Open versus Sealed Auctions in Online Labor Markets: Evidence from a Natural Experiment*

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April 21, 2025

Abstract

Online labor markets routinely use auctions to help employers recruit workers, using open or sealed formats. In open auctions, workers can observe competitors' bids and profiles, whereas in sealed auctions, they cannot. We aim to understand which format leads to more efficient matching and faster hiring. We develop and test a set of hypotheses grounded in theory using data from a natural experiment: A major platform abruptly switched from open auctions to sealed auctions. Our empirical findings align with theoretical predictions. In open auctions, workers have strong incentives to delay bidding or place initial bids higher than their valuation to learn from competitors' bids and adjust accordingly. This strategic bidding behavior can lead to misallocation and time inefficiency. Consistent with these predictions, we find that after the switch from open auctions to sealed auctions, workers bid 42.5% faster and ask for 16.5% lower wages. As a result, the actual auction duration (i.e., time spent for choosing a winning worker) decreases by 38.9%, and the probability of a successful hire rises by 6.1%. Interestingly, although employers choose from a 10.3% reduced pool of participating bidders, there is no evidence of a significantly different wage for chosen worker. Post-project outcomes also improve: Employer satisfaction ratings increase, the likelihood of rehiring increases, and winning workers are 38.8% less likely to exit the platform. Together, these findings highlight the advantages of sealed auctions in improving market efficiency, match quality, and participant retention in online labor markets. The findings are robust to alternative model specifications and matching estimators.

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

JEL Codes: D44, J4

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* We thank Gagan Ghosh, Guofang Huang, Heng Liu, Enrique Seira, Daiqiang Zhang, Yiyi Zhou, and audience at various seminars for useful suggestions. Zhang acknowledges Amazon Science and National Science Foundation (IIS-1928278) for financial support. All authors contribute equally to this research.

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1. Introduction

Online labor markets—such as Freelancer, Guru, Upwork, Toptal, and Expert360—connect employers and workers globally to complete a wide range of tasks, including software development, graphic design, transcription, and translation. By removing geographical barriers, these platforms reduce hiring costs and broaden access to diverse skill sets. However, matching the right worker to a project remains a core challenge. To address this, many platforms employ auction mechanisms to facilitate matching amid intense competition among workers.

The literature documents many auction formats (Klemperer, 1999; Krishna, 2002). Theoretically, the revenue equivalence theorem (Myerson, 1981) suggests that under assumptions such as independent private values and risk neutrality, all standard auction formats should yield the same expected payoff for the auctioneer. Empirical literature, however, reveals notable differences across auction formats—especially between open auctions, in which competitors may see one another's bids, and sealed auctions, in which bids are only visible to the auctioneer. For example, Athey et al. (2011) found that sealed auctions attracted more small bidders and generated higher revenue. Other papers also highlight the importance of auction format choices in various contexts (e.g., Shachat & Wei, 2012; Haruvy & Katok, 2013; Cho et al., 2014).

The unique characteristics of the online labor market—distinct from the product markets typically studied in the auction literature—make choosing an auction format more challenging. First, these global online labor platforms foster competition among individuals from diverse cultural and ethical backgrounds, resulting in far greater heterogeneity than is found in the product market. Differences in experiences, ethics, and communication styles further add to more complexity. 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. Communication is largely text-based, increasing the risk of miscommunication, misunderstanding, 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, with employers selecting workers based on their own (even subjective) criteria (Yoganarasimhan, 2016). The lowest bids for completing the jobs may not necessarily win. Finally, hiring in the online labor market involves greater uncertainty than purchasing a product. 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 businesses, making hiring decisions more critical and the consequences of the 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 importance of auction format choice for online labor markets, the literature is still scant. One notable exception is Hong et al. (2016), who analyzed data from a platform where employers could choose between open and sealed auctions. However, little is known about how workers and employers respond when platforms mandate a particular auction format. Understanding these responses is important, as even on platforms that offer employer choice, worker behavior under different formats has important implications for platform design and performance. As online labor markets continue to grow and integrate into core business operations, a comprehensive understanding of the tradeoffs between auction forms, particularly open and sealed auctions, is vital for informed policy and design decisions. This study attempts to fill this gap.

Building on auction theory and prior research on online labor markets, we first develop a series of hypotheses about how workers behave differently in open versus sealed auctions. 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 observe others' bids, workers frequently delay submitting their bids, wait for competitors to bid first, or begin with higher bids and subsequently lower them. These strategic behaviors are especially pronounced among new workers, who may react more to competitors' bids. Following the platform's transition to sealed auctions, workers tend to submit bids more quickly and at lower wage levels, which benefits employers.

From the employers' perspective, open auctions attract more bids but are associated with longer decision times and a higher likelihood of not selecting any bidder. In contrast, sealed auctions lead to faster hiring decisions, greater employer satisfaction, and a lower likelihood of worker attrition. Taken together, these findings suggest that the platform's decision to switch from open to sealed auctions was well-founded.

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 findings for platforms and employers when they consider whether to implement a specific auction format.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the conceptual framework and hypotheses. Section 4 describes the data and key variables, followed by empirical results and robustness checks in Section 5. Section 6 concludes with a discussion of the main findings, theoretical and practical implications, limitations, and directions for future research.

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 employers seeking services and workers offering services. Although different platforms could have different defining features, such as the website's detailed design, most platforms follow the operating procedure described below (Lin et al., 2018).

The process starts when a registered employer initiates a potential labor contract by posting a project description on the platform as a reverse (procurement) auction.[1] In the project description, the employer needs

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

to specify worker requirements, such as specifications, expected deliverables, and workers' required skill sets. Employers can specify the reserve price (the highest wage they are willing to pay). After posting, the registered workers can browse project requirements on the site and decide whether they want to bid for a certain amount on the project. 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). Employers often do not have to commit to a predefined auction deadline. Instead, they could choose a worker and terminate the auction before the deadline, which is a feature to encourage workers to bid quickly. In addition to bid amount, employers can observe the automatically populated workers' profile information, such as their tenure on the site, geographic origins, prior worker 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, workers could view competitors' information and bid amount, while in a sealed auction, workers could not view this information (more details are provided in the next section). The employer applies a multi-attribute "beauty contest" auction in which the employers could select the winner based on both bid prices and other characteristics (e.g., reputation and certification) (Yoganarasimhan, 2016). Thus, the winning worker is not necessarily 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 employers do not necessarily need to choose a winner, as they can cancel the auction if none of the bids is satisfactory.

Once the employer selects a bidder to work on the project, the labor contract is formed. Then, the employer is required to deposit the winning bid amount into an escrow account hosted by the site. Meanwhile, the contracted worker'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 auction formats. Then, the contracted worker must work on the project and deliver the final product to the employer via the online system before the deadline. If the employer is satisfied with the deliverables, the deposit in the escrow account will be released to the contracted worker after the platform deducts a service fee, and the project is considered complete. At that moment, the employer and worker have a chance to voluntarily provide ratings for each other. If the employer is dissatisfied with the product deliverables, either party may initiate an arbitration process to resolve the dispute. 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 interest from researchers who study various features of such markets. However, since all transactions in this market are conducted over the Internet, employers and workers 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 employers to choose among competing workers, especially given the highly customizable nature of the projects.

Many existing studies examine different design features to help employers to make hiring decisions. These features include workers' disclosed characteristics such as experience, affiliation, and geographic location. Studies find that employers tend to select workers 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 workers from low-quality workers to mitigate the information asymmetry between employers and workers. These quality-signaling mechanisms include workers' 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 workers. For example, the platform usually only guarantees workers who pass predefined 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 employer-determined, project-specific auction parameters, such as auction duration, on worker 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 will affect participants in this emerging market.

2.3 Auction Formats

Although there are plenty of auction formats in auction literature, two major types are *sealed auctions* and *open auctions* (Krishna, 2002).[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 key assumptions such as symmetric, independent private value,[3] and risk-neutral bidders. This 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 formats. Notably, the revenue equivalence theorem will not hold when the assumptions are relaxed. The expected revenue in a sealed auction will be greater than that in an open auction when (1) bidders are risk-averse (Holt, 1980; Milgrom & Weber, 1982; Maskin & Riley, 1984)[4] or (2) there is

[2] For a 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 independent private value assumption, an open auction is equivalent to a second-price sealed 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 assumption that 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.
[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.

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 (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, previous empirical 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 the independent 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, a sealed auction generates higher buyer surplus (equivalent to expected revenue in a forward auction) than an open auction (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 open 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

[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.

(open ascending) auction yields a higher revenue than a dynamic Internet auction (which is an open ascending auction, but with less information released), verifying the linkage principle that more information disclosure leads to higher revenue.

While prior research has examined how auction formats affect bidding behaviors and outcomes in traditional goods and procurement markets, much less is known about how these mechanisms operate in online labor markets, where worker and employer behaviors introduce additional complexities.

2.4 Auction Formats in Online Labor Markets

The online labor market has two major features that are significantly different from traditional auction contexts. First, the online labor market employs a multi-attribute buyer-determined procurement auction, in which the employers could select the winner based on some rules on both bid amount and other characteristics of the bidder's offer (Che, 1993; Asker & Cantillon, 2008). Online labor markets often employ beauty contest auctions in which employers 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 employer knows which worker should be selected as the winner; even if an open auction is applied, the workers cannot perfectly anticipate who will be hired during the auction process.

Second, the auctioneer does not commit to the predefined 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; Ely & Hossain, 2003; Ockenfels & Roth, 2006). In our research, since the employers do not commit to any auction deadline, it incentivizes the workers to bid earlier to avoid the risk of the employers choosing the winner before the deadline. Due to the availability of competitor's bids and profiles, workers may strategically choose the time to bid in open auctions. In turn, the employer 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 impacts of auction formats 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 workers' bidding behaviors (e.g., bidding price) and employer welfare. However, they studied an online labor market in which employers can freely choose to use either open or sealed auctions in each job they post; both auction formats co-exist.[7] They assume that the worker'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 employer surplus is higher in open auctions than in sealed auctions. They attribute this result to the common value component of the worker'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 auctions to sealed auctions, a regime change that provides a natural experiment by which we identify the causal impact of auction formats on workers' bidding behavior, employers' hiring 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 Table A1 in Appendix A.

3. Hypotheses

Building on the literature on online labor markets and auction theory, we develop several hypotheses within the following conceptual framework. An employer initiates an auction by posting a project, which yields value upon completion. Workers arrive asynchronously—potentially following a Poisson process or another stochastic pattern—and view the posted project. Based on the nature of projects on the platform, we make an

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

independent private value assumption, meaning that workers 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 of completion. They usually bid a price higher than their cost, so they receive a positive surplus (price minus cost) from working. Employers can select a worker before the auction deadline if a bid, in conjunction with the worker's profile, meets their criteria—commonly through a buyer-determined beauty contest. Alternatively, they may cancel the auction if no satisfactory bid is received.

We use this framework to formulate hypotheses about how the auction format switch—from open to sealed—affects bidding behavior and outcomes. Specifically, we hypothesize changes in workers' *bid time* and *bid amount* (asking price), as well as downstream effects on auction outcomes, project outcomes, and post-project outcomes. In the pre-switch open auction format, bid information and worker profiles are visible to all parties. In the post-switch sealed format, only the employer can view this information. Based on this shift, we derive the following testable hypotheses, starting with workers' responses.

3.1. Worker Behaviors

We hypothesize that bids are submitted earlier under sealed auctions. In sealed auctions, workers have little incentive to delay bidding since competitor information is not observable, and waiting increases the risk that the employer selects another worker before the deadline. In contrast, in open auctions, early bids reveal a worker's willingness to work, potentially weakening their strategic position. While waiting too long also carries the risk of being overlooked since employers may pick a winner before the auction deadline, the visibility of others' bids creates an incentive for workers to delay and observe. Thus, in sealed auctions, bidding upon arrival is a weakly dominant strategy; in an open auction, a worker is incentivized to wait and then bid due to the possible information leakage from bidding early. Therefore, we have the following hypothesis.

Hypothesis 1. *Workers submit their bids earlier in sealed auctions than they did in open auctions.*

In open auctions, the revelation of a leading bid can create a *selection effect*: Workers whose costs exceed the leading bid are unlikely to submit a bid, reducing the pool of bidders and leading to lower observed bidding amounts compared to sealed auctions. However, open auctions also induce a *delayed bidding effect*: Because workers have limited incentives to reveal their true willingness to accept early—either to protect private information or to learn from competitors' behavior—those who bid early often demand initially absurdly high wages (in the range between the seller's cost and the revealed leading bid) and gradually reduce their bids over time. This delayed bidding behavior can raise observed bidding amounts in open auctions relative to bidding amounts in sealed auctions.

In our setting, workers compete under an unrevealed "beauty contest" rule, where both the bid amount and the worker's profile are evaluated in the hiring decision. Because workers cannot fully anticipate how the employer will select the winner, they may continue to submit bids even when facing a lower revealed bid, reducing the magnitude of the *selection effect*. Furthermore, given the minimal cost associated with placing a bid (e.g., time spent monitoring the auction), the revealed leading bid does not strongly discourage participation. Therefore, although both effects are present, we expect the *delayed bidding effect* to dominate, resulting in higher observed bidding amounts in open auctions relative to sealed auctions. This leads to the following hypothesis.

Hypothesis 2. *Workers ask for lower wages in sealed auctions than they did in open auctions.*

3.2. Auction Outcomes

Building on the predicted changes in worker bidding behavior, we next examine how auction outcomes differ between open and sealed formats. We focus on two key dimensions: *bidder arrival*, defined as the number of bidders per unit of time, and *time to accept*, defined as the time until the employer chooses the winning bidder. We further explore how these effects jointly shape the *number of bidders*, measured by the total number of bidders participating before the auction closes.

Based on the preceding discussion, we propose that sealed auctions make workers behave more competitively by submitting lower bids earlier relative to the deadline. This behavioral shift leads to auction-level theoretical predictions. First, given the differences in bidding speed between open and sealed auctions, we expect differences in the number of bidders per unit of time. In sealed auctions, where workers tend to bid immediately upon arrival, the bidder arrival rate—measured as the number of bids per unit of time—should be higher than in open auctions, where workers often delay bidding (*delayed bidding effect*). Formally, in a sealed auction, a worker'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 workers may not place a bid upon arrival. Hence, we propose Hypothesis 3, as below.

Hypothesis 3. *The expected number of bidders per unit of time is higher in sealed auctions than in open auctions.*

In our context, the employers have the discretion to terminate the auction early. 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 employers may even accept a bid if it falls sufficiently below a satisfactory level and terminate the auction. In sealed auctions, where workers bid promptly upon arrival, there is a greater chance that an acceptable bid appears earlier, increasing the likelihood that the auction ends sooner. In contrast, in an open auction, the workers' 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 duration.

Hypothesis 4. *Auctions are expected to end earlier in sealed auctions than in open auctions.*

By combining Hypothesis 3, which predicts a higher bidder arrival rate, and Hypothesis 4, which predicts faster auction termination, we can predict the expected total number of bidders. A sealed auction may attract more bidders before the auction ends if bidder arrival rate is sufficiently high (Hypothesis 3). However, because sealed auctions are more likely to end early (Hypothesis 4), the total number of bidders could be reduced. Therefore, the net effect on the total number of bidders is theoretically ambiguous, leading to the following hypothesis.

Hypothesis 5. *A sealed auction attracts (a) more or (b) fewer bidders than an open auction, depending on the relative strength of the effects in Hypotheses 3 and 4.*

3.3. Project Outcomes

The auction mechanism not only shapes bidding behavior but also influences the immediate outcomes of the hiring process. We focus on two project-level outcomes: *auction success*, measured by whether an employer successfully hires a worker, and *winning amount*, measured by the wage agreed upon in the transaction. Based on the predicted differences in bidding behavior and auction timing across formats, we develop the following hypotheses.

During the auction process, the employer accepts a bid if it is sufficiently low and terminates the auction early. In theory, a more patient employer who waits to allow more workers to compete can always select the bid from the worker with the lowest cost, regardless of the auction format employed by the platform.

However, a less patient employer may become frustrated with the longer waiting times in an open auction and choose to terminate the auction without hiring a worker. In contrast, this scenario is less likely in a sealed auction, where workers place their effective bids earlier. Consequently, employers 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, employers should be more likely to hire a worker at a lower wage in a sealed auction compared to an open auction. Hence, we posit Hypotheses 6 and 7 below.

Hypothesis 6. *Employers are more likely to successfully hire a worker in sealed auctions than they were in open auctions.*

Hypothesis 7. *Employers are more likely to hire a worker at a lower wage in sealed auctions than they were in open auctions.*

3.4 Post-Project Outcomes

Post-project outcomes provide important evidence on the quality and sustainability of matches formed through the auctions. We examine two dimensions of post-project outcomes: Employer satisfaction, reflected by worker ratings (by employer) and rehiring decisions, and *worker exit*, which is whether the winning workers leave the online labor market in the near future. Drawing on the earlier predictions about better initial matching under sealed auctions, we propose the following hypotheses.

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

Hypothesis 8. *Employers are more likely to be satisfied with the workers' work in sealed auctions than in open auctions.*

Hypothesis 9. *Employers are more likely to hire the same workers in the future in sealed auctions than in open auctions.*

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

Hypothesis 10. *Winning workers are less likely to exit the online labor market after sealed auctions than after open auctions.*

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 employers and workers 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, employer, and worker data through collaboration with the platform. Specifically, we have detailed information about each auction (e.g., when it is posted and ended), each employer (e.g., when they registered and where they came 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 employers).

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

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

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. During this narrow timeframe, no other new mechanisms or policies were introduced, and there were minimal changes in worker backgrounds that could influence employer and worker behaviors, aside from the auction format policy change. Each auction provides detailed information on worker bidding dynamics and employer and worker characteristics. The final dataset comprises 1,926 auctions launched by 967 employers; 3,421 workers 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 worker behaviors and auction, project, and post-project outcomes.

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. These variables include the number of bidders per hour (*BidderArrival*), the time elapsed between posting the project and choosing a winning bid (*TimeToAccept*), the number of bidders participating in each project (*#OfBidders*), whether an employer chose a winning worker (*AuctionSuccess*), and the winning bid amount when the project is contracted (*WinningBid*). *TimeToAccept* and *WinningBid* are only observed when the project is contracted. Post-project outcome variables include employers' satisfaction, measured by *WorkerRating*, given by the employer upon project completion, and *Rehire*, indicating whether the same employer rehired the same worker for future projects, and workers' survival—*WorkerExit*, which reflects the survival analysis outcome of the winning worker's decision to remain in or exit the market.[9]

Worker bidding behaviors. We construct several auction-bid-level variables to measure workers' bidding behaviors, regardless of whether they win the auctions. *BidTime* represents the time elapsed between posting the project and placing a bid. *BidAmount* denotes the bid price (wage) proposed by the worker to the employer 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 from open

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

format to sealed format.

Control variables. We include four groups of control variables in our analysis. Employer information controls consist of the number of projects previously completed by the employer (*EmployerExperience*) and the employer's region of origin (*Region*). Similarly, we control worker information, including the number of projects previously completed by the worker (*WorkerExperience*), tenure (*WorkerTenure*), 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 an employer 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 worker's bid within a particular auction, and *SameCountry*, which indicates whether the employer and worker are from the same country.

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 worker 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 the perfect natural experiment for us to empirically test these conjectures through a battery of empirical analyses around this regime change. This section discusses detailed empirical models and presents our findings based on these analyses.

5.1 Impact on Worker Behaviors

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

Workers decide both when to bid (i.e., bid time) and the amount to bid (i.e., bid amount) when they express interest in a posted project. We measure *BidTime* 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 worker 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 worker behavior outcomes (i.e., *BidTime* 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) *BidTime* 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 employer, *k* denotes the worker, and *t* denotes the time (the day the worker places the bid).

$$WorkerBehavior_{ijkt} = \beta_0 AfterChange_t + \beta X_{ijt} + \delta Z_{ijkt} + \alpha_k + \gamma_t + \varepsilon_{it},$$

where:

$$\beta X_{ijt} = \beta_1 EmployerExperience_{jt} + \beta_2 DescriptionLength_{it} + \beta_3 ProjectType_{it}$$
$$\delta Z_{ijkt} = \delta_1 WorkerExperience_{kt} + \delta_2 BidOrder_{ijkt} + \delta_3 SameCountry_{ijkt} \qquad (1)$$

The dependent variables in regression equation (1) are the two worker-bidding 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 employer-specific covariates X_{ijt}, as well as the worker and bid-specific covariates Z_{ijkt}. Specifically, X_{ijt} contains auction characteristics such as *DescriptionLength* and *ProjectType* dummies, along with the employer-specific variable *EmployerExperience*. Z_{ijkt} contains worker-specific variable *WorkerExperience*, as well as bid-specific variables, including *BidOrder* and *SameCountry*. To control for unobserved worker heterogeneity and days of the week, we estimate linear regression models with worker fixed effects (α_k) and weekday dummies (γ_t), respectively.

We estimate three model specifications for each worker 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 worker has any rating before the current bid) and the interaction term between *NoRating* and *AfterChange* to compare the effects of regime change on new workers versus experienced workers. 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 worker experience, measured by the number of worker ratings received.

Table 3 presents the coefficients with robust standard errors (in parentheses) clustered at the worker level. The first three columns in Table 3 report the results using *BidTime* as the dependent variable. In Column 1, the negative coefficients of *AfterChange* indicate that workers, 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 workers 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 employer may terminate 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 *BidTime* is more pronounced for new workers but less pronounced for experienced workers.

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 workers bid lower wage amounts after the regime change. Specifically, on average, workers place their bids with a 16.5% lower wage amount. This finding suggests that workers tend to bid more aggressively to secure contracts when they cannot observe competitors' bids and other information. Therefore, Hypothesis 2 is supported. 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 workers.

[Insert Table 3 about here]

Overall, we find that workers strongly respond to the auction format regime change and become more aggressive, implying more intense competition in sealed auctions than in open auctions. When the auction format shifts from open to sealed, workers take less time to bid and bid lower wage amounts. Moreover, the impact varies depending on worker heterogeneity—experienced workers are less sensitive to the auction format change than new workers. One possible explanation is that new workers 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 worker 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 workers will place bids per unit of time after the regime change, the increased aggressiveness of workers will make the "current best offer" reach the employer's threshold of satisfaction more quickly. Consequently, whether more or fewer workers will eventually place bids after the auction format regime change remains an empirical question.

We conduct several regression analyses at the auction level to examine these outcomes. Auction and project outcomes are measured in several aspects, including logged number of bidders per hour in the project (*BidderArrival*), logged time duration until the employer makes an acceptance decision (*TimeToAccept*), logged number of bidders participating in the project (*#OfBidders*). Additionally, we measure whether the employer chooses any worker to award the contract with a binary variable (*AuctionSuccess*). 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 employer 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 worker significantly decreased. 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 employer *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:

$$\beta X_{ijt} = \beta_1 EmployerExperience_{jt} + \beta_2 DescriptionLength_{it} + \beta_3 MaxBid_{it} + \beta_4 AuctionDuration_{it} + \beta_5 Region_{jt} + \beta_6 ProjectType_{it} \quad (2)$$

In regression equation (2), *Outcome* is the dependent variable, representing *BidderArrival*, *TimeToAccept*, *#OfBidders*, *AuctionSuccess*, and *WinningBid*, respectively. The primary independent variable is *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 employer-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 employer characteristics include *EmployerExperience* and employer *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 employer random effects models rather than employer fixed effects models, due to a limited number of employers posting at least two projects, which precludes sufficient within-employer variation. We use a random effects linear probability model (LPM) for the dependent variable *AuctionSuccess*.

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 workers 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 workers to bid earlier. Next, Column 2 examines *TimeToAccept*: The estimated coefficient is negative and statistically significant (a 38.9% decrease), indicating that employers took significantly less time choosing a winning worker in sealed auctions than open auctions. As a robustness check, we further apply the Cox proportional hazards model for *TimeToAccept* using a survival analysis. The results are 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 employers. 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 workers 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 worker may submit multiple bids for the same auction. According to our theoretical framework, workers 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*) an employer 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. Figure D1 in Appendix D 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 Table D1 in Appendix D, 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 *AuctionSuccess* 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 Table E1 in Appendix E. This finding suggests that under the sealed auction format, where workers place lower bid amounts, employers find it easier to identify satisfactory offers and award contracts to winning workers, 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 project is contracted, we conduct a Heckman-MLE selection model as a robustness check.[10] As reported in Table E1 in

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

Appendix E, 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 employers 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 in Table E2 in Appendix E, for most of the auction outcomes, including *BidderArrival*, *TimeToAccept*, *#OfBidders*, *AuctionSuccess*, and *WinningBid*, the estimated effects of auction format regime change are highly consistent. However, the PSM-estimator indicates that the positive impact for *AuctionSuccess* 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 bidder arrival increased, employers exhibited a higher likelihood of swiftly awarding contracts to winning workers 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 employers but did not result in lower project wages paid to selected workers. Nonetheless, it potentially saved employers' 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 employers and workers 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 Employer Satisfaction: Worker Rating and Rehire Likelihood

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

We begin by investigating the impact of the auction format on employer satisfaction. To measure this, we use the ratings provided by employers to workers upon completion of projects. Employer 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 employer satisfaction is the truncated worker rating by employer (*WorkerRating*). Additionally, we consider *Rehire*, a binary variable indicating whether employers choose to re-engage the same worker in future projects (which could be posted after the 6-month observation window), which reflects the continuous relationship between employers and workers. Let $EmployerSatisfaction_{ijt}$ denote the post-project outcome of auction *i* posted by employer *j* at time *t*. We propose the following regression model:

$$EmployerSatisfaction_{ijt} = \beta_0 AfterChange_t + \beta X_{ijt} + \varepsilon_{it},$$

where:

$$\beta X_{ijt} = \beta_1 DescriptionLength_{it} + \beta_2 EmployerExperience_{jt} + \beta_3 WorkerExperience_{jt} + \beta_4 SameCountry_{it} + \beta_5 WinningBid_{it} + \beta_6 ProjectType_{it} \quad (3)$$

Our analyses focus exclusively on contracted projects in which employers have selected a winning worker, conducting our analysis at the auction level. We employ a linear regression model for the dependent variable *WorkerRating*, which assesses employer satisfaction for the focal project, and a linear probability model (LPM) for the dependent variable *Rehire*, which indicates whether employers rehire the same workers in future projects.

[11] In our data, only 2.99% of observations will be affected by truncation, since the worker gets a rating below 7 in 24 out of 802 completed 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 employer and worker characteristics, including *EmployerExperience*, *WorkerExperience*, and *SameCountry*.

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, employers report higher satisfaction with projects completed after the regime change, as evidenced by both the *WorkerRating* metric and their decisions to *Rehire* the same worker. Thus, both Hypotheses 8 and 9 are supported. Moreover, in the full specifications (Columns 3 and 6), the inclusion of employer and worker experience variables attenuates the effect of *AfterChange*, suggesting that the enhanced satisfaction observed in sealed auctions may be partially attributable to improved matching between experienced employers and workers. As robustness checks, for *WorkerRating*, 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 Tables E3 and E4 in Appendix E.

[Insert Table 5 about here]

5.3.2 Worker Survival: Exit Rate

We next investigate how the regime change affects workers' 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 workers who registered and were active before the regime change, totaling 1,158 workers. We then extracted all transaction records for these workers. Finally, we used one year after the regime change as the cutoff date to determine whether a worker exited the market: If a worker placed bids after the cutoff date, he or she was considered to have not exited; otherwise, this worker was considered to have exited. Since we estimate how long it takes for a worker to exit the market from registration, we employ the Cox proportional hazards model (let *i* denote the auction and λ denote the hazard function).

$$\lambda\left(t_i | X_{ijt}\right) = \lambda_0(t_i) exp(\beta_0 AfterChange_t + \beta X_i),$$

where:

$$\beta X_i = \beta_1 WorkerExperience_i + \beta_2 WorkerContractValue_i + \beta_3 \#OfBids_i + \beta_4 WinningRatio_i \quad (4)$$

In this model, the event is defined as whether the worker exited, while the time to the event is the time difference (in months) between the worker registration and placing the last bid before the cutoff date. The independent variable of interest is *AfterChange*, which is a dummy variable that equals 1 if the last bid before the cutoff date was placed after the regime change. Because the worker'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 worker has placed (*#OfBids*), the probability of winning contracts (*WinningRatio*), the total number of completed projects (*WorkerExperience*), and the logged average wage for a completed project (*WorkerContractValue*). Notably, all these variables are measured at the time the worker placed their last bid before the cutoff date. The summary statistics of these variables are reported in Table F1 in Appendix F, 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 workers are 38.8% less likely to leave the market at the one-year cutoff date if they completed the focal project after the auction format change.

[Insert Table 6 about here]

In sum, we find that the auction format change positively impacts the online labor market, with higher employer satisfaction and greater worker retention, verifying the superiority of the sealed format on such platforms. Our results are highly consistent with multiple robustness checks.

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 worker bidding behaviors, auction and project outcomes, and post-project outcomes. We find that, on average, workers spend less time placing bids and offer lower wage amounts following the regime change. Conversely, employers spend less time selecting winning workers. At the auction level, despite a higher bidder 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, employers report higher satisfaction with projects completed after the regime change, while workers 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 workers' bidding decisions. Following the regime change, workers can no longer observe their competitors' bidding information. Given the platform's auction-stopping rule, whereby employers can end the auction at any time when a satisfactory bid is received, workers may be concerned that other workers might gain an advantage by bidding early. Consequently, workers tend to reduce bid time. Faced with increased uncertainty about competition, workers may also generally lower their wage amounts to enhance their chances of winning contracts, thus bidding more aggressively. From the employers' perspective, this leads to quicker decision-making when awarding contracts, reducing the time needed to select a worker. The changing decisions of both employers and workers have two significant implications observed in the analyses of auction-level outcomes. First, under the sealed format, although the bidder 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 employers more likely to successfully hire workers in a shorter time. Additionally, employers are more inclined to rehire the same workers 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 workers. On the platform, workers can be categorized into two groups: new workers, who have no ratings or completed jobs, and experienced workers, who have ratings or completed jobs. New workers, who are aware of their disadvantages compared to experienced workers due to their limited reputation, strive to better seize job opportunities. The analysis of worker behavior indicates that new workers 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 workers 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 employers and workers 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 employers 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 workers and 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 time and a quicker decision-making process for both employers and workers. 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 worker retention, particularly among workers who may feel more competitive when competitors' bidding information is not observable. The increased competition and job opportunities foster a more vibrant and active worker base, contributing to the platform's long-term growth and sustainability. Furthermore, the increase in employer satisfaction with completed projects suggests that sealed auctions might improve the overall quality of services, potentially leading to higher employer retention rates and repeat business.

For workers, particularly freelancers, adapting to the implemented auction format, which is, in our context, a sealed auction with a buyer-determined winning rule, is crucial. Workers 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 workers 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 employer satisfaction after the regime change also highlights the importance of delivering high-quality work. By doing so, workers 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 employers suggests that sealed auctions can lead to better project outcomes. Employers can expect to receive higher-quality work and develop long-term relationships with reliable workers. While there is no significant difference in the wages of contracted projects, employers should consider the overall value and quality of work received, as the efficiency gains from the sealed auctions imply higher total utility for the employers.

6.3 Limitations and Future Research

While this study offers valuable insights into the effects of switching from open to sealed auctions in an online labor market, it has several limitations. First, the reliance on data from a single platform may limit the generalizability of the findings, although the widespread use of auction mechanisms across platforms supports the relevance of our results. Second, the study focuses on short-term impacts and does not capture potential long-term effects, such as learning by workers and employers from past auction outcomes when winner identities are disclosed (Lu et al., 2019).

Building on these findings, future research could explore several avenues. First, investigating the long-term impacts of auction formats on bidding behavior and project performance would provide a more complete understanding. Second, examining how auction formats affect projects of varying complexity or collaboration requirements could reveal important differences across job categories. Third, future studies could delve into psychological and behavioral responses, such as risk tolerance, anti-competitive behavior, and overbidding, under different auction formats. Fourth, analyzing heterogeneous effects across cultural and geographical contexts could identify when sealed auctions are most effective. Finally, policy-oriented research could assess how auction regulations impact not only market efficiency, but also fairness and inclusivity.

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Tables and Figures

Table 1. Summary of Hypotheses

Outcome Dimensions	Hypotheses	Predicted Effect of Switching from Open to Sealed Auctions
Worker Behaviors	*Bid Time* (H1)	Workers submit bids earlier.
	Bid Amount (H2)	Workers submit lower bidding amounts.
Auction Outcomes	*Bidder Arrival* (H3)	Rate of bidder arrival (number of bidders per unit time) increases.
	Time to Accept (H4)	Employers choose the winning bidder earlier.
	Number of Bidders (H5)	Sealed auctions may attract more or fewer bidders depending on the relative strength of bidder arrival (H3) and "time to accept" (H4) effects.
Project Outcomes	*Auction Success* (H6)	Employers are more likely to successfully hire a worker.
	Winning Amount (H7)	Employers are more likely to hire a worker at a lower wage.
Post-Project Outcomes	*Worker Rating* (H8)	Employers are more likely to give higher satisfaction ratings.
	Rehire (H9)	Employers are more likely to rehire the same worker for future projects.
	Worker Exit (H10)	Winning workers are less likely to exit the platform.

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 whether the project was posted after the regime change day	1,926	0.750	0.433	0	1
BidderArrival	Logged number of bidders placing bids per hour (bidder 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
AuctionSuccess	A dummy variable that equals one if the employer chose a worker 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 employer took to decide to accept a bid	802	3.317	1.843	0.036	8.929
WorkerRating	A rating given by the employer to the worker after the project is completed (left truncated at 7)	802	9.729	0.714	7	10
Rehire	A dummy for if the employer hired the same worker again in future projects	802	0.269	0.444	0	1
	Employer Information					
EmployerExperience	Logged number of projects the focal employer 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 employer 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 an employer 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)					
	Worker Information					
#OfRatings	Logged number of ratings a worker 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 worker is a new worker at the time of the current bid	16,581	0.743	0.437	0	1
WorkerExperience	Logged number of projects the worker 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
BidTime	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 whether the worker and employer come from the same country	16,581	0.201	0.401	0	1

Table 3. Effects of Auction Format Change on Worker Bidding Behaviors

Dep. Variable	Bid Time (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)
EmployerExperience	-0.110***	-0.108***	-0.107***	-0.143***	-0.143***	-0.141***
	(0.016)	(0.016)	(0.016)	(0.018)	(0.018)	(0.018)
WorkerExperience	-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 Workers	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
Worker 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	Bidder 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)
EmployerExperience	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 R^2	0.254	0.306	0.145	0.091	0.063
Number of Employers	967	423	967	967	423
Employer 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 Employer Satisfaction

Dep. Variable	Worker Rating (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)
EmployerExperience			0.0543**			0.0986***
			(0.0227)			(0.0179)
WorkerExperience			0.0526**			0.0938***
			(0.0239)			(0.0194)
SameCountry			0.0252			-0.0370
			(0.0605)			(0.0319)
WinningBid		-0.0121	-0.0160		0.0179	0.00897
		(0.0209)	(0.0215)		(0.0147)	(0.0140)
Observations	802	802	802	802	802	802
Adjusted R^2	0.019	0.025	0.029	0.015	0.027	0.091
Project-type 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 Worker Exit

Dep. Variable	Worker Exit (Hypothesis 10)	
	Coefficients	Hazard Ratio
AfterChange	-0.490**	.612*
	(0.240)	(.147)
WorkerExperience	0.0750	1.078
	(0.142)	(.153)
WorkerContractValue	-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	

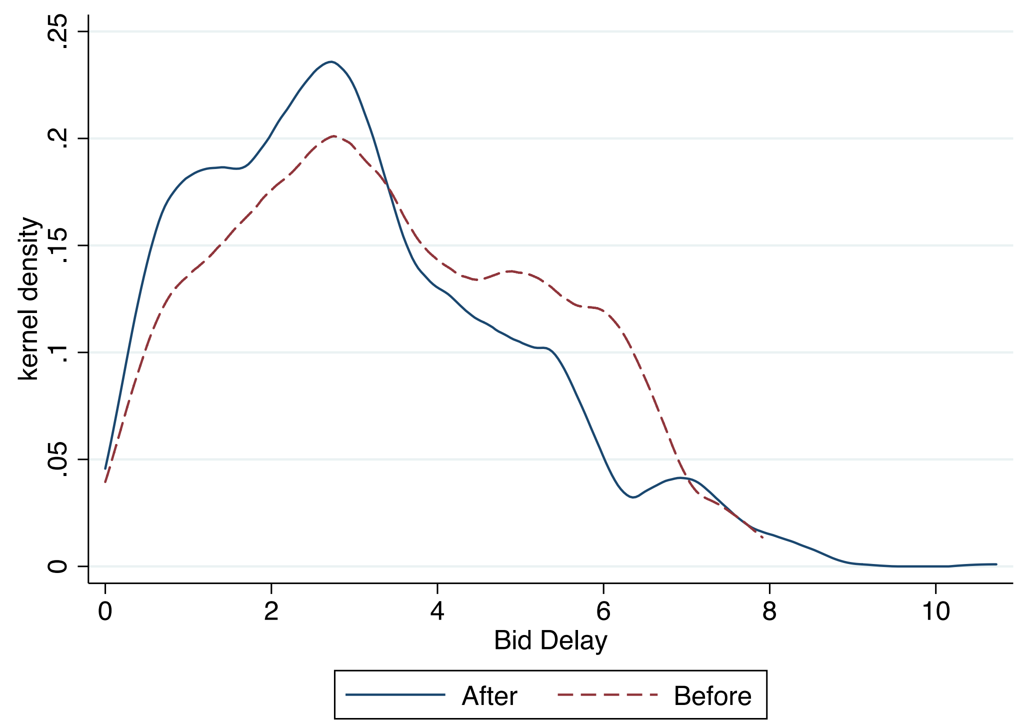
Note: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7. Summary of Key Findings

Category	Dependent Variable (Hypothesis)	Prediction	Result Summary	Supported
Worker Behavior	*Bid Time* (H1)	Open > Sealed	42.5% shorter delay in bidding	Yes
	Bid Amount (H2)	Open > Sealed	16.5% decrease in bid amount	Yes
Auction Outcomes	*Bidder Arrival* (H3)	Open < Sealed	40.1% increase	Yes
	Time to Accept (H4)	Open > Sealed	38.9% shorter time	Yes
	Number of Bidders (H5)	Open > Sealed	10.3% decrease	Yes
Project Outcomes	*Auction Success* (H6)	Open < Sealed	6.1% increase	Yes
	Winning Amount (H7)	Open > Sealed	Insignificant	No
Post-Project Outcomes	*Worker Rating* (H8)	Open < Sealed	0.249 increase out of 10 (left truncated at 7)	Yes
	Rehire (H9)	Open < Sealed	Employers are 13.9% more likely to rehire	Yes
	Worker Exit (H10)	Open > Sealed	Workers 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 *BidTime* and *BidAmount*)

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



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

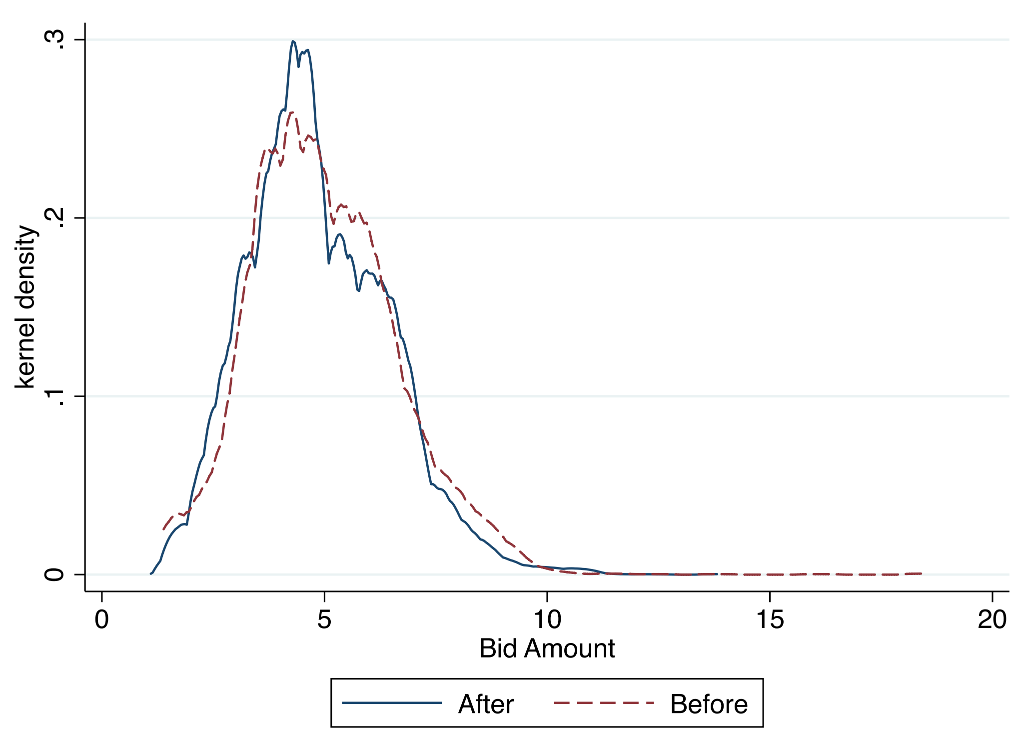
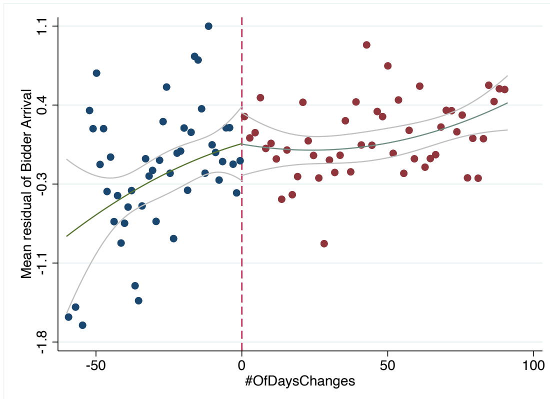
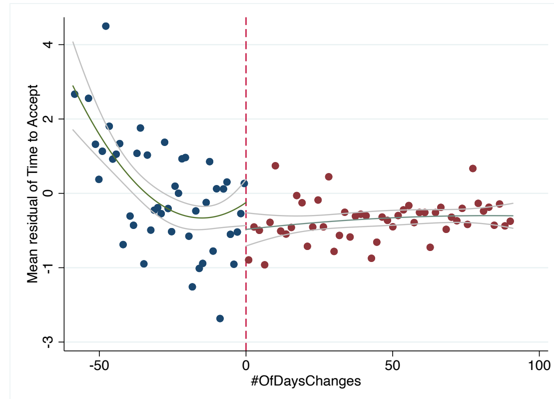


Figure 2. Comparing Auction Outcomes

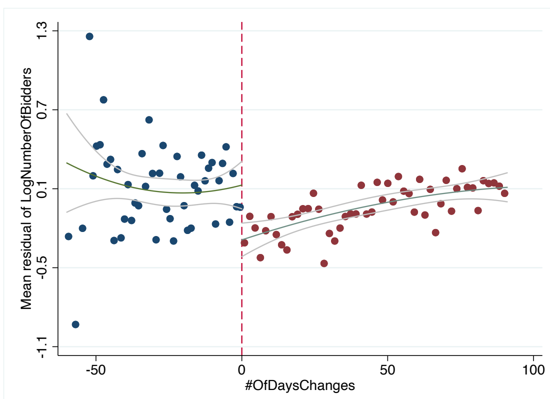
(a). Bidder Arrival



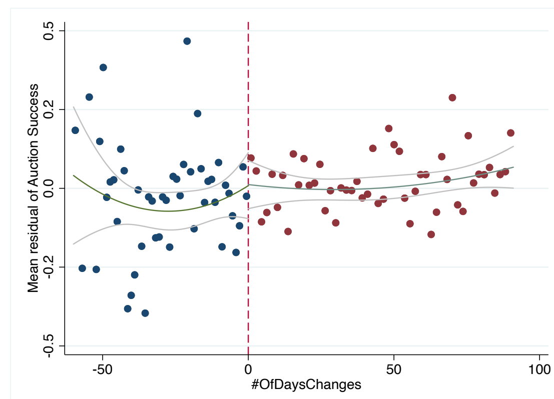
(b). Time to Accept



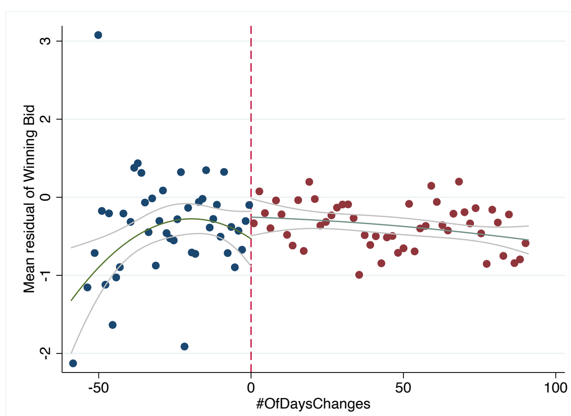
(c). Number Of Bidders



(d). Auction Success



(c). Winning Amount



Online Appendix for

"Open versus Sealed Auctions in Online Labor Markets: Evidence from a Natural Experiment"

Table A1. Empirical Studies Comparing Auction Formats

Literature	Comparison	Method	Conclusions
This study	Open versus sealed multi-attribute buyer-determined procurement auctions, with a sudden regime change in an 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).
Levin, Kagel, & Richard (1996)	Open English versus 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.
Athey et al. (2011)	First-price sealed versus open auctions	Parametric GPV-style structural model with Poisson bidder entry	Sealed auctions attract weak bidders, allocation shift toward them, and revenue is higher.
Shachat & 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.
Haruvy & Katok (2013)	Sealed versus 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.
Cho, Paarsch, & Rust (2014)	English versus 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.
Hong, Wang, & Pavlou (2016)	Open versus 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.

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	*BidderArrival*	0.092	1.000																
3	*#OfBidders*	-0.026	0.135	1.000															
4	*AuctionSuccess*	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	*WorkerRating*	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	*EmployerExperience*	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	*WorkerExperience*	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	*BidTime*	-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*, *WorkerRating*, and *Rehire* are only valid when the project is successfully contracted. Thus, their correlation with *AuctionSuccess* is n/a.

Appendix C: Distributions of Project Type and Buyer Region

Table C1. Distribution of Project Type and Employer 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**

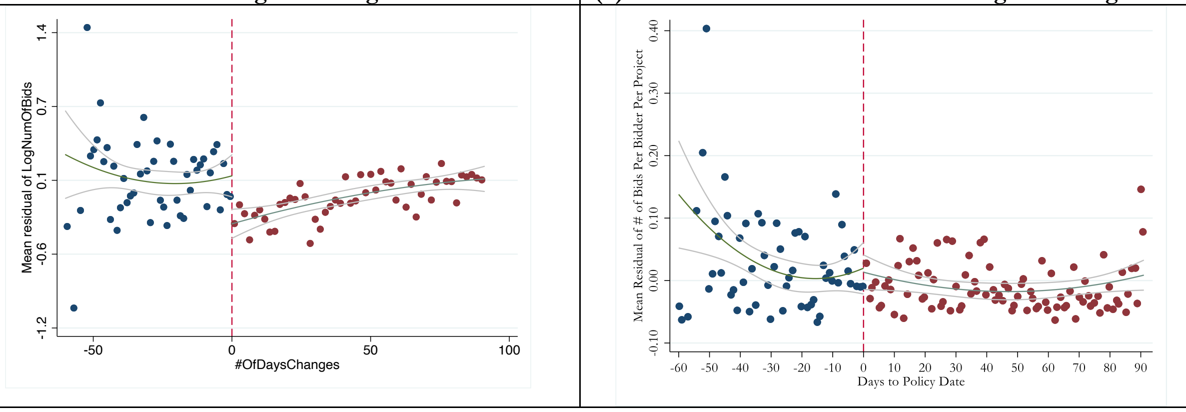


Table D1. Effects of Auction Format Change on Additional Bid Information

Dep. Variables	Number of Bids	Number of Bids Per Bidder
AfterChange	-0.1779***	-0.0356***
	(0.0470)	(0.0098)
EmployerExperience	-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 R^2	0.153	0.024
Number of Employers	967	967
Employer 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 and Winning Amount: 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)
EmployerExperience	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)
EmployerTenure					-0.002	
					(0.030)	
EmployerContractValue					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	Bidder Arrival (Hypothesis 3)	Time to Accept (Hypothesis 4)	Number of Bidders (Hypothesis 5)	Auction Success (Hypothesis 6)	Winning Amount (Hypothesis 7)
Propensity Score	0.348**	-0.713**	-0.0188**	0.065+	0.059
Matching	(0.133)	(0.263)	(0.060)	(0.035)	(0.178)
Nearest Neighbor	0.522***	-0.631***	-0.117*	0.080**	0.063
Matching	(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 Worker Rating: Robustness Checks

Dep. Variable	Worker Rating (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)
EmployerExperience			0.209			0.119*
			(0.129)			(0.0624)
WorkerExperience			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)
EmployerExperience			0.474***			0.284***
			(0.0850)			(0.0514)
WorkerExperience			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 Worker Exit Dataset Variables

Table F1. Summary Statistics for Worker Exit Dataset Variables

Variables	Explanations and Measurements	N	Mean	S.D.	Min	Max
WorkerExit	An indicator that equals 1 if the worker 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
WorkerExperience	Logged total number of completed projects a worker had at the time when the last bid before the cutoff date was placed	1,158	0.155	0.563	0	4.382
WorkerContractValue	Logged average value of completed projects a worker 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 worker 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 worker had placed at the time when the last bid before the cutoff date was placed	1,158	0.017	0.073	0	1