Matching in Two-sided Platforms for IT Services: Evidence from Online Labor Markets

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Abstract

Online labor markets, two-sided platforms that match buyers with freelancers for IT services, have become increasingly important for sourcing labor and creating jobs around the globe. However, matching buyers and freelancers is challenging, largely because of the difficulty in pricing idiosyncratic IT services, and buyers and freelancers face uncertainty over the price (termed value uncertainty) they should pay, or bid, for an IT service, respectively. We propose "bid price dispersion" as a key determinant of matching (the percentage of posted IT services that are actually contracted between buyers and freelancers), and we empirically examine the effect of bid price dispersion on the two key sequential stages of matching in online labor markets: (a) buyer indecision—whether a buyer offers a contract to any freelancer; and (b) freelancer regret—whether the freelancer accepts the contract offered by the buyer. Using panel data from a leading online labor market (Freelancer), our results show that bid price dispersion is associated with an increase in both buyer indecision and freelancer regret, thus hurting matching. The results are robust across several alternative model specifications and various measurements of bid price dispersion. We contribute to the literature on two-sided platforms by theorizing and empirically quantifying the negative effect of bid price dispersion on buyer-freelancer matching in online labor markets for IT services. We discuss the study's practical implications for enhancing the design of online labor markets and the matching capability of two-sided platforms.

Keywords: Two-sided Platforms, Bid Price Dispersion, Buyer Indecision, Freelancer Regret, Online Labor Markets, Value Uncertainty

1. Introduction

Two-sided platforms are burgeoning digital infrastructures that change people's daily activities (Parker and Van Alstyne 2014). As two-sided platforms for the transaction of IT services, such as software development and website design, online labor markets (e.g., *Freelancer* and *Upwork*) have grown rapidly, creating a new source of labor for buyers (or employers) and generating millions of jobs for freelancers (Agrawal et al. 2013; Chan and Wang 2014). According to an industry survey in 2014,[1] 53 million people in the United States (US), or over 1/3 of the US workforce, work as freelancers, contributing over $715B to the US economy annually. *Matching* entities from the two sides, such as host and travelers on Airbnb, men and women on match.com, and buyers and sellers at Amazon, has become a key capability of two-sided platforms. Like many other two-sided platforms, the capability to achieve a match between buyers and freelancers, is an important success criterion of online labor markets (e.g., Horton 2015, Horton 2016). Based on data from the focal labor market in this study – *Freelancer.com*, a 1% increase in the matching rate would lead to an over $500,000 increase in transaction volume. However, in comparison with most two-sided platforms for commodities, such as Amazon or eBay, that use a price-determined mechanism (e.g., buy-it-now or auction) to determine a match, matching buyers and freelancers in online labor markets typically use a buyer-determined auction mechanism because of the idiosyncratic nature of IT services that price-determined mechanisms do not readily apply (Snir and Hitt 2003). In buyer-determined auctions, buyers decide whether to offer a contract to any freelancer, while freelancers can also decline the contract, if offered one. Although the low matching rate has been troubling in online labor markets for a long time (Snir and Hitt 2003; Carr 2003), there is a lack of understanding of what determines the matching, calling for research to address this problem (Horton 2015). In this paper, we propose that the low matching rate in online labor markets can be partially explained by *value uncertainty* for both buyers and freelancers due to bid price dispersion. Buyers face uncertainty over how much to pay for a desired IT service in general

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[1] The survey was conducted by the independent research firm Edelman Berland and commissioned by Freelancers Union and Elance-oDesk. For details: https://www.freelancersunion.org/blog/dispatches/2014/09/04/53million/.

(termed *common value uncertainty*), and how much to pay for the IT service by a particular freelancer (termed *private value uncertainty*). Freelancers also face value uncertainty over how much to bid for the IT service given the buyers' often ambiguous project requirements. Value uncertainty is defined as the buyer's (or freelancer's) difficulty in assessing the value and determining the price of an IT service. In this study, we propose ***bid price dispersion***, measured by coefficient of variation (mean-adjusted standard deviation) of all bid prices for an IT service, as a novel determinant of buyer-freelancer matching in two-sided platforms by theorizing that bid price dispersion affects both the buyer's and also the freelancer's value uncertainty. Specifically, we empirically examine the effect of bid price dispersion on two sequential stages of matching in online labor markets: (a) *buyer indecision*—whether the buyer offers a contract to any freelancer; and (b) *freelancer regret*—whether the freelancer accepts the contract offered to him by the buyer.[2] Accordingly, we are interested in two research questions:

1) Does bid price dispersion affect buyer indecision (not offering a contract to any freelancer)?

2) Does bid price dispersion affect freelancer regret (not accepting the contract when offered one)?

Unlike physical products sold on two-sided platforms, such as eBay, that typically use posted prices or auctions, there are no standard prices for IT services in online labor markets. Therefore, a buyer has to infer the price of an IT service by observing the bid prices by freelancers, while freelancers set their bid prices by inferring the buyer's needs and by observing other freelancers' bid prices. From a buyer's perspective, she observes all the bid prices submitted by freelancers. When bid price dispersion is low, i.e., bid prices are similar to each other, the buyer will be more certain about the price she should pay for the IT service (low common value uncertainty). By contrast, when bid price dispersion is high, i.e., bid prices are significantly different from each other, it is difficult for the buyer to infer the price she should pay for the IT service (high common value uncertainty). From a freelancer's perspective, there is uncertainty over how much to bid for the IT service due to uncertainty about the buyer's requirements and competition from other freelancers (Hong et al. 2016). When bid price dispersion is high, the freelancer is more uncertain about the

[2] In the focal online labor market (Freelancer), for 18% of the projects, freelancers declined the buyers' contract offer.

bid he placed for the IT service (high value uncertainty), and he is thereby more likely to refuse the contract, if offered one. However, when bid price dispersion is low as freelancers' prices are similar to each other, the freelancer is more certain about the price he should bid for the IT service (low value uncertainty), and he is thus more likely to accept the contract, if offered one.

With a panel dataset from *Freelancer* (one of the world's largest online labor market), we empirically examine our research questions using two Logit models with buyer (freelancer) level fixed effects to account for unobserved buyer- (freelancer-) level project invariant preferences. Estimation results based on several model specifications and different measures of bid price dispersion consistently demonstrate that bid price dispersion has a negative effect on buyer-freelancer matching, which results from two sequential effects: (1) a significant effect on buyers' contract indecision and (2) a significant effect on freelancer regret.

This paper makes four contributions to the literature on online labor markets and more broadly, the literature on platforms: First, we theoretically propose and empirically examine bid price dispersion as an important determinant of matching in two-sided platforms using online labor markets as our context. Second, while the literature has primarily focused on either the buyer's (e.g., Horton 2015, Horton 2016; Moreno and Terwiesch 2014) or the freelancer's perspective (e.g., Agrawal et al. 2013; Kokkodis et al. 2015), this study examines *both* sides of the platform by decomposing the matching process into two sequential stages: (1) buyer indecision and (2) freelancer regret. Third, this study contributes to the uncertainty literature (e.g., Ghose 2009; Hong and Pavlou 2014; Pavlou et al. 2007) by theorizing the role of value uncertainty due to price dispersion in the context of IT services. Fourth, in terms of managerial implications, by empirically showing that bid price dispersion increases both the buyer's indecision to offer a contract and freelancer's regret to accept a contract, the management of online labor markets and other two-sided platforms should actively seek to reduce both buyers' and freelancers' value uncertainty to facilitate matching on two-sided platforms. In terms of generalizability, our findings apply to two-sided platforms (Parker and Van Alstyne 2005; Parker and Van Alstyne 2014) with the following characteristics: a) the price of the focal good is idiosyncratic; b) transactions on two-sided platforms are conducted via buyer-determined auctions where buyers select a winner based on both price and non-price characteristics.

2. Background and Related Literature

2.1 Overview of Online Labor Markets

Online labor markets are one of the emerging innovative two-sided platforms enabled by digital infrastructure that facilitate the transaction of IT services between buyers and freelancers via reverse, buyer-determined auctions (Engelbrecht-Wiggans et al. 2008, Hong et al. 2016). The contract process in online labor markets can be described in four stages (Snir and Hitt 2003): 1) *Posting*: buyers post request for proposals (projects) describing the desired project and specifying a budget range, and auction duration during which freelancers can bid; 2) *Bidding*: freelancers search for projects that match their expertise. When a freelancer identifies a suitable project, he can place a bid to be considered by the buyer; 3) *Contracting*: as freelancers bid for the project, buyers evaluate bids by trading off price and freelancers' non-price attributes (e.g., freelancers' reputation, experience, etc.), and decide whether to offer a contract to one of the freelancers (or not). 4) *Accepting*: Once a buyer selects a freelancer and offers the contract, the winning freelancer will decide whether to accept the contract. Therefore, only when the buyer decides to offer a contract and the freelancer accepts (not regret) the contract, a match is officially reached.

Online labor markets differ from online platforms that facilitate the transaction of physical products (e.g., eBay and Amazon) in several ways. First, most online labor markets follow a reverse auction mechanism, wherein buyers post jobs and freelancers (sellers) bid for projects (Yoganarasimhan 2013). Second, unlike standard commodities, IT services are often highly customized, idiosyncratic, and the buyer's requirements are not easily described (Snir and Hitt 2003). As a consequence, a freelancer faces uncertainty over the actual project requirements posted by the buyer (herein termed "value uncertainty"), and thus the price to bid (Hong et al. 2016). Third, given the heterogeneity of IT services, it is often difficult to estimate the price for an IT service by observing the price of other similar IT services. Therefore, a buyer estimates the price of the IT service based on the bid prices the other freelancers placed (Blouin et al. 2001). That is, buyers also face value uncertainty about the price they should pay for the IT service.

2.2 Determinants of Matching in Online Labor Markets

We categorize the literature on matching in online labor markets into two major streams. First, given that the global reach of online labor markets helps buyers to obtain more bids than they would typically receive offline, one stream of the literature explains the low matching issue from the perspective "choice overloading" theory (e.g., Iyengar et al. 2000, Hertwig et al. 2003). As the theory suggests, the buyers' limited cognitive capacity to evaluate a large number of choices could prevent them from making a decision. Carr (2003) supported this argument from the perspective of high bid evaluation costs in online labor markets. Distinct from auctions of physical products for which price dictates the outcome, the contract decision in buyer-determined auctions for IT services entails a complex set of decision variables, including bid price and the freelancer's non-price attributes (e.g., quality, experience, expertise, reputation). Carr further argued that high bid evaluation costs increase the possibility that qualified and even desirable bids could not be evaluated due to the buyers' limited cognitive capacity, leading to a low matching rate.

Second, by emphasizing information asymmetry between buyers and freelancers, another stream of literature focused on information signals that facilitate a buyer's selection of freelancers and frictions that affect the matching process in terms of the buyers' hiring preferences. For example, Yoganarasimhan (2013) examined the role of freelancers' reputation on the buyer's contracting decisions. Yoganarasimhan showed that buyers value freelancers with high average quality ratings and a large number of reviews. Similarly, Moreno and Terwiesch (2014) found that buyers weigh between the freelancers' bid prices and their reputation (both structured ratings and unstructured text reviews by previous buyers), and they pay a price premium to reputable freelancers. Kokkodis and Ipeirotis (2015) extended the understanding of reputation into different categories, arguing that each freelancer has a category-specific quality that will affect the probability to get hired by a buyer. Besides user-generated reputation measures, Agrawal et al. (2013) found that third-party certification plays an important role in buyer's contract decisions. In this respect, Goes and Lin (2012) further demonstrated that third-party certifications might actually negatively affect a freelancers' probability to win a contract when the freelancer has zero ratings. In conclusion, mitigating information asymmetry has been the main focus of research on online labor markets.

Research on freelancer regret and value uncertainty in online labor markets is scarce. For instance, using data from oDesk, Horton (2015) was among the very few to study freelancer's regret by emphasizing buyer's lack of information about freelancers' capacity. Horton showed that freelancers are more likely to reject contracts when they have more proposals from which to choose due to capacity limits. To understand freelancers' wage (price) premium in online labor markets, Stanton and Thomas (2015) were among the few to propose buyer's uncertainty over price (termed as "market value" in their paper) in online labor markets. By modeling supply and demand, they showed that one-third of a freelancer's wage premium is attributed to inexperienced buyer's uncertainty over price. While the focus of Stanton and Thomas is how freelancers gain wage premiums by taking advantage of inexperienced buyers' value uncertainty, our work seeks to study how bid price dispersion affects buyer-freelancer matching due to value uncertainty. Table 1 summarizes the key determinants of buyer contracting, freelancer hiring, and matching in online labor markets.

Table 1. Determinants of Buyer-Freelancer Contracting and Matching in Online Labor Markets

DV	Determinants	Measurement	Authors
Whether a freelancer gets hired	Freelancer experience	Verified freelancer experience information	Agrawal et al.,2013
	Freelancer country	Whether a freelancer comes from developed countries	Agrawal et al.,2013
	Freelancer country	Freelancer's country origin	Mill, 2011
	Buyer feedback	Whether a freelancer gets an evaluation from a buyer	Pallais, 2014
	Prior interaction	Whether a freelancer has worked with the buyer before	Gefen and Carmel 2008 Kokkodis et al., 2015 Hong and Pavlou 2014
	Expertise	Skill set of a freelancer	Kokkodis et al., 2015
	Bidding time	Time length between project posing and freelancer bidding	Kokkodis et al., 2015
	Agency affiliation	Whether a freelancer is affiliated with an agency	Stanton &Thomas, 2015
	Country differences	Language, time zone, culture, IT reputation	Hong & Pavlou, 2014
	Freelancer Reputation	Average rating rated by the buyer, Text reviews	Moreno &Terwiesch,2014
Whether a buyer forms a match with a freelancer	Information asymmetry about freelancer capacity	Number of simultaneous projects a freelancer wins to choose from	Horton, 2015
	Auction format	Open bid auctions are more likely to result in a buyer's decision to select	Hong et al. 2016
	System recommendation	Whether the system recommends a freelancer for the buyer	Horton, 2016
	Bid evaluation costs	Analytical model, no measurement	Carr, 2003
	Project value	The budget of a project	Snir & Hitt, 2003

In sum, to understand the matching between buyers and freelancers in online labor markets, previous studies tackled this problem mainly from the buyer's perspective, neglecting the fact that these markets are two-sided platforms where a final contract can only be reached if both sides agree to a contract and the freelancer accepts the contract offered by a buyer. Despite the abundance of research on choice overloading and information asymmetry between buyers and freelancers, few studies have studied matching from the perspective of value uncertainty. In this study, we seek to understand matching in online labor markets as two-sided platforms from the perspectives of both buyers and freelancers in terms of the value uncertainty over the IT service, and we decompose matching into the buyer's decision to offer a contract (or "buyer contracting") and the freelancer's decision to decline the contract (or "freelancer regret").

3. Theory Development and Hypotheses

As extensively studied in the literature, uncertainty is one major obstacle in online transactions (e.g., Dimoka et al. 2012; Ghose 2009; Hong and Pavlou 2014). A major feature of online labor markets that differs from other online platforms for the transaction of physical products is the difficulty in pricing IT services (Snir and Hitt 2003). Therefore, both buyers and freelancers face *value uncertainty*, herein defined as the uncertainty buyers and freelancers face over the price they should pay, or bid, for an IT service, respectively. Accordingly, we theorize that value uncertainty should affect the matching between buyers and freelancers. In this section, we first introduce a common/private value framework to decompose buyer and freelancer's value uncertainty into common value uncertainty and private value uncertainty,[3] and we theorize how bid price dispersion affects buyer's and freelancer's common and private value uncertainty, which are then hypothesized to affect buyer's indecision and freelancer's regret in online labor markets.

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[3] Value uncertainty is theoretically distinct from "seller uncertainty" and "product uncertainty". In online labor markets, a buyer faces uncertainty about a freelancer's true attributes (skills, experience, reputation) (akin to seller uncertainty), and the quality of the IT service (akin to product uncertainty). Seller uncertainty in online labor markets would refer to the buyer's difficulty in assessing the freelancer's true characteristics and predicting whether the freelancer will act opportunistically after the contract is signed. Product uncertainty would refer to the buyer's difficulty in assessing the quality of the IT service, and whether the IT service would meet her actual needs. Value uncertainty, however, focuses on the buyer's difficulty in inferring the price of the IT service, and the freelancer's difficulty in estimating how much to bid for the IT service. In fact, even if a buyer has no uncertainty over the freelancer's characteristics and the quality of the IT service, she still faces uncertainty about how much to pay for the IT service (termed buyer's value uncertainty). Hence, reducing the other types of uncertainty (seller and product) would *not* necessarily eliminate value uncertainty.

3.1 Common versus Private Value Framework

There are two key theoretical paradigms in the literature to explain the value of an auctioned item: independent private value and interdependent common value auctions (Goeree and Offerman 2002, 2003). A commonly cited example of private value is an auction of a rare painting (Goeree and Offerman 2002), where each bidder knows the value of that painting for himself, but there is uncertainty regarding other bidders' values. In contrast, a typical example of common value is an auction of an oil field where the value is the same to all bidders, although unknown to each bidder (Kagel and Levin 2009). While this dichotomy is convenient from a theoretical viewpoint, most real-world auctions exhibit both private and common value elements (Goeree and Offerman 2002). With this common/private value framework, we decompose a freelancer's bid price into a common value and a private value component, and we analyze both the buyer's common and private value, and the freelancer's common value uncertainty over the price of an IT service.

Given the difficulty in determining the price of an IT service (Snir and Hitt 2003), a buyer often estimates the price of an IT service based on bid prices (termed price discovery by Chen-Ritzo et al. 2005). To a buyer, the bid price of a particular freelancer P_i (value for freelancer *i*) actually consists of two parts: a common value *V*, which is the reasonable (common) price of that an IT service in general, unobservable to the buyer, the same to all freelancers and a private value element v_i, which is freelancer-specific, varies across freelancers (e.g., Bajari and Hortacsu 2002; Goeree and Offerman 2002) due to differences in attributes, such as expertise level. To a buyer, the average of all bid prices P_i (Equation 1) is the common value of the IT service (Goeree and Offerman 2002; Yin 2006).

$$\hat{V} = \frac{1}{n}\sum_{i=1}^{n} P_i = \frac{1}{n}\sum_{i=1}^{n} (\mathrm{V} + v_i) = V + \frac{1}{n}\sum_{i=1}^{n} v_i \quad (1)$$

For a freelancer, in contrast, other freelancers' bid prices consist of two parts: common value *V*, which is other freelancers' estimates about the price of the IT service based on the description of the project, and private value v_i, which includes the freelancer's bidding strategies and expectation for his cost and profit. To a freelancer, the average of all bid prices P_i is a reasonable estimate of the price of the IT service based on the buyer's "true" requirements. A certain buyer's "true" requirement is unknown to the freelancers, and it can only be estimated based on the project description. Table 2 summarizes the definitions of value uncertainty, common value, and private value.

Table 2. Definitions of Value Uncertainty and Common/Private Value Uncertainty	
Construct	**Definition**
Value Uncertainty	A buyer's (freelancer's) difficulty in assessing how much she needs to pay (bid/charge) for an IT service. Value uncertainty includes both common value uncertainty and private value uncertainty.
Common Value	The price component of an IT service that is unobservable to the buyer, same to every freelancer, and only differs across different IT services.
Private Value	The price component of an IT service that is specific to each freelancer.

3.2 Value Uncertainty in IT Services

3.2.1 Buyer's Value Uncertainty: Common versus Private

A buyer faces value uncertainty in online labor markets for several reasons. First, IT services in online labor markets usually consist of a certain domain-specific knowledge with which buyers may be unfamiliar, making it difficult for a buyer to estimate the "right" price she should pay for an IT service. Additionally, IT services in online labor markets are idiosyncratic; hence, it is difficult for a buyer to precisely value them ex ante. Even if a buyer has some prior knowledge of the requested IT service, determining the exact price to pay is difficult because of the lack of standardization, the high degree of customization, and the difficulty in assessing the quality of the IT service ex ante (e.g., Snir and Hitt 2003). Taken together, a buyer often has little prior domain knowledge of the customized, idiosyncratic IT service. Therefore, the buyer faces value uncertainty over the price of an IT service.

Based on the common / private value framework, a buyer faces a) uncertainty over the price of the IT service in general, termed buyer's common value uncertainty, and b) uncertainty over the price of a particular freelancer for that IT service, termed buyer's private value uncertainty. For a buyer, common value uncertainty is associated with the question "what's the price of an IT service in general I should pay?" while private value uncertainty is associated with the question "how much should I pay for the IT service provided by a particular freelancer given his/her attributes?" Common value often serves as a benchmark for a buyer to evaluate the private value of each freelancer. The buyer's common value uncertainty and private value uncertainty will jointly affect the decision to offer a contract to one of the freelancers or not.

3.2.2 Freelancer's Value Uncertainty: Common versus Private

Although a freelancer has better knowledge, in comparison to the buyer, of the price for his own IT service, he still faces value uncertainty in terms of how much to bid for the IT service due to uncertainty over the buyer's actual requirements. In online labor markets, a freelancer learns about the buyer's requirements based on the posted description. On the one hand, a buyer may not be able to fully describe what they need due to lack of relevant domain knowledge (Carr 2003; Snir and Hitt 2003), which makes it difficult for the freelancer to estimate the actual workload. On the other hand, IT services are highly customized and idiosyncratic (Snir and Hitt 2003), and a freelancer may not be able to understand the "true" requirements of a particular buyer. Thus, for a specific IT service, each freelancer who aims to bid for an IT service faces value uncertainty over how much to bid. Following the common/private value framework, we define a freelancer's common value uncertainty as the difficulty in assessing how much to bid for a project due to the buyer's ambiguous requirements and his own private value uncertainty as the difficulty in assessing his own price of an IT service given the uncertain workload. Table 3 summarizes common value uncertainty and private value uncertainty for both buyers and freelancers.

Table 3. Explanation of Value Uncertainty for Buyers and Freelancers

	Buyer	Freelancer
Common Value Uncertainty	Buyer's uncertainty over the reasonable (common) price of an IT service in general. [How much should I pay for this IT service in general]?	Freelancer's common value uncertainty results from the uncertainty over the buyer's requirements [How much should I bid for the IT service for this particular buyer?]
Private Value Uncertainty	Freelancer quality and expertise may vary, so it is possible to pay a high (low) price to an excellent (ordinary) freelancer [How much should I pay for a particular freelancer for the IT service?]	Freelancer's uncertainty over his own cost given the exact tasks [How much should I bid for the IT service given the exact workload?]

3.3 Effect of Bid Price Dispersion on Buyer Contracting (versus Contract Indecision)

Due to the complex nature of IT services and the buyer's lack of full knowledge of IT services, buyers in online labor markets face value uncertainty over how much to pay for an IT service in general (termed common value uncertainty) and how much to pay for the IT service from a particular freelancer (termed private value uncertainty). Because of the difficulty in assessing a freelancer's true characteristics (e.g., skills, expertise, capacity, etc.), the buyer cannot precisely estimate the price of a particular freelancer for an IT service given his attributes (private value). However, it is feasible to infer the common value of an IT service based on the average of all freelancers' bid prices, since each freelancer's bid price contains his estimate of the common value (besides his own private value). This process has been documented in related literature as "price discovery" (e.g., Chen-Ritzo et al. 2005). Below, we explain how the dispersion of all freelancers' bid prices will affect a buyer's common value uncertainty.

Following Bang et al. (2014), we define *Bid Price Dispersion* (BPD) as the coefficient of variation CV ($\mathrm{CV} = \frac{\sigma}{\mu}$, σ is the bidding price standard deviation and μ is the bidding price average for a project) of all freelancers' bid prices. To illustrate how bid price dispersion shapes a buyer's common value uncertainty, let us consider two scenarios where the same buyer receives three bids for the same IT service: (a) \$40, \$80, \$120 and (b) \$75, \$80, \$85 (referred as Example A). Although the average of all freelancers' bid prices, namely the estimate of the common value, is \$80 in both scenarios, the dispersion in scenario (a) is larger than that in scenario (b). In scenario (b), all three freelancers bid a price very close to \$80, which delivers a consistent message to the buyer that the common value of the IT service is \$80. Hence, the buyer is less uncertain to infer the common value as \$80. In scenario (a), however, the three freelancers offer very different bid prices, which makes a buyer more uncertain about the common value of the IT service (\$80). In sum, a buyer will have higher (lower) common value uncertainty when bid price dispersion is high (low).

We argue that the common value could serve as a practical benchmark to evaluate each freelancer's bid price and infer how much more or less a buyer should pay a particular freelancer (to overcome private value uncertainty). Using our running example, in Scenario (a), the three bids' prices (\$40, \$80, \$120) are highly dispersed around the average of \$80, and it will be very difficult for a buyer to evaluate any of these bids in terms of how much more or less she would need to pay a particular freelancer. Specifically, the lowest priced freelancer may deliver a low quality service, while the highest priced freelancer would reap the buyer's potential surplus. In contrast, in Scenario (b) of the running Example A, the three bid prices ($75, $80, $85) are less dispersed around the average of $80, and hence a buyer will be more certain about the common value, making it easier to evaluate each freelancer's bid price given a higher confidence on the benchmark price. Therefore, a buyer will also have higher (lower) private value uncertainty about each freelancer when bid price dispersion is high (low).

A buyer faces two potential losses because of value uncertainty: a) paying unnecessarily too much for a high-priced freelancer, thus suffering a loss of surplus, and b) paying insufficiently too little for a low-priced freelancer and getting a poor quality IT service. As discussed earlier, high bid price dispersion will lead to high common value and private value uncertainty. Given buyers in a transactional setting are generally risk averse, uncertainty will inadvertently lead to a loss of utility (Kahneman and Tversky 1979; Pavlou and Gefen 2005). Specifically, the uncertainty about common value of an IT service in general and private value of a particular freelancer is proposed to reduce a buyer's expected utility if he offered a contract to a freelancer, thus demotivating the buyer from offering a contract to any freelancer at all.

H1: Bid price dispersion has a negative effect on the buyer's decision to contract with any freelancer.

3.4 Effect of Bid Price Dispersion on Freelancer Regret

In online labor markets, after a buyer offers the contract to a freelancer, the winning freelancer is not obligated to accept the contract offered to him, but he still has the option to decline the contract.[4] We formally define *Regret* as a freelancer's decision to decline the contract when selected as the winner and offered a contract based on the freelancer's bid price.[5] The cost of regret in online labor markets includes

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[4] In online labor markets, a freelancer can revise the bidding price as many times as she wants before the auction ends. However, once a buyer selects a winner, the project will be "frozen" and freelancers cannot revise their bid prices anymore. This bid price will be the final contract price if the freelancer does not "regret."

[5] Regret is defined as the freelancer's decision to decline the contract offered by a buyer. We do not emphasize the psychological meaning of the term "regret".

two parts: first, there is a limit on the total number of bids a freelancer can place within a month, and freelancers have to buy additional bids if they use up their monthly allocation, creating a monetary cost to regret. Second, it takes time, effort and resources to search and read "Call for Bids" for IT services and prepare competitive bids, and it is a "sunk cost" for freelancers to decline a contract when offered one.

As theorized earlier, a freelancer faces uncertainty about the price he should bid for an IT service due to the uncertainty about the buyer's "true" requirements. Therefore, for a freelancer, other freelancers' bid prices serve as an estimate of the price for the buyer's "true" requirements. When bid price dispersion is high, other freelancers' estimates about the buyer's "true" requirements differ considerably, which makes a freelancer uncertain about the common value of the IT service. When bid price dispersion is low, other freelancers have similar estimates of the buyer's "true" requirements, thereby decreasing the freelancer's common value uncertainty over the price of the IT service.

A freelancer's goal of using online labor markets is to get contracts at an optimal price. A freelancer suffers from "winner's curse" when he wins the contract at a suboptimal price (e.g., Bajari and Hortaçsu 2003b; Kagel and Levin 2009). When a freelancer has higher common value uncertainty about the buyer's "true" requirements, he may incur potential losses due to unexpected costs to implement the IT service because of the buyer's ambiguous requirements. Once offered a contract, the freelancer's focus shifts from winning the contract to avoiding the "winner's curse" since the former has already been achieved. The fact that other freelancers' bid prices substantially differ from each other makes a freelancer perceive a higher risk of the winner's curse. Therefore, the freelancer will be more likely to regret by declining the contract to avoid the winner's curse.

H2: Bid price dispersion has a positive effect on freelancer regret.

4. Empirical Methods and Results

4.1 Variable Definition

4.1.1 Bid Price Dispersion

We used the coefficient of variation ($\mathrm{CV} = \frac{\sigma}{\mu}$, standard deviation of bid prices σ over the sample mean μ to) of bid prices as the measure of bid price dispersion to make them comparable across different IT service projects (Equation 2). CV is widely used in the economics and information systems literatures[6] (e.g., Clemons et al. 2002, Ghose and Yao 2011, Yin 2006).

$$CV = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - \frac{1}{n}\sum_{i=1}^{n} P_i)^2}}{\frac{1}{n}\sum_{i=1}^{n} P_i} \qquad (\mathbf{2})$$

To illustrate why CV is a better measure than the standard deviation of bid prices, let us consider the following example (referred as Example B): a buyer may regard three bid prices for a large project, such as "$980, $1000, $1020" (scenario *c*, STD=20, CV=0.02) as very similar and infer the common value of this project value as $1,000 with a lower level of common value uncertainty. However, three bid prices "$30, $50, $70" (scenario *d*, STD=20, CV=0.4) for a small project may be perceived as highly dispersed, and a buyer would have higher common value uncertainty. Thus, we would not be able to differentiate scenario *c* from *d* if we used the standard deviation (equal to 20 in both scenarios) as the bid price dispersion measure. In contrast, the coefficient of variation (0.02 vs. 0.4) can account for the effect of project size.

4.1.2 Buyer Contracting and Freelancer Regret

In this paper, we measure *contract* as a binary variable based on whether the buyer offers a contract to any freelancer. *Contract* equals 1 if a buyer selects any freelancer as the winner and offers him a contract; 0 otherwise. Similarly, we measure *regret* as a binary variable that indicates whether a freelancer accepts the contract conditional on being offered a contract from the buyer. *Regret* equals 1 if the winner rejects the contract when awarded, 0 otherwise. Please refer to Table 4 for descriptions/definitions of all other variables.

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[6] As the focus of this study is to investigate how bid price dispersion affects the matching decisions of both buyers (buyer contracting) and freelancers (freelancer regret), the measure (price difference) used by Ghose and Yao (2011) to capture price dispersion is not relevant to this study.

Table 4. Variable Definition

Variable	Definition
1. Contract	1-a buyer decides to select a winner and offer the contract, 0-otherwise
2. Bid price dispersion (CV)	Bid price dispersion (BPD) measured as price coefficient of variation
3. Quality Dispersion	Standard deviation of freelancers' rating gained in previous projects
4. Number of Bids	Total number of bids received for a project
5. Buyer Experience	Total number of projects a buyer has contracted before
6. Average Freelancer Exp.	Average experience (measured as number of projects a freelancer has finished in the platform) of freelancers for a project
7. Average Freelancer Rating	Average rating of all the freelancers received by a project
8. Project Size	Maximum budget of the project
9. Auction Duration	Pre-specified time window (hours) that freelancers can bid for a project
10. Arrival Rate	Average arrival time (hours) of all freelancers for a buyer
11. Bid Arrival Dispersion	Standard deviation of freelancers' arrival time
12. Project Type	1-website and software development, 2-writing and content, 3-graphic design, 4-data entry and management
13. Regret	1-a freelancer rejects to accept the contract when selected, 0-otherwise
14. Winner Price	Bid price of the winner
15. Winner Price Premium	Winner's bid price over the average of other freelancer's bidding price
16. Winner Experience	Number of projects that the winner has competed before
17. Winner Exp. Overqualified	Winner experience over average experience of other freelancers
18. Winner Rating	Buyer generated rating for the winner ranging from 0~10
19. Winner Rating Overqualified	Winner rating over the average rating of other competing freelancers
20. Buyer Rating	Freelancer generated rating for the buyer ranging from 0~10
21. Previous Interaction	Whether there is at least one freelancer that worked with the buyer before
22. Month	Dummy variable (1-7) indicating the month a project posted in
23. Quality Weighed BPD	Bid price dispersion measured as the coefficient of variation of freelancer quality weighed bid prices (p/rating)
24. Distribution Weighed BPD	Bid price dispersion (BPD) taking account of the multimodal distribution of bid prices
25. Legitimate BPD	Bid price dispersion (BPD) excluding bids that have little chance to be contracted by a buyer (what remains is called *legitimate bids*)

4.2 Data

We obtained access to a proprietary database from a leading online labor market – *Freelancer*, which has 20.4 million registered users (buyers and freelancers) contracting almost 10 million IT services since 2004. Our data are based on a snapshot of the company's database in March 2010. Matching follows a buyer-determined reverse auction mechanism (e.g., Engelbrecht-Wiggans et al. 2008, Hong et al. 2016). In the posting stage, instead of setting a specific budget a buyer chooses from one of the four budget ranges

[$30,$250], [$250,$750], [$750,$1500] and $1500 and above.[7] Freelancers have to bid a certain price within the buyer's specified budget range. In the contracting stage, a buyer selects only one freelancer as the winner and offers a contract.[8] There was no recommended freelancer feature by the online labor market platform at the time of the data collection.[9] In total, we have 67,921 project-level observations. Descriptive statistics are shown on Table 5. The final matching rate in our dataset is 54%. For 61% of the projects, buyers selected a freelancer to offer the contract, but for 11% of them, the winning freelancer did not accept the contract.

Table 5. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
1. Contract	67,921	0.606	0.489	0	1
2. Bid price dispersion (CV)	67,921	0.503	0.349	0	6.347
3. Bid price dispersion (S.D.)	67,921	1.302	2.480	0	55.084
4. Number of Bids	67,921	14.827	19.320	1	577
5. Buyer Experience	67,921	15.854	57.277	0	1179
6. Average Freelancer Experience	67,921	51.483	91.983	0	1652
7. Average Freelancer Rating	67,921	6.045	1.434	0.031	10
8. Project Size	67,921	433.660	429.951	40	3000
9. Auction Duration	67,921	282.433	406.251	24	1440
10. Arrival Rate	67,921	33.225	118.678	0.036	1440.627
11. Arrival Dispersion	67,921	41.956	98.236	0	5335.403
12. Project Category	67,921	1.979	1.057	1	4
13. Regret	41,800	0.111	0.314	0	1
14. Winner Price	41,800	187.579	480.448	20	40128
15. Winner Price Premium	41,800	0.888	0.402	0.000	12.582
16. Winner Experience	41,800	102.509	223.274	0	1657
17. Winner Exp. Overqualified	41,800	1.797	2.664	0	67.129
18. Winner Rating	41,800	1.049	0.243	0.007	2.706
19. Winner Rating Overqualified	41,800	6.492	1.965	0.031	10
20. Buyer Rating	41,800	2.300	4.024	0	10
21. Previous Interaction	67,921	0.059	0.235	0	1
22. Month	67,921	7.504	4.065	1	12
23. Quality Weighed BPD	67,921	1.178	0.539	0	17.902
24. Distribution Weighed BPD	67,921	0.301	0.239	0	6.259
25. Legitimate BPD	67,921	0.503	0.349	0	6.347

[7] In practice, a buyer can customize the range of the budget, which is extremely rare in our data set.
[8] Only a few projects have multiple winners. We exclude them for the analysis in this study.
[9] Recommended freelancer is available in the context for this study now. However, this feature hadn't been implemented yet back to the time window for the data collection.

4.3 Buyer Contracting

4.3.1 Identification Strategy

The relationship between BPD and buyer contracting is subject to several identification challenges. First, we introduced IT service categories dummies and a number of project-level control variables to account for unobserved heterogeneity. Second, we used buyer fixed effects to account for the buyer's unobserved tendency to contract or the general trust about contracting IT services in online labor markets, which may lead to *omitted variable bias* and *reverse causality*. Third, we examined the moderating role of buyer experience and number of bids to explore the observed heterogeneity of BPD on buyer contracting. These analyses also serve as falsification tests that testify the validity of our results. Fourth, a set of subsample analyses were done by fixing the number of bids to address potential endogeneity concerns from the number of bids. Finally, we used the standard deviation of bid prices (a commonly used measure of dispersion in the literature), quality weighted BPD, distribution weighed BPD, and BPD with legitimate bids as alternative measures of BPD to check the robustness of our measurement. Measurement error is not a major concern for all other variables since our data was directly obtained from the market's database, and the data recorded actual transactions and the buyers' and freelancers' activities in the online labor market.

4.3.2 "Buyer Contracting" Model Specification

As our dependent variable (buyer contracting) is a binary variable, we estimated a logit model with robust standard errors (Equation 3). U_{ij} is the latent utility a buyer i infers from project j. β_1 captures the effect of BPD on the buyer's contract decisions. $Freel_{ij}$ is a vector of the average freelancer's characteristics like average experience and mean quality rating (control variables), and quality dispersion (a potential confound that may affect both BPD and the buyer's contracting). A freelancer's average experience and mean quality rating represent the average quality of the freelancers that a project attracts. A buyer would have more high-quality freelancers to choose from with a higher average experience and mean rating, which may facilitate the buyer's contracting decision. Freelancer quality dispersion is measured as the standard deviation of all freelancers' rating, which represents the diversity of choices a buyer has; thus, it is correlated with the buyer's contracting decisions. Finally, quality dispersion is correlated with BPD since the freelancers' bid prices can vary with their experience and overall quality.

$Buyer_{ij}$ is a vector of buyer level controls, including project-variant buyer experience and rating. Buyer experience is the total number of projects a buyer has completed, while rating is the mean rating of the buyer as evaluated by the freelancers who worked with the buyer before. On the one hand, experienced, highly-rated buyers are likely to continue to have higher contract likelihood given their prior performance. Moreover, experienced, highly-rated buyers tend to be more capable to describe their posted projects, specify a more accurate budge range, and communicate better with freelancers, all of which may affect the freelancers' bid prices, and thus affecting the resulting BPD. Note that given our short observation window, after controlling for buyer fixed effects, within buyer variation for these variables tends to be very small.

Another potential threat to identification is unobserved buyer characteristics, such as the ability to describe a project for an IT service or communicate with freelancers online, effort and engagement on the online labor market, all of which do not vary across projects, but they correlate with both the BPD and with a buyer's tendency to offer a contract to a freelancer. In our data, we observe repeated transactions for the same buyer. Thus, we leveraged this feature of the data as our identification strategy, and we introduced a buyer fixed effect α_i in the model, which captures the buyer's project-invariant unobserved buyer characteristics that may confound both the BPD and the buyers' tendency to offer a contract.

$Project_j$ is a vector of project level characteristics, such as auction duration (control variables that may affect the contract), project size, total number of bids received for the project, and project type (potential confounding factors that affects both the buyer's contracting and also the BPD). Some types of IT services are more complex in nature, and thus may have a higher BPD (and a lower contracting probability). We argue that project complexity can be captured by project type and project size (measured as the maximum budget of a project for an IT service) within each project type, assuming that complex projects will generally have a higher budget. Meanwhile, the total number of bids represents the number of choices a buyer has available, which is likely to have an effect on the buyer's contracting decision.

$Dynamic_{ij}$ is a vector of dynamic bidding characteristics, such as the freelancers' arrival rate (average arrival time (hours) of all freelancers), time dispersion (time dispersion of the arrival rate) and whether there are freelancers who have worked with the buyer before. The literature has shown that the longer a buyer waits, the less likely she is going to offer a contract (e.g., Yoganarasimhan 2013). The freelancer's arrival rate captures the average waiting time for a buyer, and time dispersion captures the arrival patterns of freelancers. When time dispersion is high, it means that freelancers arrive in an inconsistent manner over time, which makes it difficult for the buyer to predict the quality of freelancers who will arrive in the future, thus discouraging the buyer from waiting and demotivating her from offering a contract. In a project, if there are freelancers that have worked with a buyer before, on the one hand, the buyer may terminate the auction early by directly contracting with this familiar freelancer. On the other hand, a buyer may face lower (common and private) value uncertainty. We therefore created a dummy variable "previous interaction", denoted as 1 if there is at least one freelancer who has worked with the buyer before, and 0 otherwise.[10]

γ_t is time fixed effects. As BPD captures the dispersion of freelancers' bid prices, which in nature is associated with the available freelancer pool within the time window when a project posted. Therefore, it's hypothetically possible that freelancer heterogeneity drives the both BPD and the buyer's likelihood to offer a contract. First, different types of projects have different freelancer pool due to the heterogeneity of the expertise needed. Second, for the same type of project, the freelancers who are willing to bid for a project can vary with the budget of the project. Third, the freelancers available at different time points can be different due to changes in the platform. We thus introduced time dummies to account for time trends of the pool of freelancers. Table 6 summarizes all control variables accounted for in the model.

$$U_{ij} = \beta_1 BPD_{ij} + \beta_{2-3} Freel_{ij} + \beta_{4-5} Buyer_{ij} + \beta_{6-8} Project_j + \beta_{9-11}\, Dynamic_{ij} + \alpha_i + \gamma_t + \varepsilon_{ij} \qquad \mathbf{(3)}$$

$$ContractProbability_{ij} = \frac{Exp(U_{ij})}{1 + Exp(U_{ij})}$$

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[10] We also ran subsample analysis by excluding projects that have at least one freelancer who worked with the buyer before. Results are consistent with our main findings (Online Supplementary Appendix A, Table A2). In our sample, 5.88% projects have freelancers that worked with the buyer before.

Table 6. Model Specification for Buyer Contracting

	Potential Confounding Variables	Control Variables
$Freel_{ij}$	Average freelancer experience, Mean freelancer quality rating	Freelancer quality dispersion
$Buyer_{ij}$	N/A	Buyer experience, Buyer rating, Unobserved buyer characteristics α_i
$Project_j$	Auction duration	Project size, Total number of bids, Project type
$Dynamic_{ij}$	Freelancer arrival rate, Freelancer arrival time dispersion, Previous Interaction	N/A

4.3.3 Buyer Contracting Main Results

Based on the estimation results shown in Table 7, we first observe a negative and significant association between bid price dispersion and buyer' s contract decision. Specifically, Columns (1) and (2) show the results of the logit estimation with and without buyer fixed effects, both of which are qualitatively similar (β=-0.206 vs. β=-0.245). In terms of economic effects, this translates to a 5.74%[11] absolute (and 9.2% relative) decrease in the probability for a buyer to offer a contract with one unit increase in BPD (bid price standard deviation increases by the mean). Given that the marginal effect of the logit model depends on other covariates, we also used a Linear Probability Model (LPM) to check the average effect of bid price dispersion on buyer's contract decisions as a robustness check.

Although LPM allows for a straightforward and meaningful interpretation of coefficients, it may introduce heteroscedasticity into the estimates and generate predicted probabilities outside the [0,1] bound. Following the Horrace and Oaxaca's (2006) approach, besides estimating cluster-robust standard errors, we further performed a post-estimation inspection, which shows that 99.71% (99.99% for LPM without buyer fixed effects) predicted probabilities remain within the [0, 1] interval. The marginal effect (5.20%) of the LPM estimates is identical to the logit estimates (5.74%) in terms of both the sign and significance, and it differs very slightly in magnitude. A possible reason, as mentioned before, is that the marginal effect of the logit (non-linear) model depends on other covariates.

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[11] All marginal effects were calculated using the default margins command in Stata 14. In particular, the marginal effect was calculated as the average predicted probability change with one unit of increase in bid price dispersion. Standard errors for the post estimation command were obtained through the delta method.

Table 7. The Role of Bid Price Dispersion in Buyer Contract

	(1)	(2)	(3)	(4)
Model:	Logit (FE)	Logit	LPM (FE)	LPM
DV: Buyer Contracting				
Bids Price Dispersion (BPD)	**-0.213*****	**-0.247*****	**-0.038*****	**-0.052*****
	(0.0369)	(0.0270)	(0.0058)	(0.0055)
Quality Dispersion	-0.037**	-0.025**	-0.004*	-0.003*
	(0.0155)	(0.0105)	(0.0023)	(0.0019)
Log Freelancer Experience	0.129***	0.183***	0.021***	0.037***
	(0.0105)	(0.0068)	(0.0016)	(0.0014)
Average Freelancer Rating	0.113***	0.135***	0.018***	0.026***
	(0.0116)	(0.0080)	(0.0018)	(0.0016)
Log Buyer Experience	-0.573***	0.133***	-0.086***	0.026***
	(0.0423)	(0.0064)	(0.0061)	(0.0012)
Buyer Rating	0.034***	0.035***	0.006***	0.007***
	(0.0033)	(0.0024)	(5.08e-94)	(4.47e-04)
Log Number of Bids	-0.102***	-0.101***	-0.016***	-0.021***
	(0.0159)	(0.0105)	(0.0025)	(0.0021)
Project Size	-0.002***	-0.0015***	-3.38e-04***	-3.34e-04***
	(7.24e-05)	(4.39e-05)	(1.14e-05)	(9.58e-06)
Auction Duration	4.90e-05	-1.25e-05	-1.04e-05	-2.78e-05***
	(4.95e-05)	(3.20e-05)	(7.69e-06)	(7.00e-06)
Log Arrival Rate	-0.057***	-0.048***	-0.010***	-0.013***
	(0.0096)	(0.0069)	(0.0015)	(0.0014)
Arrival Dispersion	-0.009***	-0.007***	-0.001***	-0.001***
	(3.14e-04)	(3.16e-04)	(3.33e-05)	(4.07e-05)
Previous Interaction	-0.041***	-0.576***	-0.107***	-0.041***
	(0.0071)	(0.0433)	(0.0070)	(0.0071)
Constant	0.546***		0.815***	0.546***
	(0.0122)		(0.0176)	(0.0122)
Observations	41,916	66,605	66,605	66,605
Number of buyer ID	5,922	—	20,906	—
Pseudo/R-squared	—	0.115	0.112	0.140
Buyer FE	YES	NO	YES	NO
Project Type	YES	YES	YES	YES
Time Dummy	YES	YES	YES	YES

Notes 1: Cluster-robust standard errors in parentheses;
Note 2: Coefficients significant at level *** p<0.01, ** p<0.05, * p<0.1
Note 3: 14,984 groups (24,689 obs.) dropped because of all positive or all negative outcomes in buyer's decision to offer a contract. The sample size for model (1) is 41916 (=66605-24689). This explanation applies to Table 8, Table 9 as well.

In terms of other effects, the number of bids has a significant, negative effect on contracting, consistent with the literatures on high bid evaluation cost (e.g., Carr 2003) and choice overloading (e.g., Iyengar et al. 2000, Hertwig et al. 2003). The buyer's experience and the quality of the freelancers (average rating and average experience) have a positive and significant effect on buyer's contracting. The coefficient of buyer experience in models (1) and (3) is negative due to buyer fixed effects, and given that the variation of experience within buyers is relatively small. Additionally, a buyer is less likely to contract for larger projects, consistent with Snir and Hitt (2003), when it takes too long for all freelancers to arrive, and when the arrival time of the freelancers' bids are too dispersed from each other.

4.3.4 Robustness Check 1: Potential Endogeneity of the Number of Bids

Although we measured bid price dispersion with a dimensionless measure: coefficient of variation (Bedeian and Mossholder 2000), the number of bids is correlated with both BPD and the buyer's contract probability, which introduces potential endogeneity from the number of bids. To capture a potential bias, we conducted another sub-sample analysis by fixing the number of bids, assuming that projects that receive the same (or similar) number of bids are free of the concern about endogeneity of the number of bids. Ideally, we should conduct the subsample analysis at each specific number of bids. However, the number of observations at each specific number of bids is relatively small, which makes it difficult to achieve adequate statistical power for estimation. We therefore conducted the analysis by combing nearby groups based on criteria to create a similar number of observations in each group. In Table 8, we report the coefficients and standard errors (in brackets) of BPD on buyer contracting for both the logit and linear probability models for different numbers of bids.[12] The marginal effect of BPD on buyer contracting varies from 3.9% to 7% (mean = 5.8%), which is qualitatively very similar to the average effect of 5.74% that we estimated in Table 7.

Table 8. The Role of Bid Price Dispersion in Buyer Contracting at Different Number of Bids

Number of Bids =	Number of Obs.	Logit	Linear
NoB = 2&3	8,865	-0.028(0.0858)	-1.11e-04(0.0132)
NoB = 4&5	7,746	-0.311***(0.0836)	-0.060***(0.0167)
NoB = 6&7	6,848	-0.170**(0.0855)	-0.039**(0.0182)
NoB = 8&9&10	8,317	-0.354***(0.0758)	-0.077***(0.0163)
NoB = [11, 15]	9,985	-0.320***(0.0714)	-0.070***(0.0152)
NoB = [16, 25]	11,472	-0.226***(0.0603)	-0.051***(0.0131)
NoB = [26, 45]	8,713	-0.204***(0.0754)	-0.045***(0.0154)
NoB = [46, maximum]	4,659	-3.39e-03(0.0920)	-1.75e-03(0.0189)

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

[12] The primary reasons we did not report a logit model and a linear probability model with buyer fixed effects are: a) we have shown in the previous section that unobserved buyer characteristics is not a serious concern in the study, and b) there are not enough observations that a buyer posts more than two projects for IT services in the focal labor market.

4.3.5 Robustness Check 2: Moderating Role of Buyer Experience

Another practical concern is whether a buyer really observes the overall BPD, perceives it as a source of value uncertainty, and draws upon it to make her contract decision. As we discussed before, value uncertainty from BPD partly results from the buyers' lack of experience. Therefore, we should expect a difference between experienced and inexperienced buyers in terms of the negative effect of BPD. To test this possible interaction effect, we conducted an additional analysis to explore whether BPD has a smaller effect for experienced buyers. This analysis also serves as a falsification test for our main results. Following Ai and Norton (2003), both BPD and buyer experience were centered to ensure the coefficients of BPD and of buyer experience capture the main effect. In Table 9, the main effect of BPD is negative and significant, which is consistent with the main results in Table 7 without the interaction term. As noted by many authors (e.g., Ai and Norton 2003, Hoetker 2007, Zelner 2009), the interpretation of interaction terms in logit models is difficult, and the coefficient of the interaction term can be inconsistent in sign, statistical significance, and magnitude, thus requiring a simulation to estimate the marginal effect of the interaction terms. We used LPM in Column (2) to verify the interaction effect between buyer experience and BPD. In this analysis, we leveraged the variation among buyers to identify the interaction effect between buyer experience and BPD. As our panel data covered a period of six months, buyer fixed effects would account for the majority of the variation in buyer experience, thus it will most likely make a buyer fixed effect model for the interaction effect not identifiable. Specifically, we estimated the model below:

$$U_{ij} = \beta_0 BPD_{ij} + \beta_0 BPD_{ij} \times \text{BuyerExp}_i + \beta_{2-3} Freel_{ij} + \beta_{4-5} Buyer_{ij} + \beta_{6-8} Project_j$$
$$+ \beta_{9-10}\, Dynamic_{ij} + \varepsilon_{ij} \qquad \mathbf{(4)}$$

$$ContractProbability_{ij} = \frac{Exp(U_{ij})}{1 + Exp(U_{ij})}$$

As shown in Columns (1) and (2) Table 9, buyer experience attenuates the negative effect of BPD on the buyer's contracting decision. In terms of economic effects, on average, 1% increase in buyer experience (0.16 more projects) would make the marginal effect of BPD on contract decrease by 19% (1% in absolute probability). This indicates that BPD has a smaller effect on buyers' contract decisions for experienced buyers (Figure 1, Left, in Appendix A for a graphic display of the interaction effect), implying that buyers do observe do BPD and use this variable in their contracting decisions.

Table 9. The Moderating Role of Buyer Experience in the Effect of Bid Price Dispersion on Buyer Contracting

VARIABLES	(1) Logit	(2) LPM
DV: Buyer Contracting		
Bid Price Dispersion (BPD)	**-0.244***(0.0270)**	**-0.052***(0.0056)**
Log Buyer Experience	**0.129***(0.0063)**	**0.025***(0.0012)**
BPD × Buyer Experience	**0.035*(0.0178)**	**0.011***(0.0034)**
Quality Dispersion	-0.023**(0.0105)	-0.000005985
Log Freelancer Experience	0.183***(0.0067)	0.037***(0.0014)
Average Freelancer Rating	0.135***(0.0079)	0.026***(0.0016)
Buyer Rating	0.035***(0.0024)	0.0069***(4.47e-04)
Log Number of Bids	-0.109***(0.0104)	-0.022***(0.0021)
Project Size	-1.52e-03***(4.39e-05)	-3.36e-04***(9.60e-06)
Auction Duration	-1.74e-05(3.20e-05)	-2.88e-05***(6.99e-06)
Log Arrival Rate	-0.049***(0.0069)	-0.013***(0.0014)
Arrival Dispersion	-0.0073***(3.16e-04)	-0.0012***(4.07e-05)
Previous Interaction	-0.117***(0.0035)	-0.051***(0.0062)
Constant	0.186***(0.0527)	0.566***(0.0112)
Observations	66,605	66,605
Pseudo/R-squared	0.121	0.140
Project Type	YES	YES
Time Dummy	YES	YES

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.3.6 Robustness Check 3: Distribution-adjusted BPD

Instead of setting a fixed budget, buyers in our research context are advised to set a budget range, such as [30, 250]. Therefore, it is possible that the distribution of the bid prices is bimodal (or multimodal) rather than unimodal, which may make the buyer interpret the BPD differently. Assume a project receives 10 bids (50, 45, 55, 50, 201, 220, 195, 200, 200, 199, referred to as Example C). Apparently, those 10 bids are distributed around 50 and 200. The BPD will be exaggerated if we use the overall dispersion measure in Equation (2). To test the robustness to bid price distribution, we constructed a distribution-adjusted measure [Equation (4)]. K (k=4 in the example) is the total number of bids whose price is lower than the median of the maximum and minimum bid price [which is 132.5=(45+220)/2]. The DABPD measure in example C would be: 0.4*the BPD of the first four bid prices + 0.6*the BPD of the rest six bid prices.

$$DABPD = \frac{\sqrt{\frac{1}{k}\sum_{i=1}^{k}(P_i - \frac{1}{k}\sum_{i=1}^{k}P_i)^2}}{\frac{1}{k}\sum_{i=1}^{k}P_i} \times \frac{k}{n} + \frac{\sqrt{\frac{1}{n-k}\sum_{i=k+1}^{n}(P_i - \frac{1}{n-k}\sum_{i=k+1}^{n}P_i)^2}}{\frac{1}{n-k}\sum_{i=k+1}^{n}P_i} \times \frac{n-k}{n} \quad (4)$$

Table 10 reports the results with distribution adjusted BPD. Again, we notice a consistently significant negative effect between BPD and buyer contracting across different model specifications. The coefficient is also qualitatively similar to the main results in Table 7, which indicates that our estimation is robust and reliable.

Table 10. Robustness Check With Distribution Adjusted Bid Price Dispersion[13]

	(1)	(2)	(3)	(4)
Model:	Logit (FE)	Logit	LPM (FE)	LPM
DV: Buyer Contracting				
Bids Price Dispersion (BPD)	**-0.329*****	**-0.231*****	**-0.055*****	**-0.050*****
	(0.0551)	(0.0398)	(0.0085)	(0.0080)
Observations	41,916	66,605	66,605	66,605
Number of buyer ID	5,922	--	20,906	--
R-squared	--	--	0.101	0.143
Buyer Fixed Effects	YES	NO	YES	NO
Project Type	YES	YES	YES	YES

Notes: Cluster-robust standard errors in parentheses;
Coefficients significant at level *** p<0.01, ** p<0.05, * p<0.1

4.3.7 Other Robustness Checks

Finally, we further report a number of additional robustness checks in the Appendices, including a sub-sample analysis with a balanced sample, interaction effects between BDP and the number of bids, excluding dominated bids, and finally an alternative measure for BPD (standard deviation). We discuss these additional robustness tests below, and we report the results in Online Supplementary Appendix A.

In the main results (Table 7), we used buyer fixed effects to account for unobserved buyer characteristics. Since the data panel is unbalanced, the sample size of model (1) with buyer fixed effects

[13] To save space, we do not report control variables. Please refer to the Appendix A, Table A1 for a complete table.

in Table 7 is smaller than that of model (2) without buyer fixed effects,[14] which makes the coefficients of BPD in Model (1) and model (2) less comparable. We thus conducted another subsample analysis with observations used in model (1). Again, results are robust (Table A1, Online Supplementary Appendix A). To further validate the assumption that buyers do infer the common value of an IT service by observing freelancers' bid prices, we checked the interaction effect between BPD and the number of bids. Theoretically, if a buyer does infer the value of an IT service, the overall BPD should have a smaller effect when there are more bids. Results in Table A4 (Appendix A) validate this prediction.

In practice, some freelancers' bids have a very low likelihood of receiving contracts as they are dominated by other freelancers in all observable attributes like rating, experience and price. Assuming there are two freelancers: Joe ($160, 7 stars mean rating, 5 completed projects) and Frank ($140, 9 stars, 15 completed projects). Joe will have little chance to win the contract as Frank outperforms him in every observable aspect. We therefore replicated the analysis with a refined measure of BPD by excluding all dominant bids. Once again, the results are robust (Table A5, Appendix A). Given that the standard deviation is the most commonly used measure of dispersion in the literature, Table A6 (Appendix A) reports the results of BPD when measured with the standard deviation of the buyer's contracting decision in order to exclude the possibility that the effect of BPD on the buyer's contracting decision is driven by the specific measure of the coefficient of variation we used. The results remain robust.

4.4 Freelancer Regret

4.4.1 Identification Strategy

We model the relationship between BPD and freelancer regret conditional on that a buyer offers a contract to a freelancer (termed as the "winner"). Similar to the analysis for buyer contracting, we included a number of important control variables, such as IT service category dummies, to account for potential

[14] There are two reasons for the sample size reduction: 1) buyers that only have one project were excluded from the analysis in Model (1), and 2) buyers who offer (or not offer) contracts for all projects for IT services were excluded from the analysis in Model (1) because of no within-group variation.

unobserved heterogeneity. Further, freelancer fixed effects were included to account for the unobserved time-invariant winner preferences and a general tendency to regret that may affect both freelancer regret and BPD. Again, measurement error and reverse causality are not major endogeneity concerns in our study.

Similar to buyer contracting, we further examined the moderating role of freelancer experience and the number of bids to explore the heterogeneity of BPD on freelancer regret, which also serve as falsification tests. To exclude the possibility that the results are driven by the particular measure of BPD we used and to ensure the robustness of the measurement of BPD, we used the standard deviation of all bid prices (a commonly used measure of dispersion in literature) as an alternative measure.

4.4.2 "Freelancer Regret" Model Specification

After the buyer offers a contract to a freelancer, the freelancer has the option to accept the contract (or not). $Regret_{kj}$ is a binary variable (1-not accept the contract, 0-accept the contract), which indicates whether a freelancer accepts the contract. Since our dependent variable is a binary variable, we used a logit model with robust standard errors (Equation 5). U_{kj} is the latent utility a freelancer k infers from project j. BPD_{kj} is the bid price dispersion for project j and β_1 captures the effect of BPD on freelancer regret. $Winner_{kj}$ is a vector of winner's characteristics like winner's bidding price, experience and quality rating, all of which are included as controls that affect a freelancer's decision to reject a contract when offered one.

Another potential identification threat is unobserved winner preferences that affect a winning freelancer's choice to bid for what type of projects (which is correlated with BPD) and overall likelihood to regret. Taking the advantage that we can repeatedly observe a winner's regret behavior in our dataset, γ_k is a winner fixed effects introduced to account for winner level unobserved confounding factors.

$Overqualify_{kj}$ is a vector that captures the relative position of the winning freelancer's price, quality, and experience relative to the rest of the non-winner freelancers. On the one hand, if the winner's quality and experience are much higher than the average of the rest of the freelancers, he is probably more likely to regret and not accept the contract since he may perceive that he is overqualified for the job.

However, if the winning freelancer's bid price is much higher than the average of the other freelancers, the winning freelancer is probably less likely to decline the contract since he already bid the highest price.

$Project_j$ is a vector of project level characteristics, including project size, project type, and the total number of bids. On the one hand, a freelancer's preference and the likelihood to decline a contract may vary with project size, project type, and the number of bids (competitors). On the other hand, we showed earlier that BPD also varies across project type and project size. Therefore, $Project_j$ also serves as control variables to account for observed heterogeneity and address potential omitted variable bias.

$Buyer_{kj}$ is a vector of buyer level controls, including the buyer's experience and mean rating. As noted before, buyer characteristics can be correlated with BPD via, for example, project description. A freelancer will also be less likely to reject the contract offered by a buyer with a higher reputation. Therefore, $Buyer_{kj}$ serves as a set of control variables to address potential omitted variable bias as well.

$Optcost_{kj}$ captures the winner's opportunity cost by measuring the number of projects the winner has bid during the period when the focal auction was open for bids.[15] As Horton (2015) showed, winning freelancers are more likely to "reject" a contract when they have more contracts to choose from. Table 11 summarizes all control variables used in the Freelancer Regret model.

Table 11. Model Specification for Freelancer Regret

	Potential Confounding Variables	Control Variables
$Winner_{kj}$	NA	Winner bid price, Winner experience, Winner rating, γ_k
$Overqualify_{kj}$	Rating over qualification, Experience over qualification, Price Premium	N/A
$Project_j$	Project size, Total number of bids, Project type	N/A
$Buyer_{kj}$	Buyer rating, Buyer experience	N/A
$Optcost_{kj}$	N/A	Number of projects the winner freelancer has won recently

[15] We also used the number of projects the winner has won during the auction period, and the results remained the same.

$$RegretProbability_{kj} = \frac{Exp(U_{kj})}{Exp(U_{kj}) + 1}$$

$$U_{kj} = \beta_1 BPD_{ij} + \beta_{2-5} Winner_{kj,} + \beta_{6-9} Overqualify_{kj,} + \beta_{10-11} Project_j + \beta_{12-13}\, Buyer_{kj} +$$

$$+\beta_{14}\, Optcost_{kj} + \gamma_k + \varepsilon_{kj}\ \mathbf{(5)}$$

4.4.3 Freelancer Regret Main Results

Table 12 reports the main results of BPD on freelancer regret. Columns (1) and (2) report the results of the logit estimation with and without winner fixed effects. The coefficient of BPD on freelancer regret is 0.14 for the logit model, which translates to a 1.33% absolute (14.5% relative) increase in the winning freelancer's probability to regret when offered a contract with a unit increase in BPD. Since it is practically impossible to calculate marginal effects for non-linear models with fixed effects, we cannot interpret the coefficient in Column (1). In comparison with the coefficient in Column (2), we can conjecture the marginal effect in Column (1) would be close, and slightly smaller than 1.33%. Given the attractive properties of LPM, Column (3) and Column (4) report the results of OLS regression. Again, we performed a post-estimation inspection, which shows that 99.69% of the predicted probabilities remained within the interval [0, 1], following the approach of Horrace and Oaxaca (2006). The marginal effect of BPD on freelancer regret is 1.1% and 1.6% for the LPM, with and without winner fixed effects, respectively. The four models in Table 12 consistently show that BPD has a positive effect on freelancer regret. Thus, Hypothesis 2 is supported.

The winning freelancer's relative rating and experience compared to the non-winning freelancers have a positive effect on freelancer regret, which confirms the over qualification logic that a winner is more likely to regret when he is more experienced and better rated compared with competing freelancers. As expected, a freelancer's price premium—relative price compared to the mean of the other freelancers—is negatively related to freelancer regret, meaning that a winner is less likely to regret when his bid price is higher than that of the other freelancers. A winning freelancer is more likely to regret for larger projects[16] (coefficient of winner bid price is positive), and when the freelancer has more projects to choose from

[16] The winning freelancer's bid price is highly correlated with project size. Results remained qualitatively the same when we used project size as the regressor.

(coefficient of opportunity cost is positive), which is aligned with the finding reported in Horton (2015). Finally, more experienced and better-rated winning freelancers are less likely to regret.

Table 12. Main Results for the Effect of Bid Price Dispersion on Freelancer Regret

	(1)	(2)	(3)	(4)
Model:	Logit (FE)	Logit	LPM (FE)	LPM
DV: Freelancer Regret				
Bids Price Dispersion (BPD)	**0.131***	**0.140*****	**0.011***	**0.016*****
	(0.0690)	(0.0520)	(0.0058)	(0.0057)
Price Premium	-0.069	-0.130***	-0.007	-0.013***
	(0.0609)	(0.0443)	(0.0050)	(0.0044)
Rating Overqualified	0.550***	0.445***	0.042***	0.043***
	(0.1180)	(0.0851)	(0.0099)	(0.0092)
Log Number of Bids	0.053**	-0.037**	0.002	-0.006***
	(0.0262)	(0.0182)	(0.0021)	(0.0018)
Log Buyer Experience	-0.081***	-0.085***	-0.006***	-0.008***
	(0.0161)	(0.0121)	(0.0013)	(0.0011)
Buyer Rating	-0.002	-0.008*	-2.71e-04	-0.001***
	(0.0113)	(0.0043)	(0.0010)	(4.12e-04)
Experience Overqualified	0.030***	0.023***	0.002***	0.001**
	(0.0086)	(0.0066)	(7.44e-04)	(6.97e-04)
Log Winner Bid Price	0.147***	0.100***	0.013***	0.009***
	(0.0290)	(0.0204)	(0.0025)	(0.0021)
Winner Experience	-0.002***	-0.002***	-9.65e-05***	-8.68e-05***
	(6.17e-04)	(1.64e-04)	(3.23e-05)	(6.84e-06)
Winner Rating	0.001	-0.104***	0.001	-0.011***
	(0.0225)	(0.0126)	(0.0020)	(0.0013)
Optcost	0.004***	0.006***	5.00e-04***	7.96e-04***
	(5.13e-04)	(5.86e-04)	(5.12e-05)	(7.53e-05)
Constant		-1.980***	0.022	0.132***
		(0.1170)	(0.0168)	(0.0121)
Observations	20,505	37,612	37,612	37,612
F-statistics			18.86	62.06
Number of winner ID	1,682		9,564	
Winner FE	YES	NO	YES	NO
Project Type	YES	YES	YES	YES

Notes: Cluster-robust standard errors in parentheses;
Coefficients significant at level *** p<0.01, ** p<0.05, * p<0.1

4.4.4 Robustness Check: Moderating Role of Winner Experience in Freelancer Regret

Similar to the buyer contracting analysis, a practical concern is that whether winners really use BPD in their decisions on whether to accept the contract. If winners indeed do use BPD in their decision, BPD should have a smaller effect on experienced winners as they know more about the market and are more capable to estimate the buyer's true requirement. Limited by the sample size, instead of analyzing the interaction effect between winner experience and BPD,[17] we ran a sub-sample analysis with winner's experience below the median and above the median. In Table 13, we show a positive and significant effect between BPD and freelancer regret in both the conditional logit model (Column 1) and LPM (Column 3) when the winner's experience is below the median. However, for winning freelancers whose experience is above the median, the coefficient is closer to zero and statistically insignificant (Column 2 and Column 4). This indicates BPD may have a larger effect on regret among inexperienced freelancers.

Table 13. The Moderating Role of Winner Experience in the Effect of BPD on Freelancer Regret: Sub-sample Analysis[18]

	(1)	(2)	(3)	(4)
Model:	Logit (FE)	Logit	LPM (FE)	LPM
DV: Freelancer Regret	Exp.< Median	Exp.> Median	Exp.< Median	Exp.>Median
Bid Price Dispersion (BPD)	**0.147****	0.038	**0.018****	0.003
	(0.0632)	(0.0934)	(0.0083)	(0.0076)
Observations	19,095	18,517	19,095	18,517
F-statistics			26.08	33.65
Winner FE	NO	NO	NO	NO
Project Type	YES	YES	YES	YES

Notes: Cluster-robust standard errors in parentheses;
Coefficients significant at level *** p<0.01, ** p<0.05, * p<0.1

4.4.5 Other Robustness Checks

Similar to the buyer contract analysis, we further report a number of additional robustness checks in Online Supplementary Appendix B, including a sub-sample analysis with a balanced sample, interaction effects between BDP and the number of bids, and an alternative measure for BPD (standard deviation). We discuss these robustness tests below and report the results in the corresponding tables in Appendix B.

In the main results Table 12, we used freelancer fixed effects to account for unobserved freelancer characteristics. Since the data panel is unbalanced, the sample size of model (1) with freelancer fixed effects in Table 12 is smaller than that of model (2) without freelancer fixed effects, which makes the coefficients

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[17] Similar analysis using interaction term between BPD and winner experience was conducted. However, the interaction term was statistically insignificant, which may be caused largely by the abrupt reduction in the sample size conditional on the buyer offering a contract. We therefore ran a sub-sample analysis instead.

[18] To save space, we do not report control variables. Please refer to the Appendix B, Table B1 for a complete table.

of BPD in Model (1) and model (2) less comparable. We thus conducted another subsample analysis with observations used in model (1). Again, the results are robust (Table B2, Appendix B). To further validate the assumption that freelancers do infer the buyer requirement by observing others' bid prices, we checked the interaction effect between BPD and the number of bids. Theoretically, if a freelancer does infer the value of an IT service from other bids, the overall BPD should have a smaller effect if there are more bids. Results in Table B3 (Appendix B) validate this prediction. Given that the standard deviation is the most commonly used measure of dispersion in the literature, Table B4 (Appendix B) reports the results of BPD when measured with the standard deviation of the buyer's contracting decision in order to exclude the possibility that the effect of BPD on the buyer's contracting decision is driven by the specific measure of the coefficient of variation we used. The results remain robust.

5. Discussion

5.1 Key Findings

Motivated by the common observation that many two-sided platforms, such as dating platforms, ride sharing platforms, and home rental platforms, face challenges in matching the two sides, and notably almost half of the projects for IT services in online labor markets end up with buyers not contracting with any freelancer (e.g., Snir and Hitt 2003; Yoganarasimhan 2013), this paper theoretically proposes and empirically examines the role of BPD (bid price dispersion) on both sides of the two-sided platform: (a) buyer's contracting and (b) freelancer's regret. Our estimation results from different model specifications consistently show that BPD has a significant negative effect on matching in online labor markets, resulting from two main effects: a negative effect on the buyers' decision on whether to contract, and a positive effect on freelancers' regret. Specifically, one-unit increase in BPD (measured as the coefficient of variation) is associated with a 6.83% decrease in the probability of matching, while a 5.74% decrease in a buyer's likelihood to offer a contract. Conditional on the buyer offering a contract to a freelancer, one-unit increase in the BPD makes the winning freelancer 1.33% more likely to decline a contract when offered one. In sum, one-unit increase in BPD renders a project 6.2% less likely to end up with a match between a buyer and freelancer (Table C1, Online Supplementary Appendix C). These findings contribute to and provide important implications for the literature on two-sided platforms, as we discuss below.

5.2 Theoretical and Practical Contributions and Implications

This paper makes several unique contributions to the emerging literature on online platforms that are empowered by the digital infrastructure (e.g., Parker and Van Alstyne 2005; Parker and Van Alstyne 2014). First, by emphasizing the difficulty in pricing IT services in online labor markets, this study introduces and empirically demonstrates ***bid price dispersion*** as an important predictor of matching in two-sided platforms. In doing so, this study extends the literature that has largely focused on mitigating information asymmetry in online labor markets, such as freelancer experience (Agrawal 2013), freelancer skills (Kokkodis et al. 2015), freelancer reputation gained in past projects (Moreno and Terwiesch 2014), freelancer's capacity (Horton 2015), platform recommendation (Horton 2016), whether the buyer and the freelancer come from the same country (Agrawal 2013), whether a freelancer worked with the buyer before (Kokkodis et al. 2015) and auction format (Hong et al. 2016). Given the importance of matching in online labor markets and two-sided platforms, bid price dispersion is introduced as a novel determinant.

Second, while prior studies have primarily focused on either the determinants of the buyer's hiring decision to offer a contract to a freelancer by estimating buyer preferences (e.g., Horton 2015, Horton 2016; Moreno and Terwiesch 2014; Agrawal et al.2013; Kokkodis et al. 2015), this study extends our understanding of the inefficient matching problem in two-sided platforms from *both* the buyer's and the freelancer's perspective by decomposing the matching into two sequential stages: buyer indecision and freelancer regret. This study, to our knowledge, is among the first studies to examine the matching problem in two-sided platforms in the context of online labor markets by examining both the buyer's and the freelancer's decisions. Our empirical results indicate that the two stages of the decisions play a significant role in determining the ultimate matching in two-sided platforms, and it is important to holistically examine both sides of the platform to fully examine the matching. These findings have implications for other two-sided platforms that regret from the responder (e.g., freelancer) side is common, such as online dating platforms, luxury home rental platforms, and even ride sharing platforms.

Third, we contribute to the broader IS literature on uncertainty in online platforms. Uncertainty was shown to negatively affect online transactions in the e-commerce literature (e.g., Ghose 2009, Dimoka et al. 2012). Bajari and Hortacsu (2003 a) noted that uncertainty arising from information asymmetry is perhaps the biggest limitation in online transactions. As previous studies on uncertainty in the e-commerce literature focused specifically on the buyer's difficulty in assessing the seller's true characteristics and predicting whether the seller will act opportunistically (seller uncertainty), evaluating the product's quality and performance (product uncertainty) (e.g., Ghose 2009, Dimoka et al. 2012), and fit with buyer's needs (product fit uncertainty) (Hong and Pavlou 2014), this study contributes to this literature by theoretically proposing and empirically testing value uncertainty in the context of IT services. Extending transactions of physical products whose value is usually known to buyers prior to the transaction, such as IT services, buyers also face *value uncertainty* beyond the types of uncertainty examined by prior literature.

Finally, by empirically demonstrating that BPD negatively affects buyer's contract decisions, positively affects freelancer's regret, and jointly has a net negative effect on matching, our findings also have important implications for practice. Different from platforms for physical products where higher price dispersion means more choices and more transactions, bid price dispersion in online labor markets may affect both buyer and freelancer's value uncertainty, thus hindering matching and transactions. Platform managers should pay particular attention to the negative effect of bid price dispersion while trying to attract diverse freelancers from which buyers to choose. Platform managers should also provide more guidance to buyers to better estimate the price of the IT service they post, thus helping buyers to set a more accurate budget range and better describe their projects to reduce value uncertainty. Generally, our findings evoke a dialectic thinking of price dispersion in matching on two-sided platforms for IT services or any products or services with idiosyncratic value that may be difficult to price.

5.3 Limitations and Suggestions for Future Research

This paper has a few limitations that create opportunities for future research. First, there may be other unobserved factors that relate to a buyer's desire to contract with a freelancer, and those may lead to potential omitted variable bias. Buyer fixed effect helped to capture those invariant ability and preferences but cannot address time variant elements, such as the desire to contract with a freelancer. Second, we can neither observe the buyer's offline contracting decisions nor her contracts in other online labor markets. This means those buyers who do not make a contracting decision in our dataset may contract offline or in other labor markets. Therefore, matching may be underestimated and so is the effect of BPD on buyer's contract decisions and freelancer regret. As online labor markets are dominated by a few large platforms, future studies could possibly acquire longitudinal data across different platforms to address buyers' and freelancers' contracting decisions across platforms. Third, both buyer and freelancer's value uncertainty may evolve as they stay longer and become more familiar with the platform. In this study, we only have a six-month panel, which is relatively a short time to observe the dynamic characteristics of the effect of BPD on buyer contracting and freelancer regret. With a longer panel, future research could examine the longer-term effects of BPD and how value uncertainty affects matching in online labor markets over time.

5.4 Concluding Remark

By leveraging the power of digital infrastructure to facilitate transactions of labor across the globe on online platforms, this study utilizes a panel dataset from *Freelancer* to examine bid price dispersion as an important hurdle for two-sided platforms to efficiently match participants from both sides of the platform. By theoretically proposing and empirically demonstrating that bid price dispersion is negatively associated with matching between buyers and freelancers on both sides of two-sided platform (online labor market), our findings bring up a new insight by showing that the matching capability of two-sided platforms can be enhanced when value uncertainty from both the buyers' and also the freelancers' perspective is considered and bid price dispersion is recognized as an important determinant of the matching in online labor markets. Our research aims to provide a modest initial step in understanding the prevalent problem of matching in two-sided platforms toward providing actionable insights for practitioners and platform managers to design more effective matching systems for two-sided platforms.

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