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RESEARCH PAPER

Buyer preferences for auction pricing rules in online outsourcing markets: fixed price vs. open price

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Abstract

Fixed-price and open-price are two mechanisms with different auction pricing rules that are popularly used in online outsourcing markets. This research empirically examines the determinants of buyers' choices between the two mechanisms with secondary data from an online outsourcing market. We found that buyers tend to use open-price auctions with large size projects, while their propensity to use fixed-price auctions increases when they are more familiar with the project, have more trading experience in the market, or less trust in the service providers. Moreover, buyer experience has significant moderating effects on the impact of project size and buyer distrust. Our empirical results reveal a unique insight that incomplete information and information asymmetry, rather than the expected buyer surplus, are critical factors to buyers' preferences on bid dimensionality.

Keywords Pricing rule · Auction mechanism · Bid dimensionality · Online outsourcing markets · Online outsourcing · Buyer-determined auctions

JEL classification L81 · L86

Introduction

Fast growing e-commerce enables small- and medium-sized companies as well as individuals to implement service procurement online, and fosters the prosperity of the freelancing industry. The freelance workforce has grown rapidly. In 2018, it accounted for 35% of the total workforce in the U.S. (upwork.com).[1] Online outsourcing markets (also known as "online labour markets") have proliferated as an intermediary to bridge buyers and service providers (Hong et al. 2015). For example, freelancer.com, a leading online marketplace, connects over 33 million employers and service providers from 247 countries, regions and territories. Online outsourcing markets have also reached a grand scale in China: epwk.com is a well-known marketplace

[1] https://www.upwork.com/press/2018/10/31/freelancing-in-america-2018/, accessed in April 2019.

(see http://www.aeaweb.org/journal/jel_class_system.html or https://www.aeaweb.org/jel/guide/jel.php)

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that has listed more than eight million projects and facilitated transactions worth over $2.4 billion (¥16.9 billion) since it was founded in 2010.[2] Another online outsourcing marketplace, zbj.com (with witmart.com as its international version), has 13 million registered service providers and seven million clients. The site completed projects worth more than $1.1 billion by the end of 2018.[3]

Online outsourcing markets are a digitized version of traditional marketplaces for service procurement (M. Lin et al. 2016; Stanton and Thomas 2016), where different types of players interact: buyers or clients who demand services; and service providers, or bidders, or freelancers, or sellers, who potentially provide services. In most online outsourcing markets, buyers award the contracts to selected bidders through multi-attribute buyer-determined auctions (Hong et al. 2015). The typical procedure is as follows: a buyer initiates a task or project by posting a Call for Bids (CFB); interested bidders submit their bids, including information on multiple attributes (e.g. price, working duration,[4] execution proposal, self-introduction, etc.); the buyer then selects the winning bidder and awards the contract. One critical decision the buyer needs to make when posting a CFB of an auction is to choose a ***pricing rule*** (the way the price of the auctioned good or service is determined). Specifically, the buyer can choose to use the *fixed-price* (FP) mechanism, or the *open-price* (OP) mechanism. Under the fixed-price mechanism, the buyer sets the price of the project in the CFB, and service providers bid for non-price attributes, such as working duration, execution proposal, etc. By contrast, the open-price mechanism relaxes the constraint on price, as this is not pre-set by the buyer. Service providers submit bids that include both price and non-price information, opening an additional dimension for them to compete against. The price in the winning bid, which is determined by the buyer, is thus the project price. Consequently, under the two pricing rules, an auction can end with different outcomes. Both pricing rules are popularly used, and buyers in online outsourcing markets can choose freely between the two. It is of both academic and managerial interest to understand the outcome differences between these two rules, and how buyers should choose between them. Existing studies on auction dimensionality have used various analytical models and experiments to examine how the number of bidding attributes affects the auction outcome. Most of these studies (Asker and Cantillon 2008; Bichler 2000; Chen-Ritzo et al. 2005) show that auctions with more bidding attributes result in a higher buyer surplus than those with fewer bidding attributes. Nevertheless, these theoretical studies can hardly explain why the fixed-price mechanism is still frequently used by buyers when they could choose the open-price option.

The main objective of our research is to explore the difference between the two pricing rules by examining buyers' *ex ante* preferences. In particular, we try to identify the contingencies where buyers prefer the open-price to the fixed-price mechanism and vice versa. Our study uses data from epwk.com, a leading Chinese online outsourcing marketplace, with 1963 fixed-price auctions and 7629 open-price auctions. We examine the impacts of a variety of factors on how buyers choose a pricing rule, including project-specific factors (e.g. project size, etc.) and buyer characteristics (e.g. experience, how familiar they are with the project, their trust in the community of service providers, etc.). These factors reflect three major concerns that potentially influence the pricing rule decision: i) the uncertainty/incomplete information that a buyer faces in evaluating the proposed project's budget; ii) the buyer's *ex ante* expectation of the auction outcome under the different pricing rules; and iii) the buyer's distrust in service providers due to the information asymmetry between the two parties. We use several regression models to estimate the effects of those explanatory factors, and the estimations are robust. Our empirical results show that concerns about incomplete information and information asymmetry are vital; buyers are inclined to use the open-price mechanism if they are unfamiliar with the project and more information is needed to estimate the project budgets. Meanwhile, if they distrust the service providers in the market, they tend to use the fixed-price mechanism. Interestingly, by measuring the impact of buyer experience on the pricing rule selection, we reveal that the concern about incomplete information is more dominant than that about outcome expectation, which seems less essential. In particular, past trading experience in the market helps buyers better understand the outcome difference between the two pricing rules, and provides them with an information advantage in estimating a project budget. As existing studies suggest that the auction mechanism with more bidding attributes (open-price mechanism) leads to a higher buyer surplus, an experienced buyer is supposed to learn its merits and prefer to use it when posting a CFB. On the other hand, being experienced also helps buyers estimate the project budget, and makes them more comfortable to use the fixed-price mechanism. Our research demonstrates significant evidence that when buyers are more experienced, they are more likely to adopt the fixed-price mechanism. This finding implies that the current theoretical understanding of outcome difference generated from bid dimensionality is incomplete; information plays a more critical role in auction design on bid dimensionality than existing modelling and experimental studies have assumed.

Our research contributes to two streams of literature. First, it adds to the literature on auction mechanisms. Existing studies on bid dimensionality focus on the mechanism difference in non-price attributes but have not investigated this aspect in price attribute. The findings are based on either game-theoretical models or lab experiments. As far as we know,

[2] http://www.epwk.com/, accessed in May 2019.
[3] http://www.witmart.com/about/overview.html, accessed in April 2019.
[4] Working duration refers to the time the service provider plans to take to complete the project.

our paper is the first empirical research that uses secondary data to examine the role of bid dimensionality. Our empirical findings provide evidence that differs from present theories and calls for further research in this field. Second, our research enriches the understanding of online outsourcing markets. Despite its increasing popularity, the extant research on this topic mainly concentrates on the bidding behaviours of service providers and the hiring decisions of buyers. Few studies have examined the buyer's *ex ante* selection on auction pricing rules.

The remainder of this article is structured as follows. In the section on research context, we introduce how the online outsourcing marketplace operates and elaborate on the auction procedures under the two mechanisms. We then review the relevant literature. Next, we present the theory and hypotheses development. We explain our empirical data and methodologies in the subsequent section, and then present the regression results and associated discussions, followed by the conclusion.

Research context

There are more than 100 online labour markets in China,[5] including epwk.com, zbj.com, taskcn.com, and k68.cn, to name a few. These marketplaces facilitate projects in various categories, from product design, website and app development, to advertising and promotion projects, house services, and so on. Multi-attribute buyer-determined auctions are usually adopted to match buyers and service providers. Buyers in these markets are generally individuals or firms who have a procurement need for services; service providers are self-employed individuals/teams as well as small and medium firms that have particular skills or capabilities to fulfil buyers' needs. Buyers initiate an auction by posting a CFB in which they provide a project description, set the duration of the auction, and determine the pricing rule (the fixed-price mechanism vs. the open-price mechanism). They also select guarantee options (whether participating bidders are required to submit a deposit as a guarantee of delivering the service in time, free after-sale services for three months, and that the work is original), as well as other relevant features. The pricing rule is a vital factor. Buyers can choose freely between the two mechanisms in the CFB without paying any additional charge. If they opt for the fixed-price mechanism, a specific price for the proposed project needs to be set. If they use the open-price mechanism, they need to select a budget range from several prespecified ranges ("¥100–¥1000," "¥1000–¥5000," "¥5000–¥10,000," "¥10,000–¥30,000," "¥30,000–¥50,000," "¥50,000–¥100,000," "¥100,000–¥200,000," and "over ¥200,000″). However, the selected budget range is more of a signal that implies the buyer's budget preference; service providers can offer bid prices outside the selected range.

Once the CFB is posted, interested service providers submit their bids, including information from multiple dimensions. In a fixed-price auction, they agree on the project price pre-set by the buyer, and their bids comprise the proposed working duration with an execution proposal that briefly describes their credentials and implementation plans. In an open-price auction, bidders bid on both price and non-price attributes (e.g. working duration, execution proposal).

After the auction is closed, the buyer selects a winning bidder and awards the contract. An auction can fail if the buyer cannot find a satisfactory bid from those received. If the buyer selects the winning bidder, a payment must first be deposited to the marketplace, and the chosen service provider then begins work on the project. If the service provider completes the project within the promised working duration, the buyer authorizes the marketplace to release payment. As the last step, the two parties rate each other via the marketplace platform. Figure 1 shows examples of two project pages (the CFBs) under the different pricing rules. Note that the one on the left is a fixed-price auction with the price pre-set at ¥680; while the one on the right is an open-price auction, with a suggestive budget range of ¥100–¥1000.

Literature review

Literature on online outsourcing markets

In recent years, considerable academic attention has been given to online outsourcing markets as a venue to facilitate transactions between buyers and service providers. Existing studies can be classified into three streams according to research subject. The first stream focuses on the role of strategies and mechanisms of the marketplace in the process of matching buyers and service providers. Through semi-structured interviews and an online questionnaire, Caraway (2010) describes and summarizes mechanism designs that oDesk.com uses to enhance mediation. Allon et al. (2012) use game theoretical models to show that the marketplace's intervention in the matching process (i.e. price screening service providers and enabling them to communicate) may result in a better market outcome in terms of equilibrium price and the marketplace's profit. Hong et al. (2015) compare the sealed-bid and open-bid auction mechanisms. This empirical study shows that while the sealed-bid mechanism attracts more bidders, the open-bid mechanism generates higher buyer surplus. Horton and Johari (2018) show that the device signalling buyers' vertical preferences (relative preference over price and quality) has a significant sorting effect on attracting service providers. High-quality service providers are attracted to

[5] https://tech.qq.com/a/20101118/000351.htm, accessed in November 2019.

(a) Fixed-Price Auction (b) Open-Price Auction

Fig. 1 Fixed versus Open-Price Mechanisms

buyers with a high preference on quality, while low-quality service providers are attracted to buyers who are more sensitive to price.

The second stream of studies consists of research that focuses on the factors that affect buyers' hiring decisions. Scholz and Haas (2011) show that bid price is the predominant factor influencing how clients make selection decisions. A few studies (Kokkodis et al. 2015; Moreno and Terwiesch 2014; Scholz and Haas 2011; Yoganarasimhan 2013) prove that as a device to alleviate information asymmetry, the service provider's reputation is another important factor. The literature has also examined other influencing factors that include service providers' work experience (Agrawal et al. 2015; Beerepoot and Lambregts 2015; Kim 2009), skills (Beerepoot and Lambregts 2015), production costs (Scholz and Haas 2011), origin (developing vs. developed countries) (Agrawal et al. 2015; Beerepoot and Lambregts 2015), linguistic and cultural differences between buyers and service providers (Hong and Pavlou 2013, 2017; Scholz and Haas 2011), and their historical collaboration relationship (Hong and Pavlou 2013).

The third stream of research investigates service providers' behaviours. Snir and Hitt (2003) study their participation decisions and bidding strategies. This analytical model shows that while high-value projects attract more bids, the rising number of bids increases the transaction costs of both buyers and service providers, and makes these projects less awarded. Benson et al. (2019) use an experimental study to reveal that projects posted by buyers with a higher reputation attract more service providers in the same unit of time. Kanat et al. (2018) explore how geo-economic factors affect the "exit" behaviour of service providers. Brink et al. (2019) examine how codes of conduct, monitoring, and penalties for dishonest reporting affect service providers' reporting behaviours (honest or not) in an online outsourcing market.

In sum, the literature regarding the online outsourcing market focuses on the impacts of matching mechanisms, how buyers select the winning bidder from the pool of service providers, and service providers' competition strategies. However, there is a lack of academic understanding about buyers' preferences and adoption decisions on matching mechanisms, even though in practice, many online outsourcing marketplaces provide them with such options. Our paper aims to fill this gap by empirically examining buyers' choices between the fixed-price and open-price mechanisms.

Literature on attribute setting in reverse auctions

Our study focuses on the comparison between fixed-price and the open-price mechanisms. The essence of the research question is the mechanism setting of the price attribute in reverse auctions. Concerns about auction attributes arise from two perspectives, and both attract considerable academic attention. The first is the nature of the attributes and how they should be integratively considered when awarding a contract (award rule). The other perspective focuses on which attributes should be open to bidders (bid dimensionality).

Studies on the award rule explore whether and how to formulate a scoring function of auction attributes used to evaluate bids. Most studies assume that the scoring function is quasi-linear, that is, linear in price (Asker and Cantillon 2008; Che 1993; David et al. 2006), except that Wang and Liu (2014) consider a non-linear scoring function in price. With the setting of a quasi-linear scoring function, Vulkan and Jennings (2000) argue that the optimal award rule should follow the buyer's utility function, so that buyer surplus will be maximized through the auction. However, other studies (Che 1993; David et al. 2006; Nishimura 2015) contend that the scoring function may deviate from the buyer utility function, due to various reasons that include buyer commitment power, motivating bidders, and cost substitutability between project attributes, etc. Moreover, "buyer-determined," sometimes called "non-binding," is a special award rule used in reverse auction markets. Under a buyer-determined auction, no scoring function is specified *ex ante,* and the buyer freely decides the winning bid after the bidding. The buyer-determined auction mechanism is attracting more and more academic attention (Engelbrecht-wiggans et al. 2007; Fugger et al. 2016; Haruvy and Jap 2013; Hong et al. 2015; Hong and Pavlou 2017), and our research aims to contribute to this growing literature.

Studies on bid dimensionality explore the optimal design of how many and which attributes should be open for bidders to bid. These studies compare the outcomes of the auctions with different bidding attributes, especially between those of single- and multi-attribute auctions. In prior literature, single-attribute auctions mainly refer to those where bidders only bid for price. Multi-attribute auctions allow bidders to submit a bid on both price and non-price attributes (e.g. quality, delivery time, etc.). Both theoretical-modelling (Asker and Cantillon 2008) and experimental studies (Bichler 2000; Chen-Ritzo et al. 2005) show a consistent result that the multi-attribute auction outperforms the single-attribute in terms of buyer surplus. The theoretical explanation is that more attributes allow bidders to better organize their resources, and to offer bids more favourable to the buyer. Using laboratory experiments to compare the two- vs. three-attribute auctions on logistics services, Bellantuono et al. (2013) show that the attitude of bidders towards the buyer becomes more positive when they can bid on more attributes.

All these studies use either analytical models or lab experiments to develop theoretical findings. However, these findings have not been empirically tested with secondary data because the buyer's utility can hardly be measured in practice. Our research explores a unique perspective – buyers' choices on bid dimensionality – which may reveal buyer surplus under auctions with different bid dimensionalities. Moreover, bid price has been proven to be the predominant factor on how buyers decide on a winning bid (Scholz and Haas 2011). Existing studies on bid dimensionality all consider price as the default bidding attribute, and investigate the outcome difference by some non-price attribute(s). Our research makes a difference by examining the impact of including an additional project price in bidding attributes.

Literature on mechanism/contract selection and comparison

In addition to the research on online outsourcing markets, intensive studies on other markets investigate the trading mechanism/contract. These provide rich economics insights, and focus on two themes: i) the determinants of trading mechanism/contract selection, and ii) the comparison between the equilibrium outcomes under different mechanisms/ contract types.

Studies that focus on the first theme have examined the various influencing factors of mechanism/contract selection, specifically those that affect choice between auctions and other trading mechanisms (e.g. negotiations, posted-price mechanism), and choice between different contract types (e.g. fixed-price contract, time-and-materials contract, performance-based contract). Project complexity is considered a major factor in determining the final trading mechanism selected between auction and negotiation (Bajari et al. 2009), and whether the contract is time-and-material or fixed-price (Bajari and Tadelis 2001; Gefen et al. 2008). Besides project complexity, the existing literature also explores the effect of other project characteristics that include project uncertainty (Gopal et al. 2003), project size (Gopal et al. 2003), and how important the project is to the buyer (Gopal et al. 2003). In addition to these characteristics, features of traders, such as their experience (Einav et al. 2018; Gopal et al. 2003), and business familiarity with the counterpart (Gefen et al. 2008) also significantly influence the final choice on trading mechanism/contract type. Furthermore, extant research highlights the importance of price discovery (Einav et al. 2018), convenience (Einav et al. 2018), *ex ante* profit expectation (Gopal and Sivaramakrishnan 2008), and the verifiability of buyer and seller's efforts (Roels et al. 2010) on the trading mechanism/ contract type chosen.

Research on the second theme falls into three classes: comparisons between auctions and other trading mechanisms (e.g. negotiations, posted-price mechanism); comparisons between auctions with different auction mechanisms; and comparisons between different contract types. Using laboratory experiments, Bellantuono et al. (2013) find that sellers' profits are higher and their attitudes towards the buyer more positive with negotiations than with auctions. Einav et al. (2018) use eBay data to show that compared with posted-price mechanisms, auctions generally result in a higher success rate, but lower prices. Chen et al. (2007) contend that group-buying auctions outperform the posted-price mechanism when the seller is risk-seeking and economies of scale are considered. Studies on reverse auctions compare the performances of various mechanisms that differ in pricing rule (e.g. first-score vs. second-score) (Branco 1997; Che 1993; David et al. 2006; Hanazono et al. 2013), information revelation policy (e.g. open-bid vs. sealed-bid) (Gwebu et al. 2012; Haruvy and Katok 2013; Hong et al. 2015; Millet et al. 2004; Strecker 2010), award rules (e.g. price-based vs. buyer-determined) (Engelbrecht-wiggans et al. 2007), and bid dimensionality (e.g. single-attribute vs. multi-attribute) (Asker and Cantillon 2008; Bichler 2000; Chen-Ritzo et al. 2005; Hong and Wu 2018).

Previous literature compares the outcome of contract types between fixed-price and time-and-materials contracts. Gopal and Sivaramakrishnan (2008) contend that the impacts of profit drivers can be different when the contract type changes (fixed-price vs. time-and-materials contract). Dey et al. (2010) claim that a time-and-materials contract performs better than a fixed-price contract if a client has an effective and efficient process of monitoring and auditing. Gopal (2010) shows that contract type (fixed-price vs. time-and-materials) predicts the service quality provided by the vendor.

In sum, existing studies explore the determinants of mechanism/contract choice and compare the performance among various auction mechanisms and contract types. Our research follows the literature to study two specific auction pricing rules – fixed-price vs. open-price mechanism – and to explore the determinants of how buyers choose between them. Current research provides a theoretical background for our hypothesis development, which we will elaborate on in the next section.

Theory and hypotheses

Information, evaluation uncertainty on the project

How buyers decide the pricing rules depends on how confident they are in accurately estimating project budgets. Being certain of a cost assessment would intuitively lead to a tendency to choose the fixed-price mechanism, under which a buyer *ex ante* determines the payment for a project. In addition, a buyer's confidence is determined by the gap between the information needed for an accurate estimation and the project information already acquired. The smaller the gap, the more confident the buyer is in budget estimation.

Empirical studies have shown that project size leads to cost estimation error (Sauer and Gemino 2007; van Oorschot et al. 2005). The larger the project, the greater the potential for deviation between the estimated and actual costs. Dolado (2000) shows that larger-sized projects consist of more components or modules, and intuitively, to evaluate the budget, the buyer needs to estimate the cost of each individual component and sum up the total. This approach is called "bottom-up" in project management literature (Heemstra 1992; Jørgensen 2004). The cost estimation for each component requires specific information. Hence, the more components a project contains, the greater the amount and the more comprehensive the information is needed to obtain an overall budget estimate. Moreover, multiple components in one project often interact with, and interdepend, on each other, which induces further complexity (Nickerson and Zenger 2004; Simon 1969) and is highly related to uncertainty in cost estimation (Ahmad and Minkarah 1987). This would further discourage buyers' confidence in budget estimation. Our research, therefore, proposes the following hypothesis.

> *H1: Buyers prefer the OP mechanism to the FP mechanism when their projects are characterized as of a larger size.*

The amount of information buyers possess – aside from the total extent needed – can significantly affect their pricing rule decision. As the literature has shown, familiarity with a focal subject, considered a reflection of the amount of information individuals possess (Goodman and Leyden 1991; Park and Lessig 2002), is also a critical factor influencing their decisions (e.g. adoption decision of online payment systems, internet banking, purchase decision, etc.) (Dimitriadis and Kyrezis 2010; Gefen 2000; Rouibah et al. 2016). The greater the amount of information individuals have, the less uncertainty they face in accurately predicting the outcome (Milliken 1987). In an online outsourcing market, buyers with more information about the auctioned project face less uncertainty in evaluating the budget, are more confident to name their prices, and therefore are more likely to use a fixed-price auction. How much a buyer knows about a project is a critical feature impacting auction outcome, yet it has been barely investigated in previous auction literature. We propose the following hypothesis.

> *H2: Buyers prefer the FP mechanism to the OP mechanism when they are more familiar with the focal project.*

Historical information gained from past experience with similar projects are commonly used as references for cost estimation for the project at hand (Heemstra 1992; Stamelos and Angelis 2001). Estimation accuracy improves when estimation experiences about past analogies are used (Al-Harbi et al. 1994; Jørgensen 2014; Liu and Zhu 2007). In online outsourcing markets, buyers accumulate experience along with their ongoing activities. By observing and comparing bids, as well as communicating with bidders on previous projects, buyers gain more understanding about market prices and project cost structures. This helps them estimate costs and set prices in the future. Consequently, buyers who are more experienced with the online freelance marketplace become better at setting the price for their projects and are more inclined to use the fixed-price mechanism. Therefore, we propose the following hypothesis.

> *H3a: Buyers prefer the FP mechanism to the OP mechanism when they are more experienced with this market.*

In addition, experience can increase one's information processing capabilities (Mao and Benbasat 2000) and it affects one's use of relevant information (Perkins and Rao 1990). In online outsourcing markets, buyers with more experience are better at absorbing and analyzing information. They are more capable of conducting accurate cost estimations on each component of a project with limited information. In other words, when handling the same-sized project, experienced buyers would need less information to give a confident cost estimate, compared to those who are inexperienced. Therefore, the positive effect of project size on the buyer's selection of open-price mechanism would be weakened. We propose the following hypothesis.

H4: Buyer experience attenuates the positive effect of project size on the selection probability of the OP mechanism.

Ex ante expectation of the auction outcome

Previous research using laboratory experiments on bid dimensionality has shown that multi-attribute auctions outperform single-attribute ones in terms of buyer surplus (Bichler 2000; Chen-Ritzo et al. 2005). In online outsourcing markets that use reverse auctions, bidders bid for price, working duration, and submit an execution proposal that includes their credentials and implementation plans under the open-price auction mechanism; under the fixed-price mechanism, they only bid for working duration and execution proposal. From the perspective of bid dimensionality, the difference between the fixed-price and open-price mechanisms is that the latter adds an additional attribute for bidders to compete against. Following the intuition of experimental studies, the open-price mechanism should result in a greater buyer surplus than the fixed-price mechanism, and if buyers expect this difference – and are given the option – they should select the open-price mechanism.

With experience, buyers can predict the difference in outcome between the fixed-price and open-price auctions. A number of studies have demonstrated the presence of learning effects in auctions (Kannan 2012), as well as the learning effect on buyers in the online outsourcing market (Agrawal et al. 2013). As buyers gain experience with online outsourcing marketplaces, they become better at identifying and analysing market signals (Kim 2009), to avoid losses from opportunistic or low-quality providers (Hong and Pavlou 2013), and to understand the advantages and disadvantages of different auction mechanisms. As a result, buyers should gradually obtain the knowledge that "the open-price mechanism often brings me more gains than the fixed-price mechanism". They should then be more likely to choose the open-price mechanism, ceteris paribus. Therefore, we propose the following hypothesis.

H3b: Buyers prefer the OP mechanism to the FP mechanism when they are more experienced with this market.

Trust and distrust

Existing literature (Ba and Pavlou 2002; Gregg and Walczak 2010; Pavlou and Gefen 2004) has shown that buyers' trust in sellers is a critical factor that influences outcomes in online markets. As several studies (Hwang and Lee 2012; McKnight et al. 2002; Okazaki et al. 2010; Schlosser et al. 2006) have shown, the trust buyers place in sellers stems from three attributes: a) the sellers' *integrity*, e.g. whether the service providers are honest and will keep their promises; b) the sellers' *ability and competence*, e.g. whether the service providers have sufficient skills and are capable of completing the project in time; and c) the sellers' *benevolence*, e.g. whether the service providers care about and act in the buyer's interest. Information asymmetry in online outsourcing markets makes buyers' trust in service providers scarce and valuable (Yoganarasimhan 2013). As service providers' capabilities, resources and cost structure are private information unobservable to buyers (Bapna et al. 2016), they may take the opportunity to extract information rents (Gopal and Sivaramakrishnan 2008). Moreover, the intangibility of traded services and the "one-shot" or "non-repetitive" feature of online outsourcing market transactions nourish opportunistic behaviours in service providers, such as delaying the job and delivering services with lower quality than promised (Chong 2004; Yoganarasimhan 2013). As a result, the online auction environment becomes "fraud-friendly" (Chong 2004), and buyers frequently distrust service providers.

This distrust may affect a buyer's decision on pricing rule selection. Many studies (Kim et al. 2008; Okazaki et al. 2010; Pavlou and Gefen 2004) contend that trust decreases perceived risk in various contexts. When buyers are sceptical of bidders' integrity, ability and benevolence, they may perceive considerable uncertainties and risks in bidders' prices and are more likely to trust their own budget estimations. Consequently, they are more inclined to select the fixed-price mechanism. In addition, distrust in service providers may also motivate them to simplify the transaction procedure. Compared with the open-price mechanism, a buyer's decision about a winning bid becomes less complicated (with no need to consider the price factor) under the fixed-price mechanism. Therefore, we propose the following hypothesis.

H5: Buyers prefer the FP mechanism to the OP mechanism when they have less trust in the community of service providers.

As noted earlier, buyers accumulate experience with online freelance markets, and this helps them to acquire knowledge in order to properly identify and analyze credible signals (Kim 2009). Experienced buyers learn to avoid losses from opportunistic service providers (Hong and Pavlou 2013) and are better at gauging the reliability and quality of bidders. With this greater awareness and screening capability, the negative effect of distrust on perceived risk in forthcoming bid prices would be mitigated. Therefore, we suggest the following hypothesis.

> *H6: Buyer experience attenuates the negative effect of buyer distrust on the selection probability of the OP mechanism.*

In general, our research hypotheses are summarized in the framework in Fig. 2.

Data and methodology

Data and variables

The data for this research is collected from a leading online outsourcing marketplace in China. The marketplace owns more than 19 million registered service providers. Since its inception, buyers have posted over eight million projects, and the marketplace has facilitated transactions worth more than \$2.4 billion (¥16.9 billion) by May 2019. We collected auction-level data from January to July 2016 and obtained observations of 9592 auctions posted by 7966 unique buyers, including 1963 FP auctions and 7629 OP auctions. The data contains project characteristics (e.g. project budget level, project category and project description), auction characteristics (e.g. auction pricing rule, auction duration, the buyer's requirement for guarantees) and buyer characteristics (e.g. buyer experience, buyer location, and buyer authentication).

Table 1 summarizes the variables used in the empirical analysis. Table 2 presents descriptive statistics and correlations between key variables. The detailed descriptions of major variables are as follows:

OPMech is a dummy variable of a buyer's selection between fixed-price and open-price mechanisms. It equals to 1 if the buyer selects the OP mechanism and 0 if the buyer selects the FP mechanism.

ProjectSize refers the size of a project. Costs or money value is often regarded as one important dimension that reflects project size (Jiang et al. 2000; Martin et al. 2005; Might and Fischer 1985; Papke-shields et al. 2010). The literature often uses project budget as a proxy of project size (Bajari et al. 2009; Zheng et al. 2016), and we use the same measure as in these previous studies. When buyers post an OP auction, they need to mark their project budget level from eight potential budget ranges levels (¥100–¥1000, ¥1000–¥5000, ¥5000–¥10,000, ¥10,000–¥30,000, ¥30,000–¥50,000, ¥50,000–¥100,000, ¥100,000–¥200,000, over ¥200,000). We code *ProjectSize* from 1 to 8 for the 8 project budget levels, respectively. When posting an FP auction, a buyer is required to set an exact payment amount. *ProjectSize* of an FP project is coded according to which budget range the exact payment amount is located in. For example, a payment amount ¥4000 of an FP project is located in the budget range of "¥1000–¥5000." Therefore, the *ProjectSize* of this project is 2.

BuyerFami refers to the level of buyer familiarity with the project and is proxied by the length of the project description, i.e. the number of words. Project description is the result of acquiring, understanding, assimilating and expressing information related to the current project. The more familiar buyers are with the project, the more information they can disclose in the project description.

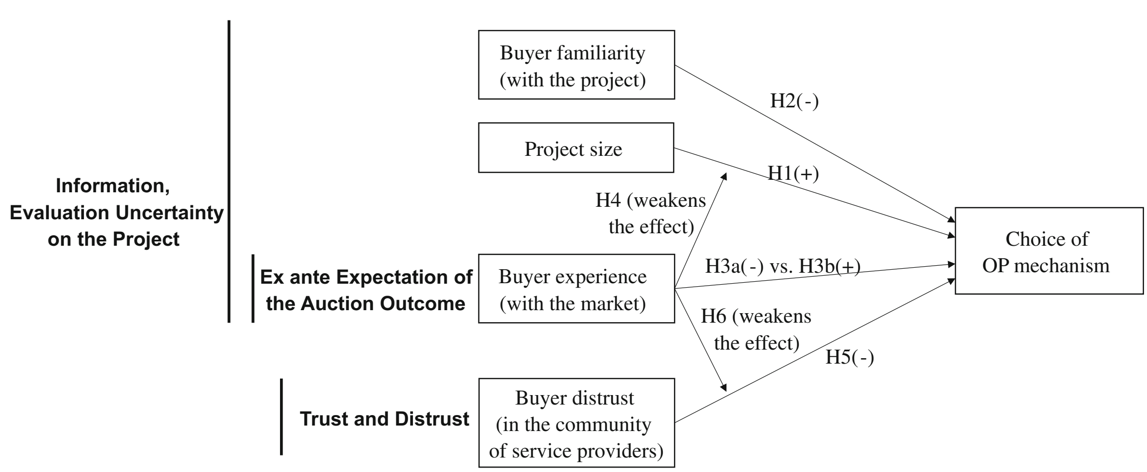


Fig. 2 Research model

Table 1 Definition of key variables

Variable	Variable Definition
OPMech	Equals 1 if the buyer chooses to post the project under the OP mechanism, 0 otherwise
ProjectSize	The level of the buyer's budget
BuyerFami	The buyer's familiarity with the current project; number of words in the project description
BuyerExp	Number of projects the buyer has posted before
BuyerDistrust	Equals 1 if the buyer requires any of the three types of guarantees, 0 otherwise
AucDuration	Number of days the auction keeps active
BuyerLoc	The buyer's location
BuyerAuth	Equals 1 if the buyer has passed identify verification, 0 otherwise
ProjectCate	The project category of the focal project
Month	The month when the project was posted

Buyers always intend to elaborate on this description: clarity and detail provide potential service providers with the information they need, which attracts more bids. It also reduces communication costs for both the buyer and the service provider, demonstrates the buyer's know-how with the project, and prevents potential cheating behaviour on the part of the service provider. The amount of project information provided reflects the buyer's familiarity with it, ceteris paribus.

BuyerExp, a buyer's experience, is measured by the number of projects (including both FP and OP projects) that the buyer has posted before in this focal market.

BuyerDistrust refers to the degree of a buyer's distrust in the community of service providers. For this, we use a buyer's requirement on guarantees as a proxy. The marketplace offers *guarantee* options for buyers to control risks in project implementation. Service providers can offer three types of service guarantees: to guarantee the project will be completed on time, to guarantee free after-sale services for three months, and to guarantee the work is original. To claim a service guarantee, a service provider needs to place a deposit at the marketplace, which can be withdrawn after the guarantee period. When buyers post a project, they can require one or all three guarantees, and only the service providers who offer those that are required can bid for the project. These guarantee options do not incur any financial cost to buyers, so distrust in service providers is the primary, if not sole, reason for buyers to use them. Our measure differs from those used in previous studies. Ba and Pavlou (2002), Li et al. (2009), Pavlou and Dimoka (2006) use reputation scores or feedback as indicators of a buyer's trust in individual sellers, because the research focuses on the impact of seller idiosyncrasy on buyer's trust. Our research considers trust as the individual buyer's psychological perception regarding the whole community of service providers. Hence, a measure that reflects the buyer's overall attitude toward the pool of the potential service providers is chosen instead.

Several control variables are also used in the analysis, including *AucDuration* (auction duration), *BuyerLoc* (buyer location dummies) and *BuyerAuth* (buyer authentication, whether the buyer passed identity verification).

The projects are taken from seven categories: design, web & software development, writing & translation, decoration, sales & marketing, business services, and creative ideas. We use dummy variables (*ProjectCate*) to control the category effect, as well as month dummies (*Month*) to control time effect when the project was posted.

Empirical models and estimation methods

Equation (1) outlines the empirical model for estimating how buyers choose between the OP and FP mechanisms. We index the project by *i*, the buyer of the project by *u,* and the time when the project was posted by *t*. The dependent variable is a binary indicator of whether the buyer chooses the OP mechanism. The explanatory variables include project size, buyer familiarity with the project, buyer experience and buyer distrust in service providers. We control for auction characteristics, i.e. auction duration; buyer characteristics including buyer location dummies and buyer authentication dummy; project category dummies and month dummies. We took natural logarithms of the highly skewed variables (*AucDuration*, *BuyerExp*, *BuyerFami*) in the estimation to address non-normality (Y. Hong et al. 2015; Khern-am-nuai et al. 2018; Lin et al. 2019).[6] We conduct binary logistic regression analyses to test the hypotheses, as this is a common regression model to examine agents' dichotomous choices. As only 11% of the the buyers posted more than one project during the research time window, the dataset as a panel cannot be used to consider buyers' fixed effect. The buyers in the online outsourcing market set the value of three explanatory

[6] For variables that contain zero (*BuyerExp*), the lowest non-zero value (+1) was added before logarithm transformation (Y. Hong et al. 2015; McCune and Grace 2002).

Table 2 Descriptive statistics and correlations

Variable	Mean	SD	1	2	3	4	5	6
1. OPMech	0.795	0.403						
2. ProjectSize	2.278	1.387	0.166*					
3. BuyerFami	4.148	0.767	−0.068*	0.103*				
4. BuyerExp	0.356	0.732	−0.188*	−0.105*	0.069*			
5. BuyerDistrust	0.105	0.307	−0.093*	0.008	0.096*	0.031*		
6. AucDuration	1.961	0.694	0.238*	0.255*	0.093*	−0.103*	0.061*	
7. BuyerAuth	0.122	0.328	−0.129*	−0.051*	0.047*	0.333*	0.079*	−0.047*

Coefficient significance level: *$p < 0.05$. To address non-normality in the variables, we took natural logarithms of the highly skewed variables (*AucDuration, BuyerExp* and *BuyerFami*)

variables (project size, buyer familiarity with the project, buyer distrust in service providers) and that of dependent variable (pricing rule) at almost the same time. However, these explanatory variables are mainly determined by either the project characteristics, or the buyers' overall perception of the online outsourcing market. They are not significantly influenced by the pricing rule of a specific auction. Moreover, the choice of pricing rule is located at the bottom of the CFB-generating page.[7] Or, cognitively, buyers make decisions of the explanatory variables before they decide the pricing rule. Therefore, reverse causality in this study is not considered to be a serious issue. When constructing the interaction term of project size and buyer experience, as well as the interaction of buyer distrust and buyer experience, we standardize the independent variable and the moderator to eliminate the possible multicollinearity.

$$\begin{aligned} OPMech_{i,u,t} &= \beta_0 + \beta_1 \times ProjectSize_i + \beta_2 \times BuyerFami_{i,u} \\ &+ \beta_3 \times BuyerExp_{i,u} + \beta_4 \times BuyerDistrust_{i,u} + \beta_5 \\ &\times ProjectSize_i \times BuyerExp_{i,u} + \beta_6 \times BuyerDistrust_{i,u} \\ &\times BuyerExp_{i,u} + \beta_7 \times (AuctionControls_i) + \beta_{8-12} \times \left(BuyerControls_{i,u}\right) \\ &+ ProjectCate_i + Month_t + \varepsilon_{i,u,t} \end{aligned} \tag{1}$$

Analyses and results

Main analysis

Table 3 reports the logistic regression results with estimated coefficients. In Column (1), we examined the baseline model with only controls. Column (2) adds independent variables, i.e. the effect of project size, buyer familiarity with the project, buyer experience, and buyer distrust in the community of service providers on the buyer's selection of pricing rule. Column (3) and Column (4) indicate the interaction effects separately. Column (5) is the full model. As shown in Column (2), the coefficient of project size is significantly positive ($\beta = 0.324$, $p < 0.001$), indicating that buyers tend to choose the OP mechanism when the project is large and complex. Thus, H1 is supported. Buyer's familiarity with the project has a strongly negative impact on the buyer's selection of the OP mechanism ($\beta = -0.234$, $p < 0.001$), supporting H2. Buyer experience is significantly negatively related to the buyer's selection of the OP mechanism ($\beta = -0.31$, $p < 0.001$), which indicates that buyers are more likely to choose the FP mechanism when they are more experienced in this marketplace. This is consistent with the conjecture in H3a and rejects H3b. Buyer distrust has a significantly negative influence on buyer's selection of the OP mechanism ($\beta = -0.619$, $p < 0.001$). H5 is supported.

All the above results of the relationship between independent variables and dependent variables are further reinforced in the full model as shown in Column (5). The positive effect of project size ($\beta = 0.333$, $p < 0.001$), the negative effect of buyer's familiarity with the current project ($\beta = -0.228$, $p < 0.001$), the negative effect of buyer experience ($\beta = -0.36$, $p < 0.001$), and the negative effect of buyer distrust ($\beta = -0.643$, $p < 0.001$) on the buyer's selection of the OP mechanism are all significant.

As shown in Column (3), the interaction of project size and buyer experience has a significantly negative effect on the buyer's pricing rule choice ($\beta = -0.088$, $p < 0.01$). H4 is supported. It means that the positive effect of project size on buyer's preference of OP mechanisms is weakened as a buyer's experience increases. Experienced buyers have a higher capability of absorbing and analyzing information, and thus are more confident in providing an accurate budget estimate when facing the same-sized project. Column (4) shows a significant positive effect of the interaction of buyer experience and buyer distrust ($\beta = 0.071$, $p < 0.01$). H6 is supported. The negative effect of buyer distrust on the choice of OP mechanism is weakened as the buyer's experience increases. The result proves that buyer experience does help to acquire knowledge in identifying and analyzing credible

[7] The CFB-generating page is a page the buyer uses to create a CFB. It is different from the "CFB" page (examples shown in Fig. 1) that is displayed to service providers.

Table 3 Logit model to study buyers' selection of pricing rule

DV: OPMech	(1)	(2)	(3)	(4)	(5)
Constant	−0.426(0.111)***	0.454(0.18)*	0.451(0.18)*	0.453(0.18)*	0.45(0.179)*
Control Variables					
AucDuration	0.782(0.037)***	0.723(0.038)***	0.72(0.038)***	0.724(0.038)***	0.721(0.038)***
BuyerAuth	−0.508(0.086)***	−0.331(0.088)***	−0.306(0.088)***	−0.337(0.088)***	−0.31(0.088)***
BuyerLoc_East	−0.303(0.283)	−0.133(0.288)	−0.141(0.287)	−0.128(0.288)	−0.138(0.287)
BuyerLoc_Cent	−0.387(0.162)*	−0.145(0.166)	−0.164(0.166)	−0.138(0.167)	−0.16(0.166)
BuyerLoc_West	−0.143(0.184)	0.03(0.188)	0.029(0.187)	0.022(0.187)	0.021(0.187)
BuyerLoc_NorEas	−0.379(0.081)***	−0.12(0.085)	−0.139(0.085)	−0.11(0.085)	−0.131(0.085)
Independent Variables					
ProjectSize		0.324(0.027)***	0.337(0.027)***	0.319(0.026)***	0.333(0.027)***
BuyerFami		−0.234(0.034)***	−0.232(0.034)***	−0.23(0.034)***	−0.228(0.034)***
BuyerExp		−0.31(0.035)***	−0.355(0.038)***	−0.31(0.035)***	−0.36(0.038)***
BuyerDistrust		−0.619(0.079)***	−0.602(0.08)***	−0.653(0.08)***	−0.643(0.08)***
Interactions					
ProjectSize*BuyerExp			−0.088(0.029)**		−0.1(0.029)***
BuyerDistrust*BuyerExp				0.071(0.024)**	0.08(0.024)***
Fixed Effects					
Project Category effect	Yes	Yes	Yes	Yes	Yes
Time (Month) effect	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.082	0.120	0.121	0.121	0.122
VIF (Max)	2.85	2.87	2.87	2.87	2.87
VIF (Mean)	1.58	1.53	1.52	1.51	1.5
CIS	11.81	21.85	21.89	21.85	21.89
Log likelihood	−4460.383	−4279.307	−4274.904	−4275.054	−4269.435
# of Buyers	7966	7966	7966	7966	7966
# of Auctions	9592	9592	9592	9592	9592
# of Observations	9592	9592	9592	9592	9592

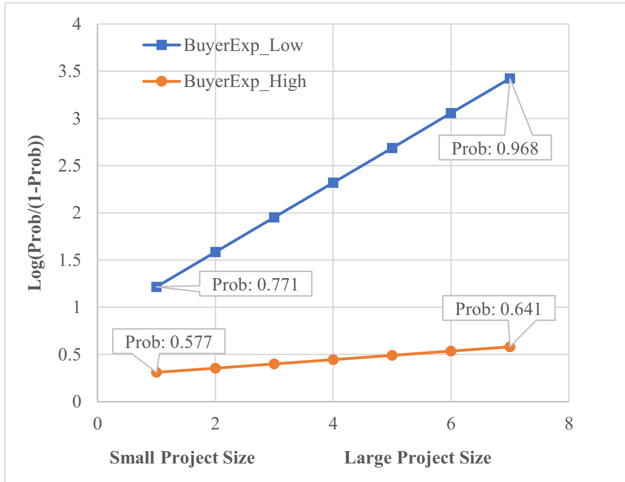
Standard errors are reported in parentheses; Coefficient significance level: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$; Two-tailed tests

signals. The significance of the two interaction effects are also supported by the full model in Column (5).

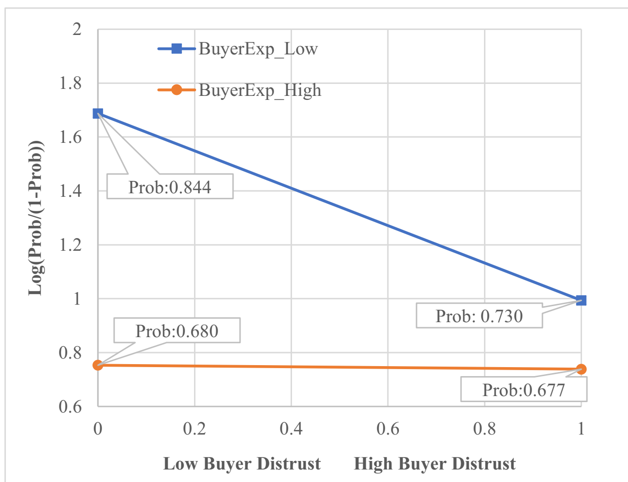
Figure 3 elaborates on the economic meanings of two interaction terms. Figure 3(a) illustrates the effect of the interaction of buyer experience and project size; Fig. 3(b) demonstrates the effect the interaction of buyer experience and buyer distrust. The lines with circular points in Fig. 3(a) and Fig. 3(b) show how the propensity for experienced buyers (when they have posted 40 projects before) to choose the OP mechanism changes, along with project size and buyer distrust in potential service providers, respectively. The lines with square dots show the case of inexperienced buyers (when the buyer has not posted projects before). Note that "Prob" in the figure refers to the buyer's probability of choosing the open-price mechanism. In both Fig. 3(a) and 3(b), the line with square dots is higher than the line with circular points, supporting H3a that experienced buyers, compared with inexperienced buyers, are more willing to use the fixed-price mechanism.

In Fig. 3(a), the slopes of both lines are positive. That means the buyer's propensity to select the open-price mechanism increases with project size (H1). The difference in the slopes of the two lines represents the impact of the interaction of project size and buyer experience. The square dotted line has a larger slope than the circular dotted line, indicating that inexperienced buyers are more affected by project size compared with experienced buyers. H4 is supported. In other words, when buyers deal with large-sized projects where more information is needed for budget estimation, they are inclined to use the open-price mechanism. In this instance, service providers provide additional information on the project budget in their bids. Trading experience helps buyers reduce the anxiety of incomplete information and moderates the impact of project size on their willingness to use the open-price mechanism.

Both lines in Fig. 3(b) have negative slopes, which support H5 that buyers are more likely to select the fixed-price mechanism when they trust service providers less. Furthermore, the line



(a) Interaction of Project Size and Buyer Experience in Predicting Buyers' Selection of OP Mechanism



(b) Interaction of Buyer Distrust and Buyer Experience in Predicting Buyers' Selection of OP Mechanism

Fig. 3 Interactions in Predicting Buyer's Selection of the OP Mechanism

with square points is on a steeper negative slope than the line with circular dots, implying that inexperienced buyers are more influenced by distrust. Or, buyer experience moderates the influence of buyer distrust on the tendency to use the open-price mechanism. H6 is therefore supported.

Robustness check

We test the robustness of the results in several alternative perspectives. First, we use alternative measures for some variables, with a different measure for buyer authentication. Besides identity verification, buyers on the platform can verify their contact phone number, email address and bank account. These verifications are all optional to buyers. The number of verifications a buyer has passed (*BuyerAuth_All*) is used to measure buyer authentication, instead of the original measure "whether the buyer has passed identification verification". The value of the new measure, *BuyerAuth_All,* is from the set $\{0, 1, 2, 3, 4\}$, while the original measure, *BuyerAuth,* is a binary variable. The estimation result with this new measure is presented in Column (1) of Table 4. We also replace the proxy for buyer familiarity with the number of attached documents (*ProjectFami_Attach*) that the buyer provided when the project was posted, and the result is presented in Column (2) of Table 4. Column (3) reports the estimation results when both the above measures are used, instead of those in the main analyses. Overall, the findings are consistent when using different measures.

Second, we examine multicollinearity in model estimations, and this provides additional support for the robustness of the results. The collinearity diagnostics tests for all

Table 4 Robustness checks on buyers' selection of pricing rule

DV: OPMech	(1)	(2)	(3)
Constant	0.632(0.18)***	−0.421(0.117)***	−0.148(0.119)
Control Variables			
AucDuration	0.688(0.038)***	0.7(0.038)***	0.668(0.038)***
BuyerAuth		−0.314(0.088)***	
BuyerAuth_All	−0.343(0.031)***		−0.35(0.03)***
BuyerLoc_East	0.352(0.292)	−0.121(0.287)	0.376(0.292)
BuyerLoc_Cen	0.279(0.17)	−0.189(0.165)	0.264(0.17)
BuyerLoc_West	0.433(0.191)*	0.016(0.187)	0.439(0.192)*
BuyerLoc_NorEast	0.188(0.087)*	−0.126(0.085)	0.202(0.088)*
Independent Variables			
ProjectSize	0.316(0.027)***	0.317(0.027)***	0.301(0.027)***
BuyerFami	−0.206(0.034)***		
BuyerFami_Attach		−0.128(0.033)***	−0.114(0.033)***
BuyerExp	−0.254(0.039)***	−0.365(0.038)***	−0.256(0.039)***
BuyerDistrust	−0.558(0.08)***	−0.663(0.08)***	−0.575(0.08)***
Interactions			
ProjectSize*BuyerExp	−0.075(0.03)*	−0.104(0.029)***	−0.078(0.03)**
BuyerDistrust*BuyerExp	0.073(0.025)**	0.082(0.024)***	0.074(0.025)**
Fixed Effects			
Project Category effect	Yes	Yes	Yes
Time (Month) effect	Yes	Yes	Yes
Pseudo R^2	0.133	0.119	0.131
VIF (Max)	2.88	2.87	2.88
VIF (Mean)	1.53	1.5	1.53
CIS	22.39	13.81	14.35
Log likelihood	−4212.896	−4284.397	−4225.165
# of Buyers	7966	7966	7966
# of Auctions	9592	9592	9592
# of Observations	9592	9592	9592

Standard errors are reported in parentheses; Coefficient significance level: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$; Two-tailed tests

models was performed. The max variance inflation factors (VIF) is below 3 in all models, indicating multicollinearity is not a problem (Kutner et al. 2004). Table 5 presents the VIFs of the regression models. The condition index statistics (CIS) is checked for the full model and it is 21.89, less than 30, suggesting multicollinearity is not an issue in this dataset (Belsley et al. 2004). In summary, the findings are robust throughout these tests.

Discussion

Table 6 summarizes our major empirical findings.

The empirical results show that information, both the information needed (H1) and the information possessed (H2) by a buyer in evaluating a project budget, plays a critical role in the pricing rule decision. Specifically, the more information needed for accurate budget estimation, measured by the project size in regression, the more likely the buyer prefers to use the open-price mechanism. Meanwhile, the project information that the buyer possesses, reflected by the length of the project description, is negatively related to the propensity to choose the open-price mechanism. This implies that when buyers face incomplete information about a project, they are inclined to use the open-price mechanism to listen to bid prices from service providers. When they have sufficient information, they would prefer to control the project budget directly through the fixed-price mechanism.

There is also evidence that buyers are inclined to use a fixed-price mechanism when they have less trust in service providers. Compared with the fixed-price mechanism, the open-price mechanism allows service providers to bid on one additional attribute, project price. Selecting the winning bid hence becomes more comprehensive, as more information

Table 5 The variance inflation factors in model estimation

DV: OPMech	(1)	(2)	(3)	(4)	(5)
Control Variables					
AucDuration	1.1	1.15	1.15	1.15	1.15
BuyerAuth	1.45	1.49	1.5	1.5	1.5
BuyerLoc_East	1.04	1.04	1.04	1.04	1.04
BuyerLoc_Cen	1.1	1.1	1.1	1.1	1.1
BuyerLoc_West	1.07	1.08	1.08	1.08	1.08
BuyerLoc_NorEast	1.33	1.41	1.42	1.42	1.42
Independent Variables					
ProjectSize		1.32	1.32	1.32	1.32
BuyerFami		1.05	1.05	1.05	1.05
BuyerExp		1.24	1.33	1.24	1.33
BuyerDistrust		1.04	1.04	1.05	1.05
Interactions					
ProjectSize*BuyerExp			1.11		1.12
BuyerDistrust*BuyerExp				1.02	1.03
Fixed Effects					
Project Category effect	Yes	Yes	Yes	Yes	Yes
Time (Month) effect	Yes	Yes	Yes	Yes	Yes
VIF (Max)	2.85	2.87	2.87	2.87	2.87
VIF (Mean)	1.58	1.53	1.52	1.51	1.5
CIS	11.81	21.85	21.89	21.85	21.89

is contained in the bids. However, to find the optimal match, the buyer incurs increased transaction costs with the more comprehensive selection. When buyers have less trust in the community of service providers, they perceive more risks in the bid prices offered. Therefore, evaluating and comparing the bids with price attribute becomes more costly for buyers, so using the fixed-price mechanism and relying on their own budget estimation is preferred. With the online outsourcing market, buyer distrust in service providers mainly results from information asymmetry between the two parties. Our study suggests that when facing severe information asymmetry, buyers tend to simplify the matching process (the fixed-price mechanism rather than the open-price mechanism).

These results explore the significant role of buyer experience in deciding on pricing rules through both direct and indirect (moderating) effects. Two opposite hypotheses are proposed from two different perspectives regarding the direct effect of buyer experience. H3a, from the perspective of transaction cost theory, contends that a buyer's experience brings an information advantage in estimating the project budget, and consequently motivates the buyer to use the fixed-price mechanism. H3b presumes that experience helps a buyer better understand expected buyer surplus under the two pricing rules. As existing modelling and experimental studies have shown that the auction with more bidding attributes engenders more buyer surplus, experienced buyers should be more willing to use open-price auctions, where one more attribute (i.e. project price) is open for bidding. Our empirical results demonstrate a significantly negative impact of buyer experience on the propensity to use the open-price mechanism. This means the information advantage effect of buyer experience, or the transaction cost concern, is dominant. Opening the price attribute to bid in auctions either does not generate more buyer surplus, or the generated additional buyer surplus is so limited that its influence is much weaker than concern about incomplete information on how buyers choose pricing rule. This finding calls for further study on auction bid dimensionality. Uncertainty and risk should be introduced and carefully examined in future analytical models or experiment designs. It is possible that incomplete information influences the bidding strategies of service providers and the buyer's winning bid selection process. The expected buyer surplus might be lower when more attributes are open to bid in auctions.

Conclusion

In this paper, we empirically identified conditions under which the buyer prefers the open-price mechanism to the fixed-price mechanism. Based on a dataset from an online labour market in China, it was found that buyers tend to use the open-price mechanism when their projects are larger, while their propensity to use the fixed-price mechanism increases if they are more familiar with the project, have greater trading experience in the

Table 6 Main Findings

Hypotheses	Findings
H1: Buyers prefer the OP mechanism to the FP mechanism when their projects are characterized as of a larger size.	S
H2: Buyers prefer the FP mechanism to the OP mechanism when they are more familiar with the focal project.	S
H3a: Buyers prefer the FP mechanism to the OP mechanism when they are more experienced with this market.	S
H3b: Buyers prefer the OP mechanism to the FP mechanism when they are more experienced with this market.	NS
H4: Buyer experience attenuates the positive effect of project size on the selection probability of the OP mechanism.	S
H5: Buyers prefer the FP mechanism to the OP mechanism when they have less trust in the community of service providers.	S
H6: Buyer experience attenuates the negative effect of buyer distrust on the selection probability of the OP mechanism.	S

S is short for "supported"; NS is short for "Not Supported" market, and less trust in service providers. Moreover, buyer experience has significant moderating effects on the impact of project size and buyer distrust. Alternative measures for buyer authentication and buyer familiarity with the current project were used to check the robustness of this empirical study. The results remained consistent. Multicollinearity was also examined with VIF and CIS, which further reinforced the results.

The empirical results reveal that incomplete information and information asymmetry – rather than the expected buyer surplus – play critical roles in multi-attribute buyer-determined auctions, especially on buyers' preference on bid dimensionality. Although existing analytical and experimental studies show that auctions with more bidding attributes benefit buyers more than those with less bidding attributes, our study indicates different insights. Experienced buyers, who are supposed to have more accurate *ex ante* expectation of auction outcomes under the two pricing rules, are not allured by the theory-suggested higher buyer surplus with the open-price mechanism. Instead, compared with inexperienced peers, experienced buyers are more willing to use the fixed-price mechanism. Based on this empirical evidence, further research is called on to investigate strategic decisions by both buyers as well as service providers in multi-attribute auctions, especially when the concerns about incomplete information and information asymmetry are considered.

This research contributes to both the literature on online labour markets and that of reverse auctions, especially on bid dimensionality. It also offers several managerial implications for online labour market platforms. By understanding the reasons behind how buyers decide on pricing rules, the marketplace can better design its matching mechanisms and provide particular incentives to enhance its activeness and sustainability.

Our analysis is subject to a few limitations. First, we use several proxies for the variables of buyer characteristics. For example, the number of words in the project description is used to proxy for a buyer's familiarity with the proposed project, and the buyer's requirement of guarantee(s) to proxy for distrust in the community of service providers. These proxies are essentially buyers' decisions, and although they are believed to be highly associated with their respective characteristics, the possibility of measurement error cannot be completely ruled out. Future research could use first-hand data to accurately measure the specific features of buyers to obtain more convincing results. Second, this research only investigated how buyer characteristics and project features (specifically project size) affect buyers' decision choice on pricing rules, but did not explore the detailed difference between the performances under the two mechanisms, which might be of more substantial meaning to both academic understanding and business practices. Future research with more accurate measures and more sophisticated econometric models could further investigate how these pricing rules affect project outcomes.

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