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Online Service Outsourcing Auctions With Endogenous Reviews

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ABSTRACT In the emerging online service outsourcing platforms where services are commonly transacted through buyer-determined auctions, review systems are usually provided to alleviate information asymmetry and opportunistic behavior between transaction parties. This paper develops a game-theoretic model of online service outsourcing auctions with endogenous reviews, where freelancers (service providers) with private information on service expertise compete the client's service contract through bidding, and the winning freelancer exerts effort to improve service quality, in anticipation of possible penalty and negative review for low-quality delivery. We obtain the optimal decisions of the client (service scope, penalty) and the freelancers (bidding strategy, effort), and examine the impacts of online review on the decision results of the transaction parties as well as the platform. Results show that the online review system drives the client to set smaller service scope and lower penalty, while leading to higher service effort and lower bidding price from freelancers. Both the client and the freelancers benefit from the review system. Numerical simulations also show that the platform should charge lower commission fees when the online review system is more effective.

INDEX TERMS Buyer-determined auctions, online outsourcing platforms, online review, reputation, service quality.

I. INTRODUCTION

In recent years, large-scale, web-based service outsourcing marketplaces, such as Upwork, Freelancer, and Amazon Mechanical Turk, are emerging rapidly. Millions of freelancers (service providers) and clients all over the world meet in these platforms to transact various services such as website design, data processing, and business consulting [1], [2]. Just take Freelancer and Upwork (two leading platforms on online service outsourcing) as example: Freelancer has more than 48.6 million registered users and over 18.9 million posted service requests by November 2020 (www.freelancer.com), while Upwork is facilitating 3 million service transactions annually and generating more than \$1 billion in freelancer earnings per year [3]. According to a report by McKinsey Global Institute, the online service outsourcing market could

contribute \$2.7 trillion to global GDP by 2025 [4]. Due to its significance in both economic volume and growth rate, the online service outsourcing market is receiving increasing attentions from both the industry [5] and the academia [6].

In online services outsourcing platforms, services are commonly traded through buyer-determined auctions (e.g., [7], [8]), in which freelancers interested in a client's service request compete with each other by bidding the prices at which they are willing to provide the service, and the client is then free to choose any submitted bid (not necessarily the lowest-price bid) as the winning bid. Comparing to sourcing auctions for standardized goods (e.g., raw materials, parts, and manufactured goods), service outsourcing auctions face prominent problems of both adverse selection (i.e., screening freelancers with private information) and moral hazard (i.e., regulating the freelancers' opportunism behaviors) [9]. In traditional sourcing auctions for goods, most transaction terms can be arranged contingent on the delivery quality,

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since the specifications of the goods can be easily defined *ex ante* and verified *ex post*, which largely reduces the occurrence of moral hazard problems. In contrast, in the outsourcing of customized services which are mainly “experience goods” [10], it is usually difficult to pre-define the service details and measure the service qualities, which makes the moral hazard problems prominent.

To reduce information asymmetry, regulate opportunistic behaviors and facilitate trading trust, online service outsourcing platforms commonly provide the review system [10], [11]. With the review system, clients can rate and comment on the freelancers’ service performances, which in turn incentivizes the freelancers to provide high quality services to win more favorable reviews and hence higher future reward from the market. However, online review brings new challenges to the decision making of the freelancers, clients, and platform. For the freelancers, the online review system creates a tradeoff between present revenue and future revenue: in order to maintain a good reputation to reap more benefit in the future, the freelancers may choose to sacrifice some benefit in the present transaction (e.g., bidding low or exerting high service effort). For the clients, the *ex ante* design of service outsourcing terms and interim selection of winning freelancers become more challenging and intriguing, since they have to take into account the aforementioned freelancers’ tradeoff regarding online reviews. Finally, expecting the impacts of the review system on the clients’ and freelancers’ decision results (such as transaction volumes and prices), the platform also needs to change its policies (e.g., commission rates) in order for profit maximization.

Despite the prevalence of both buyer-determined auctions and online review in online service outsourcing platforms, the interactive relationship between the two is not sufficiently understood. In this paper, we develop a game-theoretical model of online service outsourcing auctions with endogenous reviews. Regarding the auction format, we focus on the buyer-determined auction, because it is the most widely adopted trading mechanism in online service outsourcing platforms. We aim to address the following two main questions:

- (a) How would the client and the freelancers interact with each other in online service outsourcing auctions with endogenous reviews?
- (b) How does online review impact the decision results of the client, the freelancers, and the platform?

As for question (a), we derive the optimal decisions of the client in designing the service scope and penalty (in case of low-quality delivery) and in selecting the winning freelancers, and we obtain the freelancers’ optimal bidding strategy and the winning freelancer’s optimal service effort. As for question (b), we examine how the the client’s optimal scope, optimal penalty and expected profit, as well as the freelancer’s service effort, bidding price and expected profit, would change with the marginal effect of online review. We also resort to numerical simulation to investigate how

should the platform optimize the commission rates under different marginal effects of online review.

The rest of the paper is organized as follows. Below we review the related literature and summarize our main contribution, followed by the description of the model framework. Then the transaction parties’ optimal decisions are derived and analyzed by backward induction, followed by a section highlighting the impacts of online review. The last section summarizes the main findings and concludes the study.

II. RELATED LITERATURE

This study belongs to the emerging literature on online service outsourcing platforms, also known as online labor markets (e.g., [10]) or digital platforms for knowledge work (e.g., [6]). Although online service outsourcing has become a significant part of the world economy [4], relevant research on this new form of work and its mediating platforms is still at the start stage [12], and readers may refer to [6] for a scoping review of the related literature. In this literature, the majority of work resorts to empirical research methods to examine the impacts of different factors on, e.g., the client’s outsourcing decision (e.g., [8], [13], [14]), the matching success/efficiency between clients and freelancers (e.g., [9], [15], [16]), freelancers’ signaling behavior (e.g., [17]), or the service outsourcing performance (e.g., [18]).

Among the literature on online service outsourcing platforms, a branch of works pay particular attention to the role of online review (or reputation, rating). Some researches examine the impact of reputation information on the trading outcome. For example, [19] presents a dynamic structural framework to estimate the effects of freelancer reputations on freelancer returns; [20] investigate the effects of freelancer reputation on clients’ outsourcing decisions and show that the effectiveness of reputation information depends largely on contract form; [11] evidence that freelancer earnings positively correlate with higher reputation scores; [2] find that freelancers’ prices or winning probabilities increase with their reputations. Some studies shed lights on the relationship between reputation information and other information. For instance, [21] investigates the effectiveness of assessment signals (e.g., rating, tests) and conventional signals (e.g., self-promotion, ingratiation) in predicting freelancer earnings; [22] study the relative importance of *ex-ante* observable information (e.g., reviews) and experiential information in affecting the clients’ hiring decisions; [23] finds that information on verified work history disproportionately benefits contractors from less developed countries; [24] examines the complementary effects of dispute resolution and reputation systems on clients’ hiring decisions and project outcomes. Some other studies focus on the causes, consequences, or solutions of shortcomings of reputation systems, such as reputation inflation (e.g., [25], [26]), the cold-start problem (e.g., [27]), and reputation transferability (e.g., [10]).

The above studies commonly regard reputation as exogenous factors or ignore the interactive decision-making process of the clients and freelancers. One exception is [19] which provides a formal model for the clients' dynamic optimization problem. Another two exceptions are [10] and [26], both providing algorithm models to calculate freelancer reputations in different contexts. However, these papers do not model the strategic interactions between the clients and freelancers, which, in contrast, is the focus of our paper. We notice two most relevant studies that involve both endogenous reviews and strategic interactions between trading parties. One is [28], which studies the impacts of reputation feedback system on the interactions between the clients (decide to trade or not) and the freelancers (choose between cheating and acting honestly). Another is [29] which studies the provision of collaborative services under endogenous online reviews. We model endogenous online review based on [29], but the decision context we consider (online service outsourcing auctions with unilateral freelancer effort) is quite different from both [28] (generic peer-to-peer trading ignoring service efforts) and [29] (service outsourcing decision where the provider decides both her own and the client's efforts).

Regarding the trading mechanism, this study is related to the literature on buyer-determined auctions. In this literature, a main focus is comparing the effectiveness of different bidding formats under different situations, e.g., buyer-determined auctions v.s. price-based auctions (e.g., [30]–[32]), buyer-determined auctions v.s. scoring auctions (e.g., [33]), and open-bid v.s. sealed-bid buyer-determined auctions (e.g., [7]). Some other studies examine information revelation issues in buyer-determined auctions (e.g., [34]–[36]).

This study contributes to the literature from two aspects. First, to the broad literature on online service outsourcing where an overwhelming majority of studies are empirical, this work contributes by providing a game-theoretical analysis of interactive service outsourcing with endogenous online reviews. Second, this paper contributes to the literature on buyer-determined auctions by involving endogenous online review as a consideration in client's freelancer selection process as well as in winning freelancer's post-auction efforts.

III. MODEL FRAMEWORK

Consider a typical service transaction between a client (buyer) and $n \geq 2$ potential freelancers (service providers) in an online labor market (platform). The service to be transacted is modeled by two dimensions, i.e., scope and quality (e.g., [37]). The service scope, denoted by s , captures the number of deliverables covered in the service, while the service quality captures the average effectiveness of the deliverables. To reflect the uncertain process of service delivering, we assume that the service quality, denoted by q_D , depends on the delivery state D which takes a binary value of either H (high-quality delivery) or L (low-quality delivery). Without loss of generality, we normalize $q_H = 1$ and let $q_L = q \in (0, 1)$.

Building on [29], we model the generative process of the delivery state D as follows. We assume that the value of D depends on a latent variable δ which represents the combination of all possible factors affecting the service outcome. We have $D = H$ if $\delta > 0$, and $D = L$ if $\delta \leq 0$. Specifically, δ is modeled as

$$\delta(\xi; \theta, x) = \theta x + \xi. \quad (1)$$

Here, θ reflects the innate ability or "expertise" of the freelancer who delivered the service. Note that there are $n \geq 2$ potential freelancers who compete for delivering the service, and their expertise $\{\theta_i\}_{i=1}^n$ are heterogeneous. Moreover, we assume that θ_i is the private information (type) of freelancer $i \in \{1, \dots, n\}$, and it is common knowledge that $\{\theta_i\}_{i=1}^n$ are *i.i.d.* over $[\underline{\theta}, \bar{\theta}]$ ($0 \leq \underline{\theta} < \bar{\theta}$), with *c.d.f.* $F(\cdot)$ and *p.d.f.* $f(\cdot)$. The term x in Equation (1) represents the quality-improvement attempt (effort) of the transacting freelancer. Without loss of generality, we normalize x such that $x \in [0, 1]$. To exert an effort x , the transacting freelancer bears an effort cost ax^2 , where $a > 0$ is a constant. Such quadratic format of effort cost reflects the increasing marginal cost of exerting effort, and it is a common assumption in the literature. The last term ξ in Equation (1) is a random variable capturing other idiosyncratic factors that could possibly affect the service outcome. We assume that ξ follows a uniform distribution $G(\xi) = 1 + \xi/\bar{\theta}$ over the support $[-\bar{\theta}, 0]$. The support is chosen such that $\delta(\xi) \leq 0$ holds for all possible ξ when the deterministic term θx takes its minimum value 0, and that $\delta(\xi) \geq 0$ holds for all possible ξ when θx takes its maximum value $\bar{\theta}$. Note that neither the distribution nor the support of ξ is critical for our results to hold. Based on the above assumptions, one obtains that the probability of high-quality delivery, given the transacting freelancer's true type θ and effort x , is given by

$$\begin{aligned} \Pr\{D = H|\theta, x\} &= \Pr\{\delta(\xi) > 0|\theta, x\} = 1 - G(-\theta x) \\ &= \theta x/\bar{\theta}, \quad \theta \in [\underline{\theta}, \bar{\theta}] \end{aligned} \quad (2)$$

Given the delivery state D , the client writes an online review of the freelancer's service. We adopt a binary review structure $R \in \{0, 1\}$, where $R = 1$ stands for a positive review and $R = 0$ for a negative review. Such binary structure is commonly observed in online reviews and is also common in the literature (e.g., [29], [38]). Specifically, we assume that the client gives a positive review ($R = 1$) under high-quality delivery ($D = H$), and a negative review ($R = 0$) under low-quality delivery ($D = L$). The client's review matters because it impacts the freelancer's future transactions in the market. To model such impact, we regard the market as a player which has a prior belief about the freelancer's probability ρ_i of high-quality delivery. To facilitate the calculation convenience with Bernoulli random variables $\{\rho_i\}_{i=1}^n$, we assume that the market's prior belief about ρ_i is a Beta distribution with parameters $\alpha_0 > 0$ and $\beta_0 > 0$. Upon the observation of the client's review R , the market forms a posterior belief about ρ_i based on Bayesian rule. Let $r_R = \mathbb{E}[\rho_i|R]$, and then

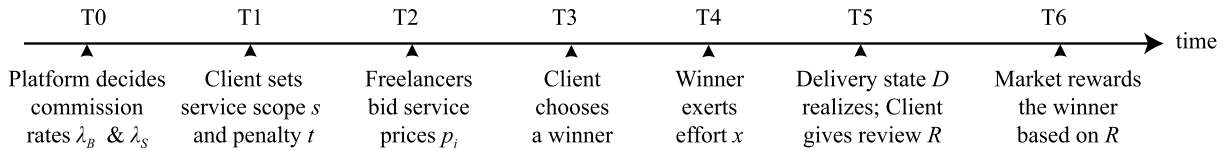


FIGURE 1. Sequence of events.

it can be derived that

$$r_R = \alpha + \beta R \tag{3}$$

where $\alpha = \frac{\alpha_0}{\alpha_0 + \beta_0 + 1}$ and $\beta = \frac{1}{\alpha_0 + \beta_0 + 1}$. The market rewards the freelancer with a payoff equal to $r_R m_H + (1 - r_R) m_L$, where $m_L < m_H$ so it is more rewarding to be viewed as with a higher probability of high-quality delivery. To simplify notation, we normalize $m_H = 1$ and $m_L = 0$ without loss of generality. Intuitively, β measures the marginal effect of the client’s review on the present value of the freelancer’s future payoff.

Given the service scope s and the delivery state D , the client obtains a value $v(s, q_D)$ from the service, where $v(s, q_D)$ is increasing in both the scope (s) and quality (q_D) of the service. Moreover, $v(s, q_D)$ is also concave in both s and q_D to reflect the diminishing marginal value. To derive clean analytical results, we assume $v(s, q_D) = \ln(sq_D)$. The payment to the transacting freelancer also depends on the delivery state D . If $D = H$, then the payment would be the auction price p ; if $D = L$, then the payment would be the auction price p deducting a penalty t , i.e., $p - t$. Therefore, given the service scope s , penalty t , auction price p , and delivery state D , the client’s profit from the service is

$$\pi(s, t; p, D) = \ln(sq_D) - (1 + \lambda_B)(p - t\mathbf{1}_{\{D=L\}}) \tag{4}$$

where $\mathbf{1}_{\{\cdot\}}$ is the indicator function, and $\lambda_B \in [0, 1)$ is the client’s commission rate to the platform. Correspondingly, the transacting freelancer bears a service-providing cost $c(s, q_D)$ to deliver the service, where $c(s, q_D)$ is increasing in both s and q_D . For simplicity, we assume $c(s, q_D) = csq_D$, where $c > 0$ is a constant. As a result, the transacting freelancer’s net payoff when he bids price p and exerts effort x can be written as

$$u(p, x; \theta, s, t, D, R) = (1 - \lambda_S)(p - t\mathbf{1}_{\{D=L\}}) - csq_D - ax^2 + r_R \tag{5}$$

where $\lambda_S \in [0, 1)$ is the freelancer’s commission rate to the platform. Apparently, the commission rates charged by the platform, λ_B and λ_S , effectively cause transaction costs to the transaction parties. For ease of notation, we denote $k \equiv \frac{1 - \lambda_S}{1 + \lambda_B}$, which can be regarded as a measure of the transaction efficiency for the subsystem composed of the client and the freelancers.

The sequence of events is as follows (see Figure 1). At T0, the platform determines the commission rates λ_B and λ_S for the client and freelancers, respectively. The client then posts

a service requirement announcement at T1, which includes descriptions of the service scope s and the penalty t in case of low-quality delivery. Then interested freelancers submit their service prices $\{p_i\}_{i=1}^n$ to the client at T2, and the client selects one of the freelancers as winner at T3. The winner’s bidding price is determined as the auction price. The winner then performs the service at a service-providing cost csq_D at T4; meanwhile, the winner also exerts effort x in an attempt to produce high-quality delivery. At T5, the service is completed with high or low quality (i.e., the delivery state D realizes), which generates a value $\ln(sq_D)$ to the client, and the client makes payment $(p - t\mathbf{1}_{\{D=L\}})$ and writes online review R accordingly. Finally, at T6, the market responds to the client’s review R and rewards the winner with r_R .

IV. ANALYSIS

We analyze the model by backward induction. Since T6 and T5 do not involve effective decisions, we start our analysis from the winner’s effort decision at T4.

A. WINNING FREELANCER’S EFFORT DECISION

At T4, the winning freelancer decides his effort level x , given his expertise θ , the auction price p and the service scope s . The winning freelancer’s expected profit at T4 when he chooses effort x is given by

$$\begin{aligned} u(p, x; \theta, s, t) &= \mathbb{E}_D \{ \mathbb{E}_R [u(p, x; \theta, s, t, D, R)] | \theta, x \} \\ &= \mathbb{E}_D \{ (1 - \lambda_S)(p - t\mathbf{1}_{\{D=L\}}) - csq_D - ax^2 + (\alpha + \beta\mathbf{1}_{\{D=H\}}) | \theta, x \} \\ &= (1 - \lambda_S)(p - t) - csq - ax^2 + \alpha + \theta\gamma(s, t)x / \bar{\theta} \end{aligned}$$

where

$$\gamma(s, t) = (1 - \lambda_S)t - cs(1 - q) + \beta \tag{6}$$

is the (adjusted) marginal revenue of effort for the winning freelancer. Maximizing Equation (6) subject to $x \geq 0$ reveals the winning freelancer’s optimal effort x^* , as formalized in the following proposition.

Proposition 1: The winning freelancer’s optimal effort x^* and the corresponding expected profit $u(p; \theta, s, t) \equiv u(p, x^*; \theta, s, t)$ are respectively given by

$$x^*(\theta, s, t) = \theta \max \{0, \gamma(s, t)\} / (2a\bar{\theta}) \tag{7}$$

$$u(p; \theta, s, t) = (1 - \lambda_S)(p - t) - csq + \alpha \tag{8}$$

$$+ \theta^2 [\max \{0, \gamma(s, t)\}]^2 / (4a\bar{\theta}^2). \tag{9}$$

All proofs are provided in the Appendix. Two implications can be obtained from Proposition 1. First, the winning freelancer would exert positive quality-improving effort (i.e., $x^* > 0$) when and only when the marginal revenue of effort for him is positive, i.e., $\gamma(\theta, s, t) > 0$. This is the first-level tradeoff underlying the winning freelancer's decision of whether to exert effort or not. Second, when the winning freelancer decides to exert positive effort, he faces the question of what level of effort is optimal. This is determined by the second-level tradeoff between the marginal revenue (i.e., $\theta\gamma(s, t)/\bar{\theta}$) and marginal cost (i.e., $2ax$) of exerting effort. As a result, the winning freelancer tends to exert more effort x^* when the market has higher reward β for positive review, when the service scope s is lower, when the penalty t for low-quality delivery is higher, when the difference between high and low quality $(1 - q)$ is lower, or when the coefficient of effort cost a is lower.

B. CLIENT'S SELECTION OF WINNING FREELANCER

At T3, observing all bids $\{p_i\}_{i=1}^n$ and anticipating the winning freelancer's subsequent optimal effort decisions, the client's expected profit when she selects a winning freelancer with price p and expertise θ (non-observable) is given by:

$$\begin{aligned} \pi(s, t; p, \theta) &= \mathbb{E}_D[\pi(s, t; p, D)|\theta] \\ &= \underbrace{\ln(sq) - (1 + \lambda_B)(p - t)}_{\text{(i) profit from low-quality delivery}} \\ &\quad + \underbrace{\theta x^*(\theta, s, t) [\ln(1/q) - (1 + \lambda_B)t]}_{\text{(ii) expected surplus from quality-improvement}} / \bar{\theta} \end{aligned} \quad (10)$$

Although the winning freelancer's expertise θ is unknown, the client can anticipate that the relationship between θ and $\pi(s, t; p, \theta)$ is as given by Equation (10). The client's expected profit $\pi(s, t; p, \theta)$ can be regarded as composing of two parts: the profit from low-quality delivery (Part (i) of Equation (10)), and the expected surplus from quality-improvement (Part (ii) of Equation (10)). To keep the analysis relevant, we restrict our attention to the situation where the client's expected surplus from quality-improvement is non-negative, i.e., $\ln(1/q) - (1 + \lambda_B)t \geq 0$; as will be shown in subsection IV-D, the client's optimal decision indeed induces this situation. It follows that $\pi(s, t; p, \theta)$ is increasing in θ and decreasing in p , which indicates the following proposition:

Proposition 2: *If the bidding equilibrium $p^*(\theta)$ is non-increasing, then the client will choose the lowest-price bidder as the winning freelancer.*

In the subsequent analysis, we focus only on non-increasing bidding equilibrium $p^*(\theta)$, so the result of Proposition 2 can be anticipated by all bidding freelancers. Although Proposition 2 indicates that the auction is effectively a price-based auction, we should note that the identity of the winning freelancer is not trivial for the client, since the winning freelancer's expertise θ also has direct impact on the client's expected profit (Equation (10)).

Effectively, $\pi(s, t; p, \theta)$ (or any increasing function of $\pi(s, t; p, \theta)$) can be regarded as the bidding score function of the freelancer with expertise θ .

C. FREELANCERS' BIDDING STRATEGY

At T2, given the service scope s and penalty t , the n potential freelancers submit their service prices $\{p_i\}_{i=1}^n$, anticipating the client's bid-taking rule $\pi(s, t; p, \theta)$. To derive the bidding equilibrium, we should integrate $\pi(s, t; p, \theta)$ into the freelancer's expected profit $u(p; \theta, s, t)$, which makes a weighted channel profit $\psi(\theta, s, t)$ as follows:

$$\begin{aligned} \psi(\theta, s, t) &\equiv k\pi(s, t; p, \theta) + u(p; \theta, s, t) \\ &= k \ln(sq) - csq + \alpha + \frac{\theta^2 \max\{0, \gamma(s, t)\}}{4a\bar{\theta}^2} \\ &\quad \times \{\gamma(s, t) + 2k [\ln(1/q) - (1 + \lambda_B)t]\} \end{aligned} \quad (11)$$

Note that Equation (11) does not depend on p because p is canceled out in the calculation. Intuitively, the weighted channel profit $\psi(\theta, s, t)$ is composed of the freelancer's expected profit $u(p; \theta, s, t)$ and the client's expected profit $\pi(s, t; p, \theta)$, weighted by the transaction efficiency k . The first-order derivative of $\psi(\theta, s, t)$ with respect to θ is

$$\begin{aligned} \frac{\partial \psi(\theta, s, t)}{\partial \theta} &= \frac{\theta \max\{0, \gamma(s, t)\}}{2a\bar{\theta}^2} \\ &\quad \times \{\gamma(s, t) + 2k [\ln(1/q) - (1 + \lambda_B)t]\} \end{aligned}$$

When $\gamma(s, t) > 0$, we have $\frac{\partial \psi(\theta, s, t)}{\partial \theta} > 0$, and thus the inverse function of $\psi(\theta, s, t)$ with respect to θ , denoted by $\psi^{-1}(\cdot)$, exists and is increasing in θ .

Let $y_i = \psi(\theta_i, s, t)$ denote the weighted channel profit associated with freelancer i , $H(y_i) = F(\psi^{-1}(y_i))$ denote the *p.d.f.* of y_i , and $b_i = k\pi(s, t; p, \psi^{-1}(y_i))$ denote the adjusted bidding score of freelancer i . Suppose there exists a bidding score equilibrium $b^*(\cdot)$ that is symmetric and increasing in y_i . Given that all other freelancers adopt the equilibrium $b^*(\cdot)$, the expected profit of freelancer i when bids a score b_i is written as

$$\begin{aligned} U(p_i; \theta_i, s, t) &= u(p_i; \theta_i, s, t) \Pr\{\text{win}\} \\ &= (y_i - b_i) \Pr\left\{b_i > \max_{j \neq i} b^*(y_j)\right\} \\ &= (y_i - b_i) H\left(b^{*-1}(b_i)\right)^{n-1} \end{aligned} \quad (12)$$

where $b^{*-1}(\cdot)$ is the inverse function of $b^*(\cdot)$. Maximizing Equation (12) with respect to b_i yields the following proposition.

Proposition 3: *In equilibrium, freelancer $i \in \{1, \dots, n\}$ bids a service price $p^*(\theta_i, s, t)$ as given by*

$$\begin{aligned} (1 - \lambda_S) (p^*(\theta_i, s, t) - t) \\ = \int_{\underline{\theta}}^{\theta_i} \frac{F^{n-1}(x)}{F^{n-1}(\theta_i)} \frac{\partial \psi(x, s, t)}{\partial x} dx \\ + csq - \alpha - \theta^2 [\max\{0, \gamma(s, t)\}]^2 / (4a\bar{\theta}^2) \end{aligned} \quad (13)$$

and obtains an expected profit of

$$\begin{aligned}
 U^*(s, t) &= \mathbb{E}_{\theta_{(1)}} [U(p^*(\theta_{(1)}, s, t); \theta_{(1)}, s, t)] \\
 &= \mathbb{E}_{\theta_{(1)}, \theta_{(2)}} [\psi(\theta_{(1)}, s, t) - \psi(\theta_{(2)}, s, t)] \quad (14) \\
 &= \frac{1}{2} (A_1 - A_2) \max\{0, \gamma(s, t)\} \\
 &\quad \times \{\gamma(s, t) + 2k [\ln(1/q) - (1 + \lambda_B)t]\} \quad (15)
 \end{aligned}$$

where $A_i \equiv \mathbb{E}_{\theta_{(i)}} [\theta_{(i)}^2] / (2a\bar{\theta}^2)$, $i = 1, 2$.

The implications of Proposition 3 are as follows. First, substituting Equation (13) into Equation (9), we have

$$u(p^*(\theta_i, s, t); \theta_i, s, t) = \int_{\underline{\theta}}^{\theta_i} \frac{F^{n-1}(x)}{F^{n-1}(\theta_i)} \frac{\partial \psi(x, s, t)}{\partial x} dx \geq 0. \quad (16)$$

This implies that freelancer $i \in \{1, \dots, n\}$ arranges his bid in such a way that he can reap an information rent $\int_{\underline{\theta}}^{\theta_i} \frac{F^{n-1}(x)}{F^{n-1}(\theta_i)} \frac{\partial \psi(x, s, t)}{\partial x} dx$ if he wins the auction. Second, Equation (14) indicates that the expected information rent to the winning freelancer is determined by the gap between the weighted channel profit associated with the winning freelancer $\psi(\theta_{(1)}, s, t)$ and that associated with the best-losing freelancer $\psi(\theta_{(2)}, s, t)$. When $\gamma(s, t) > 0$, the winning freelancer is able to generate a higher weighted channel profit than the best-losing freelancer, thus leading to a positive expected information rent. When $\gamma(s, t) \leq 0$, however, the winning freelancer obtains no information rent, since all potential freelancers can generate the same weighted channel profit due to the fact that no freelancer would exert positive quality-improving effort (Equation (7)). Third, Equation (15) implies that the winning freelancer's expected profit is weakly decreasing in the service scope s and weakly increasing in the penalty t .

D. CLIENT'S DECISION ON SERVICE SCOPE AND PENALTY

At T1, the client chooses the service scope s and penalty t to maximize the following expected profit

$$\Pi(s, t) = \mathbb{E}_{\theta_{(1)}} [\pi(s, t; p^*(\theta_{(1)}, s, t), \theta_{(1)})] \quad (17)$$

By Equations(11)(12) (13)(15), Equation (17) can be rewritten as

$$\begin{aligned}
 \Pi(s, t) &= \frac{1}{k} \mathbb{E}_{\theta_{(2)}} [\psi(\theta_{(2)}, s, t)] \\
 &= \frac{k \ln(sq) - csq + \alpha}{k} + \frac{1}{2k} A_2 \max\{0, \gamma(s, t)\} \\
 &\quad \times \{\gamma(s, t) + 2[k \ln(1/q) - (1 - \lambda_S)t]\} \quad (18)
 \end{aligned}$$

Maximizing $\Pi(s, t)$ with respect to (s, t) yields the following proposition.

Proposition 4: The client's optimal service scope s^ , optimal penalty t^* , and maximized expected profit $\Pi(s^*, t^*)$ are respectively given by*

$$s^* = \begin{cases} \frac{1 + A_2XY - \sqrt{\Delta}}{2A_2Yc(1 - q)} & X > kY \\ \frac{k}{cq} & X \leq kY \end{cases} \quad (19)$$

$$t^* = \begin{cases} \frac{X - \beta}{1 - \lambda_S} & X > kY \\ \frac{kY - \beta}{1 - \lambda_S} & X \leq kY \end{cases} \quad (20)$$

$$\Pi(s^*, t^*) = \begin{cases} \frac{(1 - A_2XY)^2 - 2(1 + kA_2Y^2)}{4kA_2Y^2} + \frac{(1 + A_2XY)\sqrt{\Delta}}{4kA_2Y^2} + \frac{\alpha}{k} + \ln\left(\frac{1 + A_2XY - \sqrt{\Delta}}{2cA_2Y^2}\right) & X > kY \\ \ln\left(\frac{k}{c}\right) - 1 + \frac{\alpha}{k} & X \leq kY \end{cases}$$

where $X = \beta + k \ln(1/q)$, $Y = 1/q - 1$, and $\Delta = (1 - A_2XY)^2 + 4A_2Y(X - kY)$.

Proposition 4 indicates that the client's optimal decision are divided into two pieces by the relationship between X and kY . By definition, $X > kY$ can be rewritten as

$$\beta > k [1/q - 1 - \ln(1/q)] \quad (21)$$

In Equation (21), the left hand side is the marginal effect of a positive review on the freelancer's expected profit, while the right hand side captures the adjusted cost (adjusted by k) of service-quality improvement to the subsystem of the client and the winning freelancer: improving the service quality from $q_L = q$ to $q_H = 1$ inflates the freelancer's service-providing cost by $1/q - 1$ but generates an additional client value of $\ln(1/q)$, thus leading to a subsystem cost of $1/q - 1 - \ln(1/q)$. Therefore, the relationship between X and kY reflects the tradeoff between present cost and future profit regarding the determination of service quality, and Proposition 4 conveys the following simple implication: when service-quality improvement generates higher benefit than cost to the subsystem, the client should set the service scope s^* and penalty t^* such that $\gamma(s^*, t^*) > 0$, thus inducing the winning freelancer to exert positive quality-improving effort (Equation (7)); otherwise, the client should set the service scope s^* and penalty t^* such that $\gamma(s^*, t^*) = 0$, thus preventing the winning freelancer from exerting quality-improving effort (Equation (7)). Therefore, we may refer to the client's strategy (s^*, t^*) when $X > kY$ ($X \leq kY$) as the effort-inducing (effort-preventing) strategy. We have the following corollary regarding the client's choice between effort-inducing strategy and effort-preventing strategy.

Corollary 1: The client is more likely to choose the effort-inducing strategy over the effort-preventing strategy when:

- (i) the marginal effect of online review, β , is higher;
- (ii) the transaction efficiency k is lower; or
- (iii) the service quality of delivery state L , q , is higher.

The results of Corollary 1 is also depicted in Figure 2. When online review has greater impact on freelancers, a high-quality delivery will induce more future benefit to the subsystem of the winning freelancer and the client, and thus the client is more likely to adopt the effort-inducing strategy. The transaction efficiency k serves as a amplifier of the

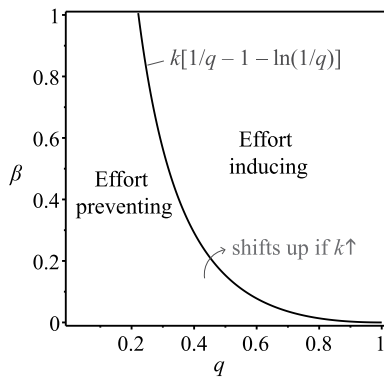


FIGURE 2. The client’s choice between effort-inducing and effort-preventing strategies.

subsystem’s decision results. With a higher k , the adjusted cost of service-quality improvement to the subsystem is amplified, thus making it more likely for the client to adopt the effort-preventing strategy. Due the assumption of diminishing marginal value of service quality and linear cost in service quality providing, the marginal cost of service-quality improvement to the subsystem is reduced when the magnitude of service-quality improvement is lower (i.e., q is higher). Therefore, the client is more likely to adopt the effort-inducing strategy with a higher q .

V. IMPACTS OF ONLINE REVIEW

In our model, the marginal effect of the client’s online review on the winning freelancer’s profit is given by the parameter β . With a higher β , the online review system is more effective. When $\beta \rightarrow 0$, the model is identical to the case with no review system. In this section, we examine how the value of β affects the transacting parties’ decision results.

A. ON THE CLIENT

Regarding the impacts of online review on the client’s optimal decision results, we have the following proposition.

Proposition 5: When the marginal effect of online review increases (i.e., with a higher β):

(i) the client with effort-inducing strategy ($X > kY$) sets a lower service scope s^* and obtains a higher expected profit $\Pi(s^*, t^*)$, while the penalty t^* is unaffected;

(ii) the client with effort-preventing strategy ($X \leq kY$) sets a lower penalty t^* , while the service scope s^* and expected client profit $\Pi(s^*, t^*)$ are unaffected.

The results of Proposition 5 are also depicted in Figure 3. When the client adopts the effort-inducing strategy ($X > kY$), the winning freelancer is always induced to exert positive effort $x^*(\theta, s^*, t^*) > 0$, such that high-quality delivery occurs with a positive probability. In this case, if service-quality improvement is achieved, the client will obtain a marginal revenue of $\ln(1/q)$ from project value improvement; at the same time, the client also bears a marginal cost of $(1 + \lambda_B)t$ due to the exemption of penalty on the winning freelancer.

Therefore, the optimal penalty would be chosen such that $\ln(1/q) = (1 + \lambda_B)t^*$, which is independent of online review. As regards the impacts of online review on the client’s choice of service scope, we note that decreasing service scope has negative effect of decreasing project value and positive effect of increasing freelancer effort. With a higher β , the positive effect of increasing freelancer effort is strengthened, thus leading the client tends more to reduce the service scope. Finally, as a higher β implies higher market reward to the subsystem of the winning freelancer and the client, the client’s expected profit is increased. On the other hand, when the client adopts the effort-preventing strategy ($X \leq kY$), low-quality delivery is always the case since the winning freelancer never exerts positive effort. In this case, the client’s service scope and expected profit are independent of β (since positive review never occurs). However, to maintain the existence of such a decision case, the client should set the penalty such that the boundary constraint $\gamma(s^*, t^*) = 0$ holds, which leads to a penalty t^* decreasing in β .

B. ON FREELANCERS

Under the client’s optimal decision (s^*, t^*) , the winning freelancer’s expected effort $\mathbb{E}[x^*]$ (shorthand for $\mathbb{E}_{\theta(1)}[x^*(\theta(1), s^*, t^*)]$), expected auction price $\mathbb{E}[p^*]$ (shorthand for $\mathbb{E}_{\theta(1)}[p^*(\theta(1), s^*, t^*)]$) and expected profit $U^*(s^*, t^*)$ are respectively given by

$$\mathbb{E}[x^*] = \frac{(X - kY)^+ \mathbb{E}[\theta(1)]}{a\bar{\theta}(\sqrt{\Delta} + 1 - A_2XY)}, \tag{22}$$

$$\mathbb{E}[p^*] = [k(Y + 1) - \beta - \alpha] / (1 - \lambda_S) + \frac{(X - kY)^+}{Y(1 - \lambda_S)} \left[Y + 1 - \frac{2(\sqrt{\Delta} + 1 - A_2kY^2)}{(\sqrt{\Delta} + 1 - A_2XY)^2} \right] \tag{23}$$

$$U^*(s^*, t^*) = \frac{2(A_1 - A_2)[(X - kY)^+]^2}{(\sqrt{\Delta} + 1 - A_2XY)^2}. \tag{24}$$

Examining the impacts of online review on the freelancer’s decision results, we have the following proposition.

Proposition 6: When the marginal effect of online review increases (i.e., with a higher β):

(i) the winning freelancer is more likely to exert quality-improvement effort, and the expected effort $\mathbb{E}[x^*]$ increases;

(ii) the expected auction price $\mathbb{E}[p^*]$ decreases;

(iii) the winning freelancer’s expected profit ($U^*(s^*, t^*)$) weakly increases.

The results of Proposition 6 are illustrated in Figure 4. When online review has greater impact on freelancers, the winning freelancer has more incentive to exert higher effort to improve the service quality, thus increasing the probability of getting a positive review and obtaining more future revenue. This is in line with Corollary 1 which states that the client is more likely to induce the effort-inducing strategy with a higher β . Part (ii) of Proposition 6 uncovers

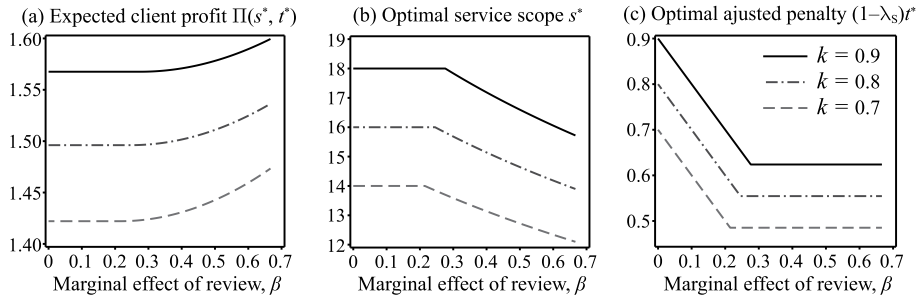


FIGURE 3. Impacts of online review on the client's decision results. Values of parameters: $n = 3$; $q = 0.5$; $a = 1$; $c = 0.1$; $\underline{\theta} = 1$; $\bar{\theta} = 2$; $\alpha = \frac{1}{3}$.

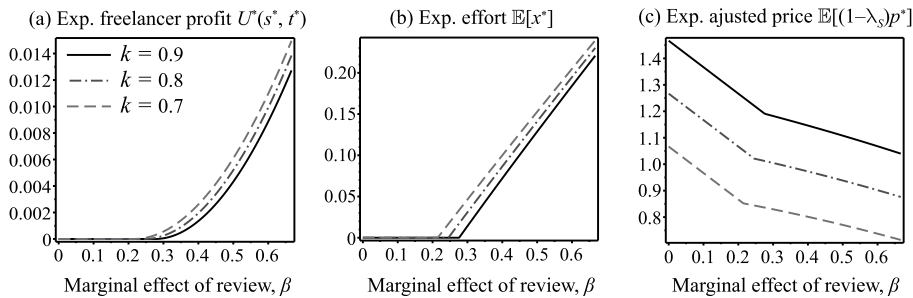


FIGURE 4. Impacts of online review on the freelancers' decision results. Values of parameters: $n = 3$; $q = 0.5$; $a = 1$; $c = 0.1$; $\underline{\theta} = 1$; $\bar{\theta} = 2$; $\alpha = \frac{1}{3}$.

the impact of online review on freelancers' bidding strategy. When the marginal effect of online review increases, the freelancers can expect more from future revenue by winning the present transaction and getting a positive review, which drives them more aggressive in bidding for the present transaction. Finally, similar to the impact on the client's expected profit (Proposition 5), a more effective online review system also increases the winning freelancer's expected profit since it implies higher market reward to the subsystem of the winning freelancer and the client.

C. ON THE PLATFORM

Anticipating the optimal decisions of the client and freelancers, the platform's expected profit when it sets commission rates (λ_S, λ_B) is given by

$$\begin{aligned} \Gamma(\lambda_S, \lambda_B) &= \mathbb{E}_{\theta(1)} \left[(\lambda_S + \lambda_B) \left(p^* - t^* + \frac{\theta(1)x^*}{\theta} t^* \right) \right] \\ &= \frac{(1-k)(k-\alpha)}{k} + \frac{(1-k)(X-kY)^+}{kY} \\ &\quad \times \left[\frac{1}{2} + \frac{2A_1Y(X-\beta) - A_2XY - 1}{\sqrt{\Delta} + 1 - A_2XY} \right] \end{aligned} \quad (25)$$

where p^* and x^* are shorthand for $p^*(\theta(1), s^*, t^*)$ and $x^*(\theta(1), s^*, t^*)$, respectively.

Note that Equation (25) involves no separate λ_S or λ_B ; λ_S and λ_B always come in pairs in the form of $k = \frac{1-\lambda_S}{1+\lambda_B}$. This implies that the platform should decide λ_S and λ_B jointly by selecting the k that maximizes Equation (25).

Due to intractability of the platform's problem, we resort to numerical simulation to illustrate how could the platform

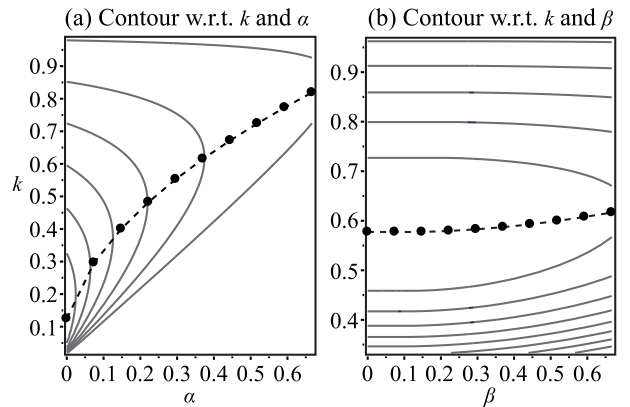


FIGURE 5. Contour plot of the platform's expected profit Γ . The solid lines are contours of Γ with respect to k and α or β , while the dash lines with dots are the loci of optimal k^* as functions of α (subplots (a)) or β (subplots (b)). Values of parameters: $n = 3$; $q = 0.5$; $a = 1$; $c = 0.1$; $\underline{\theta} = 1$; $\bar{\theta} = 2$; $\beta = \frac{1}{3}$ for subplot (a) and $\alpha = \frac{1}{3}$ for subplot (b).

choose the optimal k^* and explore how online review affects the platform's selection of k^* . In Figure 5, we plot the contours of Γ with respect to (k, α) (Figure 5(a)) and (k, β) (Figure 5(b)), respectively. One can observe that given α or β , the platform's expected profit Γ is concave in k , and thus the optimal k^* can be computed by solving the first-order conditions. As α or β increases (both indicating greater impact of the online review system), we observe that the optimal k^* for the platform increases, implying that the platform should charge lower commission fees when the online review system is more effective.

VI. CONCLUSION

Motivated by the emergence of online service outsourcing platforms where buyer-determined auctions are commonly used as the service trading mechanism and review systems are provided to facilitate transaction trust, this paper develops a game-theoretical model of online service outsourcing auctions with endogenous reviews. In the model, the client first announces the service scope and the penalty in case of low-quality delivery, and then interested freelancers possessing private information about their service expertise bid the service prices. The client selects one winning freelancer on the buyer-determined basis, and the winning freelancer exerts efforts to improve the service quality, anticipating the client's ex post review behavior.

We address the two main questions put forward in introduction as follows. For question (a), i.e., how the client and the freelancers would interact with each other in online service outsourcing auctions with endogenous reviews, we have the following findings. We find that in equilibrium, freelancers with higher service expertise bid lower prices, and the lowest-price bidder is always selected as the winning freelancer. When service-quality improvement generates lower benefit than cost to the transaction parties as a whole, the client adopts the effort-preventing strategy: the service scope and penalty are set such that the winning freelancer never exerts quality-improving effort. Otherwise, the client adopts the effort-inducing strategy, under which the winning freelancer is induced to exert positive quality-improving effort. In this case, greater effort will be induced when the market has higher reward for positive review, when the service scope is lower, or when the penalty for low-quality delivery is higher. For questions (b), i.e., how the online review system impacts the decision results of the client, the freelancers, and the platform, we obtain the following results. We find that when the marginal effect of online review increases, the client is more likely to choose the effort-inducing strategy over the effort-preventing strategy, and the client with effort-inducing strategy sets a lower service scope and obtains a higher expected profit, while the client with effort-preventing strategy sets a lower penalty. Moreover, when the marginal effect of online review increases, the winning freelancer's expected service effort increases and the expected auction price decreases, which further leads to a weakly increased expected profit for the winning freelancer. By numerical simulation, we observe that the platform should charge lower commission fees from the clients and freelancers when the online review system is more effective.

Several implications can be obtained from the above results regarding the impacts of the online review system. First, although the online review system helps to facilitate transaction trust, our finding suggests that this does not necessarily mean that the online review system also helps to increase the transaction volume. Instead, in our model, the more effective the review system is, the smaller scope of services will be transacted. This seemingly counterintuitive result lies in the fact the freelancer's service effort is decreasing in the service

scope. When online review is more effective, the marginal cost of incentivizing service effort is lower, and thus the client is motivated to reduce the service scope to induce the highest possible service effort. Second, our analysis also reveals that the review system has the impact of intensifying the competition in the bidding process. This is because the review system can bring higher future return to freelancers if they deliver high quality services, which makes the transaction opportunity more valuable to bid on. Third, our result also implies that the review system helps to reduce the transaction cost between the clients and the freelancers, in the form of reducing the commission rates they are charged. However, this does not mean that the platform is worse off, since the review system also increases the possibility of high-quality delivery, i.e., the payment with the review system is more likely the total auction price rather than the auction price minus the penalty.

This paper has some limitations which may be overcome to obtain more findings in future researches. For example, to focus on the client's ex post review behavior, we do not consider the heterogeneity in freelancers' initial reputation. It may be an interesting direction to examine how ex ante heterogeneous reviews interact with ex post endogenous reviews. Moreover, due to mathematical complexity, we do not obtain analytical results regarding the platform's decision. It is still unclear how should the platform treat the review system strategically under different situations.

APPENDIX

Proof of Proposition 1: It is easy to verify that $u(p, x; \theta, s, t)$ (Equation (6)) is concave in x . Therefore, the winning freelancer's optimal effort x^* can be obtained by solving the first-order condition $\frac{\partial}{\partial x} u(p, x; \theta, s, t) = 0$ subject to $x \geq 0$, which yields Equation (7). Substituting Equation (7) back into Equation (6) yields Equation (9), which concludes the proof. \square

Proof of Proposition 2: One can check that part (ii) of Equation (10) is increasing in the freelancer's expertise θ . Therefore, the client's expected profit $\pi(s, t; p, \theta)$ will be increasing in θ in equilibrium, if the bidding equilibrium $p^*(\theta)$ in part (i) of Equation (10) is decreasing in θ . This indicates Proposition 2. \square

Proof of Proposition 3: Regarding $U(p_i; \theta_i, s, t)$ in Equation (12) as a function of b_i . The problem of freelancer i is choosing a bidding score b_i to maximize his expected profit $U(p_i; \theta_i, s, t)$. Since $b^*(\cdot)$ is the bidding equilibrium, the first-order condition $\frac{\partial U}{\partial b_i} = 0$ must be satisfied when freelancer i chooses the equilibrium strategy $b_i = b^*(y_i)$, i.e.,

$$\begin{aligned} \frac{\partial U}{\partial b_i} \Big|_{b_i=b^*(y_i)} &= \frac{y_i - b^*(y_i)}{b^{*'}(y_i)} \frac{\partial [H(y_i)^{n-1}]}{\partial y_i} - H(y_i)^{n-1} \\ &= 0 \end{aligned} \quad (26)$$

Equation (26) can be rewritten as

$$\frac{\partial [H(y_i)^{n-1} b^*(y_i)]}{\partial y_i} = y_i \frac{\partial [H(y_i)^{n-1}]}{\partial y_i} \quad (27)$$

Integrating both sides of Equation (27) with respect to y_i from $\underline{y} \equiv \psi(\underline{\theta}, s, t)$ to y_i and applying $H(\underline{y}) = F(\underline{\theta}) = 0$, we obtain

$$\begin{aligned} b^*(y_i)H(y_i)^{n-1} &= \int_{\underline{y}}^{y_i} x_i dH(x_i)^{n-1} \\ &= y_i H(y_i)^{n-1} - \int_{\underline{y}}^{y_i} H(x_i)^{n-1} dx_i \end{aligned}$$

which leads to

$$b^*(y_i) = y_i - \int_{\underline{y}}^{y_i} \frac{H(x_i)^{n-1}}{H(y_i)^{n-1}} dx_i \quad (28)$$

One can verify that $b^*(y_i)$ given by Equation (28) is indeed increasing in y_i . Substituting $y_i = \psi(\theta_i, s, t)$, $H(y_i) = F(\psi^{-1}(y_i))$ and $b_i = k\pi(s, t; p, \psi^{-1}(y_i))$ into Equation (28), we obtain the equilibrium bidding price $p^*(\theta_i, s, t)$, as characterized by Equation (13).

Next we derive the winning freelancer's expected profit. Given type θ , the winning freelancer's expected profit in equilibrium is $u(p^*(\theta, s, t); \theta, s, t)$, as given in Equation 16. Since $b^*(y_i)$ is increasing in y_i while y_i is increasing in θ_i , the freelancer with the highest expertise $\bar{\theta}$ will bid the highest score in equilibrium, hence being selected as the winner. Therefore, from an ex ante point of view, the winning freelancer's expected profit is

$$U^*(s, t) = \int_{\underline{\theta}}^{\bar{\theta}} \int_{\underline{\theta}}^y \frac{F^{n-1}(x)}{F^{n-1}(y)} \frac{\partial \psi(x, s, t)}{\partial x} dx f_1(y) dy \quad (29)$$

where $f_1(\theta) = nF(\theta)^{n-1}f(\theta)$ is the *p.d.f.* of $\theta_{(1)}$. Changing the order of integration, Equation (29) can be rewritten as

$$\begin{aligned} U^*(s, t) &= \int_{\underline{\theta}}^{\bar{\theta}} nF^{n-1}(x) \frac{\partial \psi(x, s, t)}{\partial x} \int_x^{\bar{\theta}} f(y) dy dx \\ &= \int_{\underline{\theta}}^{\bar{\theta}} [F_2(x) - F_1(x)] \frac{\partial \psi(x, s, t)}{\partial x} dx \\ &= \mathbb{E}_{\theta_{(1)}} [\psi(\theta_{(1)}, s, t)] - \mathbb{E}_{\theta_{(2)}} [\psi(\theta_{(2)}, s, t)] \quad (30) \end{aligned}$$

where $F_1(\theta) = F(\theta)^n$ and $F_2(\theta) = F(\theta)^n + nF(\theta)^{n-1} [1 - F(\theta)]$ are the *c.d.f.* of $\theta_{(1)}$ and $\theta_{(2)}$, respectively. Substituting the expression of $\psi(\theta, s, t)$ (Equation (11)) into Equation (30), we obtain Equation (15). \square

Proof of Proposition 4: Because the expression of $\Pi(s, t)$ is piece-wise, depending on the sign of $\gamma(s, t)$, we will derive the local optimal solutions for $\gamma(s, t) < 0$ and $\gamma(s, t) \geq 0$ respectively, and then determined the global optimal solution.

(i) When $\gamma(s, t) < 0$, Equation (18) can be rewritten as $\Pi(s, t) = [k \ln(sq) - csq + \alpha] / k$, which is maximized at $s^* = \frac{k}{cq}$. The condition $\gamma(s, t) < 0$ requires $t^* < \frac{kY - \beta}{1 - \lambda_S}$. Substituting $s^* = \frac{k}{cq}$ and $t^* < \frac{kY - \beta}{1 - \lambda_S}$ back into $\Pi(s, t)$, we obtain that the client's expected profit in this case is $\Pi(s^*, t^*) = \ln(\frac{k}{c}) - 1 + \frac{\alpha}{k}$.

(ii) When $\gamma(s, t) \geq 0$, Equation (18) can be rewritten as

$$\begin{aligned} \Pi(s, t) &= \frac{k \ln(sq) - csq + \alpha}{k} + \frac{A_2 \max\{0, \gamma(s, t)\}}{2k} \\ &\quad \times \{\gamma(s, t) + 2[k \ln(1/q) - (1 - \lambda_S)t]\} \quad (31) \end{aligned}$$

One can check that $\frac{\partial^2 \Pi}{\partial t^2} < 0$ and $\frac{\partial^2 \Pi}{\partial s \partial t} = \frac{\partial^2 \Pi}{\partial t \partial s} = 0$ hold. Therefore, the condition ensuring the concavity of $\Pi(s, t)$ with respect to (s, t) (i.e., the Hessian matrix of $\Pi(s, t)$ being negative definite, or equivalently, $\frac{\partial^2 \Pi}{\partial s^2} < 0$ and $\frac{\partial^2 \Pi}{\partial s^2} \frac{\partial^2 \Pi}{\partial t^2} - \frac{\partial^2 \Pi}{\partial s \partial t} \frac{\partial^2 \Pi}{\partial t \partial s} > 0$) is equivalent to $\frac{\partial^2 \Pi}{\partial s^2} < 0$, i.e.,

$$c(1 - q)s < \sqrt{k / A_2} \quad (32)$$

Below we suppose Equation (32) holds. Then the optimal solution of Equation (31) subject to $\gamma(s, t) = (1 - \lambda_S)t - c(1 - q)s + \beta \geq 0$ can be obtained by solving the following KKT conditions:

$$\begin{cases} -\frac{\partial \Pi}{\partial s} + \mu c(1 - q) = 0 \\ -\frac{\partial \Pi}{\partial t} - \mu(1 - \lambda_S) = 0 \\ \mu [(1 - \lambda_S)t - c(1 - q)s + \beta] = 0 \\ \mu \geq 0 \end{cases}$$

which yields (s^*, t^*) as characterized by Equations (19) and (20). Under (s^*, t^*) , one can check that Equation (32) indeed holds. Substituting (s^*, t^*) back into Equation (31), we obtain that the client's expected profit in this case as characterized in Equation (21).

Comparing the above cases (i) and (ii), we find that case (i) is weakly dominated by case (ii). Therefore, we can use the local optimal solution of case (ii) to represent the client's global optimal solution. \square

Proof of Corollary 1: In Equation (21), the left hand side is increasing in β , while the right hand side is increasing in k and decreasing in q . Therefore, the inequality is more likely to hold with higher β , lower k , or higher q . \square

Proof of Proposition 5: When $X > kY$, we have $\frac{\partial t^*}{\partial \beta} = 0$,

$$\begin{aligned} \frac{\partial s^*}{\partial \beta} &= \frac{-2kA_2Y^2}{c(1 - q) [\Delta + (1 + A_2XY) \sqrt{\Delta}]} < 0 \\ \frac{\partial \Pi(s^*, t^*)}{\partial \beta} &= \frac{2A_2(X - kY)}{k [\sqrt{\Delta} + (1 - A_2XY)]} > 0 \end{aligned}$$

which proves part (i) of Proposition 5. When $X \leq kY$, we have $\frac{\partial t^*}{\partial \beta} = -(1 - \lambda_S)^{-1} < 0$ and $\frac{\partial s^*}{\partial \beta} = \frac{\partial \Pi(s^*, t^*)}{\partial \beta} = 0$, which indicates part (ii) of Proposition 5. \square

Proof of Proposition 6: When $X > kY$, taking the first-order derivatives of Equations (22), (23) and (24) with respect to β , respectively, we obtain that

$$\begin{aligned} \frac{\partial \mathbb{E}[x^*]}{\partial \beta} &= \frac{(\sqrt{\Delta} + 1 + A_2XY) \mathbb{E}_{\theta_{(1)}}[\theta_{(1)}]}{4a\bar{\theta} \sqrt{\Delta}} > 0 \\ \frac{\partial \mathbb{E}[p^*]}{\partial \beta} &= -\frac{A_2}{1 - \lambda_S} \left[\frac{2(X - kY)}{\sqrt{\Delta} + 1 - A_2XY} + \frac{kY}{\sqrt{\Delta}} \right] < 0 \\ \frac{\partial U^*}{\partial \beta} &= \frac{(A_1 - A_2)(X - kY) (\sqrt{\Delta} + 1 + A_2XY)}{\sqrt{\Delta} [\sqrt{\Delta} + (1 - A_2XY)]} > 0 \end{aligned}$$

When $X \geq kY$, we have $\partial \mathbb{E}[x^*] / \partial \beta = 0$, $\partial \mathbb{E}[p^*] / \partial \beta = -1 / (1 - \lambda_S) < 0$, and $\partial U^* / \partial \beta = 0$. Therefore, overall, we have $\partial \mathbb{E}[x^*] / \partial \beta \geq 0$, $\partial \mathbb{E}[p^*] / \partial \beta < 0$, and $\partial U^* / \partial \beta \geq 0$. \square

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