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 draw on auction theories 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. 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.

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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). 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).

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. The heterogeneity among labor markets is significantly greater than that among merchandise markets, due to variations in cultural backgrounds, experiences, ethics, and communication styles. Second, the virtual nature of online labor markets significantly amplifies the signaling and screening challenges found in traditional labor markets, primarily due to the absence of face-to-face interactions. Instead, lean, text-based communication dominates these platforms, increasing the likelihood of miscommunication, misunderstandings,

and misalignment of expectations. Third, unlike merchandise market auctions in which 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 wage 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 scant. One notable exception is Hong et al. (2016). 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 auctions is critical for their future growth. This study will fill this gap. Drawing on the literature on auction theory and online labor markets, we first develop a series of hypotheses to examine the contrasting behaviors of workers under different auction formats in an online labor market. We then exploit a unique natural experiment 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, in which workers can view 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 more quickly and ask for a lower wage, benefiting employers. From the employer's perspective, under open auction format, 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 by studying the consequences of auction format choice in a global, online labor market, and documented novel findings. We also contribute to the growing literature that focuses on online labor markets. The issue of information asymmetry in this nascent market has attracted attention from scholars in a wide range of fields, including information systems, marketing, operations 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 (Hong et al., 2016). 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 our conceptual framework 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 below (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 wage they are willing to pay). After posting, the registered sellers can browse project requirements on the site and decide whether they want to bid on the project for a certain amount. It is worth noting that such platforms have a very different termination rule compared to well-known online auction sites such as eBay (Roth & Ockenfels, 2002; Ockenfels & Roth, 2006). 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 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 buyer applies 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) (Yoganarasimhan, 2016). Thus, the winning seller does not necessarily pick the bidder who asks for the lowest wage (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 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

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

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. In this case, 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 the prior literature. In this study, we fill this gap by comparing how different auction formats (i.e., open versus sealed) will affect participants in this emerging market.

2.3 Related Literature on Auction Formats

Although there are plenty of auction formats in auction literature, two major auction mechanism types are *sealed auction* and *open auction* (Krishna, 2009).[2] From both theoretical and practical perspectives, the major 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 auctioneers under certain key assumptions such as symmetric, independent private value,[3] and risk-neutral bidders, which is the revenue equivalence theorem (Vickrey, 1961; Myerson, 1981; Riley & Samuelson, 1981). The expected revenues in open and sealed auctions are the same; therefore, 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;

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[2] For sealed auction, we typically refer to a first-price sealed auction, in which the bidder with the highest valuation wins the item and pays the bidding price. With private value assumption, an open auction is equivalent to a second-price sealed (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 the second highest valuation drops out (Milgrom & Weber, 1982).

[3] Independent private value (IPV) is the assumption that valuations of auction items are only known to bidders themselves and can only be realized from item consumption. 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. An auction could have both IPV and CV components.

Maskin & Riley, 1984)[4] and (2) there is potential collusion among the bidders (Athey et al., 2011; Cho et al., 2014).[5] In contrast, the drop of 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 in Milgrom & Weber, 1982). Finally, when the bidders' valuation distributions are asymmetric and auction entry is endogenous, expected revenue will be higher or lower depending on the value distributions (Maskin & Riley, 2000).[6]

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 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, which is a typical case of collusion. By contrast, Shachat & Wei (2012) found that the prices to procure a commodity 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 open English and sealed first-price auctions in the common value paradigm and found that the English auctions derive higher revenue when bidders do not suffer from the winner's curse, while experienced bidders could use information released in English auctions to avoid winner's curse. Cho et al. (2014) showed that an English

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[4] Intuitively, since bidders have uncertainty about other bidders' valuations in a sealed auction, risk-averse bidders will bid more aggressively; consequently, auctioneers prefer a sealed auction to an open auction in this situation.

[5] If the bidders collude in the auction, the expected revenue will surely be much lower. Since open auctions facilitate collusion because bidders can observe competitors' behaviors, it is more vulnerable to collusion than a sealed auction.

[6] In theory, a sealed auction gives "weaker" bidders (whose valuation distributions are stochastically dominated by those of "stronger" bidders) an extra incentive to enter the auction because they expect stronger bidders to shade their bids (i.e., bid lower than their true valuations) so that they have a chance to win. Therefore, weaker bidders will bid more aggressively than stronger bidders in sealed auctions.

auction yields higher 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

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 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). The key feature of a buyer-determined auction is that only the buyer knows which seller should be selected as the winner; even if an open auction is applied, the sellers cannot perfectly anticipate who will be hired during the auction process.

Second, the auctioneer does not commit to the pre-defined deadline of the auction, 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. Previous studies on online auctions have revealed that the termination rule could play an important role in altering the bidders' equilibrium bidding strategies. Notably, a fixed auction deadline could lead to the so-called "sniping" strategic 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, since the buyers do not commit to any auction deadline, it incentivizes the sellers to bid earlier to avoid the risk of the buyer choosing the winner before the deadline. Due to the availability of competitor's bids and profiles, sellers may strategically choose the time to bid in open auctions compared to sealed auctions; in turn, the buyer may choose the winner and close the auction differently. Therefore, our study could be viewed as showing the bidding and revenue differences of different auctions when the auctioneer discounts the future in a setting with the dynamic arrival of bidders, a realistic and inevitable feature of online labor markets. To sum up, existing theories and empirical evidence do not provide sufficient support to conclude the impact of an auction format in the online labor market context.

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 in which buyers can (endogenously) choose to use either open or sealed auctions in each job they post; both auction formats co-exist.[7] They assume the seller's valuation of the project contains both the independent private value and common value components. They found that sealed auctions attract a higher number of bidders per project than open auctions. They argue that the independent private value 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 component of the seller's valuation of the project since the linkage principle suggests that opening bids to all potential bidders will reduce their search costs and allow them to bid at lower prices. In contrast, notably, the online platform we study has suddenly switched from open auction to sealed auction, a regime change that provides a natural experiment by which we identify the causal impact of auction formats on sellers' bidding behavior, buyers' contracting decisions, and auction outcomes. Due to the significant difference in the setting (free choice versus regime change), we do not expect to derive the same results as Hong et al. (2016) did. We summarize the empirical studies (and the current study) comparing auction formats in Appendix A Table A1.

3. Hypotheses Development

Drawing on the literature on online labor markets and auction theories, we propose several hypotheses under the following conceptual framework. A buyer posts an auction, asking for workers on a project, which is worth a value for the buyer upon the project's completion. Workers arrive at the platform and check the posted project over time; for example, they may arrive according to a Poisson arrival (i.e., the probability of arrival of a seller is constant across time) or some other stochastic processes. Based on the nature of projects on the platform, we make *independent private value* assumption, meaning that sellers have heterogeneous costs of completing the task, and that information is private. They are willing to work if the wage they receive is higher than their cost

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[7] Buyers will pay for a premium for using a sealed auction (for example, on sites such as Freelancer and Guru).

of completion. They usually bid an amount of wage higher than their cost, so they receive a positive surplus (wage minus cost) from working. The buyer may pick a bid earlier than the pre-determined auction deadline if a bid, along with the seller's profile, is satisfactory according to a buyer-determined rule, often called the beauty-contest mechanism, which is very common in online labor markets (Yoganarasimhan, 2016). The buyer could also cancel the auction without picking any winner before or at the auction deadline if she finds none of the bids, along with the seller's profile, is satisfactory.

In an open auction—before the regime switch—all information about bids and seller profiles is public to the posting buyer and all potential sellers who have placed or have not placed a bid. In a close auction—after the regime switch—all information is available only to the posting buyer. Under this conceptual framework, we derive the following empirically testable hypotheses.

3.1. Seller Behaviors

Regarding the timing of bidding, we predict that the bids will be submitted earlier in a sealed auction. This is because sellers lack the incentives to wait and bid later in a sealed auction: No useful information about competitors' bids is released, but waiting is only associated with the risk of the buyer picking another winner before the deadline. In an open auction, sellers have weaker incentives to bid immediately upon arrival at the auction because bidding early will reveal their willingness to work. However, they should not wait until the last minute because the seller may pick a winner before the auction deadline. In a sealed auction, a seller's weakly dominant strategy is to bid at his arrival time. In an open auction, a seller is incentivized to wait to bid due to the possible information leakage from bidding early. Therefore, we propose Hypothesis 1 as follows.

Hypothesis 1. *Bidding is faster in a sealed auction than in an open auction.*

Regarding the bidding amount, in an open auction, suppose there is a revealed leading bid placed by a previous bidder, a seller with a cost higher than the revealed leading bid will not place a bid since the project is unprofitable for him, which leads to a *selection effect*, implying the observed bidding amounts are lower than those in a sealed auction. In contrast, a seller with a cost below the leading bid would bid in the range between the seller's cost and the revealed leading bid. Importantly, since there is no incentive for sellers to reveal their true bid early in open auctions, either to protect their private information or to wait for competitors to bid first (so

that they can learn from their bids). Instead, those who decide to bid early tend to demand initially absurdly high wages (in the range) and gradually lower their bids to beat the current leading bid, which leads to a *delayed bidding effect*, implying the observed bidding amounts are higher than those in a sealed auction. In our research context, the sellers are competing with each other through an unrevealed "beauty contest" rule that takes into account both the bidding amounts and the sellers' profiles (Che, 1993; Asker & Cantillon, 2008). Since sellers do not know exactly how the buyer will choose a winner, it is difficult to predict whether they will lose in the auction; even if a lower leading bid exists, they will still place a bid, thus reducing the selection effect. In addition, since there is only a minimal cost to place a bid (e.g., the time spent to check the auction progress), a revealed leading bid will not necessarily discourage sellers from bidding, thus softening the selection effect. Therefore, we predict that, in our research context, the delayed bidding effect should dominate the selection effect; thus, we have our Hypothesis 2 below.

Hypothesis 2. *The bidding amount is lower in a sealed auction than in an open auction.*

3.2. Auction Outcomes

Based on the previous discussion, we propose that sealed auctions make sellers behave more competitively by placing lower bids earlier than the deadline. From this, we can derive auction-level theoretical predictions. First, given the difference in speed at which sellers bid in open and sealed auctions, we can further predict the number of bidders per unit of 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 to bid (*delayed bidding effect*). Formally, in a sealed auction, a seller's weakly dominant strategy is to bid at the time of arrival. For example, if bidders arrive according to a Poisson process with arrival rate λ, the expected number of bidders by time t in a sealed auction is λt. In contrast, in an open auction, the expected number of bidders by time t is weakly smaller than λt. In addition, the selection effect of an open auction implies that high-cost sellers may not place a bid upon arrival. Thus, we propose Hypothesis 3, as below.

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

Notice that the buyer can terminate the auction earlier in our research context. In our context, many projects are intermediate goods that require further processing before being delivered to their customers (e.g., software development). Thus, the employers are eager to have the project completed on time. In practice, the buyer may even accept a bid if it falls sufficiently below a satisfactory level and terminate the auction. In a sealed auction, where sellers bid upon arrival, there exists a positive probability of bids being below the threshold, increasing the likelihood of the auction ending early. In contrast, in an open auction, the sellers' equilibrium strategy is to bid later (or bid a high wage and adjust the bid later) to avoid revealing bids prematurely to competitors. Hence, we propose Hypothesis 4 for the auction-stopping rule.

Hypothesis 4. *When the buyer can stop the auction, a sealed auction is expected to end more quickly than an open auction.*

By combining Hypothesis 3, which addresses the expected number of bidders per unit of time, and Hypothesis 4, which addresses the expected auction stopping time, we can make a prediction on the expected total number of bidders. By Hypothesis 3, a sealed auction has more bidders per unit of time due to an open auction's delayed bidding and selection effects. Intuitively, a sealed auction should attract more bidders before the auction ends if the buyer commits to a fixed auction deadline; however, by Hypothesis 4, the buyer tends to terminate the sealed auction earlier. The two theoretical predictions combine to generate an ambiguous, mixed effect on the expected total number of bidders. The net effect depends on the relative strength of the mechanisms behind Hypothesis 3 and Hypothesis 4. We do not predict the direction of the impact of the auction format on the expected total number of bidders; thus, we posit Hypothesis 5 below.

Hypothesis 5. A *sealed auction attracts (a) more or (b) fewer bidders than an open auction, depending on the relative strength of effects in H3 and H4.*

3.3. Project Outcomes

During the auction process, the buyer can accept a bid if it is sufficiently low and terminate the auction early. In theory, a more patient buyer who waits to allow more 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, a less patient buyer may become frustrated with the longer waiting times in an open auction and choose to terminate the auction without hiring a seller. In contrast, this scenario is less likely in a sealed auction,

where sellers place their effective bids earlier. Consequently, buyers are more likely to find a satisfactory bid in a sealed auction than in 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. Hence, we posit Hypotheses 6 and 7 below.

Hypothesis 6. *Buyers are more likely to successfully hire a seller in a sealed auction than in an open auction.*

Hypothesis 7. *Buyers are more likely to hire a worker asking for a lower wage in a sealed auction than in an open auction.*

3.4 Post-Project Outcomes

The online labor market aims to enhance matching between buyers and sellers by implementing auctions. A well-designed auction mechanism is expected to result in higher buyer and seller satisfaction. 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 sellers' work in a sealed auction than in an open auction.*

Hypothesis 9. *After the projects are completed, buyers are more likely to hire the same seller in the future, in a sealed auction than in an open auction.*

Regarding sellers' post-project decisions, a sealed auction format increases the likelihood of selecting a winning seller, thereby potentially enhancing the satisfaction of the winning 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 than in an open auction.*

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 categories such as website and software development, graphical design, data entry and management, and writing. We have access to a comprehensive project, buyer, and seller data through collaboration with the platform. 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 provides detailed information on seller bidding dynamics and buyer and seller characteristics. The final dataset comprises 1,926 auctions launched by 967 buyers; 3,421 sellers place 16,581 bids; among these auctions, 802 of them are contracted. Our empirical analyses are structured into two levels: auction-bid level analyses uncovering bidding behavior and auction-level analyses studying auction, project, and post-project outcomes.

4.2 Variables

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

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[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).

Auction, project, and post-project outcomes. Auction and project 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 time elapsed between posting the project and choosing a winning bid (*TimeToAccept*), the number of bidders participating in each project (*#OfBidders*), whether a buyer chooses a winning seller (*Contracted*), and the winning bid amount when a project is contracted (*WinningBid*). *TimeToAccept* and *WinningBid* are only observed when the project is *Contracted*. Post-project outcome variables 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 market.[9]

Seller bidding behaviors. We construct several auction-bid-level variables to measure sellers' bidding behaviors, regardless of whether they win the auctions. *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*. This indicator variable denotes whether the auction was posted after the regime change date when the platform suddenly transitioned the auction format from open to sealed.

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-specific information such as the length of the project description (*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.

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

To reduce skewness, we apply a logarithmic transformation for most continuous variables. Table 2 provides the main variable descriptions and summary statistics, and Appendix B provides a correlation matrix.

[Insert Table 2 about here]

5. Empirical Results

As discussed in the theoretical section, the auction format change may dramatically impact seller behaviors, auction and project outcomes, and 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.

This section discusses detailed empirical models and presents 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 observable differences in their bidding behaviors before and after the regime change. 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. We further apply the non-parametric two-sample Kolmogorov-Smirnov (K-S) tests for distributional difference, verifying that distributions of (logged) *BidDelay* and *BidAmount* are significantly different before and after regime change (p-value<0.001 for both K-S tests).

[Insert Figure 1 about here]

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

$SellerBehavior_{ijkt} = \beta_0 AfterChange_t + \beta X_{ijt} + \delta Z_{ijkt} + \alpha_k + \gamma_t + \varepsilon_{it}$, where
$\beta X_{ijt} = \beta_1 BuyerExperience_{jt} + \beta_2 DescriptionLength_{it} + \beta_3 ProjectType_{it}$
$\delta Z_{ijkt} = \delta_1 SellerExperience_{kt} + \delta_2 BidOrder_{ijkt} + \delta_3 SameCountry_{ijkt}$ (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 *BidOrder* and *SameCountry*. To control for unobserved seller heterogeneity and days of week, we estimate linear regression models with seller fixed effects (α_k) and weekday dummies (γ_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 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.

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 42.5% less time deciding whether to bid and determining their bid amount after the regime change. This suggests that the sealed auction incentivizes sellers to bid earlier than the open auction, 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 change to sealed auctions on *BidDelay* 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, on average, sellers place their bids with a 16.5% lower wage amount. This finding suggests sellers tend to bid more aggressively to secure contracts when they cannot observe competitors' bids and other information, 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, indicating that the impact of change to sealed auctions on *BidAmount* is more pronounced for new sellers.

[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 auctions compared to the open auctions. 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—experienced sellers are less sensitive to the auction format change than new sellers. One possible explanation is that new sellers tend to exhibit more *delayed bidding* to learn from the competitors' bidding behavior in open auctions; when the auction format is suddenly changed to sealed, they are forced to place more aggressive (lower) bids earlier.

5.2 Impact on Auction and Project Outcomes

The impacts of the auction format change on seller bidding behaviors likely further lead to changes in the auction and project 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 an earlier auction ending. 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, fewer sellers will have already placed bids when the buyer ends the auction earlier.

We conduct several regression analyses at the auction level to verify these outcomes. Auction and project 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 a minimal change. 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:

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

In regression equation (2), *Outcome* is the dependent variable, representing *BidArrival*, *TimeToAccept*, *#OfBidders*, *Contracted*, 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 *DescriptionLength*, *MaxBid*, *AuctionDuration,* and *ProjectType* dummies, while buyer characteristics include *BuyerExperience* and buyer *Region* dummies. Additionally, we incorporate weekday dummies (i.e., Tuesday to Sunday, denoted by γ_t) to control the day-of-week effects. Like previous models, for continuous variables, we take logarithmic transformation to avoid skewed distributions. We estimate buyer random effects models rather than buyer fixed effects models, due to a limited number of buyers

posting at least two projects, which precludes sufficient within-buyer variation. We use a random effects linear probability model (LPM) for the dependent variable *Contracted*.

5.2.1. Result for Auction Outcomes

Table 4 presents empirical results. In Column 1, 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*. This finding supports Hypothesis 3, suggesting that sealed auctions encourage sellers to bid earlier. Next, Column 2 examines *TimeToAccept*. The estimated coefficient is negative and statistically significant (a 38.9% decrease), indicating that buyers took significantly less time to choose a winning seller in sealed auctions compared to open auctions. As a robustness check, we further apply the Cox proportional hazards model for *TimeToAccept* using a survival analysis. The results is qualitatively consistent. We provide detailed estimation results in Appendix E Table E1. This supports Hypothesis 4, which suggests that sealed auctions lead to quicker decision-making by buyers. Column 3 focuses on *#OfBidders*, where the coefficient of *AfterChange* shows a decrease of 10.3% 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 5b.

[Insert Table 4 about here]

We verify a reduction in the number of bidders expected to participate in each auction following the auction format change. However, a single seller may submit multiple bids for the same auction. According to our theoretical framework, sellers lack incentives to reveal their "true" bids early, often initially bidding higher and adjusting bids later in an open auction. Therefore, we expect the number of bids per bidder (#BidsPerBidder) to decrease after transitioning to a sealed format. Given the decrease in 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.

Therefore, we 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. Appendix D Figure D1 demonstrates 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. As reported in Appendix D Table D1, 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 graphical evidence.

5.2.2 Result for Project Outcomes

In Column 4 of Table 4, where *Contracted* is the dependent variable, the coefficient of *AfterChange* is significantly positive. The estimated increase in the probability of contract awarding after the auction format change is 6.1%. As robustness checks, we apply random effects Logit and Probit models, and the results are highly consistent (with estimated average marginal effects of 6.61% and 6.59%, respectively). We provide detailed estimation results in Appendix E Table E1. 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, Column 5 reveals that the coefficient of *AfterChange* is not statistically significant when *WinningBid* is the dependent variable. Since *WinningBid* is only valid when the auction is contracted, we conduct a Heckman-MLE selection model as a robustness check.[10] As reported in Appendix E Table E1, the estimated effect of *AfterChange* on *WinningBid* is still statistically insignificant, consistent with the estimated effect without correction for selection bias. This indicates that the auction format change did not significantly change 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 auction format, the actual contracted wages did not significantly differ.

For robustness checks, we also implement matching estimators to estimate the causal impact of auction format regime change on auction and project outcomes. Specifically, we apply propensity score matching and nearest neighbor matching with one-to-one matching with replacement to estimate the average treatment effect (ATE) of auction format change based on the covariates we used in the regression model. According to the results reported

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[10] To satisfy the exclusion restriction, we include additional covariates in the selection equation, namely *BuyerTenure* (logged number of days since registration of the focal buyer at time *t*), and *BuyerContractValue* (logged average value of completed projects of the focal buyer at time *t*).

in Appendix E Table E2, for most of the auction outcomes, including *BidArrival*, *TimeToAccept*, *#OfBidders*, *Contracted*, and *WinningBid*, the estimated effects of auction format regime change are highly consistent. However, the PSM-estimator indicates that the positive impact for *Contracted* is merely weakly statistically significant. We believe that the weak statistical significance could be attributed to the small sample size, but the magnitude of the effect is very close.

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) during active auction periods and avoided subsequent auctions when initial attempts failed to secure a contract. From the platform's perspective, the sealed auction format facilitated more time-efficient matching between buyers and sellers in the online labor market, thereby enhancing the platform's revenue through increased transaction fees.

5.3 Impact on Post-Project Outcomes

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 decisions. 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 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 on buyer satisfaction. To measure this, we use the ratings provided by buyers to sellers upon completion of projects. Buyer numerical rating (from 0 to 10 in our context) 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.[11] Therefore, our first dependent variable for buyer satisfaction is 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 could be posted after the 6-month observation window), which reflects the continuous relationship between buyers and sellers. Let $BuyerSatisfaction_{ijt}$ denote the post-project outcome of auction *i* posted by buyer *j* at time *t*. We propose the following regression model:

$$BuyerSatisfaction_{ijt} = \beta_0 AfterChange_t + \beta X_{ijt} + \varepsilon_{it}, \text{ where}$$
$$\beta X_{ijt} = \beta_1 DescriptionLength_{it} + \beta_2 BuyerExperience_{jt} + \beta_3 SellerExperience_{jt} + \beta_4 SameCountry_{it} +$$
$$\beta_5 WinningBid_{it} + \beta_6 ProjectType_{it} \tag{3}$$

Our analyses 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 E3 and E4.

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),

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[11] 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.

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.

[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 1,158 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 from registration, we employ the Cox proportional hazards model (let i denote the auction and λ denote the hazard function).

$$\lambda\big(t_i|X_{ijt}\big) = \lambda_0(t_i)exp(\beta_0 AfterChange_t + \beta X_i), \ where$$
$$\beta X_i = \beta_1 SellerExperience_i + \beta_2 SellerContractValue_i + \beta_3 \#OfBids_i + \beta_4 WinningRatio_i \qquad (4)$$

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 registration and placing the last bid before the cut-off date. The independent variable of interest is *AfterChange*, which is a dummy variable that equals 1 if the last bid before the cut-off date was placed after the regime change. 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 Appendix F Table F1, and the estimation result is shown in Table 6. Importantly, the hazard ratio of the variable *AfterChange* is statistically significant and much smaller than 1, supporting Hypothesis 10. With an estimated hazard ratio of 0.612 (p-value = 0.041), the results indicate that sellers are 38.8% less likely to leave the market at the one-year cut-off date if they completed the focal project

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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. Discussions

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. Drawing on the literature on auction theories and online labor markets, we first generate a series of hypotheses and 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 and project 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

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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 conceptual framework to

predict the causal 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 & 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 (i.e., 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 sealed auctions over open auctions for online labor market platforms. By implementing the sealed auction, 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 can help enhance seller retention, particularly among

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 are essential strategies in 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)". In our context, the increased likelihood of contract formation and higher buyer satisfaction after the regime change also highlights 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 sealed auctions enable 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 sealed auctions 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 wages of contracted projects, buyers should consider the overall value and quality of work received, as the efficiency gains from the sealed auctions 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 auctions 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 this study's findings, several future research directions could be explored to deepen our understanding of auction formats in online labor markets. Firstly, researchers could investigate the long-term impacts of auction formats on seller bidding behaviors and project performance. Secondly, examining the effects of auction formats on different types of projects, such as those requiring varying levels of complexity or collaboration, could provide insights into how auction formats influence sellers' bidding behaviors and buyers' 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 metrics such as risk tolerance, anti-competitive behavior (e.g., use of fraudulent information), and over-bidding behavior 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 open auctions in different cultural and geographical contexts and identifying the conditions under which sealed auctions are most effective. Lastly, policy-oriented research could assess the implications of auction mechanism regulations, exploring how policy interventions can enhance not only market efficiency and allocation (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
Bidding Behaviors	*BidDelay* (H1)	Bidding is faster in a sealed auction than in an open auction.
	BidAmount (H2)	The bidding amount is lower in a sealed auction than in an open auction.
Auction Outcomes	*BidArrival* (H3)	The expected number of bidders per unit of time is higher in a sealed auction than in an open auction.
	TimeToAccept (H4)	When the buyer can stop the auction, a sealed auction is expected to end more quickly than an open auction.
	#OfBidders (H5)	Sealed auction attracts more/fewer bidders than open auction.
Project Outcomes	*Contracted* (H6)	Buyers are more likely to successfully hire a seller in a sealed auction than in an open auction.
	WinningBid (H7)	Buyers are more likely to hire a seller with a lower wage in a sealed auction than in an open auction.
Post-Project Outcomes	*RatingByBuyer* (H8)	After the projects are completed, buyers are more likely to be satisfied with the selected sellers' work in a sealed auction than in an open auction.
	Rehire (H9)	After the projects are completed, buyers are more likely to hire the same seller in the future in a sealed auction than in an open auction.
	SellerExit (H10)	After the projects are completed, winning sellers are less likely to exit the online labor market in a sealed auction than in an open auction.

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 for 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 decide 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	A dummy for 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 bid amount 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 for 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	-0.553***	-0.235*	-0.607***	-0.180***	-0.035	-0.238***
	(0.065)	(0.100)	(0.065)	(0.054)	(0.105)	(0.051)
NoRating		0.547***			0.124	
		(0.111)			(0.100)	
AfterChange×NoRating		-0.418***			-0.191+	
		(0.116)			(0.115)	
#OfRatings			0.018			-0.239*
			(0.140)			(0.115)
AfterChange×#OfRatings			0.313***			0.329***
			(0.079)			(0.069)
DescriptionLength	-0.024*	-0.024*	-0.024*	0.093***	0.094***	0.093***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
BuyerExperience	-0.110***	-0.108***	-0.107***	-0.143***	-0.143***	-0.141***
	(0.016)	(0.016)	(0.016)	(0.018)	(0.018)	(0.018)
SellerExperience	-0.045	0.014	-0.308**	0.220***	0.188**	0.156+
	(0.049)	(0.062)	(0.104)	(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	-0.016	-0.017	-0.014	-0.145***	-0.146***	-0.145***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
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 Dummies	YES	YES	YES	YES	YES	YES

Note: Robust standard errors are 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)
AfterChange	0.337***	-0.493**	-0.109*	0.061*	-0.053
	(0.094)	(0.163)	(0.047)	(0.028)	(0.108)
DescriptionLength	0.024	0.145**	0.142***	0.017	0.030
	(0.043)	(0.050)	(0.018)	(0.012)	(0.034)
BuyerExperience	0.469***	-0.354***	-0.144***	0.068	-0.032
	(0.061)	(0.080)	(0.039)	(0.042)	(0.072)
MaxBid	0.060***	-0.049+	-0.013	0.011*	0.042*
	(0.017)	(0.025)	(0.009)	(0.005)	(0.020)
AuctionDuration	-1.154***	1.115***	0.130***	-0.124***	0.130+
	(0.049)	(0.095)	(0.028)	(0.015)	(0.069)
Observations	1,926	802	1,926	1,926	802
Adjusted R²	0.254	0.306	0.145	0.091	0.063
Number of Buyers	967	423	967	967	423
Buyer Region Dummies	YES	YES	YES	YES	YES
Weekday Dummies	YES	YES	YES	YES	YES
Project Type Dummies	YES	YES	YES	YES	YES

Note: Robust standard errors are 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	Rating by Buyer (Hypothesis 8)			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 R²	0.019	0.025	0.029	0.015	0.027	0.091
Project-type Dummies	No	YES	YES	No	YES	YES

Note: Robust standard errors are 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	Seller Exit (Hypothesis 10)	
	Coefficients	Hazard Ratio
AfterChange	-0.490**	.612*
	(0.240)	(.147)
SellerExperience	0.0750	1.078
	(0.142)	(.153)
SellerContractValue	-0.0547	.947
	(0.0502)	(.048)
#OfBids	-0.132	.876
	(0.0959)	(.084)
WinningRatio	0.429	1.536
	(0.948)	(1.457)
Observations	1,158	
# of failures	274	

Note: Robust standard errors 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	42.5% shorter delay in bidding	Yes
	BidAmount (H2)	Open > Sealed	16.5% decrease in bid amount	Yes
Auction Outcomes	BidArrival (H3)	Open < Sealed	40.1% increase	Yes
	TimeToAccept (H4)	Open > Sealed	38.9% shorter time	Yes
	#OfBidders (H5)	Open > Sealed	10.3% decrease	Yes
Project Outcomes	Contracted (H6)	Open < Sealed	6.1% increase	Yes
	WinningBid (H7)	Open > Sealed	Insignificant	No
Post-Project Outcomes	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 38.8% less likely to exit given a time after the focal project is completed (hazard ratio 0.612)	Yes

Figure 1. Model Free Evidence (Distributions of *BidDelay* and *BidAmount*)
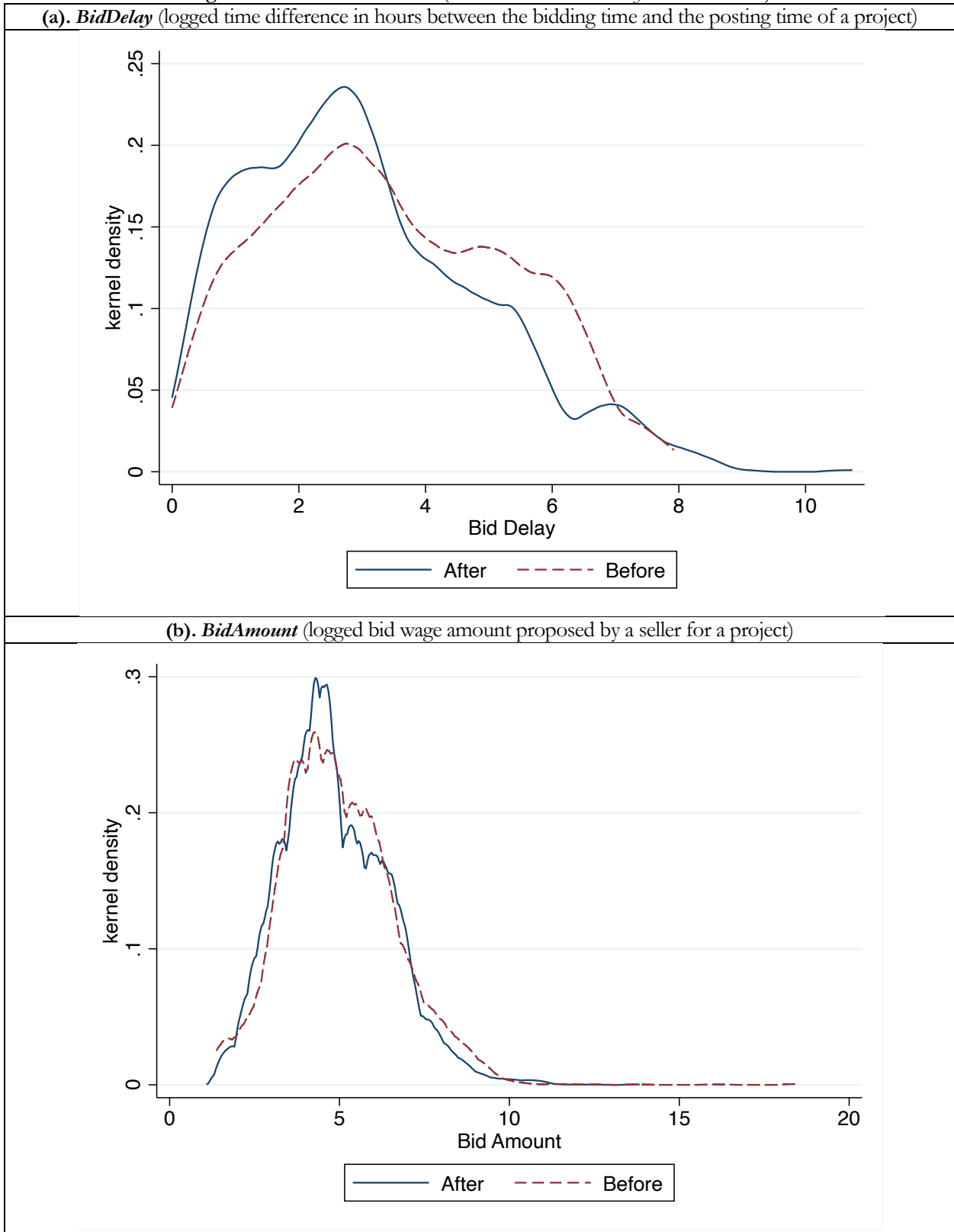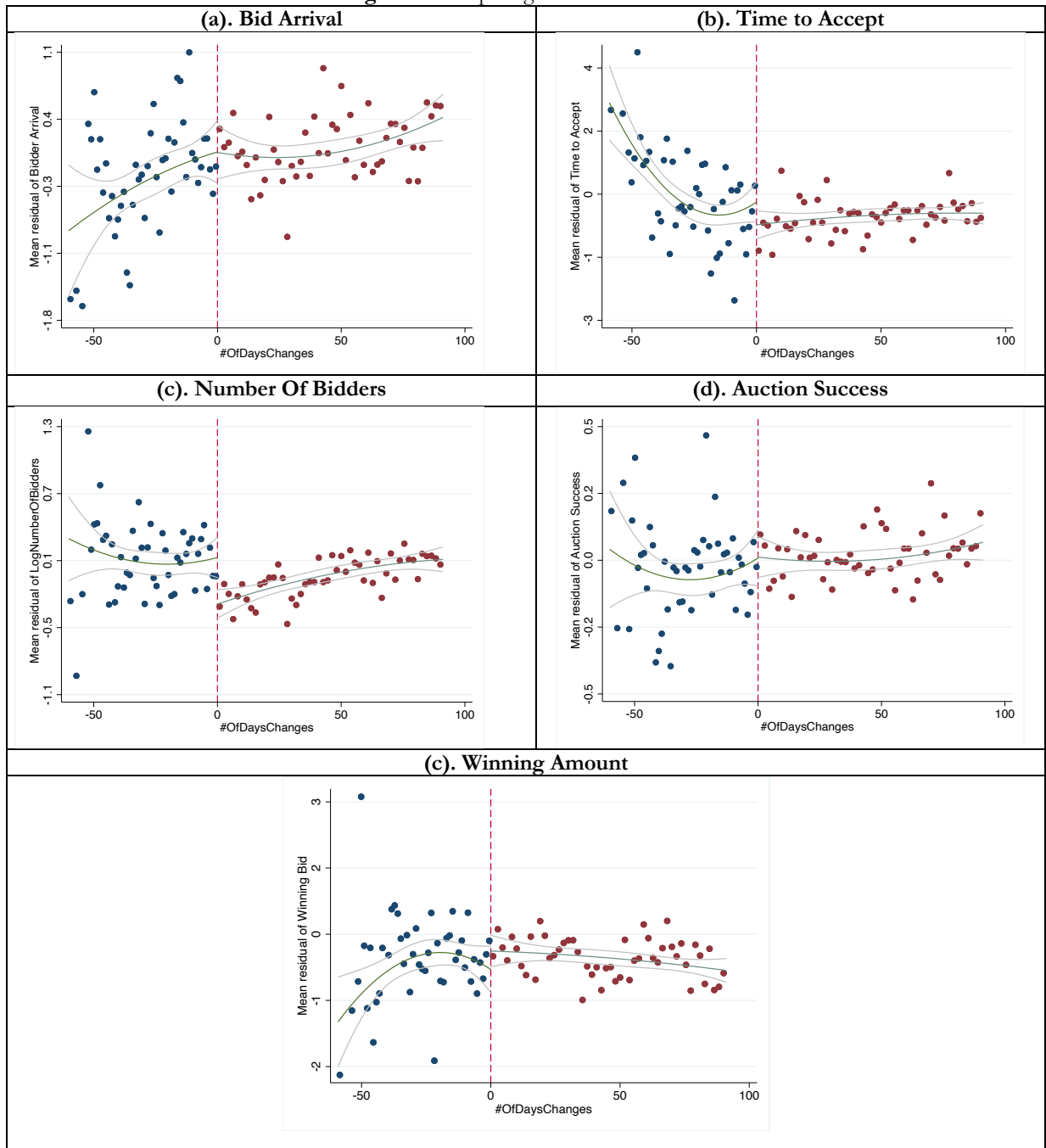
Figure 2. Comparing Auction Outcomes

Appendix A. Empirical Studies Comparing Auction Formats

Table A1. Empirical Studies Comparing Auction Formats

Literature	Comparison	Method	Conclusions
Athey et al. (2011)	First-price Sealed vs. open auctions	Parametric GPV-style structural model with Poisson bidder entry	Sealed auctions attract weak bidders, allocation shift toward them, and revenue is higher.
Cho, Paarsch, and Rust (2014)	English vs. dynamic Internet auctions, probably with common value component	Field data	Verified link-principle, in which English auctions (which deliver more information to the bidders) have higher expected revenue than Internet auctions.
Haruvy and Katok (2013)	Sealed vs. open, multi-attribute buyer-determined procurement auction	Lab experiment	Sealed auctions (request for proposals) generate higher buyer surplus than open dynamic auctions. This advantage is independent of quality transparency (sealed or open quality). In open auctions, bidders decrease quality in response to bids they observe. Open auctions generate lower buyer surplus when quality is public.
Levin, Kagel, and Richard (1996)	Open English vs. first-price sealed auctions, common value auction	Lab experiment	For inexperienced bidders, revenue is higher in sealed auctions, probably due to severe winner's curse. Experienced bidders could use information in English auction to overcome winner's curse, so revenue is higher in English auction.
Shachat and Wei (2012)	Open English vs first-price sealed auctions, procurement	Lab experiment, HMM	Procurement prices are lower in sealed bid auction than English auction. English auction data fit the game-theoretical prediction, but not for sealed bid auction. The bidders who deviate from game-theoretical prediction follow some constant absolute markup rule (decision rules of thumb) rather than strategic best response.
Hong, Wang, and Pavlou (2016)	Open vs. sealed multi-attribute buyer-determined procurement auctions, chosen by the employers in online labor market	Field data	Sealed auctions attract more bidders, probably due to independent private value component; buyer surplus is higher in open auctions, probably due to the common value component.
This study	Open vs. sealed multi-attribute buyer-determined procurement auctions, a sudden regime change in online labor market	Natural experiment	Although sealed auctions attract fewer bidders, buyers can contract with winning sellers in a shorter time with an equivalent winning price (buyer surplus).

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 and Buyer Region

Table C1. Distribution of Project Type and Buyer Region

Dummy Code	Description	Frequency	Percent
	Project Type*		
1	Website and Software Development	1,869	95.94%
2	Writing and Content	89	4.57%
3	Graphical Design	269	13.81%
4	Data Entry and Management	568	29.16%
	Region		
1	Asian	105	5.39%
2	Europe	398	20.43%
3	North America	945	48.51%
4	South America	17	0.87%
5	Australia/Oceania	34	1.75%
6	Africa	12	0.62%
0	N/A	437	22.43%

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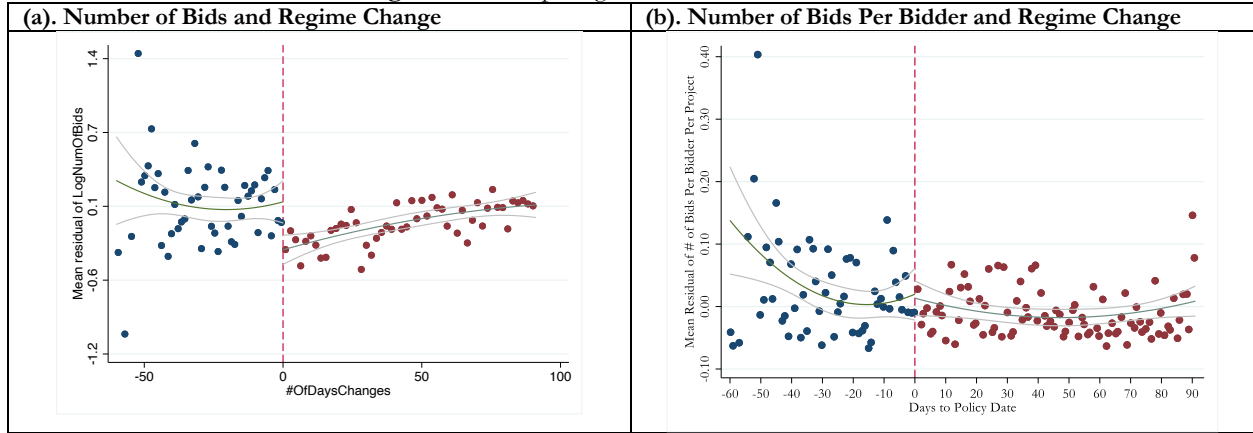
Table D1. Effects of Auction Format Change on Additional Bid Information

Dep. Variables	Number of Bids	Number of Bids Per Bidder
AfterChange	-0.1779***	-0.0356***
	(0.0470)	(0.0098)
BuyerExperience	-0.1283***	0.0028
	(0.0309)	(0.0062)
DescriptionLength	0.1312***	0.0049
	(0.0202)	(0.0038)
MaxBid	-0.0113	0.0008
	(0.0091)	(0.0017)
AuctionDuration	0.1333***	0.0080
	(0.0283)	(0.0056)
Observations	1,926	1,926
Adjusted R²	0.153	0.024
Number of Buyers	967	967
Buyer Region Dummies	YES	YES
Weekday Dummies	YES	YES
Project Type Fixed Effects	YES	YES

Note: Robust standard errors are 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: Robustness Checks

Dep. Variable	Time to Accept (Hypothesis 4)		Auction Success (Hypothesis 6)		Heckman-MLE (Hypotheses 6 and 7)	
	Cox: Coef.	Cox: Hazard Ratio	RE-Logit	RE-Probit	Auction Success	Winning Amount
AfterChange	0.360**	1.433**	0.367*	0.218*	0.167*	0.036
	(0.115)	(0.165)	(0.163)	(0.096)	(0.072)	(0.113)
DescriptionLength	-0.064+	0.938+	0.099	0.059	0.042	0.041
	(0.035)	(0.033)	(0.066)	(0.039)	(0.028)	(0.038)
BuyerExperience	0.315***	1.370***	0.155	0.096	-0.085	-0.082
	(0.090)	(0.123)	(0.230)	(0.135)	(0.078)	(0.075)
MaxBid	0.027	1.027	0.063*	0.037*	0.031*	0.032
	(0.017)	(0.017)	(0.027)	(0.016)	(0.013)	(0.021)
AuctionDuration	-0.736***	0.479***	-0.671***	-0.401***	-0.371***	0.351**
	(0.066)	(0.032)	(0.091)	(0.053)	(0.047)	(0.120)
BuyerTenure					-0.002	
					(0.030)	
BuyerContractValue					0.127***	
					(0.029)	
Observations	802		1,926	1,926	1926 (802 selected)	
Number of Buyers	423		967	967	967	
Log-Likelihood					-2458.4577	
Buyer Region Dummies	YES		YES	YES	YES	YES
Weekday Dummies	YES		YES	YES	YES	YES
Project Type Dummies	YES		YES	YES	YES	YES

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

Table E2. Effect of Auction Format Change on Auction Outcomes: Matching Estimators

Dep. Variable	Bid Arrival (Hypothesis 3)	Time to Accept (Hypothesis 4)	Number of Bidders (Hypothesis 5)	Auction Success (Hypothesis 6)	Winning Amount (Hypothesis 7)
Propensity Score Matching	0.348**	-0.713**	-0.0188**	0.065+	0.059
	(0.133)	(0.263)	(0.060)	(0.035)	(0.178)
Nearest Neighbor Matching	0.522***	-0.631***	-0.117*	0.080**	0.063
	(0.110)	(0.175)	(0.052)	(0.030)	(0.125)

Note: The Abadie-Imbens standard errors are in parentheses. For PSM, a caliper of 0.01 (maximum propensity score distance) is applied, dropping up to 40 observations; for NNM, a caliper of 5 (maximum Mahalanobis distance) is applied, dropping up to 24 observations.

Table E3. Effects of Auction Format Change on Rating by Buyer: Robustness Checks

Dep. Variable	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 are in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$, +$p<0.1$

Table E4. Effects of Auction Format Change on Rehire: Robustness Checks

Dep. Variable	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 are 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 cutoff date	1,158	0.237	0.425	0	1
AfterChange	A dummy variable that equals one if the last bid before the cutoff date was placed after the regime change	1,158	0.391	0.488	0	1
SellerExperience	Logged total number of completed projects a seller had at the time when the last bid before the cutoff date was placed	1,158	0.155	0.563	0	4.382
SellerContractValue	Logged average value of completed projects a seller had at the time when the last bid before the cutoff date was placed	1,158	0.483	1.506	0	7.306
#OfBids	Logged number of bids a seller had placed at the time when the last bid before the cutoff date was placed	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 at the time when the last bid before the cutoff date was placed	1,158	0.017	0.073	0	1