc.). The baseline model is specified in the form of Equation 1:

$$Y_{ijt} = \beta X_j + \gamma E_j + \boldsymbol{\rho Z}_{ij} + \alpha_i + \mu_t + \varepsilon_{ijt} \quad (1)$$

where α_i and μ_t represent a set of freelancer and year fixed effects, respectively, and ε_{ijt} captures the idiosyncratic error. Because we hypothesize that client satisfaction is lower under a TM contract, we expect β to be negative. To examine the moderating role of the project's required expertise level, we add the interaction term $X_j * E_j$ to the model, leading to Equation 2:

$$Y_{ijt} = \beta X_j + \gamma E_j + \delta(X_j * E_j) + \boldsymbol{\rho Z}_{ij} + \alpha_i + \mu_t + \varepsilon_{ijt} \quad (2)$$

where coefficient δ captures the moderating effect.

3.4. Addressing Endogenous Contract Type Choice

Despite the use of freelancer fixed effects models and including relevant controls to rule out the effect of unobserved heterogeneities, some unobserved factors that influence the contract type choice may be also correlated with the client's perceived project performance, leading to potential biases in our estimation. We address this concern by treating the choice of contract type as endogenous and identifying a couple of variables that serve as instruments for the nonrandom assignment of contract type. Using these instruments, we employ a linear regression model with endogenous treatment effects to account for the endogeneity of the contract type. As an alternative identification strategy, we also employ a matching sample approach in which each treatment observation (a project under a TM contract) is matched to a control observation (a project under an FP contract) using a propensity score matching algorithm. Particularly, for each observation associated with a TM contract, we apply a one-to-one nearest neighbor matching without replacement to identify a matched control observation under an FP contract that is comparable in its probability of treatment assignment based on observed freelancer and project characteristics. We then test the regression models using the resulting matching sample. The use of this matching sample method therefore helps overcome issues of selection bias under our non-experimental setting.

4. Results

4.1. Baseline Results

We show the regression results from the fixed-effects models as specified in equations 1 and 2 in Table 2. We take the log transformation of *project duration, platform experience,* and *earnings* to account for the right skewness of the variables. We first run the baseline model with the main independent variables of interest, *contract type*, along with other control variables as predictors (Column I). We then add the interaction between *contract type* and *expertise* to examine the moderating effect of expertise level (Column II).

In column I where we show the direct effect of contract type on client satisfaction, we find that compared to an FP contract, a freelancer's performance rating under a TM contract is lower by approximately 0.18 points on a 1-5 scale ($\beta = -0.182$, $p < 0.01$). Given the sample mean client satisfaction of 4.54, this translates to a 3.9% decrease in performance rating. The result is consistent with our argument that under a TM contract a freelancer has less incentive to execute the project and manage her progress efficiently since she is not responsible for time and material overruns, and thus moral hazard is more likely to occur. Unable to perfectly monitor the freelancer's effort, the client is uncertain about the degree of moral hazard and bears considerable risk under an hourly payment scheme, and therefore is less satisfied with the project outcome than under an FP contract. We further note that intermediate-level and expert-level projects on average receive a higher rating than entry-level projects ($\beta = 0.075$, $p < 0.01$ and $\beta = 0.241$, $p < 0.01$, respectively), and clients on average give higher ratings to freelancers with higher match with the project skillset requirement ($\beta = 0.169$, $p < 0.01$).

Column II shows the interaction effects of expertise levels and the TM contract type. We find that when a project requires intermediate-level or expert-level skills, the negative impact of a TM contract on the client's satisfaction is not as severe as a project that requires entry-level skills ($\beta = 0.186$, $p < 0.01$ and $\beta = 0.124$, $p < 0.01$, respectively). To evaluate Hypothesis 2, we conduct a likelihood ratio (LR) test comparing column I—which excludes the moderating effect of expertise—and column II—which includes the moderating effect—and the result provides strong support to the hypothesis ($\chi^2(2) = 47.34$, $p < 0.01$).

Table 2. Fixed effects model

	DV = Client Satisfaction	
	I	II
TM contract	-0.182***	-0.230***
	(0.017)	(0.019)
expertise = intermediate	0.075***	-0.016
	(0.025)	(0.029)
expertise = expert	0.241***	0.184***
	(0.029)	(0.030)
intermediate X TM contract		0.186***
		(0.032)
expert X TM contract		0.124***
		(0.028)
skill match	0.169***	0.162***
	(0.044)	(0.045)
earnings	0.003	0.003
	(0.005)	(0.005)
project duration	0.010	0.011*
	(0.006)	(0.006)
platform experience	0.010	0.010
	(0.008)	(0.008)
first-time interaction	-0.003	-0.004
	(0.023)	(0.023)
constant	4.303***	4.346***
	(0.117)	(0.117)
Observations	12,388	12,388
R-squared	0.232	0.235
Freelancer FE	YES	YES
Programming language dummies	YES	YES
Year FE	YES	YES

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

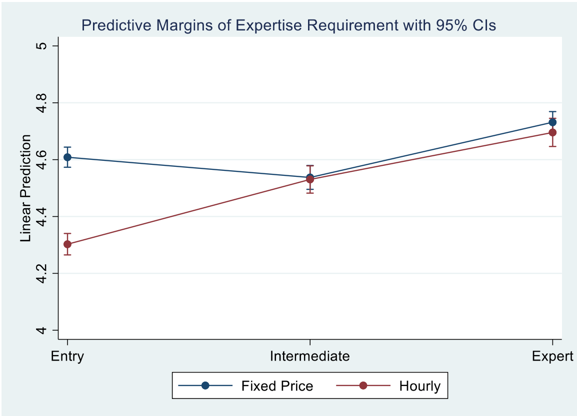

Figure 1. Predictive margins of expertise level

Based on results from column II, Figure 1 presents a plot showing the difference in the marginal effects of contract type on perceived performance under different levels of expertise. For an average entry-level project, the value of predicted client satisfaction under a TM contract is significantly lower than under an FP contract (*diff* = -0.305, on a scale of 1 to 5, $p < 0.01$). In contrast, the difference in predictive margins between the two contract types is not salient when the project requires intermediate-level skills (*diff* = -0.008, not significant), nor is it significant when the project requires expert-level of skills (*diff* = -0.039, not significant).

4.2. Models with Endogenous Treatment Effects

We further examine the degree to which our findings may suffer from estimation biases due to endogenous contract type and test the endogenous treatment effects model as described earlier. For this exercise, we identify a couple of instruments for the endogenous choice of contract type. First, because monitoring effort is greater if the client and the worker are geographically distant (McElheran, 2014), a client is more inclined to use a TM contract if she is physically close to the freelancer she hires. OLMs make it possible for workers and clients from across the globe to connect, overcoming traditional geographical boundaries. As a result, workers and clients may have to work across different cultures and time zones, potentially generating more risk in the coordination process and increasing monitoring costs (Handley & Benton Jr, 2013). We determine whether both contract parties are in the same country and use the binary variable *same country* as an instrument. Since the freelancers in our sample are all from the U.S., the *same country* variable is set to 1 if the client is also located in the U.S., and to 0 otherwise.

Second, we consider a significant change in the monitoring mechanism provided by *Upwork* during our sample period which involves the debut of a real-time chat service on the platform. This new service, introduced on May 5th, 2015, features *Slack*-like, real-time instant messaging capabilities, allowing clients to see if workers are online and start a conversation right away to discuss the project's progress. We expect that the debut of the real-time monitoring feature would exogenously shift the likelihood of using a TM contract in a project. On the one hand, the introduction of such a mechanism reduces the cost of monitoring, leading to an increased propensity of clients employing a TM contract (Liang et al., 2019). On the other hand, earlier research shows that freelancers on gig platforms often resent *Slack*-like monitoring tools to protect their privacy, so much so that they may avoid bidding on hourly contracts altogether (Sutherland et al., 2020). Many freelancers are drawn to gig platforms by the promise of flexible work schedules, and real-time monitoring systems take the flexibility and autonomy away from the workers. Therefore, the effect of the debut of the new feature on the likelihood of a TM contract will likely depend on the interplay of the two countervailing forces. We create a dummy variable, *monitoring system*, as the second instrument, with its value set to 1 if a project has a start date later than May 15th, 2015, and to 0 otherwise.

Table 3. Endogenous Treatment Effects Model

	DV = Client Satisfaction	
	I	II
TM contract	-0.198***	-0.227***
	(0.067)	(0.077)
expertise = intermediate	0.052***	-0.007
	(0.020)	(0.023)
expertise = expert	0.162***	0.137***
	(0.023)	(0.024)
intermediate X TM contract		0.148***
		(0.029)
expert X TM contract		0.087***
		(0.025)
skill match	0.023	0.021
	(0.033)	(0.033)
earnings	-0.017***	-0.016***
	(0.004)	(0.004)
project duration	0.009	0.012**
	(0.006)	(0.006)
platform experience	-0.006	-0.007
	(0.007)	(0.007)
first-time interaction	-0.031	-0.030
	(0.021)	(0.021)
constant	4.779***	4.791***
	(0.105)	(0.108)
Observations	12,388	
Programming language dummies	YES	
Year FE	YES	

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

The results of the endogenous treatment effects regressions, which make use of the two instruments, are reported in Table 3. In keeping with the prior literature (e.g., Liang et al. 2016), we also include project expertise levels as predictors in the first-stage contract choice equation. The first stage results show how the instrumental variables affect the choice of contract type. As expected, we find that the variable *same country* is positively associated with the use of a TM contract ($p < 0.01$), confirming that physical proximity reduces monitoring costs. In contrast, the variable *monitoring system* negatively predicts the selection of a TM contract ($p < 0.01$), suggesting that freelancers eschew TM contracts after the introduction of the real-time chat feature due to privacy concerns. The second stage regressions model the outcome equations with perceived contractual performance as the dependent variable. In the baseline model (Column I), we again find results in support of Hypothesis 1 that the use of TM contract negatively affects the perceived performance ($\beta = -0.198$, $p < 0.01$). In the full model (Column II), we find supportive evidence that the negative impact of a TM contract on client satisfaction is moderated by a project's expertise requirement: the difference in performance ratings between the two contract types are reduced for a project with intermediate-level or expert-level skill requirement relative to an entry-level project ($\beta = 0.148$, $p < 0.01$ and $\beta = 0.087$, $p < 0.01$). Again, an LR test comparing the models of column I and column II provides support to Hypothesis 2 ($\chi^2(2) = 25.35$, $p < 0.01$). In summary, both hypotheses are supported under the endogenous treatment effects model, suggesting that our findings are robust to endogenous contract type choice.

4.3. Matched Sample Analyses

To further address the non-random assignment of contract type, we construct a sample composed of a treatment group and a control group that is comparable on the probability of treatment assignment using propensity score matching (PSM), a method that has been employed in various non-experimental settings when the assignment of treatment is not controlled by the researcher (Dehejia & Wahba, 2002). We first predict the propensity score of a project choosing the FP contract type using a logistic regression in which project- and individual-level covariates (such as skill similarity score, project expertise requirement, the programming language, project length, and the worker's platform experience, etc.) are used as explanatory variables. To minimize the bias in the estimated contract type effect, for every observation of an FP contract we apply a one-to-one nearest neighbor matching without replacement to identify a matched control observation under a TM contract (Austin et al., 2010). The PSM process results in 3,847 projects under an FP contract and a matched sample of projects under a TM contract with the same sample size. A balance check of the covariates reveals that the control sample and the treatment sample are not significantly different in observed freelancer and project characteristics after matching.

Table 4. Matched Sample Analyses

	Fixed effects models	
	I	II
TM contract	-0.195***	-0.237***
	(0.022)	(0.024)
expertise = intermediate	0.061*	-0.024
	(0.033)	(0.036)
expertise = expert	0.231***	0.177***
	(0.037)	(0.039)
intermediate X TM contract		0.167***
		(0.040)
expert X TM contract		0.098***
		(0.034)
skill match	0.174***	0.162***
	(0.060)	(0.060)
earnings	0.007	0.007
	(0.007)	(0.007)
project duration	-0.000	-0.002
	(0.008)	(0.008)
platform experience	0.008	0.008
	(0.010)	(0.010)
first-time interaction	0.002	0.001
	(0.030)	(0.029)
constant	4.247***	4.299***
	(0.156)	(0.156)
Observations	7,694	7,694
R-squared	0.271	0.273
Freelancer FE	YES	YES
Programming language dummies	YES	YES
Year FE	YES	YES

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

We replicate the fixed effect models using the matched sample and report the results in columns I and II of Table 4. We find a consistent result that projects under a TM contract receive a lower performance rating compared to those under an FP contract on average ($\beta = -0.195$, $p < 0.01$), supporting Hypothesis 1. In addition, the effect of contract type is again shown to be moderated by project expertise requirement: the negative effect of a TM contract is weaker when a project requires intermediate-level skills ($\beta = 0.167$, $p < 0.01$) or expert level skills ($\beta = 0.098$, $p < 0.01$). An LR test comparing the models of column I and column II lends support to Hypothesis 2 as well ($\chi^2(2) = 24.73$, $p < 0.01$).

5. Conclusions and Discussion

Due to their unique characteristics, OLMs are particularly susceptible to information asymmetry both before and after contracting (Kanat et al., 2018). Based on the economics of information, we advance arguments that contract type choice—i.e., between the fixed-price contract and the time-and-material contract—has important implications for preventing moral hazard during contract execution, and therefore will influence the client's perceived contractual performance upon project completion. We assemble a dataset of data analytics projects completed by freelancers on *Upwork* and empirically evaluate the propositions. We find that freelancers under a TM contract receive significantly lower ratings by their clients on average compared to those under an FP contract, consistent with our theorizing that the use of a TM contract leads to increased monitoring costs and the client's greater concerns over moral hazard (Liang et al., 2019). Notably, we also find that the expertise required for a project moderates the effect of contract choice on client satisfaction: particularly, the negative impact of TM contract is weaker when a project requires intermediate-level or expert-level skills. Our interpretation is that the degree of contract incompleteness and the difficulty in outcome verification are both increasing with project complexity (Al-Najjar, 1995; Bapna et al., 2010). Therefore, for an expert-level project, the advantage of an FP contract over a TM contract in curbing moral hazard is greatly reduced.

Our study makes several contributions to the existing IS research. First, although earlier studies in the IT outsourcing literature have examined the various factors that contribute to the choice of contract type (e.g., Gopal et al., 2003; Kalnins & Mayer, 2004), very few of them examine the implications of such choice on the outcome of a contractual relationship. By studying the relationship between the contract choice and the client's perceived contractual performance, we reveal how the incentive problems unfold under the different contract terms, which in turn influences vendor performance evaluation. Second, our analyses also add to the current understanding of the issue of information asymmetry in OLMs. Compared to the traditional labor market, OLMs have a lower entry barrier and lack effective screening and monitoring mechanisms, leading to more severe information asymmetry problems. Whereas much of this line of literature has been focusing on solutions to the adverse selection issues and the role of reputation in contractor selection in particular (e.g., Hong & Pavlou, 2017; Lin et al., 2018; Moreno & Terwiesch, 2014), our study approaches the research topic from a different angle and focuses on the issue of moral hazard that, with a few exceptions (e.g., Liang et al., 2016), has not been thoroughly investigated. Finally, earlier studies of OLMs reveal that clients frequently use the reputation systems in OLMs as a basis for vendor screening (Lin et al., 2018; Moreno & Terwiesch, 2014), but the effectiveness of these reputation systems is predicated on the assumption that a freelancer's online reputation genuinely reflects her innate ability and/or work ethics. Our study challenges this assumption and points to the possibility that institutional factors—such as the contract type used for the project—may contribute to potential bias in the reputation generation process, and therefore clients should take the reputation ratings with a grain of salt.

Our research also reveals some important managerial implications for practitioners in OLMs. For example, freelancers' historical performance ratings are prominently displayed in their OLM profiles and form the basis of their OLM reputations (Lin et al., 2018; Moreno & Terwiesch, 2014). Our findings help freelancers better understand how different contract types may impact their performance ratings, and these insights can be used to guide their bidding behavior and maintain their reputation. They inform freelancers to anticipate a lower performance evaluation when a TM contract is selected by the client, and they should take preemptive actions to alleviate the client's concerns over moral hazard under such conditions. In addition, to the extent that clients frequently make vendor selection decisions based on the bidders' reputation, they need to be cognizant of the potential biases caused by the contract type under which the freelancer had worked in the past and correct for such biases in their decision process if necessary. Our finding regarding the moderating effect of project expertise requirement suggests that the bias induced by contract type is most significant when the freelancer frequently works entry-level jobs under a TM contract, and clients need to be particularly mindful in screening bidders of this type. Finally, for OLM platforms, our study suggests that it might be helpful to present freelancers' performance ratings under different contract types separately in their profile and provide guidelines to assist clients in interpreting this information, which will increase transparency and aid the vendor screening process.

Several limitations of our study lead to avenues for future research. First, due to data availability, we cannot determine whether the lower performance evaluation under a TM contract is attributed to real moral hazard or the clients' perception of moral hazard (Bellavitis et al., 2019), whereas the latter can also be affected by other factors such as the variance in freelancers' innate abilities or the clients' unrealistic expectations. Second, because our sample consists of contractual relationships between non-enterprise clients and individual freelancers, one should exercise caution when generalizing the findings of this study to other IT outsourcing contexts where the contracting parties are commercial enterprises that often forge long-term contractual relationships with repeated interactions (Corts & Singh, 2004; Gulati, 1995). We hope our work will ignite sparks of interest in pursuing these potentially fruitful research directions.

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