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Buyer-Side Institution-Based Trust-Building Mechanisms: A 3S Framework with Evidence from Online Labor Markets

Zhijuan Hong[a], Hui Zhu[b], and Kunxiang Dong[a]

[a]School of Management Science and Engineering, Shandong University of Finance and Economics, Shandong, P. R. China; [b]School of Information Technology, Jiangxi University of Finance and Economics, Jiangxi, P. R. China

ABSTRACT
Buyer-side, institution-based trust-building mechanisms, which usually appear in the form of guarantee-required schemes, are prevalently provided by the online labor marketplace for buyers to voluntarily adopt. We integrate signaling theory and organization theories of organizational slack and contractual incompleteness to propose a 3S (screening, signaling, and slack) effect framework to explain how the adoption of buyer-side trust-building mechanisms (i.e., guarantee-required schemes) affects freelancers' participation and bidding behavior. Based on a data set from one of the leading online labor markets in China, this study finds that guarantee-required tasks attract fewer but higher-quality freelancers. Furthermore, freelancers bid shorter durations but less-detailed proposals in guarantee-required tasks. This research also examines and finds support for the moderating role of task complexity in weakening screening and slack effects. Our research complements literature on trust-building mechanisms and online labor markets by providing a new framework (i.e., 3S effect framework) and empirical evidence with large-scale observational real-life data. Our study suggests that buyers should take both the advantages (e.g., bidders with higher-quality features, bids with shorter bidding durations) and disadvantages (e.g., fewer bids, bids with less-detailed proposals) into consideration and make appropriate trade-offs when making decisions on the adoption of buyer-side trust-building mechanisms.

KEY WORDS AND PHRASES
Bidding behavior; bidding strategy; freelancer participation; institution-based mechanisms; online labor markets; trust-building mechanisms

Online markets, including both online product and service markets, have grown steadily in popularity in the past few decades. In 2018, eBay.com—the pioneer online retail and auction market—earned more than $10 billion in net revenue.[1] In the fiscal year ending March 31, 2019, the Alibaba Group, which owns the most well-known online product marketplaces in China—Taobao.com and Tmall.com—reported that the number of annual active consumers in China's retail marketplaces had reached 654 million, an increase of 102 million over the previous fiscal year. The gross merchandise volume of physical goods traded on Tmall.com showed a year-on-year growth of 31% and on Taobao.com showed a year-on-year growth of 19%.[2] Although they appeared later than traditional online product markets, online labor markets—also known as online service markets—have also achieved great success in matching buyers who have service procurement needs with sellers who can provide the relevant services [29]. For example, freelancer.com,

CONTACT Zhijuan Hong hongye0401@163.com School of Management Science and Engineering, Shandong University of Finance and Economics 7366 East Erhuan Road, Jinan, Shandong 250014, P. R. China

[1]https://www.statista.com/statistics/507881/ebays-annual-net-revenue/(accessed in June 2019).
[2]https://www.chinainternetwatch.com/29315/alibaba-q1-2019/(accessed in June 2019).

a prime online labor marketplace, has helped buyers post more than 15 million projects.[3] By the end of 2018, zbj.com (with witmart.com as its international version), a well-known online labor marketplace in China, had facilitated transactions worth over $1.1 billion, and as of June 2019 it has almost 13 million registered service providers.[4]

Two types of players interact in online labor markets: buyers (i.e., clients who have service demands) and bidders (i.e., freelancers, sellers, or service providers who provide services). Matches between these two players are usually made via buyer-determined multiattribute auctions [27]. Typically, buyers who have service demands initiate a task by posting a call for bid (CFB), and interested freelancers then submit bids with multiple attributes (i.e., price, working duration, and execution proposal). Subsequently, buyers select a winner from the available choice pool (i.e., the participating bidders and their bids), to whom the service contract is awarded. An auction fails if the buyer cannot find a satisfactory bidder or bid from the choice pool. If the buyer selects a winner, a payment must be deposited to the platform and the chosen freelancer then starts to work. After a specified period, the freelancer delivers the work to the buyer. The buyer then releases the payment to the freelancer from the platform if the buyer is satisfied with the work, otherwise, the buyer can lodge a complaint with the platform, and the final payment amount should be a result of negotiation or arbitration. One crucial decision that a buyer needs to make when posting a CFB is whether to adopt *guarantee-required schemes*. Together with aspects such as the auction duration, task budget range, and task description, the choice to adopt such a scheme constitutes a complete CFB. Buyers can freely adopt these schemes without paying an additional charge. Specifically, tasks with guarantee-required schemes require freelancers to offer certain types of guarantees (e.g., guarantees of on-time service delivery, free after-sale services for three months, and originality of the work) before allowing them to submit bids. To claim an offer of corresponding guarantees, freelancers need to place a deposit with the marketplace. Once the guarantee money is deposited, a "guarantee" logo will appear on the seller's profile page when he or she participates in a subsequent task (both tasks with and without guarantee-required schemes). In tasks with guarantee-required schemes, buyers can claim compensation if the contracted freelancer fails to fulfill the commitment as guaranteed. The effect of guarantee-required schemes on the behavior of contracted freelancers after they start to work is intuitive: to avoid losing compensation, they are less likely to behave opportunistically. As a result, the buyer's trust is enhanced, the perceived risk is reduced, and the buyer's willingness to match a transaction increases, as predicted by the previous trust literature [20, 52]. However, the trust literature has not explored how the adoption of guarantee-required schemes affects freelancers' participating and bidding behaviors and, consequently, the choice pool (i.e., participating bidders and their bids) for buyers before the contract is awarded and the work actually starts. The choice pool refines the range from which a buyer can choose, and consequently its features naturally affect buyers' willingness to select a winner—that is, the match probability. Both academically and managerially, it is important to understand the impact of the adoption of guarantee-required schemes on outcomes, particularly the impact on the choice pool.

[3] https://www.freelancer.com/(accessed in June 2019).
[4] http://www.witmart.com/about/overview.html (accessed in June 2019).

In online markets, trust plays a crucial role in matching deals between buyers and sellers [52, 60]. In practice, many *trust-building mechanisms* are created to nurture buyers' trust and thus to encourage buyers to purchase a product or procure a service. In essence, *guarantee-required schemes*—the goal of which is "to enhance buyer trust and facilitate transactions" as stated by the marketplace (https://www.epwk.com/integrity-view-wk.html) —are one of these trust-building mechanisms. One unique feature of these schemes is that their adoption is a decision made by buyers when initiating a task. In this paper, we refer to trust-building mechanisms with this feature as *buyer-side trust-building mechanisms* or *buyer-initiated trust-building mechanisms*. Accordingly, we define *seller-side* (or *seller-initiated*) *trust-building mechanisms* as mechanisms in which the adoption decision is made by sellers and *mandatory trust-building mechanisms* as mechanisms that have their usage mandated by regulations. Typical examples of mandatory trust-building mechanisms are feedback or reputation systems under which reviews and reputation scores are mandatorily revealed to every user [36, 45, 52]. Examples of seller-side trust-building mechanisms include protection schemes, seven-day return policies, repair services, and e-assurances or guarantees [31, 49]. Note that although the preceding examples are seller-side trust-building mechanisms in most cases, they should be classified as mandatory trust-building mechanisms if the platform mandatorily requires every seller to adopt them. Because online labor marketplaces allow buyers to initiate a transaction by posting a CFB and the adoption of buyer-side trust-building mechanisms is one decision made in the CFB, buyer-side trust-building mechanisms often exist in online labor markets. As a result, the adoption and impact of buyer-side trust-building mechanisms are highly associated with the operation procedures in online labor marketplaces.

Mandatory and seller-side trust-building mechanisms have been investigated extensively, with most studies in this literature set in online retailing (including forward auctions) markets such as eBay and Taobao. The results are generally consistent in showing that seller-side and mandatory trust-building mechanisms enhance buyers' trust, strengthen buyers' purchase intentions, and thus increase the probability of reaching a deal. However, to the best of our knowledge, few studies have explored the effect of buyer-side trust-building mechanisms. Consequently, the following question arises:

Research Question 1: Do buyer-side trust-building mechanisms have the same effects as seller-side and mandatory trust-building mechanisms?

Intuitively, the answer is "no," as the contexts in which buyer-side mechanisms are used and in which seller-side and mandatory mechanisms have been researched are very different. Buyer-side mechanisms often exist in online labor marketplaces, whereas the seller-side and mandatory mechanisms investigated in the previous literature exist in online product marketplaces. Specifically, buyer-side trust-building mechanisms are mainly applied to transactions of intangible goods (i.e., services), whereas the other two types of mechanisms are generally applied to transactions of tangible goods. Buyers purchasing services face more uncertainty, as services are generally complex and changeable [26, 58]. In addition, seller-side and mandatory trust-building mechanisms are generally embedded in online retail or forward auctions, whereas buyer-side mechanisms are embedded in buyer-determined multiattribute auctions, which have a particular *winner selection* procedure before the transaction contract is reached. During this procedure, the buyer selects the most satisfactory bidder (and her bid) from the choice pool and awards the contract to her. Because the choice pool is the basis for reaching a transaction contract, under the trust-building mechanisms-outcome framework, we need to pay special attention to it. Therefore, in this paper, we intend to answer the following question toward learning how buyer-side trust-building mechanisms affect auction outcomes:

Research Question 2: How many freelancers participate in the task and form the choice pool, and what kinds of freelancers (and their bids) constitute the choice pool?

Furthermore, most extant research examines the performance of trust-building mechanisms through the lens of *signaling* theory, particularly quality signaling and competitive-edge building [6, 10, 18, 49, 51]. To the best of our knowledge, few studies have explored other effects. A broader search of studies on other mechanisms (i.e., not trust-building mechanisms) provides us with insights into other possible effects. Horton and Johari demonstrated the existence of a *preference-signaling effect* generated by a "three-tier" mechanism (a mechanism that allows buyers to directly choose their relative preferences over price and quality) in online labor markets [28]. Lee and Niederle posited that the preference-signaling effect prevails in online dating markets [38]. Hong et al. showed that compared with sealed-bid auctions, open-bid auctions in online labor markets attract fewer participants as a result of the *screening effect* [27]. A third question arises:

Research Question 3: Is it possible that these effects also exist as a result of trust-building mechanisms?

In this paper we intend to fill the gaps and answer these three questions. Specifically, we try to understand how the choice pool (i.e., the number of bidders/bids, the average bidder quality, and the average bid quality) is shaped by guarantee-required schemes. By integrating signaling theory and organization theories of organizational slack and contractual incompleteness, we propose a 3S (screening, signaling, and slack) effect framework to explain this shaping. Specifically, the screening effect means that buyers use the mechanisms to directly rule out unqualified freelancers. The signaling effect refers to the effect generated by releasing signals with regard to buyers' relative preferences over different attributes. The slack effect relates to how buyer-side trust-building mechanisms affect bidders' behavior via a consideration of the possible cushion of resources. We also assess the possible moderating role of task complexity and task description in the screening and slack effects.

Our empirical study is based on data collected from one of the leading online labor marketplaces in China. To establish a causal inference of the effect of buyer-side trust-building mechanisms on the characteristics of the choice pool, we perform instrumental variable (IV) analyses in addition to ordinary least squares (OLS) analyses. Additional analyses with different measurements reinforce our results.

Our empirical results show that the adoption of guarantee-required schemes does indeed screen out bidders of a worse quality (less experience, lower reputation) by setting up a threshold (screening effect). Guarantee-required tasks attract fewer but higher-quality bidders (screening and signaling effects). Regarding the effect on bid quality (signaling or slack effect), our estimation results indicate that the signaling effect dominates the slack effect in the "time" (duration) dimension (negative), whereas the reverse occurs in the "proposal" dimension (negative). In regard to moderating effects, the results indicate that task complexity significantly weakens the screening effect, which is implied by the substantial change in the relationship between the adoption of guarantee-required schemes and bidder participation behavior (the number of bids, bidder quality); simultaneously, it significantly weakens the slack effect implied by the vital change in the relationship between the adoption of guarantee-required schemes and bidders' bidding strategies (bid quality). However, we do not find evidence to support the moderating role of the level of detail of task description.

This study contributes to several strands of literature. First, it complements the literature on institution-based trust-building mechanisms in online markets by focusing on the underexplored buyer-side trust-building mechanisms that often exist in online labor markets. This paper paints a clearer picture of the rationale according to which buyer-side trust-building mechanisms (i.e., guarantee-required schemes) affect bidders' participation and bidding decisions by proposing a 3S effect conceptual model and performing an empirical examination with secondhand data collected from a well-known Chinese online labor marketplace. Second, this study contributes to online labor markets literature by exploring one of the operation mechanisms and bidder behaviors. Although mechanisms such as preference-signaling [28] and sealed-bid [27] mechanisms have been investigated in the previous literature, buyer-side trust-building mechanisms have received little attention. Previous studies have investigated extensive factors that affect bidders' participation behavior, such as an open format [27], the auction length [58], and the project value [58]. However, to the best of our knowledge, few studies have examined the role of buyer-side trust-building mechanisms in changing bidders' participation and bidding decisions.

The remainder of this paper is structured as follows. In the next section, we briefly review the literature on institution-based trust-building mechanisms and online labor markets. The third section proposes the 3S effect conceptual framework and related hypotheses. The fourth section describes the methodologies applied in this paper. The fifth section presents our main empirical results and additional analyses. We conclude in the sixth section.

Literature Review

Institution-Based Trust-Building Mechanisms

McKnight et al. [46] identified five kinds of trust in their work: knowledge-, calculative-, personality-, cognitive-, and institution-based trust. Institution-based trust refers to trust induced by institutional mechanisms created by third parties to facilitate transaction success [52]. These institutional mechanisms are commonly termed *institution-based trust-building mechanisms* in the extant literature.

Existing studies of institution-based trust-building mechanisms mainly focus on two themes: (1) the relationship between trust-building mechanisms and trust and (2) the relationship between trust-building mechanisms and transaction outcomes (e.g., buyers' purchase intention and sellers' performance). Research on the first theme either establishes theoretical models to illustrate how trust-building mechanisms enhance trust or empirically examines the effect of trust-building mechanisms on trust. Theoretically, variables such as perceived effectiveness of e-commerce institutional mechanisms [13, 14, 19] or perceived effectiveness of institutional structures [42] have been incorporated to explain how these mechanisms influence trust. Empirically, a vast number of studies have examined the effects of reputation or feedback on buyers' trust [6, 50, 52].

Studies that focus on the second theme explore the effect of trust-building mechanisms on transaction outcomes. The concerns of research on this theme arise from two perspectives: the buyer perspective or the seller perspective. Studies from the buyer perspective mainly explore the relationship between trust-building mechanisms and buyers' purchase intention as well as the associated moderators and mediators. Lu, Fan, and Zhou [41] and Lu, Zeng, and Fan [42] investigated the effect of trust-building mechanisms on buyers' initial purchase intention, and Chong, Lacka, Boying, and Chan [14] and Fang et al. [19] examined this effect on buyers' repeated purchase intention. Some studies further explore the possible mediators or moderators of this relationship, such as online coupons [43] and perceived risk [52]. Most of the literature on this theme uses firsthand data collected via surveys.

Research from the seller perspective explores how trust-building mechanisms affect sellers' performance (e.g., price premiums, product returns, number of views, number of bids). The signaling effect is widely used in the literature from this perspective to explain the underlying rationale of how sellers' performance is affected by trust-building mechanisms. Good ratings, feedback, and reviews signal an individual seller's credibility and high quality and help the seller differentiate themselves to gain price premiums [3, 6, 16, 39, 51]. Similarly, less "helpful" reviews induce more product returns [18]. The adoption of seller-side trust-building mechanisms, such as consumer protection schemes, seven-day return policies, repair services, and money-back guarantees, also has a signaling effect [49] and increases sellers' performance (e.g., the number of views, the number of bids received) [10, 39].

In summary, the literature regarding online trust-building mechanisms has extensively explored how these mechanisms generate buyer trust, enhance buyers' purchase intentions, and increase sellers' performance. However, these studies almost exclusively focus on mandatory and seller-side trust-building mechanisms in online retailing or auction product markets where multiple buyers correspond to one seller in one product or auction. There is an insufficient academic understanding of how the adoption of buyer-side trust-building mechanisms, which are prevalent in online labor markets (multiple sellers correspond to one buyer in a task auction), affects transaction outcomes. Furthermore, while existing research consistently confirms the signaling effect generated by trust-building mechanisms, there have been few attempts to analyze the possibility of the existence of other effects. Our study aims to complement the extant literature by exploring other possible effects (e.g., screening, preference-signaling effects) and by empirically examining the impact of buyer-side trust-building mechanisms on the characteristics of the choice pool.

Online Labor Markets

Our study focuses on buyer-side trust-building mechanisms that exist in online labor markets. This uniqueness makes the effects of these mechanisms susceptible to the features of such markets. Therefore, our research draws valid insights from the extant online labor market literature.

The existing literature can be divided into three streams according to the research subject. The first stream of research focuses on the hiring decisions of buyers. The literature has examined various factors that affect buyers' hiring decisions, including the bid price [55], freelancer's reputation [35, 47, 55, 64], work experience [1, 9, 34], skills [9], production costs [55], origin (developed/Western countries) [1, 9], linguistic and cultural differences between the buyer and the freelancer [25, 26, 55], and whether the buyer and the freelancer have previously conducted transactions [25].

The second stream of research focuses on freelancers' participating behavior and can be divided into two categories according to the research level (the freelancer level and the task level). Studies at the freelancer level mainly explore the motives that promote freelancers' participation. Such motives identified in the previous literature include making money [11, 66], gaining recognition [66], acquiring new skills [37], and desiring to learn [11, 37]. Snir and Hitt [58] established a theoretical model to show that project value affects freelancers' participation decisions. Research at the task level investigates the factors that affect the number of bids received for a task. Yang et al. [63] empirically showed that the award amount, project time cost, description length, contest duration, project type, and marketplace maturity significantly influence the emerging number of solvers. Hong et al. [27] explored how the number of bids is influenced by the design of bid visibility. Conducting field experiments, Horton and Johari [28] examined how the number of bids changes along with the revelation of buyers' vertical preferences.

The third stream of research focuses on the role of mechanisms or devices provided by the marketplace.[5] Caraway [12] described the mechanism designs that oDesk.com provides to enhance mediation, such as surveillance systems and forums. Allon et al. [2] explored how market outcomes, in terms of equilibrium price and marketplace profits, are changed by providing price screening and communications among freelancers. Hong et al. [27] compared the outcome (e.g., the number of bids and buyer surplus) differences between open-bid and sealed-bid mechanisms; they highlighted a screening effect generated by the open-bid mechanism in which bidders with a low surplus provision from bidding are likely to choose to stay out of auctions to save on bidding costs. Horton and Johari [28] found that when a signaling mechanism revealing buyers' vertical preference (relative preference over price and quality) is used, freelancers are better sorted (i.e., high-quality freelancers are attracted to buyers who prefer quality, and low-quality freelancers are attracted to buyers with a high preference for price).

In summary, the existing literature has explored buyers' hiring decisions, freelancers' participation decisions, and the role of mechanisms/devices in online labor marketplaces. Our research follows the second and third literature streams to examine how the adoption of buyer-side trust-building mechanisms, particularly the adoption of guarantee-required schemes, affects freelancers' participation and bidding strategies at the task level. Furthermore, the previous literature has investigated the screening effect and preference-signaling effect produced by some online labor marketplace mechanisms, providing insights for us as we also consider them in our theoretical framework.

[5]Note that the usage of some of these mechanisms is mandatory, whereas other mechanisms are optional for buyers or freelancers to voluntarily choose.

Theory and Hypotheses

Building a 3S Effect Framework

In the focal marketplace, freelancers can provide three types of guarantees: on-time completion of the task (completion guarantee), three months of free after-sales service (service guarantee), and the originality of the work (originality guarantee).[6] To claim an offer of one or more guarantees, freelancers need to place a deposit with the marketplace, which can be withdrawn after the valid guarantee period. A buyer can lodge a complaint and claim compensation if the trading partner offers guarantees but fails to fulfill them.

With these three freelancer guarantees, the focal marketplace provides three types of guarantee-required schemes for buyers to voluntarily adopt: a completion-guarantee-required scheme, a service-guarantee-required scheme, and an originality-guarantee-required scheme. Buyers do not incur a cost in adopting guarantee-required schemes. If buyers choose guarantee-required schemes when posting a task, they allow only freelancers who offer the corresponding guarantees to participate.

In this paper, we explore how the adoption of guarantee-required schemes affects the features of the choice pool–the number of bids, the average quality of bidders (bidder experience, bidder reputation), and the average quality of bids (bidding duration, bidding proposal). Based on signaling theory and organization theories of organizational slack and contractual incompleteness, we propose a 3S effect model–that is, a model of the screening, signaling, and slack effects. The theoretical model is presented in Figure 1. We explain the hypotheses in the following sections.

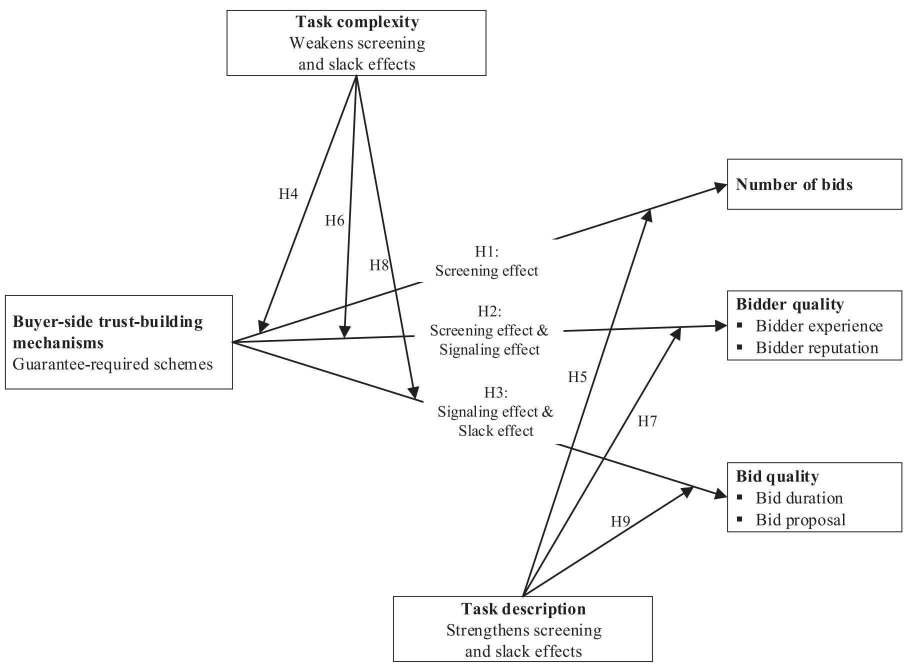

Figure 1. Research Model and Hypotheses

[6]This third guarantee scheme is usually used by bidders when bidding for design tasks.

Screening Effect

The screening effect demonstrates who is unable or unwilling to participate in the auction as a result of expected costs that are too high. Guarantee-required schemes allow only freelancers who offer guarantees to submit bids, naturally creating an entry threshold. First, to offer the guarantee(s) required by the guarantee-required schemes, freelancers need to deposit a certain sum of money with the platform. Intuitively, freelancers who are less active and who have earned little money through this platform are reluctant to make this deposit. Second, in the working process, low-quality bidders are less capable of fulfilling the guarantees required by guarantee-required schemes, increasing the probability that they will receive complaints and be involved in future disputes. As a result, the anticipated indemnity costs add to the sum of expected costs and discourage "bad" bidders from placing bids. Third, placing a bid is always accompanied by costs [58]. This bidding cost might be the last critical strike in changing "bad" bidders' participation decisions, considering that other expected costs are already high. Overall, guarantee-required schemes function as devices to screen out less active and low-capability bidders. As a result, fewer bidders participate in guarantee-required tasks, and the bidders who actually participate are those of high quality, which can be indicated by experience and reputation scores [40]. Therefore, we propose the following hypotheses.

Hypothesis 1: Guarantee-required tasks attract fewer bids.

Hypothesis 2: Guarantee-required tasks attract higher-quality bidders; alternatively, guarantee-required tasks screen out lower-quality bidders.

Signaling Effect

The signaling effect reveals the kinds of bidders and bids that participate as a response to the buyer's indication of relative preference for different attributes released by the choice to adopt guarantee-required schemes. Although all buyers value bidder quality (more bidder experience, higher bidder reputation) and bid quality (shorter bidding durations, bidding proposals with more details), they differ in their willingness to pay for them. Some buyers are price sensitive and are content with work that is "good enough," while others want their work done at a very high-quality level and by highly experienced and well-reputed sellers, even if this involves a great expense. This difference in vertical preference reflects different "types" of buyers and can be conveyed to potential bidders through the choice to adopt guarantee-required schemes. Note that this is preference signaling rather than quality signaling.

Service deals in online labor markets are reached through buyer-determined multi-attribute auctions, in which bidders are allowed to submit a bid composed of several attributes [24]. In traditional procurement auctions for tangible goods, an ex ante scoring rule directly reveals buyers' preferential trade-offs among different attributes [5]. However, in most cases, these trade-offs are kept secret throughout service auctions in online labor markets. Nonetheless, some devices other than scoring rules can partially convey buyers' vertical preferences, and a guarantee-required scheme is one such device.

The choice to offer guarantees for freelancers to choose from is essentially a quality-signaling device, as it meets the two conditions described by Spence [59]. First, the schemes induce upfront costs for a freelancer to adopt. Second, it costs more for “bad” freelancers than “good” freelancers to participate, as “bad” freelancers are more likely to be involved in future disputes and be forced to compensate the buyer under the guarantee schemes. The warranty literature also contends that guarantees (termed “warranties” in this literature) signal quality [53, 54] and serve as a persuasive sales variable in marketing [32].

Freelancers who offer guarantees signal their high quality; therefore, buyers requiring guarantees intuitively imply their relative preference for high quality. Specifically, a *completion-guarantee-required scheme* requires bidders to guarantee that they will provide work of the promised quality before the promised deadline. The quality of future deliverables is highlighted in this scheme, which naturally conveys that buyers prefer relatively high quality. Similarly, the adoption of a *service-guarantee-required scheme* and an *originality-guarantee-required scheme* also implies that buyers generally prefer to obtain a higher quality of work over paying a lower price.

The expected quality of the work delivered by a bidder is a mathematical product of the quality she promised (the promised bidding duration and the promised deliverables in the bidding proposal) and the probability that she will fulfill the promise. The latter is highly associated with the bidder’s *integrity/willingness* (which can be inferred from bidder reputation) and *ability/capability* (which can be inferred from bidder experience and reputation) to meet the promised quality. Therefore, buyers’ relative preferences for high quality actually manifest as their preferences for high *bidding/promised quality* and the *quality/trustworthiness of the bidder* (having the integrity and ability to realize this promised quality).

The revelation of buyers’ relative preferences for quality and price affects bidders’ participation decisions, and consequently it impacts the pool of applicants. Potential bidders sort buyers of the right “type” as a result of calculations of their probability to be awarded a contract. Under tasks with guarantee-required schemes, buyers convey their preference signals that they favor bidders of high quality. Higher-quality bidders (i.e., more experience and higher reputation) know that they are more suitable for the buyer’s needs and thus have a higher chance of winning. Consequently, they are more likely to enter auctions with guarantee-required schemes. In contrast, low-quality bidders relinquish participation given their low probability of winning and nonnegligible bidding costs [58]. Horton and Johari [28] showed that tasks conveying buyers’ preference for quality attract bidders with more experience. Thus, we propose Hypothesis 2 again.

Hypothesis 2: Guarantee-required tasks attract higher-quality bidders.

The adoption of guarantee-required schemes also affects bidders’ bidding strategies and thus the characteristics of the bids that the buyer receives. When choosing guarantee-required schemes, buyers signal that they favor the bidding/promised quality. Bidders tend to adjust their bidding strategies to cater to buyers’ preferences to gain a better chance of winning. As a result, bidders tend to bid a higher quality (i.e., shorter duration and more detailed proposal) given the same requested price. Therefore, we propose the following hypothesis.

Hypothesis 3a: Holding the bidding price constant, guarantee-required tasks attract higher-quality bids.

Slack Effect

Organizational slack, which has long been discussed in the organization literature [4, 17, 56, 61], is defined as the excess of available resources allocated over the total necessary resources to accomplish the assigned tasks [4, 17]. Similarly, in service outsourcing in online labor markets, slack refers to the cushion of money, time, or other resources that are the excess of those required in case of any unexpected incidents occurring in the forthcoming project execution period. This resource cushion provides firms with a safety net [33] and enables them to "hang in there" during "rainy days" [33, 56]. Slack can provide a hedge against uncertainty [48] or function as a buffer on the effects of uncertainty [17]. Apparently, more slack increases bidders' ability to resist risk and decreases the possibility of a future breach of contract. Bidders who participate in guarantee-required tasks have placed a deposit with the marketplace. If they fail to keep their promises and receive complaints lodged by buyers, they are unlikely to have their deposits returned to them. This potential penalty encourages bidders in guarantee-required tasks to prepare as much slack as possible, including extending the future execution time (bidding duration) and simplifying the bidding proposal. Overall, the slack effect in online service auctions refers to the changing behavior of bidders, usually the behavior of directly decreasing the promised quality in the contract (extending the bidding duration and simplifying the bidding proposal) as a way to proactively improve slack and reduce the possibility of broken promises.

Therefore, we propose the following hypothesis.

Hypothesis 3b: Holding the bidding price constant, guarantee-required tasks attract lower-quality bids.

Note that the direction of the effect of the adoption of guarantee-required schemes on bidding duration and the level of detail of the bidding proposal predicted by the slack effect (H3b) is opposite to that predicted by the signaling effect (H3a), which renders the total effect an empirical issue.

Moderating Effect

In general, the buyer and the selected bidder (winner) enter into a service contract once the buyer transfers payment to the platform. A contract is incomplete if not all of the contingencies are arranged [23]. The degree of *contractual incompleteness* approximately equals the difference between all contingencies that may arise during the course of the trading relationship and those that have already been specified in the contract.

It is prohibitively expensive to craft an ex ante complete contract that specifies each possible contingency [8, 22, 30]; this is particularly true for complex projects, as they are less standardized, exposed to more uncertainties, and prone to contingences [15]. As a result, in practice the parties are likely to end up writing a highly incomplete contract as a compromise [23], especially when the focal project is complex.

In addition to task complexity, brief task descriptions imply a higher degree of contractual incompleteness. A task description generally contains a short introduction to the task and the buyer's requirements for deliverables. The information naturally becomes part of the transaction contract in online labor markets.

It is more difficult for buyers to lodge a complaint when their contracts with bidders are less complete. The reason is that "default behavior" becomes harder to identify and confirm, as many contingencies are not clearly specified. Bidders expect that there will be costs associated with disputes that arise from guarantees on tasks with guarantee-required schemes; however, these costs decrease as the difficulty of lodging complaints increases. As a result, when the degree of contractual incompleteness is high, it might become profitable for low-quality bidders who had already been screened out under guarantee-required tasks to participate. Therefore, the screening effect is weakened. We propose the following hypotheses:

Hypothesis 4: Task complexity moderates the relationship between the adoption of guarantee-required schemes and the number of bids; specifically, task complexity weakens the negative effect of the adoption of guarantee-required schemes on the number of bids.

Hypothesis 5: Task description moderates the relationship between the adoption of guarantee-required schemes and the number of bids; specifically, the level of detail of the task description strengthens the negative effect of the adoption of guarantee-required schemes on the number of bids.

Hypothesis 6: Task complexity moderates the relationship between the adoption of guarantee-required schemes and the average quality of the bidders attracted; specifically, task complexity weakens the positive effect of the adoption of guarantee-required schemes on the average quality of the bidders attracted.

Hypothesis 7: Task description moderates the relationship between the adoption of guarantee-required schemes and the average quality of the bidders attracted; specifically, the level of detail of the task description strengthens the positive effect of the adoption of guarantee-required schemes on the average quality of the bidders attracted.

Contractual incompleteness is also highly associated with the relative slack that a bidder has in the working process. As the requirements for the deliverables are not clear, the constraints on work quality naturally become more relaxed. In other words, the quality of the service delivered can fluctuate within a range without being judged as a breach of contract. Given a fixed amount of allocated resources, this phenomenon essentially endows bidders with more slack, as they can always choose to deliver the lowest quality of the allowed range. Consequently, under guarantee-required tasks, bidders' concerns over unfulfilled guarantees and their fear that their deposits will be confiscated are reduced. Their motives for proactively increasing slack decrease, and therefore the slack effect is weakened when contracts are incomplete. Hence, we propose the following hypotheses:

Hypothesis 8: Task complexity moderates the relationship between the adoption of guarantee-required schemes and the average quality of the bids induced; specifically, task complexity weakens the negative effect of the adoption of guarantee-required schemes on the average quality of the bids induced.

Hypothesis 9: Task description moderates the relationship between the adoption of guarantee-required schemes and the average quality of the bids induced; specifically, the level of detail of the task description strengthens the negative effect of the adoption of guarantee-required schemes on the average quality of the bids induced.

Methodology

Data Collection

Our data were collected from one of the leading online labor marketplaces in China. As of June 2019, this marketplace has attracted more than 19 million freelancers and facilitated transactions worth more than $2.7 billion (¥17 billion) since its establishment. The Website basically includes three types of Web pages: the task page, the buyer home page, and the bidder home page. The task page presents the basic information about the posted task and the bids attracted to the task. The buyer home page presents previous jobs that the buyer has posted, the buyer's introduction, and feedback received from bidders. The bidder home page presents the bidder's introduction and past reviews received from buyers. Using Python, we wrote a Web crawler tailored to the structure of the Website to automatically collect data from January 2016 to December 2016. Our final data set includes 18,721 tendering auctions with 331,681 bids placed. Among these auctions, 1,610 used guarantee-required schemes, and the rest did not. Objective data on task characteristics (e.g., task budget range, task category, and task description), auction characteristics (e.g., auction duration), buyer characteristics (e.g., buyer experience, buyer location, buyer pin level), bidder characteristics (e.g., bidder previous winning times, bidder credit score), and bid characteristics (e.g., bidding price, bidding duration, bidding proposal) were collected.

Measures

Dependent Variables

The variable *BidNum* denotes the total number of bids received in the auction. We use the average number of bids won of all the participating bidders to measure their average experience, denoted by *BidderExp*. For example, for a task with three participants, the first participant had won two contracts before the current task, the second participant three contracts, and the third participant four contracts; then, the *BidderExp* of this task is (2 + 3 + 4)/3 =3. The variable *BidderRep* is defined as the average credit score of all the participating bidders of the auction. *BidderExp* and *BidderRep* are used to proxy for bidder quality. We use *BidDuration* to denote the average bidding duration of the submitted bids in the auction. The auction variable *BidProposal* refers to the average number of words in the bidding proposals; it measures the average level of detail of the bidding proposals placed. *BidDuration* and *BidProposal* are used to proxy for bid quality.

Independent Variables

As stated earlier, the three kinds of guarantee-required schemes provided by the platform are completion-guarantee-required, service-guarantee-required, and originality-guarantee-required schemes. We construct the variable *GuarAnyReq*, which is equal to 1 if the buyer adopted any of the three guarantee-required schemes, and 0 otherwise.

Moderating Variables

The first moderator, task complexity (*TaskComplex*), is measured by the task budget posted by the buyer. The marketplace provides eight budget range levels (¥100–1000, ¥1000–5000, ¥5000–10,000, ¥10,000–30,000, ¥30,000–50,000, ¥50,000–100,000, ¥100,000–-200,000, and over ¥200,000) from which a buyer must choose when posting a tendering auction task; we code *TaskComplex* from 1 to 8, respectively, for these eight levels. We use the task budget (i.e., task size) to proxy for task complexity because we believe that complexity is highly related to size. Complexity is defined as the number of components that interact within a system [57]. Larger projects usually consist of more components and have a higher degree of uncertainty [21]. Previous studies have also used task budget or size to proxy for task complexity in empirical tests [7, 65]. The second moderator—the level of detail of the task description (*TaskDesc*)—is operationalized as the number of words or the length of the task description.

Control Variables

We use several control variables in our analyses. We utilize the number of successful tendering tasks that the buyer has posted before to control for buyer experience (*BuyerExp*). We use *AuctDuration* to denote the number of days that the auction was active. The variable *Referred* represents a feature specific to this platform; we code *Referred* as 1 if the buyer was introduced to the platform by a sales agent, and 0 otherwise. The variable *BuyerLoc* documents in which part of the country the buyer is located (Eastern China, Central China, Western China, Northern-Eastern China, or location information not provided). We also control for task categories (*TaskCateg*); the tasks of the auctions can fall into seven project categories: design, web and software development, writing and translation, decoration, sales and marketing, business services, and creative ideas. We also include year–month dummies to control for time effects (*Month*). Additionally, in the bid quality analyses, we control for *BidPrice* (average bidding price of the bids submitted in the auction).

Table 1 presents the descriptive statistics. Table 2 reports the correlations between key variables.

Table 1. Descriptive Statistics.

Variable	*N*	*M*	*SD*	Min	Max	Mdn
1. BidNum	18,721	17.717	18.469	0	390	12
2. BidderExp	17,688	9.249	25.357	0	539	2.667
3. BidderRep	17,688	27.392	11.292	0	105	27.174
4. BidPrice	16,791	1058863	42300000	10	2500000000	4333.333
5. BidDuration	16,791	24.526	52.232	1	999	15
6. BidProposal	16,791	133.867	114.487	6.875	1707	99.76
7. GuarAnyReq	18,721	0.086	0.28	0	1	0
8. TaskComplex	18,721	2.995	1.757	1	8	3
9. TaskDesc	18,721	82.284	118.756	1	3031	49
10. AuctDuration	18,721	7.571	4.726	0	110	7
11. BuyerExp	18,721	0.111	1.145	0	34	0
12. Referred	18,721	0.19	0.393	0	1	0
13. BuyerPinLevel	17,134	8.560	1.257	1	9	9

Empirical Models and Econometric Identification

Equations (1) to (6) outline our empirical models for estimating the effect of the adoption of guarantee-required schemes. We index the task by *i*, the buyer of the task by *u*, and the time of posting by *t*. In all equations, we control for task characteristics (task complexity, the length of the task description, the auction duration, the month in which the task was posted) and buyer characteristics (buyer experience, referred, buyer location). In addition to OLS, we conduct negative binomial (NB) regressions to estimate Equations (1) and (2), as the dependent variable *BidNum* constitutes count data with overdispersion. In Equations (3) and (4), *BidderQuality* refers to either *BidderExp* or *BidderRep*. In Equations (5) and (6), *BidQuality* is either *BidDuration* or *BidProposal*. Note that we estimate Equations (2) and (4) only when we find a significant screening effect in the results of Equations (1) and (3); we estimate Equation (6) only when we find a significant slack effect in the results of Equation (5). To address nonnormality in the variables, we take the natural logarithm of the highly skewed variables (*BidNum, TaskDesc, BidPrice, BidDuration, BidProposal*).[7] When constructing the interaction terms, we standardize the independent variable and the moderator to eliminate any possible multicollinearity.

$$BidNum_{i,u,t} = \beta_0 + \beta_1 \times GuarAnyReq_i + \beta_{2-4} \times (TaskControls_i) + \beta_{5-6} \times \left(BuyerControls_{u,t}\right) + BuyerLoc_u + TaskCateg_i + Month_t + \varepsilon_{i,u,t} \quad (1)$$

$$BidNum_{i,u,t} = \beta_0 + \beta_1 \times GuarAnyReq_i + \beta_2 \times GuarAnyReq_i \times TaskComplex_i + \beta_3 \times GuarAnyReq_i \times TaskDesc_i + \beta_{4-6} \times (TaskControls_i) + \beta_{7-8} \times \left(BuyerControls_{u,t}\right) + BuyerLoc_u + TaskCateg_i + Month_t + \varepsilon_{i,u,t} \quad (2)$$

$$BidderQuality_{i,u,t} = \beta_0 + \beta_1 \times GuarAnyReq_i + \beta_{2-4} \times (TaskControls_i) + \beta_{5-6} \times \left(BuyerControls_{u,t}\right) + BuyerLoc_u + TaskCateg_i + Month_t + \varepsilon_{i,u,t} \quad (3)$$

[7] For variables that contain zero (BidNum, BuyerExp), we add the lowest nonzero value (+1) before the log transformation [27, 44].

Table 2. Correlations Between Key Variables.

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1. BidNum												
2. BidderExp	0.023*											
3. BidderRep	0.125*	0.556*										
4. BidPrice	−0.008	−0.006	−0.011									
5. BidDuration	−0.117*	−0.069*	0.013	0.020*								
6. BidProposal	−0.160*	0.150*	0.102*	0.008	−0.009							
7. GuarAnyReq	−0.140*	0.294*	0.281*	−0.004	0.004	0.083*						
8. TaskComplex	−0.200*	−0.147*	0.035*	0.012	0.307*	0.006	0.035*					
9. TaskDesc	−0.079*	0.004	−0.022*	0.013	0.048*	0.025*	0.072*	0.078*				
10. AuctDuration	0.048*	−0.037*	−0.081*	0.012	0.070*	0.025*	0.041*	0.128*	0.074*			
11. BuyerExp	−0.052*	0.013	0.049*	−0.002	−0.023*	−0.039*	0.004	−0.069*	0.012	−0.088*		
12. Referred	0.038*	−0.064*	−0.064*	0.003	0.005	−0.103*	−0.068*	0.052*	−0.016*	0.037*	−0.041*	
13. BuyerPinLevel	0.090*	−0.036*	−0.026*	−0.001	0.031*	0.010	−0.067*	0.066*	−0.079*	0.117*	−0.468*	0.095*

Notes: $N = 16{,}791$.
$^*p < 0.05$.

$$BidderQuality_{i,u,t} = \beta_0 + \beta_1 \times GuarAnyReq_i + \beta_2 \times GuarAnyReq_i \times TaskComplex_i + \beta_3 \times GuarAnyReq_i \times TaskDesc_i + \beta_{4-6} \times (TaskControls_i) + \beta_{7-8} \times \left(BuyerControls_{u,t}\right) + BuyerLoc_u + TaskCateg_i + Month_t + \varepsilon_{i,u,t} \tag{4}$$

$$BidQuality_{i,u,t} = \beta_0 + \beta_1 \times GuarAnyReq_i + \beta_2 \times BidPrice_i + \beta_{3-5} \times (TaskControls_i) + \beta_{6-7} \times \left(BuyerControls_{u,t}\right) + BuyerLoc_u + TaskCateg_i + Month_t + \varepsilon_{i,u,t} \tag{5}$$

$$BidQuality_{i,u,t} = \beta_0 + \beta_1 \times GuarAnyReq_i + \beta_2 \times GuarAnyReq_i \times TaskComplex_i + \beta_3 \times GuarAnyReq_i \times TaskDesc_i + \beta_4 \times BidPrice_i + \beta_{5-7} \times (TaskControls_i) + \beta_{8-9} \times \left(BuyerControls_{u,t}\right) + BuyerLoc_u + TaskCateg_i + Month_t + \varepsilon_{i,u,t} \tag{6}$$

As a major challenge in identifying the effect of guarantee-required schemes from our data, the adoption of such schemes is decided by the buyer when she posts the task rather than being set randomly. This self-selection issue might generate estimation bias as a result of unobserved buyer and task characteristics. As shown in the preceding equations, we already include three sets of fixed effects to control for unobserved heterogeneity: buyer location effects, task category dummies, and monthly dummies. We also control for various task- and buyer-related features. These controls help us alleviate the concern caused by unobserved time-invariant buyer and task characteristics, temporal, and category differences. To further strengthen the causal interpretation of the estimated effects of the adoption of guarantee-required schemes, we consider the IV and two-stage least squares approach. We use the buyer pin level (*BuyerPinLevel*) as the IV for the adoption of guarantee-required schemes; this buyer pin level is a nine-level rank and is calculated by the platform based on the good reviews received and the total amount of payments paid by the buyer. The first level is the highest level, representing more good reviews and more payments. The rationale behind our IV choice is as follows. First, the buyer pin level is an important feature of the buyer, reflecting their knowledge of the marketplace and affecting their choice to adopt guarantee-required schemes. In general, buyers with higher pin levels are more proficient in using various schemes and devices in the marketplace and are therefore more likely to adopt guarantee-required schemes. There is a significant correlation between the endogenous independent variable (*GuarAnyReq*) and our chosen IV (*BuyerPinLevel*), as shown in Table 2. Second, the buyer-pin-level information is not listed on the task page, and the buyer home page, where this information is presented, cannot be directly linked via the task page in our focal marketplace. Therefore, we believe that buyer-pin-level information is unobservable for bidders and should not significantly affect bidders' participation and bidding decisions.

When we have an endogenous variable, we should also consider the endogeneity of the interaction terms constructed by the endogenous variable ($GuarAnyReq_i \times TaskComplex_i$ and $GuarAnyReq_i \times TaskDesc_i$). We instrument the interaction term with the interaction of the instrument for the adoption of guarantee-required schemes and the other exogenous variable. Specifically, the interaction term $GuarAnyReq_i \times TaskComplex_i$ is instrumented with the interaction of *BuyerPinLevel* and *TaskComplex*; additionally, the interaction term $GuarAnyReq_i \times TaskDesc_i$ is instrumented with the interaction of *BuyerPinLevel* and *TaskDesc*.[8]

Results

Adoption of Guarantee-Required Schemes and the Number of Bids

OLS and NB Analyses

As shown in Table 3, Columns 1 to 3 demonstrate the OLS regression results. Specifically, Column 1 is the baseline model with the control variables. Column 2 adds the effect of the adoption of guarantee-required schemes on the number of bids. Column 3 is the full model with two interaction terms. Columns 4 to 5 illustrate the NB regression results.

Based on the results shown in Columns 2 and 4, we observe a negative and significant association between the adoption of guarantee-required schemes and the number of bids $(\text{Column2}, \beta = -1.924,\ p < 0.001; \text{Column4}, \beta = -2.662,\ p < 0.001)$. Thus, Hypothesis 1, which predicts a screening effect on the number of bids, is supported. According to

Table 3. Effect of the Adoption of Guarantee-Required Schemes on the Number of Bids (OLS and NB).

	Ln(BidNum)			BidNum	
Dependent variable	OLS: 1	OLS: 2	OLS: 3	NB: 4	NB: 5
Constant	1.499***	1.545***	1.564***	1.943***	1.924***
	(0.125)	(0.108)	(0.108)	(0.113)	(0.113)
Control Variables					
TaskComplex	0.004	0.003	0.001	−0.009*	−0.006
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Ln(TaskDesc)	−0.137***	−0.081***	−0.083***	−0.099***	−0.098***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Ln(BuyerExp)	−0.285***	−0.374***	−0.381***	−0.34***	−0.347***
	(0.035)	(0.03)	(0.03)	(0.032)	(0.032)
AuctDuration	0.016***	0.021***	0.021***	0.025***	0.025***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Referred	0.357***	0.059**	0.061**	0.029	0.031
	(0.023)	(0.02)	(0.02)	(0.02)	(0.02)
Independent Variables					
GuarAnyReq		−1.924***	−1.941***	−2.662***	−2.688***
		(0.024)	(0.025)	(0.032)	(0.033)
Interactions					
GuarAnyReq × TaskComplex			0.041***		0.067***
			(0.006)		(0.008)
GuarAnyReq × Ln(TaskDesc)			0.009†		0.005
			(0.005)		(0.007)
Fixed Effects					
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes
Model Summary					
R^2	0.1663	0.3848	0.3865		
Adjusted R^2	0.1652	0.3839	0.3856		
F	143.44	432.99	406.09		
LR χ^2				9,163.89	9,239.28
No. of Obs.	18,721	18,721	18,721	18,721	18,721

Notes: Standard errors are reported in parentheses. Columns are numbered consecutively in the headings and referenced in text. OLS = ordinary least squares; NB = negative binomial; Obs. = observations.
†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

[8]The variables are first standardized to construct the instruments for the interaction terms.

Columns 3 and 5, guarantee-required scheme adoption and task complexity have a strongly positively significant interaction effect on the number of bids $(\text{Column3}, \beta = 0.041,\ p < 0.001; \text{Column5}, \beta = 0.067,\ p < 0.001)$, lending support to H4. The positive and significant coefficient $(\beta = 0.009,\ p < 0.1)$ of the interaction term of the adoption of guarantee-required schemes and task description shown in Column 3 suggests a significant negative moderating role of task description. The NB results illustrated in Column 5 suggest a positive but insignificant effect of this interaction $(\beta = 0.005,\ p > 0.1)$. This result is the opposite of our prediction; thus, Hypothesis 5 is not supported. The reason might be that, although a longer task description in guarantee-required tasks implies a larger expected cost of disputes, it provides more information about the task, which might save on bidders' future search or communication costs. These two opposite directions of costs might blur the final moderating effect of task description.

IV *Analyses*

As discussed in the previous section, it is important to note that the adoption of guarantee-required schemes is the choice of the buyer, which renders the estimation susceptible to selection bias. We conduct two-stage least squares analyses with the *BuyerPinLevel* of the buyer as the IV for the adoption of guarantee-required schemes to establish a causal interpretation of our findings.

We check for the validity of the IV using two metrics. First, *BuyerPinLevel* is significantly correlated with the adoption of guarantee-required schemes (*GuarAnyReq*) (corr = −0.067, $p < 0.0001$), as shown in Table 2. Second, the Anderson-Rubin Wald *F* statistic, which tests the joint significance of the endogenous regressors, is significant in the full model (48.19).

As shown in Table 4, the estimation results are consistent with the NB results. Tasks with guarantee-required schemes attract significantly fewer bids, as shown in Column 1

Table 4. Effect of the Adoption of Guarantee-Required Schemes on the Number of Bids (2SLS).

Dependent variable: Ln(BidNum)	1	2
Constant	1.605*** (0.284)	3.358 (2.145)
Control Variables		
TaskComplex	−0.009 (0.012)	−0.088† (0.05)
Ln(TaskDesc)	0.131 (0.082)	0.072 (0.312)
Ln(BuyerExp)	−0.69*** (0.144)	−1.4** (0.543)
AuctDuration	0.039*** (0.008)	0.043** (0.016)
Referred	−1.12* (0.448)	−2.141† (1.179)
Independent variable		
GuarAnyReq	−9.6*** (2.906)	−18.527* (9.462)
Interactions		
GuarAnyReq × TaskComplex		2.692† (1.433)
GuarAnyReq × Ln(TaskDesc)		1.268 (1.914)
Fixed Effects		
Buyer Location Effect	Yes	Yes
Task Category Effect	Yes	Yes
Time (Month) Effect	Yes	Yes
Model Summary		
Anderson-Rubin Wald *F*	51.46	48.19
No. of Obs.	17,134	17,134

Notes: Standard errors are reported in parentheses. Columns are numbered consecutively in the headings and referenced in text. 2SLS = two-stage least squares; Obs. = observations.
†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

($\beta = -9.6,\ p < 0.001$), lending support to Hypothesis 1. As shown in Column 2, task complexity plays a negative role in moderating the relationship between guarantee-required scheme adoption and the number of bids ($\beta = 2.692,\ p < 0.1$), whereas task description demonstrates no significant moderating effect ($\beta = 1.268,\ p > 0.1$).

Adoption of Guarantee-Required Schemes and Bidder Quality

OLS Analyses

Table 5 reports the OLS analysis results of the effect of the adoption of guarantee-required schemes on the average bidder quality (experience and reputation) of the participants attracted to the task. Hypothesis 2 is supported, as tasks with guarantee-required schemes attract bidders with more experience, as shown in Column 1 ($\beta = 26.837,\ p < 0.001$), and higher reputations, as shown in Column 3 ($\beta = 19.368,\ p < 0.001$). In addition, the interaction effects of task complexity and the adoption of guarantee-required schemes on average bidder quality are statistically significant and negative, as shown in Column 2 ($\beta = -2.089,\ p < 0.001$) and Column 4 ($\beta = -0.612,\ p < 0.001$). This finding suggests that task complexity attenuates the positive relationship between guarantee-required scheme adoption and average bidder quality, lending support to Hypothesis 6. However, our results do not support Hypothesis 7, which refers to the moderating role of task description. Column 2 indicates an opposite direction to what we predicted ($\beta = -0.376,\ p < 0.05$), and Column 4 presents no significant effect of the interaction term of guarantee-required scheme adoption and task description ($\beta = 0.011,\ p > 0.1$). Again, the opposite direction of the coefficient might be because task descriptions with more detail imply lower search and communication costs, which might render participation in guarantee-required tasks profitable for low-quality bidders.

Table 5. Effect of the adoption of guarantee-required schemes on average bidder quality (OLS)

	BidderExp		BidderRep	
Dependent variable	1	2	3	4
Constant	−6.294* (3.111)	−5.682† (3.101)	10.239*** (1.24)	10.395*** (1.239)
Control Variables				
TaskComplex	0.019 (0.115)	−0.095 (0.115)	1.157*** (0.046)	1.125*** (0.046)
Ln(TaskDesc)	0.509* (0.217)	0.488* (0.216)	−0.147† (0.086)	−0.149† (0.086)
Ln(BuyerExp)	−1.514† (0.791)	−1.227 (0.789)	2.028*** (0.315)	2.114*** (0.315)
AuctDuration	0.016 (0.037)	0.025 (0.037)	−0.112*** (0.015)	−0.109*** (0.015)
Referred	2.023*** (0.538)	1.953*** (0.536)	0.62** (0.215)	0.593** (0.214)
Independent Variable				
GuarAnyReq	26.837*** (0.846)	28.57*** (0.883)	19.368*** (0.337)	19.714*** (0.352)
Interactions				
GuarAnyReq × TaskComplex		−2.089*** (0.203)		−0.612*** (0.081)
GuarAnyReq × Ln(TaskDesc)		−0.376* (0.187)		0.011 (0.075)
Fixed Effects				
Buyer Location Effect	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes
Month Effect	Yes	Yes	Yes	Yes
Model Summary				
R^2	0.2065	0.2118	0.3639	0.3659
Adjusted R^2	0.2053	0.2105	0.3629	0.3649
F	170.24	163.63	374.11	351.41
No. of Obs.	17,688	17,688	17,688	17,688

Note: Standard errors are reported in parentheses. Columns are numbered consecutively in the headings and referenced in text. OLS = ordinary least squares; Obs. = observations.
†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

IV Analyses

We also conduct IV analyses with *BuyerPinLevel* as the IV for the adoption of guarantee-required schemes to alleviate the issue of endogeneity. The second stage of the 2SLS results are reported in Table 6. We believe that this instrument is valid because the Anderson-Rubin Wald *F* statistics are all significant. The results of the IV analyses validate our findings from the OLS regressions. As shown in Columns 1 and 3, the adoption of guarantee-required schemes has a significantly positive impact on average bidder experience ($\beta = 91.036,\ p < 0.01$) and reputation ($\beta = 40.121,\ p < 0.001$). Therefore, Hypothesis 2 is once again supported. The interaction coefficient of the adoption of guarantee-required schemes and task complexity is negative and significant, as shown in Column 2 ($\beta = -21.607,\ p < 0.05$) and Column 4 ($\beta = -9.816,\ p < 0.1$). This finding is consistent with the OLS results shown in Table 5, once again lending support to Hypothesis 6. Moreover, the IV results demonstrate no significant interaction effects of task description and the adoption of guarantee-required schemes ($\text{Column2}, \beta = 3.452,\ p > 0.1; \text{Column4}, \beta = 17.011,\ p > 0.1$).

Adoption of Guarantee-Required Schemes and Bid Quality

OLS Analyses

To examine bid quality, we checked both the bidding durations and bidding proposals. Table 7 reports the OLS analysis results. Note that we include the average bidding price as a control variable. Columns 1 and 2 indicate that the adoption of guarantee-required schemes has no significant impact on either bidders' bidding duration or bidding proposal ($\text{Column1}, \beta = 0.003,\ p > 0.1; \text{Column2}, \beta = 0.053,\ p > 0.1$); thus, Hypothesis 3 is not supported. This insignificant result might be attributed to the opposite forces of the signaling effect (which predicts a negative effect for the bidding duration and a positive

Table 6. Effect of the Adoption of Guarantee-Required Schemes on Average Bidder Quality (2SLS).

	BidderExp		BidderRep	
Dependent variable	1	2	3	4
Constant	−3.411 (3.753)	2.832 (10.348)	11.62*** (1.495)	11.67† (6.696)
Control Variables				
TaskComplex	−0.525† (0.271)	−2.168* (0.949)	1.003*** (0.108)	0.157 (0.614)
Ln(TaskDesc)	−0.179 (0.452)	−0.669 (1.428)	−0.429* (0.18)	−0.259 (0.924)
Ln(BuyerExp)	0.041 (1.071)	4.241 (2.944)	2.471*** (0.427)	5.254** (1.905)
AuctDuration	−0.091 (0.061)	−0.058 (0.086)	−0.142*** (0.024)	−0.121* (0.056)
Referred	8.182*** (2.862)	11.99* (5.033)	2.559* (1.14)	5.751† (3.257)
Independent Variable				
GuarAnyReq	91.036** (29.993)	150.899* (61.908)	40.121*** (11.948)	70.06† (40.057)
Interactions				
GuarAnyReq × TaskComplex		−21.607* (9.209)		−9.816† (5.959)
GuarAnyReq × Ln(TaskDesc)		3.452 (35.97)		17.011 (23.274)
Fixed Effects				
Buyer Location Effect	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes
Model Summary				
Anderson-Rubin Wald *F*	12.18	5.93	11.63	8.62
No. of Obs.	16,240	16,240	16,240	16,240

Notes: Standard errors are reported in parentheses. Columns are numbered consecutively in the headings and referenced in text. 2SLS = two-stage least squares; Obs. = observations.
†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 7. Effect of the Adoption of Guarantee-Required Schemes on Average Bid Quality (OLS).

Dependent variable	Ln(BidDuration): 1	Ln(BidProposal): 2
Constant	-0.281*** (0.088)	3.317*** (0.107)
Control Variables		
TaskComplex	0.113*** (0.005)	-0.124*** (0.006)
Ln(TaskDesc)	0.009 (0.006)	0.043*** (0.007)
Ln(BuyerExp)	0.012 (0.021)	-0.233*** (0.026)
AuctDuration	0.008*** (0.001)	0.007*** (0.001)
Referred	0.03* (0.014)	-0.061*** (0.017)
Ln(BidPrice)	0.278*** (0.006)	0.105*** (0.007)
Independent Variable		
GuarAnyReq	0.003 (0.029)	0.053 (0.035)
Fixed Effects		
Buyer Location Effect	Yes	Yes
Task Category Effect	Yes	Yes
Time (Month) Effect	Yes	Yes
Model Summary		
R^2	0.6534	0.2632
Adjusted R^2	0.6528	0.2619
F	1128.68	213.8
No. of Obs.	16,791	16,791

Notes: Standard errors are reported in parentheses. Columns are numbered consecutively in the headings and referenced in text. OLS = ordinary least squares; Obs. = observations.
$^*p < 0.05$. $^{***}p < 0.001$.

effect for the bidding proposal) and the slack effect (which predicts a positive effect for the bidding duration and a negative effect for the bidding proposal). We do not estimate Equation (6), as no significant slack effect is found.

IV *Analyses*

We use *BuyerPinLevel* as the IV for the adoption of guarantee-required schemes. This instrument is valid because the correlation between *BuyerPinLevel* and *GuarAnyReq* is highly significant; simultaneously, all Anderson-Rubin Wald *F* statistics are significant.

When we try to alleviate the endogeneity issue by using an IV, the results change from those of the OLS analyses. Results are reported in Table 8. Column 1 shows a significantly negative effect of the adoption of guarantee-required schemes on the average bidding duration ($\beta = -2.108,\ p < 0.05$), suggesting the existence of a signaling effect and providing support for Hypothesis 3a. Hypothesis 3b, pertaining to the presence of a slack effect on bid quality, receives support, as the coefficient of the effect of guarantee-required scheme adoption on bidding proposals is significant and negative, as shown in Column 2 ($\beta = -1.807,\ p < 0.1$). We further examine the moderating role of task complexity and task description in the bidding proposal model, as the existence of the slack effect is proven. As shown in Column 3, the coefficient of task complexity and guarantee-required scheme adoption is significant at the 10 percent level when one-tailed tests are used ($\beta = 0.377,\ p < 0.1$), providing support for Hypothesis 8. However, our results indicate no significant moderating effect of task description; thus, Hypothesis 9 is not supported.

Additional Analyses

Based on a large data set of practical data, we prove the existence of screening, signaling, and slack effects on the relationship between the adoption of buyer-side trust-building

Table 8. Effect of the Adoption of Guarantee-Required Schemes on Average Bid Quality (2SLS).

Dependent variable	Ln(BidDuration): 1	Ln(BidProposal): 2	Ln(BidProposal): 3
Constant	−0.474*** (0.118)	3.185*** (0.135)	2.489*** (0.527)
Control Variables			
TaskComplex	0.109*** (0.007)	−0.13*** (0.008)	−0.093*** (0.028)
Ln(TaskDesc)	0.026** (0.01)	0.061*** (0.011)	0.172 (0.107)
Ln(BuyerExp)	0.006 (0.024)	−0.233*** (0.028)	−0.253*** (0.057)
AuctDuration	0.01*** (0.002)	0.009*** (0.002)	0.008*** (0.002)
Referred	−0.056 (0.041)	−0.138** (0.047)	−0.15* (0.062)
Ln(BidPrice)	0.305*** (0.008)	0.123*** (0.009)	0.132*** (0.015)
Independent Variable			
GuarAnyReq	−2.108* (0.926)	−1.807† (1.057)	−3.043† (1.819)
Interactions			
GuarAnyReq × TaskComplex			0.377† (0.241)
GuarAnyReq × Ln(TaskDesc)			0.508 (0.554)
Fixed Effects			
Buyer Location Effect	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes
Model Summary			
Anderson-Rubin Wald *F*	6.6	3.34	2.27
No. of Obs.	15,403	15,403	15,403

Notes: Standard errors are reported in parentheses. Columns are numbered consecutively in the headings and referenced in text. One-tailed tests for the coefficients of the interaction terms. 2SLS = two-stage least squares; Obs. = observations.
†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

mechanisms and bidder behavior. Fewer bidders are attracted to guarantee-required tasks as a result of the screening effect. Guarantee-required tasks require bidders to deposit a certain amount of money with the platform to compensate for possible future complaints. First, this requirement discourages the participation of bidders who do not have much winning experience. Second, it screens out bidders who are less capable of completing tasks as promised. Simultaneously, the adoption of guarantee-required schemes conveys information on the buyer's vertical preference for quality over price, thus attracting bidders with high-quality features because a better fit with the buyer's preference implies a higher winning probability. The double positive effect (screening and signaling) of guarantee-required schemes on average bidder quality is supported by our data results. Bid quality shows interesting results; the results support a dominant signaling effect on the time dimension and a dominant slack effect on the proposal dimension when we include the bidding price as a control variable.

In this section, we report several additional analyses to test the robustness of the results. First, we consider the propensity score matching (PSM) approach to alleviate self-selection issues. Second, we use two alternative measures—the mean of the lower and upper bounds of the task budget and task budget per daily work—for task complexity. Third, we reestimate the models with IT service projects samples. Finally, we test the effects of the adoption of each specific guarantee-required scheme (completion-guarantee-required, service-guarantee-required, and originality- guarantee-required schemes) and the number of schemes adopted on bidders' behavior.

Propensity Score Matching

PSM is a commonly used approach to alleviate concerns caused by endogeneity. To implement PSM, we use buyer and task characteristics as matching variables. Following Hong et al. [27], we use the task budget (in our paper, *task complexity*), the auction duration, the buyer experience, the buyer location, task categories and year–month dummies as matching covariates. We also add the length of task description and whether the buyer was referred to the platform through a salesperson as matching covariates. Task description affects freelancers' participation [62], and whether the buyer was referred to the platform through a salesperson is a buyer feature that might affect potential freelancers' perception of the buyer and thus their participation and bidding strategies.

We estimate the propensity scores using a Probit model on the binary treatment variable (the adoption of guarantee-required schemes). The estimated propensity scores are then used to match tasks that do and do not adopt the schemes. Other matching algorithms are also considered, such as kernel matching, nearest neighbor matching ($n = 4$), and radius matching. The average treatment effect on the treatment versus control variables is identified and reported in Table 9. In summary, the PSM results validate our main findings, except for the bidding duration results. We report the balance checks in Appendix B online.

We also reestimate the empirical models with OLS and NB regressions using matched samples. The results, reported in Table 10, are consistent with those of the whole-sample OLS analyses.

Robustness Checks on the Effect of Task Complexity (Alternative Measures)

We consider two alternative measures for task complexity. First, we use the mean value of the lower and upper bounds of the task budget (*TaskBudgMean*); the OLS and IV results, which are reported in Table 11 and Table 12, respectively, are basically consistent with the results of our main analyses. Second, we consider the budget for daily work (*TaskBudgPerDay*) or the upper bound of the task budget divided by the average bidding duration of the bids submitted in the task. The OLS and IV estimation results, which are reported in Table 13 and Table 14, respectively, are basically consistent with our main analyses. Note that we do not include the interaction of task description and the adoption of guarantee-required schemes, because task description is not our focus here.

Robustness Checks on the Effect of Task Complexity (with the IT Services Sample)

To alleviate the measurement for complexity across different task types, here we focus on a commonly researched category: IT service projects. IT service projects are treated

Table 9. Matching Estimates (Treatment Effect for the Adoption of Guarantee-Required Schemes).

	BidNum	BidderExp	BidderRep	BidDuration	BidProposal
1-1 Matching	−15.341***	26.291***	19.290***	2.096	−16.326*
	(0.473)	(2.820)	(0.749)	(1.978)	(7.67)
	(N = 3,297)	(N = 1,700)	(N = 1,700)	(N = 886)	(N = 1,700)
Kernel matching	−16.274***	26.511***	19.349***	0.209	−20.971**
	(0.209)	(2.717)	(0.662)	(1.334)	(6.814)
	(N = 18,683)	(N = 17,532)	(N = 17,532)	(N = 16,214)	(N = 17,532)
k nearest neighbor matching (k = 4)	−15.831***	25.592***	19.474***	−0.847	−18.119*
	(0.318)	(2.756)	(0.690)	(1.981)	(7.166)
	(N = 5,985)	(N = 3,228)	(N = 3,228)	(N = 1,866)	(N = 3,228)
Radius matching	−17.985***	26.603***	19.113***	1.179	−25.973***
	(0.138)	(2.711)	(0.655)	(1.267)	(6.737)
	(N = 18,721)	(N = 17,625)	(N = 17,625)	(N = 16,734)	(N = 17,625)

Notes: Standard errors are reported in parentheses. Standard errors do not take into account that the propensity score is estimated.

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 10. OLS and NB Estimation Results With Matched Samples

	Ln(BidNum)	BidNum	BidderExp	BidderRep	Ln(BidDuration)	Ln(BidProposal)
Dependent variable	OLS	NB	OLS	OLS	OLS	OLS
Constant	2.104***	0.276	−39.451***	10.468***	−0.36†	3.852***
	(0.268)	(0.371)	(8.369)	(2.224)	(0.205)	(0.237)
Control Variables						
TaskComplex	−0.004	0.017†	0.939	1.019***	0.011	−0.128***
	(0.011)	(0.009)	(0.875)	(0.233)	(0.022)	(0.025)
Ln(TaskDesc)	−0.105***	−0.047**	2.54	0.428	0.004	0.059*
	(0.019)	(0.016)	(1.559)	(0.414)	(0.018)	(0.024)
Ln(BuyerExp)	−0.037	−0.047	9.067	5.202***	0.253***	−0.298**
	(0.103)	(0.111)	(5.817)	(1.546)	(0.078)	(0.113)
AuctDuration	0.009***	0.006*	0.539**	−0.001	0.005†	0.009*
	(0.003)	(0.003)	(0.2)	(0.053)	(0.003)	(0.004)
Referred	0.117†	0.069	2.295	1.692	−0.189†	−0.039
	(0.07)	(0.07)	(6.064)	(1.611)	(0.108)	(0.128)
Ln(BidPrice)					0.378***	0.06*
					(0.027)	(0.03)
Independent Variable						
GuarAnyReq	−1.919***	−1.45***	30.53***	20.086***	0.004	0.083
	(0.029)	(0.039)	(2.44)	(0.648)	(0.037)	(0.051)
Interactions						
GuarAnyReq × TaskComplex	0.046***	0.041***	−2.099***	−0.7***		
	(0.008)	(0.01)	(0.617)	(0.164)		
GuarAnyReq × Ln(TaskDesc)	0.018**	−0.005	−0.918	−0.087		
	(0.007)	(0.009)	(0.562)	(0.149)		
Fixed Effects						
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes	Yes
Model Summary						
R^2	0.6292		0.2717	0.4618	0.7389	0.2629
Adjusted R^2	0.6259		0.2595	0.4528	0.7306	0.2475
F	191.13		22.27	51.2	89.91	17.04
LR χ^2		2269.18				
No. of Obs.	3,297	3,297	1,700	1,700	886	1,318

Notes: Standard errors are reported in parentheses. OLS = ordinary least squares; NB = negative binomial; Obs. = observations.
†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

separately in many studies [27, 65]. Based on our data set, we construct the IT service sample by including tasks with "APP," "app," "website," "platform," "system," or "software" in their task titles from the original design and Web and software development categories. Note that all the keywords except app and APP were originally Chinese characters; we have translated them for convenience of comprehension. The estimation results are reported in Table 15 and Table 16. Note that we do not include the interaction of task description and the adoption of guarantee-required schemes, because task description is not our focus here.

Alternative Measures for the Adoption of Guarantee-Required Schemes

The variable *GuarCompReq* is equal to 1 if the buyer required bidders to offer a completion guarantee and 0 otherwise. *GuarServReq* is coded 1 if the buyer required bidders to offer a service guarantee and 0 otherwise. *GuarOrigReq* is equal to 1 if the buyer required bidders to offer an originality guarantee and 0 otherwise. We empirically test how the adoption of each specific guarantee-required scheme affects the characteristics of the choice pool. The results are shown in Table 17 and Table 18. The results for the number of bids and bidder

Table 11. Estimation Results for the Number of Bids and Average Bidder Quality (*TaskBudgMean* as a Proxy for Task Complexity).

	Ln(BidNum)		BidderExp		BidderRep	
Dependent variable	OLS	IV	OLS	IV	OLS	IV
Constant	1.549***	3.066*	−5.071	18.69	2.988*	13.286*
	(0.111)	(1.466)	(3.202)	(12.761)	(1.277)	(5.24)
Control Variables						
Ln(TaskBudgMean)	0.001	−0.146	−2.18***	−2.707*	1.357***	0.289
	(0.005)	(0.122)	(0.204)	(1.266)	(0.054)	(0.52)
Ln(TaskDesc)	−0.081***	0.493	−0.12	−0.754	−0.158†	−0.697*
	(0.008)	(0.498)	(0.134)	(0.829)	(0.086)	(0.34)
Ln(BuyerExp)	−0.381***	−1.763	0.502*	4.135	2.115***	4.287***
	(0.03)	(1.176)	(0.216)	(2.834)	(0.315)	(1.164)
AuctDuration	0.021***	0.052†	−1.215	−0.063	−0.11***	−0.13***
	(0.001)	(0.031)	(0.789)	(0.081)	(0.015)	(0.033)
Referred	0.061**	−2.972	0.027	11.962*	0.564**	4.227†
	(0.02)	(2.643)	(0.037)	(5.435)	(0.214)	(2.232)
Independent Variable						
GuarAnyReq	−1.927***	−22.941	28.044***	153.315*	19.709***	67.926*
	(0.024)	(18.169)	(0.851)	(66.111)	(0.339)	(27.146)
Interactions						
GuarAnyReq × Ln(TaskBudgMean)	0.043***	3.215†	−2.18***	−22.401*	−0.629***	−9.901**
	(0.006)	(2.497)	(0.204)	(9.769)	(0.082)	(4.011)
Fixed Effects						
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes	Yes
Model Summary						
R^2	0.3864		0.2116		0.3677	
Adjusted R^2	0.3855		0.2103		0.3667	
F	420.4	3.01	169.26	42.76	366.71	86.13
No. of Obs.	18,721	17,134	17,688	16,240	17,688	16,240

Notes: Standard errors are reported in parentheses. One-tailed tests for the coefficients of the interaction terms. OLS = ordinary least squares; IV =instrumental variable; Obs. = observations.
†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

quality are consistent with those of the main analyses. However, the adoption of each specific guarantee-required scheme does not demonstrate a significant effect on bid quality (bidding duration and bidding proposal; we do not present the results here).

We also consider *GuarReq*, which is defined as the number of guarantee-required schemes that a buyer used, ranging from none to three. The results, which are presented in Table 19 and Table 20, are basically consistent with the main analyses.

Conclusion

Key Findings

In this paper, we propose a 3S effect model (comprising screening, signaling, and slack effects) to explain how the adoption of buyer-side trust-building mechanisms (i.e., the adoption of guarantee-required schemes) affects bidders' participation and bidding behavior or the characteristics of the choice pool. This 3S framework can help us directly answer the third research question raised in the Introduction. With a large data set from one of the leading online labor markets in China, we empirically tested the impact of the adoption of guarantee-required schemes on the number of bids received, the average bidder quality (experience and reputation), and the average bid quality (bidding duration, the level of detail

Table 12. Estimation Results for Average Bid Quality (*TaskBudgMean* as a Proxy for Task Complexity).

	Ln(BidDuration)		Ln(BidProposal)		
Dependent variable	OLS	IV	OLS	IV	IV
Constant	−1.01***	−1.172***	4.118***	4.02***	3.566***
	(0.085)	(0.122)	(0.103)	(0.14)	(0.417)
Control Variables					
Ln(TaskBudgMean)	0.139***	0.133***	−0.154***	−0.163***	−0.12***
	(0.006)	(0.008)	(0.007)	(0.009)	(0.034)
Ln(TaskDesc)	0.009	0.026**	0.043***	0.062***	0.071***
	(0.006)	(0.01)	(0.007)	(0.011)	(0.017)
Ln(BuyerExp)	0.011	0.006	−0.232***	−0.233***	−0.275***
	(0.021)	(0.024)	(0.026)	(0.028)	(0.045)
AuctDuration	0.008***	0.01***	0.007***	0.009***	0.008***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Referred	0.028*	−0.057	−0.059***	−0.136**	−0.148*
	(0.014)	(0.041)	(0.017)	(0.047)	(0.058)
Ln(BidPrice)	0.272***	0.299***	0.112***	0.132***	0.14***
	(0.006)	(0.008)	(0.007)	(0.01)	(0.014)
Independent Variable					
GuarAnyReq	0.004	−2.09*	0.052	−1.826†	−2.795
	(0.029)	(0.923)	(0.035)	(1.056)	(1.775)
Interactions					
GuarAnyReq × Ln(TaskBudgMean)					0.346†
					(0.243)
Fixed Effects					
Buyer location effect	Yes	Yes	Yes	Yes	Yes
Task category effect	Yes	Yes	Yes	Yes	Yes
Time (month) effect	Yes	Yes	Yes	Yes	Yes
Model Summary					
R^2	0.6544		0.2651		
Adjusted R^2	0.6539		0.2639		
F	1133.73	814	215.98	166.92	111.7
No. of Obs.	16,791	15,403	16,791	15,403	15,403

Notes: Standard errors are reported in parentheses. One-tailed tests for the coefficients of the interaction terms. OLS = ordinary least squares; IV = instrumental variable; Obs. = observations.
† $p < 0.1$. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

of bidding proposals). We found that although adopting guarantee-required schemes induces fewer bidders to participate, the average quality feature of the participating bidders is improved. Bid quality presents different results in the "time" and "proposal" dimensions—that is, guarantee-required tasks attract bids with shorter bidding durations (signaling effect) and less detailed bidding proposals (slack effect). Our second research question about how many and what kinds of freelancers (and their bids) are attracted are thus addressed. Task complexity weakens the screening and slack effects, as it increases the difficulty with which buyers can lodge a reasonable complaint and decreases the possibility that bidders default. However, the length of the task description basically demonstrates no significant moderating effect. We summarize the results in Table 21. In all, our study provides evidence that compared with seller-side and mandatory, buyer-side trust-building mechanisms do have different impacts on transaction outcomes (first research question is answered).

Implications and Future Research Directions

This study provides several theoretical implications. First, it provides the online institutional trust-building mechanism literature with insights into buyer-side trust-building mechanisms using large-scale observational data from real-life online markets. Second,

Table 13. Estimation Results for the Number of Bids and Average Bidder Quality (*TaskBudgPerDay* as a Proxy for Task Complexity).

	Ln(BidNum)		BidderExp		BidderRep	
Dependent variable	OLS	IV	OLS	IV	OLS	IV
Constant	2.019***	0.136	2.255	16.068†	4.224***	9.257*
	(0.125)	(0.735)	(3.32)	(9.542)	(1.329)	(3.986)
Control Variables						
Ln(TaskBudgPerDay)	−0.025***	0.246*	−1.506***	−3.679**	0.876***	0.172
	(0.007)	(0.106)	(0.19)	(1.382)	(0.076)	(0.578)
Ln(TaskDesc)	−0.077***	0.011	0.535*	0.304	0.015	−0.144
	(0.008)	(0.029)	(0.218)	(0.383)	(0.087)	(0.16)
Ln(BuyerExp)	−0.364***	−0.43***	−1.599*	−0.948	1.811***	1.983***
	(0.03)	(0.067)	(0.81)	(0.871)	(0.324)	(0.364)
AuctDuration	0.022***	0.03***	0.009	−0.025	−0.092***	−0.105***
	(0.001)	(0.004)	(0.038)	(0.051)	(0.015)	(0.022)
Referred	0.057**	−0.291**	1.45**	2.945*	0.811***	1.437*
	(0.02)	(0.106)	(0.539)	(1.376)	(0.216)	(0.575)
Independent Variable						
GuarAnyReq	−1.448***	−11.726***	49.352***	96.785**	19.614***	39.173*
	(0.043)	(2.88)	(1.142)	(37.385)	(0.457)	(15.618)
Interactions						
GuarAnyReq × Ln(TaskBudgPerDay)	0.035***	1.054**	−4.155***	−13.626**	−0.539***	−3.343†
	(0.01)	(0.441)	(0.277)	(5.727)	(0.111)	(2.392)
Fixed Effects						
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes	Yes
Model Summary						
R^2	0.2169		0.2562		0.3392	
Adjusted R^2	0.2156		0.255		0.3381	
F	165.78	26.87	206.2	108.57	307.26	195.44
No. of Obs.	16,791	15,403	16,791	15,403	16,791	15,403

Notes: Standard errors are reported in parentheses. One-tailed tests for the coefficients of the interaction terms. OLS = ordinary least squares; IV = instrumental variable; Obs.= observations.
†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 14. Estimation Results for Average Bid Quality (*TaskBudgPerDay* as a Proxy for Task Complexity).

	Ln(BidDuration)		Ln(BidProposal)		
Dependent variable	OLS	IV	OLS	IV	IV
Constant	0.434***	0.352***	4.222***	4.135***	4.321***
	(0.072)	(0.094)	(0.105)	(0.142)	(0.324)
Control Variables					
Ln(TaskBudgPerDay)	−0.404***	−0.42***	−0.1***	−0.1***	−0.131**
	(0.005)	(0.005)	(0.007)	(0.007)	(0.042)
Ln(TaskDesc)	0.029***	0.039***	0.039***	0.055***	0.054***
	(0.005)	(0.007)	(0.007)	(0.011)	(0.012)
Ln(BuyerExp)	0.015	0.013	−0.235***	−0.235***	−0.23***
	(0.018)	(0.018)	(0.026)	(0.028)	(0.029)
AuctDuration	0.006***	0.006***	0.006***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Referred	0.072***	0.035	−0.07***	−0.142**	−0.143**
	(0.012)	(0.031)	(0.017)	(0.046)	(0.046)
Ln(BidPrice)	0.518***	0.542***	0.027***	0.037***	0.037***
	(0.003)	(0.006)	(0.005)	(0.009)	(0.009)
Independent Variable					
GuarAnyReq	0.038†	−0.943†	0.045	−1.668†	−1.485
	(0.024)	(0.699)	(0.036)	(1.054)	(1.208)
Interactions					
GuarAnyReq					−0.141
× Ln(TaskBudgMean)					(0.189)
Fixed Effects					
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes
Model Summary					
R^2	0.7588		0.2561		
Adjusted R^2	0.7584		0.2548		
F	1883.25	1678.74	206.07	161.2	156.25
No. of Obs.	16,791	15,403	16,791	15,403	15,403

Notes: Standard errors are reported in parentheses. One-tailed tests for the coefficients of the independent variables and the interaction terms. OLS = ordinary least squares; IV = instrumental variable; Obs. = observations.
† $p < 0.1$. ** $p < 0.01$. *** $p < 0.001$.

Table 15. Estimation Results for the Number of Bids and Average Bidder Quality (IT Service Tasks).

	Ln(BidNum)		BidderExp		BidderRep	
Dependent variable	OLS	IV	OLS	IV	OLS	IV
Constant	2.549***	2.518***	2.092† (1.189)	2.016	17.386***	18.396***
	(0.067)	(0.232)		(1.33)	(0.736)	(1.094)
Control Variables						
TaskBudget	0.042***	0.046**	−0.621***	−0.844***	1.194***	0.768***
	(0.005)	(0.016)	(0.094)	(0.234)	(0.058)	(0.193)
Ln(TaskDesc)	−0.101***	−0.093	0.213	−0.078	0.05	−0.595†
	(0.011)	(0.112)	(0.192)	(0.401)	(0.119)	(0.33)
Ln(BuyerExp)	−0.201***	−0.174	2.285*	3.534**	1.448*	2.34*
	(0.062)	(0.115)	(1.06)	(1.134)	(0.656)	(0.932)
AuctDuration	0.007***	0.009	0.055†	0.078†	−0.069***	−0.084*
	(0.002)	(0.007)	(0.032)	(0.047)	(0.02)	(0.039)
Referred	−0.023	−0.082	1.339**	2.124	0.465	2.88†
	(0.028)	(0.49)	(0.481)	(2.056)	(0.298)	(1.69)
Independent Variable						
GuarAnyReq	−1.928***	−2.073	22.012***	49.401*	20.466***	62.557***
	(0.033)	(3.214)	(0.817)	(22.191)	(0.506)	(18.246)
Interactions						
GuarAnyReq × Ln(TaskBudgMean)	0.032***	−0.065	−1.81***	−7.936***	−0.913***	−7.045***
	(0.008)	(0.218)	(0.177)	(2.463)	(0.11)	(2.025)
Fixed Effects						
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes	Yes
Model Summary						
R^2	0.3304		0.099		0.272	
Adjusted R^2	0.3288		0.0967		0.2702	
F	205.69	40.79	43.39	7.34	147.57	34.48
No. of Obs.	9,193	8,509	8,711	8,086	8,711	8,086

Notes: Standard errors are reported in parentheses. One-tailed tests for the coefficients of the independent variables and interaction terms. OLS = ordinary least squares; IV = instrumental variable; Obs. = observations.

†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 16. Estimation Results for Average Bid Quality (IT Service Tasks).

	Ln(BidDuration)		Ln(BidProposal)			
Dependent variable	OLS	IV	OLS	OLS	IV	IV
Constant	−0.132*	−0.374**	4.11***	4.112***	4.032***	3.977***
	(0.067)	(0.128)	(0.088)	(0.088)	(0.118)	(0.199)
Control Variables						
Ln(TaskBudgMean)	0.104***	0.115***	−0.131***	−0.131***	−0.135***	−0.125***
	(0.006)	(0.011)	(0.008)	(0.008)	(0.01)	(0.027)
Ln(TaskDesc)	−0.01	0.016	0.065***	0.065***	0.08***	0.082***
	(0.008)	(0.015)	(0.01)	(0.01)	(0.014)	(0.018)
Ln(BuyerExp)	−0.046	0.094	−0.152**	−0.151**	−0.109	−0.121†
	(0.043)	(0.08)	(0.056)	(0.056)	(0.074)	(0.066)
AuctDuration	0.004***	0.01***	0.005**	0.005**	0.007**	0.007**
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Referred	0.054**	−0.161*	−0.028	−0.028	−0.107	−0.104
	(0.019)	(0.081)	(0.025)	(0.025)	(0.075)	(0.072)
Ln(BidPrice)	0.309***	0.336***	0.094***	0.094***	0.106***	0.108***
	(0.007)	(0.014)	(0.01)	(0.01)	(0.012)	(0.015)
Independent Variable						
GuarAnyReq	0.001	−4.022**	−0.347***	−0.331***	−1.716†	−2.089
	(0.039)	(1.423)	(0.051)	(0.061)	(1.308)	(1.99)
Interactions						
GuarAnyReq × Ln(TaskBudgMean)				−0.006		0.11
				(0.012)		(0.228)
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes	Yes
Model Summary						
R^2	0.5473		0.194	0.194		
Adjusted R^2	0.5461		0.1918	0.1917		
F	451.45	192.36	89.86	85.96	72.32	68.09
No. of Obs.	8,238	7,646	8,238	8,238	7,646	7,646

Notes: Standard errors are reported in parentheses. One-tailed tests for the coefficients of the independent variables and interaction terms. OLS = ordinary least squares; IV = instrumental variable; Obs. = observations.

†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 17. Estimation Results for the Number of Bids (Specific Schemes).

	Ln(BidNum)			BidNum		
Dependent variable	OLS	OLS	OLS	NB	NB	NB
Constant	1.56***	1.526***	1.455***	1.933***	1.933***	1.922***
	(0.11)	(0.112)	(0.117)	(0.115)	(0.116)	(0.118)
Control Variables						
TaskComplex	0.004	0.005	0.011*	−0.006	−0.008†	−0.008†
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Ln(TaskDesc)	−0.087***	−0.096***	−0.11***	−0.101***	−0.106***	−0.115***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
Ln(BuyerExp)	−0.371***	−0.354***	−0.338***	−0.338***	−0.327***	−0.31***
	(0.031)	(0.031)	(0.033)	(0.033)	(0.033)	(0.034)
AuctDuration	0.02***	0.02***	0.019***	0.024***	0.024***	0.023***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Referred	0.104***	0.133***	0.216***	0.055**	0.072***	0.114***
	(0.02)	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)
Independent Variables						
GuarCompReq	−1.903***			−2.677***		
	(0.026)			(0.036)		
GuarServReq		−1.889***			−2.704***	
		(0.028)			(0.038)	
GuarOrigReq			−1.775***			−2.505***
			(0.034)			(0.043)
Interactions						
GuarCompReq × TaskComplex	0.038***			0.066***		
	(0.006)			(0.008)		
GuarCompReq × Ln(TaskDesc)	0.009			0.005		
	(0.005)			(0.007)		
GuarServReq × TaskComplex		0.032***			0.056***	
		(0.006)			(0.008)	
GuarServReq × Ln(TaskDesc)		0.01†			0.005	
		(0.006)			(0.007)	
GuarOrigReq × TaskComplex			0.025***			0.033***
			(0.006)			(0.008)
GuarOrigReq × Ln(TaskDesc)			0.01†			0.005
			(0.006)			(0.007)
Fixed Effects						
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes	Yes
Model Summary						
R^2	0.361	0.3372	0.2786			
Adjusted R^2	0.36	0.3361	0.2775			
F	364.14	327.83	248.9			
LR χ^2				8620.14	8026.72	6496.13
No. of Obs.	18,721	18,721	18,721	18,721	18,721	18,721

Notes: Standard errors are reported in parentheses. OLS = ordinary least squares; NB=negative binomial; Obs. = observations.
†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

this study sheds lights on the effects of the adoption of guarantee-required schemes by providing a new framework (the 3S effect framework). Third, this study complements online labor markets literature on bidder behaviors by providing evidence on how bidders' participation and bidding strategies are affected by guarantee-required schemes.

This research also provides several practical implications. We provide suggestions for buyers who are indecisive about the adoption of buyer-side trust-building mechanisms. The adoption of guarantee-required schemes attracts bidders with high-quality features (e.g., more experience and higher reputations) and induces bids with a shorter bidding duration. However, the adoption of these schemes also reduces the number of bids placed,

Table 18. Estimation Results for Average Bidder Quality (Specific Schemes).

	BidderExp			BidderRep		
Dependent variable	OLS	OLS	OLS	OLS	OLS	OLS
Constant	−5.86†	−5.788†	−6.284*	10.291***	10.275***	10.059***
	(3.105)	(3.121)	(3.122)	(1.248)	(1.268)	(1.276)
Control Variables						
TaskComplex	−0.082	−0.056	−0.01	1.134***	1.156***	1.172***
	(0.115)	(0.116)	(0.115)	(0.046)	(0.047)	(0.047)
Ln(TaskDesc)	0.533*	0.561**	0.634**	−0.115	−0.085	−0.038
	(0.216)	(0.217)	(0.217)	(0.087)	(0.088)	(0.089)
Ln(BuyerExp)	−1.358†	−1.412† (0.794)	−1.4†	2.012***	1.954***	1.942***
	(0.79)		(0.794)	(0.318)	(0.323)	(0.325)
AuctDuration	0.031	0.044	0.042	−0.105***	−0.097***	−0.096***
	(0.037)	(0.037)	(0.037)	(0.015)	(0.015)	(0.015)
Referred	1.685**	1.314*	1.115*	0.365†	0.112	−0.088
	(0.536)	(0.538)	(0.537)	(0.216)	(0.219)	(0.22)
Independent Variables						
GuarCompReq	29.34***			19.656***		
	(0.922)			(0.371)		
GuarServReq		28.825***			19.208***	
		(1.004)			(0.408)	
GuarOrigReq			30.575***			19.787***
			(1.08)			(0.441)
Interactions						
GuarCompReq × TaskComplex	−2.025***			−0.562***		
	(0.203)			(0.082)		
GuarCompReq × Ln(TaskDesc)	−0.238			0.055		
	(0.188)			(0.075)		
GuarServReq × TaskComplex		−2.155***			−0.546***	
		(0.207)			(0.084)	
GuarServReq × Ln(TaskDesc)		0.004			0.064	
		(0.19)			(0.077)	
GuarOrigReq × TaskComplex			−1.743***			−0.361***
			(0.19)			(0.078)
GuarOrigReq × Ln(TaskDesc)			−0.022			0.078
			(0.176)			(0.072)
Fixed Effects						
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes	Yes
Model Summary						
R^2	0.2098	0.2021	0.2011	0.3558	0.3357	0.3271
Adjusted R^2	0.2085	0.2008	0.1998	0.3547	0.3346	0.326
F	161.70	154.19	153.31	336.30	307.66	296.00
No. of Obs.	17,688	17,688	17,688	17,688	17,688	17,688

Notes: Standard errors are reported in parentheses. OLS = ordinary least squares; Obs. = observations.
$^{\dagger}p < 0.1$. $^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

Table 19. Estimation Results for the Number of Bids and Bidder Quality (Number of Schemes Adopted).

	Ln(BidNum)		BidderExp		BidderRep	
Dependent variable	OLS	IV	OLS	IV	OLS	IV
Constant	1.515***	3.211	−5.727†	6.421	10.344***	15.405***
	(0.11)	(2.88)	(3.101)	(9.355)	(1.248)	(4.383)
Control Variables						
TaskComplex	0.006	−0.088	−0.101	−2.488*	1.125***	0.055
	(0.004)	(0.08)	(0.115)	(1.233)	(0.046)	(0.577)
ln(TaskDesc)	−0.089***	0.196	0.527*	−1.175	−0.111	−0.809
	(0.008)	(0.323)	(0.216)	(1.2)	(0.087)	(0.562)
Ln(BuyerExp)	−0.371***	−1.984	−1.25	5.017	2.049***	5.189***
	(0.031)	(1.386)	(0.789)	(3.341)	(0.318)	(1.565)
AuctDuration	0.02***	0.044†	0.036	−0.013	−0.102***	−0.111**
	(0.001)	(0.027)	(0.037)	(0.076)	(0.015)	(0.036)
Referred	0.11***	−2.886	1.698**	12.161*	0.358†	5.221*
	(0.021)	(2.641)	(0.535)	(5.615)	(0.215)	(2.631)
Independent Variables						
GuarReq	−0.748***	−11.711	11.549***	74.24*	7.631***	34.96*
	(0.01)	(9.977)	(0.357)	(34.093)	(0.144)	(15.972)
Interactions						
GuarReq × TaskComplex	0.046***	4.48	−2.18***	−25.969*	−0.579***	−11.476*
	(0.006)	(3.94)	(0.196)	(12.459)	(0.079)	(5.837)
GuarReq × Ln(TaskDesc)	0.008	1.914	−0.023	−2.833	0.13†	5.225
	(0.005)	(3.013)	(0.182)	(18.292)	(0.073)	(8.569)
Fixed Effects						
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes	Yes
Model Summary						
R^2	0.3583		0.212		0.3561	
Adjusted R^2	0.3573		0.2107		0.3551	
F	359.81	1.9	163.79	32.31	336.81	49.68
LR χ^2						
No. of Obs.	18,721	17,134	17,688	16,240	17,688	16,240

Notes: Standard errors are reported in parentheses. OLS = ordinary least squares; IV = instrumental variable; Obs. = observations.
†$p < 0.1$. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Table 20. Estimation Results for Average Bid Quality (Number of Schemes Adopted).

	Ln(BidDuration)		Ln(BidProposal)		
Dependent variable	OLS	IV	OLS	IV	IV
Constant	−0.281**	−1.191***	3.317***	3.162***	1.996
	(0.088)	(0.131)	(0.107)	(0.144)	(1.607)
Control Variables					
TaskComplex	0.113***	0.132***	−0.124***	−0.131***	−0.085*
	(0.005)	(0.008)	(0.006)	(0.008)	(0.034)
Ln(TaskDesc)	0.009	0.027**	0.043***	0.062***	0.272
	(0.006)	(0.01)	(0.007)	(0.012)	(0.375)
Ln(BuyerExp)	0.012	0.011	−0.233***	−0.229***	−0.221
	(0.021)	(0.025)	(0.026)	(0.028)	(0.159)
AuctDuration	0.008***	0.01***	0.007***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Referred	0.03*	−0.054	−0.061***	−0.135**	−0.119
	(0.014)	(0.04)	(0.017)	(0.046)	(0.123)
Ln(BidPrice)	0.278***	0.302***	0.105***	0.125***	0.132***
	(0.006)	(0.009)	(0.007)	(0.01)	(0.033)
Independent Variables					
GuarReq	0.004	−0.923*	0.049	−0.798†	−1.234
	(0.012)	(0.417)	(0.037)	(0.473)	(1.335)
Interactions					
GuarReq × TaskComplex					0.48†
					(0.339)
GuarReq × Ln(TaskDesc)					1.106
					(2.193)
Fixed Effects					
Buyer Location Effect	Yes	Yes	Yes	Yes	Yes
Task Category Effect	Yes	Yes	Yes	Yes	Yes
Time (Month) Effect	Yes	Yes	Yes	Yes	Yes
Model Summary					
R^2	0.6534		0.2631		
Adjusted R^2	0.6529		0.2619		
F	1128.69	777.55	213.77	160.97	72.95
No. of Obs.	16,791	15,403	16,791	15,403	15,403

Notes: Standard errors are reported in parentheses. One-tailed tests for the coefficients of the interaction terms. OLS = ordinary least squares; IV = instrumental variable; Obs. = observations.
$^{\dagger}p < 0.1$. $^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

leaving the buyer fewer available choices; moreover, bidders tend to bid proposals with less detail. Given the coexistence of these advantages and disadvantages, buyers need to think carefully about what they really value and make appropriate trade-offs when deciding whether to adopt buyer-side trust-building mechanisms.

Buyers choose to adopt guarantee-required schemes or not, which leads to an endogeneity issue. In this paper, we have used several approaches to relieve this issue, including controlling various task-specific and buyer-specific features, using IV analyses and PSM. Although we believe our findings are robust, the instrumental variable *BuyerPinLevel* mainly addresses endogeneity resulting from unobserved buyer-specific features and did not deal very well with that from task-specific features. Future research could use other approaches for identification, such as field experiments, to further strengthen our findings. Although we provided inferences of the impact of guarantee-required scheme adoption on the characteristics of the choice pool, we did not provide empirical evidence on how the adoption of guarantee-required schemes affects other outcomes, such as match rate and buyer satisfaction. Analyses with more sophisticated econometric models of buyer-side trust-building mechanisms and their effects on outcomes other than the characteristics of

Table 21. Summary of the Findings.

Outcome	Hypothesis	Effects	Results
BidNum	H1	Screening (−)	S
Bidder Quality (Averaged)			
BidderExp	H2	Screening (+) and signaling (+)	S
BidderRep	H2	Screening (+) and signaling (+)	S
Bid Quality (Averaged)			
BidDuration	H3	Signaling (−) and slack (+)	S (Signaling)
BidProposal	H3	Signaling (+) and slack (−)	S (Slack)
Moderating Effects			
TaskComplex: GuarAnyReq→BidNum	H4	Weakens the negative screening effect (+)	S
TaskComplex: GuarAnyReq→BidExp	H6	Weakens the positive screening effect (−)	S
TaskComplex: GuarAnyReq→BidRep	H6	Weakens the positive screening effect (−)	S
TaskComplex: GuarAnyReq→BidDuration	H8	Weakens the positive slack effect (−)	Did not test
TaskComplex: GuarAnyReq→BidProposal	H8	Weakens the negative slack effect (+)	S
TaskDesc: GuarAnyReq→BidNum	H5	Strengthens the negative screening effect (−)	NS
TaskDesc: GuarAnyReq→BidderExp	H7	Strengthens the positive screening effect (+)	NS
TaskDesc: GuarAnyReq→BidderRep	H7	Strengthens the positive screening effect (+)	NS
TaskDesc: GuarAnyReq→BidDuration	H9	Strengthens the positive slack effect (+)	NS
TaskDesc: GuarAnyReq→BidProposal	H9	Strengthens the negative slack effect (−)	NS

Notes: S = supported; NS = not supported.

the choice pool would be an interesting endeavor for future work. Furthermore, although we articulated the 3S effects (i.e., screening, signaling, and slack effects) separately in the third section, the real-life data tested only a combined effect. Studies using firsthand survey or interview data may be conducted to further explore the 3S effects separately.

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References

1. ~~Agrawal, A.; Horton, J.; Lacetera, N.; and Lyons, E. Digitization and the contract labor market: A research agenda. In A. Goldfarb, S.M. Greenstein, and C.E. Tucker (eds.), *Economic Analysis of the digital economy*. Chicago: University of Chicago Press, 2015, pp. 219–250.~~
2. ~~Allon, G.; Bassamboo, A.; and Çil, E.B. Large-scale service marketplaces: The role of the moderating firm. *Management Science*, *58*, 10 (2012), 1854–1872.~~
3. Amblee, N., and Bui, T. Harnessing the influence of social proof in online shopping: The effect of electronic word of mouth on sales of digital microproducts. *International Journal of Electronic Commerce*, *16*, 2 (2011), 91–114.

Amblee2011

4. ~~Antle, R., and Eppen, G.D. Capital rationing and organizational slack in capital budgeting. *Management Science*, *31*, 2 (1985), 163–174.~~
5. ~~Asker, J., and Cantillon, E. Properties of scoring auctions. *RAND Journal of Economics*, *39*, 1 (2008), 69–85.~~
6. Ba, S., and Pavlou, P.A. Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior. *MIS Quarterly*, *26*, 3 (2002), 243–268.

Ba2002

7. ~~Bajari, P.; McMillan, R.; and Tadelis, S. Auctions versus negotiations in procurement: An empirical analysis. *Journal of Law, Economics, and Organization*, *25*, 2 (2009), 372–399.~~

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

9. ~~Beerepoot, N., and Lambregts, B. Competition in online job marketplaces: Towards a global labour market for outsourcing services? *Global Networks, 15*, 2 (2015), 236–255.~~

Bockstedt2012 10. Bockstedt, J., and Goh, K.H. Seller strategies for differentiation in highly competitive online auction markets. *Journal of Management Information Systems*, *28*, 3 (2011), 235–268.

11. ~~Brabham, D.C. Moving the crowd at iStockphoto : The composition of the crowd and motivations for participation in a crowdsourcing application. *First Monday, 13*, 6 (2008). https://firstmonday.org/ojs/index.php/fm/article/view/2159.~~

12. ~~Caraway, B. Online labour markets: An inquiry into oDesk providers. *Work Organisation, Labour & Globalisation, 4*, 2 (2010), 111–125.~~

Chen2015f 13. Chen, X.; Huang, Q.; Davison, R.M.; and Hua, Z. What drives trust transfer? The moderating roles of seller-specific and general institutional mechanisms. *International Journal of Electronic Commerce*, *20*, 2 (2015), 261–289.

Chong2018 14. Chong, A.Y.L.; Lacka, E.; Boying, L.; and Chan, H.K. The role of social media in enhancing guanxi and perceived effectiveness of e-commerce institutional mechanisms in online marketplace. *Information and Management*, *55*, 5 (2018), 621–632.

15. ~~Cruz, C.O., and Marques, R.C. Exogenous determinants for renegotiating public infrastructure concessions: Evidence from Portugal. *Journal of Construction Engineering and Management, 139*(2013), 1082–1090.~~

Cui2012a 16. Cui, G.; Lui, H.-K.; and Guo, X. The effect of online consumer reviews on new product sales. *International Journal of Electronic Commerce*, *17*, 1 (2012), 39–58.

17. ~~Cyert, R., and March, J.G. *A Behavioral Theory of the Firm*. Englewood Cliffs, NJ: Prentice Hall, 1963.~~

Sahoo2018 18. Dellarocas, C.; Sahoo, N.; and Srinivasan, S. The impact of online product reviews on product returns. *Information Systems Research*, *29*, 3 (2018), 723–738.

Fang2014 19. Fang, Y.; Qureshi, I.; Sun, H.; McCole, P.; Ramsey, E.; and Lim, K.H. Trust, satisfaction, and online repurchase intention: The moderating role of perceived effectiveness of e-commerce institutional mechanisms. *MIS Quarterly*, *38*, 2 (2014), 407–427.

Gefen2012 20. Gefen, D., and Pavlou, P.A. The boundaries of trust and risk : The quadratic moderating role of institutional structures. *Information Systems Research*, *23*, 3 (2012), 940–959.

21. ~~Gopal, A.; Sivaramakrishnan, K.; Krishnan, M.S.; and Mukhopadhyay, T. Contracts in offshore software development: An empirical analysis. *Management Science, 49*, 12 (2003), 1671–1683.~~

22. ~~Hart, O., and Moore, J. Foundations of incomplete contracts. *The Review of Economic Studies, 66*, 1 (1999), 115–138.~~

23. ~~Hart, O.; Moore, J.; Hart, B.Y.O.; and Moore, J. Incomplete contracts and renegotiation. *Econometrica, 56*, 4 (1988), 755–785.~~

24. ~~Haruvy, E.; Popkowski Leszczyc, P.T.L.; Carare, O.; Cox, J.C.; Greenleaf, E.A.; Jank, W.; Jap, S.; Park, Y.; and Rothkopf, M.H. Competition between auctions. *Marketing Letters, 19*, 3 (2008), 431–448.~~

25. ~~Hong, Y.; and Pavlou, P.A. *Online Labor Markets: An Informal "Freelancer Economy."* IBIT Report, February 2013. Available at SSRN: https://ssrn.com/abstract=2132869 or http://dx.doi.org/10.2139/ssrn.2132869.~~

Hong2017a 26. Hong, Y., and Pavlou, P.A. On buyer selection of service providers in online outsourcing platforms for IT services. *Information Systems Research*, *28*, 3 (2017), 547–562.

Hong2016a 27. Hong, Y.; Wang, C.; and Pavlou, P.A. Comparing open and sealed bid auctions: Evidence from online labor markets. *Information Systems Research*, *27*, 1 (2015), 49–69.

28. H~~orton, J.J., and Johari, R. Buyer Signaling Improves Matching: Evidence from a Field Experiment, October 2018. Available at SSRN: https://ssrn.com/abstract=3245704 or http://dx.doi.org/10.2139/ssrn.3245704.~~

29. ~~Howe, J. The rise of crowdsourcing. *Wired Magazine, 14*, 6 (2006), 1–5.~~

Jung2005 30. Jung, W.; Olfman, L.; Ryan, T.; and Park, Y. An experimental study of the effects of representational data quality on decision performance. *AMCIS 2005 Proceedings* (2005), 149–154.

31. ~~Karimov, F.P., and Brengman, M. An examination of trust assurances adopted by top internet retailers: unveiling some critical determinants. *Electronic Commerce Research, 14*, 4 (2014), 459–496.~~
32. ~~Kendall, C.L., and Russ, F. A. Warranty and complaint policies: An opportunity for marketing management. *Journal of Marketing, 39*, 2 (1975), 36–43.~~
33. ~~Kim, H.; Kim, H.; and Lee, P.M. Ownership structure and the relationship between financial slack and R&D investments: Evidence from Korean firms. *Organization Science, 19*, 3 (2008), 404–418.~~

Kim2009d 34. Kim, J.Y. Online reverse auctions for outsourcing small software projects: Determinants of vendor selection. *e-Service Journal*, *6*, 3 (2009), 40–55.

35. ~~Kokkodis, M.; Papadimitriou, P.; and Ipeirotis, P.G. Hiring behavior models for online labor markets. In *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining*. New York: ACM, 2015, pp. 223–232.~~

36. Koufaris, M., and Hampton-Sosa, W. The development of initial trust in an online company by new customers. *Information and Management*, *41*, 3 (2004), 377–397.
Koufaris2004

37. ~~Lakhani, K.R.; Lohse, P.; Panetta, J.; and Jeppesen, L.B. The value of openness in scientific problem solving. Working Paper no. 07-050 (2007).~~
38. ~~Lee, S., and Niederle, M. Propose with a rose? Signaling in internet dating markets. *Experimental Economics, 18*, 4 (2014), 731–755.~~
39. ~~Li, S.; Srinivasan, K.; and Sun, B. Internet auction features as quality signals. *Journal of Marketing, 73*, 1 (2009), 75–92.~~
40. ~~Lin, M.; Liu, Y.; and Viswanathan, S. Effectiveness of reputation in contracting for customized production: evidence from online labor markets. *Management Science, 64*, 1 (2016), 345–359.~~
41. ~~Lu, B.; Fan, W.; and Zhou, M. Social presence, trust, and social commerce purchase intention: An empirical research. *Computers in Human Behavior, 56*(2016), 225–237.~~

42. Lu, B.; Zeng, Q.; and Fan, W. Examining macro-sources of institution-based trust in social
Lu2016b commerce marketplaces: An empirical study. *Electronic Commerce Research and Applications*, *20*(2016), 116–131.

43. Lu, X.; Ba, S.; Huang, L.; and Feng, Y. Promotional marketing or word-of-mouth? Evidence
Lu2013 from online restaurant reviews. *Information Systems Research*, *24*, 3 (2013), 596–612.

44. ~~McCune, B., and Grace, J.B. *Analysis of Ecological Communities*. Gleneden Beach, OR: MjM Software Design, 2002.~~

McKnight2002a 45. McKnight, D.H.; Choudury, V.; and Kacmar, C. Developing and validating trust measure for e-commerce: An integrative typology. *Information Systems Research*, *13*, 3 (2002), 334–359.

46. ~~McKnight, D.H.; Cummings, L.L.; and Chervany, N.L. Initial trust formation in new organizational relationships. *Academy of Management Review, 23*, 3 (1998), 473–490.~~

Moreno2014 47. Moreno, A., and Terwiesch, C. Doing business with strangers : Reputation in online service marketplaces. *Information Systems Research*, *25*, 4 (2014), 865–886.

48. ~~Onsi, M. Factor analysis of behavioral variables affecting budgetary slack. *Accounting Review, 48*, 3 (1973), 535–548.~~

49. Ou, C.X.J., and Chan, K.C.C. Developing a competitive edge in electronic markets via
Ou2014a institutional and social based quality signaling mechanisms. *Information and Management*, *51*, 5 (2014), 532–540.

50. Pavlou, P.A. Consumer acceptance of electronic commerce : Integrating trust and risk with the
Pavlou2003 technology acceptance model. *International Journal of Electronic Commerce*, *7*, 3 (2003), 101–134.

Pavlou2006 51. Pavlou, P.A., and Dimoka, A. The nature and role of feedback text comments in online marketplaces: Implications for trust building, price premiums and seller differentiation. *Information Systems Research*, *17*, 4 (2006), 392–414.

52. Pavlou, P.A., and Gefen, D. Building effective online marketplaces with institution-based
Pavlou2004 trust. *Information Systems Research*, *15*, 1 (2004), 37–59.

53. ~~Priest, G.L. A theory of the consumer product warranty. *The Yale Law Journal, 90*, 6 (1981), 1297–1352.~~
54. ~~Purohit, D., and Srivastava, J. Effect of manufacturer reputation, retailer reputation, and product warranty on consumer judgments of product quality: A cue diagnosticity framework. *Journal of Consumer Psychology, 10*, 3 (2001), 123–134.~~

Scholz2011

55. Scholz, M., and Haas, N. Determinants of reverse auction results: An empirical examination of Freelancer.com. In *19th European Conference on Information Systems, ECIS 2011 Proceedings*, Helsinki, Finland, June 9–11, 2011.
56. ~~Sharfman, M.P.; Wolf, G.; Chase, R.B.; and Tansik, D.A. Antecedents of organizational slack. *The Academy of Management Review*, *13*, 4 (1988), 601–614.~~
57. ~~Simon, H.A. The Science of Artificial. Cambridge, MA, USA: MIT Press, 1969.~~
58. ~~Snir, E.M.; and Hitt, L.M. Costly bidding in online markets for IT services. *Management Science*, *49*, 11 (2003), 1504–1520.~~
59. ~~Spence, M. Job market signaling. *The Quarterly Journal of Economics*, *87*, 3 (1973), 355–374.~~

Sun2010

60. Sun, H. Sellers' trust and continued use of online marketplaces. *Journal of the Association for Information Systems*, *11*, 4 (2010), 182–211.
61. ~~Tan, J., and Peng, M.W. Organizational slack and firm performance during economic transitions: two studies from an emerging economy. *Strategic Management Journal*, *24*, 13 (2003), 1249–1263.~~

Yang2009

62. Yang, Y.; Chen, P.-Y.; and Pavlou, P.A. Open innovation: An empirical study of online contests. In *ICIS 2009 Proceedings*. 2009, pp. 1–16. Phoenix, Arizona, USA; AIS Electronic Library (AISeL).
63. ~~Yang, Y.; Chen, P.; and Pavlou, P. Open innovation: Strategic design of online contests. *Workshop of Information Systems and Economics* (2009), 1–9.~~
64. ~~Yoganarasimhan, H. The value of reputation in an online freelance marketplace. *Marketing Science*, *32*, 6 (2013), 860–891.~~
65. ~~Zheng, A.Z.; Hong, Y.; and Pavlou, P.A. *Matching in Two Sided Platforms for IT Services : Evidence from Online Labor Markets*. 2016. Available at SSRN: https://ssrn.com/abstract=2838720 or http://dx.doi.org/10.2139/ssrn.2838720.~~

Zheng2011a

66. Zheng, H.; Li, D.; and Hou, W. Task design, motivation, and participation in crowdsourcing contests. *International Journal of Electronic Commerce*, *15*, 4 (2011), 57–88.

About the Authors

Zhijuan Hong (hongye0401@163.com, corresponding author) is an assistant professor in the School of Management Science and Engineering at the Shandong University of Finance and Economics, China. She received her Ph.D. from Fudan University, China. Her research interests include electronic commerce, online labor markets and online volunteering.

Hui Zhu (hzhu365@hotmail.com) is an assistant professor in the School of Information Technology at Jiangxi University of Finance and Economics, China. He received his Ph.D. in School of Economics and Management from Southeast University, China. He specializes in the data-driven optimization techniques with applications in decision and supply chain management. His research interests include business analytics, production and operations management, scheduling and data mining. His work has been published in *Computers & Industrial Engineering* and *International Journal of Production Research.*

Kunxiang Dong (dkxgood@163.com) is an assistant professor in the School of Management Science and Engineering at the Shandong University of Finance and Economics, China. He received his Ph. D. from Nankai University, China. His research interests include information security and electronic commerce.