**Is Ignorance Bliss? Sealed versus Open Auctions in Online Labor Markets***

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**Abstract**

Online labor markets routinely employ auction mechanisms to assist the project providers (i.e., buyers or employers) in recruiting eligible participants (i.e., sellers or workers) who have placed bids in either sealed or open auctions. In a sealed auction, participants know only the number of competitors, but not their profiles and bidding amounts. Conversely, in an open auction, all this information is public. To understand which auction format results in more optimal allocation (i.e., effectively matching buyers and sellers) and greater time efficiency, we build a theoretical model to generate a series of hypotheses, then test these hypotheses using data from an abrupt change of auction format in an online labor market. Our findings indicate that in sealed auctions, where sellers cannot observe their competitors' bids, they tend to place lower bids and bid more quickly than sellers in open auctions. Additionally, the effect of auction format switching is less pronounced for experienced sellers compared to new sellers. The empirical results align with our theoretical explanation: In open-bid auctions, sellers have strong incentives to delay bidding or place initial bids higher than their valuation to learn from competitors' bids and adjust accordingly (if there is a chance). This strategic bidding behavior can lead to misallocation and time inefficiency. Specifically, while open auctions attract more participants, buyers take longer to make hiring decisions, and the likelihood of hiring decreases. Furthermore, sealed auctions result in better project completion and fewer seller exits.

*Keywords*: Online labor market, labor contracts, procurement, sealed auctions, open auctions, natural experiment

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## 1. Introduction

Online labor markets are platforms that connect workers and employers from around the world to complete various types of jobs ranging from software development and graphic design to transcription and translation. Examples of such online labor markets include Freelancer, Guru, Upwork, Toptal, and Expert360. Due to the removal of geographical barriers, online labor markets have apparent advantages over traditional offline labor markets in reducing hiring costs and expanding access to global labor forces with a broader spectrum of skill sets. Along with the benefit of global reach, a fundamental challenge for these platforms is to match the right worker to the employer for the specific project needs. Given the competition among potential workers, many platforms use auctions to match workers with employers.

The literature documents an abundance of auction formats (Klemperer, 1999; Milgrom, 2004). From a theoretical point of view, the revenue equivalence theorem (Myerson, 1981) posits that under conditions such as independent private values and risk neutrality, all standard auction formats should yield the same expected payoff for the auctioneer. The empirical literature, however, has documented many nontrivial differences across auction formats, particularly between open auctions—in which competitors may see one another's bids—and sealed auctions—in which bids are only visible to the auctioneer. Athey et al. (2011), for example, found that sealed auctions attracted more small bidders and yielded higher revenue. There are other studies that have documented the significance of auction format choices in various contexts (e.g., Shachat & Wei, 2012; Haruvy & Katok, 2013; Cho et al., 2014; Hu & Zhang, 2023).

The distinct characteristics of the online labor market, which differentiates it from the product markets typically examined in the literature, make choosing an auction format for this evolving market more challenging. First, these global online labor platforms foster competition among individuals from diverse cultural and ethical backgrounds. This heterogeneity is significantly greater than that among products, due to variations in cultural backgrounds, experiences, ethics, and communication styles. Second, the virtual nature of these platforms significantly amplifies the signaling and screening challenges found in traditional labor markets, primarily due to the absence of face-to-face interactions. Lean, text-based communication dominates these platforms, increasing the likelihood of miscommunication, misunderstandings, and misalignment of expectations. Third, unlike product market auctions where the bid amount determines the outcome (e.g., buyers competing for an item on eBay), auctions in online labor markets resemble a beauty contest based on buyer determined winning rules—workers offering the lowest bids (i.e., the lowest asking price for completing the job) may not necessarily win (Yoganarasimhan, 2016). Last, employers in the online labor market face greater challenges in selecting workers compared to choosing products. Services in the online labor market are experience goods, where quality is only evident after use. Each delivery is unique and often an intermediate product for downstream business, making hiring decisions more critical and the consequences of a wrong choice more significant. Compounding the complexity of this emerging market, the choice of auction formats can significantly influence the behaviors of both employers and workers. This, in turn, affects the satisfaction of both parties and the platform's long-term viability. Therefore, selecting the appropriate auction format is crucial.

Despite the significance of auction format choice for online labor markets, the literature is still quite thin. One notable exception is Hong et al. (2016), where the authors primarily used data from a platform that allows employers to choose between open and sealed auction formats. It remains an open question how workers and employers respond when platforms mandate a particular auction format, making it essential to understand the tradeoffs between different formats. Even on platforms where employers have a choice, studying worker responses to various auction formats is crucial for informed decision-making. As online labor markets expand and integrate into business workflows, a comprehensive understanding of the tradeoffs between open and sealed auction formats is critical for their future growth.

This study will fill this gap. We first develop a theoretical model to examine the contrasting behaviors of workers under different auction formats in an online labor market, generating a series of empirically testable hypotheses. We then exploit a unique opportunity in a large online labor market that unexpectedly switched all auctions from an open format to a sealed format, removing the employer's choice of auction format. Using administrative data from the platform before and after this change, we test our hypotheses.

We find that in open auctions, where workers can see each other's bids, workers often delay their bids, wait for competitors to bid first, or start with higher bids and then revise them lower. This behavior is more pronounced in new workers, who may react more irrationally to competitors' bids. However, after the platform switches to sealed auctions, workers tend to bid lower amounts and place bids more quickly, benefiting employers compared to their behavior under open auctions.

From the employer's perspective, under open auctions, they receive more bids but are more likely to end up not choosing anyone, and it takes them longer to make a hiring decision. Under the sealed auction format, employers are more satisfied with their hires, and workers are less likely to exit the platform. Overall, our analysis suggests that the platform was correct in switching from open auctions to sealed auctions.

Our analyses have significant implications both theoretically and practically. We contribute to the vast literature related to auctions (see Krishna (2009) for an excellent review) by studying the consequences of auction format choice in a global, online labor market, and documented novel findings not existing in the literature. We also contribute to the growing literature that focuses on online labor markets. The issue of information asymmetry in this nascent market has attracted research attention from scholars in a wide range of fields, including information systems, marketing, management, and economics (e.g., Yoganarasimhan, 2013; Moreno & Terwiesch, 2014; Lin et al., 2018; Kokkodis, 2021). We complement existing research by showing that when platforms mandate an auction format, market participant behavior seems to deviate significantly from cases where employers can freely choose the auction format. From a practical point of view, our study's findings provide additional theoretical and empirical evidence for platforms and employers when they consider whether to implement a specific auction format.

The rest of the paper is organized as follows. We will begin our investigation with a review of the literature in Section 2. In Section 3, we introduce the theoretical model and propose hypotheses. Following Section 4, which describes data and variables, Section 5 reports empirical results and robustness checks. Finally, we discuss the main findings, theoretical and practical implications, limitations, and future studies in Section 6.

## 2. Research Context and Related Literature

### 2.1 The Online Labor Markets

Online labor markets have become increasingly popular in recent years. They provide an opportunity to connect globally dispersed buyers seeking services and sellers offering services. Although different platforms could have unique features, such as the website's detailed design, most followed the common operating procedure described next (Lin et al., 2018).

The process starts when a registered buyer initiates a potential labor contract by posting a project description on the platform as a reverse (procurement) auction.[1] In the project description, the buyer needs to specify worker requirements, such as specifications, expected deliverables, and required seller skill sets. Buyers can specify the reserve price (the highest price they are willing to pay). After posting, the registered sellers can browse project requirements on the site and decide whether they want to bid to work on the projects for a certain amount. It is worth noting that such platforms have a very different terminating rule compared to well-known online auction sites such as eBay (Roth & Ockenfels, 2002; Zhang, 2021a, 2021b). Buyers often do not have to commit to the predefined auction deadline. Instead, they could choose a seller and terminate the auction before the deadline, which is a feature to encourage sellers to bid quickly. In addition to bid amount, buyers can observe the automatically populated sellers' profile information, such as their tenure on the site, geographic origins, prior seller ratings, and skill certifications (if there are any).

Most importantly, whether a bidder (seller) for a project can or cannot view other competing bidders' information depends on the type of auction: In an open auction, sellers could view competitors' information and bid amount, while in a sealed auction, sellers could not view this information (more details are provided in the next section). The market applied a multi-attribute "beauty contest" auction in which the buyers could select the winner based on both bid prices and other characteristics (e.g., reputation and certification). Thus, the winning seller does not necessarily have the lowest bid (Asker & Cantillon, 2008). This is another obvious distinction from other online auctions, where the participants with either the highest or lowest bidding price win the auctions. Additionally, the buyers do not necessarily need to choose a winner, as they can cancel the auction if none of the bids is satisfactory.

Once the buyer selects a bidder to work on the project, the labor contract is formed. Then, the buyer is required to deposit the winning bid amount into an escrow account hosted by the site. Meanwhile, the contracted seller's identity (with a link to their profile page) and the bid amount are disclosed to the public to prevent fraud

[1] Since each auction is associated to a project, we use the word auction and project interchangeably.

or collusion under both types of auction formats. Then, the contracted seller is required to work on the project and deliver the final product to the buyer via the online system before the project deadline. Suppose the buyer is satisfied with the deliverables. In that case, the deposit in the escrow account will be released to the contracted seller after the platform deducts a service fee, and then the project is considered complete. At that moment, the buyer and seller have a chance to voluntarily provide ratings for each other. If the buyer is dissatisfied with the product deliverables, either party may initiate an arbitration process to resolve the dispute. Then, the platform will send an administrator who serves as an arbitrator to decide on the dispute.

### 2.2 Design Features in Online Labor Markets

As a new type of online marketplace, online labor markets draw tremendous interests from researchers who study various features of such markets. However, since all transactions in this market are conducted over the Internet, buyers and sellers are online "strangers" who know little about one another. Thus, the virtual nature of these marketplaces exacerbates the information asymmetry, which also exists in the offline labor markets. As a result, it is difficult for buyers to choose among competing sellers, especially given the high customization nature of the projects.

Many existing studies examine different design features to help employers to make hiring decisions. These features include disclosed sellers' characteristics such as experience, affiliation, and geographic location. Studies find that employers tend to select sellers with whom they have had a prior exchange (Gefen & Carmel, 2008), who have verified experience (Agrawal et al., 2013), who receive more detailed feedback or disclose more detailed information (Pallais, 2014), who are affiliated with outsourcing agencies (Stanton & Thomas, 2015), who have high capacities (Horton, 2019), who send polite direct messages to the employer (Hong et al., 2021), who have explored new skills (Kokkodis, 2023), who have more trustworthy profile picture (Troncoso & Luo, 2023), or who come from certain countries or belong to certain demographic groups (Chan & Wang, 2018; Ghani et al., 2014; Hong & Pavlou, 2017; Mill, 2011).

Online labor markets have also developed mechanisms to distinguish high-quality sellers from low-quality sellers to mitigate the information asymmetry between buyers and sellers. These quality-signaling mechanisms include seller reputation as a rating by previous employers (Yoganarasimhan, 2013; Moreno & Terwiesch, 2014;

Kokkodis & Ipeirotis, 2015; Lin et al., 2018; Gu & Zhu, 2021), platform-offered money-back guarantee (Barach et al., 2020), monitoring mechanism (Liang et al., 2023), and third-party certifications (Bai et al. 2023).

The common characteristics of these studies are that these mechanisms only affect some rather than other individual sellers. For example, the platform usually only guarantees workers who pass pre-defined thresholds (Barach et al., 2020). Only workers who attempt and pass certification tests can benefit from the certification mechanism (Bai et al., 2023). Cold start (i.e., workers having no reputation) is a well-known issue for new workers without reputation in online labor markets (Lin et al., 2018). Previous studies have explored the impact of buyer-determined, project-specific auction parameters, such as auction duration, on seller bidding behaviors and auction outcomes (Liang et al., 2022). In contrast, auction formats, as design features that can equally change the information structure of every participant in the market, are understudied in literature. In this study, we fill this gap by comparing how different auction formats (i.e., open versus sealed auction formats) will affect participants in this emerging market. Next, we will start with previous literature on auction formats.

### 2.3 Related Literature on Auction Formats

Two major types of auction mechanisms are sealed and open auctions. Based on that, auctions can be further divided into English auctions, Dutch auctions, sealed first-price auctions, and sealed second-price auctions (see Krishna (2009) for an excellent review). The English auction is an ascending price auction commonly used in offline antique auctions and online auction platforms such as eBay. On the contrary, the Dutch auction is a descending price auction and was initially adopted to sell fish and followers in the Netherlands. In such a format, the price will keep dropping until the first bidder claims the item and pays the exact price when they claim the item. Both English and Dutch auctions are oral auctions. In contrast, a sealed first-price auction (or, respectively, a second-price auction) allows bidders to participate in the auction by submitting a bid price in a sealed envelope; the bidder with the highest bid will win the item and pay the highest price (or correspondingly, second highest price). Among these formats, an English auction is theoretically equivalent to a sealed second price (Vickrey) auction since the price will keep rising until all the other bidders drop out, except that the bidder with the highest valuation remains active (but the winner will pay the price when the bidder with second-highest valuation drops out) (Milgrom & Weber, 1982). In theory, both the

English auction and Vickrey auction generate efficient allocations and lead to a truth-telling dominant strategy, in which each bidder will bid their true value, regardless of what the rivals do. Similarly, a Dutch auction is theoretically equivalent to a sealed first-price auction. But both formats are no longer truth-telling, and bidders bid lower than the true value. Therefore, there are two major auction mechanisms in the existing literature: sealed and open auctions.

For both practical and theoretical reasons, the main debate between auction formats concentrates on the relative superiority of open versus sealed auctions. Although the two auction formats yield different equilibrium bidding strategies, in theory, the two formats will lead to the same expected revenue for the sellers (i.e., auctioneers) under certain key assumptions such as symmetric, independent private value, and risk-neutral bidders, which is the revenue equivalence theorem (Vickrey 1961; Myerson, 1981; Riley & Samuelson 1981). That is to say, the expected revenues in open and sealed auctions are the same; thus, a risk-neutral seller should be indifferent between the two auction formats. Notably, the revenue equivalence theorem will not hold when the assumptions are relaxed. Briefly, the expected revenue in a sealed auction will be greater than that in an open auction, when (1) bidders are risk-averse (Holt, 1980; Milgrom & Weber, 1982; Maskin & Riley, 1984),[2] (2) bidders' valuation distributions are asymmetric and auction entry is endogenous (Maskin & Riley, 2000),[3] and (3) there is potential collusion among the bidders (Athey et al., 2011; Cho et al., 2014).[4] In contrast, the drop in the independent private values assumption means that the true valuation depends on the information from all bidders (that is, there is a common value component). Since an open auction has an advantage over a sealed auction in terms of information acquisition, its expected revenue will be higher than that in a sealed auction in this situation (i.e., the linkage principle, by Milgrom & Weber (1982)).

Since the revenue equivalence theorem only holds with strong assumptions, in the previous empirical literature, studies comparing open and sealed auctions often uncover significant differences between the two

[2] Intuitively, since bidders have uncertainty about other bidders' valuations in a sealed auction, risk-averse bidders will bid more aggressively; consequently, sellers prefer a sealed auction to an open auction in this situation.
[3] In theory, a sealed auction would give weaker bidders (whose valuation distributions are stochastically dominated by those of stronger bidders) extra incentives to enter the auction because they would expect stronger bidders to bid lower than their true valuations so that they have a chance to win.
[4] If the bidders collude in the auction, the expected revenue will surely be much lower. Since open auctions facilitate collusion because bidders can observe other bidders' behavior, it is more vulnerable to collusion than a sealed auction.

auction formats. For instance, Athey et al. (2011) built an empirical model under private values assumption and endogenous entry. According to their result, sealed auctions attract more weak bidders, so that allocation shifts toward weak bidders, and actual revenue is higher. Haruvy & Katok (2013) found that in multi-attribute procurement auctions, the sealed auction format generates higher buyer surplus (equivalent to expected revenue in a forward auction) than the open auction format (English auction) since bidders tend to decrease quality in response to bids that they observe in an open-bid environment. By contrast, Shachat & Wei (2012) found that the mean and variance of prices are lower in sealed auctions than in English auctions, because bidders in sealed auctions follow some simple decision-theoretical rule instead of strategic best responses predicted by game theory. Empirical studies on auctions with a common value component also provide some interesting findings. For instance, Levin et al. (1996) conducted a lab experiment to compare the English and sealed first-price auctions in the common value paradigm and found that the linkage principle only holds when bidders do not suffer from the winner's curse, while experienced bidders could use information released in English auction to avoid winner's curse. Cho et al. (2014) showed that an English auction yields higher expected revenue than a dynamic Internet auction (which is an open ascending second-price auction, but with less information released), verifying the linkage principle that more information disclosure leads to higher revenue.

### 2.4 Auction Formats in Online Labor Markets

Despite the significance of auction format choice for online labor markets, very limited literature exists on this topic. One notable exception is Hong et al. (2016). They compared the impact of open and sealed auction formats on seller bidding behaviors (e.g., bidding price) and buyer welfare. However, they studied an online labor market where buyers can "endogenously" choose to use either open or sealed bid auction mechanisms in each job they post (both auction formats co-exist).[5] They assume the project's valuation contains both the independent private value (IPV) and common value (CV) components.[6] They found that sealed auctions have a higher number of bidders per project than open auctions. They consider that the independent private value

[5] Buyers will pay for a premium for using a sealed auction (for example, Freelancer and Guru).
[6] Independent private value (IPV) is the assumption that the valuations of auction items are only known to bidders themselves and can only be realized from item consumption alone—each seller has own valuation. Common value (CV) is the valuation of auction items that is identical but unknown to all bidders and can be derived by aggregating every bidder's information.

component causes this effect because revealing competing bids in an open auction reduces competition uncertainty. As a result, the open auction format prevents weaker workers from bidding. They also find that the buyer surplus is higher in open auctions than in sealed auctions. They attribute this result to the common value (CV) component (of the project's valuation) since the linkage principle suggests that opening bids to all potential bidders will reduce their searching cost and allow them to bid at lower prices. In contrast, notably, the online platform we study has suddenly switched from open auction format to sealed auction format, a regime change that provides a natural experiment by which we could identify the causal impact of auction formats on sellers' bidding behavior, buyers' decisions, as well as auction outcomes. Due to the significant difference in the setting (endogenous choice versus regime change), we do not expect our empirical study to derive the same results as Hong et al. (2016) did.

Our research context has two major features that are significantly distinctive from traditional auction contexts. First, the online labor market employs a multi-attribute buyer-determined (BD) procurement auction, in which the buyers could select the winner based on some rules on both bid price and other characteristics of the bidder's offer (Che, 1993; Asker & Cantillon, 2008). Online labor markets often employ beauty contest auctions in which the buyers use unrevealed rules, which could be learned from the bidders in the long run, to determine the winners (Yoganarasimhan, 2016). Second, the buyers, as the auctioneers, do not commit to any ending time to the auctions, as they could choose the winner and close the auction at any time after the auction gets started, or even, at any time, they could close the auction without choosing any winner. Our paper can be viewed as showing the bidding and revenue differences of different auctions when the auctioneer discounts the future in a setting with dynamic arrival of bidders, a realistic and inevitable feature of online labor markets. Previous studies on online auctions have revealed that ending rule could play an important role in altering the bidders' equilibrium bidding strategies. Notably, a fixed auction deadline could lead to many "sniping" behavior, in which bidders bid very late so that the rivals do not have time to respond (Roth & Ockenfels, 2002; Ockenfels & Roth, 2006; Ely & Hossain, 2003). In our research context, since the buyers do not commit to any auction deadlines, we are interested in exploring whether (and which) sellers should bid earlier or later in the sealed auction compared to the open auction. To sum up, existing theories and empirical evidence do not provide sufficient support to draw conclusions about the impact of an auction format change in our study context. In the next section, we develop a simple model for auction formats and hypothesize the possible effects.

## 3. The Theoretical Model and Hypotheses Development

### 3.1. A Simple Economic Model

We present a simple model to illustrate the fundamental economic forces the buyers and sellers face and derive testable hypotheses based on that. Suppose the buyer gets value $V$ from finishing the project and has an instantaneous discount rate $\delta$. The buyer, as an auctioneer, announces to run the procurement auction from time $0$ to a fixed time $T > 0$. We will consider the setting in which the buyer may choose to stop the auction early. Suppose that sellers are unaware of the buyer's possibility of stopping the auction early. Contractors see the auction at Poisson arrival rate $\lambda$. Hence, the number of sellers who view the auction from time $0$ to time $t$ is distributed according to Poisson distribution with parameter $\lambda t$. From each individual bidder's perspective, the number of competitors he faces is also distributed according to Poisson distribution with parameter $\lambda t$. Namely, $\Pr(N = k) = (\lambda T)^k e^{-\lambda T}/k!$ indicates the probability that the number of contractors or competitors is $k$. These nice properties about the total number of bidders and competitors enable a tractable characterization of equilibrium bidding in the auctions we consider.

Let seller $i$'s total cost of completing the project be $c_i = C + \epsilon_i$. The range of cost is $[\underline{c}, \overline{c}]$. Without loss of generality, assume $\bar{c} = V$; otherwise, we can redefine an upper bound $\bar{c}' \equiv V$. There is a common fixed cost $C$ that each bidder is bound to incur when completing the task, but beyond that, the marginal cost of completing the task ($\epsilon_i$) is independent and private. Altogether, bidders have independent private total costs for the auction, which follow a distribution that has cumulative distribution function $F$ and probability distribution function $f$.

Next, we derive the sellers' bidding strategies under both sealed and open auction formats.

#### 3.1.1. Sellers' Bidding in a Sealed Auction

In a sealed auction, there is no incentive for sellers to delay, and since no information is revealed prior to the end of the auction, sellers would place their bids immediately after they see the auction. Placing his bid immediately after he sees the auction becomes a weakly dominant strategy when there is even a tiny positive chance that the auction may end earlier than $T$. Their bids will be the equilibrium bids in a standard *first-price auction with independent private values and an uncertain number of bidders*. In theory, their equilibrium bids will be exactly equal to the expected lowest cost of the competitors. In our model setup, we have a simple expression of the equilibrium bid function, specified below in Lemma 1.

**Lemma 1.** *In a sealed auction, a contractor of cost $c$ who sees the auction at time $t$ places a bid at time $t$ according to*

$$b_{sealed}(c) = c + \int_c^{\bar{c}} e^{-(F(x)-F(c))\lambda T} dx.$$

In general, the bidding function is strictly decreasing in auction time length $T$. When $T \to 0$, $b(c) \to \bar{c}$: If the buyer ends the auction very early, then there will be no competing bidders, and a bidder can ask for a high wage. When $T \to \infty$, $b(c) \to c$: If the buyer ends the auction very late, then there will be a large number of competing bidders, and a bidder must offer his true cost to have a chance of winning. If the buyer ends the auction normally, in a sealed auction, the equilibrium bid should be higher than the seller's private total cost. For example, when assuming that private total cost follows a uniform distribution, the equilibrium bid could be simplified to:

$$b_{sealed}^{uniform}(c) = c + \frac{1}{\lambda T}\left[1 - e^{-(1-c)\lambda T}\right].$$

**Proof of Lemma 1:** Please refer to Appendix A.

**3.1.2. Sellers' Bidding in an Open Auction**

In an open auction, sellers can choose to reveal their bids immediately after they view the auction (and adjust their bids later) or wait until the deadline to bid ("snipe"). When the auction has a fixed deadline and private costs are independent, there is no strict benefit to revealing their bids. In equilibrium, a seller arrives at the auction at any time $t$ will wait until time $T$ to bid. Suppose he observes the revealed leading bid $B_T$, which is the lowest revealed bid by time $T$, we have the equilibrium bid function, specified below in Lemma 2.

**Lemma 2.** *In an equilibrium of an open auction, a bidder of cost $c$ who sees the auction at time $t$, if his cost is below revealed leading bid $B_T$, bids at time $T$ according to*

$$b_{open}(c|B_T) = c + \int_c^{B_T} e^{-(F(x)-F(c))\lambda T} dx.$$

**Proof of Lemma 2**: Please refer to Appendix A.

Note that $b_{sealed}(c) = b_{open}(c|\bar{c})$. That is, if there is no relevant bid by time $T$ (the lowest "revealed" bid is $\bar{c}$), the bidding in an open auction is the same as in that in a sealed auction. However, in general, $B_T \leq \bar{c}$, so in general $b_{open}(c|B_T) \leq b_{sealed}(c)$. In addition, notice that there is no strict gain for sellers to bid earlier than time $T$, if they do not believe that the buyer will close the auction early. However, there is also no strict loss for sellers to bid earlier than time $T$ and adjust to the equilibrium bid at time $T$. Hence, in practice, we may observe some sellers place higher bids before time $T$ and adjust bids lower at time $T$, and the remaining sellers bid at time $T$.[7] Consequently, the open auction delays bids but generates weakly more competitive bidding than the sealed auction.

### 3.1.3. Buyer's Optimal Stopping

In our context, the buyer could stop the auction early. However, because we assume that bidders are unaware of the auctioneer's possibility of stopping the auction early, the bidders will bid as if the auction ends at time $T$. It could be proved that the buyer will secretly use the cutoff rule that any bid weakly below $B_\tau^*$ is accepted at time $\tau$. Suppose the buyer can decide between stopping at time $\tau < T$ and waiting until time $T$ (without the sellers knowing the possibility and thus not influencing the sellers' equilibrium bids). Suppose the current leading bid at time $\tau$ is $B_\tau$. The buyer would take the bid if:

$$V - B_\tau \geq e^{(T-\tau)\delta} \cdot E_{B_T}\{V - Min[B_\tau, B_T]\}.$$

where $B_T$ is the lowest bid by time $T$. For any $\tau$, there is a unique threshold $B_\tau^* > \underline{c}$ such that the buyer is indifferent between taking the offer $B_\tau^*$ and waiting for a better offer at time $T$ but with a delay cost.

$$V - B_\tau^* = e^{(T-\tau)\delta} \cdot E_{B_T}\{V - Min[B_\tau^*, B_T]\}.$$

Therefore, if the buyer has a chance to stop the auction, and if there is a positive probability of sellers bidding before time $T$, as in a sealed auction, there is a positive probability that the auction will stop before

[7] In our research context, empirical evidence suggests that more than 95% of bidders bid once, and more than 99% of bidders bid at most twice. There is no dynamic competition and back-and-forth in the open auctions, which is consistent with our theoretical prediction. In addition, because the auction in practice is based on a secret scoring rule of the buyer, the bidders have no strong incentives to engage in price war.

time $T$. In contrast, in an open auction, the stopping probability is smaller: the probability of stopping early is zero in equilibrium. Intuitively, in an open auction, sellers have strong incentives to delay their bid until time $T$. In the extreme case, the buyer will only receive a low enough bid to accept until time $T$ and will stop the auction at that time. Conversely, in a sealed auction, sellers bid earlier, and the buyer stops the auction before time $T$.

**3.2. Hypotheses**

Based on the analytical framework we derived in the previous subsection, we propose hypotheses that could and will be empirically tested by our data.

**3.2.1. Seller Behaviors**

First, regarding the timing of bidding, we predict that the bids will be submitted earlier in a sealed auction because sellers lack the incentives to wait and bid later. In an open auction, sellers have minimum incentives to bid immediately upon arrival at the auction. Formally, in a sealed auction, a seller's weakly dominant strategy is to bid at his time of arrival, which is $t$. The cumulative distribution of bidding by time $t$ is $P_{sealed}(t) = t/T$ for all $t \leq T$. In an open auction, a seller has a strict incentive to wait until time $T$ to bid. The cumulative distribution of bidding by time $t$ is $P_{open}(t) = 0$ for all $t < T$ and $P_{open}(T) = 1$. Therefore, we propose *Hypothesis 1*, as follows.

**Hypothesis 1.** *Bidding is faster in a sealed auction than in an open auction. Mathematically, bids arrive first-order stochastically earlier in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change).*

Regarding the bidding amount, according to *Lemma 2*, in an open auction, a seller with a cost below the revealed leading bid (i.e., $B_T \leq \bar{c}$) would bid not higher than the amount he would bid in a sealed auction (i.e., $b_{open}(c|B_T) \leq b_{sealed}(c)$). However, because there is no incentive for sellers to reveal their equilibrium bid early in open auctions, those who decide to bid early tend to bid higher amounts before time $T$ and lower their bids at time $T$. Thus, we have our *Hypothesis 2* below.

**Hypothesis 2.** *The bidding amount is lower in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change).*

Next, knowing the speed at which sellers bid in open and sealed auctions, we can further predict the number of bidders per unit time observed throughout the auctions. In sealed auctions, where sellers tend to bid immediately upon arrival, the number of bids per unit of time should be higher compared to open auctions, where sellers typically wait until the end of the auction to bid. Formally, in a sealed auction, a seller's weakly dominant strategy is to bid at the time of arrival. Hence, the expected number of bidders by time $t$ in a sealed auction is $\lambda t$ for all $t \leq T$. In contrast, in an open auction, the expected number of bidders by time $t < T$ is $0$ and is weakly smaller than $\lambda T$ at time $T$. Thus, we propose Hypothesis 3, as below.

**Hypothesis 3**. *The expected number of bidders per unit of time (i.e., bid arrival rate) is higher in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change).*

We have demonstrated that in our context, the buyer will accept a bid if it falls sufficiently below a positive threshold value $B_\tau^*$ and stop the auction before time $T$. In a sealed auction, where sellers bid upon arrival, there exists a positive probability of bids being below the threshold before time $T$, increasing the likelihood of the auction ending early. In contrast, in an open auction, the sellers' equilibrium strategy is to bid at time $T$ to avoid revealing bids prematurely to competitors. Hence, we propose Hypothesis 4 for the auction-stopping rule.

**Hypothesis 4.** *When the auctioneer can stop the auction, a sealed auction (i.e., after the regime change) is expected to end more quickly than an open auction (i.e., before the regime change).*

By combining Hypothesis 3, which addresses the expected number of bidders per unit of time, and Hypothesis 4, concerning the expected auction stopping time, we derive the following hypothesis on the expected total number of bidders. Specifically, because the expected ending time of a sealed auction is strictly smaller than $T$, the expected total number of bidders is strictly smaller than $\lambda T$. In contrast, in equilibrium in an open auction, the expected ending time is $T$, and the expected number of bidders in an open auction is $\lambda T$. Therefore, we have Hypothesis 5 below.

**Hypothesis 5.** *The expected total number of bidders is lower in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change).*

### 3.2.2. Auction Outcomes

Based on the previous discussion, we propose that sealed auctions make sellers behave more competitively by placing lower bids earlier than time $T$. From this, we can derive two auction-level theoretical predictions. During the auction process, the buyer will accept a bid if it is sufficiently low and terminate the auction before time $T$.

In theory, a "patient" buyer who waits until time $T$ to allow all possible sellers to complete their bids can always select the bid from the seller with the lowest cost, regardless of the auction format employed by the platform. However, an "impatient" buyer may become frustrated with the longer waiting times in an open auction and choose to stop the auction without hiring a seller. In contrast, this scenario is less likely in a sealed auction, where sellers place their bids earlier. Consequently, buyers are more likely to find a satisfactory bid in a sealed auction compared to an open auction. Additionally, given Hypothesis 2, which posits that bid amounts are lower, buyers should be more likely to hire a seller at a lower wage in a sealed auction compared to an open auction. Thus, we posit Hypotheses 6 and 7 below.

**Hypothesis 6.** *Buyers are more likely to successfully hire a seller, in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change).*

**Hypothesis 7.** *Buyers are more likely to hire a seller with a lower wage (i.e., winning bid), in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change).*

### 3.2.2. Post-Project Outcomes

The online labor market aims to enhance matching between buyers and sellers through the implementation of auction mechanisms. A well-designed auction mechanism is expected to result in higher satisfaction for both buyers and sellers. In terms of buyers' post-project decisions, previous literature in online labor markets commonly uses *worker ratings by employers* and *whether the employer rehires the worker for future projects* as direct measures of the quality of work delivered by the selected seller (e.g., Barach et al., 2020). In a sealed auction, buyers are more likely to successfully hire a seller at a lower wage, leading to cost savings and preferred matching outcomes. This tends to result in higher rating feedback from buyers to winning sellers and an increased likelihood of rehiring the same sellers for future projects. Consequently, we propose Hypotheses 8 and 9, as follows.

**Hypothesis 8.** *After the projects are completed, buyers are more likely to be satisfied with the selected sellers' work in a sealed auction (i.e., after regime change) than in an open auction (i.e., before regime change).*

**Hypothesis 9.** *After the projects are completed, buyers are more likely to hire the same seller in the future, in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change).*

Regarding sellers' post-project decisions, a sealed auction format increases the likelihood of selecting a winning seller, thereby potentially enhancing the satisfaction of the selected seller. With satisfactory work experience upon project completion, the winning seller is more inclined to remain active on the online labor market, seeking future employment opportunities. Hence, we propose Hypothesis 10 below.

***Hypothesis 10.*** *After the projects are completed, winning sellers are less likely to exit the online labor market in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change).*

We summarize our hypotheses in Table 1.

[Insert Table 1 about here]

## 4. Data and Variables

### 4.1 Data

Our research focuses on one of the largest online labor markets headquartered in the US, where buyers and sellers from around the world engage in thousands of projects annually.[8] The platform hosts a variety of projects, with popular categories including software development, website design, and translations. Through collaboration with the platform, we have access to comprehensive project, buyer, and seller data. Specifically, we have detailed information about each auction (e.g., when it is posted and ended), each buyer (e.g., when he or she registered and where he or she comes from), each worker (e.g., reputation, past bidding, winning, and performance history), each bid (e.g., bid amount and placed order and time), auction outcome (e.g., who wins), and post-auction outcome (e.g., rating given by buyers).

The platform originally operated using the open auction format but transitioned abruptly to the sealed auction format one day without prior notice to participants. This format-switching event presents an ideal natural experiment to empirically assess the impact of auction formats, while maintaining consistency in other platform operations shortly before and after the regime change. We collected data on all auctions and their bids posted three months before and after this regime change event. Each auction and bid provide detailed information on auction dynamics, as well as buyer and seller characteristics. The final dataset comprises 1,926

[8] We cannot disclose the platform and other details (e.g., dates and exact platform feature names) that may reveal this platform due to non-disclosure agreement (NDA).

auctions launched by 967 buyers; there are 16,581 bids placed by 3,421 sellers; among these auctions, 802 of them are contracted. Our empirical analyses are structured into two levels: auction-bid level analyses and auction-level analyses. Consequently, we organize our data into separate tables for each set of analyses.

### 4.2 Variables

**Dependent variables.** Based on our hypotheses, we investigate the effects of transitioning auction formats on multiple dependent variables, including auction and post-auction outcomes, and seller behaviors.

*Auction and post-Auction outcome.* Auction outcome variables are assessed at the auction level and encompass economic efficiency metrics specific to each auction mechanism. These variables include the rate of bid arrivals per hour (*BidArrival*), the number of bidders participating in each project (*#OfBidders*), whether a buyer selects a winning seller (*Contracted*), the winning bid amount (*WinningBid*) when a project is contracted, and the time until a winning bid is selected (*TimeToAccept*). Post-auction outcomes include buyers' satisfaction (measured by *RatingByBuyer*, given by the buyer upon project completion, and *Rehire*, indicating whether the same buyer rehired the same seller for future projects) and sellers' survival--*SellerExit*, which reflects the survival analysis outcome of the winning seller's decision to remain in or exit the online labor market.[9]

*Seller bidding behavior.* We use several auction-bid-level variables to measure sellers' bidding behaviors. *BidDelay* represents the time elapsed between posting the project and placing a bid. *BidAmount* denotes the bid price (wage) proposed by the seller to the buyer for the project.

**Independent variables**. The main independent variable of interest is *AfterChange,* the indicator variable that denotes whether the auction was posted after the regime change date when the platform suddenly transitioned from the open auction format to the sealed auction format.

**Control variables.** We include four groups of control variables in our analysis. Buyer information controls consist of the number of projects previously completed by the buyer (*BuyerExperience*) and the buyer's region of origin (*Region*). Similarly, we control seller information, including the number of projects previously completed by the seller (*SellerExperience*), tenure (*SellerTenure*), and the number of ratings received from previous projects *(#OfRatings*). Additionally, we include auction information such as the length of project description

[9] The data for survival analysis will be introduced in Section 5.3.2.

(*DescriptionLength*), the maximum bid a buyer is willing to accept (*MaxBid*), the duration of time the project remained active (*AuctionDuration*), and a series of dummy variables for project types (*ProjectType*). Furthermore, bidding information includes *BidOrder*, which denotes the rank order of a seller's bid within a particular auction, and *SameCountry*, which indicates whether the buyer and seller are from the same country.

For most of the continuous variables, we apply logarithmic transformation to reduce skewness. Table 2 provides the main variable descriptions and summary statistics. Appendix B provides correlations.

[Insert Table 2 about here]

## 5. Empirical Results

As discussed in the theoretical section, the auction format change may dramatically impact seller behaviors and auction outcomes, as well as post-project outcomes. An unexpected regime change from the open auction format to the sealed auction format in our studied platform creates a perfect natural experiment for us to empirically test these conjectures through a battery of empirical analyses around this regime change.

Our dataset comprises all transactions occurring within three months before and after the regime change date when the auction format shifted from open to sealed. During this narrow timeframe, no other new mechanisms or policies were introduced, and there were minimal changes in seller backgrounds that could influence buyer and seller behaviors, aside from the auction format policy change.

In this section, we discuss detailed empirical models and present our findings based on these analyses.

### 5.1 Impact on Seller Behaviors

We first examine the impact of the regime change on seller behaviors. If the change influences sellers, we anticipate some observable differences in their bidding behaviors before and after the policy. Thus, we use all sellers' bids for these analyses.

Sellers decide both when to bid (i.e., time of bid delay after job posting) and the amount to bid (i.e., bid amount) when they express interest in a posted project. We measure *BidDelay* as the logged time difference in hours between the bidding time and the posting time of a project, and *BidAmount* as the logged bid wage amount proposed by a seller for a project. To provide model-free evidence, we first plot the distributions of these two dependent variables before and after the regime change. Figure 1 reveals that both seller behavior outcomes (i.e., *BidDelay* and *BidAmount*) are lower following the regime change.

[Insert Figure 1 about here]

To validate these results through regression analysis, we specify the baseline model as follows, where *i* denotes the project, *j* denotes the buyer, *k* denotes the seller, and *t* denotes the time (the day on which the seller places the bid).

$$SellerBehavior_{ijkt} = \beta_0 AfterChange_t + \beta X_{ijt} + \delta Z_{ijkt} + \alpha_k + \gamma_t + \varepsilon_{it}, \text{where}$$
$$\beta X_{ijt} = \beta_1 BuyerExperience_{jt} + \beta_2 DescriptionLength_{it} + \beta_3 ProjectType_{it}$$
$$\delta Z_{ijkt} = \delta_1 SellerExperience_{kt} + \delta_2 BidOrder_{ijkt} + \delta_3 SameCountry_{ijkt} + \delta_4 BidAmount_{ijkt} \quad (1)$$

The dependent variables in regression equation (1) are the two seller bid behavior outcomes described above. The primary independent variable of interest is the binary variable *AfterChange*, which equals 1 if the project was posted after the regime change and 0 otherwise. We control for auction and buyer-specific covariates $X_{ijt}$, as well as the seller and bid-specific covariates $Z_{ijkt}$. Specifically, $X_{ijt}$ contains auction characteristics such as *DescriptionLength* and *ProjectType* dummies, along with the buyer-specific variable *BuyerExperience*. $Z_{ijkt}$ contains seller-specific variable *SellerExperience*., as well as bid-specific variables, including *BidAmount*, *BidOrder*, and *SameCountry*.[10] To control for unobserved seller heterogeneity and time trends, we estimate linear regression models with seller fixed effects ($\alpha_k$) and weekday dummies ($\gamma_t$), respectively.

We estimate three model specifications for each seller bidding outcome variable. The first specification is the baseline model, using *AfterChange* as the primary independent variable to verify the overall effect of regime change. The second specification has further added *NoRating* (i.e., whether the seller has any rating before the current bid) and the interaction term between *NoRating* and *AfterChange* to compare the effects of regime change on new sellers versus experienced sellers. The third specification incorporates *#OfRatings* (i.e., the number of ratings given by previous employers) and the interaction term between *#OfRatings* and *AfterChange* to examine the moderating role of seller experience, measured by the number of seller ratings received. We apply logarithmic transformations for continuous variables in the regression to mitigate skewed distributions.

[10] When *BidAmount* is the dependent variable, we exclude itself from the set of regressors.

Table 3 presents the coefficients with robust standard errors (in parentheses) clustered at the seller level. The first three columns in Table 3 report the results using *BidDelay* as the dependent variable. In Column 1, the negative coefficients of *AfterChange* indicate that sellers, on average, spend 41.2% less time deciding whether to bid and determining their bid amount after the regime change. This suggests that the sealed format incentivizes sellers to bid earlier than the open format, as hypothesized, since they have no reason to delay bidding to conceal private information from competitors, and the buyer may stop the auction before the predetermined ending time. Therefore, Hypothesis 1 is supported. Additionally, the coefficients of the interaction terms (*AfterChange*×*NoRating* and *AfterChange*×*#OfRatings*) in Columns 2 and 3 indicate that the impact of switching to a sealed format is more pronounced for new sellers but less pronounced for experienced sellers.

Columns 4 to 6 present the results using *BidAmount* as the dependent variable. In Column 4, the coefficients of *AfterChange* are statistically significantly negative, indicating that sellers bid lower wage amounts after the regime change. Specifically, sellers, on average, place their bids with a 16.5% lower wage amount. This finding suggests that sellers tend to bid more aggressively to secure contracts when they cannot observe competitors' bids and other information, thereby supporting Hypothesis 2. In Columns 5 and 6, the coefficient of *AfterChange*×*NoRating* is negative but only weakly significant, while the coefficient of *AfterChange*×*#OfRatings* is significantly positive. This demonstrates that experienced sellers are less sensitive to the regime change compared to new sellers, as they can better anticipate competitors' bidding.

[Insert Table 3 about here]

Overall, we find that sellers strongly respond to the auction format regime change and become more aggressive, implying more intense competition in the sealed format compared to the open format. When the auction format shifts from open to sealed, sellers take less time to make bidding decisions and bid lower wage amounts. Moreover, the impact varies depending on seller heterogeneity: New sellers exhibit more aggressive bidding, but experienced sellers tend to exhibit more conservative (less aggressive) bidding.

## 5.2 Impact on Auction Outcomes

### 5.2.1. Main Analyses

The impacts of the auction format change on seller bidding behaviors likely further lead to changes in the auction outcomes. For instance, more aggressive bidding behavior could result in a lower winning bid amount and a higher chance of auction success, while faster bidding might lead to earlier ending of the auction. We predict that although more sellers will place bids per unit of time after the regime change, the increased aggressiveness of sellers will make the "current best offer" reach the buyer's threshold of satisfaction more quickly. Consequently, when the buyer ends the auction earlier, there will be fewer sellers who have already placed bids.

To verify these outcomes, we conduct several regression analyses at the auction level. Auction outcomes are measured in several aspects, including logged number of bidders per hour in the project (*BidArrival*), logged time duration until the buyer makes an acceptance decision (*TimeToAccept*), logged number of bidders participating in the project (*#OfBidders*). Additionally, we measure whether the buyer chooses any seller to award the contract with a binary variable (*Contracted*). Conditional on contracting success, the last outcome is logged winning bid amount (*WinningBid*).

Before conducting any regression analysis, we first explore the relationships between the regime change and the auction outcomes using a model-free approach. Figure 2 plots the mean residual of auction outcome variables after controlling for auction and buyer characteristics, aggregated in each equally wide interval along the timeline before and after the regime change. This figure indicates that after the regime change, on average, the number of bidders in the auction and average hours taken to select a winning seller significantly decrease. However, the bidder arrival rate, contracting probabilities, and average value of the winning bid show less substantial changes. These initial results suggest that the regime change does impact some auction outcomes at the aggregate level.

[Insert Figure 2 about here]

To have more detailed estimations, we leverage the natural experiment on the platform to conduct regression analysis using auction-level data. Let $outcome_{ijt}$ denote the outcome of auction *i* posted by buyer *j* at time *t*. We propose the following regression model:

$$Outcome_{ijt} = \beta_0 AfterChange_t + \beta X_{ijt} + \alpha_j + \gamma_t + \varepsilon_{it},\ \ where$$
$$\beta X_{ijt} = \beta_1 BuyerExperience_{jt} + \beta_2 DescriptionLength_{it} + \beta_3 MaxBid_{it} + \beta_4 AuctionDuration_{it} + \beta_5 Region_{jt} + \beta_6 ProjectType_{it} \quad (2)$$

In regression equation (2), *Outcome* is the dependent variable, representing *BidArrival*, *TimeToAccept*, *#OfBidders*, *Contracted*[11], and *WinningBid*, respectively. The primary independent variable is the binary variable *AfterChange*, which equals 1 if the auction posting day *t* is after the auction format regime change. Since the regression model is at the auction level, we only control for auction and buyer-specific characteristics measured at time *t*, which is denoted by the covariate set $X_{ijt}$. Specifically, auction characteristics include variables such as *DescriptionLength*, *MaxBid*, *AuctionDuration,* and *ProjectType* dummies, while buyer characteristics include variables such as *BuyerExperience* and buyer *Region* dummies. Additionally, we incorporate weekday dummies (i.e., Tuesday to Sunday, denoted by $\gamma_t$) to control the time effects. Like previous models, for continuous variables, we take logarithmic transformation to avoid skewed distributions. We estimate both buyer random effects and pooled OLS models, omitting buyer fixed effects models due to a limited number of buyers posting at least two projects, which precludes sufficient within-buyer variation.

Table 4 presents the empirical results. In Columns 1 and 2, we observe a significant increase of approximately 40.1% in the number of sellers placing bids per hour after the regime change, as indicated by the positive and statistically significant coefficients of *AfterChange* in both the random effects (RE) and pooled OLS models. This finding supports Hypothesis 3, suggesting that sealed auctions encourage sellers to bid earlier. Next, Columns 3 and 4 examine *TimeToAccept*: The estimated coefficients are negative and statistically significant in both models (38.9% in RE and 40.6% in OLS), indicating that buyers took significantly less time to choose a winning seller in sealed auctions compared to open auctions. This supports Hypothesis 4, which suggests that sealed auctions lead to quicker decision-making by buyers. Columns 5 and 6 focus on *#OfBidders*, where the coefficients of *AfterChange* show a decrease of 10.3% (RE) and 13.9% (OLS) in the number of unique bidders per project after the auction format change. This result aligns with the findings from the model-free approach, indicating a reduction in the number of sellers participating in auctions after the switch to the sealed format, thus supporting Hypothesis 5.

In Columns 7 and 8, where *Contracted* is the dependent variable, the coefficients of *AfterChange* are significantly positive in both the random effects (RE) and pooled OLS models. The estimated increase in the probability of

[11] For dependent variable *Contracted*, we use Linear Probability Model (LPM). As a robustness check, we also used random effects Logit and Probit models and the results are highly consistent (with estimated average marginal effect 6.61% and 6.59%, respectively). We provide detailed estimation results in Appendix E Table E1.

contract award after the auction format change is 6.1% (RE) and 6.6% (OLS). This finding suggests that under the sealed auction format, where sellers place lower bid amounts, buyers find it easier to identify satisfactory offers and award contracts to winning sellers, supporting Hypothesis 6. Notably, despite a decrease in the number of bidders per project before the auction concludes, auction success rates do not suffer. Conversely, Columns 9 and 10 reveal that the coefficients of *AfterChange* are not statistically significant when *WinningBid* is the dependent variable. This indicates that the auction format change did not lead to a significant difference in the winning bid amounts. Therefore, Hypothesis 7, which posited that the sealed auction format would lead to lower winning bid amounts, is not supported. In summary, while buyers made decisions more quickly under the new format, the actual contracted wages did not significantly differ.

[Insert Table 4 about here]

In summary, the auction-level results illustrate that following the switch from the open format to the sealed format, while the rate of bid arrival increased, buyers exhibited a higher likelihood of swiftly awarding contracts to winning sellers from a reduced pool of bidders. However, there was no significant change observed in the winning bid amounts. The sealed auction format improved contracting probabilities for buyers but did not result in lower project wages paid to selected sellers. Nonetheless, it potentially saved buyers time (i.e., opportunity cost), both during active auction periods and in avoiding subsequent auction retries when initial attempts failed to secure a contract. From the platform's perspective, the sealed auction format facilitated more efficient matching between buyers and sellers in the online labor market, thereby enhancing the platform's revenue through increased transaction fees.

### 5.2.2. Additional Analyses

In the previous subsection, we verified a reduction in the number of bidders expected to participate in each auction following the auction format change. However, on the platform, a single seller may submit multiple bids for the same auction. According to our theoretical framework, in an open auction, sellers lack incentives to reveal their equilibrium bids early, often initially bidding higher and adjusting bids later. Therefore, we expect that the number of bids per bidder (*#BidsPerBidder*) should decrease after the transition to a sealed format. Given the decrease in both the number of bidders and the number of bids per bidder, we further predict that the total number of bids (*#OfBids*) a buyer receives in an auction should also decline.

We therefore conduct two additional analyses to test these conjectures as follow-up checks of our findings on the *number of bidders*. We first plot the average values of the logged number *of bids* and the logged *number of bids per bidder* before and after the auction format change. Figures in Appendix D demonstrate that both metrics significantly decreased after the auction format switched from open to sealed. Finally, we estimate the same regression model, replacing the dependent variables with *#OfBids* and *#BidsPerBidder*, respectively. The findings indicate that both the number of bids and the number of bids per bidder are significantly smaller after the regime change, consistent with our visual conclusions in Appendix D.

In summary, our results indicate that the auction format regime change affects sellers' bidding behavior and buyers' hiring decisions. Sellers, on average, spend shorter periods deciding to bid and bid lower wage amounts after the regime change. Meanwhile, buyers, on average, spend shorter periods selecting a winning seller. At the auction level, while there is an increase in the bid arrival rate, we observe a sudden drop in the number of bidders per project but an increase in the likelihood of contracting after the regime change. However, we do not observe any difference in the final wages of the contracted projects.

### 5.3 Impact on Post-Project Outcome

#### 5.3.1 Buyer Satisfaction: Rating and Rehiring Likelihood

All preceding analyses demonstrate that the transition in auction formats impacts sellers' bidding behaviors and subsequent buyers' hiring behaviors. Given the platform's objective of optimizing matches between buyers and sellers, it is crucial to examine the ramifications of this regime change on post-project outcomes. Specifically, how does the auction format change affect the buyer's satisfaction and future hiring intention toward the same seller? Will the seller decide to stay on the platform for future job opportunities or leave (or exit) the online labor market? Positive outcomes such as increased buyer satisfaction and higher seller retention would validate the superiority of the sealed format on such platforms. Conversely, decreased buyer satisfaction or reduced seller retention would indicate potential drawbacks of the sealed format on market performance.

We begin by investigating the impact of the auction format regime change on buyer satisfaction. To measure this, we use the ratings provided by buyers to sellers upon completion of projects. Buyer rating (from 0 to 10) is a common performance evaluation metric used on e-commerce platforms like eBay and Amazon.

Given the scarcity of ratings below 7, we truncate lower ratings at 7, resulting in a truncated rating scale from 7 to 10.[12] Therefore, our first dependent variable for buyer satisfaction is defined as the truncated buyer rating (*RatingByBuyer*). Additionally, we consider *Rehire*, a binary variable indicating whether buyers choose to re-engage the same seller in future projects, which reflects longer-term satisfaction and relationship continuity between buyers and sellers.

For our analyses, we focus exclusively on contracted projects in which buyers have selected a winning seller, conducting our analysis at the auction level. We employ a linear regression model for the dependent variable *RatingByBuyer*, which assesses buyer satisfaction for the focal project, and a linear probability model (LPM) for the dependent variable *Rehire*, which indicates whether buyers rehire the same seller in future projects. We estimate three model specifications for each dependent variable. The first specification includes only the main independent variable (*AfterChange*) to isolate the direct effect of the regime change. The second specification adds project characteristics such as *DescriptionLength*, *WinningBid*, and *ProjectType* dummies. Finally, the third specification further includes buyer and seller characteristics, including *BuyerExperience*, *SellerExperience*, and *SameCountry*. As robustness checks, for *RatingByBuyer*, we also estimate ordered Logit and ordered Probit models; for *Rehire*, we further estimate Logit and Probit models. All results are highly consistent and are reported in Appendix E Tables E2 and E3.

Table 5 presents the estimation results. The marginal effects of *AfterChange* are consistently positive and statistically significant across all models, except for the full specification with *Rehire* as the dependent variable (Column 6). These findings indicate that, on average, buyers report higher satisfaction with projects completed after the regime change, as evidenced by both the *RatingByBuyer* metric and their decisions to *Rehire* the same seller. Thus, both Hypotheses 8 and 9 are supported. Moreover, in the full specifications (Columns 3 and 6), the inclusion of buyer and seller experience variables attenuates the effect of *AfterChange*, suggesting that the enhanced satisfaction observed in sealed auctions may be partly attributable to improved matching between experienced buyers and sellers.

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[12] In our data, only 2.99% of observations will be affected by truncation, since the seller gets a rating below 7 in 24 out of 802 completed projects.

[Insert Table 5 about here]

#### 5.3.2 Seller Survival: Exit Rate

We next investigate how the regime change affects sellers' decisions to leave the marketplace by examining their survival rates after the regime change. To this end, we constructed a new survival dataset. First, we identified all sellers who registered and were active before the regime change, totaling 1,258 sellers. We then extracted all transaction records for these sellers. Finally, we used one year after the regime change as the cut-off date to determine whether a seller exited the market: If a seller placed bids after the cut-off date, she was considered to have not exited; otherwise, she was considered to have exited.

Since we estimate how long it takes for a seller to exit the market, we employ the Cox conditional proportional hazards model. In this model, the event is defined as whether the seller exited, while the time to the event is the time difference (in months) between the seller registering and placing the last bid before the cut-off date. Because the seller's decision to stay or exit is highly influenced by their previous experience in the market, we control for the following variables: the logged number of bids a seller has placed (*#OfBids*), the probability of winning contracts (*WinningRatio*), the total number of completed projects (*SellerExperience*), and the logged average wage for a completed project (*SellerContractValue*). Notably, all these variables are measured at the time the seller placed their last bid before the cut-off date. The summary statistics of these variables are reported in Table F1 in Appendix F, and the estimation results are shown in Table 6. Importantly, the hazard rate of the variable *AfterChange* is statistically significant and much smaller than 1, supporting Hypothesis 10. With an estimated hazard ratio of 0.145 (p-value < 0.01), the results indicate that sellers are 85.5% less likely to leave the market at the one-year cut-off date if they completed the focal project after the auction format change.

[Insert Table 6 about here]

In sum, we find that the change in auction format generally positively impacts the operation of the online labor market. Buyers are more satisfied with projects completed under a sealed auction, and sellers are more likely to remain active in the online labor market.

## 6. Conclusions, Implications, and Future Research

### 6.1 Main Findings

Our paper investigates the effect of auction formats, specifically open versus sealed formats, on various outcomes in an online labor market. We first build a simple theoretical model and generate a series of empirically testable hypotheses, then exploit a natural experiment within an online labor market to compare the effects of open and sealed auction formats on seller bidding behaviors, auction outcomes, and post-project outcomes. We find that, on average, sellers spend less time placing bids and offer lower wage amounts following the regime change. Conversely, buyers spend less time selecting winning sellers. At the auction level, despite a higher bid arrival rate, there is a noticeable decrease in the number of bidders per project, accompanied by an increase in the likelihood of contract formation post-regime change. However, no significant difference is observed in the final wages of contracted projects. Regarding post-project outcomes, buyers report higher satisfaction with projects completed after the regime change, while sellers demonstrate a reduced likelihood of exiting the online labor market. Table 7 below summarizes the main findings of this study.

[Insert Table 7 about here]

To underscore our findings, we begin with the impact on sellers' bidding decisions. Following the regime change, sellers can no longer observe their competitors' bidding information. Given the platform's auction-stopping rule, whereby buyers can end the auction at any time when a satisfactory bid is received, sellers may be concerned that other sellers might gain an advantage by bidding early. Consequently, sellers tend to reduce bid delays. Faced with increased uncertainty about competition, sellers may also generally lower their wage amounts to enhance their chances of winning contracts, thus bidding more aggressively. From the buyers' perspective, this leads to quicker decision-making when awarding contracts, reducing the time needed to select a seller. The changing decisions of both buyers and sellers have two significant implications observed in the analyses of auction-level outcomes. First, under the sealed format, although the bid arrival rate (i.e., number of bidders per hour) increases, the number of bidders per project decreases. Second, the chance of projects entering contracts increases. While the sealed-bid auction format does not result in cost savings, as winning bids do not significantly differ, it enhances matching efficiency, with buyers more likely to successfully hire sellers in a shorter time. Additionally, buyers are more inclined to rehire the same sellers due to the high satisfaction anticipated in future projects, as shown by the analyses of post-project outcomes.

Furthermore, the estimated effects vary by the experience of sellers. On the platform, sellers can be categorized into two groups: new sellers, who have no ratings or completed jobs, and experienced sellers, who have ratings or completed jobs. New sellers, who are aware of their disadvantages compared to experienced sellers due to their limited reputation, strive to better seize job opportunities. The analysis of seller behavior indicates that new sellers accelerate their bidding and lower their bid amounts more significantly when competitors' bidding information becomes unobservable after the auction format change. As a result, new sellers may have higher probabilities of winning contracts than before, making them pay more attention to jobs they might not have previously secured. Consequently, they may work harder, deliver more satisfactory products and services, and remain active in the online labor market, as evidenced by the post-project outcomes.

This study highlights the significant impacts of open versus sealed auction formats in an online labor market. These findings suggest that the sealed auction format enhances matching efficiency and overall satisfaction, benefiting both buyers and sellers on the platform, which serves as evidence that sealed auctions have become more prevalent in such online labor markets (e.g., Toptal, Expert360, Gun.io, and premium plans on Freelancer and Guru).

### 6.2 Theoretical and Practical Implications

Our research has important implications both theoretically and practically. This research joins the rich existing auction literature (e.g., Holt, 1980; Milgrom & Weber, 1982; Maskin & Riley, 1984; Maskin & Riley, 2000; Athey et al., 2011; Cho et al., 2014) in exploring auction formats. This study develops a theoretical model to predict the impact of different auction formats on participants in a much more complex online labor environment. It also provides new empirical evidence to verify our theoretical predictions.

In addition to these contributions to the long and rich literature on auctions, our paper also contributes to a growing literature that focuses on the emerging phenomenon of online labor markets that connect employers and workers. Previous studies have examined various platform-implemented signaling mechanisms such as ratings, money-back guarantee, and certifications (e.g., Moreno and Terwiesch, 2014; Kanat et al., 2018; Lin et al., 2018; Barach et al., 2020; Huang et al., 2020; Hong et al., 2021; Gu & Zhu, 2021) to facilitate transactions.

Generally, these signaling mechanisms have limited impact on all participants due to either platform-defined rules or workers' self-selection. Our study is among the first to document the effects of a platform-level policy (auction format switching) on all participants. Furthermore, this study joins the growing trend to explore auction mechanisms in online labor markets. Existing studies explore workers' self-selected auction format (Hong et al., 2016) or auction parameters such as duration (Liang et al., 2022). This study expands them to provide empirical evidence on the effects of platform-wide policy in auction implementation on both auction and post-auction outcomes. Notably, we explore a freelancing platform where buyers could stop the auctions before the predetermined deadline by accepting a bid or canceling the auction, which has been a common feature of modern online labor markets, but none of these studies have covered its impact on market efficiency and allocation.

Our research findings have multiple practical implications for the platform developers, as well as sellers (i.e., workers) and buyers (i.e., employers) in these online labor markets. Our study demonstrates the advantages of the sealed auction format over the open auction format for online labor market platforms. By implementing the sealed auction format, platforms can enhance overall matching efficiency, which is empirically supported by a reduction in bid delay time and a quicker decision-making process for both buyers and sellers. This can lead to faster project initiation and completion, improving user experience for all parties involved. It is especially important for online auction-based markets, where bidders are located globally with diversified available timeframes to make decisions or bidders are impatient with the high perceived costs of waiting time or auction failure (Carare & Rothkopf, 2005; Katok & Kwasnica, 2008). Additionally, a sealed auction format can help enhance seller retention, particularly among new sellers who may feel more competitive when competitors' bidding information is not observable. The increased competition and job opportunities foster a more vibrant and active seller base, contributing to the platform's long-term growth and sustainability. Furthermore, the increase in buyer satisfaction with completed projects suggests that sealed auctions might improve the overall quality of services, potentially leading to higher buyer retention rates and repeat business.

For sellers, particularly freelancers, adapting to the implemented auction format, which is, in our context, a sealed auction with a buyer-determined winning rule, is crucial. Sellers should focus on placing quicker and more competitive bids, understanding that early bidding might provide an advantage due to the flexible auction-stopping rule. Efficient bid preparation and submission become essential strategies in such an increasingly popular environment. Additionally, offering more competitive wage amounts can increase their chances of winning contracts, which is especially important for new sellers looking to build their reputation and secure initial contracts to overcome the "cold-start problem (Stanton & Thomas, 2015)". The increased likelihood of contract formation and higher buyer satisfaction after the regime change in our context also highlight the importance of delivering high-quality work. By doing so, sellers can receive positive reviews, foster repeat business, and achieve long-term success in the online labor market (Yoganarasimhan, 2013).

For employers, the sealed auction format allows for more efficient hiring processes. The auction format enables quicker decision-making, reducing the time and effort spent on selecting contractors and leading to faster project starts and completions, which is particularly beneficial for time-sensitive projects in which time is costly (Carare & Rothkopf, 2005). The higher satisfaction reported by buyers suggests that a sealed auction format can lead to better project outcomes. Buyers can expect to receive higher quality work and develop long-term relationships with reliable sellers. While there is no significant difference in the final wages of contracted projects, buyers should consider the overall value and quality of work received, as the efficiency gains from the sealed auction format imply higher total utility for the buyers.

### 6.3 Limitations and Future Research

While this study provides valuable insights into the effects of regime change from open to sealed auction formats in an online labor market, it is not without limitations. One significant limitation is the reliance on a single online platform for data, which may limit the generalizability of the findings to other platforms or contexts. However, the wide adoption of auction mechanisms on such platforms demonstrates the value of our findings and implications. Additionally, the study primarily focuses on short-term impacts and does not account for potential long-term effects of the auction format change on seller and buyer behavior. In the long term, both sellers and buyers can learn from previous auction winners if their identity is disclosed (Lu et al., 2019). Moreover, the observational nature of the study presents challenges in establishing causal relationships, as unobserved factors could influence the observed outcomes. To strengthen causality, we rely on estimation using data within a narrow time window before and after the regime change. Future research addressing these limitations could provide a more comprehensive understanding of auction formats in online labor markets.

Building on the findings of this study, several directions for future research could be explored to deepen our understanding of auction formats in online labor markets. Firstly, researchers could investigate the long-term impacts of sealed auction format on seller performance and career trajectories, focusing on how sustained exposure to competitive bidding environments influences skill development and reputation building. Secondly, examining the effects of sealed auctions on different types of projects, such as those requiring varying levels of complexity or collaboration, could provide insights into how auction formats influence bidding behaviors and contracting outcomes across diverse categories of jobs.

Additionally, future studies could explore the psychological and behavioral aspects of sellers and buyers in different auction formats. Understanding how factors such as risk tolerance, anti-competitive behavior (e.g., use of fraudulent information), and decision-making processes are affected by the visibility of competitors' bids could inform the design of more effective auction mechanisms. Another valuable direction for research could focus on heterogeneous effects, analyzing how sealed auctions perform relative to other auction formats in different cultural and geographical contexts, identifying the conditions under which sealed auctions are most effective. Lastly, policy-oriented research could assess the implications of auction format regulations and guidelines, exploring how policy interventions can enhance not only market efficiency (the focus of our study), but also fairness and inclusivity.

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## Tables and Figures

**Table 1.** Summary of Hypotheses

| Category | Dependent Variable (Hypothesis) | Description |
|---|---|---|
| Seller Behavior | *BidDelay* (H1) | Bidding is faster in a sealed auction than in an open auction. Mathematically, bids arrive first-order stochastically earlier in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change). |
| | *BidAmount* (H2) | The bidding amount is lower in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change). |
| Auction Outcome | *BidArrival* (H3) | The expected number of bidders per unit of time (i.e., bid arrival rate) is higher in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change). |
| | *TimeToAccept* (H4) | When the auctioneer can stop the auction, a sealed auction (i.e., after the regime change) is expected to end more quickly than an open auction (i.e., before the regime change). |
| | *#OfBidders* (H5) | The expected total number of bidders is lower in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change). |
| | *Contracted* (H6) | Buyers are more likely to successfully hire a seller, in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change). |
| | *WinningBid* (H7) | Buyers are more likely to hire a seller with a lower wage (i.e., winning bid), in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change). |
| Post-Project | *RatingByBuyer* (H8) | After the projects are completed, buyers are more likely to be satisfied with the selected sellers' work in a sealed auction (i.e., after regime change) than in an open auction (i.e., before regime change). |
| | *Rehire* (H9) | After the projects are completed, buyers are more likely to hire the same seller in the future, in a sealed auction (i.e., after the regime change) than in an open auction (i.e., before the regime change). |
| | *SellerExit* (H10) | |

**Table 2.** Variable Definitions, Measurements, and Summary Statistics

| Variable | Description | N | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|---|
| | ***Auction and Post-Auction Information*** | | | | | |
| *AfterChange* | A dummy variable that equals one if the project was posted after the regime change day | 1,926 | 0.750 | 0.433 | 0 | 1 |
| *BidArrival* | Logged number of bidders placing bids per hour (bid arrival rate) for a project | 1,926 | -2.721 | 1.985 | -8.921 | 3.313 |
| *#OfBidders* | Logged number of bidders for a project | 1,926 | 1.872 | 0.860 | 0.693 | 4.860 |
| *Contracted* | A dummy variable that equals one if the buyer chose a seller for a posted project | 1,926 | 0.416 | 0.493 | 0 | 1 |
| *WinningBid* | Logged winning bid for a project | 802 | 3.945 | 1.219 | 0 | 8.140 |
| *TimeToAccept* | Logged number of hours the buyer took to make a decision to accept a bid | 802 | 3.317 | 1.843 | 0.036 | 8.929 |
| *RatingByBuyer* | A rating given by the buyer to the seller after the project is completed (left truncated at 7) | 802 | 9.729 | 0.714 | 7 | 10 |
| *Rehire* | An indicator that equals 1 if the buyer hired the same seller again in future projects | 802 | 0.269 | 0.444 | 0 | 1 |
| | ***Buyer Information*** | | | | | |
| *BuyerExperience* | Logged number of projects the focal buyer has completed at the time of posting the current project | 1,926 | 0.342 | 0.738 | 0 | 3.584 |
| *Region* | A set of dummy variables to show the regions where the buyer comes from (detailed information in Appendix C) | | | | | |
| | ***Project Information*** | | | | | |
| *DescriptionLength* | Logged length of a project description (i.e., total number of words). | 1,926 | 3.897 | 1.132 | 0 | 6.094 |
| *MaxBid* | Logged max bid a buyer would like to accept | 1,926 | 1.754 | 2.371 | 0 | 11.51 |
| *AuctionDuration* | Logged number of days a project remained active on the studied platform. | 1,926 | 2.639 | 0.828 | 0.693 | 7.551 |
| *ProjectType* | A group of dummy variables for the type of projects (detailed information in Appendix C) | | | | | |
| | ***Seller Information*** | | | | | |
| *#OfRatings* | Logged number of ratings a seller has at the time of the current bid | 16,581 | 0.219 | 0.578 | 0 | 3.761 |
| *NoRating* | An indicator that equals 1 if the seller is a new seller at the time of the current bid | 16,581 | 0.743 | 0.437 | 0 | 1 |
| *SellerExperience* | Logged number of projects the seller has completed at the time of the current bid | 16,581 | 0.329 | 0.656 | 0 | 3.892 |
| | ***Bid Information*** | | | | | |
| *BidAmount* | Logged amount the seller bids for a project | 16,581 | 4.887 | 1.592 | 1.099 | 18.42 |
| *BidDelay* | Logged time differences in hours between posting project and biding | 16,581 | 3.148 | 1.867 | 0 | 10.73 |
| *BidOrder* | Logged sequence order of the current bid among all bids for a project | 16,581 | 11.55 | 13.38 | 1 | 139 |
| *SameCountry* | A dummy variable that equals one if the seller and buyer come from the same country | 16,581 | 0.201 | 0.401 | 0 | 1 |

**Table 3.** Effects of Auction Format Change on Seller Bidding Behaviors

| Dep. Variable | Bid Delay (Hypothesis 1) | | | Bid Amount (Hypothesis 2) | | |
|---|---|---|---|---|---|---|
| *AfterChange* | -0.531*** | -0.231* | -0.578*** | -0.180*** | -0.035 | -0.238*** |
| | (0.063) | (0.100) | (0.064) | (0.054) | (0.105) | (0.051) |
| *NoRating* | | 0.531*** | | | 0.124 | |
| | | (0.110) | | | (0.100) | |
| *AfterChange×NoRating* | | -0.395*** | | | -0.191+ | |
| | | (0.115) | | | (0.115) | |
| *#OfRatings* | | | 0.047 | | | -0.239* |
| | | | (0.140) | | | (0.115) |
| *AfterChange×#OfRatings* | | | 0.273*** | | | 0.329*** |
| | | | (0.081) | | | (0.069) |
| *DescriptionLength* | -0.036** | -0.035** | -0.036** | 0.093*** | 0.094*** | 0.093*** |
| | (0.011) | (0.011) | (0.011) | (0.012) | (0.012) | (0.012) |
| *BuyerExperience* | -0.092*** | -0.090*** | -0.090*** | -0.143*** | -0.143*** | -0.141*** |
| | (0.016) | (0.016) | (0.016) | (0.018) | (0.018) | (0.018) |
| *SellerExperience* | -0.072 | -0.009 | -0.327** | 0.220*** | 0.188** | 0.156+ |
| | (0.051) | (0.065) | (0.100) | (0.046) | (0.067) | (0.089) |
| *BidOrder* | 0.065*** | 0.065*** | 0.065*** | 0.001 | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) |
| *SameCountry* | 0.002 | 0.001 | 0.004 | -0.145*** | -0.146*** | -0.145*** |
| | (0.035) | (0.035) | (0.035) | (0.035) | (0.035) | (0.035) |
| *BidAmount* | 0.124*** | 0.123*** | 0.122*** | | | |
| | (0.010) | (0.010) | (0.010) | | | |
| Observations | 16,581 | 16,581 | 16,581 | 16,581 | 16,581 | 16,581 |
| Number of Sellers | 3,421 | 3,421 | 3,421 | 3,421 | 3,421 | 3,421 |
| Adjusted R-squared | 0.277 | 0.279 | 0.279 | 0.065 | 0.065 | 0.067 |
| Seller Fixed Effects | YES | YES | YES | YES | YES | YES |
| Weekday Fixed Effects | YES | YES | YES | YES | YES | YES |
| Project Type Fixed Effects | YES | YES | YES | YES | YES | YES |

***Note:*** Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

**Table 4.** Effects of Auction Format Change on Auction Outcomes

| Dep. Variable | Bid Arrival (Hypothesis 3) | | Time to Accept (Hypothesis 4) | | Number of Bidders (Hypothesis 5) | | Auction Success (Hypothesis 6) | | Winning Amount (Hypothesis 7) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | RE | OLS | RE | OLS | RE | OLS | RE | OLS | RE | OLS |
| *AfterChange* | 0.337*** | 0.337*** | -0.493** | -0.521*** | -0.109* | -0.150*** | 0.061* | 0.066** | -0.053 | 0.080 |
| | (0.094) | (0.084) | (0.163) | (0.138) | (0.047) | (0.043) | (0.028) | (0.025) | (0.108) | (0.106) |
| *DescriptionLength* | 0.024 | 0.024 | 0.145** | 0.138** | 0.142*** | 0.128*** | 0.017 | 0.012 | 0.030 | 0.049 |
| | (0.043) | (0.038) | (0.050) | (0.049) | (0.018) | (0.016) | (0.012) | (0.010) | (0.034) | (0.036) |
| *BuyerExperience* | 0.469*** | 0.469*** | -0.354*** | -0.552*** | -0.144*** | -0.126*** | 0.068 | 0.066*** | -0.032 | -0.036 |
| | (0.061) | (0.069) | (0.080) | (0.079) | (0.039) | (0.027) | (0.042) | (0.017) | (0.072) | (0.059) |
| *MaxBid* | 0.060*** | 0.060*** | -0.049+ | -0.054* | -0.013 | -0.011 | 0.011* | 0.011* | 0.042* | 0.040* |
| | (0.017) | (0.017) | (0.025) | (0.026) | (0.009) | (0.008) | (0.005) | (0.005) | (0.020) | (0.020) |
| *AuctionDuration* | -1.154*** | -1.154*** | 1.115*** | 1.074*** | 0.130*** | 0.129*** | -0.124*** | -0.132*** | 0.130+ | 0.253** |
| | (0.049) | (0.051) | (0.095) | (0.100) | (0.028) | (0.028) | (0.015) | (0.015) | (0.069) | (0.079) |
| Observations | 1,926 | 1,926 | 802 | 802 | 1,926 | 1,926 | 1,926 | 1,926 | 802 | 802 |
| Adjusted $R^2$ | 0.254 | 0.254 | 0.306 | 0.314 | 0.145 | 0.149 | 0.091 | 0.092 | 0.063 | 0.089 |
| Number of Buyers | 967 | 967 | 423 | 423 | 967 | 967 | 967 | 967 | 423 | 423 |
| Buyer Region Dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Weekday Dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Project Type Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

*Note:* Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

**Table 5.** Effects of Auction Format Change on Buyer Satisfaction

| Dep. Variable | DV: Rating by Buyer (Hypothesis 8) | | | DV: Rehire (Hypothesis 9) | | |
|---|---|---|---|---|---|---|
| *AfterChange* | 0.249*** | 0.245*** | 0.205** | 0.139*** | 0.124*** | 0.0437 |
| | (0.0858) | (0.0852) | (0.0866) | (0.0353) | (0.0357) | (0.0359) |
| *DescriptionLength* | | 0.00456 | 0.0116 | | -0.0193 | -0.00370 |
| | | (0.0250) | (0.0246) | | (0.0147) | (0.0126) |
| *BuyerExperience* | | | 0.0543** | | | 0.0986*** |
| | | | (0.0227) | | | (0.0179) |
| *SellerExperience* | | | 0.0526** | | | 0.0938*** |
| | | | (0.0239) | | | (0.0194) |
| *SameCountry* | | | 0.0252 | | | -0.0370 |
| | | | (0.0605) | | | (0.0319) |
| *WinningBid* | | -0.0121 | -0.0160 | | 0.0179 | 0.00897 |
| | | (0.0209) | (0.0215) | | (0.0147) | (0.0140) |
| Observations | 802 | 802 | 802 | 802 | 802 | 802 |
| Adjusted $R^2$ | 0.019 | 0.025 | 0.029 | 0.015 | 0.027 | 0.091 |
| Project-type Fixed Effects | No | YES | YES | No | YES | YES |

***Note:*** Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

**Table 6.** Effect of Auction Format Change on Seller Exit

| Dep. Variable | DV: Seller Exit (Hypothesis 10) | |
|---|---|---|
| | Coefficients | Hazard Ratio |
| *AfterChange* | -1.933*** | .145*** |
| | (0.331) | (.048) |
| *SellerExperience* | 0.0795 | 1.083 |
| | (0.111) | (.121) |
| *SellerContractValue* | -0.0352 | .965 |
| | (0.0381) | (.037) |
| *#OfBids* | -0.179* | .837* |
| | (0.0927) | (.078) |
| *WinningRatio* | 0.0603 | 1.062 |
| | (0.855) | (.909) |
| Observations | 650 | |
| # of failures | 214 | |

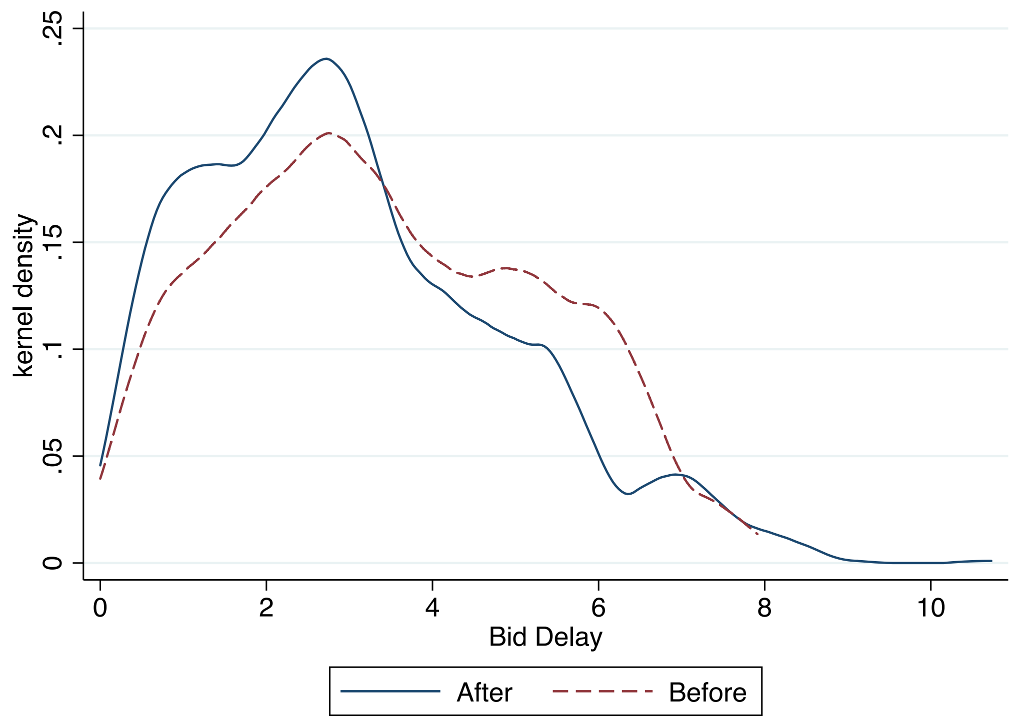
***Note:*** Robust standard errors (clustered at the seller level) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table 7.** Summary of Key Findings

| Category | Dependent Variable (Hypothesis) | Prediction | Result Summary | Supported |
|---|---|---|---|---|
| Seller Behavior | *BidDelay* (H1) | Open > Sealed | 41.2% (FE) shorter delay in bidding | Yes |
| | *BidAmount* (H2) | Open > Sealed | 16.5% (FE) decrease in bid amount | Yes |
| Auction Outcome | *BidArrival* (H3) | Open < Sealed | 40.1% (RE) or 40.1% (OLS) increase | Yes |
| | *TimeToAccept* (H4) | Open > Sealed | 39.0% (RE) or 40.6% (OLS) shorter time | Yes |
| | *#OfBidders* (H5) | Open > Sealed | 10.3% (RE) or 13.9% (OLS) decrease | Yes |
| | *Contracted* (H6) | Open < Sealed | 5.6% (RE) or 6.0% (OLS) increase | Yes |
| | *WinningBid* (H7) | Open > Sealed | Insignificant | No |
| Post-Project | *RatingByBuyer* (H8) | Open < Sealed | 0.249 increase out of 10 (left truncated at 7) | Yes |
| | *Rehire* (H9) | Open < Sealed | Buyers are 13.9% more likely to rehire | Yes |
| | *SellerExit* (H10) | Open > Sealed | Sellers are 85.5% less likely to exit given a time after the focal project is completed (hazard ratio 0.145) | Yes |

**Figure 1.** Model Free Evidence (Distributions of *BidDelay* and *BidAmount*)

**(a). *BidDelay*** (logged time difference in hours between the bidding time and the posting time of a project)




**(b). *BidAmount*** (logged bid wage amount proposed by a seller for a project)

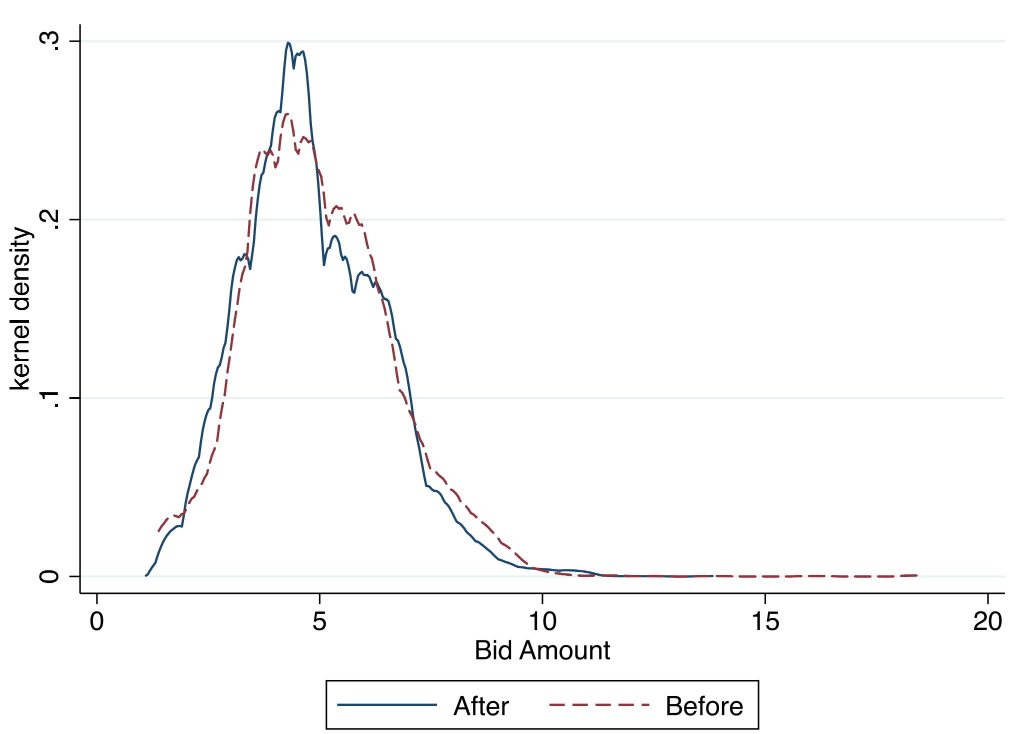
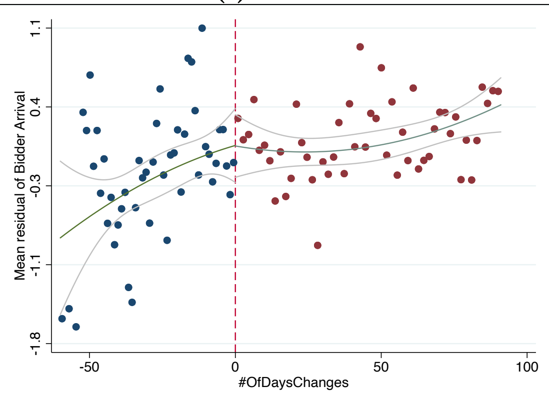
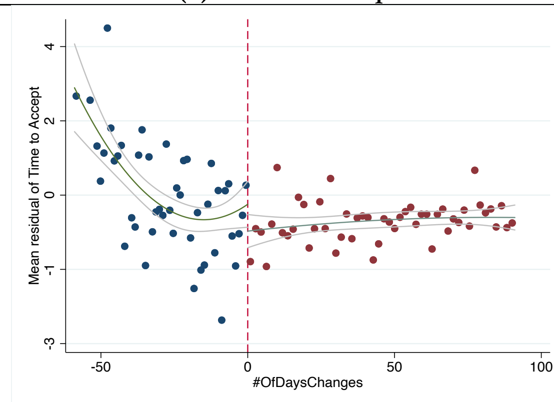


**Figure 2.** Comparing Auction Outcomes

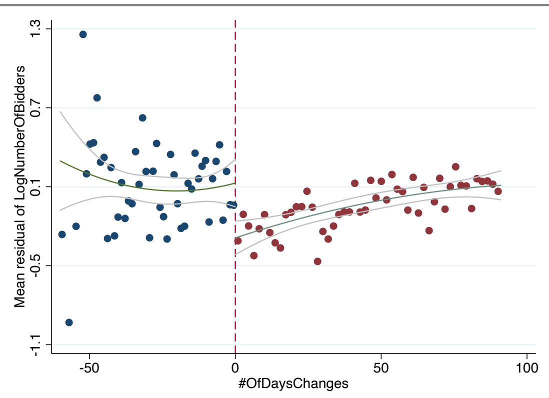
**(a). Bid Arrival**



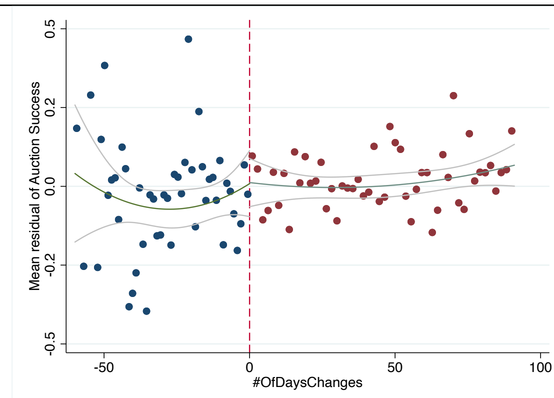

**(b). Time to Accept**



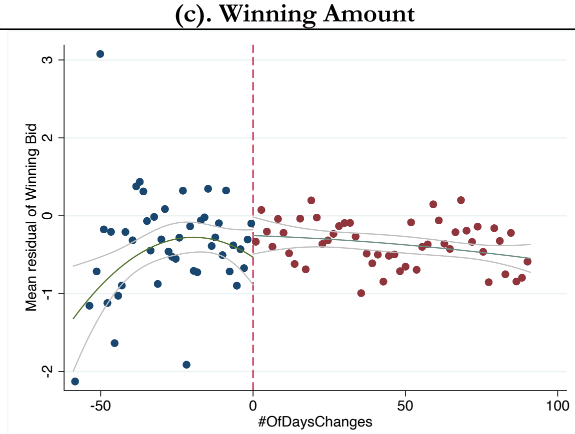

**(c). Number Of Bidders**




**(d). Auction Success**




**(c). Winning Amount**



## Appendix A. Proofs

**Proof of Lemma 1.** Let's solve for a symmetric Bayes-Nash equilibrium in which each bidder bids according to a strictly increasing and continuous equilibrium bid function $b(\cdot)$, that is, a bidder of cost $c$ bids $b(c)$. Let $G(x)$ represent the probability of winning when the bidder bids $b(x)$ and other bidders bid according to $b(\cdot)$. Note $G(x)$ is strictly decreasing in $x$. The expected payoff of a cost-$c$ bidder bidding $b(x)$ is

$$u(b(x), c) = G(x)(b(x) - c).$$

By the definition of Bayes-Nash equilibrium, the best response of a cost-$c$ bidder to others' equilibrium bids is $b(c)$, that is,

$$u(b(c), c) \geq u(b(x), c) \ \forall x.$$

Maximizing the expected utility with respect to $x$,

$$\frac{\partial u(b(x), c)}{\partial x}|_x = G'(x)(b(x) - c) + G(x)b'(x),$$

and first-order condition is satisfied at $x = c$, that is,

$$0 = \frac{\partial u(b(x), c)}{\partial x}|_{x=c} = G'(c)b(c) + G(c)b'(c) - G'(c)c,$$

$$\big(G(x)b(x)\big)'|_{x=c} = G'(x)x|_{x=c}.$$

Since the expression above holds for any $c$, by the fundamental theorem of calculus, for any $c$,

$$\int_c^{\bar{c}} d\big(G(x)b(x)\big) = \int_c^{\bar{c}} x \, dG(x) + K.$$

Because, by the definition of $\bar{c}$, we have $K = 0$, so the equation is simplified to

$$\int_c^{\bar{c}} d\big(G(x)b(x)\big) = \int_c^{\bar{c}} x \, dG(x).$$

Using integration by parts, we have

$$G(\bar{c})b(\bar{c}) - G(c)b(c) = G(\bar{c})\bar{c} - cG(c) - \int_c^{\bar{c}} G(x) \, dx.$$

Because of the boundary condition $b(\bar{c}) = V \equiv \bar{c}$, $G(\bar{c})b(\bar{c}) = G(\bar{c})\bar{c}$. We get an expression of $b(c)$:

$$b(c) = c + \int_c^{\bar{c}} \frac{G(x)}{G(c)} dx.$$

In our setup,

$$G(x) = \frac{(\lambda T)^0 e^{-\lambda T}}{0!} + \sum_{k=1}^{\infty} \frac{(\lambda T)^k e^{-\lambda T}}{k!} \int_x^{\bar{c}} k f(y)\big(1 - F(y)\big)^{k-1} dy,$$

which simplifies to

$$G(x) = \frac{(\lambda T)^0 e^{-\lambda T}}{0!} + \sum_{k=1}^{\infty} \frac{(\lambda T)^k e^{-\lambda T}}{k!} \left( -\big(1 - F(y)\big)^k |_x^{\infty} \right) = \frac{(\lambda T)^0 e^{-\lambda T}}{0!} + \sum_{k=1}^{\infty} \frac{(\lambda T)^k e^{-\lambda T}}{k!} \big(1 - F(x)\big)^k.$$

Given that $x^0 = 1$,

$$G(x) = \sum_{k=0}^{\infty} \frac{(\lambda T(1 - F(x))^k e^{-\lambda T}}{k!}.$$

By multiplying and dividing the same term $e^{-(1-F(x))\lambda T}$, we get

$$G(x) = \left[ \sum_{k=0}^{\infty} \frac{(\lambda T(1 - F(x))^k e^{-(1-F(x))\lambda T}}{k!} \right] e^{(1-F(x))\lambda T} e^{-\lambda T}.$$

The term in the square bracket equals 1 because it is the sum of the probability for a Poisson distribution with parameter $\big(1 - F(x)\big)\lambda T$. Hence,

$$G(x) = e^{-F(x)\lambda T}.$$

Plugging $G(x)$ and $G(c)$ in the bid function, in terms of bid "shading," we have

$$b(c) = c + \int_c^{\bar{c}} e^{-(F(x)-F(c))\lambda T} dx.$$

When the cost distribution is uniform $[0,1]$, $F(x) = x$,

$$b(c) = c + \int_c^1 e^{(c-x)\lambda T} dx = c - \frac{1}{\lambda T} e^{(c-x)\lambda T} |_c^1 = c - \frac{1}{\lambda T} (e^{-(1-c)\lambda T} - 1).$$

*QED*

**Proof of Lemma 2.** The bidding function for a bidder is derived similarly as in the sealed auction. Any seller with a cost above $B_T$ does not bid, and seller of the cost $B_T$ bids $B_T$. Following the same steps for proof of Lemma 1, we have the following equality for all $c$:

$$\int_c^{B_T} d\big(G(x)b(x)\big) = \int_c^{B_T} x \, dG(x).$$

We have different boundary conditions $b(B_T) = B_T \leq V \equiv \bar{c}$ and $G(B_T)b(B_T) = G(B_T)B_T$. We get an expression of $b(c)$ for all $c < B_T$:

$$b(c) = c + \int_c^{B_T} \frac{G(x)}{G(c)} dx.$$

*QED*

## Appendix B: Correlations of Key Independent Variables

**Table B1. Correlations among Key Independent Variables**

| # | Variable Names | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | *AfterChange* | 1.000 | | | | | | | | | | | | | | | | | |
| 2 | *BidArrival* | 0.092 | 1.000 | | | | | | | | | | | | | | | | |
| 3 | *#OfBidders* | -0.026 | 0.135 | 1.000 | | | | | | | | | | | | | | | |
| 4 | *Contracted* | 0.062 | 0.47 | -0.067 | 1.000 | | | | | | | | | | | | | | |
| 5 | *WinningBid* | 0.018 | -0.125 | 0.017 | n/a | 1.000 | | | | | | | | | | | | | |
| 6 | *TimeToAccept* | -0.159 | -0.857 | 0.483 | n/a | 0.112 | 1.000 | | | | | | | | | | | | |
| 7 | *RatingByBuyer* | 0.143 | 0.051 | 0.025 | n/a | -0.004 | -0.042 | 1.000 | | | | | | | | | | | |
| 8 | *Rehire* | 0.128 | 0.133 | -0.070 | n/a | 0.043 | -0.152 | 0.148 | 1.000 | | | | | | | | | | |
| 9 | *BuyerExperience* | 0.163 | 0.156 | -0.059 | 0.074 | -0.059 | -0.260 | 0.088 | 0.208 | 1.000 | | | | | | | | | |
| 10 | *DescriptionLength* | 0.076 | 0.047 | 0.104 | 0.067 | 0.066 | 0.200 | -0.005 | -0.076 | -0.035 | 1.000 | | | | | | | | |
| 11 | *MaxBid* | -0.029 | 0.060 | -0.013 | 0.011 | 0.064 | -0.112 | -0.062 | -0.003 | -0.065 | -0.010 | 1.000 | | | | | | | |
| 12 | *AuctionDuration* | -0.025 | -0.596 | 0.301 | -0.212 | 0.195 | 0.404 | -0.059 | -0.060 | -0.071 | -0.057 | -0.067 | 1.000 | | | | | | |
| 13 | *#OfRatings* | 0.136 | 0.147 | -0.107 | 0.124 | 0.076 | -0.163 | 0.091 | 0.216 | 0.041 | -0.012 | 0.005 | -0.116 | 1.000 | | | | | |
| 14 | *NoRating* | -0.152 | -0.169 | 0.125 | -0.134 | -0.102 | 0.185 | -0.079 | -0.186 | -0.056 | 0.007 | -0.016 | 0.138 | -0.637 | 1.000 | | | | |
| 15 | *SellerExperience* | 0.175 | 0.168 | -0.126 | 0.138 | 0.101 | -0.182 | 0.101 | 0.241 | 0.055 | -0.008 | 0.011 | -0.132 | 0.933 | -0.834 | 1.000 | | | |
| 16 | *BidAmount* | -0.037 | -0.241 | 0.116 | -0.233 | 0.885 | 0.210 | -0.026 | 0.037 | -0.101 | 0.095 | -0.013 | 0.213 | -0.068 | 0.052 | -0.062 | 1.000 | | |
| 17 | *BidDelay* | -0.096 | -0.482 | 0.286 | -0.287 | 0.152 | 0.723 | 0.002 | -0.069 | -0.096 | 0.003 | -0.041 | 0.473 | -0.240 | 0.304 | -0.288 | 0.184 | 1.000 | |
| 18 | *BidOrder* | -0.028 | 0.056 | 0.663 | -0.030 | 0.079 | 0.369 | 0.033 | 0.015 | -0.032 | 0.040 | -0.028 | 0.270 | -0.132 | 0.176 | -0.163 | 0.072 | 0.570 | 1.000 |
| 19 | *SameCountry* | -0.126 | -0.003 | 0.006 | -0.014 | -0.054 | 0.029 | -0.011 | -0.079 | -0.062 | -0.001 | 0.000 | 0.000 | -0.060 | 0.043 | -0.064 | 0.001 | 0.016 | 0.010 |

Note: *WinningBid*, *TimeToAccept*, *RatingByBuyer*, and *Rehire* are only valid when the project is successfully contracted. Thus, their correlation with *Contracted* is n/a.

## Appendix C: Distributions of Project Type

**Table C1.** Distribution of Project Type

| Dummy Code | Description | Frequency |
|---|---|---|
| | Project Type* | |
| 1 | Website and Software Development | 18,233 |
| 2 | Writing and Content | 921 |
| 3 | Graphical Design | 3,027 |
| 4 | Data Entry and Management | 7,500 |
| Region | | |
| 1 | Asian | 1,037 |
| 2 | Europe | 3,688 |
| 3 | North America | 9,266 |
| 4 | South America | 166 |
| 5 | Australia/Oceania | 346 |
| 6 | Africa | 107 |
| 0 | N/A | 4,092 |

*Most projects belong to multiple types; the values are not mutually exclusive.

## Appendix D: Impact on Number of Bids Per Project and Number of Bids Per Bidder Per Project

**Figure D1.** Comparing Additional Bid Information

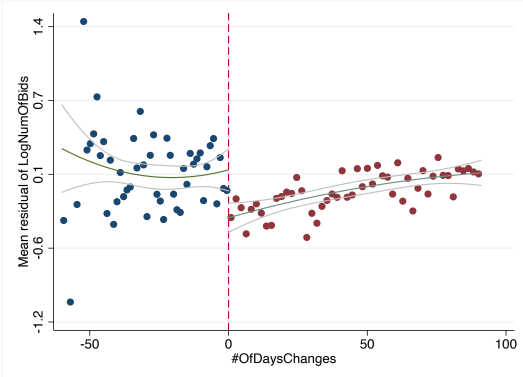
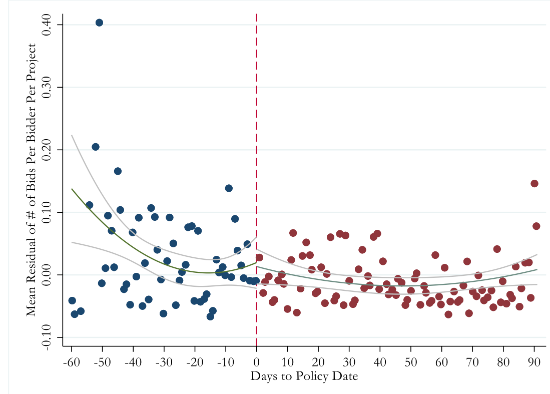
| **(a). Number of Bids and Regime Change** | **(b). Number of Bids Per Bidder and Regime Change** |
|---|---|
|  |  |





**Table D1.** Effects of Auction Format Change on Additional Bid Information

| Dep. Variables | Number of Bids | | Number of Bids Per Bidder | |
|---|---|---|---|---|
| | RE | OLS | RE | OLS |
| *AfterChange* | -0.1352*** | -0.1779*** | -0.0356*** | -0.0356*** |
| | (0.0482) | (0.0470) | (0.0098) | (0.0098) |
| *BuyerExperience* | -0.1445*** | -0.1283*** | 0.0028 | 0.0028 |
| | (0.0393) | (0.0309) | (0.0062) | (0.0062) |
| *DescriptionLength* | 0.1458*** | 0.1312*** | 0.0049 | 0.0049 |
| | (0.0182) | (0.0202) | (0.0038) | (0.0038) |
| *MaxBid* | -0.0138 | -0.0113 | 0.0008 | 0.0008 |
| | (0.0088) | (0.0091) | (0.0017) | (0.0017) |
| *AuctionDuration* | 0.1357*** | 0.1333*** | 0.0080 | 0.0080 |
| | (0.0278) | (0.0283) | (0.0056) | (0.0056) |
| Observations | 1,926 | 1,926 | 1,926 | 1,926 |
| Adjusted $R^2$ | 0.148 | 0.153 | 0.024 | 0.024 |
| Number of Buyers | 967 | 967 | 967 | 967 |
| Buyer Region Dummies | YES | YES | YES | YES |
| Weekday Dummies | YES | YES | YES | YES |
| Project Type Fixed Effects | YES | YES | YES | YES |

***Note:*** Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

## Appendix E. Robustness Checks

**Table E1.** Effects of Auction Format Change on Auction Success

| Dep. Variable | Auction Success (Hypothesis 6) | |
|---|---|---|
| | RE-Logit | RE-Probit |
| *AfterChange* | 0.367* | 0.218* |
| | (0.163) | (0.096) |
| *DescriptionLength* | 0.099 | 0.059 |
| | (0.066) | (0.039) |
| *BuyerExperience* | 0.155 | 0.096 |
| | (0.230) | (0.135) |
| *MaxBid* | 0.063* | 0.037* |
| | (0.027) | (0.016) |
| *AuctionDuration* | -0.671*** | -0.401*** |
| | (0.091) | (0.053) |
| Observations | 1,926 | 1,926 |
| Number of Buyers | 967 | 967 |
| Buyer Region Dummies | YES | YES |
| Weekday Dummies | YES | YES |
| Project Type Fixed Effects | YES | YES |

***Note:*** Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

**Table E2.** Effects of Auction Format Change on Rating by Buyer

| Dep. Variable | DV: Rating by Buyer (Hypothesis 8) | | | | | |
|---|---|---|---|---|---|---|
| | Ordered Logit | | | Ordered Probit | | |
| *AfterChange* | 0.571** | 0.567** | 0.416 | 0.411*** | 0.404*** | 0.320** |
| | (0.257) | (0.257) | (0.265) | (0.136) | (0.136) | (0.142) |
| *DescriptionLength* | | -0.0143 | 0.0109 | | -0.00120 | 0.0142 |
| | | (0.106) | (0.106) | | (0.0541) | (0.0534) |
| *BuyerExperience* | | | 0.209 | | | 0.119* |
| | | | (0.129) | | | (0.0624) |
| *SellerExperience* | | | 0.235** | | | 0.128** |
| | | | (0.117) | | | (0.0605) |
| *SameCountry* | | | 0.143 | | | 0.0788 |
| | | | (0.248) | | | (0.130) |
| *WinningBid* | | -0.108 | -0.122 | | -0.0410 | -0.0485 |
| | | (0.0843) | (0.0850) | | (0.0442) | (0.0446) |
| Observations | 802 | 802 | 802 | 802 | 802 | 802 |
| Project-type Fixed Effects | No | YES | YES | No | YES | YES |

***Note:*** Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

**Table E3.** Effects of Auction Format Change on Rehire

| Dep. Variable | DV: Rehire (Hypothesis 9) | | | | | |
|---|---|---|---|---|---|---|
| | | Logit | | | Probit | |
| *AfterChange* | 0.806*** | 0.744*** | 0.324 | 0.467*** | 0.437*** | 0.206 |
| | (0.236) | (0.240) | (0.254) | (0.132) | (0.135) | (0.142) |
| *DescriptionLength* | | -0.0949 | -0.0178 | | -0.0572 | -0.0121 |
| | | (0.0730) | (0.0680) | | (0.0433) | (0.0397) |
| *BuyerExperience* | | | 0.474*** | | | 0.284*** |
| | | | (0.0850) | | | (0.0514) |
| *SellerExperience* | | | 0.479*** | | | 0.284*** |
| | | | (0.0965) | | | (0.0574) |
| *SameCountry* | | | -0.217 | | | -0.129 |
| | | | (0.198) | | | (0.114) |
| *WinningBid* | | 0.0933 | 0.0531 | | 0.0558 | 0.0311 |
| | | (0.0752) | (0.0791) | | (0.0453) | (0.0468) |
| Observations | 802 | 802 | 802 | 802 | 802 | 802 |
| Project-type Fixed Effects | No | YES | YES | No | YES | YES |

***Note:*** Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, +p<0.1

## Appendix F: Summary Statistics for Seller Exit Dataset Variables

**Table F1.** Summary Statistics for Seller Exit Dataset Variables

| Variables | Explanations and Measurements | N | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|---|
| *SellerExit* | An indicator that equals 1 if the seller exited the market at the end of study period | 1,158 | 0.237 | 0.425 | 0 | 1 |
| *AfterChange* | A dummy variable that equals one if the project was posted after the regime change | 1,158 | 0.391 | 0.488 | 0 | 1 |
| *SellerExperience* | Logged total number of completed projects a seller had till the end of the study period | 1,158 | 0.155 | 0.563 | 0 | 4.382 |
| *SellerContractValue* | Logged average value of completed projects a seller had till the end of the study period | 1,158 | 0.483 | 1.506 | 0 | 7.306 |
| *#OfBids* | Logged number of bids a seller had placed till the end of the study period | 1,158 | 1.592 | 1.074 | 0.693 | 6.897 |
| *WinningRatio* | The ratio of the number of winning bids to the number of total bids a seller had placed till the end of the study period | 1,158 | 0.017 | 0.073 | 0 | 1 |