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The Screening Role of Design Parameters for Service Procurement Auctions in Online Service Outsourcing Platforms

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Abstract. This paper provides a novel theoretical angle and robust empirical evidence demonstrating that the auction duration and item description length are two essential auction design parameters that can function as a screening mechanism for bidder quality on online service outsourcing platforms. These outsourcing platforms use buyer-determined reverse auctions to find providers of services (primarily IT services). Using data from a major online outsourcing platform that connects buyers with bidders, we examine the effects of the auction duration and the item description length on both bidder entry (i.e., the number of bids and bidder quality) and contract outcomes (i.e., whether a project is contracted and the buyer's expected utility from the winning bid) based upon not only project-level, but also bidder-level analyses. Our results show that auctions with longer durations and item descriptions attract more bids (i.e., higher quantity of bidders), and they also attract disproportionately more bidders with lower completion rates (i.e., lower quality of bidders), creating a double whammy of higher evaluation costs and adverse selection for buyers. This, in turn, leads to contracting inefficiency in terms of less successful contracting as well as lower buyer utility. Our research shows strong support for the screening role of the auction duration and the item description length for buyers on online outsourcing platforms for service procurement: by shortening auction durations and item descriptions, buyers can expect higher quality bidders, increase contracting probability, and enhance utility.

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1. Introduction

During the COVID-19 pandemic, many business owners had to shutter their brick-and-mortar operations and move their businesses online. Meanwhile, many of them turned to online outsourcing platforms to hire temporary workers rather than full-time employees to maintain the needs of operations.[1] For instance, Fiverr experienced a 28% increase in the number of active buyers in the second quarter of 2020 and more than a 200% increase in searches for web developers between April and September in 2020.[2] Other online outsourcing platforms, such as Freelancer, Upwork, and Guru, also experienced similar growth in demand and had been expanding at an astounding pace. Because of their significant impact on the economy, online outsourcing platforms have drawn much attention from information systems (IS) researchers (Snir and Hitt 2003, Moreno and Terwiesch 2014, Hong et al. 2016).

These online outsourcing platforms typically operate in the form of buyer-determined reverse auctions in which buyers post "calls for bids" to procure services and service providers submit bids to compete for contracts. Despite the extensive literature on buyers' preferences (e.g., Banker and Hwang 2008, Moreno and Terwiesch 2014, Pallais 2014) and bidders' strategic behaviors *after* an auction begins (e.g., Roth and Ockenfels 2002, Ariely and Simonson 2003, Albano et al. 2009, Simonsohn 2010, Kreye 2011), few studies to date examine the impact of important auction design parameters that are set *before* an auction starts. Accordingly, there is limited understanding of how auction design parameters affect bidder entry, contracting decisions, and the buyer's expected utility from the winning bid.[3] Whereas there are notable exceptions that investigate the auction design problem, they mainly focus on such factors as auction duration

(Mithas and Jones 2007, Bapna et al. 2008) and bid decrement (Mithas and Jones 2007) in auctions for products. On online outsourcing platforms, auctions are mainly for labor services, which are not standardized and whose bids usually are evaluated with multiple attributes (e.g., price and bidder quality) (Moreno and Terwiesch 2014). As such, apart from the *quantity* of bidders, the *quality* of the bidder pool is equally critical and arguably more so to both the outcome of an auction and the buyer's utility from the contracted service on these platforms. Bearing this in mind, this paper aims at providing a new theoretical lens focusing on the screening role of design parameters for procurement auctions.

In auction theory, auction design has long been a focal area of interest.[4] Prior research examines several different auction design parameters, such as bid price visibility (Hong et al. 2016), quality visibility (Stoll and Zöttl 2017), reserve price (Mithas and Jones 2007), and bid increment (Mithas and Jones 2007). Similar to other auction settings, online outsourcing platforms often allow buyers to vary design parameters, such as project category, required skills, project budget, auction duration, and item description.[5] Among them, project category is dictated by task requirements (e.g., software development, web design, etc.), whereas required skills and project budget are largely predetermined by the project's nature and the buyer's budget, so examining the impact of those characteristics on bidder entry has limited practical implications. Notably, the auction duration and the item description length can be more freely set by buyers and can potentially influence outcomes. Here, we note that the *auction duration* and *item description*[6] during the auction stage are different from the actual *project duration* and *requirement description* during the contract stage, which occurs after a service provider is chosen by the buyer. The goal of the auction stage is to solicit bids and choose a service provider, followed by the contract stage with the service provider, and subsequently the actual project execution stage. The project duration and requirement description are most relevant during the contract and project execution stages and are highly dictated by project scope and complexity; on the other hand, the auction duration and the item description are less dependent on project complexity and more on buyer discretion. For instance, even for projects of similar complexity, buyers can set long or short auction durations, which may attract different bidders' entries. Similarly, for the item description, buyers may provide just a brief overview of the project at the auction stage, opting to provide a more detailed description and requirements after a service provider has been selected. Buyers, thus, have a high degree of freedom in setting the auction duration and item description to influence bidder entry and contract outcomes.[7] In essence, the auction duration and the item description are two design parameters that buyers can vary when launching auctions, and both of them likely affect bidder entry and, accordingly, contract outcomes as discussed.

Intuitively, one expects that auctions with longer bidding durations and more detailed item descriptions could potentially benefit buyers because they can help attract more bidders by providing more bidding time and reducing the uncertainty regarding the project. However, even with the assumed positive effect on the quantity of bidders attracted, the net effect on buyer utility depends more critically on how longer auction durations and more detailed item descriptions also impact the quality of bidders. Furthermore, as pointed out by Fu et al. (2021), buyers tend to place more emphasis on the skill match between bidders and project requirements in high-skilled projects than in low-skilled ones, suggesting buyers' sensitivity to the quality of bidders in our context of IT service procurement projects. If auctions with longer durations and more detailed item descriptions attract more bidders but with lower quality, they may actually reduce buyer utility.

Bidder quality is a critical factor in auctions for labor services in which a winning bid is determined by multiple attributes (e.g., price and quality). There is a related stream of literature focusing on buyers' optimal buying mechanism under various assumptions in scoring auctions in which buyers preannounce their scoring rules (Che 1993, Branco 1997, Asker and Cantillon 2006). Buyers usually evaluate multidimensional bids by assigning weights to different relevant attributes and computing an overall score for each bid (Adomavicius et al. 2012). Among them, *price* and *quality* are two of the most important attributes affecting buyer utility (Che 1993, Adomavicius et al. 2012) as revealed by buyers' contracting decisions. Despite considerable effort devoted to quantifying the effect of design parameters on price (e.g., Lucking-Reiley 2000, Mithas and Jones 2007), the literature on their effect on other outcomes (especially bidder quality and buyer utility) is quite limited.

To fill this gap, we first focus on the auction duration and seek to answer the following: how does the auction duration affect bidder entry (i.e., the number of bids and bidder quality) and contract outcomes (i.e., the project being contracted and the buyer's expected utility from the winning bid)? The auction duration is an essential part of online auction design. Unlike traditional auctions in which bidders gather at an auction house to bid for a product over the course of a few minutes, online auctions can last for days, sometimes even weeks. On major online outsourcing platforms, the auction duration is a parameter that the buyer decides a priori, and it may have a significant effect on prospective bidders' decisions to submit their bids.

There is a stream of literature exploring the effect of the auction duration on the number of bids and final prices of online auctions. However, the contexts for most of these previous studies are auctions of products that mainly involve traditional forward auctions with price as the single bid attribute (Bapna et al. 2008; 2009; Haruvy and Leszczyc 2010). In those cases, a longer auction duration tends to attract more bidders and leads to better contracting outcomes given that bids in product auctions are homogenous except for the price, which tends to go up as the auction continues. By contrast, in our context, labor services are bid through reverse, buyer-determined auctions, and both price and bidder quality are critical bid attributes that buyers consider (Che 1993). Further, as the emerging literature on service procurement auctions and multidimensional auctions suggests, bid price is usually decided upon both bidder quality (Che 1993, Adomavicius et al. 2012) and buyer price sensitivity (Hong et al. 2020, Fu et al. 2021), which entails a more comprehensive contract outcome than price alone. Drawing on the literature on multidimensional auctions (Che 1993, Adomavicius et al. 2012), we first examine buyers' sensitivities to price and bidder quality and further quantify the effects of design parameters on their utility derived from both price and bidder quality.

In our view, the effect of the auction duration may be different from the findings of prior studies for two reasons. First, a longer auction duration may discourage the entry of high-quality bidders and lead to lower quality of the bidder pool. Because high-quality service providers tend to have higher opportunity costs associated with the waiting time compared with low-quality service providers (Kwasnica and Katok 2007), they are likely to favor shorter duration auctions that offer quicker decisions on the contract-winning bids. Relatedly, in the innovation contest context, Chen et al. (2021) also find that long contest durations can reduce the incentive for high-quality contestants to participate because of the long wait. Consequently, long auction durations may drive away high-quality bidders with high opportunity costs, inadvertently resulting in adverse selection and negatively impacting contract outcomes. Second, unlike the forward product auctions in which the outcome variable of price always goes up as the auction proceeds, in the reverse service auctions, there is a nonmonotonic relationship between bid price and auction process because high-quality service providers have some pricing power based on their reputation (Moreno and Terwiesch 2014). For example, when the average quality of an existing bidder pool is relatively low, high-quality bidders can command a reputation premium if they decide to bid (Liu et al. 2012). Therefore, even though longer auction durations may attract more bidders, it does not necessarily lead to a lower price or higher buyer utility. Taken together, the effect of the auction duration on the number of bidders seems intuitive, but its effects on bidder quality, contracting decisions, and buyer utility are not as straightforward as assumed and warrant an in-depth empirical investigation.

In comparison with the auction duration, the item description is less studied but equally important given the lack of standardization in labor services. A similar intuitive view holds that detailed descriptions reduce bidder uncertainty about the projects as longer descriptions help bidders better understand project requirements, and hence, they improve contract outcomes. This view suggests that projects should have fairly detailed descriptions when calls for bids are posted by buyers. However, whereas detailed descriptions may reduce bidder uncertainty and likely lead to more entries, we argue there can be a divergent effect for high- versus low-quality bidders as high-quality bidders may not face the same uncertainty faced by low-quality bidders because of their experience/expertise, which gives them good perspectives of what the project may entail. That is, high-quality bidders may have less need for description details, whereas novice or less-capable bidders need more specific project requirements to decide whether they are capable of completing the projects. If this is the case, longer item descriptions may (unintentionally) lead to looser screening in bidder quality and attract a larger proportion of low-quality bidders, negatively impacting outcomes. Our second research question is, thus, the following: how does the item description affect bidder entry (i.e., the number of bids and bidder quality) and contract outcomes (i.e., the project being contracted and the buyer's expected utility from the winning bid)?

To sum up, we conjecture that the effects of the auction duration and item description may extend beyond attracting more bids, and both can potentially play a screening role for bidder quality that affects the composition of bidders entering an auction as well as the outcomes of contracting a project. This study aims at providing a comprehensive empirical examination that links both design parameters to bidder entry and consequently to contract outcomes.

Using a unique data set obtained from a leading online outsourcing platform primarily for IT service procurement, we examine several aspects of bidder entry, contracting decisions, and buyer utility by considering four dependent variables: the number of bids, bidder quality, whether an auction results in a contract, and the buyer's expected utility from the winning bid (conditional on a contract being granted). Employing the coarsened exact matching (CEM) method to find auctions that are similar in all characteristics (e.g., category, required skills, description sentiment, etc.) other than the auction duration and the item description length (Subramanian and Overby 2017, Wang et al.

2018), we examine the relationship between the auction duration/item description and the four dependent variables. To be specific, we match projects on project category, required skills, sentiment in the description, project description semantics (using unsupervised machine learning), project budget, length of the title, and buyer rating.

Our analyses show that, for buyer-determined reverse auctions on online outsourcing platforms, longer auction durations and item descriptions indeed attract more bids for otherwise similar auctions. However, they also disproportionately attract more low-quality bidders who have lower prior completion rates. A higher quantity combined with a lower quality of bidders likely renders the buyer overwhelmed with higher evaluation costs in an adverse selection situation, leading to a lower probability of contracting. Using a random utility framework, we employ a latent class conditional logit model to estimate the impact of price and bidder quality on buyer utility, considering the unobserved preference (scoring) heterogeneity across buyers. We find buyers differ in their sensitivities to bidder quality (i.e., experienced buyers are more quality sensitive). For buyers with different sensitivities to quality, their expected utilities from winning bids all decrease as the auction duration or the description length increases.

At the bidder level, to help understand how the auction duration and the item description influence bidders' bidding choices, we leverage our rich data set to construct the relevant choice sets[8] (or proxied consideration sets) for bidders when making bidding decisions. Estimating bidders' choices with a conditional logit model, we find high-quality bidders when compared with low-quality bidders are less likely to bid for auctions with longer durations or item descriptions. This bidder-level analysis lends support to our arguments that the auction duration and the item description can serve as a screening mechanism. That is, shorter auction durations and item descriptions help screen out low-quality bidders and lead to higher contracting probabilities and higher buyer utility from the winning bid. Equipped with both project- and bidder-level analyses, our study provides strong evidence for the screening role of the auction duration and the item description length in affecting bidder entry, contracting decisions, and buyer utility.

2. Literature Review

2.1. Reverse Auction Design

Reverse auctions are auction formats that begin with a buyer's announcement of requirements with auction parameters. Bidders then submit bids for the contract or product (Mithas et al. 2008, Whitaker et al. 2010). Currently, reverse auctions are prevalent on online outsourcing platforms (Hong et al. 2016) and in B2B procurements (Mithas and Jones 2007). Given the burgeoning usage of reverse auctions on various online platforms, limited IS research empirically investigates the design of reverse auctions to see how it affects outcomes, such as bidder entry and contract outcomes.

Some studies examine the effect of the auction duration. Although the positive effect of the auction duration on the number of bids received has long been established (Cox 2005), the findings regarding the impact of the auction duration on the final price are still mixed. The literature suggests that the impact of the auction duration on price is contingent on the user base, seller ratings, and auction format. Haruvy and Leszczyc (2010) systematically review the impact of the auction duration on different websites. They find that the impact of the auction duration on forward auctions seems to be mediated by the number of potential bidders. For forward auctions on eBay, the auction duration tends to correlate positively with the final price by attracting more bids. Also on eBay, Bapna et al. (2008) find that the auction duration has a positive effect on the final price for highly reputable sellers but a negative price effect for less reputable sellers. However, for forward auctions listed on local auction sites featuring a generally steady number of bidders, the auction duration can negatively correlate with the final price (Haruvy and Leszczyc 2010). Interestingly, Mithas and Jones (2007) report that, in the reverse auction setting, the auction duration does not affect the buyer surplus as measured by the bid price relative to the historical price after controlling for the number of bids received.

Other studies focus on information disclosure. Kannan (2012) finds that the question of whether complete information leads to a higher buyer surplus than incomplete information is inconclusive. However, the author focuses on the information regarding competitors' bid prices rather than project requirements or demand information of buyers. In a similar vein, from the perspective of valuation uncertainty and competition uncertainty, Hong et al. (2016) examine the auction design of bid visibility (i.e., sealed versus open bids) in buyer-determined reverse auctions and find that sealed-bid auctions attract more bids, whereas open-bid auctions offer buyers a higher surplus. Guo et al. (2017) study description uncertainty on online labor platforms and find that the item description is related to matching efficiency. Horton (2019) studies supply constraints in online matching markets, and Huang et al. (2022) design information disclosure mechanisms to address the capacity constraint issue (i.e., users may be too busy to respond to all the inquiries at some point).

In summary, except for a few studies, the existing literature primarily explores bidder entry based on the single attribute of price in traditional forward auctions and ignores bidder quality and other attributes that may be more important in reverse auctions. In particular, in traditional forward auctions, bidders are buyers who compete to buy products or services, and the bids with the highest prices win (Bapna et al. 2008). On the other hand, in reverse auctions, bidders are sellers who compete to supply products or services, and buyers select the bids with the highest utility after assessing multiple attributes, among which price and quality are two commonly used differentiators (Che 1993). As Choudhury et al. (1998) note, when choosing inventory providers in the aircraft parts industry, it is quality rather than price that plays the most important role. This is also in line with the extensive literature on buyers' decision weights on price and quality in multidimensional auctions (Che 1993, Branco 1997, Asker and Cantillon 2006, Adomavicius et al. 2012). Hence, the quality of bidders may be more important than price to buyers on online outsourcing platforms using reverse auctions. Against this backdrop, we seek to investigate how two design parameters for service procurement auctions (i.e., the auction duration and the item description length) influence bidder entry (e.g., the number of bids and bidder quality) and contract outcomes (e.g., the project being contracted and the buyer's expected utility from the winning bid).

2.2. Information, Duration, and Behavior Decisions

Based on behavioral decision theory (Einhorn and Hogarth 1981), information representation influences the uncertainty assessment in one or more of the following phases: (1) information acquisition, (2) uncertainty evaluation, (3) action and choice implementation, and (4) learning or feedback. On online outsourcing platforms, the item description influences bidders' information advantage and uncertainty assessment. Meanwhile, the auction duration influences bidders' opportunity cost concerning bidding actions and their learning behavior.

The information asymmetry between sellers and buyers in auctions is well recognized (Wilson 1967). When bidders are faced with an auction decision, they cope with three types of information—namely, private information, public information, and cost uncertainty (Brocas et al. 2017)—as shown in Table 1. In traditional forward auctions, Wilson (1977) and Milgrom (1979) find that, in the presence of unknown attributes of the auction item and limited information available to bidders, the price of the winning bid may converge to the true value of the auction item as the number of bidders grows large. In multidimensional reverse auctions, the information asymmetry between bidders and buyers is influenced by item descriptions. The length or comprehensiveness of an item description increases public information and lowers

Table 1. Types of Information Cues and Implicit Cost in Auction Decisions

Cues	Subcategory	Type	Characteristics	Time dimension	Description
Information cues	Information	Private information	Information known to one bidder but not the others	Can be known to more bidders as the auction duration increases, especially for low-quality bidders	Private information regarding self-assessed task content and difficulties
		Public information	Information known to all bidders	Unrelated to the auction duration but dependent on the item description	The project description, the project budget, the buyer's reputation, etc.
	Uncertainty	Project cost uncertainty	Information that is common or specific across all the bidders but known to no bidder	Can be known to more bidders as the auction duration increases, especially for low-quality bidders	Uncertainties regarding the project's true value to the buyers, the variation of the production cost to be incurred (Schwartz and Moon 2000), and the possibility that a catastrophic event may occur before the project is completed
Implicit cost	Opportunity cost	Opportunity cost of waiting	Opportunity cost when a bidder participates in the auction and waits for the buyer's decision	Will increase as the auction duration increases, especially for high-quality bidders	The best alternative use of time when bidding and waiting for the buyer's decision; tends to be greater for high- than for low-quality bidders

uncertainty in general. As such, a longer item description attracts more bids. Further, the effect of the item description may vary with bidder quality. By providing more public information and lowering uncertainty, a longer item description may benefit low-quality bidders more who tend to have less private information and face higher project cost uncertainty.

Because the previous literature tends to explain and predict bidders' auction entry and bidding behaviors after an auction starts (e.g., Roth and Ockenfels 2002, Ariely and Simonson 2003, Simonsohn 2010), there is a void in the literature empirically investigating how setting up design parameters by altering information cues before an auction starts could influence bidders' entry behaviors and lead to different contract outcomes. To fill this gap, we reconstruct the bidders' relevant choice sets at the time they submit bids and employ a conditional logit model to investigate the effect of design parameters on bidder decisions as a complementary analysis to further our understanding of the relationships between the two design parameters and bidder entry as well as contract outcomes.

3. Hypotheses Development

In this section, we start by proposing the effects of setting the auction duration and the item description on bidder entry. We consider two measures of bidder entry: the number of bids and bidder quality. The number of bids captures the interest of prospective bidders and is considered an important measure of auction success (Hong et al. 2016). However, perhaps more important is the quality of bidders entering the auction that can substantially influence the subsequent contract decisions and buyer utility. We, therefore, also investigate the effects of the auction duration and the item description on the eventual contract outcomes, including the contract decisions and the buyer's expected utility from the winning bid. Figure 1 presents our research model.

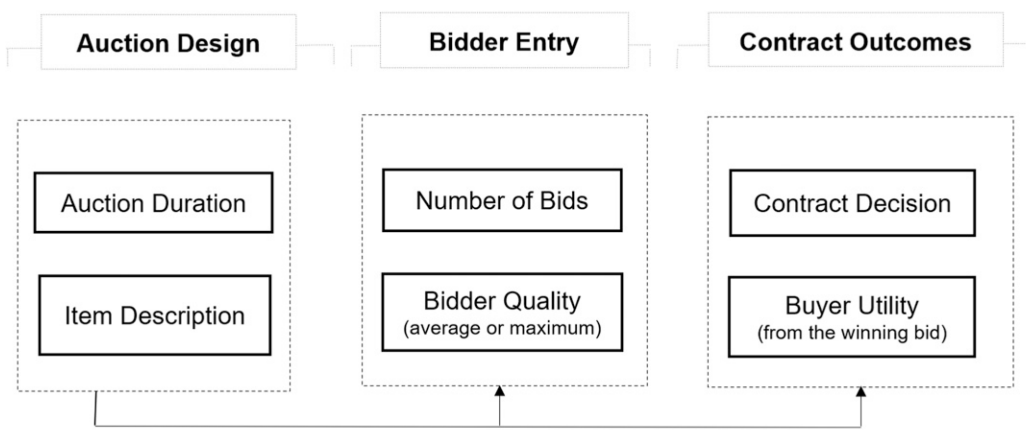
3.1. Bidder Entry

According to behavioral decision theory, the item description may influence a provider's bid decision during the phases of information acquisition and uncertainty evaluation, whereas the auction duration may affect the action and implementation of choices as well as the learning and feedback processes. Moreover, the auction duration and item description may have heterogeneous effects on bidders of different quality.

3.1.1. Auction Duration and Bidder Entry. We first theorize that the auction duration has an effect on bidder entry (i.e., the number of bids and bidder quality). It is believed that an auction with a longer duration attracts more bids because it is exposed to more service providers, everything else being equal. For instance, longer durations increase the probability of the project being discovered by service providers when they browse through the directory of open auctions for projects listed on an online outsourcing platform.

A more interesting question to explore is how the auction duration affects bidder quality. For one thing, the auction duration influences bidders' actions and choices because of the opportunity costs involved in the waiting period (Kwasnica and Katok 2007). This is particularly true for high-quality bidders with higher reservation wages (Moreno and Terwiesch 2014), for whom the opportunity costs associated with longer auction durations are higher and discourage them from entering an auction to avoid waiting a long time for buyers' final contract decisions. For another, compared with low-quality service providers, high-quality service providers tend to have stronger pricing power (Moreno and Terwiesch 2014) and, hence, be less susceptible to the price dynamics throughout the whole auction duration. On the other hand, low-quality service providers might be more inclined to place bids for auctions of longer durations because they can leverage the time to learn from existing bids

Figure 1. Research Framework



and infer the project value and uncertainty (Roth and Ockenfels 2002). Additionally, when a buyer posts an auction with a longer duration (either intentionally or unintentionally), bidders may view this as a signal that the buyer is trying to minimize service provider surplus by encouraging more competition among bidders. This signal may, in turn, drive away high-quality service providers as they can easily find another project whose buyer is more munificent and reputable (Turban and Cable 2003, Benson et al. 2020) and for which they are more likely to earn a higher wage. Specifically, we proxy bidder quality using their success rate up to the time of the current bidding. The success rate is the probability of successfully completing projects awarded prior to the current bid.[9] We, thus, propose the following hypotheses on the relationships between the auction duration and bidder entry.

Hypothesis 1a. *Ceteris paribus, longer auction durations lead to more bids in total.*

Hypothesis 1b. *Ceteris paribus, longer auction durations lead to lower bidder quality (in terms of the average and maximum project success rate of bidders).*

3.1.2. Item Description and Bidder Entry. We explicate and explore how item descriptions affect bidder entry and shift bidder quality distribution. When buyers post auctions, they describe projects in varied detail through their call for bids (note that buyers always have the option to provide more details during the later contracting stage). Detailed item descriptions during the auction stage provide all bidders with more public information and help them better understand project requirements to form reasonable expectations about project complexity. Precontract item descriptions, thus, alleviate bidders' concerns by reducing the uncertainty of a project's cost and valuation and, in turn, attract more bidders who otherwise might forego bidding in the presence of high uncertainty of project costs and benefits.

Regarding the effect of the item description on the quality of bidders who enter the auction, high-quality bidders have more private information because of their experience and technical capabilities (e.g., project requirement analysis) in assessing what a project likely entails, and therefore, they are less susceptible to the benefit of detailed item descriptions. In essence, high-quality bidders are likely to face less uncertainty and are better at inferring a project's value based on limited information (Beach 1975). In contrast, when presented with shorter item descriptions, low-quality bidders are likely to feel less confident about submitting bids as they face greater uncertainty and possess less technical skills in assessing the real risks. Accordingly, longer (shorter) item descriptions may help attract (screen out) low-quality bidders. In other words, although longer item descriptions attract more bids in total, they likely attract disproportionately more low-quality bidders. Therefore, we propose our second set of hypotheses on the relationships between the item description and bidder entry.

Hypothesis 2a. *Ceteris paribus, longer item descriptions lead to more bids in total.*

Hypothesis 2b. *Ceteris paribus, longer item descriptions lead to lower bidder quality (in terms of the average and maximum project success rate of bidders).*

3.2 Contract Outcomes

3.2.1. Auction Design and Contract Decision. Whether a buyer can find a capable service provider with which to contract depends on the number of bids received and the quality of bidders attracted, and the quality of the bidder pool affects both whether the project results in a contract and the buyer's expected utility from the winning bid. Therefore, bidder entry has important implications for contact outcomes. In this study, we examine how the bidder entry (i.e., the number of bids and bidder quality), which is affected by the auction duration and the item description, affects the contract outcomes (i.e., the contracting probability and the buyer's expected utility from the winning bid).

The buyer's decision to contract with one of the service bidders is largely based on the buyer's decision confidence. In Hypotheses 1 and 2, we postulate that both longer auction durations and more detailed item descriptions increase the total number of bids received and shift the bidder's quality distribution to the lower end. In turn, lower bidder quality stands to negatively impact the buyer's decision confidence. A larger number of bids may also lead to lower decision confidence because of increased evaluation costs and the paradox of choice. Carr (2003) argues that, on a matching platform such as the one we study, the burden of evaluation is on buyers, and significant evaluation costs render buyers unable or reluctant to evaluate all the bids, leaving some qualified bids unevaluated.

The paradox of choice also offers an explanation as to why more choices (bids) do not necessarily lead to better outcomes (Schwartz 2009). When a decision maker tries to make the best decision, the decision maker needs to carefully compare all the alternatives, which imposes a psychologically daunting challenge and becomes even more significant as the number of alternatives increases. Iyengar and Lepper (2000) find that too many choices can lead to buyer indecision as well as fewer sales on the vendor side. In our context, auctions with a large number of bids may be eventually left unconsummated (Carr 2003, Snir and Hitt 2003). Thus, we propose that longer auction durations and item descriptions lead to a larger number of bids, which subsequently lowers the probability of the project being contracted. At the same time, when there are many bids but the overall quality of the bidder pool is lower (in terms of both average and maximum quality), buyers may perceive the submitting bidders as low quality and hence reduce the likelihood of contracting the project. Accordingly, we propose the third set of our hypotheses on the relationships between auction design and the contract decision.

Hypothesis 3a. *Ceteris paribus, longer auction durations lead to a lower probability that a project will be contracted.*

Hypothesis 3b. *Ceteris paribus, longer item descriptions lead to a lower probability that a project will be contracted.*

3.2.2. Auction Design and Buyer Utility. Another important contracting outcome is the buyer's expected utility from the winning bid. In multidimensional auctions, buyers evaluate different relevant attributes of bids submitted to the same auction and choose a winning bid. Buyers assess the expected utility of each bid by assigning weights to different attributes, primarily the bid price and the quality of the bidder, in order to select a winning bid that provides the highest expected utility (e.g., Che 1993). As buyers' sensitivities to bidder quality increase (i.e., when buyers put more weight on bidder quality than bid price), buyers are more inclined to hire bidders of higher quality.[10]

We expect that the hypothesized negative effects of long auction durations and item descriptions on the quality of bidder entry can decrease the subsequent buyer utility. First, longer auction durations and more detailed item descriptions shift the quality of bidder entry to the lower end, which means that the chosen bidder is likely to be of lower quality. Because buyer utility is positively related to the quality of the chosen bidder, buyer utility is likely to be lower as the auction duration and the item description length increase. Second, when the number of bids is large enough, the higher share of low-quality bidders creates a quasi-adverse selection scenario. In such a case, if high-quality bidders decide to bid for this auction, their bid prices are likely to be higher than they would bid in a bidder pool with a larger share of high-quality bidders (Liu et al. 2012), suggesting a negative effect on the buyer's expected utility. We, thus, propose our set of hypotheses on the relationships between auction design and buyer utility.

Hypothesis 4a. *Ceteris paribus, longer auction durations lead to a lower buyer utility from the winning bid conditional on the project being contracted.*

Hypothesis 4b. *Ceteris paribus, longer item descriptions lead to a lower buyer utility from the winning bid conditional on the project being contracted.*

By studying the relationship between design parameters and bidder entry (i.e., the number of bids and bidder quality) as well as contract outcomes (i.e., the project being contracted and the bidder's utility from the winning bid) in two stages, we hope to provide a comprehensive lens through which to further validate the importance of design parameters such as the auction duration and the item description length.

4. Study Context and Data

4.1. Study Context

The context of our study is online outsourcing platforms, which are primarily used for the procurement of IT services. In addition to the rich data to which we have access, the popularity of reverse auctions also makes this context ideal for studying the proposed research questions. Moreover, online outsourcing platforms are economically important in their own right. For example, both Upwork and Freelancer host millions of registered service providers and facilitate billions of dollars' worth of transactions, serving as an exemplar for the emerging gig economy (Hong et al. 2016). These platforms have also seen tremendous growth as the telecommuting mode of "work from home" surges during the COVID-19 pandemic.

Our empirical data were obtained from the proprietary database of one of the largest online labor platforms (herein referred to as our corporate partner). It is a major online outsourcing platform that employs the mechanism of buyer-determined reverse auction (e.g., Snir and Hitt 2003, Hong et al. 2016). To start an auction by initiating a call for bids, a buyer needs to specify parameters such as the auction duration, the item description, and other project-related information, including the project category, required skills, and the budget. There was no fee for posting auctions with different durations during our observation period, and the buyer could end the auction early at any time (i.e., the buyer did not need to wait until the full auction duration elapsed). A typical auction on the platform involves the following three steps: (1) A buyer posts a project depending on the need and specifies the auction duration and the item description for accepting bids. (2) After an auction starts, bidders (i.e., service providers) can bid with a price at which they are willing to complete the project. (3) The buyer chooses the winning bid by deciding with which bidder to contract. The buyer could close the auction with or without selecting a winning bid. The auction automatically closes for bidding after the auction duration expires. The following are details of the two main parameters of interest.

Auction duration: To post a project, the buyer must specify the duration of the auction in the number of days to accept bids, but the buyer can terminate the auction at any time during the auction period and award the contract to a particular bidder. However, because bidders have no idea whether the buyer will end an auction early or not, it is the preset auction duration (not the actually elapsed auction duration) that influences bidders' decisions to submit their bids or not.[11]

Item description: To post a project, the buyer must also provide a high-level description of the auction item (i.e., what service is being requested and procured). The description does not have to be a full contract or actual requirement specification, but is meant to inform potential bidders of the nature of the project. The buyer can also provide further details of the project later after selecting a winning bidder.

4.2. Data

We obtained our archival data from August 2009 to February 2010 from the proprietary database of our corporate partner, a large online outsourcing platform that connects millions of buyers and service providers around the globe for service procurement (primarily IT services). This unique data set allowed us to observe every aspect of the projects, including design parameters for service procurement auctions, characteristics of bidders (service providers), bidder entry, and contract outcomes free of measurement error. For our observational period, we obtained a random sample of 74,757 projects, which attracted 1,325,437 bids. Further, we limited our main analysis sample to the most common, free-to-post, open-bid projects, which account for more than 91% of all the projects. Special projects, such as trial projects, are excluded from our sample. Focusing on the most common form of auctions allows us to have a better estimate of the effects of the auction duration and the item description without being influenced by other confounding factors. To rule out the potential confounding effect of project budget, we focus on projects with the same $250 budget (i.e., the most common budget on the platform), which account for more than 76% of the whole sample (note that the results are highly consistent when we include projects with other maximum budgets). To rule out buyer heterogeneity as a potential driver of results, we leverage the within-buyer variation in design parameters for service procurement auctions by controlling for buyer-level fixed effects and limit our sample to those projects posted by buyers who posted more than one project during our observational period, which ends up with 51,445 projects. In addition, to alleviate the potential endogeneity concern that the auction duration or the item description length is determined by project characteristics, we perform analyses on a matched sample of projects. After the matching process, 17,196 projects remain for analysis. Next, we explain how we conduct the matching procedure to ensure comparability among projects.

4.2.1. Matching Process.

Matching approaches are widely used in empirical studies to create a quasi-experimental condition for identification purposes (e.g., Ho et al. 2007, Hong et al. 2016). Following prior literature (e.g., Iacus et al. 2012, Subramanian and Overby 2017, Wang et al. 2018), we employ the CEM method to match projects that are identical in all observable characteristics other than the auction duration and the item description length. First, we define two dummies, *long_duration* and *long_description*, which are equal to one if they are greater than the median of the whole sample. Figure 2 illustrates the matching process of our study. In step 1, we first use CEM to generate a matched auction sample in which projects are similar except for their duration categorization (long/short). In step 2, we apply CEM to match auctions in terms of the description length categorization (long/short) within the matched sample obtained from step 1. In step 3, we limit our sample to those projects that are kept in the matching with respect to both the auction duration and the item description.

The detailed list of variables used in the matching is provided in Table 2. A challenging task is to ensure that we are comparing projects with similar characteristics, particularly complexity (i.e., the matched projects should be of similar project complexity). In addition to matching projects on their required skills, project category, and budget, we extract a series of important textual features. First, we leverage the Microsoft Text Analytics API to assess the general sentiment score of the item description[12] because description sentiment may affect bidder entry. To further increase the semantic similarity of auctions in terms of the project requirement and complexity, we jointly embed documents (item descriptions) and words in the same semantic space to discover topics and group

Figure 2. Process of Matching

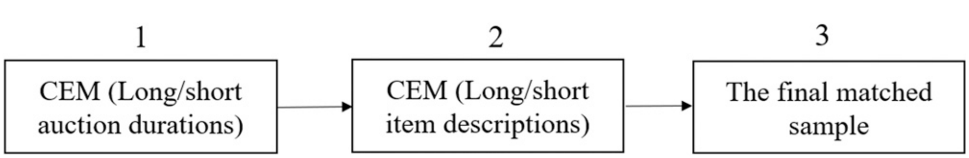


Table 2. Covariates Used for CEM

Dimension	Variable	Variable description
Project type	Project category	The category of the project (e.g., IT, design, etc.)
Project complexity	Skill requirement dummies	The dummies of skills that are required for these projects
Project size	Minimum budget	Project minimum budget shown on the project page
Length of title	*Title_length*	Number of words in the project title
Rating of buyer	*Buyer_avg_rating*	The buyer's average rating
Description sentiment	Sentiment dummies	Sentiment dummies of descriptions (i.e., positive, neutral, or negative). The API returns a numeric sentiment score between zero and one. Zero denotes the extreme negative sentiment, whereas one denotes the extreme positive sentiment. We classify the sentiment of the project description as positive if its score is above or equal to 0.70, as neutral if its score is less than 0.70 and greater than 0.3, and as negative if its score is less or equal to 0.30.[a]
Description semantics	*Topic_group_number*	The category variable denoting which topic group the project has been assigned to based on the joint document and word semantic embedding with the Top2Vec approach.

[a]See https://cran.r-project.org/web/packages/mscstexta4r/README.html. The input features of the sentiment classifier API include *n*-grams, features generated from part-of-speech tags, and word embeddings.

projects that are semantically similar based on their descriptions with the Top2Vec topic modeling approach (Angelov 2020). Compared with bag-of-word topic modeling approaches (e.g., latent dirichlet allocation), the Top2Vec approach can learn the semantic association between documents and words to generate more informative and representative topics (Angelov 2020). We also validate the appropriateness of the project clustering based on Top2Vec by manually checking the similarity of projects within the same topic cluster. More details regarding the text-mining process and the balance checks are reported in Online Appendices A and B, respectively. We find that the matched sample is balanced at all the prior covariates. Manual examination of the matched projects by the authors supports that those projects matched with CEM are similar in many aspects.

4.2.2. Data Description for the Project-Level Analysis. For the project-level analysis, the unit of analysis is an auction (i.e., project). Each project is associated with one auction and one buyer, whereas one buyer can hold multiple auctions. Table 3 defines our variables and the corresponding measures for the project-level analysis. We summarize the descriptive statistics of key variables in Table C1 of Online Appendix C and report the correlation matrix in Online Table C2.

4.2.3. Data Description for the Bidder-Level Analysis. Aside from the project-level analysis, in order to better understand whether and how the auction duration and the item description affect bidder entry from the *bidder's* perspective, we compiled another data set by reconstructing bidders' relevant choice sets of other similar projects that were concurrently live in order to perform a bidder-level analysis. It is noted that the auction literature typically only uses auction- or project-level data (Mithas and Jones 2007) because bidders' decisions are unobserved and difficult to analyze. The reconstruction of the bidder-level data requires a granular observation of the entire data-generation process and also requires overcoming computational challenges. We elaborate on our procedure to reconstruct a bidder's potential decision-making process as follows.

To begin, we observed a list of active bidders and open projects on the market for each day during our

Table 3. Definitions and Measures of Key Variables

Design variables	
duration	Number of days the auction is active
description	Number of words in the item description
Bidder entry variables	
num_bids	Total number of bids received by the auction
avg_success_rate	Average project success rate of all bidders entering this auction
max_success_rate	Maximum project success rate among all bidders entering this auction
Contract outcome variables	
awarded	Dummy variable for whether the project is awarded to a service provider
Control variables	
time	Year–month dummies
project category	Project category dummies

study period. Active bidders are defined as those who had at least submitted one bid on day t. We constructed active bidders' relevant choice sets (or proxied consideration sets) by identifying other auctions that were similar in various characteristics and were open for bidding at around the same time as the chosen auction (for which the bid was submitted). Specifically, we required that auctions in the "consideration set" were in the same project category.[13] To further ensure that auctions in each consideration set were indeed substitutes for each other, we limited the proxied consideration sets to projects within the CEM sample we noted earlier (by matching auctions based on project budget, description semantics, required skills, description sentiment, buyer reputation, etc.). In addition, given that the corporate partner platform's catalog page ranks auctions based on the recency of auction opening time by default, we limited the consideration set to auctions whose opening times are close to the chosen auction by requiring that the gap between their opening times should be less than or equal to two days.[14]

In essence, we investigate bidders' revealed preferences for design parameters based on their bid decisions given the alternative auctions that were open for bids at around the same time and were similar in various characteristics except for the two design parameters. We present descriptive statistics and a correlation matrix of key variables for our bidder-level analysis in Online Tables C3 and C4.

5. Empirical Models and Results

5.1. Bidder Entry

In contrast to forward auctions for specific goods for which transaction price is the main concern, in the buyer-determined reverse auctions for services, the key objective for buyers is to find a capable bidder who is able to deliver the project on time and with a result of high quality, which cannot be measured directly. Therefore, we focus on the relationships between the two design parameters, the auction duration and the item description length, and bidder entry (i.e., the number of bids and the quality of the bidders attracted to an auction) with two levels of analysis. First, we conduct a project-level analysis by controlling for buyer-level fixed effects and show, on average, how the auction duration and the item description length relate to bidder entry in terms of both quantity and quality. Second, we conduct a bidder-level analysis to explore how high- versus low-quality bidders respond to auctions of different durations and item description lengths when they decide for which projects to bid. In the following, we explain how both levels of analysis jointly corroborate our hypotheses.

5.1.1. Project-Level Analysis. We follow extant studies (Hong et al. 2016) that examine auctions on online outsourcing platforms to set up empirical models. Equation (1) specifies our empirical model for estimating the effects of design parameters on the number of bids received and bidder quality in an auction. The empirical model includes our two main variables (i.e., *Duration* and *Description*), buyer fixed effects $Buyer_{j(i)}$, project category fixed effects $\text{Category}_{c(i)}$, and time fixed effects $\text{Time}_{t(i)}$. In Equation (1), i is used to index auctions, j is used to index buyers, c is used to index project categories, and t is used to index time in terms of year–month. We take a natural log transformation for the number of bids, the auction duration, and the item description length given that the distributions of these variables are skewed. The log-transformation also allows for percentage interpretations of their coefficient estimates.

$$\begin{aligned}\textbf{Auction Outcome}_{ij} &= \beta_0 + \beta_1 \times Duration_i + \beta_2 \times Description_i + Category_{c(i)} \\ &\quad + Time_{t(i)} + Buyer_{j(i)} + \varepsilon_{ij}. \qquad (2b)\end{aligned}$$

Tables 4 and 5 report the main findings of the effects of the auction duration and item description length on the number of bids and bidder quality using the matched sample. In Table 4, our main dependent variable is the number of bids. As column (1) shows, both the auction duration and the item description length have a significantly positive effect on the number of bids received. Specifically, a 10% increase in the auction duration (on average, one day) leads to 2.33% more bids, and a 10% increase in the description length (on average, 10 words) leads to 3.09% more bids. Therefore, both Hypotheses 1a and 2a are supported.

In Table 5, the dependent variables of interest are measures of bidder quality as defined and measured in Table 3. Interestingly, we find consistent effects across both measures of bidder quality, that is, the average and maximum success rate of bidders. The estimations show that auctions with longer durations are associated with a bidder pool of lower average and maximum quality, and auctions with longer item descriptions are also associated with a bidder pool of lower average and maximum quality for otherwise similar auctions. For example, column (1) of Table 5 shows a 10% increase (one day) in the auction duration reduces the average success rate by 0.36%.[15] In addition, a 10% increase (10 words) in the item description length decreases the average success rate by 0.52%.[16] Column (2) of Table 5 considers the best bidder quality (instead of the average bidder quality) in the bidder pool for the auction and shows similar results. Together, these findings provide empirical support that the auction duration and the item description length influence bidder behaviors such that shorter auction durations and item descriptions discourage low-quality bidders from entering

Table 4. Results for Number of Bids Received

Variable	(1) Fixed effects *ln(num_bids)*	(2) Negative binomial *num_bids*	(3) Poisson *num_bids*
ln(duration)	0.233***(0.014)	0.178***(0.011)	0.177***(0.012)
ln(description)	0.309***(0.015)	0.200***(0.014)	0.148***(0.011)
Observations	17,196	17,196	17,196
R^2	0.147	–	–
Number of buyers	5,871	5,871	5,871
Buyer fixed effects	Yes	Yes	Yes
Project category fixed effects	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes

Notes. Robust standard errors are clustered at the buyer level. Results are highly consistent if we include all types of auctions, such as sealed auctions, featured auctions, etc. Results are highly consistent if we include projects with other maximum budgets.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

bids,[17] thus helping screen out low-quality bidders. In essence, both Hypotheses 1b and 2b are supported.[18]

5.1.2. Bidder-Level Analysis. In order to further investigate how the design parameters for auctions influence bidders' auction choices, we construct a list of active bidders and their consideration set for each bid decision during our study period. We estimate, among auctions that are similar in all other dimensions except for the auction duration and the item description length, how the auction duration and the item description length affect the probability of receiving a bid from each active bidder. We specify the econometric model at the bidder level as follows:

$$\begin{aligned} Y_{itj} = {} & \beta_0 + \beta_1 \times Duration_j + \beta_2 \times Description_j \\ & + \beta_3 \times Duration_j \times BidderQuality_{it} \\ & + \beta_4 \times Description_j \times BidderQuality_{it} \\ & + Controls_j + \alpha_{it} + \varepsilon_{itj}. \end{aligned} \tag{2}$$

Here, Y_{itj} denotes whether bidder i, who is active on day t (i.e., bid for at least one project on day t) bids for project/auction j. We estimate Model (2) using both the conditional logit and linear probability models with bidder–day pair level fixed effects α_{it}. Note that, because all the projects in the same proxied consideration set are required to have similar opening times, the time effect has been subsumed by α_{it}.

As Table 6 shows, the main effects of the auction duration and item description length are significantly positive. In other words, the longer the auction duration or the item description is, the more likely a service provider is to bid on the auction and, hence, the greater the number of bids an auction attracts, lending empirical support for Hypotheses 1a and 2a.

More importantly, we also find the interaction between the auction duration and a bidder's quality to be significantly negative as is the interaction between the item description length and a bidder's quality. Thus, if bidders are of high quality, as indicated by a good track record of successfully completing projects on time, they are less likely than low-quality bidders to bid on projects with longer auction durations or item descriptions. Thus, projects with longer auction durations or item descriptions tend to attract disproportionately more low-quality bidders. Hypotheses 1b and 2b are further supported by the results in Table 6.

5.2. Contract Outcomes

After establishing the relationships between the two design parameters (i.e., the auction duration and the item description length) and bidder entry, we further investigate their relationships with the two contract outcomes (i.e., the probability of a project being contracted and the buyer's expected utility from the

Table 5. Results for Bidder Quality

Variable	(1) Fixed effects *avg_success_rate*	(2) Fixed effects *max_success_rate*
ln(duration)	−0.014***(0.002)	−0.007***(0.003)
ln(description)	−0.020***(0.002)	−0.021***(0.003)
ln(num_bids)	−0.043***(0.002)	0.112***(0.002)
Observations	17,196	17,196
R^2	0.154	0.281
Number of buyers	5,871	5,871
Buyer fixed effects	Yes	Yes
Project category fixed effects	Yes	Yes
Time dummies	Yes	Yes

Notes. Robust standard errors are clustered at the buyer level. Results are highly consistent if we include all types of auctions, such as sealed auctions, featured auctions, etc. Results are highly consistent if we use an alternative measure of bidder quality, that is, *win_rate*, the probability of winning among all the prior bids from the bidder. Results are highly consistent if we include projects with other maximum budgets.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 6. Results for Bidders' Auction Choices (DV = Whether a Bid Was Placed)

	(1) Fixed effects logit	(2) Fixed effects logit	(3) Fixed effects LPM	(4) Fixed effects LPM
ln(duration)	0.138***(0.016)	0.261***(0.031)	0.003***(0.000)	0.004***(0.001)
ln(description)	0.105***(0.017)	0.189***(0.033)	0.002***(0.000)	0.003***(0.001)
ln(duration) × *success_rate*		−0.268***(0.058)		−0.004***(0.001)
ln(description) × *success_rate*		−0.177***(0.060)		−0.002*(0.001)
buyer_avg_rating	−0.007 (0.004)	−0.007 (0.004)	−0.000 (0.000)	−0.000 (0.000)
buyer_experience	−0.003**(0.001)	−0.003**(0.001)	−0.000*(0.000)	−0.000*(0.000)
buyer_gold_member	0.080**(0.040)	0.081**(0.040)	0.001 (0.001)	0.001 (0.001)
buyer_ppp	−0.000 (0.001)	−0.000 (0.001)	−0.000 (0.000)	−0.000 (0.000)
Bidder–day pair fixed effects	Yes	Yes	Yes	Yes
Observations	182,780	182,780	182,780	182,780

Notes. Robust standard errors clustered by bidder–day pairs are reported in parentheses for the LPM models. Results are highly consistent if we use an alternative measure of bidder quality, that is, *win_rate*, the probability of winning among all the prior bids from the bidder. Results are highly consistent if we include projects with other maximum budgets.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

winning bid). Because the buyer's expected utility is not directly observable, we first elaborate our model to estimate buyer utility and report the effects of the two design parameters on buyer utility. After that, we examine the effects of the auction duration and the item description length on the probability of a project being contracted.

To estimate the effects of the two design parameters for service procurement auctions on buyer utility, we use a latent class conditional logit model to estimate how design parameters may affect buyers' expected utility from the winning bid. Similar to the earlier analyses, we use matched projects that are similar in all other project characteristics except for the auction duration and the item description length.

In the random utility model setting (McFadden 1974, Banker and Hwang 2008, Train 2009), buyer i's utility from hiring bidder j for project t is

$$U_{ijt} = \beta_1 \ln(\times\, BidPrice_{ijt}) + \beta_2 \times BidderQuality_{ijt} + \beta_3 \ln(\times\, TimeNeeded_{ijt}) + \beta_4 \times Invited_{ijt} + \epsilon_{ijt}. \quad (3)$$

Here, the error term ϵ_{ijt} follows the logistic distribution. For simplicity, we use a row vector $\boldsymbol{x}_{ijt}$ to represent the list of bid attributes (i.e., bid price, bidder quality in terms of the success rate, the time needed to complete the project, whether the bidder is invited to bid for the project), and a column vector $\boldsymbol{\beta}$ to denote the coefficients of our interest. Based on the first principles of utility or profit maximization for buyers (Park and Bradlow 2005), the probability of buyer i choosing bidder j for project t is

$$P(y_{ijt} = 1) = P(\max(U_{i1t}, \ldots, U_{iJt}) = U_{ijt}). \quad (4)$$

The joint likelihood of buyer i's contract decisions in T projects is

$$L_i(\beta) = \prod_{t=1}^{T_i}\prod_{j=1}^{J} L_{ijt} = \prod_{t=1}^{T_i}\prod_{j=1}^{J}\left(\frac{P(y_{ijt}=1)}{\sum_{k=1}^{J} P(y_{ikt}=1)}\right)^{y_{ijt}} = \prod_{t=1}^{T_i}\prod_{j=1}^{J}\left(\frac{\exp(\boldsymbol{x}_{ijt}\boldsymbol{\beta})}{\sum_{k=1}^{J}\exp(\boldsymbol{x}_{ikt}\boldsymbol{\beta})}\right)^{y_{ijt}}. \quad (5)$$

Furthermore, by extending the conditional logit estimator with the latent class model (e.g., Bapna et al. 2011, Ladenburg et al. 2020), we consider unobserved preference heterogeneity across different buyers. In particular, we assume that there are C classes of buyers and each class of buyers put different weights (β_c) on bid characteristics. The probability of buyer i being of class c is given by

$$\pi_{ic} = \frac{\exp(\boldsymbol{z_i}\boldsymbol{\theta_c})}{\sum_{c'=1}^{C}\exp(\boldsymbol{z_i}\boldsymbol{\theta_{c'}})}. \quad (6)$$

Here, $\boldsymbol{z_i}$ is a row vector of two regressors, including whether buyer i is experienced and the intercept. Specifically, we use the median of all the buyers' numbers of prior projects as the cutoff to define whether the buyer is experienced or not.[19] Then, the complete likelihood function is

$$L = \prod_{c=1}^{C}\prod_{t=1}^{T_i}\prod_{j=1}^{J}\pi_{ic}L_{ijt}(\boldsymbol{\beta_c}) = \prod_{c=1}^{C}\prod_{t=1}^{T_i}\prod_{j=1}^{J}\pi_{ic}\left(\frac{\exp(\boldsymbol{x}_{ijt}\boldsymbol{\beta_c})}{\sum_{k=1}^{J}\exp(\boldsymbol{x}_{ikt}\boldsymbol{\beta_c})}\right)^{y_{ijt}}. \quad (7)$$

We further use the expectation-maximization algorithm (Train 2008) to maximize the likelihood function and identify coefficients of buyers' preference on different bid attributes. We set the class number at two.[20] We find that, on average, 61.8% of buyers are in class 2. Table 7 shows that experienced buyers are less likely to be of class 1, and Table 8 suggests that buyers

Table 7. Class Membership Model Parameter (Class 2 = Reference Class)

	Being in class 1
experienced_buyer	−0.857***(0.192)

of classes 1 and 2 have different sensitivities to bidder quality. Class 1 buyers are willing to pay 13.7% more (i.e., $(2.329 \times 0.1/(1.696)) = 13.7\%$) for an absolute increase of 0.1 in bidder's success rate. In contrast, class 2 buyers are willing to pay 56.0% more (i.e., $(3.113 \times 0.1/(0.556)) = 56.0\%$) for an absolute increase of 0.1 in the bidder's success rate, implying that they are less likely to choose low-quality bidders. Overall, the results suggest that experienced buyers are less price-sensitive and prefer high-quality bidders.

We further predict the class membership for each buyer and estimate the following utility measures based on the random utility model: (1) the expected utility from the winning bid $\hat{U}_{ijt} = (\hat{U}_{ijtc}|c = \hat{c})$ assuming that buyer i is in the predicted class; (2) weighted $\hat{U}_{ijt} = \sum_{c=1}^{2} \hat{\pi}_{ic}\hat{U}_{ijtc}$, the expected utility from the winning bid ($\hat{U}_{ijt}$) weighted by the probability of buyer i being in each class; and (3) the expected utility if buyer i is in either of the two classes (i.e., $\hat{U}_{ijt1} = (\hat{U}_{ijtc}|c = 1)$ and $\hat{U}_{ijt2} = (\hat{U}_{ijtc}|c = 2)$, respectively). We find that there is a significantly negative relationship between the buyer's expected utility and the auction duration as well as the item description length. Table 9 shows that the buyer's utility from the winning bid decreases as the auction duration or the item description length increases, which lends support to our Hypotheses 4a and 4b.

Table 8. Results Regarding Buyer Preference

Dependent variable: Whether the bid was selected by the buyer		
Variables	(1) Class 1 *selected*	(2) Class 2 *selected*
ln(bid_price)	−1.696***(0.125)	−0.556***(0.068)
success_rate	2.329***(0.127)	3.113***(0.100)
ln(time_needed)	−0.101 (0.067)	0.033 (0.048)
invited	0.965***(0.326)	4.580***(0.313)
Project fixed effects	Yes	
Observations	130,002	
Number of projects	8,672	

Notes. Robust standard errors in parentheses. Results are highly consistent if we use *win_rate* as an alternative measure of bidder quality. In this analysis, we limit our sample to those matched projects that have received more than one bid and successfully awarded to one and only one bidder. Results are highly consistent if we include projects with other maximum budgets.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Moreover, Model (5) of Table 9 shows that longer auction durations and item description lengths both have a significantly negative effect on the probability of an auction being awarded. On the whole, both our Hypotheses 3a and 3b are supported. We also show in Online Appendix D that the lower quality of the bidder pool has a negative effect on the probability of the auction being completed, which further supports the negative effects of the auction duration and the item description length on buyer utility.

Finally, based on the estimated relationship between the bid price/quality and buyers' utility, we do a back-of-the-envelope calculation to estimate the welfare change of increasing the auction duration and the item description length. Following the prior literature (e.g., Pendleton and Mendelsohn 2000), we estimate the welfare change based on the compensating variation[21] for a change in the auction duration or the item description length. Given that the median price of the winning bids in all the projects with the most prevalent budget (i.e., \$250) is \$50, the negative effect of increasing the auction duration by 10% (on average, one day) equals a 0.023 decrease (i.e., $(-0.240) \times \ln(1.1) = -0.023$) in utility for buyers of class 1 and a 0.015 decrease in utility for buyers of class 2 (i.e., $(-0.161) \times \ln(1.1) = -0.015$), which means a weighted mean increase in *ln*(*bid_price*) by 0.020 (i.e., $38.2\% \times (-0.023)/(-1.696) + 61.8\% \times (-0.015)/(-0.556) = 0.020$). This means the compensating variation of increasing the auction duration by 10% is equivalent to \$1.010 (i.e., $(\exp(0.020) - 1) \times 50 = \$1.010$). Similarly, the negative effect of increasing the item description length by 10% (on average, 10 words) equals a weighted mean increase in *ln*(*bid_price*) by 0.021,[22] suggesting that its compensating variation is equivalent to \$1.061.[23] In addition, as noted by Abaluck and Gruber (2011), the utility analysis does not take into account the time cost of the buyers' evaluation process. Given that shorter auction durations and item descriptions can reduce the number of bids and simplify the evaluation process, the monetary value of the time saved in the evaluation process may not be trivial, suggesting that our models most likely underestimate the positive effects of shorter auction durations and item descriptions on the buyer's expected utility.

6. Robustness Checks

6.1. Placebo Tests

To alleviate the concern of potential spurious relationships between the two design parameters for service procurement auctions and bidder entry, we further ran a placebo test (e.g., Abadie et al. 2015, Burtch et al. 2018). Specifically, we randomly assigned long auction durations and long item descriptions to auctions within our sample, respectively. For the placebo long

Table 9. Results of Effect of Design Parameters on Buyer's Expected Utility and Contract Decision

Variables	(1) $\hat{U}_{ijt}$	(2) weighted $\hat{U}_{ijt}$	(3) $\hat{U}_{ijt1}$	(4) $\hat{U}_{ijt2}$	(5) *awarded*
ln(duration)	−0.170***(0.028)	−0.192***(0.029)	−0.240***(0.028)	−0.161***(0.033)	−0.073***(0.006)
ln(description)	−0.252***(0.034)	−0.236***(0.030)	−0.193***(0.028)	−0.268***(0.038)	−0.060***(0.005)
Observations	8,672	8,672	8,672	8,672	17,196
R^2	0.044	0.057	0.065	0.045	0.045
Number of buyers	4,149	4,149	4,149	4,149	5,871
Buyer fixed effects	Yes	Yes	Yes	Yes	Yes
Project category fixed effects	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes

Notes. Robust standard errors clustered at the buyer level. We calculate the weighted $\hat{U}_{ijt}$ with the prior probabilities that buyer i in a particular class based on the class membership model parameter estimates. We find similar results when using weighted $\hat{U}_{ijt}$ calculated based on the posterior probabilities that buyer i in a particular class, taking into account the buyer's sequence of hiring choices. Number of observations in Models (1)–(4) is smaller than in Model (5) because auctions that were not awarded were excluded in Models (1)–(4). Also, we limit our sample to those matched projects that have received more than one bid and successfully awarded to one and only one bidder in Models (1)–(4). Results are highly consistent if we use *win_rate* as an alternative measure of bidder quality.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

auction duration and long item description dummies, we reran the model of our main analysis and estimated the effects of long auction durations and long item descriptions on bidder entry (i.e., the number of bids and the quality of the bidder pool). After repeating this permutation procedure 1,000 times, we obtained the distributions of placebo effects of long auction durations and long item descriptions on bidder entry.

As shown in Online Appendix E, the effects of placebo long durations and placebo long item descriptions on bidder entry are not significantly different from zero. Moreover, based on the distributions of the placebo effects, we find that it is almost impossible to observe a similar size of the effects of the auction duration and the item description length on bidder entry by chance (i.e., outside the 95% confidence interval). This lends support to our finding that it is the auction duration and the item description length, instead of other auction characteristics, that drive the observed increase in the number of bids and the decrease in bidder quality.

6.2. Effect on Bidder Quality at Various Quantiles

Although we show that the average and maximum of bidder quality both decrease when buyers increase the auction duration and the item description length, one may wonder how the other quantiles of bidder quality in the bidder pool are affected by these two design parameters. Especially for inexperienced buyers whose sensitivities to quality are relatively lower than experienced ones, they may rather hire a bidder at the 80th or 90th percentile of the quality measure instead of the bidder with the highest quality to save cost. To this end, we calculate the bidder quality at various quantiles for each auction to better understand how the auction duration and the item description length affect the whole distribution of bidder quality. As described in Online Appendix F, the bidder quality at all the percentiles (i.e., 10th, 20th, … , 90th) consistently decreases as the auction duration or the item description length increases.

6.3. Alternative Measures of Bidder Quality

As an alternative way to measure the effects of the auction duration and the item description on bidder quality, we conducted robustness checks with two alternative measures of bidder quality: (1) *win_rate*, that is, the probability of winning among all the prior bids from the service provider, and (2) an absolute measure of bidder pool quality, that is, the number of high-quality bidders in the bidder pool. In Online Appendix G, we consistently find that longer auction durations and item descriptions lead to lower quality of the bidder pool.

6.4. Other Robustness Checks

We further conducted a series of other robustness checks. First, to rule out the potential confounding effect of buyers' stopping the auction earlier than the prespecified duration, we ran a robustness check by limiting our sample to bids received within the first day[24] of the auction. Detailed results are reported in Online Appendix H, which shows consistent results. Second, apart from bidder entry, we further investigated how bidder quality influences the final contract outcomes. Specifically, we find that the lower quality of the bidder pool leads to a lower probability of projects being awarded, lower quality of the chosen bidder, and a lower probability of projects being eventually completed (see Online Appendix D). Third, to alleviate the potential concern that the quality of the existing bidder pool may affect future potential providers' bidding decisions, we conducted a robustness check based on sealed auctions. The results regarding bidder entry are highly consistent (see Online Appendix I). Fourth, to avoid the double whammy of higher evaluation costs and adverse selection, we find that buyers tend to reduce the auction duration and the item description length as they accumulate more auction experience. Nevertheless, our results are highly consistent if we control for the effect of buyers' auction experience (see Online Appendix J). Fifth, to account for the potential nonlinear effect of design parameters, we conducted an additional test by dividing both design parameters into multiple bins and find little evidence of nonlinearity (see Online Appendix K). Sixth, instead of controlling for month dummies, we further controlled for the category-specific time trends by adding the category–month pair dummies and find consistent results (see Online Appendix L). Finally, to further alleviate the potential issue resulting from category heterogeneity, we also reran our project-level analysis on only IT projects, which is the most popular project category. All the results remain the same (see Online Appendix M).

7. Discussion and Conclusion

This paper provides a theoretical view regarding the potential screening effect of the auction duration and item description length and offers robust empirical evidence that auction duration and the item description can function as screening mechanisms that help improve outcomes on online outsourcing platforms. We find that shorter auction durations and item descriptions lead to fewer bids submitted, but they help discourage low-quality bidders from entering bids and, hence, lead to a higher quality of the bidder pool and higher buyer utility. The results suggest that, for our corporate partner, that is, a leading online outsourcing platform on which a typical auction attracts many bids (15 on average), it is advantageous for buyers to post calls for bids that are shorter in terms of the auction duration and the item description.

This paper contributes to the stream of research focusing on the intersection between information systems, platform operations, and auction design in several ways. First, we extend prior studies (e.g., Mithas and Jones 2007, Bapna et al. 2008, Hong et al. 2016) by exploring and evaluating the effects of important design parameters in reverse auctions on key nonprice outcomes. In this paper, we take a novel perspective by examining the effects of the auction duration and the item description length on bidder entry through the number of bids received and the quality of bidders attracted. We provide evidence regarding buyers' weights on bidder quality and price, which underscores the importance of understanding the entry process for bidders of different quality. Furthermore, we study subsequent contract outcomes to show how long auction durations and item descriptions actually have negative effects on project contracting and buyer utility. To the best of our knowledge, we are among the first to empirically demonstrate the effects of the auction duration and the item description length on buyer utility. This study deepens our understanding of how buyers on online outsourcing platforms can make better choices in the reverse auction context.

Second, we contribute to the emerging literature on online outsourcing platforms by investigating the bidder-entry preference for auctions with different auction durations and item description lengths (Hong and Pavlou 2017). Specifically, we leverage the granularity of our observations to construct the consideration set for each active bidder at the point of time the bidder placed a bid on the platform. In our bidder-level analysis, we find consistent evidence that, compared with high-quality bidders, low-quality bidders have a higher tendency to bid for auctions with long auction durations or item descriptions. This finding presents important managerial implications for buyers on online outsourcing platforms by pointing out the potential screening efficacy of design parameters for service procurement auctions.

Third, our study also contributes to the market design literature on two-sided platforms, which are usually saddled with information asymmetry problems. Although the auction mechanism can be designed to help reduce the buyer's disadvantage of information asymmetry by inducing fiercer competition among bidders, design parameters may also have unintended side effects on the supply side. Our study shows that longer auction durations and item descriptions attract more bids and, thus, intensify the competition, but they also attract a higher proportion of low-quality bidders and discourage the entry of high-quality bidders. As a result, they have a negative effect on the eventual contract outcomes.

The implications that can be drawn from our findings are as follows. On the practical side, buyers of IT services interested in using online outsourcing platforms need to understand that their intuition may work against their interests. Longer auction durations and more detailed item descriptions, despite attracting more bids, may actually end up attracting more low-quality service providers and also lead to more contract indecision and eventually to lower buyer utility. Although each auction for IT service projects is different and, hence, requires unique design specifics, buyers, in general, are advised to keep auction durations and item descriptions short to the extent possible. On the research side, we find that the design space is more complex than initially assumed. With the evidence from both project- and bidder-level analyses, our study suggests that design parameters such as the auction duration and item description length, as straightforward as they appear, deserve a more in-depth analysis that may lead to interesting and perhaps even counterintuitive findings.

Furthermore, our additional analysis suggests that buyers do learn from their auction experience and reduce the durations and item descriptions of their later auctions (see Online Appendix J). Such learning is also in line with experienced buyers' higher sensitivities to bidder quality (see Section 5.2). This echoes the extant literature on auction design that suggests auctioneers may constantly evolve their auction design strategies (Einav et al. 2013; 2015). For instance, Einav et al. (2015) find that eBay sellers constantly learn from prior auctions and experiment by engineering their sale parameters. Consistent with Einav et al. (2015), we find that service buyers are learning from their prior auction experience. Specifically, even within our short observation window (i.e., seven months), there is a decreasing trend in the two design parameters (i.e., the auction duration and the item description length) as buyers accumulate auction experience. Future studies can further examine what factors may affect the effectiveness of buyers' learning process and how this may affect the long-term equilibrium.

As with any observational empirical research, our study is not free of limitations. One limitation is that the design parameters examined are choices of the buyers, so these design parameters for service procurement auctions might potentially suffer from an unknown and uncontrolled selection effect. In this paper, we control for buyer fixed effects and used the CEM method to find auctions that are similar in all characteristics other than the auction duration and the item description to alleviate the concern for the selection effect. However, future research may seek to randomize such design features with field experiments on online outsourcing platforms. A field experiment could be conducted in which researchers post quasi auctions with varying auction durations and item descriptions to elicit bids from service providers and study their effects. A caveat of such field experiments with synthetic projects to solicit bids is that they tend to pose some ethical challenges as the platform and bidders incur costs without real benefits.

Moreover, our study is conducted on an online service outsourcing platform on which most jobs are short-term and temporary. Our findings may not be generalized to long-term contract contexts, such as B2B procurement projects, in which the opportunity cost associated with waiting time may be trivial. Besides, our result suggests that the negative effect on buyer utility is contingent on buyers' sensitivities to bidder quality. Therefore, our findings should be carefully applied to other platforms on which most jobs are entry-level or highly standardized. Future research can explore how the auction duration and the item description length may affect bidder entry and contract outcomes in such homogeneous markets.

In addition, an interesting follow-up question is whether and to what extent technological advances and regulatory changes may alleviate the double-whammy phenomenon (i.e., a high-quantity and low-quality bidder pool). For one thing, during our observation window (August 2009–February 2010), most filtering and recommendation tools were not available on our corporate partner's website. Nowadays, most platforms have automated tools available to reduce buyers' evaluation costs, which is intended to alleviate the double-whammy phenomenon. For another, the labor market has undergone various regulatory changes (e.g., Garrett et al. 2020) over the last decade. Those regulatory changes may encourage labor force participation and intensify the competition on the supply side, which subsequently attenuates the double whammy phenomenon. Future research using longer panel data and leveraging the exogenous shocks induced by technological or regulatory changes is worth pursuing.

To conclude, our study contributes to the related literature by providing new insights into the effective design of auctions on online outsourcing platforms. We evaluate the effects of two main design parameters, namely, the auction duration and the item description length, on bidder entry (i.e., bidder quantity and bidder quality) and contract outcomes (i.e., the project being contracted and the buyer's expected utility from the winning bid). Our empirical results reveal that auctions with longer durations and item descriptions receive more bids, but they also attract more low-quality service providers with lower completion rates. The joint effects of high bidder quantity and low bidder quality represent a double whammy wherein the buyer incurs higher evaluation costs in an adverse-selection situation, leading to a lower probability of the project being contracted. Additionally, buyers' expected utility from winning bids tends to decrease as the auction duration and the item description length increase. We find that the auction duration and the item description length can serve as a potential screening mechanism for bidder quality on online outsourcing platforms.

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Endnotes

[1] See https://www.upwork.com/resources/why-covid-19-is-leading-businesses-to-adjust-hiring-models.

[2] See https://investors.fiverr.com/press-releases/press-releases-details/2020/Fiverr-Announces-Second-Quarter-2020-Results/default.aspx and https://www.fiverr.com/news/smallbusinessindex.

[3] The winning bid is the bid chosen by the buyer if a project is contracted.

[4] In 2020, the Nobel Prize in Economic Sciences was awarded jointly to Paul R. Milgrom and Robert B. Wilson "for improvements to auction theory and inventions of new auction formats." (See https://www.nobelprize.org/prizes/economic-sciences/2020/summary/.)

[5] Following the prior auction literature (McDonald and Slawson 2002), we use the term "item description" to refer to the description about the item (i.e., what service is being requested and procured) provided to all potential bidders during the auction stage. This is also commonly named as the call for bids on online outsourcing platforms.

[6] The auction duration represents the time open for service providers to enter the bidder pool, and the item description contains a high-level description of the project during the auction stage. Note that, typically, the auction duration is a design parameter set by the auctioneer, whereas the item description is a design parameter set by the user of reverse auctions. In the online service procurement context, however, buyers are both the auctioneers and the auction users. Therefore, both design parameters can be manipulated by buyers. We thank the AE for pointing out the conceptual distinction between these two design parameters.

[7] The screening effect we are measuring includes the potential framing effects when buyers set the auction duration and the item description in a way to signal the type of bidders they prefer, which subsequently also affects bid entries (i.e., framing-resulted screening effects). That is, the screening effect we measure also includes the screening effect of the "framed" design parameters as part of the screening effects, either through framing or actual screening of bidders, the goal of buyers is the same: to attract higher quality bidders. We thank the AE for pointing out the potential framing effect.

[8] Note that we cannot recover the full set of projects considered by each bidder. Here, the consideration set is defined as a set of auctions that are highly similar to the auction for which a bidder actually bid and that have similar opening times. We assume bidders have seen these other similar auctions before making their bidding decisions. Please find details regarding the construction of bidders' consideration sets in Section 4.2.3 and the robustness check in Online Appendix H.

[9] For bidders who have never been awarded projects, the success rate shown on the website is zero. Results are consistent if we limit our sample to those bidders who have been awarded to projects at least once. Additionally, results are consistent if we use an alternative quality measure (i.e., the win rate that indicates a bidder's probability of winning auctions based on prior bids).

[10] In the reverse auctions (especially scoring auctions) context, scholars and practitioners usually use an additive linear utility function over different attributes (e.g., price, quality, etc.) (Che 1993, Branco 1997, Asker and Cantillon 2006). We follow this common practice; however, there might be scenarios with nonlinear buyer utility functions, which we do not consider in the present study. Nevertheless, we believe that our study could provide implications for reverse auctions in general by underscoring the effects of the auction duration and the item description on bidder entry and contract outcomes.

[11] It is worth noting that bidders may form an expectation about auctions closing early, and presumably, those highly experienced bidders are more able to predict which auctions would close early. However, this only implies that our estimates are generally conservative as we show later that long auction durations tend to drive away high-quality bidders.

[12] See https://azure.microsoft.com/en-us/services/cognitive-services/.

[13] We find that, for those categories (e.g., accounting, human resources, etc.) whose demands are relatively small on this platform, matched projects within those categories submitted at similar times are rare. Therefore, in the bidder-level analysis, we focus on the most popular category (i.e., IT services), which accounts for 44% of the matched projects.

[14] On average, 75% of bids were submitted and received within the first day of an open auction. In Online Appendix H, we show the robustness of our results when bidders only consider the auctions opened within 24 hours. We further require that all alternative auctions opened exactly on the same day as the chosen auction, which implies that all the auctions in the consideration set for the bid decision made on day t opened on day t. Results are highly consistent.

[15] Note that the average success rate of bidders across auctions is 0.366. If we increase the auction duration by 10%, *avg_success_rate* decreases $0.014 \times \ln(1.1) = 0.0013$, which is a $0.0013/0.366 = 0.36\%$ decrease.

[16] Similarly, if we increase item description length by 10%, *avg_success_rate* decreases $0.020 \times \ln(1.1) = 0.0019$, which is a $0.0019/0.366 = 0.52\%$ decrease.

[17] Note that the regression models describe the effects relative to the mean, not the extreme. In this regard, we conduct an additional analysis regarding the potential nonlinear effect and report related results in Online Appendix K.

[18] We conduct an additional analysis with only bids submitted on the first day of auctions because a significant number of bids are submitted on the first day of auctions (on average 75% of bids were received within the first day) and consistently find that short auction durations and item descriptions lead to more bids and lower quality of the bidder pool (see Online Appendix H).

[19] Because z_i should be fixed within buyer i, we compare the buyers' numbers of prior projects at the beginning of our observation window with the corresponding sample median to define whether buyer i is experienced or not.

[20] Setting the class number at three produces qualitatively similar results. The latent class conditional logit model does not converge when we set the class number greater than three.

[21] Here, compensating variation refers to "the amount of additional money an agent would need to reach their initial utility" after a change in the auction duration or the item description length. (See https://en.wikipedia.org/wiki/Compensating_variation.)

[22] Here, $38.2\% \times (-0.193 \times \ln(1.1)/(-1.696)) + 61.8\% \times (-0.268 \times \ln(1.1)/(-0.556)) = 0.021$.

[23] Here, $(\text{Exp}(0.021) - 1) \times 50 = \$1.061$.

[24] On average, 75% of bids were submitted and received within the first day of an open auction.

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