Open or Sealed Bids in Buyer-Determined Auctions? Evidence from Online Labor Markets

Kevin Yili Hong[1], Alex Chong Wang[2], Paul A. Pavlou[1]

[1] Temple University
[2] City University of Hong Kong

Abstract

Online labor markets recently emerged as a novel avenue for companies to identify and hire IT labor. These markets provide platforms facilitating Buyer-Determined (BD) auctions. In this paper, we study the effect of two BD auction designs–open bids and sealed bids–on bidder behavior and market performance. We first theoretically analyze equilibrium bidder entry and surplus, and derive our hypotheses on the comparison of the two auction designs in terms of entry barrier and market performance. Using a proprietary dataset based on 1,816,886 bids from 106,147 open bids and 9,950 sealed bids auctions posted on *Freelancer.com* by 41,530 unique buyers, we found open bids to consistently outperform sealed bids BD auctions in terms of buyer surplus, contract rate, and buyer satisfaction. We attribute performance differences to the "screening effect" that filters out low quality bidders in open bids auctions. We discuss implications for auction design and online labor markets.

Key Words: Auction format, Online Labor Markets, Auction Performance, Bidder Behavior

***Note**:* Kevin Yili Hong is a 4th year Ph.D. student at MIS Department of Temple University, who has done the bulk of the work of this study.

Introduction

Ubiquitous access to the Internet and supporting technologies gave birth to online labor markets (Malone and Laubacher 1998). Firms now are able to greatly expand their workforce and bring a large arsenal of labor to bear on jobs such as software development and graphical design, etc., using Internet-enabled labor procurement platforms such as *Freelancer, eLance, or TopCoder*. Generally, these labor markets are information systems that enable job posting using a reverse, scoring, buyer-determined (BD) auctions[1] (Asker and Cantillon 2008, Hong and Pavlou 2013b). Various auction designs are used in these markets. For example, buyers[2] can post a request for a project and call for bids (CFB) in either an *open bids format* (bids and bidder information are public) or a *sealed bids format* (bids and bidder information can only be observed by the buyer). In current practices, some online labor markets choose to fix the auction format while others allow users to choose, for example, between open and sealed bids BD auctions. Open bids auctions offer more information to potential bidders. However, sealed bids auctions could be perceived as more protective to both buyers and bidders. Although more bids are likely to offer more choices for the buyer and potentially offer a higher buyer surplus, the positive effect of sealed bids may be jeopardized by costly bid evaluation that hinders the buyer from fully examining all bids (Carr 2003). Furthermore, whether bidders enter different formats of auctions in the same fashion remains an unanswered question. Therefore, it is not clear which auction format (open bids versus sealed bids) performs better in practice.

There is a mature body of theoretical discussions in the auction literature about the relationship between choice of auction mechanism and market efficiency (Krishna 2009). However, much less is known empirically about the strategic behavior of bidders (such as entry behavior) across different bidding formats (sealed bids versus open bids) as well as the relative advantages of each format (Athey et al. 2011) in terms of auction performance such as buyer surplus, contract performance and buyer satisfaction.

---

[1] A reverse auction is a type of auction in which the roles of buyer and seller (as in a forward auction) are reversed. The sellers compete to offer labor to the buyer. Scoring auction is a type of buyer-determined auction, in which buyers assign values over price and non-price attributes of the bidder, and pick one that maximizes the overall value.

[2] In this paper, the term “buyer” refers to the demand side of the labor market, and is used interchangeably with “auctioneer”, “employer”; the term “bidder” refers to the supply side of the labor market, and is used interchangeably with “provider”.

Besides providing an opportunity to investigate the effects of auction design, online labor markets are economically interesting and important in their own right. Online labor markets are vaunted for significant trading volume and societal benefits. As a renowned example, the research site of our study, *Freelancer.com* has over 7 million registered IT professionals who have completed over 4 million projects worth over $1 billion (see Appendix 1 for detailed descriptions of *Freelancer.com*).

In this paper, we are interested in the strategic and performance differences between auction formats in the context of BD auctions in online labor markets, and we seek to answer the following question:

"*What is the role of auction design (sealed bids vs. open bids) on bidder behavior (bidder entry and bidder quality) and auction performance (buyer surplus, contract decision and buyer satisfaction)?*"

To this end, we provide new empirical evidence with micro level proprietary data that allows us to observe bidding histories in both open and sealed bids BD auctions. Sealed bids are not publically observable, accessing to a proprietary database of a leading online labor market offers the unique opportunity. Our empirical context offers unique research opportunities because it allows us to identify not only bidding strategy but also market performance and buyer surplus, which are both theoretically and practically significant. Both our theoretical analysis and empirical observations provide support that open bids format auctions outperform sealed bids format auctions, albeit the sealed bids format does attract more bids. Empirically, our results show that, compared with sealed bid BD auctions, open bid auctions attract 8.1% fewer bids, also, they result in 3.59% fewer bids from inexperienced suppliers, 50% more likely to get contracted, and in at least 19% more in buyer's surplus.

In what follows, we first describe our research context and survey related literature. Then we introduce our theoretical model, and derive our hypotheses for empirical testing. Theoretical analysis is followed by a description of the empirical data set, estimation models and results. We discuss the implications of our research for theory and practice.

Literature Review

Online Markets for Labor

Prior research in information systems about online markets links some aspects of auctions to market efficiency, such as project size (Snir and Hitt 2003), bid evaluation cost (Carr 2003), and effective communications (Allon et al. 2012). Snir and Hitt (2003) found that due to non-negligible bidding cost for providers, low quality providers are more likely to bid for high value jobs. Recent research discusses the winner determination and information structure in online labor markets. Several extant studies have focused on bidder reputation. For example, using a dynamic structural framework, Yoganarasimhan (2012) estimated the returns to provider reputations in online labor markets. They found that buyers on such sites place significant weight on provider reputation information (quality signal). In a recent study, Stoll and Zöttl (2012) showed that bidders are aware of their rival bidders' profiles and they take non-price information into consideration; and provision of additional information increases platform turnovers and buyer's welfare. While these studies focus on a single type of auction mechanism and thus offer no insights on the impact of auction design on market competition and efficiency, we seek to extend our understanding about the effect of auction design (open bids versus sealed bids) in these marketplaces.

Auction Design in Online Markets for Labor

Auction design is an important topic that multiple disciplines have made contributions on. For example, IS scholars have a keen interest in online auctions' mechanism design (Bapna et al. 2010), price discovery (Bapna et al. 2008b; Bapna et al. 2009; Goes et al. 2010) and consumer surplus (Bapna et al. 2008a; Mithas and Jones 2008). Besides, there have been extensive discussions on auction design in the economics literature. Seminal works by Vijay Krishna (2009), Paul Milgrom (2004), and Paul Klemperer (2004) offers comprehensive and systematic summary of previous theoretical discussions.

An important characteristic that makes online procurement auctions fundamentally different from most consumer auctions is that price is typically *not* the sole criterion used to award contracts (Haruvy and Katok 2012). In these auctions, also known as BD auctions, the buyer takes into consideration non-price attributes according to an explicit or implicit scoring rule, and awards the contract to the provider whose bid provides the highest value (Jap 2002; Rangan 1998; Asker and Cantillon 2008). It is typically assumed that at the time before contract is awarded, the buyer will articulate non-price attribute trade-offs clearly enough to be able to compare the final bid delivers the highest surplus and providers know this allocation rule (Engelbrecht-Wiggans et al. 2007; Kostamis et al. 2009). In this stream of research, Engelbrecht-Wiggans et al. (2007) compared BD and price-determined auctions and found that for a small number of bidders, price-based auctions might provide greater buyer surplus but that BD auctions provided greater buyer surplus for a sufficiently large number of bidders. However, the use of BD award rules can be detrimental to the buyer-provider relationship (Jap 2003; Jap and Haruvy 2007). Jap (2007) found that full price visibility English (reverse) auctions raise providers' beliefs that the buyer is using such auctions to opportunistically gain price concessions. Using data from over 14,000 auctions, Millet et al. (2004) found that revealing the lowest bid and bid rank to providers can yield greater price savings than less visible formats. Jap (2007) showed that partial price visible formats are better at preserving the buyer–provider relationship (e.g., minimizing opportunism suspicions, protecting overall satisfaction, and future expectations) than full price visibility formats. Extending their work, our study is based on a huge real-life data set (more than 1 million bid-level observations) collected from an online market, offering new evidence on the comparison between open bid auctions and sealed bid auctions in online markets.

Theoretical Analysis

Model Set-up

To understand the differences between open bid and sealed bid auctions in online labor markets, we first analyze the following theoretical model. In the model, we focus on a single BD auction. Our target is to understand the difference between sealed bid BD auction (SBD) and open bid BD auction (OBD) in terms of (1) provider's entry and bidding strategy, (2) buyer's expected surplus.

Consider a setting where N risk-neutral providers compete to provide services to a buyer by participating in an online BD auction. The contract is indivisible. Providers are heterogeneous in quality (in terms of non-price attribute) and provider i has private knowledge about his quality q_i, which is drawn from a common distribution $F(q)$. The value that the buyer derive from a provider of quality q_i is denoted by $V(q_i, b_i) = v \times q_i - b_i$, where b_i is the bid submitted and v is value derived per unit of quality.

To serve the contract, provider i incurs a cost of c_i. We assume that the cost of serving the contract is linear in quality, i.e., $c_i = c \times q_i$. In other words, it is more costly for providers of higher quality to serve the contract. We further assume that $v > c$, that is, the project is value adding. Similar set up has been used in Snir and Hitt (2003) in a SBD setting.

During the auction, each provider submits a bid at a bidding cost of c_T. A total of n bidders entered the auction. The providers are allowed to revise their bids at no additional cost. A bid also reveals the quality of the provider to the buyer; and in OBD auctions, it also reveals the quality of the provider to its competitors. The contract is rewarded to the bid that generates the highest expected buyer's surplus, $V(q_i, b_i)$. The rewarded provider will be paid according to its bid (b_i).

Equilibrium Bidding Strategy

In the OBD auction, since both the buyer and the provider i know q_i, we can think of provider as bidding in the score space of $(vq_i - b_i)$ where $b_i \geq cq_i$. The dominant strategy for each provider, conditional on bidding, is to bid up to the maximum value offer $v_i = (v - c)q_i$. As a result, $b^O(q_i; n) = cq_i$ and provider with the highest offer of surplus wins the auction (open bid auction is efficient). With bidding cost, only providers with non-negative expected profit will bid. Provider i's expected profit conditional on bidding and quality q_i is:

$$\pi_i^{O*}(q_i; n) = \int_{q_m^O}^{q_i} (v - c)(q_i - q) d[F(q)]^{n-1} + (vq_m^O - cq_m^O)[F(q_m^O)]^{n-1} - c_T \quad (1)$$

In the auction game described above, only bidders with quality q_m^O that satisfies $(vq_m^O - cq_m^O)[F(q_m^O)]^{n-1} \geq c_T$ will submit bids.

In the SBD auction, provider i is only informed of his own cost and quality. The expected profit is:

$$\pi_i^S(q_i;n) = \max_{b \geq cq_i}\{b - cq_i\} \prod_{j \in n \setminus i} G_j(b;n) \tag{2}$$

where $G_j(b;n) = F_j\left(b_j^{-1}(b;n)\right)$ denotes the probability that provider j will bid a surplus that is less than b. The following bidding function represents the equilibrium in sealed bid auctions (Snir and Hitt 2003).

$$b^S(q_i;n) = \begin{cases} No\ Bid & if\ q < q_m^S \\ vq_m^S & if\ q = q_m^S \\ cq + \dfrac{1}{[F(q)]^{n-1}}\left\{(v-c)\displaystyle\int_{q_m^S}^{q}[F(z)]^{n-1}dz + c_T\right\} & if\ q > q_m^S \end{cases} \tag{3}$$

In this game, there exists a symmetric, pure strategy, Nash, subgame perfect equilibrium provider bidding strategy in which only provider with quality above threshold q_m^S satisfying $(vq_m^S - cq_m^S)[F(q_m^S)]^{n-1} = c_T$ will enter the auction. And provider i's expected profit, given that $q_i \geq q_m^S$ is:

$$\pi_i^{S*}(q_i;n) = (v-c)\int_{q_m^S}^{q}[F(z)]^{n-1}dz \tag{4}$$

Equilibrium bidding strategy $b^S(q_i;n)$ is no less than cq_i. Compared with the open bids auction case, providers are more prone to hide their true cost in sealed bids auctions.

Entry

Despite the difference in bidding format, theoretically the entry thresholds for OBD auctions and SBD auctions are the same (quality above threshold q_m, which satisfies $(vq_m - cq_m)[F(q_m)]^{n-1} = c_T$). Therefore both formats will attract the same pool of potential providers. However, since bids are submitted sequentially rather than simultaneously, in open bids auctions, once provider of quality q has placed a bid, all the other bidders with quality level lower than q are less likely to bid on the same job. Further, bidders with low quality level are likely to wait longer before submitting the bids. We label this effect "screening effect" of OBD auctions. This screening effect of prior bids, which does not exist in SBD auctions as prior bids are not publically observable, results in fewer bids being submitted in OBD auctions than SBD auctions. Therefore, we propose:

Hypothesis 1: OBD auctions will receive fewer bids than SBD auctions, ceteris paribus.

Bidder Quality

The "screening effect" of open bids auctions will create higher entry barrier for low quality bidders because they do not want to incur the bidding cost to compete with prior bidders who have a higher chance of winning. Therefore, although OBD auctions might attract fewer bids, the bids are more likely to be submitted by higher quality bidders. Therefore, we propose:

Hypothesis 2: OBD auctions will receive bids from providers with higher quality than SBD auctions, ceteris paribus.

By empirically testing hypotheses 1 and 2, we will be able to infer the existence of screening effect.

Buyer Surplus

Based on the equilibrium bidding strategy, we can calculate and compare the expected buyer's surplus in OBD auctions and SBD auctions. Expected Buyer Surplus ($q_{(k)}$ is the kth order statistics) is calculated as follows (see Appendix 2 for derivations).

OBD:
$$E[V^{OBD}] = E\left[(v-c)q_{(n-1)} \middle| q_{(n-1)} \geq q_m^O\right] \tag{5}$$

SBD:
$$\begin{aligned} E[V^{SBD}] &= E\left[vq_{(n)} - bq_{(n)} \middle| q_{(n)} \geq q_m^S\right] \\ &= E\left[(v-c)q_{(n-1)} \middle| q_{(n)} \geq q_m^S\right) - \frac{nc_T}{1-[F(q_m^S)]^n}\int_{q_m^S}^{\infty} f(q)dq \end{aligned} \tag{6}$$

It is easy to show that the expected buyer surplus in OBD auctions is higher than that from the SBD auctions given at least two bids are observed. The reason is that entry cost c_T only affects the entry decision in OBD format. Once a provider decides to bid, their bidding function is not affected by the bidding cost c_T any more. However, in SBD auctions, every provider takes a potential loss in bidding cost c_T into their bidding functions, as shown in Equation (3), which increases all bids received. In other words, in SBD auctions, the buyer pays for the incurred bidding cost c_T of the providers. We propose:

Hypothesis 3: OBD auctions result in higher buyer's surplus than SBD auctions, ceteris paribus.

Contract Performance

There are several reasons contract performance (contract rate and buyer satisfaction) may vary with different auction formats. First, Carr (2003) showed bid evaluation cost may drive quality-sensitive buyers to decide not to evaluate bids, and abstain from choosing a provider to contract with. Given that bid evaluation is costly, the screening effect of OBD is a desirable feature that could reduce the complexity of the bid selection process and may result in better auction performance. Second, as proposed earlier, OBD auctions receive fewer bids, but those bids tend to be submitted by higher quality bidders; therefore, it may be more comfortable for buyers to select a bidder to contract with, and also achieve higher satisfaction with OBD auctions. Therefore, we propose:

Hypothesis 4: OBD auctions result in higher contract rate than SBD auctions, ceteris paribus.

Hypothesis 5: OBD auctions result in higher buyer satisfaction than SBD auctions, ceteris paribus.

Empirical Methodology

In this section we try to test our theoretical hypotheses empirically. Our empirical analyses closely follow the theoretical discussions. We mainly compare two aspects of the labor market dynamics with regard to auction format (SBD vs. OBD): entry and competition, and auction performance.

Data Set

Our dataset is retrieved from a proprietary database from a leading online labor marketplace *Freelancer.com*. The dataset spans the period between August 2009 and February 2010, and is based on 1,816,886 bids from 106,147 OBD and 9,950 SBD auctions posted on the marketplace, initiated by 41,530 unique buyers. Table 1 and 2 provides the definition, correlation matrix and descriptive statistics for our main variables based on project level data. Project types are mainly software development, graphical design, content writing and data entry. In what follows we show our empirical models, estimation and identification strategies and results.

[Insert Tables 1&2 Here]

Empirical Models and Estimations

Entry and Competition

<u>*Number of Bids Received*</u>

We first estimate the effect of auction format on aggregate bidder entry behavior measured by number of bids. We first use ordinary least squares (OLS) and buyer fixed effect OLS (FE OLS) to estimate the effect of auction format on total number of bids, in order to understand the effect of auction format on the number of bids received controlling for auction and buyer characteristics. Since number of bids can be seen as a count variable with a distribution of long tail and high dispersion, we employ fixed effect negative binomial (FE NB) model (Hausman et al. 1984) as a robustness check.

The following equation outlines our empirical model for estimation. This model includes the main variable auction format ("sealed"); buyer fixed effects, δ; project category effects, λ; time effects, ψ; time-variant buyer control variables, such as average buyer rating, buyer experience and gold member buyer; and auction/project level control variables, such as project budget, auction duration, featured project and non public projects. In Equation (7), i is used to index projects, j is used to index project categories, q is used to index buyers and t is used to index the time periods (year-month pairs).

$$\begin{aligned}\textbf{num\_bids}_{\boldsymbol{ijqt}} = \alpha + \beta_1 \times Sealed_{ijqt} + \beta_{2-8} \times (AuctionControls_i) + \beta_{9-10} \\ \times \left(BuyerControls_{jq}\right) + \psi_t + \delta_q + \lambda_j + \varepsilon_{ijqt}\end{aligned} \tag{7}$$

As the results in Table 3 attest, on average, SBD auctions attract 1.23 more bids (p<0.001) than OBD auctions, translating to an 8.1% difference. The effect is consistent across different estimators. Our results support Hypothesis 1 and confirm the existence of "screening effect" of open bids auction format.

[Insert Table 3 Here]

Bidder Quality

In order to capture a complete picture of bidder entry, we estimated the entry barrier by looking at the average bidder quality for an SBD or OBD auction. A higher average quality would suggest a higher entry barrier. We calculated two measures for bidder quality. Since there are two types of bidders on the labor market: bidders with no project experience (therefore no ratings), and bidders with project experience (who have ratings), we measure them separately. First, we calculate the average quality of bidders with ratings. Second, we calculated the ratio of inexperienced bidders (bidders with no project experience). Similarly, this model controls for auction/project level control variables, buyer fixed effects, δ_q, project category effects, λ_j, time effects, ψ_t, and time-variant buyer effects:

$$\begin{aligned}&\mathbf{avg\_bidder\_quality}_{ijqt}|\mathbf{new\_bidder\_ratio}_{ijqt}\\&\quad= \alpha + \beta_1 \times Sealed_{ijqt} + \beta_{2-8} \times (AuctionControls) + \beta_{9-10}\\&\quad\times \left(BuyerControls_{jq}\right) + \psi_t + \delta_q + \lambda_j + \varepsilon_{ijqt}\end{aligned} \tag{8}$$

As the results in Table 4 attest, on average, SBD auctions attract higher quality bidders. Based on the OLS estimation with buyer fixed effects, bidders with ratings in SBD auctions have lower ratings than bidders in OBD auctions ($\beta = -0.117, p < 0.001$). We also found evidence with a fractional response model (estimated with GLM) that SBD auctions have more inexperienced bidders, i.e., bidders with no project experience on the labor market ($\beta = 0.0359, p < 0.001$). Therefore, Hypothesis 2 is supported. Combining the evidence for bidder quality and number of bids received, we find that SBD auctions are likely to receive more bids, albeit those bids tend to be submitted by low quality or inexperienced bidders.

[Insert Table 4 Here]

Auction Performance

We proceed to estimate the effect of auction format on auction performance using three different measures: buyer surplus, contract decision, and buyer satisfaction. These measures have been used in the literature and are economically meaningful for the buyers and the marketplace.

<u>Buyer Surplus</u>

Buyer surplus is defined as the difference between buyer's willingness to pay (WTP) and the actual price paid. Since the contract price is given (selected bid), our task is to estimate buyers' WTP. We have two measures for WTP. Construction of the first measure follows Bapna et al. (2003) and Mithas et al. (2008), and construction of the second measure follows Ghose et al. (2012) with a discrete choice framework.

For the first measure, we use proxies for WTP. On the labor marketplace, when buyers post jobs, they specify their maximum and minimum budget. Although budget information may not exactly be the true WTP, it can be quite accurate as buyers are incentivized to correctly specifying the amount they are willing to pay as the budget, since providers treat the budget as buyers' WTP and take that information into account when placing a bid (Hong and Pavlou 2012). Therefore, we use maximum budget and mean budget as proxies for WTP, respectively. Therefore, buyer surplus can be calculated as $budget^{max/avg}$ −

$SelectedBid$. Buyers reap an average surplus of \$202.15 (st.d.=174.85) using maximum budget as proxy for WTP, and \$61.22 (STD=149.3) using average budget as WTP, respectively. Since the surplus measure is highly skewed, we log-transform this variable.

For the second measure, we estimate the marginal utility of income by looking at the coefficient estimate of bid price in the discrete choice analysis. The procedure is provided in Appendix 3. We then estimate the effect of auction format on buyer surplus using a similar specification as our analyses for other outcome variables. Fixed effects OLS is used for parameter estimations.

$$\boldsymbol{CS_{ijqt}} = \alpha + \beta_1 \times Sealed_{ijqt} + \beta_{2-8} \times (AuctionControls) + \beta_{9-10} \times \left(BuyerControls_{jq}\right) + \psi_t + \delta_q + \lambda_j + \varepsilon_{ijqt} \tag{9}$$

As Table 4 attest, on average, buyers of OBD auctions enjoy at least 19.2% higher surplus (based on maximum budget as the proxy for buyer WTP) than buyers in SBD auctions. Using average budget as the proxy for WTP, OBD auctions offer an average of 41.2% more buyer surplus than SBD auctions; and using the estimated surplus from discrete choice conditional Logit analysis, OBD auctions offer an average of 23% more surplus to buyers than SBD auctions. Therefore, Hypothesis 3 is supported.

[Insert Table 6 Here]

<u>*Contract Decision and Buyer Satisfaction*</u>

To understand the effect of auction format on auction performance, in addition to buyer surplus, there are two important measures of the success of an auction that need to be considered: (a) whether the auction results in a contract between the buyer and the provider; and (b) the buyer's satisfaction about the service provided by the contracted provider. First, an auction will become a waste of time and resources for all stakeholders (buyer, bidder, and the marketplace) if it cannot result in a contract either because the buyer cannot find a suitable supplier or the selected provider did not provide the service. After an auction results in a contract, buyer's satisfaction with the service provided are critical as they measure the actual quality received and has a significant impact on subsequent buyer behavior (for example, repeated transactions and willingness to pay for additional IT services provided in the market). Therefore, we formulate the following empirical models to understand the effect of auction design format (OBD versus SBD) on contract decision and buyer satisfaction.

$$\begin{aligned}\mathbf{logit}\left(\boldsymbol{contract}_{\boldsymbol{ijqt}} = \mathbf{1}\right) \mid \mathbf{Satisfaction}_{\boldsymbol{ijqt}} \\ = \alpha + \beta_1 \times Sealed_{ijqt} + \beta_{2-8} \times (AuctionControls) + \beta_{9-10} \\ \times \left(BuyerControls_{jq}\right) + \psi_t + \delta_q + \lambda_j + \varepsilon_{ijqt}\end{aligned} \tag{10}$$

We estimated contract decision (binary outcome) using a Logit model with buyer fixed effects. Buyer's satisfaction, measured by an interval rating between 1 to 10, is estimated by an ordered Logit model with fixed effect. In estimating the fixed effect ordered Logit model, we follow the "blow-up and cluster" (BUC ordered logit) method proposed by Baetschmann et al. (2011) to derive a consistent estimator.

Estimation results are shown in Table 7. First, we estimate three Logit models with buyer fixed effects for the selection decision, award status, and completed status. After a buyer selected a bid, he still has the right to revoke the selection and the bidder can refuse to accept the contract; additionally, it takes efforts of both the buyer and the bidder to complete the project. Therefore, award status and completion status serve as additional robustness checks for the contract selection decision estimation. We found consistently significant effect for auction format across the three related outcomes. Using odds ratio to interpret the Logit estimation results, OBD auctions have 50% more odds of having a selected bidder, 47% more odds of getting contracted, and 38% more odds of project completion than SBD auctions. Therefore, Hypothesis 4 is supported. Based on an ordered Logit estimation with fixed effects estimation, we found evidence that SBD auctions are likely to offer less satisfactory results than OBD auctions ($\beta = -0.124$, $p < 0.05$), supporting Hypothesis 5.

[Insert Table 7 Here]

Conclusion and Implications

Key Findings

In this research, we compared open bid (OBD) auctions versus sealed bid (SBD) auctions in the context of online labor markets. Our theoretical analysis suggests that despite that sealed bids auction format is able to attract more bids, open bids auctions are more likely to result in a contract and provide higher buyer’s surplus due to the fact that a sequential open bid auction helps “screen out” ineffective bids and avoid bidding costs to bidders. Our empirical analysis based on a unique proprietary dataset at Freelancer.com confirms these theoretical predictions and finds a significant effect of auction format on bidding behavior and auction performance. Specifically, we quantified the economic effects of auction design format on four auction performance outcomes. Compared with SBD auctions, OBD auctions attract 8.1% fewer bids, they result in 3.59% fewer bids from inexperienced suppliers, they are 50% more likely to get contracted, and they extract at least 19% more in buyer’s surplus.

Implications for Theory

This research contributes to the theoretical literature on (a) auction design and (b) online labor markets by proposing an extended theoretical analysis and exploring unique empirical observations. Specifically, we fill the research gap in the literatures in market mechanism selection and empirical comparison between market mechanisms with respect to participation, bidding, and market performance.

First, our study provides insights to auction design theory. Based on our theoretical analyses and empirical observations, in the context of BD auctions such as ones adopted by most online labor markets, open bids format creates a “screening” mechanism that affect bidders’ equilibrium entry and bidding strategy. Therefore, we observe that in the context of online labor markets, OBD auctions consistently outperform SBD auctions with various different performance measures. Our empirical validation confirms the existence of the screening effect of open-bids format, which renders the assumptions for revenue equivalence theorem invalid in the context of BD auctions, mainly due to the nature of sequential bidding associated with OBD auction format. Our study extends Athey et al. (2011)’s discussion on comparing auction mechanisms in terms of bidder entry strategy in the context of US Timber auctions. We show evidence of “auction format effect” in a different auction context (BD auctions) and empirical context (labor markets) with more observations and more outcome measures. Compared with the research design and results from Haruvy and Katok (2012) who used lab experiments, our study incorporates the notions of bidding sequence and bidding cost, in which the real-world auction context has a significant impact on bidders' behavior. Our large-scale observational data also provided enough power for rigorous econometric identification and estimations.

Second, our study examines auction format as an important theoretical problem for online labor markets. Auction design is an information system design. Due to the emerging nature of online labor markets, there is a dearth of research on the optimal design and performance effects of these markets. Our study links auction mechanism design with provider entry strategy, and provide theoretical support for OBD format auction as a popular auction format among auctioneers. In addition, the performance measures such as bidder quality, new bidder ratio, proxied and estimated buyer surplus can be used in future research that try to understand effect of other auction designs on auction performance.

Implications for Practice

This study has implications for practitioners as well. First, the number of bids has been seen as a measure for auction success as more bids indicate more choices for the auctioneer, potentially increasing buyer surplus. Therefore, it is a common practice for online labor market intermediaries to impose a fee related to posting jobs using SBD format. The insight from our work for practitioners is that more bids may not directly translate into higher performance. Since OBD auctions consistently outperform SBD auctions, charging a fee for SBD format may be misleading to buyers. Based on the welfare difference between the two auction formats, the marketplace should design different pricing systems for different auction formats. Second, for buyers, blindly pursuing more bids by using SBD auctions may not be the best strategy. First, posting SBD auction jobs usually come with a cost (e.g., *Freelancer* currently charges $9 for posting a SBD auction), which can be avoided by using the default OBD format. Second, more bids entail higher evaluation costs. If the buyer cannot afford to evaluate all bids (especially low quality bids), posting jobs with OBD auctions will be a better choice. One caveat needs to be mentioned in terms of buyers' auction format selection. Poorer auction performance notwithstanding, sealed bid auction format still has its attractiveness in some scenarios. For example, potential for collusive bidding (Athey et al. 2011) among providers can be mitigated by sealed bids format. In addition, when providers are concerned about opening their bids to the public, sealed bids format could be used to alleviate provider concerns.

Limitations and Future Research

The current study is not without limitations. First, for analytical tractability, we choose a relatively restricted theoretical model set up. While this allows clear theoretical predictions to be made, it may fail to capture the subtleness of the marketplace. For example, bidder quality may not be fully revealed to the buyer, which generates signal heterogeneity among bids in addition to the inherent quality difference. More general and flexible models may be derived to allow for incomplete information. Second, our discussion is limited to sealed bids BD auctions and open bids BD auctions considering the data we collected. There are other different mechanisms that could be implemented in online marketplaces for services and products. For example, some online labor markets adopt open innovation contests where suppliers not only bid in price but also provide final products to compete. It is interesting to extend the study here to compare between more alternative designs and it might also be interesting for the platforms to experiment with alternative designs to enhance market performance. Third, future research could utilize field experiments approach to identify the effect of auction format on bidder entry behavior.

Concluding Remark

Integrating the literature of auction format and bidder strategy, we theoretically compared the bidding strategy and buyer surplus for sealed and open bids BD auctions. We then leveraged a large unique data set from a proprietary firm database to empirically validate our theoretical predictions. This paper shows the screening effect of open bids BD auctions, which helps enhances their relative market performance over sealed bids BD auctions. Our study invites information systems scholars and practitioners to look at the effect of auction format on the strategic behavior of bidders and market performance in online labor markets toward obtaining a better understanding and designing of online auction mechanisms.

References

Anwar, S., McMillan, R., and Zheng, M. 2006. "Bidding Behavior in Competing Auctions: Evidence from Ebay," *European Economic Review* (50:2), pp 307-322.

Arozamena, L., and Cantillon, E. 2004. "Investment Incentives in Procurement Auctions," *The Review of Economic Studies* (71:1), pp 1-18.

Athey, S., Levin, J., and Seira, E. 2011. "Comparing Open and Sealed Bid Auctions: Evidence from Timber Auctions," *The Quarterly Journal of Economics* (126:1), pp 207-257.

Bajari, P., and Hortacsu, A. 2004. "Economic Insights from Internet Auctions," *Journal of Economic Literature* (42:2), pp 457-486.

Bajari, P., and Ye, L. 2003. "Deciding between Competition and Collusion," *Review of Economics and Statistics* (85:4), pp 971-989.

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

Bapna, R., Chang, S.A., Goes, P., and Gupta, A. 2009. "Overlapping Online Auctions: Empirical Characterization of Bidder Strategies and Auction Prices," *MIS Quarterly* (33:4), pp 763-783.

Bapna, R., Dellarocas, C., and Rice, S. 2010. "Vertically Differentiated Simultaneous Vickrey Auctions: Theory and Experimental Evidence," *Management Science* (56:7), pp 1074-1092.

Bapna, R., Jank, W., and Shmueli, G. 2008. "Price Formation and Its Dynamics in Online Auctions," *Decision Support Systems* (44:3), pp 641-656.

Bapna, R., Jank, W., and Shmueli, G. 2008. "Consumer Surplus in Online Auctions," *Information Systems Research* (19:4), pp 400-416.

Branco, F. 1997. "The Design of Multidimensional Auctions," *The RAND Journal of Economics* (28:1), pp 63-81.

Bulow, J., and Klemperer, P. 2009. "Why Do Sellers (Usually) Prefer Auctions?," *American Economic Review* (99:4), pp 1544-1575.

Campbell, C., Ray, G., and Muhanna, W.A. 2005. "Search and Collusion in Electronic Markets," *Management Science* (51:3), pp 497-507.

Carr, S.M. 2003. "Note on Online Auctions with Costly Bid Evaluation," *Management Science* (49:11), pp 1521-1528.

Che, Y.-K. 1993. "Design Competition through Multidimensional Auctions," *The RAND Journal of Economics* (24:4), pp 668-680.

Chen, F. 2007. "Auctioning Supply Contracts," *Management Science* (53:10), pp 1562-1576.

Chen-Ritzo, C.-H., Harrison, T.P., Kwasnica, A.M., and Thomas, D.J. 2005. "Better, Faster, Cheaper: An Experimental Analysis of a Multiattribute Reverse Auction Mechanism with Restricted Information Feedback," *Management Science* (51:12), pp 1753-1762.

Davis, A.M., Katok, E., and Kwasnica, A.M. 2011. "Do Auctioneers Pick Optimal Reserve Prices?," *Management Science* (57:1), pp 177-192.

Ellison, G., Fudenberg, D., and Möbius, M. 2004. "Competing Auctions," *Journal of the European Economic Association* (2:1), pp 30-66.

Elmaghraby, W. 2007. "Auctions within E-Sourcing Events," *Production and Operations Management* (16:4), pp 409-422.

Engelbrecht-Wiggans, R., Haruvy, E., and Katok, E. 2007. "A Comparison of Buyer-Determined and Price-Based Multiattribute Mechanisms," *Marketing Science* (26:5), pp 629-641.

Engelbrecht-Wiggans, R., and Katok, E. 2006. "E-Sourcing in Procurement: Theory and Behavior in Reverse Auctions with Noncompetitive Contracts," *Management Science* (52:4), pp 581-596.

Engelbrecht-Wiggans, R., and Katok, E. 2008. "Regret and Feedback Information in First-Price Sealed-Bid Auctions," *Management Science* (54:4), pp 808-819.

Goes, P.B., Karuga, G.G., and Tripathi, A.K. 2010. "Understanding Willingness-to-Pay Formation of Repeat Bidders in Sequential Online Auctions," *Information Systems Research* (21:4), pp 907-924.

Graham, D.A., and Marshall, R.C. 1987. "Collusive Bidder Behavior at Single-Object Second-Price and English Auctions," *The Journal of Political Economy* (95:6), pp 1217-1239.

Haruvy, E., and Katok, E. 2012. "Increasing Revenue by Decreasing Information in Procurement Auctions," *Production and Operations Management* (22:1), pp 19-35.

Haruvy, E., Popkowski Leszczyc, P.L., Carare, O., Cox, J., Greenleaf, E., Jank, W., Jap, S., Park, Y.-H., and Rothkopf, M. 2008. "Competition between Auctions," *Marketing Letters* (19:3-4), pp 431-448 LA - English.

Hausman, J.A., Hall, B.H., and Griliches, Z. 1984. "Econometric Models for Count Data with an Application to the Patents-R&D Relationship." National Bureau of Economic Research Cambridge, Mass., USA.

Heyman, J.E., Orhun, Y., and Ariely, D. 2004. "Auction Fever: The Effect of Opponents and Quasi-Endowment on Product Valuations," *Journal of Interactive Marketing* (18:4), pp 7-21.

Hong, Y., and Pavlou, P.A. 2012. "Strategic Bidding and Personalized Pricing in Global E-Markets for Services Outsourcing," *Academy of Management Proceedings*: Academy of Management.

Hong, Y., and Pavlou, P. 2013a. "An Empirical Investigation on Provider Pricing in Online Crowdsourcing Markets for It Services," the Proceedings of the 2012 International Conference on Information Systems, Orlando, FL.

Hong, Y. and Pavlou, P. A. 2013b. “Online Labor Markets: An Informal Freelancer Economy”. *The IBIT Report*, available at: http://ibit.temple.edu/blog/2013/02/13/online-labor-markets-an-informal-freelancer-economy/

Horton, J.J., Rand, D.G., and Zeckhauser, R.J. 2011. "The Online Laboratory: Conducting Experiments in a Real Labor Market," *Experimental Economics* (14:3), pp 399-425.

Ivanova-Stenzel, R., and Salmon, T.C. 2004. "Bidder Preferences among Auction Institutions," *Economic Inquiry* (42:2), pp 223-236.

Jap, S.D. 2002. "Online Reverse Auctions: Issues, Themes, and Prospects for the Future," *Journal of the Academy of Marketing Science* (30:4), pp 506-525.

Jap, S.D. 2003. "An Exploratory Study of the Introduction of Online Reverse Auctions," *Journal of Marketing* (67:3), pp 96-107.

Jap, S.D. 2007. "The Impact of Online Reverse Auction Design on Buyer-Supplier Relationships," *Journal of Marketing* (71:1), pp 146-159.

Jap, S.D., and Haruvy, E. 2008. "Interorganizational Relationships and Bidding Behavior in Industrial Online Reverse Auctions," *Journal of Marketing Research (JMR)* (45:5), pp 550-561.

Jin, G.Z., and Kato, A. 2006. "Price, Quality, and Reputation: Evidence from an Online Field Experiment," *The RAND Journal of Economics* (37:4), pp 983-1005.

Kannan, K.N. "Effects of Information Revelation Policies under Cost Uncertainty," *Information Systems Research* (23:1), pp 75-92.

Kostamis, D., Beil, D.R., and Duenyas, I. 2009. "Total-Cost Procurement Auctions: Impact of Suppliers' Cost Adjustments on Auction Format Choice," *Management Science* (55:12), pp 1985-1999.

Kuruzovich, J., Viswanathan, S., and Agarwal, R. 2010. "Seller Search and Market Outcomes in Online Auctions," *Management Science* (56:10), pp 1702-1717.

List, J.A. 2001. "Do Explicit Warnings Eliminate the Hypothetical Bias in Elicitation Procedures? Evidence from Field Auctions for Sportscards," *The American Economic Review* (91:5), pp 1498-1507 CR - Copyright ґ 2001 American Eco.

List, J.A., and Lucking-Reiley, D. 2000. "Demand Reduction in Multiunit Auctions: Evidence from a Sportscard Field Experiment," *The American Economic Review* (90:4), pp 961-972 CR - Copyright © 2000 American Econo.

Maskin, E., and Riley, J. 2000. "Asymmetric Auctions," *The Review of Economic Studies* (67:3), pp 413-438.

Millet, I., Parente, D.H., Fizel, J.L., and Venkataraman, R.R. 2004. "Metrics for Managing Online Procurement Auctions," *Interfaces* (34:3), pp 171-179.

Mithas, S., and Jones, J.L. 2007. "Do Auction Parameters Affect Buyer Surplus in E-Auctions for Procurement?," *Production and Operations Management* (16:4), pp 455-470.

Olivares, M., Weintraub, G.Y., Epstein, R., and Yung, D. "Combinatorial Auctions for Procurement: An Empirical Study of the Chilean School Meals Auction," *Management Science* (58:8), pp 1458-1481.

Park, Y.-H., and Bradlow, E.T. 2005. "An Integrated Model for Bidding Behavior in Internet Auctions: Whether, Who, When, and How Much," *Journal of Marketing Research* (42:4), pp 470-482.

Porter, R.H., and Zona, J.D. 1993. "Detection of Bid Rigging in Procurement Auctions," *Journal of Political Economy*), pp 518-538.

Snir, E.M., and Hitt, L.M. 2003. "Costly Bidding in Online Markets for It Services," *Management Science* (49:11), pp 1504-1520.

Stoll, S., and Zottl, G. 2012. "Information Disclosure in Dynamic Buyer-Determined Procurement Auctions: An Empirical Study."

Tunca, T.I., Wu, D.J., and Zhong, F. 2010. "An Empirical Analysis of Price, Quality, and Incumbency in Service Procurement Auctions." pp. 41-41.

Vickrey, W. 1961. "Counterspeculation, Auctions, and Competitive Sealed Tenders," *The Journal of Finance* (16:1), pp 8-37.

Zeithammer, R. 2006. "Forward-Looking Bidding in Online Auctions," *Journal of Marketing Research (JMR)* (43:3), pp 462-476.

Zeithammer, R., and Adams, C. 2010. "The Sealed-Bid Abstraction in Online Auctions," *Marketing Science* (29:6), pp 964-987.

Tables and Figures

Table 1. Variable Definition and Summary Statistics

	Variable Name	Definition	Mean	Std. Dev.
1.	number_bids	Total number of bids received in an auction.	15.23	21.12
2.	average_bidder_quality	Average rating of the experienced bidders in an auction.	5.96	1.61
3.	new_bidder_ratio	Ratio of inexperienced bidders in an auction.	0.40	0.29
4.	completed_project	Whether the project is completed.	0.33	0.47
5.	lnsurplus_max	Log transformed buyer surplus with maximum buyer budget as the proxy for buyer WTP.	4.85	1.79
6.	lnsurplus_avg	Log transformed buyer surplus with average buyer budget as the proxy for buyer WTP.	2.83	3.44
7.	lncs_preference	Log transformed buyer surplus with buyer WTP estimated by buyer preference.	5.13	3.85
8.	ex post_rating	The rating a buyer left for the provider.	5.21	4.95
9.	sealed-bid	Whether the project is posted with a sealed bids auction.	0.09	0.28
10.	max_budget	The higher bound of buyer's budget.	466.65	502.42
11.	auction_duration	Number of days an auction is alive.	12.53	17.45
12.	featured_project	Whether a project is featured/highlighted.	0.05	0.21
13.	nonpublic_project	Whether log in is needed to view the project.	0.09	0.28
14.	trial_project	Whether a project is "trial".	0.15	0.35
15.	buyer_rating	Buyer's average rating.	5.26	4.69
16.	buyer_experience	Number of projects the buyer has contracted.	14.15	55.79

Table 2. Descriptive Statistics

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.	number_bids	1.00															
2.	average_bidder_quality	-0.06	1.00														
3.	new_bidder_ratio	0.32	-0.11	1.00													
4.	completed_project	-0.07	0.19	-0.16	1.00												
5.	lnsurplus_max	0.02	0.05	-0.01	0.07	1.00											
6.	lnsurplus_avg	0.02	0.05	0.00	0.10	0.71	1.00										
7.	lncs_preference	-0.11	0.16	-0.20	0.22	0.16	0.21	1.00									
8.	ex post_rating	-0.09	0.21	-0.16	0.78	0.08	0.11	0.21	1.00								
9.	sealed-bid	0.04	-0.01	0.01	-0.01	-0.04	-0.05	-0.04	-0.02	1.00							
10.	max_budget	0.11	-0.07	0.02	-0.16	0.04	-0.10	-0.51	-0.16	0.05	1.00						
11.	auction_duration	0.12	-0.07	0.15	-0.11	-0.07	-0.08	-0.13	-0.11	0.05	0.10	1.00					
12.	featured_project	0.11	-0.04	0.05	-0.05	-0.07	-0.10	-0.13	-0.05	0.11	0.20	0.06	1.00				
13.	nonpublic_project	0.02	0.00	-0.02	0.01	-0.05	-0.07	-0.05	0.00	0.31	0.09	-0.01	0.16	1.00			
14.	trial_project	0.04	-0.10	0.24	-0.08	0.01	0.00	-0.13	-0.07	-0.06	0.04	0.04	-0.04	-0.06	1.00		
15.	buyer_rating	-0.11	0.15	-0.16	0.17	0.04	0.06	0.16	0.18	0.04	-0.12	-0.08	-0.09	0.05	-0.28	1.00	
16.	buyer_experience	-0.09	0.12	-0.05	0.09	0.02	0.03	0.07	0.11	-0.02	-0.04	-0.01	-0.05	-0.03	-0.05	0.18	1.00

Table 3. Estimation Results (DV=number of bids received)

	Model 1 - OLS	Model 2 FE OLS	Model 3 FE NB
Sealed	**1.137*** (0.217)**	**1.234*** (0.339)**	**0.091*** (0.0123)**
Project Budget	0.004*** (0.00027)	0.003*** (0.0004)	5.6e-05*** (3e-06)
Auction Duration	0.18*** (0.005)	0.2*** (0.0086)	0.008*** (0.0002)
Featured Project	5.789*** (0.359)	7.091*** (0.595)	0.355*** (0.0167)
Project For Gold Members	20.66** (9.106)	2.654 (3.301)	0.437 (0.278)
Nonpublic Projects	-0.497** (0.199)	-0.0770 (0.356)	0.052*** (0.0128)
Trial Projects	0.839*** (0.243)	-1.754*** (0.562)	-0.024 (0.0208)
Fulltime Projects	9.721*** (2.069)	8.385*** (2.949)	0.252*** (0.0469)
Average Buyer Rating	-0.225*** (0.0150)	-0.125*** (0.0283)	-0.0181*** (0.001)
Buyer Experience	-0.015*** (0.0009)	0.0322*** (0.0114)	-0.0007*** (8.2e-05)
Buyer Gold Member	-0.503*** (0.132)	0.219 (0.168)	0.008 (0.007)
Constant	38.09*** (0.373)	41.28*** (0.653)	0.200*** (0.01)
Time FE	Yes	Yes	Yes
Project Category FE	Yes	Yes	No
Observations	112,815	112,815	87,882
R-squared	0.102	0.072	--
Number of buyer_id	--	40,429	14,394

For OLS models, Robust standard errors in parentheses; For FE models, cluster-robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

Table 4. Estimation Results for Bidder Quality

Estimation Strategy	OLS	FE OLS	GLM
DV	Avg_Bidder_Quality	Avg_Bidder_Quality	New_Bidder_Ratio
Sealed	**-0.0761*** (0.0153)**	**-0.117*** (0.0266)**	**0.0359*** (0.081)**
Project Budget	-0.00014*** (1.6e-05)	-8.8e-05*** (1.9e-05)	2.2e-05*** (6.2e-06)
Auction Duration	-0.003*** (0.0003)	-0.003*** (0.0005)	0.01*** (0.0002)
Featured Project	-0.110*** (0.019)	-0.186*** (0.036)	0.111*** (0.0143)
Project For Gold Members	-0.171 (0.264)	0.034 (0.245)	-1.497*** (0.114)
Nonpublic Projects	0.032** (0.01)	-0.115*** (0.028)	-0.136*** (0.0124)
Trial Projects	-0.594*** (0.026)	-0.453*** (0.085)	1.328*** (0.0103)
Fulltime Projects	-0.128* (0.07)	-0.028 (0.102)	0.498*** (0.049)
Average Buyer Rating	0.0244*** (0.001)	0.001 (0.003)	-0.0240*** (0.001)
Buyer Experience	0.002*** (0.0001)	-0.002 (0.002)	-0.00118*** (0.0001)
Buyer Gold Member	-0.046*** (0.01)	-0.008 (0.013)	0.0486*** (0.008)
Constant	6.762***(0.0278)	7.218***(0.0530)	-0.102***(0.0211)
Time Effect	Yes	Yes	Yes
Project Category Effect	Yes	Yes	Yes
Observations	99,509	99,509	112,815
R-squared	0.090	0.034	--
Number of users_id	--	33,498	--

For OLS models, Robust standard errors in parentheses; For FE models, cluster-robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

Table 5. Estimation of Buyer Preference

Estimation Strategy	Conditional Logit
VARIABLES	Selection Decision
Bid Price	**-0.0019***** (0.0001)
Days to Finish	**-0.0027***** (0.00065)
Hidden Bid	**-3.768***** (0.063)
Bidder Rating	**0.114***** (0.002)
Bidder Completion Rate	**0.742***** (0.018)
Highlighted Bid	**-9.871***** (1.000)
Bidder Experience	**0.0009***** (2.58e-05)
Bidder Gold Member	**0.0483***** (0.011)
Same Country	**0.486***** (0.032)
Invited Bidder	**2.409***** (0.047)
Bidder PPP[1]	**0.014***** (5.23e-04)
Pseudo R^2	0.172
Observations	683,662

Cluster-robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

Table 6. Estimation Results for Buyer Surplus

	FE OLS	FE OLS	FE OLS
VARIABLES	$\ln(\text{surplus\_proxy}^{max})$	$\ln(\text{surplus\_proxy}^{avg})$	ln(surplus_estimated)
Sealed	**-0.192*** (0.0538)**	**-0.412*** (0.0956)**	**-0.230*** (0.0841)**
Project Budget	0.000779*** (6.08e-05)	0.0003** (0.0001)	-0.0044*** (7.9e-05)
Auction Duration	-0.00988*** (0.00123)	-0.02*** (0.002)	-0.015*** (0.002)
Featured Project	-0.600*** (0.0936)	-0.992*** (0.156)	-0.371*** (0.137)
Project For Gold Members	-11.39*** (0.0757)	-8.928*** (0.134)	-3.753 (3.226)
Nonpublic Projects	-0.187*** (0.0511)	-0.476*** (0.0937)	-0.165* (0.0892)
Trial Projects	0.117 (0.0832)	0.205 (0.174)	-2.657*** (0.226)
Fulltime Projects	-0.811 (0.506)	-0.120 (0.774)	-1.494*** (0.557)
Average Buyer Rating	-0.0202*** (0.00371)	-0.0419*** (0.00692)	0.00652 (0.00725)
Buyer Experience	-0.00241*** (0.000861)	-0.00746*** (0.00211)	-0.000320 (0.00235)
Buyer Gold Member	0.0138 (0.0235)	0.0266 (0.0451)	0.000647 (0.0400)
Constant	4.651*** (0.0486)	2.877*** (0.0909)	6.660*** (0.147)
Time Effect	Yes	Yes	Yes
Project Category Effect	Yes	Yes	Yes
Observations	56,198	56,175	56,194
R-squared	0.030	0.025	0.171
Number of users_id	19,433	19,421	19,316

Cluster-robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

[1] PPP is purchasing power adjusted GDP per capita. The data for PPP is collected from CIA World Factbook and matched onto the main dataset.

Table 7. Estimation Results for Contract Decision and Buyer Satisfaction

VARIABLES	FE Logit Selected	FE Logit Awarded	FE Logit Completed	FE OLogit Satisfaction
Sealed	**-0.406***(0.045)**	**-0.385***(0.044)**	**-0.320***(0.046)**	**-0.124*(0.06)**
Project Budget	-0.001***(3.1e-05)	-0.001***(3.2e-05)	-0.002***(4.4e-05)	-0.001***(7.1e-05)
Auction Duration	-0.03***(0.0007)	-0.03***(0.0008)	-0.03***(0.001)	-0.012***(0.001)
Featured Project	0.0796(0.0643)	0.0647(0.0621)	-0.0995(0.0659)	-0.199**(0.0839)
Project For Gold Members	0.783(0.971)	-0.0494(1.051)	0.638(1.178)	-15.71***(1.003)
Nonpublic Projects	-0.160***(0.0474)	-0.183***(0.0458)	-0.185***(0.0462)	-0.177***(0.0572)
Trial Projects	-0.582***(0.0718)	-0.745***(0.0736)	-0.927***(0.0859)	-0.718***(0.112)
Fulltime Projects	-1.194***(0.205)	-1.064***(0.210)	-0.337(0.228)	-0.0172(0.387)
Average Buyer Rating	-0.0566***(0.004)	-0.0563***(0.004)	-0.0798***(0.004)	-0.0759***(0.005)
Buyer Experience	-0.018***(0.002)	-0.022***(0.002)	-0.021***(0.0017)	-0.016***(0.005)
Buyer Gold Member	0.00757(0.0246)	0.0204(0.0240)	0.0313(0.0246)	0.0391(0.0311)
Time Effect	Yes	Yes	Yes	No
Project Category Effect	Yes	Yes	Yes	No
Observations	67,556	69,123	66,913	393,287
Number of users_id	8,371	8,712	8,037	5,895

Cluster Robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

Appendix 1: Research Context

Online labor marketplaces for the outsourcing of software development services, such as *Freelancer* (www.freelancer.com), serve as intermediaries that bring together buyers (clients) and service providers (suppliers). These markets place typically implement buyer-driven auctions, a mechanism where buyers seek bids from service providers and evaluate bids with multiple criteria such as price and non-price attributes. For example, on *Freelancer*, in its "requests for bids", a client provides a project description together with information about requested expertise, budget range and sets the duration of the auction. Registered service providers read the project descriptions and decide whether and how much to bid. Projects follow either an "open bids" format where all service providers can see both the competing bids and the characteristics of other providers or "sealed bids" format where other bidders' information, including bids is not publically visible. The marketplace maintains a reputation system which keeps track of all feedback ratings the providers had received from clients from previous transactions. When an auction ends, the client evaluates all bids and service providers' attributes and makes a decision on whether and to which provider to award the contract. Given the distributed global nature of this marketplace, it provides an escrow service to resolve disputes if the client is dissatisfied with the provider.

Appendix 2: Derivation of Buyer Surplus

For OBD, the supplier with the highest quality bids to match the surplus provided by the supplier with the second highest quality who bid at the level of service cost. As a result, the expected surplus is the expected surplus to be generated by the supplier who has the second highest quality.

For SBD, from Equation 3 we have:

$$
\begin{aligned}
&E[MaxV^{SBD}] \\
&= E\left[vq_{(n)} - bq_{(n)} | q_{(n)} \geq q_m^S\right] \\
&= \frac{1}{1-[F(q_m^S)]^n}\left\{\int_{q_m^S}^{\infty}(v-c)nf(q)F(q)^{n-1}dq - (v-c)\int_{q_m^S}^{\infty} nf(q)\int_{q_m^S}^{q}[F(z)]^{n-1}dz\,dq - \int_{q_m^S}^{\infty} nf(q)c_T dq\right\} \\
&= \frac{1}{1-[F(q_m^S)]^n}\left\{\int_{q_m^S}^{\infty}(v-c)nf(q)F(q)^{n-1}dq - (v-c)n\int_{q_m^S}^{\infty}[F(q)^{n-1} - F(q)^n]dq - \int_{q_m^S}^{\infty} nf(q)c_T dq\right\} \\
&= \frac{1}{1-[F(q_m^S)]^n}\left\{(v-c)\int_{q_m^S}^{\infty} 1 - \left[F(q)^n + nF(q)^{n-1}[1-F(q)]\right]dq - \int_{q_m^S}^{\infty} nf(q)c_T dq\right\} \\
&= \frac{1}{1-[F(q_m^S)]^n}\left\{(v-c)\int_{q_m^S}^{\infty} 1 - F_{(n-1)}(q)dq - \int_{q_m^S}^{\infty} nf(q)c_T dq\right\}.
\end{aligned}
$$

Appendix 3: Estimating Consumer Surplus

We assume in each BD auction, a buyer select the bid to maximize her expected utility. Our context (most buyers pick one bidder to contract with) gives us a discrete choice framework with Logit assumptions. Therefore, buyer surplus associated with a set of alternatives takes a closed form that is possible to calculate (Train 2009) as:

$$CS_n = \frac{1}{\alpha_n} max_j\left(U_{nj} + \varepsilon_{nj}\right) \tag{1}$$

where a_n is the marginal utility of income. In the discrete choice framework, researchers do not directly observe the utility of a buyer, but the buyer's choice that maximizes his utility. Following McFadden (1974)'s discrete choice framework with conditional *Logit* specification, let *I*=*i* client *t* awards the project to bidder *i* in particular, then we assume that among the *N* providers who bided on the project, provider *i* maximizes client *t*'s utility for project *j*. Hence, $U_{ij} > U_{kj}$ for all $k \neq i$. Assuming the error term e_{ijt} follows a Gumbel (Type I extreme value) distribution (McFadden 1974), then the probability that the winning bidder for the project is *i* (and not any of the other providers) is:

$$\Pr(I = i) = \frac{\exp(Bidder\_attribute_{ij} \times \beta - p_{ji}\lambda)}{\sum_{i=1}^{N} exp\left(Bidder\_attribute_{ij} \times \beta - p_{ji}\lambda\right)} \tag{2}$$

Therefore, we estimate the following Equation:

$$logit(I = i) = Bidder\_attribute_{ij} \times \beta - p_{ji}\lambda + c_j + u_{ij}; E\left(u_{ijt}\middle|Bidder\_attribute_{ij}, c_j\right) = 0, j = 1,2, \dots, N \tag{3}$$

In this conditional Logit estimation equation, c_j is the auction fixed effect. λ is the cost coefficient that indicates the utility rise due to an one-dollar decrease in costs. A one-dollar reduction in costs is equivalent to a one-dollar increase in income, since the person gets to spend the dollar that he saves in project costs just the same as if he got the extra dollar in income. λ is therefore the same as marginal utility of income α . By estimating this buyer preference function, we are able to estimate the effect of other bidder related variables on her expected utility. In estimating the preference function, we include the main variables identified in the literature (Snir and Hitt 2003, Banker and Hwang 2008, Gefen and Carmel 2008, Hong and Pavlou 2013b), such as bid price, days to finish a project, whether a bid is hidden, bidder's rating, bidder's project completion rate, whether a bid is highlighted, bidder project experience, whether bidder is gold member, whether bidder and the buyer are in the same country, whether the bidder is invited, and bidder's PPP. Estimation results are summarized in Table 5.

[Insert Table 5 Here]

Therefore, based on the above buyer preference estimates, we calculate estimated buyer surplus for each bids as:

$$\boldsymbol{E(CS)} = [-0.027 \times DaysToFinish - 3.768 \times HiddenBid + 0.114 \times BidderRating + 0.742 \times BidderCompletionRate - 9.87 \times HighlightedBid + 0.0009 \times BidderExperience + 0.0483 \times BidderGoldMember + 0.4861 \times SameCountry + 2.409 \times InvitedBidder + 0.014 \times BidderPPP] \,/\, 0.0019 - BidPrice \tag{4}$$