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**How Does Bid Visibility Matter in Buyer-Determined Auctions?
Comparing Open and Sealed Bid Auctions in Online Labor Markets**

Kevin Yili Hong
Temple University

Alex Chong Wang
City University of Hong Kong

Paul A. Pavlou
Temple University

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**HOW DOES BID VISIBILITY MATTER IN BUYER-DETERMINED AUCTIONS?
COMPARING OPEN AND SEALED BID AUCTIONS IN ONLINE LABOR MARKETS**

NET INSTITUTE WORKING PAPER¹

KEVIN YILI HONG^{*}
hong@temple.edu

ALEX CHONG WANG^{**}
alex.wang@cityu.edu.hk

PAUL A. PAVLOU^{***}
pavlou@temple.edu

*Kevin Yili Hong is a doctoral candidate at the Fox School of Business, Temple University.

**Alex Chong Wang is an assistant professor at College of Business, City University of Hong Kong

***Paul A. Pavlou is the Milton F. Stauffer Professor at the Fox School of Business, Temple University

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Abstract

Online labor markets are platforms that facilitate Buyer-Determined (BD) auctions in which buyers can identify and hire service providers who bid to offer IT services. We examine the effect of *bid visibility* (i.e., open bid versus sealed bid) on the bidders' entry strategies (number of bids and quality of bids) and auction performance (buyer surplus, contract probability, and buyer satisfaction). We first theoretically analyze equilibrium bidder entry, and we derive hypotheses on the effect of open bid versus sealed bid on bidder strategic entry and auction performance. Using a proprietary large-scale dataset that allows us to observe 1,816,886 bids from 106,147 open bid and 9,950 sealed bid auctions posted on *Freelancer.com* by 41,530 unique buyers, we find that, while sealed bid BD auctions receive more bids, open bid BD auctions consistently outperform sealed bid BD auctions in terms of the quality of bids and auction performance. Specifically, compared with sealed bid BD auctions, while open bid BD auctions attract 8.1% fewer bids, they receive 3.59% more bids from experienced service providers, they are 50% more likely to get contracted, and they result in at least 19% more in buyer's surplus. These findings are robust to different econometric specifications and propensity score matching estimators. Our study suggests that empirically, BD auctions do *not* exhibit revenue equivalence across auction designs, as predicted in the literature. The performance difference is attributed to the "screening effect" of open bid BD auctions that helps filter out low quality, inexperienced, bidders. Notably, the additional bids in sealed bid BD auctions result from the lack of pre-evaluation self-screening, and they are thus unusable, if not harmful, to auction performance by increasing buyers' bid evaluation costs. Contrary to conventional wisdom and industry practice that expect "the more bids, the better", which favors sealed bid BD auctions, our results demonstrate that fewer bids (albeit of higher quality), and thus open bid BD auctions, are a preferred option for online labor markets.

Key Words: Auction design, Bid Visibility, Online Labor Markets, Bidder Entry, Auction Performance

1. Introduction

Labor, traditionally supplied offline, has recently moved onto the Internet with online labor markets emerging as a viable means for sourcing (Malone and Laubacher 1998, Howe 2006). Nowadays, buyers have expanded their reach globally and have brought a large arsenal of labor to bear on IT services, notably software development projects in online labor markets, such as *Freelancer*, *eLance*, and *TopCoder* (e.g., Cummings et al. 2009, Espinosa et al. 2007). Online labor markets are economically attractive and practically important, and they have been touted for their significant trading volume and societal benefits (Malone and Laubacher 1998). For example, *eLance* alone has nearly 2.9 million jobs posted and has facilitated transactions worth over \$3 billion by the end of 2012.² The online labor market in our study, *Freelancer*, the largest in the world, has already connected over 8 million buyers and service providers from over 234 countries and regions, and it has over 4.7 million posted projects worth over \$9 billion.

While online labor markets strive to help buyers hire quality labor (service providers), a key factor that contributes to the success of online labor markets is the use of reverse Buyer-Determined (BD) auctions,³ which match buyers with service providers (e.g., Asker and Cantillon 2008). Typically, in BD auctions, a buyer who seeks a service will create a Call for Bids (CFB) with a project description to elicit bids from service providers who offer to complete the project at a certain bid price. Buyers face several decisions with regard to CFBs – from estimating the project budget, writing the project description, and soliciting bids by choosing an auction design.⁴ Among different auction designs, *bid visibility* is a critical design choice that varies both across online labor markets and also across auctions within the same labor market.

² <https://www.elance.com/trends/skills-in-demand>, accessed in June 2013.

³ A buyer-determined auction (BD) is a type of reverse auction in which the winning bid is selected by the buyers rather than determined by some pre-specified rule (such as lowest price wins). In a reverse auction, the roles of buyer and seller as in a forward auction are reversed. Sellers compete to offer services to buyers. Scoring auction is a type of BD auction, in which buyers assign values to both price- and non-price attributes according to a score function and pick the one that has the maximum score.

⁴ Online labor markets often allow buyers to customize the design of BD auctions (e.g., hourly rate based versus project-based, non-public versus public, open bid versus sealed bid) to their needs. While some of the options are project-related (e.g., payment pattern, public access to the project description), others are related to the bidding rules that have critical implications for auction performance in general (e.g., bid visibility). We focus on the effect of bid visibility while controlling for other project-related auction design options.

Whether auction bids (bid and bidder information) are *visible (open bid)* or *not (sealed bid)* to other bidders may significantly alter the pattern of interactions among bidders and the outcome of the auction (Jap 2002). Notably, despite the difference in bid visibility, revenue equivalence theorem in the auction literature states that under the condition that both auction designs attract the same pool of bidders, the expected revenue (surplus in BD auctions) is equivalent between open bid and sealed bid auctions, a property that has been analytically proven and empirically tested in multiple auction contexts (e.g., Engelbrecht-Wiggans 1988, Heydenreich et al. 2009, Myerson 1981, Riley and Samuelson 1981, Tenorio 1993, Vickrey 1961). Subsequent work in auction literature focused on how the bidding environment (e.g., bidder heterogeneity, entry costs, and risk aversion) affect the comparison between auction designs. Recent experimental studies show that online BD auctions may not exhibit revenue equivalence between open bid and sealed bid designs (e.g., Haruvy and Katok 2012). However, the literature is inconclusive on which online BD auction design offers a higher surplus to buyers, and there is no clear evidence that the laboratory results on the effects of bid visibility on auction performance are transferrable to real-world labor market transactions.

Besides academics, industry practitioners are interested in auction design in online BD auctions⁵ as well. Industry practice treats “sealed bid” as a premium feature and charges extra fees for sealed bid BD auctions (\$1 at *Freelancer* since June 3, 2009, which was raised to \$9 on April 10, 2013). The rationale behind this practice is that sealed bid BD auctions attract more bids and thus offer buyers more choices and presumably better quality services. However, such reasoning is based on an untested assumption that “more choices” are equivalent to “higher quality”. Thus, it is not clear to us which BD auction design (open versus sealed bid) actually does perform better. It is hence necessary to understand the effect of auction design, specifically, bid visibility (open bid versus sealed bid) on service providers’ entry strategies and auction performance.

⁵ Compared with traditional physical auctions, instead of simultaneous face-to-face bidding in a single auction, service providers in online BD auctions use a computer-mediated interface to explore multiple projects and CFBs, submit and modify bids, and observe other bidders’ information (in the case of open bid BD auctions). Moreover, given the global nature of online BD auctions, the bidder pool is significantly larger than that of traditional auctions. On the other side of the market, buyers select a service provider from a large number of submitted bids based on evaluation of bid price and non-price attributes (e.g., skills and reputation), whom they have never met before. Thus, online BD auctions differ from traditional auctions in terms of the the volume of bids and ease of information access.

Accordingly, this paper seeks to address the following research question about the effect of bid visibility on bidders' strategic entry and auction performance in the context of BD auctions in online labor markets:

“What are the effects of BD auction design (bid visibility - open bid versus sealed bid BD auctions) on service providers' strategic entry (number of bids, quality of bidders) and auction performance (buyer's surplus, contract probability, and buyer's satisfaction)?”

To answer this research question, we present both analytical results and empirical evidence on the effect of bid visibility on bidder entry and auction performance in online labor markets. To compare between open versus sealed bid BD auctions, we first conduct a game theoretic analysis on equilibrium bidding and buyer surplus. To reflect the unique characteristics of online BD auctions, we assume that buyers take both the price and non-price attributes of service providers into consideration in making a discrete choice of a provider to contract with. Building on prior work (Carr 2007, Snir and Hitt 2003) and following a common practice in online labor markets (e.g. *Freelancer* limits the total number of bids per month for bidders), we incorporate bidders' bidding cost into our analytical model. Guided by the theoretical analysis, we then empirically compare open bid versus sealed bid BD auctions with respect to (a) *bidders' strategic entry* (the *number of bids* attracted, the *quality of the bidders* who submitted a bid), and (b) *auction performance* (*buyer surplus*, *contract probability*---whether the employer selected any provider; whether a CFB resulted in a contract, and whether the project was completed---, and *buyer satisfaction* with the service delivered). Beyond buyer surplus, contract probability and buyer satisfaction are important dimensions of auction performance in the context of online labor markets. First, a CFB will become a waste of time and effort for all stakeholders (buyers and service providers) if it does not result in a contract either because the buyer cannot find a suitable service provider or if the selected service provider ends up failing to complete the contract (Snir and Hitt 2003). After a project is completed, buyer's satisfaction with the actual service delivered is critical, and it was shown to have a significant effect on subsequent buyer/bidder participation (e.g., repeated transactions and willingness to post/bid on other CFBs) (Mittal and Kamakura 2001).

Our empirical investigation is carried out based on a unique proprietary data set collected from a leading online labor market, *Freelancer* (<http://www.freelancer.com>), with 1,816,886 bids from 106,147 open bid

and 9,950 sealed bid auctions posted by 41,530 unique buyers. Unlike most other auction marketplaces, *Freelancer* allows CFBs to be auctioned in either an open bid or a sealed bid BD format, thus enabling a within-site comparison between projects posted under these two key BD auction designs. Our data cover the entire bidding history of all projects posted on the marketplace, which includes proprietary data of all bids in sealed bid BD auctions, which are unavailable from public access. We also observe the performance outcomes of all auctions in our data, including contract probability and buyers' post-project evaluations of service providers' performance (buyer satisfaction), which are also not publicly accessible either.

Notwithstanding that sealed bid BD auctions do attract more bids, as expected by industry expectations, both our theoretical analysis and empirical findings favor open bid design as a superior choice of BD auctions in online labor markets. This is because the extra bids are submitted by lower quality providers due to lack of pre-evaluation self-screening in providers' entry decisions. Accordingly, they are inconsequential, if not harmful, to auction performance because of the additional effort required by buyers for bid evaluation. Empirically, our results show that on average, open bid BD auctions do result in 8.1% fewer bids compared with sealed bid BD auctions. However, the percentage of experienced bidders is 3.59% higher, and the quality of bidders is 2.34% higher in open bid versus sealed bid BD auctions. In terms of auction outcomes, projects posted under open bid BD auctions are 50% more likely to get contracted, result in at least 19% higher buyer surplus, and offer a significantly higher buyer satisfaction. To assure the robustness of our findings, alternative model specifications and propensity score matching estimators were also undertaken.

Auction design received much theoretical discussion in the economics literature (e.g. Athey et al. 2011, Krishna 2009, Vickrey 1961), albeit empirical studies using field data are still limited. To our knowledge, this is one of the first large-scale empirical studies on the effect of BD auction design on service provider's strategies and auction performance in real-life online labor markets. Most existing empirical studies remain silent on bid visibility due to the inability to access or observe the posted bids in sealed bid BD auctions. This study contributes to the BD auctions literature in online labor markets and extends our understanding of the effect of online BD auctions design on buyers, service providers, and auction performance in real-life market transactions. It also offers tangible practical guidance to all key stakeholders in online labor markets.

In what follows, Section 2 describes the background and the context of our study. In Section 3, we present our theoretical analysis and derive our hypotheses for empirical testing. Our empirical context, data, estimation models, key findings and robustness checks are presented in Section 4. Finally, Section 5 discusses this study’s contributions and implications for theory and practice.

2. Background and Literature

2.1 Research Context

Online labor markets, such as *eLance* and *Freelancer*, serve as intermediaries that bring together buyers and service providers. To match buyers and service providers and facilitate service price discovery, these markets typically implement Buyer-Determined (BD) auctions, a mechanism in which buyers seek bids from service providers and evaluate bids by considering both price and non-price attributes, such as providers’ reputation, prior project experience and skills in their profiles. In the CFB system of *Freelancer*, a buyer posts a project description together with information about requested expertise, estimated budget, and auction duration. Registered service providers read the project descriptions and decide whether and how much to bid. Service providers can place a limited number of bids per month, and they can purchase additional bids at a cost. Service providers can revise bids before the auction ends without an extra cost. Auctions that follow the “open bid” design allow service providers to observe both competing bids and the attributes of competing providers, while “sealed bid” auctions do not allow providers to observe other price bids or other bidders’ information. When an auction ends, the buyer evaluates all price bids and service providers’ attributes⁶ and makes a decision on whether and to which service provider to contract. The winning service provider is then contracted to provide the service. After the project is completed, both the service provider and the buyer are required to provide feedback on their satisfaction with each other.⁷

2.2 Online Labor Markets

Academic interest in the emerging online labor markets has picked up in recent years. There have been

⁶ These attributes include demographics, self-reported skills, on-site qualification exams, etc.. The marketplace also maintains a reputation system, which keeps track of all feedback ratings providers had received from previous buyers.

⁷ Given the distributed global nature of this market, the marketplace provides an escrow service to resolve disputes if the buyer is dissatisfied with the service provider.

a few theoretical studies on online labor markets. With respect to BD auctions in online labor markets, Snir and Hitt (2003) showed that, with non-negligible bidding cost for providers, low quality providers are more likely to bid for higher value projects. Their analysis confirmed that higher-value projects attract significantly more bids, albeit of lower quality, and that overbidding for high value jobs by low quality providers makes the online labor market less suitable for large projects. Carr (2003) modeled the role of bids evaluation cost on equilibrium bidding strategy and argued that buyers may disregard perfectly acceptable bids simply because they cannot evaluate all of them. Stoll and Zöttl (2012) showed that bidders in online BD auctions are aware of their rival bidders' profiles, and they take non-price profile information into consideration when posting their bids. The provision of additional information was shown to increase the buyers' welfare. Finally, Allon et al. (2012) discussed the moderating role of online labor markets in facilitating information gathering, operational efficiency, and communication.

Another stream of research discusses buyer's hiring decision in online labor markets. Several extant studies have focused on the effect of providers' reputation. For example, Banker and Hwang (2008) and Scholz and Hass (2011) found that information of service providers' past performance could predict their chance of winning future contracts. Using a dynamic structural model, Yoganarasimhan (2012) estimated the return to reputation in online labor markets. The author also found that buyers are forward looking, and they place significant weight on providers' reputation information (as quality signals) in selecting winners. Beyond individual reputation, Mill (2011) found country reputation had an effect on buyers' selection. Besides reputation, Gefen and Carmel (2008) found that buyers prefer providers with whom they have had prior interactions, and Agarwal et al. (2013) confirmed the role of verified work experience on buyers' selection. Lin and Goes (2012) investigated factors that motivated providers to seek third party certification in online labor markets. This line of research is informative in estimating buyer surplus in online BD auctions by shedding light on how buyers assess providers' non-price attributes in online labor markets.

In sum, the literature on online labor markets has largely focused on a single type of auction mechanism and remained silent on the role of auction designs, specifically, *bid visibility* on bidders' strategic entry and auction performance. Accordingly, the effect of auction design (open bid versus sealed bid) is our focus.

2.3 Design of Online Auctions

Auction design is an important topic that has been studied extensively by scholars in disciplines such as information systems, economics, operations research and marketing. Seminal works by Krishna (2009), Milgrom (2004) and Klemperer (2004) offer systematic reviews of previous theoretical studies. As one renowned example, revenue-equivalence theorem states that, under the assumptions that two auctions attract the same pool of bidders, open and sealed bid auctions produce the same amount of expected revenue despite differences in strategic actions of the bidders (Vickrey 1961). Online markets use a wide variety of auctions for price discovery, such as *eBay* (forward commodity auctions), *Google Adwords* (keywords auctions), *Freelancer* (BD auctions for labor). Thus, there is a growing interest in the mechanism design, bidding behavior and buyer surplus in online auctions in the literature (e.g, Bapna et al. 2008a, b; Bapna et al. 2010; Goes et al. 2010; Mithas and Jones 2008; Xu et al. 2011; Zhang and Feng 2011).

An important characteristic that makes BD auctions fundamentally different from most other auctions is that price is *not* the sole determinant of the auction's winner (Haruvy and Katok 2012). In BD auctions, the buyer takes into consideration both price and non-price attributes of bids according to an explicit or implicit scoring rule, and awards the contract to the service provider whose bid scores the highest utility (Jap 2002; Rangan 1998; Asker and Cantillon 2008). It is typically assumed in the literature that the buyer can clearly weigh price and non-price attributes to compare her expected surplus; similarly, service providers are assumed to know the buyer's scoring rule (Engelbrecht-Wiggans et al. 2007; Kostamis et al. 2009). Notably, Engelbrecht-Wiggans et al. (2007) compared BD and price-determined (PD) auctions and found BD auctions to generate a higher buyer surplus than PD auctions when the number of bidders is large.

With respect to auction design, bid visibility is among the most critical design features. There has been growing interest, from both practitioners and academics, in the manipulation of bid visibility in auctions. Theoretically, Kannan (2012) found information revelation policies (reveal only the winning bid or all bids) in procurement auctions to have an effect on bidder learning. 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 savings than less visible formats (i.e., low bid only or rank bid only). Jap (2007) showed that partial price

visibility formats (particularly rank format over low price format) are better at preserving the buyer–provider relationship (e.g., minimizing opportunism, ensuring satisfaction, and maintaining future expectations) than full price visibility formats. This is because full bid visibility raises providers’ beliefs that the buyer is using such auctions to opportunistically gain price concessions. There are some recent experimental studies on the effect of auction design on BD auction performance. Notably, Cason et al. (2011) found information revelation policy has an effect on bidders’ behavior to prevent an opponent from learning private information in a sequential procurement auction setting. On bid visibility, Haruvy and Katok (2012) compared dynamic open bid auctions and sealed bid auctions with different information structures in laboratory experiments. The authors found that sealed bid auctions provided greater buyer surplus, and they thus stated that higher price transparency resulted in a lower buyer surplus. In contrast to their lab environment where a small number of student subjects served as bidders and no bidding costs were considered, online BD auction in real-life markets cast to a much larger and more heterogeneous pool of bidders who bare bidding costs. Our study is based on a large-scale field data set (more than 1 million bid-level observations) collected from a real-life online labor market, thus offering real-world evidence on the comparison between open and sealed bid auctions in online markets.

3. Theoretical Analysis

3.1 Model Set-up

To understand the differences between open bid and sealed bid BD auctions in online labor markets and to guide our empirical investigation, we first analyze the following theoretical model. In the model, we focus on a single BD auction and compare sealed bid BD auction and open bid BD auction under the same model setting. Our objective is to understand the difference between sealed bid and open bid BD auctions in terms of: (1) the service provider’s entry and bidding strategy that determines the pool of bids (price and quality of service providers) received in an auction, and (2) the buyer’s expected surplus. Based on these, we seek to derive and test the broader effect of bid visibility on auction performance.

Consider a setting where N risk-neutral service providers compete to provide services to a buyer by participating in a BD auction. The contract is indivisible. Service 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 derives 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 from 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 comparable sealed bid BD auction setting.

During the BD auction, each provider submits a bid at a bidding cost of c_T . A total of n bidders enter an auction. Service providers are allowed to revise their bids at no additional cost.⁸ In equilibrium, a bid reveals the quality of the service provider to the buyer; in open bid BD auctions, it also reveals the quality of the service provider to its competitors. The contract is awarded to the bid that generates the highest expected buyer's surplus $V(q_i, b_i)$. The winning service provider will be paid according to its bid (b_i).

3.2 Equilibrium Bidding Strategy

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

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

In the open bid BD auction setting 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.

⁸ Bidding cost includes both the cost of bidding, communication and opportunity cost. For example, in our empirical context, the number of projects that a service provider can bid per month is limited and could be increased at a cost. After submitting a bid, the service provider needs to maintain communication with the buyer and to monitor bids from others and revise their bids accordingly. In our data, we observed more than 7% of the bids were revised. Meanwhile, we do not observe a significant number of "last-minute" bidding (snipping) in this context.

In sealed bid BD auctions, however, provider i is only informed about his own cost and quality. The expected profit from bidding in sealed bid BD auctions is:

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

where $G_j(b; n) = F_j(b_j^{-1}(b; n))$ 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 BD auctions (Snir and Hitt 2003):

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

In this auction game, there exists a symmetric, pure strategy, Nash, subgame perfect equilibrium provider bidding strategy in which only service providers 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. Provider i 's expected profit, given that $q_i \geq q_m^S$ is:

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

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

3.2.1 Number of Bids⁹

Despite the difference in bidding format, theoretically the entry thresholds for open bid and sealed bid BD auctions are the same (quality above threshold q_m , which satisfies $(vq_m - cq_m)[F(q_m)]^{n-1} = c_T$). Therefore, under our model setting, both formats will attract the same pool of potential service providers. Since bids are submitted sequentially rather than simultaneously, in open bid BD auctions, once a service provider of quality q has placed a bid, all other providers with quality level lower than q are less likely to bid on the same job. In other words, the bidder pool in the open bid BD auctions depends on the existing bids¹⁰. We label this as the “screening effect” of open bid BD auctions. This screening effect of prior bids,

⁹ We do not include revised bids. Hence, the number of bids equals the number of distinct bidders entering an auction.

¹⁰ We can show that, for example, under a Poisson arrival process, the expected number of bids is lower and average

which does not exist in sealed bid BD auctions where prior bids are not publically observable, results in fewer bids being submitted in open bid BD auctions than sealed bid BD auctions. Therefore, we propose:

Hypothesis 1: Open bid BD auctions will receive fewer bids than sealed bid BD auctions, ceteris paribus.

3.2.2 Quality of Bidders

The “screening effect” of open bid BD auctions implies that the entry barrier for low quality bidders will escalate over the course of the auction. To save the cost of bidding, low-quality providers are likely to refrain from entering an open bid auction to compete with existing high quality providers. Therefore, although open bid BD auctions may attract fewer bids (H1), the bids are more likely to be submitted by higher quality bidders. Despite the clear theoretical prediction from the model, in practice, sealed bid BD auctions are beneficial to providers by protecting the proposed solution from a public view. Therefore, when the need to protect intellectual property from imitation is high, such as crowdsourcing open innovation tournaments where full solutions needs to be submitted during the time of bid entry¹¹ (e.g., Terwiesch and Xu 2008), sealed bid BD auctions could attract more bids from high quality providers who would prefer to hide their solutions. However, in sealed bid BD auctions, providers work on the projects after a contract is reached, thus revealing little information about their intended service solutions at the time of bid entry. Participation cost and winning probability are main drivers for the entering/bidding decision. Therefore, we propose:

Hypothesis 2: Open bid BD auctions will receive bids from service providers with higher quality than sealed bid BD auctions, ceteris paribus.

3.2.3 Buyer Surplus

Based on the equilibrium bidding strategy, we can calculate and compare the expected buyer’s surplus in open bid and sealed bid BD auctions. Expected buyer surplus ($q_{(k)}$ is the k th order statistics) is calculated as follows (please see Appendix I for the derivation for buyer surplus).

bid quality is higher in open bid BD auctions.

¹¹ The literature also refers to this type of online auctions as Call for Proposal (CFP), or an open innovation contest.

Open Bid:
$$E[V^{OBD}] = E[(v - c)q_{(n-1)} | q_{(n-1)} \geq q_m^O] \quad (5)$$

Sealed Bid:
$$E[V^{SBD}] = E[vq_{(n)} - bq_{(n)} | q_{(n)} \geq q_m^S] \\ = E[(v - c)q_{(n-1)} | q_{(n)} \geq q_m^S] - \frac{nc_T}{1 - [F(q_m^S)]^n} \int_{q_m^S}^{\infty} f(q) dq \quad (6)$$

Thus, the expected buyer surplus in open bid BD auctions is higher than that from the sealed bid BD auctions given that at least two bids are observed. In sealed bid BD auctions, the service provider does not see other bids, and his bidding decision is made at the same time of bidding, every service provider takes a potential loss in bidding cost c_T into their bidding function, as shown in Equation (3), which increases all bids received. However, in open bid BD auction, submitting the first bid is costly, but bid revisions are not. Entry cost (bidding cost) c_T only affects entry decision in open bid BD auctions. Once service providers decide to bid, their bidding function is not affected by the bidding cost c_T any more. For example, in open bid BD auctions, if *Provider A* has a reservation value of 10 for a project, he could bid \$20 at the first shot (and he can then revise the bid later at no additional bidding cost), but when another provider (with same quality) beats him by bidding \$11, *Provider A* needs to bid $\$11 - \epsilon$ ($\epsilon > 0$) in order to win, even if his bidding cost is \$1. Theoretically, the bidding cost in open bid BD auctions is a sunk cost, which does not affect his equilibrium bid. However, in a sealed bid BD auction, *Provider A* will take into consideration that some other provider may bid \$11 when he decides to bid. Although bid revisions are free in both open and sealed bid BD auctions, as a bidder does not see other bidders' information in sealed bid auctions, he has no incentive to revise the bid after it is submitted. Summarizing this logic, in sealed bid BD auctions, the buyer pays for the incurred bidding cost c_T of the service providers. Therefore, we propose:

Hypothesis 3: Open bid BD auctions will result in higher buyer's surplus than sealed bid BD auctions, ceteris paribus.

3.2.4 Contract Probability and Buyer Satisfaction

In our theoretical analysis, we assume that once an auction ends, the winner with the highest score will be selected and contracted to deliver the service to the buyer (that is, zero reservation value for contract).

In reality, not all BD auctions successfully result in a contract. In our data set, 45% of the projects listed

ended without picking out a winning bid, while only 32% of all posted projects were eventually completed. There are many reasons that contract probability may vary across auction designs. First, as per our model, open bid BD auctions receive fewer bids, but those bids tend to be submitted by higher quality bidders, which result in a higher expected surplus. In real-life transactions, buyers may have non-zero reservation values ($p^e > 0$). In that case, contract probability (r) under expected surplus of $E(V)$ and evaluation cost of $c_e(n)$ can be written as:

$$r = \begin{cases} 0, & \text{if } E(V) - p^e - c_e(n) \leq 0 \\ 1, & \text{if } E(V) - p^e - c_e(n) > 0 \end{cases} \quad (7)$$

The contract probability will be positively caused by expected buyer surplus $E(V)$, which is higher in the case of open bid BD auctions. Second, Carr (2003) showed that bid evaluation cost might drive quality-sensitive buyers to decide not to evaluate all bids, and abstain from contracting with a provider. Given that bid evaluation is costly and monotonically increases with the number of bids n , the proposed “screening effect” of open bid BD auctions is a desirable feature that reduces the complexity of the bid selection process, thus resulting in a higher contract probability and a more optimal selection of bids. Integrating the two effects, contract probability should be higher for open bids auctions. Thus, we propose:

Hypothesis 4: Open bid BD auctions result in a higher contract probability than sealed bid BD auctions, *ceteris paribus*.

Buyer’s satisfaction (SAT) is another downstream variable that indicates different levels of the service quality eventually delivered by the chosen provider. In most online labor markets, buyers report their satisfaction on a scale of 1-10 after completion of the project. If we assume that the market is generally efficient and buyers have rational expectations, we write:

$$SAT \propto E(V) - c_e(n) \quad (8)$$

As open bid BD auctions have a higher expected surplus and lower evaluation costs than sealed bid BD auctions, buyers in open bid BD auctions will have higher satisfaction. Therefore, we propose:

Hypothesis 5: Open bid BD auctions result in higher buyer satisfaction than sealed bid BD auctions, *ceteris paribus*.

4. Empirical Methodology

In this section, we relate bid visibility in auction design (open bid versus sealed bid) on bidders' entry (number of bids and bidder quality) and auction performance (buyer surplus, contract probability, and buyer satisfaction).

4.1 Data Set

Our dataset is retrieved from a proprietary database of a leading online labor market *Freelancer.com*. The dataset spans the period between August 2009 and February 2010, and it contains 1,816,886 bids from 106,147 open bid BD auctions and 9,950 sealed bid BD auctions posted by 41,530 unique buyers. We focus on three major categories of projects, namely, software development, graphical design, and content writing. Special projects, such as projects open only to gold members, trial projects, and long-term contracts are excluded from the sample. Table 1 summarizes the definition and descriptive statistics for our key variables based on project level data, and Table A-3 in Appendix III provides the correlation matrix. In our sample, a project received around 15 bids, on average, among which about 40% were from service providers that are new to the market. On the other hand, buyers in our sample had completed an average of 18 projects before. The average auction is about 11 days. Ten (10) percent of the auctions in our sample used sealed bid format.

Table 1. Variable Definition and Summary Statistics (Auction/project-level)

Variable Name	Definition	Mean	Std. Dev.
<i>number_bids</i>	Total number of bids received in an auction.	15.14	18.12
<i>average_bidder_quality</i>	Average rating of the experienced bidders in an auction.	6.14	1.42
<i>new_bidder_ratio</i>	Ratio of inexperienced bidders in an auction.	0.40	0.49
<i>completed_project</i>	Whether the project is completed.	0.32	0.25
<i>surplus_proxy^{max}</i>	Buyer surplus with maximum buyer budget as the proxy for buyer WTP.	198.31	169.66
<i>surplus_proxy^{avg}</i>	Buyer surplus with average buyer budget as the proxy for buyer WTP.	58.29	150.29
<i>surplus_preference</i>	Buyer surplus with buyer WTP estimated by buyer preference.	709.74	707.35
<i>ex post_rating</i>	The rating a buyer left for the provider.	9.86	0.81
<i>sealed-bid</i>	Whether the project is posted with a sealed bid auction.	0.10	0.30
<i>max_budget</i>	The higher bound of buyer's budget.	436.75	444.94
<i>auction_duration</i>	Number of days an auction is alive.	11.36	16.52
<i>featured_project</i>	Whether a project is featured/highlighted.	0.05	0.22
<i>nonpublic_project</i>	Whether log in is needed to view the project.	0.11	0.31
<i>buyer_rating</i>	Buyer's average rating.	9.27	1.28
<i>buyer_experience</i>	Number of projects the buyer has contracted.	17.87	64.58

4.2 Empirical Models and Estimations

4.2.1 Strategic Entry

Number of Bids: We first estimate the effect of auction design on aggregate bidder entry behavior measured by the number of bids received. We use ordinary least squares (OLS) regression and OLS with buyer fixed effect (OLS with FE) to estimate the effect of auction design on the total number of bids to capture the effect of auction design on the number of bids (controlling for auction / buyer characteristics). Since the number of bids can be seen as a count variable with a non-normal distribution with a long tail and high dispersion, we use a fixed effect negative binomial (NB with FE) model (Hausman et al. 1984) as a robustness check (Model 3). In these estimations, we control for buyer fixed effects using within transformations, and we control for time and project category fixed effects using dummy variables.

Equation 9 outlines our empirical model for estimation. This empirical model includes the main variable “auction design” (Sealed equals to 1 if the auction is sealed bid and 0 if the auction is open bid); buyer fixed effects, δ_q ; project category fixed effects, λ_j ; time fixed effects, ψ_t ; time-variant buyer control variables including average buyer feedback rating; buyer experience and a dummy for gold membership¹²; and auction/project level control variables including project budget, auction duration, featured project, and nonpublic projects. In Equation (9), 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).

$$\begin{aligned} \text{num_bids}_{ijqt} = & \alpha + \beta_1 \times \text{Sealed}_{ijqt} + \beta_{2-8} \times (\text{AuctionControls}_i) + \beta_{9-10} \\ & \times (\text{BuyerControls}_{iq}) + \psi_t + \delta_q + \lambda_j + \varepsilon_{ijqt} \end{aligned} \quad (9)$$

As the results in Table 2 attest, on average, sealed bid BD auctions attract 1.29 more bids ($p < 0.001$) than open bid BD auctions, translating to an 8.1% difference. The effect is robust to different estimators, supporting H1. Also, our estimation result suggest that projects of higher budget, longer auction durations, promoted as featured projects, posted by less experienced/reputable buyers receive more bids, on average.

¹² Gold members enjoy premium services and deduction in transaction fees that are not available to standard users.

Table 2. Effect of Bid Visibility on Total Bids Received (DV= *number_bids*)

	Model 1	Model 2	Model 3
Estimation Methods:	OLS	OLS with FE	NB with FE
Sealed	1.047*** (0.218)	1.294*** (0.367)	0.0778*** (0.0137)
Project Budget	0.00537*** (0.000195)	0.00451*** (0.000327)	0.000177*** (7.90e-06)
Auction Duration	0.181*** (0.00540)	0.200*** (0.00865)	0.00907*** (0.000221)
Featured Project	5.953*** (0.389)	7.948*** (0.654)	0.391*** (0.0189)
Nonpublic Projects	-1.310*** (0.195)	-0.573* (0.340)	0.0296** (0.0141)
Average Buyer Rating	-0.254*** (0.0148)	-0.133*** (0.0301)	-0.0189*** (0.00117)
Buyer Experience	-0.0143*** (0.000832)	0.0212** (0.00987)	-0.000515*** (8.73e-05)
Buyer Gold Member	-0.721*** (0.132)	0.110 (0.170)	0.00666 (0.00785)
Constant	39.71*** (0.372)	41.43*** (0.647)	1.585*** (0.493)
Period Dummies	Yes	Yes	Yes
Project Category Dummies	Yes	Yes	Yes
Buyer Fixed Effect	No	Yes	Yes
Num. of Observations	77,899	77,899	66,531
R-squared	0.110	0.073	--
Number of Buyers	--	22,639	11,271

Notes: For OLS models, Robust standard errors are reported in parentheses.

For models with buyer fixed effect, cluster-robust standard errors are reposted in parentheses;

*** p<0.01, ** p<0.05, * p<0.1

Quality of Bids: H2 states that open bid BD auctions will attract bids from bidders with higher quality than sealed bid BD auctions. To test this, we calculated two measures of average bidder quality at the auction (project) level. There are generally two types of bidders on the labor market, bidders with no project experience (new to the market, quality cannot be measured by feedback ratings) and bidders with project experience (who already have feedback ratings). First, for each auction, we calculated the average quality of experienced bidders whose quality is measured as the average of their ratings received prior to bidding on the current auction. Second, we calculated the ratio of bids submitted by inexperienced bidders (bidders with no project experience) to each auction. Similarly to Equation (9), this model includes the main variable auction design (“sealed”), auction/project level control variables, buyer fixed effects, δ_q , project category fixed effects, λ_j , time fixed effects, ψ_t , and time-variant buyer effects:

$$\begin{aligned} \text{avg_bidder_quality}_{ijqt} | \text{new_bidder_ratio}_{ijqt} \\ = \alpha + \beta_1 \times \text{Sealed}_{ijqt} + \beta_{2-8} \times (\text{AuctionControls}_i) + \beta_{9-10} \\ \times (\text{BuyerControls}_{iq}) + \psi_t + \delta_q + \lambda_j + \varepsilon_{ijqt} \end{aligned} \quad (10)$$

As the results in Table 3 attest, on average, open bid BD auctions attract higher quality bidders. Based on the OLS estimation with buyer fixed effects, bidders with ratings in sealed bid BD auctions have lower ratings than bidders in open bid BD auctions ($\beta = -0.117, p < 0.001$). We also found evidence with a fractional response Logit model (Papke and Wooldridge 2000) that sealed bid BD auctions attract a higher proportion of inexperienced bidders ($\beta = 0.0359, p < 0.001$). Therefore, H2 is supported. Combining the empirical evidence concerning the number of bids received and average bidder quality, we conclude that sealed bid BD auctions are more likely to receive more bids, albeit those bids tend to be submitted by lower quality or inexperienced bidders. We also confirm the literature that higher-budget projects, longer auction duration, and featured projects are more likely to attract lower quality/less experienced bidders.

Table 3. Effect of Bid Visibility on Bidder Quality

	Model 1	Model 2	Model 3
DV:	<i>avg bidder quality</i>		<i>new bidder ratio</i>
Estimation Methods:	OLS	OLS with FE	Fractional Logit
Sealed	-0.0705*** (0.0162)	-0.144*** (0.0291)	0.0362*** (0.0134)
Project Budget	-0.000160*** (1.05e-05)	-0.000123*** (1.63e-05)	3.91e-05*** (8.10e-06)
Auction Duration	-0.00401*** (0.000301)	-0.00350*** (0.000501)	0.0106*** (0.000221)
Featured Project	-0.113*** (0.0196)	-0.194*** (0.0398)	0.116*** (0.0158)
Nonpublic Projects	0.0450*** (0.0158)	-0.135*** (0.0306)	-0.144*** (0.0136)
Average Buyer Rating	0.0259*** (0.00115)	0.00385 (0.00298)	-0.0225*** (0.000939)
Buyer Experience	0.00207*** (0.000114)	-0.00147 (0.00162)	-0.000890*** (0.000113)
Buyer Gold Member	-0.0565*** (0.0114)	-0.00766 (0.0141)	0.0637*** (0.00916)
Constant	6.766*** (0.0286)	7.304*** (0.0579)	-0.210*** (0.0243)
Period Dummies	Yes	Yes	Yes
Project Category Dummies	Yes	Yes	Yes
Buyer Fixed Effect	No	Yes	No
Num. of Observations	73,697	73,697	77,899
R-squared	0.077	0.028	0.066(AIC)
Number of Buyers	--	22,121	--

Notes: For OLS models, Robust standard errors are reported in parentheses.

For models with buyer fixed effect, cluster-robust standard errors are reported in parentheses;

*** p<0.01, ** p<0.05, * p<0.1

4.2.2 Auction Performance

Buyer Surplus: Buyer surplus is defined as the difference between buyer's willingness to pay (WTP) and the actual price paid (for a product or service). Since the contract price is given (selected bid), in order to measure buyer surplus, we need to estimate buyers' WTP. We considered two measures for WTP.

First, following Bapna et al. (2003) and Mithas et al. (2008), we use proxies for WTP. In labor markets, when buyers post jobs, they need to specify their estimated budget range with a maximum and a minimum budget. Although the stated budget range may not represent the exact WTP, it can be an accurate proxy as buyers have an incentive to correctly specify the budget according to their WTP as bidders take that information into account when evaluating the project and placing bids (Hong and Pavlou 2012). We use the maximum budget and average budget as two proxies for WTP, and we estimate buyer surplus as $budget^{max/avg} - SelectedBid$, the difference between stated maximum/average budget and the price offered by the selected bid. As Table 1 shows, buyers in our sample reap an average surplus of \$202.15 (STD=\$174.85) when using the maximum budget as a proxy for WTP, and \$61.22 (STD=\$149.3) when using the average budget as a proxy for WTP, respectively. Because the buyer surplus measure is skewed, we log-transformed this variable in our subsequent estimation.

Second, following Ghose et al. (2012), we first estimated a buyer's utility function and the marginal utility of income by looking at bid selection decisions with discrete choice models and the coefficient estimates therein. We then calculated dollar-equivalent utility buyer surplus for each auction. In the discrete choice model, while we do not directly observe utility, we assume that a buyer selects the bid to maximize her expected utility. The choice a buyer made among bids received thus reveals the buyer's preference for both price and non-price attributes. Based on the estimated utility function, we can then derive the dollar equivalent utility from non-price attributes and translate a bid to dollar equivalent surplus (utility). Details about the estimation of buyer preference are presented in Appendix II.

With these two measures of buyer surplus, we estimate the effect of auction design on buyer surplus using OLS with buyer fixed effect and similar specifications as analyses for other outcome variables.

$$BS_{ijqt} = \alpha + \beta_1 \times Sealed_{ijqt} + \beta_{2-8} \times (AuctionControls_i) + \beta_{9-10} \times (BuyerControls_{iq}) + \psi_t + \delta_q + \lambda_j + \varepsilon_{ijqt} \quad (11)$$

As Table 4 attest, on average, buyers in open bid BD auctions enjoy at least 19.2% higher surplus than buyers in sealed bid BD auctions, based on estimation results where the maximum budget is considered as the proxy for buyer's WTP. The estimated surplus gain from offering projects using open bid BD auctions is even greater if we use mean budget as the proxy for WTP (41.2% higher than sealed bid). Consistently, in the model where buyer surplus estimated by the discrete choice model, we found that open bid BD auctions offer an average of 23% more surplus to buyers than sealed bid BD auctions. H3 is thus supported.

Table 4. Effect of Bid Visibility on Buyer Surplus

DV:	Model 1 <i>ln(surplus proxy^{max})</i>	Model 2 <i>ln(surplus proxy^{avg})</i>	Model 3 <i>ln(surplus preference)</i>
Sealed	-0.186*** (0.0579)	-0.421*** (0.104)	-0.257*** (0.0914)
Project Budget	0.000793*** (6.66e-05)	0.000335*** (0.000117)	-0.00441*** (8.72e-05)
Auction Duration	-0.0106*** (0.00134)	-0.0231*** (0.00235)	-0.0148*** (0.00216)
Featured Project	-0.567*** (0.107)	-0.974*** (0.180)	-0.446*** (0.154)
Nonpublic Projects	-0.240*** (0.0561)	-0.547*** (0.102)	-0.172* (0.0969)
Average Buyer Rating	-0.0172*** (0.00401)	-0.0391*** (0.00783)	0.00832 (0.00773)
Buyer Experience	-0.00275*** (0.00102)	-0.00859*** (0.00210)	0.00152 (0.00273)
Buyer Gold Member	0.00531 (0.0255)	0.0131 (0.0491)	-0.0124 (0.0424)
Constant	4.679*** (0.0528)	2.915*** (0.101)	6.748*** (0.159)
Period Dummies	Yes	Yes	Yes
Project Category Dummies	Yes	Yes	Yes
Buyer Fixed Effect	Yes	Yes	Yes
Num. of Observations	45,270	45,270	44,707
R-squared	0.026	0.021	0.169
Number of Buyers	15,372	15,372	15,129

Notes: Cluster-robust standard errors are reposted in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Contract Probability and Buyer Satisfaction: For contract probability and buyer satisfaction with the service provided, we formulate the following empirical models to understand the effect of bid visibility (open bid versus sealed bid). Again, we include buyer fixed effects, project category and time dummies, as well as auction/buyer controls in the model specifications.

$$\begin{aligned} \text{logit}(\text{contract}_{ijqt} = 1) \\ = \alpha + \beta_1 \times \text{Sealed}_{ijqt} + \beta_{2-8} \times (\text{AuctionControls}_i) + \beta_{9-10} \\ \times (\text{BuyerControls}_{iq}) + \psi_t + \delta_q + \lambda_j + \varepsilon_{ijqt} \end{aligned} \quad (12)$$

$$\begin{aligned} \text{Satisfaction}_{ijqt} \\ = \alpha + \beta_1 \times \text{Sealed}_{ijqt} + \beta_{2-8} \times (\text{AuctionControls}_i) + \beta_{9-10} \\ \times (\text{BuyerControls}_{iq}) + \psi_t + \delta_q + \lambda_j + \varepsilon_{ijqt} \end{aligned} \quad (13)$$

To reflect critical stages in service contract in online labor market, we consider three contract outcomes (binary), namely, *selected* (whether the buyer selected a winner from bids received), *awarded* (whether the winner and the buyer successfully signed a contract), and *completed* (whether the project contracted was complete successfully). After a buyer receives bids for his project, she first need select a winner to contact. The buyer may choose not to select a winner if the auction fails to attract appropriate bids or the buyer is overwhelmed by the large number of bids that she need to evaluate. After a buyer selects a winning bidder, they need to reach an agreement and sign the formal contract. A service contract may fail to be awarded to the winning bidder if the buyer revokes the selection or the service provider refuses to accept the contract. After a contract is signed, the contracted service provider will provide the service and get paid accordingly. The project is left incomplete if the service provider fails to deliver the promised service. All three stages are critical to the successful delivery of a service contract in online labor markets and may be influenced by how the project is auctioned. In the empirical implementation, we consider three sequential stages of contract probability (1) whether a winner was selected; (2) whether the winner and the buyer signed a contract (awarded); and (3) whether the project was successfully completed. Estimation results are shown in Columns 1, 2 and 3 in Table 5. We found consistently significant effect for auction design across the three contract outcomes. Using odds ratio to interpret the Logit estimation results, open bid BD auctions have 50% higher odds of having a winning bid selected, 47% higher odds of getting contracted, and 38% higher odds of completion than sealed bid BD auctions. Therefore, H4 is supported.

Buyer satisfaction in a completed project is measured by self-reported feedback ratings (integer ratings from 1 to 10). Considering its ordinal nature, we estimate the model using an ordered Logit model with fixed effect. To consistently estimate the fixed effect ordered Logit model, we follow the “blow-up and

cluster” (BUC ordered Logit) method proposed by Baetschmann et al. (2011). As shown in Column 4 of Table 5, our estimation results suggest that sealed bid BD auctions offer less satisfactory results than open bid BD auctions ($\beta = -0.124, p < 0.05$), supporting H5.

Table 5. Effect of Bid Visibility on Contract probability and Buyer Satisfaction

DV:	Model 1	Model 2	Model 3	Model 4
	<i>Selected</i>	<i>Awarded</i>	<i>Completed</i>	<i>Satisfaction</i>
Sealed	-0.393*** (0.0548)	-0.383*** (0.0503)	-0.298*** (0.0513)	-0.130** (0.0670)
Project Budget	-0.00103*** (5.20e-05)	-0.00101*** (3.73e-05)	-0.00156*** (4.93e-05)	-0.00112*** (7.88e-05)
Auction Duration	-0.0256*** (0.00115)	-0.0284*** (0.000892)	-0.0264*** (0.00100)	-0.0102*** (0.00150)
Featured Project	0.136 (0.0854)	0.0704 (0.0724)	-0.0801 (0.0754)	-0.226** (0.0933)
Nonpublic Projects	-0.173*** (0.0558)	-0.193*** (0.0513)	-0.189*** (0.0517)	-0.188*** (0.0634)
Average Buyer Rating	-0.0529*** (0.00548)	-0.0506*** (0.00487)	-0.0721*** (0.00472)	-0.0748*** (0.00608)
Buyer Experience	-0.0192*** (0.00507)	-0.0223*** (0.00230)	-0.0251*** (0.00209)	-0.0195*** (0.00671)
Buyer Gold Member	-0.00779 (0.0283)	0.00690 (0.0270)	0.0219 (0.0273)	0.0181 (0.0343)
Period Dummies	Yes	Yes	Yes	Yes
Project Category Dummies	Yes	Yes	Yes	Yes
Buyer Fixed Effect	Yes	Yes	Yes	Yes
Num. of Observations	50,872	52,919	51,739	310,685
Number of Buyers	6,509	6,921	6,628	4,840

Notes: Cluster-robust standard errors are reposted in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

We also found that projects that have higher budget and longer auction duration, restrain public access, and are posted by experience/reputable buyers are less likely to select a winner, be contracted, and be completed, while they result in lower buyer satisfaction. Featured projects are less likely to result in higher buyer satisfaction. We also observe experienced buyers to become more selective in winner selection and are more critical in the evaluation of the service provided.

4.3 Identify and Quantify the “Screening Effect”

The analyses above provide support for the open bid BD auction mechanism as a superior choice for buyers in online labor markets. We attribute the advantage of open bid auctions to the “screening effect” that filters out low quality bidders. However, since all bidders are bounded in rationality (Simon 1982, Arthur 1994) and they may not have the cognitive resource to go over all the information supplied on the

marketplace to make a utility maximizing bidding decision, it will be useful to empirically examine whether bidders' entry behavior support our proposed "screening effect". Therefore, to further identify the existence of a "screening effect" of open bid BD auctions, we analyze the observations of service providers' bidding dynamics in both sealed and open bid BD auctions. As our theory predicts, compared with sealed bid BD auctions in which bidders cannot observe prior bids, open bid BD auctions would exhibit higher probability of lower quality bids after a high quality bid is submitted. Figure 1 illustrates the screening effect. And we explain our identification method below.

Figure 1. Bidder Quality and Bid Sequence in Sealed and Open Bid BD auctions

To examine this screening effect, we constructed a variable *Bid Sequence* based on the time stamp of bid submission (the first bid will be recorded as 1, the second bid 2, ..., the nth bid n), and relate bid sequence to measures of bid quality (the average rating and experience of the bidder) and expected buyer surplus from the bid (calculated using the method based on discrete choice framework described in Appendix II). Our results, as shown in Table 7, support the existence of "screening effect" in open bid BD auctions. Interestingly, bidder entry in neither sealed bid nor open bid BD auctions is random. High quality bids submitted by capable service providers tend to enter an auction earlier, as they might be less concerned about losing the competition, and they thus are less inclined to spend time observing other bids. Therefore, high quality bids - bids that provide higher surplus and posted by providers who have higher average ratings and more experience - tend to strategically enter an auction earlier. For all measures of bid quality, we consistently found later bids to have higher quality in open bid BD auctions (negative coefficient estimates for the interaction term, *Bid Sequence* * *Sealed*), supporting the "screening effect". Based on the coefficient

estimates, we can quantify the marginal effect of bid sequence on the measures of bid quality. The results show that the negative effect of bid sequence on provider average rating in open bid BD auctions is 26% lower than sealed bid auctions; the positive effect of bid sequence on the probability of the bidder being inexperienced in open bid is 17% lower than sealed bid BD auctions; the negative effect of bid sequence on provider project experience in open bid auctions is 38% smaller than sealed bid auctions; the negative effect of bid sequence on expected surplus of the bid in open bid auctions is 25% smaller than sealed bid auctions.

Table 7. Estimating the “Screening Effects”

	Model 1	Model 2	Model 3	Model 4
DV:	Average Rating	New Bidder	Experience	Expected CS
Bid	0.00045*** (0.00001)	-0.00036*** (0.00001)	0.0280*** (0.0005)	-1.098*** (0.003)
Bid Sequence	-0.0376*** (0.000492)	0.0401*** (0.000346)	-0.548*** (0.0201)	-6.219*** (0.0819)
Bid Sequence * Sealed	-0.0133*** (0.00176)	0.00829*** (0.00116)	-0.340*** (0.0672)	-2.117*** (0.307)
Constant	3.069*** (0.00707)		35.64*** (0.278)	473.2*** (1.369)
Project Fixed Effect	Yes	Yes	Yes	Yes
Observations	1,237,053	1,155,675	1,237,053	1,094,116
R-squared	0.01	-	0.003	0.205
Number of project_id	115,467	84,565	115,467	113,241

Notes:

Cluster robust standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

4.4 Propensity Score Matching (PSM)

In our main analyses, control variables as well as multiple fixed effects were included in the model specification to assure proper identification of the effect of bid visibility and to alleviate concerns about omitted variables and buyer selection bias. Although our empirical observation is robust to different model specifications and estimators, we cannot fully rule out endogenous buyer selection of auction design. In other words, the assignment of the auction design to buyers may not be random, leading to difficulty in identifying a causal effect. To alleviate this concern, we implemented Propensity Score Matching (PSM) (e.g., Rosenbaum and Rubin 1983; Abadie and Imbens 2006). Matching estimators are commonly used to address self-selection issues by creating a quasi-experimental condition for identification purpose. The basic idea is to create a sample of the control group (open bid BD auctions) that is statistically equivalent to the treatment group (sealed bid BD auctions) in all relevant observed pre-treatment characteristics. The method

has been utilized in recent IS studies to address selection issues in archival data observational studies (e.g., Aral et al. 2009, Oestreicher-Singer and Zalmanson 2013, Rishika et al. 2013). We conducted PSM by following Caliendo and Kopeinig (2008), Guo and Frasier (2010), and Rishika et al. (2013).

First, we identified the observed buyer, auction and project characteristics that are statistically different across the two groups, including buyer rating, buyer experience, buyer gold membership, auction duration, project budget, featured project, nonpublic project and also project categories dummies. We also included the year-month pair dummy variables (*ym1-ym6*). Second, we conducted the propensity score analysis using a probit model formulation because the treatment variable (*Sealed* vs. *Open*) is binary (same results will be produced using a logistic model). Specifically, we estimated the conditional probability of receiving a given treatment (sealed bid auction) given a vector of observed covariates. The groups of sealed bid auctions and open bid auctions with similar propensity scores are then expected to have similar values across all observed covariates, in aggregate. The results along with fit statistics are reported in Table 6. We then performed the process of matching the open bid auctions (control observations) on sealed bid auctions (treatment observations) using the estimated propensity scores. Multiple matching algorithms are available. To ensure the robustness of the results, we performed kernel matching, stratification matching, and nearest neighbor (NN) matching (maximum number of nearest neighbor observation = 4). The descriptive statistics and covariate comparison before and after NN matching are reported in Table 7. We were able to match 9,969 out of 40,899 open bid auctions to 4,353 sealed bid auctions. Next, we checked the assumptions of using PSM. We tried to detect if there is substantial overlap in the variables used in the matching process. As in Rishika et al. (2013), we used methods suggested by Lechner (2002) by visualizing the propensity score distributions of both sealed and open bids auctions, before and after. Both Figure 2 (box-plots) and Figure 3 (kernel density distributions) provide evidence that sealed and open bid auctions have common support for the distributions of propensity scores. Also, we checked if the covariates are balanced between the treatment and control groups before and after matching. Table 7 shows the results: the mean difference for each covariate is calculated by subtracting the mean of the control group from the mean of the treatment group; the *t* statistics for these differences in mean are also reported. The mean differences are not

significant from zero after matching, indicating improvement in covariate balancing due to matching.

Table 6. Probit Regression Model of Bid Design (Sealed vs. Open) Choice

DV:	Sealed Bid	
	Parameter	Standard Error
Project Budget	0.00005**	0.00002
Auction Duration	0.00626***	0.00061
Featured Project	0.33347***	0.03578
Nonpublic Projects	1.09270***	0.02125
Average Buyer Rating	0.01574***	0.00219
Buyer Experience	0.00009	0.00012
Buyer Gold Member	-0.07037***	0.01946
Category2	0.01216	0.01999
Category3	-0.03870	0.02566
ym1	0.00693	0.03323
ym2	-0.01680	0.03296
ym3	-0.02852	0.03233
ym4	-0.04385	0.03263
ym5	-0.04005	0.03299
ym6	-0.01904	0.03317
Constant	-1.713746	0.0227805
Num. of Observations		45, 252
LR Chi ² (9)		3177.41
Pseudo R-squared		0.12

Note: Robust standard errors are reported.

*** p<0.01, ** p<0.05, * p<0.1

Figure 2. Distribution of Propensity Score Before and After Matching

Table 7. Summary Statistics and Covariate Comparison Before and After Matching

	Treatment Group	Control Group (Open Bid)							
		Before Matching				After Matching			
<i>Variables</i>	<i>mean</i>	<i>mean</i>	<i>mean diff.</i>	<i>s.e.</i>	<i>t stat.</i>	<i>mean</i>	<i>mean diff.</i>	<i>s.e.</i>	<i>t stat.</i>
<i>Project Budget</i>	423.499	362.994	60.505	5.393	11.22	426.077	-2.578	8.135	-0.32
<i>Auction Duration</i>	10.075	8.068	2.007	0.204	9.83	10.384	-0.309	0.295	-1.05
<i>Featured Project</i>	0.110	0.038	0.072	0.003	21.89	0.101	0.008	0.006	1.43
<i>Nonpublic Projects</i>	0.403	0.079	0.323	0.005	68.00	0.402	0.000	0.009	0.01
<i>Buyer Rating</i>	7.377	6.878	0.499	0.067	7.48	7.304	0.073	0.077	0.95
<i>Buyer Experience</i>	20.693	22.355	-1.662	1.182	-1.41	19.967	0.726	1.428	0.51
<i>Buyer Gold Member</i>	0.263	0.291	-0.028	0.007	-3.89	0.250	0.013	0.009	1.52
<i>Category2</i>	0.540	0.497	0.043	0.008	5.41	0.548	-0.008	0.010	-0.85
<i>Cateogry3</i>	0.167	0.212	-0.045	0.007	-6.96	0.159	0.008	0.008	1.09
<i>ym1</i>	0.142	0.133	0.010	0.005	1.79	0.154	-0.012	0.007	-1.64
<i>ym2</i>	0.142	0.143	0.000	0.006	-0.02	0.136	0.007	0.007	0.94
<i>ym3</i>	0.156	0.156	-0.001	0.006	-0.11	0.151	0.005	0.007	0.63
<i>ym4</i>	0.146	0.154	-0.008	0.006	-1.43	0.138	0.008	0.007	1.16
<i>ym5</i>	0.132	0.128	0.004	0.005	0.78	0.135	-0.003	0.007	-0.43
<i>ym6</i>	0.142	0.145	-0.003	0.006	-0.53	0.141	0.001	0.007	0.17
<i>ym7</i>	0.139	0.141	-0.002	0.006	-0.35	0.145	-0.006	0.007	-0.84

After matching on propensity scores, we were able to identify the “treatment effect” of sealed bid auction (vs. control of open bid auction) on our performance measures. The results of our matching analyses using Kernel matching, stratification matching, and NN matching, as reported in Table 8. Different matching algorithms yielded parameter estimates that are qualitatively the same, further strengthening the robustness of our findings concerning the effect of bid visibility on bidder strategic entry and auction performance.

Table 8. Propensity Score Matching Estimates

	Model 1	Model 2	Model 3	Model 4
(Sample size = 45, 252)	Number of Bids	New Bidder Ratio	Buyer Surplus	Satisfaction
Sealed Bid Effect (Kernel matching)	1.751*** (0.200)	0.010** (0.004)	-0.133*** (0.041)	-0.241*** (0.084)
Sealed Bid Effect (Stratification method matching)	0.962*** (0.230)	0.008*** (0.003)	-0.113** (0.044)	-0.197** (0.084)
Sealed Bid Effect (Nearest neighbor matching)	0.950*** (0.283)	0.00789** (0.00396)	-0.0782** (0.0402)	-0.226** (0.102)

Notes: Bootstrapped standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

5. Conclusion and Implications

5.1 Key Findings

In this study, we compared open versus sealed bid BD auctions in the context of online labor markets. Our theoretical analysis shows that whereas the sealed bid BD auctions are indeed able to attract more bids, open bid BD auctions attract higher quality bids that are more likely to be contracted and offer a higher buyer surplus and satisfaction. This is because high quality bids in open bid BD auctions helps “screen out” low quality bids and avoid bidding costs to providers and corresponding bid evaluation costs to buyers. Our empirical results based on a unique proprietary dataset from *Freelancer* with both sealed and open bids confirm our analytical results and find significant effects of auction design (bid visibility) on strategic entry and auction performance. Notably, we quantified the economic effects of auction design on BD auctions. Compared with sealed bid BD auctions, open bid BD auctions attract 8.1% fewer bids, they result in 3.59% fewer bids from lower quality or inexperienced providers, they are 50% more likely to get contracted, and they extract at least 19% more in buyer’s surplus. They also result in significantly higher buyer satisfaction.

5.2 Implications for Theory

This research contributes to the literature on (a) auction design and (b) online labor markets by proposing an extended theoretical model and providing unique real-life empirical observations. Specifically, we seek to fill the research gap in the literature on auction design between sealed and open bid BD auctions in online labor markets with respect to bidder strategic entry, bidder quality, and auction 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 bid creates a “screening” mechanism that affect bidders’ equilibrium entry and bidding strategy. Therefore, we observe that open bid BD auctions consistently outperform sealed bid BD auctions with various different performance measures, such as contract probability, buyer surplus and buyer satisfaction. Our empirical validation confirms the existence of the screening effect of open-bids BD auction format, which renders the assumptions for revenue equivalence theorem invalid in the context of BD auctions (Vickrey 1961), mainly due to the non-negligible cost of bidding (Snir and Hitt 2003), which is prevalent

in online labor markets. Our study thus extends Athey et al. (2011)'s work on comparing auction designs in terms of bidder entry strategy from the context of forward commodity auction (US timber auctions) to reverse BD auctions (online labor markets). We empirically show the effects of "bid visibility" in a distinct auction context (BD auctions) and empirical context (labor markets) with more observations and additional important performance measures. Compared with the research design (lab experiments) and results from Haruvy and Katok (2012), our study incorporates the notions of both bidding sequence and bidding costs and also bid evaluation, both of which have a significant impact on bidders' strategic entry. Our large-scale observational data also renders enough power for rigorous econometric identification and estimation.

Second, our study examines auction design as an important theoretical problem for BD auctions and online labor markets. Auction design is a prime example of information system design that involves the moderation of the marketplace (Allon et al. 2012), which has a significant effect on bidding strategy of the service providers and resulting surplus of the buyers. Despite the proliferation of online labor markets, there is a dearth of research on the optimal design and performance effects of these markets. Our study links auction design with the service providers' entry strategy and provides theoretical support for open bid BD auction as an increasingly popular auction design in online labor markets. As labor markets are usually buyer (demand) driven, intermediary's proper incentives for buyers in terms of selecting appropriate auction mechanisms have practical consequences for the sustainability of such markets.

Finally, we proposed several important performance measures for online labor markets, such as bidder quality, inexperienced bidder ratio, and estimated buyer surplus. These performance measures can be used by future research that seeks to understand effect of other auction designs on auction performance.

5.3 Implications for Practice

This study has concrete and actionable 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 buyers, potentially increasing buyer surplus. Therefore, it is a common practice for online labor market intermediaries to charge a fee when posting jobs using the sealed bid BD auction format. The direct implication for practitioners is that more bids may not translate into higher surplus or better performance.

We found that open bid BD auctions consistently outperform sealed bid BD auctions, despite fewer bids received. Charging fees for sealed bid auctions may be misleading, and even harmful for intermediaries.

Second, for buyers, blindly pursuing more bids by using sealed bid auctions may not be a good strategy. First, posting jobs using sealed bid BD auction usually comes at a cost (e.g., *Freelancer* used to charged \$1 for posted a sealed bid BD auction, and the cost has recently increased to \$9), which can be avoided by using the default open bid format. Second, more bids entail a higher evaluation cost. If the buyer cannot afford to evaluate all bids (especially low quality bids), posting jobs with open bid BD auctions will be a superior choice. Nevertheless, one caveat merits mention in terms of the selection of auction design. Poorer auction performance notwithstanding, sealed bid BD auction design still has its attractiveness in some cases. For example, potential for collusive bidding (Athey et al. 2011) among service providers can be mitigated by sealed bids. In addition, when providers are concerned about opening their bids to the public (potentially due to privacy reasons), sealed bid design should be used to alleviate provider concerns.

Finally, this study has implications for other practical contexts as well. What we found in this study was that the visibility of bids could filter out low quality bidders and indirectly reduce buyers' evaluation costs. The open auction design can be used in contexts such as grant proposal submission and job market postings, and other similar contexts that the screening effect is needed to weed out low-quality bidders.

5.4 Limitations and Future Research

The current study is not without limitations, which create interesting opportunities for future research:

First, for analytical tractability and our focus on empirical comparisons, we chose a relatively restricted partial equilibrium theoretical model set up. While this set up allowed for clear theoretical comparisons to be readily made, it may be inadequate to capture the general equilibrium and 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 across service providers. Future research could derive more general and flexible models to allow for incomplete information. For example, risk aversion might lead service providers in sealed bid auctions to bid a higher price as they have imperfect information.

Second, we focus our attention on CFB situation where little pre-contract investment on the project is required. There are other examples of call-for-proposals where significant pre-contract investment is

needed to form the proposal in order to compete for the project. For example, some online labor markets have adopted open innovation tournaments (Terwisch and Xu 2008) where service providers not only bid with a price quote, but they also submit a final product as part of their bid. It would be interesting for future research to extend the discussion about auction design to that context.

Third, buyers choose to select either “sealed” or “open” auction designs to post their CFBs. Although we have employed both buyer fixed effects and propensity score matching to parse out selection bias, the identification is not perfect since we cannot control for unobserved, time variant buyer attributes, or hidden project characteristics. Although this limitation is typical for observational studies and should not seriously jeopardize our main findings, future research could use other research methodologies other than econometrics methods for identification. For example, future studies might implement field experiments to further confirm findings from archival data analysis. It might also be interesting for the marketplaces to experiment with alternative designs to enhance auction performance.

Fourth, as bidders observe the winner in open bids auctions, therefore there may exist “learning effects” in open bid auctions. When providers accumulate experience on the marketplace, they may get to know the exact preference of buyers and optimize their chance of winning a contract. Future research could study the learning effect using dynamic structural models on how providers update their bidding strategy over time.

6. Concluding Remark

To conclude, online labor markets have changed the way firms and service providers interact and the way labor is exchanged globally. One important issue facing online labor markets today is to how the design of the auction mechanism (bid visibility) would affect market competition and auction performance. Despite recent progress, the effect of bid visibility on bidder entry and auction performance in BD auctions remains unclear. Leveraging unique proprietary data on both open and sealed (hidden from the public) bid auctions, we identify the “screening effect” of open bid BD auctions. Interestingly, open bid auctions attract fewer but higher quality bids, thus being a superior option for buyers in online labor markets. As many other design features are being proposed by practitioners to facilitate labor exchange, our study invites IS scholars and practitioners to look at the effect of auction design on the strategic behavior of bidders and auction performance in online labor markets to obtain a better grasp on the design of online auctions.

References

1. Abadie, A. and Imbens, G. W. 2006. "Large Sample Properties of Matching Estimators for Average Treatment Effects." *Econometrica*, (74:1), 235–267.
2. Agrawal, A.K., N. Lacetera, E. Lyons. (2013). "Does Information Help or Hinder Job Applicants from Less Developed Countries in Online Markets?" *NBER Working Paper No. 18720*. (Available at: <http://www.nber.org/papers/w18720>).
3. Allon, G., Bassamboo, A., & Çil, E. B. (2012). "Large-scale Service Marketplaces: The Role of the Moderating Firm." *Management Science*, 58(10), 1854-1872.
4. Anwar, S., McMillan, R., and Zheng, M. 2006. "Bidding Behavior in Competing Auctions: Evidence from Ebay," *European Economic Review* (50:2), pp 307-322.
5. Aral, S., Muchnik, L., and Sundararajan, A. 2009. "Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks," *Proceedings of the National Academy of Sciences*, (106:51), pp 21544–21549.
6. Arozamena, L., and Cantillon, E. 2004. "Investment Incentives in Procurement Auctions," *The Review of Economic Studies* (71:1), pp 1-18.
7. Arthur, W. 1994. "Inductive reasoning and bounded rationality." *The American Economic Review* (84:2) pp 406-411.
8. 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.
9. Bajari, P., and Hortacsu, A. 2004. "Economic Insights from Internet Auctions," *Journal of Economic Literature* (42:2), pp 457-486.
10. Bajari, P., and Ye, L. 2003. "Deciding between Competition and Collusion," *Review of Economics and Statistics* (85:4), pp 971-989.
11. 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.
12. 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.
13. Bapna, R., Dellarocas, C., and Rice, S. 2010. "Vertically Differentiated Simultaneous Vickrey Auctions: Theory and Experimental Evidence," *Management Science* (56:7), pp 1074-1092.
14. Bapna, R., Jank, W., and Shmueli, G. 2008. "Price Formation and Its Dynamics in Online Auctions," *Decision Support Systems* (44:3), pp 641-656.
15. Bapna, R., Jank, W., and Shmueli, G. 2008. "Consumer Surplus in Online Auctions," *Information Systems Research* (19:4), pp 400-416.
16. Baetschmann, G., Staub, K. E. and Winkelmann, R. 2011 "Consistent Estimation of the Fixed Effects Ordered Logit Model," *IZA Discussion Paper No. 5443*.
17. Branco, F. 1997. "The Design of Multidimensional Auctions," *The RAND Journal of Economics* (28:1), pp 63-81.
18. Bulow, J., and Klemperer, P. 2009. "Why Do Sellers (Usually) Prefer Auctions?" *American Economic Review* (99:4), pp 1544-1575.
19. Caliendo, M., and Kopeinig, S. (2008). "Some Practical Guidance for the Implementation of Propensity Score Matching." *Journal of Economic Surveys*, (22:1), pp 31-72.
20. Campbell, C., Ray, G., and Muhanna, W.A. 2005. "Search and Collusion in Electronic Markets," *Management Science* (51:3), pp 497-507.
21. Carr, S.M. 2003. "Note on Online Auctions with Costly Bid Evaluation," *Management Science* (49:11), pp 1521-1528.
22. Cason, T. N., Kannan, K. N., and Siebert, R. (2011). "An Experimental Study of Information Revelation Policies in Sequential Auctions." *Management Science*, (57:4), pp 667-688.
23. Che, Y.-K. 1993. "Design Competition through Multidimensional Auctions," *The RAND Journal*

- of Economics* (24:4), pp 668-680.
24. Chen, F. 2007. "Auctioning Supply Contracts," *Management Science* (53:10), pp 1562-1576.
 25. 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.
 26. Cummings, J.N., Espinosa, J.A., and Pickering, C.K. 2009. "Crossing Spatial and Temporal Boundaries in Globally Distributed Projects: A Relational Model of Coordination Delay," *Information Systems Research* (20:3), pp. 420-439.
 27. Davis, A.M., Katok, E., and Kwasnica, A.M. 2011. "Do Auctioneers Pick Optimal Reserve Prices?" *Management Science* (57:1), pp 177-192.
 28. Ellison, G., Fudenberg, D., and Möbius, M. 2004. "Competing Auctions," *Journal of the European Economic Association* (2:1), pp 30-66.
 29. Elmaghraby, W. 2007. "Auctions within E-Sourcing Events," *Production and Operations Management* (16:4), pp 409-422.
 30. 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.
 31. 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.
 32. Engelbrecht-Wiggans, R., and Katok, E. 2008. "Regret and Feedback Information in First-Price Sealed-Bid Auctions," *Management Science* (54:4), pp 808-819.
 33. Espinosa, J.A., Slaughter, S.A., Kraut, R.E., and Herbsleb, J.D. 2007. "Familiarity, Complexity, and Team Performance in Geographically Distributed Software Development," *Organization Science* (18:4), pp. 613-630.
 34. 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.
 35. 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.
 36. Guo, S., and Fraser, M. W. 2010. *Propensity Score Analysis: Statistical Methods and Applications*. (Sage, Menlo Park, CA).
 37. Haruvy, E., and Katok, E. 2012. "Increasing Revenue by Decreasing Information in Procurement Auctions," *Production and Operations Management* (22:1), pp 19-35.
 38. 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.
 39. 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.
 40. 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.
 41. Hong, Y., and Pavlou, P.A. 2012. "Strategic Bidding and Personalized Pricing in Global E-Markets for Services Outsourcing," *Academy of Management Best Paper Proceedings*: Academy of Management.
 42. 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 (ICIS)*, Orlando, FL.
 43. 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/>
 44. 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.

45. Howe, J. 2006 "The Rise of Crowdsourcing." *Wired Magazine* (14:6), pp 1-4.
46. Ivanova-Stenzel, R., and Salmon, T.C. 2004. "Bidder Preferences among Auction Institutions," *Economic Inquiry* (42:2), pp 223-236.
47. 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.
48. Jap, S.D. 2003. "An Exploratory Study of the Introduction of Online Reverse Auctions," *Journal of Marketing* (67:3), pp 96-107.
49. Jap, S.D. 2007. "The Impact of Online Reverse Auction Design on Buyer-Supplier Relationships," *Journal of Marketing* (71:1), pp 146-159.
50. Jap, S.D., and Haruvy, E. 2008. "Interorganizational Relationships and Bidding Behavior in Industrial Online Reverse Auctions," *Journal of Marketing Research* (45:5), pp 550-561.
51. 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.
52. Kannan, K.N. "Effects of Information Revelation Policies under Cost Uncertainty," *Information Systems Research* (23:1), pp 75-92.
53. Kostamis, D., Beil, D.R., and Duenyas, I. 2009. "Total-Cost Procurement Auctions: Impact of Suppliers' Cost Adjustments on Auction design Choice," *Management Science* (55:12), pp 1985-1999.
54. Kuruzovich, J., Viswanathan, S., and Agarwal, R. 2010. "Seller Search and Market Outcomes in Online Auctions," *Management Science* (56:10), pp 1702-1717.
55. Lin, M. and P. Goes (2012), "Does Information Really 'Unravel'? Understanding Factors That Motivate Sellers to Seek Third-Party Certifications in an Online Labor Market," University of Arizona working paper.
56. List, J.A. 2001. "Do Explicit Warnings Eliminate the Hypothetical Bias in Elicitation Procedures? Evidence from Field Auctions for Sports cards," *The American Economic Review* (91:5), pp 1498-1507.
57. List, J.A., and Lucking-Reiley, D. 2000. "Demand Reduction in Multiunit Auctions: Evidence from a Sports card Field Experiment," *The American Economic Review* (90:4), pp 961-972.
58. Maskin, E., and Riley, J. 2000. "Asymmetric Auctions," *The Review of Economic Studies* (67:3), pp 413-438.
59. Mill, R. 2011. Hiring and Learning in Online Global Labor Markets. NET Institute Working Papers No. 11-17. (Available at: <http://archive.nyu.edu/handle/2451/31411>)
60. 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.
61. 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.
62. Mittal, Vikas, and Wagner A. Kamakura. 2001. "Satisfaction, repurchase intent, and repurchase behavior: investigating the moderating effect of customer characteristics." *Journal of Marketing Research* (38:1), pp 131-142.
63. Oestreicher-Singer, G., and Zalmanson, L. 2013. "Content or Community? A Digital Business Strategy for Content Providers in the Social Age," *MIS Quarterly* (37:2), pp. 591-616.
64. 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.
65. Papke, L. E., and Wooldridge, J. M. 2000. "Econometric Methods for Fractional Response Variables with an Application to 401 (K) Plan Participation Rates." *Journal of Applied Econometrics* (11:6), pp 619-632.
66. 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.
67. Porter, R.H., and Zona, J.D. 1993. "Detection of Bid Rigging in Procurement Auctions," *Journal*

- of Political Economy* (10:3), pp 518-538.
68. Rishika, R., Kumar, A., Janakiraman, R., and Bezawada, R. (2013). "The Effect of Customers' Social Media Participation on Customer Visit Frequency and Profitability: An Empirical Investigation." *Information Systems Research*, (24:1), pp 108-127.
 69. Scholz, M., N. Haas. (2011). "Determinants of reverse Auction Results: An Empirical Examination of Freelancer.com." *Proceedings of the European Conference on Information Systems (ECIS)*.
 70. Snir, E.M., and Hitt, L.M. 2003. "Costly Bidding in Online Markets for It Services," *Management Science* (49:11), pp 1504-1520.
 71. Stoll, S., and Zottl, G. 2012. "Information Disclosure in Dynamic Buyer-Determined Procurement Auctions: An Empirical Study." Working Paper.
 72. Simon, H. A. 1982. "Models of Bounded Rationality: Empirically Grounded Economic Reason." Vol. 3. MIT Press.
 73. Terwiesch, C., and Xu, Y. (2008). "Innovation Contests, Open Innovation, and Multiagent Problem Solving," *Management Science* (54:9), pp 1529-1543.
 74. 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.
 75. Vickrey, W. 1961. "Counterspeculation, Auctions, and Competitive Sealed Tenders," *The Journal of Finance* (16:1), pp 8-37.
 76. Xu, L., Chen, J., and Whinston, A. 2011. "Price Competition and Endogenous Valuation in Search Advertising," *Journal of Marketing Research* (48:3), pp 566-586.
 77. Zeithammer, R. 2006. "Forward-Looking Bidding in Online Auctions," *Journal of Marketing Research* (43:3), pp 462-476.
 78. Zeithammer, R., and Adams, C. 2010. "The Sealed-Bid Abstraction in Online Auctions," *Marketing Science* (29:6), pp 964-987.
 79. Zhang, X.M., and Feng, J. 2012. "Cyclical Bid Adjustments in Search-Engine Advertising," *Management Science* (57:9), pp 1703-1719.

Appendix I: Derivation of Buyer Surplus

For open bid BD auctions, the provider with the highest quality bids to match the surplus provided by the provider 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 provider of the second highest quality.

For sealed bid BD auctions, from Equation 3, we have:

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

Appendix II: Estimating Buyer Surplus Using Discrete Choice Models

We estimate buyer surplus from an auction using discrete choice framework. Mathematically, buyer surplus associated with a set of alternatives takes a closed form solution that is possible to calculate (Train 2009) as:

$$CS_n = \frac{1}{\alpha_n} \max_j (U_{nj} + \varepsilon_{nj}) \quad (A1)$$

where α_n is the marginal utility of income. In the discrete choice framework, we do not directly observe the utility of a buyer. Rather, we assume that the buyer's choice maximizes his utility and thus reveals 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 bid 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 ε_{nj} 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:

$$\Pr(I = i) = \frac{\exp(\text{Bidder_attribute}_{ij} \times \beta - p_{ji}\lambda)}{\sum_{i=1}^N \exp(\text{Bidder_attribute}_{ij} \times \beta - p_{ji}\lambda)} \quad (A2)$$

Therefore, we estimate the following equation:

$$\begin{aligned} \text{logit}(I = i) &= \text{Bidder_attribute}_{ij} \times \beta - p_{ji}\lambda + c_j + u_{ijt}; E(u_{ijt} | \text{Bidder_attribute}_{ij}, c_j) = 0, j \\ &= 1, 2, \dots, N \end{aligned} \quad (A3)$$

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 cost is equivalent to a one-dollar increase in income, since the buyer 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. 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 significant variables that influence bid selection decisions as identified in the literature (e.g., Banker and Hwang 2008, Gefen and Carmel 2008, Hong and Pavlou 2013b), including 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 A1.

Table A1. Buyer Preference in Bid Selection ^a
(DV=whether a bid is selected to contract with)

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 ^b	0.014*** (5.23e-04)
Num. of Observations	683,662
Pseudo R-squared	0.172

Note:

a. We estimate buyer preference using conditional Logit model.

b. PPP denotes the purchasing power parity adjusted GDP per capita. PPP data is collected from the *CIA World Factbook* and merged into the main dataset.

Cluster robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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

$$\begin{aligned}
 E(\mathbf{BS}) = & [-0.027 \times DaysToFinish - 3.768 \times HiddenBid + 0.114 \times BidderRating + 0.742 \\
 & \times BidderCompletionRate - 9.87 \times HighlightedBid + 0.0009 \\
 & \times BidderExperience + 0.0483 \times BidderGoldMember + 0.4861 \\
 & \times SameCountry + 2.409 \times InvitedBidder + 0.014 \times BidderPPP] \\
 & / 0.0019 - BidPrice
 \end{aligned}
 \tag{A4}$$

Appendix III: Additional Descriptive Statistics

Table A3. Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. <i>number_bids</i>														
2. <i>average_bidder_quality</i>	-0.06													
3. <i>new_bidder_ratio</i>	-0.07	0.19												
4. <i>completed_project</i>	0.32	-0.10	-0.15											
5. <i>lnsurplus_max</i>	0.06	0.00	-0.02	0.00										
6. <i>lnsurplus_avg</i>	0.01	0.03	0.06	0.00	0.89									
7. <i>lncs_preference</i>	-0.03	0.06	0.06	-0.05	0.01	0.07								
8. <i>ex post_rating</i>	-0.09	0.22	0.78	-0.15	-0.02	0.06	0.06							
9. <i>sealed-bid</i>	0.04	-0.02	-0.01	0.02	-0.01	-0.04	-0.01	-0.02						
10. <i>max_budget</i>	0.11	-0.06	-0.16	0.01	0.41	-0.04	-0.12	-0.16	0.05					
11. <i>auction_duration</i>	0.13	-0.07	-0.11	0.14	-0.01	-0.06	-0.03	-0.11	0.05	0.10				
12. <i>featured_project</i>	0.11	-0.05	-0.05	0.06	0.04	-0.06	-0.04	-0.05	0.10	0.20	0.06			
13. <i>nonpublic_project</i>	0.03	0.00	0.01	-0.01	0.00	-0.05	-0.01	-0.01	0.31	0.09	0.00	0.16		
14. <i>buyer_rating</i>	-0.11	0.13	0.16	-0.10	-0.02	0.04	0.04	0.17	0.03	-0.11	-0.07	-0.11	0.03	
15. <i>buyer_experience</i>	-0.08	0.12	0.09	-0.04	0.00	0.02	0.03	0.11	-0.02	-0.04	0.00	-0.05	-0.04	0.17