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Learning from Winners: A Strategic Perspective of Improving Freelancers' Bidding Competitiveness in Crowdsourcing

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ABSTRACT

The rapid growth of crowdsourcing grants freelancers unprecedented opportunities to materialize their expertise by bidding in specific tasks. Despite lowering freelancers' participation costs, the bidding mechanism meanwhile induces intense competition, rendering it difficult for freelancers to submit competitive bids. Although previous research has disentangled several bidding strategies, scant attention was paid to whether and how freelancers should learn to adjust their bidding strategies and improve bidding competitiveness during the journey of participating in multiple tasks. To fill in this gap, we adapt a set of bidding strategies from auction literature into the crowdsourcing context. Leveraging the lens of vicarious learning, we advance that freelancers' learning from winners on bidding strategies will enhance their bidding competitiveness, which is moderated by task complexity. Our preliminary results suggest a significant relationship between strategic learning and bidding competitiveness, along with the moderating effect of task complexity. Expected contributions and future schemes are discussed finally.

Keywords

Crowdsourcing, Bidding Competitiveness, Bidding Strategies, Vicarious Learning, Task Complexity.

INTRODUCTION

Crowdsourcing is gaining momentum, with a batch of crowdsourcing platforms serving as online intermediaries that connect clients and freelancers to accomplish given tasks. According to the World Bank, freelancers have occupied 47% of global workforce. Most crowdsourcing tasks are operated based on the bidding mechanism (Liang et al. 2022), in which clients post task descriptions to recruit potential freelancers who can fulfill particular requirements (Gu et al. 2021). In response, freelancers submit bids that outline their skillset, expected price, work duration, and concrete proposals (Hong et al. 2020). Clients then evaluate these candidates' bids and determine the winner to execute tasks . Despite bidding mechanism empowering freelancers more opportunities to participate in different kinds of tasks and demonstrate unique advantages, it meanwhile induces intense competition. Many freelancers are struggling with submitting competitive bids and repeatedly suffering failures. As a matter of fact, 50% of freelancers quit after one year, and 80% quit within three years. To guarantee freelancers' substantial earnings in the long run, an in-depth appreciation is needed on how to improve their bidding competitiveness in crowdsourcing tasks.

Alongside the extensive implementation of bidding mechanism in crowdsourcing tasks, freelancers tend to develop certain bidding strategies (Hong et al. 2020). In this study, we define bidding strategies as a set of bidding behaviors freelancers have shaped in the bidding process to fulfill clients' requirements and defeat other rivals. Despite unraveling several kinds of bidding strategies that facilitate freelancers to submit competitive bids (Hong et al. 2016; Hwang et al. 2019; Ke et al. 2021), previous literature has not investigated whether freelancers would adjust their bidding strategies to continuously improve bidding competitiveness. Basically, most freelancers on crowdsourcing platforms do not submit bids only once. During the journey of participating in multiple tasks, freelancers may encounter varied requirements and rivals. On this occasion, freelancers may seek strategic adjustment by learning others' bids. Since winners possess extraordinary expertise and experience, it is critical to disentangle the relationship between learning from winners on bidding strategies and bidding competitiveness. Furthermore, our research diverges from previous literature on freelancers' learning in crowdsourcing, which views learning as a static outcome (Ye 2022). We argue that learning related to bidding strategies should be seen as a dynamic process, where different task features may influence freelancers' decision-making during each bidding process. Given the empirical evidence indicating that task complexity is a crucial contingent factor in crowdsourcing (Hong et al. 2020), whether it will influence the effectiveness of learning on bidding strategies is also worth investigating.

To address the knowledge gaps mentioned above, we turn to the auction literature, which has extensively studied bidding strategies such as bid sniping, bid shading, and bid bundling (Cui et al. 2020; Gupta et al. 2020; Subramaniam et al. 2009). Drawing upon the theoretical lens of vicarious learning, we propose that a positive relationship between learning from successful bidders on these strategies and freelancers' bidding competitiveness, with task complexity moderating this relationship. To test our hypotheses, we gather objective data from a large-scale crowdsourcing platform and employ linear growth modeling techniques.

Findings derived from this study are expected to contribute to existing literature and practice on three fronts. Firstly, we advance a set of bidding strategies derived from the auction literature by taking the unique features of crowdsourcing tasks into consideration. In this regard, we provide an actionable guideline for freelancers on specific strategies they should learn to submit competitive bids. Secondly, we explicate the vital important role of winners as the learning object, which complements the extant research on vicarious learning by trimming down the learning focus from a group of peers to a designated target. Thirdly, we shed light on the role of task complexity as a moderator in strategic learning, providing valuable insights for freelancers to refine their learning strategies when faced with varying levels of task complexity.

THEORETICAL FOUNDATION AND HYPOTHESES FORMULATION

Bidding Mechanism and Bidding Competitiveness in Crowdsourcing

The bidding mechanism employed in online platforms is derived from traditional auctions. The bidding process entails clients announcing auction requirements and relevant parameters, followed by bidders submitting bids to compete for given goods (Liang et al. 2022). Similarly, freelancers in crowdsourcing tasks submit bids to demonstrate their skills and expertise that can fulfill clients' requirements on particular products or services (Hong et al. 2016; Hong et al. 2020). The bidding mechanism is designed to encourage a sufficient number of freelancers to participate in tasks, but as more freelancers engage in bidding, it can lead to intense competition and increase the difficulty for freelancers to submit competitive bids.

Several studies have shed light on how freelancers should submit competitive bids in crowdsourcing tasks. Hong et al. (2016) argued that observing other rivals' bids was helpful to increase freelancers' bidding competitiveness. Ke et al. (2021) indicated freelancers could use pricing strategies to match clients' quality preferences and demonstrate their bidding competitiveness. Hwang et al. (2019) discovered that freelancers who concentrated on particular task domains would outperform generalists in submitting competitive bids. Specifically, we define bidding competitiveness as the extent to which a freelancer's bid can meet clients' requirements and outperform competitors, including the winner's bid.

Vicarious Learning

Vicarious learning refers to the process of obtaining new knowledge through the observation of others' behaviors rather than individuals' own experience (Bandura 1977). People do not learn from their direct experience of behavioral outcomes. Instead, they learn by observing others' behaviors to avoid unnecessary costs. Vicarious learning relies on information functions, through which observers gradually comprehend the model's iconic features (Bandura 1977). When observers continuously concentrate on relevant information, they can behave like the model in an autonomous manner and as a result, the effectiveness of vicarious learning will improve.

Specific to crowdsourcing, Riedl et al. (2018) studied how freelancers summarized extant experience and leveraged rivals' information signals to enhance performance. Ye (2022) found that vicarious learning would facilitate freelancer performance, which was moderated by the uncertainty of competitions and tasks. In crowdsourcing tasks, vicarious learning can help freelancers to better understand the structure of successful bids and adjust their bidding strategies (Riedl et al. 2018). Given the superior abilities and abundant experience of winners, freelancers can disentangle essential features of winners' bidding strategies and learn from these strategies accordingly. More importantly, although Ye (2022) has examined the boundary condition of freelancers' vicarious learning in crowdsourcing tasks, there is a dearth of research that considers how the effect of learning on bidding strategies may be contingent on task-related factors. We argue that freelancers' learning on bidding strategies pertains to a dynamic process influenced by each task's characteristics. Specifically, task complexity has been demonstrated as a key factor to impact how freelancers mobilize cognitive resources and leverage expertise (Hong et al. 2020; Mo et al. 2018). To this end, task complexity may also affect the effect of learning on bidding strategies.

Learning on Bidding Strategies

Crowdsourcing tasks involve an intense competition (Gu et al. 2021), Since the bidding mechanism of crowdsourcing tasks are stemmed from online auctions, we turn to the auction research that probes into bidding strategies including bid sniping (Cui et al. 2020), bid shading (Gupta et al. 2020), and bid bundling (Subramaniam et al. 2009). Specifically, bid sniping pertains to the strategy where a bidder waits until an appropriate moment to place a bid. In crowdsourcing tasks, freelancers' bidding sequence relates to the degree to which they can attract clients' attention and absorb strengths from others' bids. Bid shading denotes the strategy where a bidder places a bid lower than their maximum price with the aim of winning at a lower price. In crowdsourcing tasks, bidding pricing concerns how freelancers weight their profits and competitive advantages over other rivals. Bid bundling is the strategy where a bidder groups several smaller items or services into a single bid, intending to win the entire package. Contextualized to crowdsourcing tasks, the participation pattern of task category represents whether freelancers accumulate deep or diverse experience, which subsequently determines how they can utilize different pieces of knowledge in given tasks. The large number of candidates per task may prompt freelancers to scrutinize earlier winners' bids and adjust their bidding strategies. Adapting the aforementioned bidding strategies into crowdsourcing tasks, we argue that freelancers' strategic learning is related to their observations of winners' **bidding sequence**, **bidding pricing**, and **bidding specialization**.

First, crowdsourcing research has illuminated the importance of freelancers' bidding sequence (Bockstedt et al. 2016; Bockstedt et al. 2022; Yao et al. 2020). There has been a mixed conclusions in these studies. Bockstedt et al. (2016) emphasized that early bidding provides freelancers more opportunity to obtain evaluations from clients; whereas Bockstedt et al. (2022) argued that late bidding could avoid the free-riding by other rivals and safeguarded freelancers' intellectual property. Yao et al. (2020) discovered that both early and late bidding would result in superior performance. As a departure from the previous debate, the purpose of our study is to assert that freelancers' learning on bidding sequence can render their bids more competitive.

Learning on bidding sequence is defined as the extent to which a freelancer observes and imitates the bidding sequence of prior winners in the current task. The extant literature on organizational behaviors suggested that vicarious learning shed light on the direction for employees' future behaviors and prevent them from getting into the same trap (Kim et al. 2007). Likewise, in crowdsourcing tasks, the bidding sequence of winners manifests their competencies to attract client attention and rich experience in dealing with competition. On this occasion, learning on the winner's bidding sequence can illustrate an appropriate entry timing that not only caters to clients' taste, but also relative advantages to existing rivals.

Hypothesis 1: Learning on bidding sequence is positively associated with bidding competitiveness.

Second, a variety of pricing strategies have been developed in crowdsourcing literature. Fu et al. (2021) illustrated how freelancers' experience and pricing strategies interacted to influence their bidding performance. Foong et al. (2021) detailed how freelancers' job status was related to their pricing strategies. To maximize the interests of clients and achieve competitive advantages, freelancers may lower their price relative to earlier rivals (Ludwig et al. 2022).

Learning on bidding pricing refers to the extent to which a freelancer observes and imitates the pricing of prior winners in the current task. Winners' pricing denotes their abilities on two fronts. On the one hand, pricing indicates the winner's accurate judgment of the cost to fulfill clients' requirements. Therefore, by learning the winner's pricing in previous tasks, freelancers are more certain about the value of targeted products or services and their bidding competitiveness should increase. On the other hand, pricing also reflects winners' unique understanding of task difficulty. To this end, learning on bidding pricing can help freelancers to mitigate the misfit between their abilities and clients' requirements, which facilitates their bids to be more competitive.

Hypothesis 2: Learning on bidding pricing is positively associated with bidding competitiveness.

Third, because crowdsourcing platforms encompass an array of tasks, bidders can analyze rivals' features across a variety of fields and determine whether to concentrate on a particular field (Hwang et al. 2019). Task specialization, despite receiving little attention in crowdsourcing, was shown to have mixed effects on organizational performance. Ferguson et al. (2013) showed that operating a wide range of businesses could nevertheless lead to poor fit with any particular category. As opposed to this, Durand et al. (2013) advocated the value of category spanning when firms achieved a smooth categorical combination.

Learning on bidding specialization refers to the extent to which a freelancer observes and imitates the bidding specialization of prior winners in the current task. A high level of bidding specialization entails freelancers' expertise and skillset. When accumulating more experience in a given task category, freelancers will conceive such tasks as routinized ones and finish them in an efficient way. Moreover, bidding specialization manifests freelancers' capabilities of knowledge absorption and offering feasible proposals (Hwang et al. 2019). As the successful model, winners are more familiar with clients' requirements and competition environment in different types of tasks. From this respect, learning on bidding specialization can furnish concentrated experience and competitive advantages for freelancers.

Hypothesis 3: Learning on bidding specialization is positively associated with bidding competitiveness.

Task Complexity

Task complexity has been demonstrated to influence individuals' learning effect (Nahrgang et al. 2013). In this study, we define task complexity as the extent to which freelancers need to spend cognitive and capability resources on fulfilling the given task (Sun et al. 2012). Simple tasks involve easy jobs, requiring lower level of skills . Therefore, these tasks provide more autonomy for freelancers' use of bidding strategies. On the contrary, complex tasks consume more cognitive resources and effort from freelancers, which reinforces the importance of learning on bidding strategies.

The effect of strategic learning on bidding competitiveness is likely to be contingent on task complexity. First, winners' bidding sequence suggests their abilities to acquire bidding information and detect other rivals' competitiveness in an appropriating entry timing. Extant literature claimed that with the increase of task complexity, organizational members were faced with more uncertainty, because they could not identify relevant evidence or infer changes of task environment (Porck et al. 2019). Similarly, in complex tasks, it is more difficult for freelancers to obtain information that is helpful for submitting competitive bids. As a consequence, Freelancers possess a higher tendency to learn on winners' bidding sequence to enhance their bidding competitiveness.

Hypothesis 4: Task complexity positively moderates the relationship between learning on bidding sequence and bidding competitiveness.

Task complexity may also strengthen the effect of learning on bidding pricing. Previous research justified that employees might yield uncertainty about the fulfillment cost when encountering a high level of task complexity (Yee et al. 2021). Under this circumstance, employees are more likely to seek relevant information from other colleagues. Contextualizing this argument to crowdsourcing tasks, when task complexity is high, freelancers cannot ascertain the exact value of required products or services. It is possible that their bidding price is overshadowed by other rivals and their bids lose attention from clients. On this occasion, they have a higher tendency to trace and imitate prior winners' bidding pricing in order to improve their bidding competitiveness. By contrast, in simple tasks, freelancers are more confident in assessing the concrete value of clients' requirements rather than relying on learning from prior winners.

Hypothesis 5: Task complexity positively moderates the relationship between learning on bidding pricing and bidding competitiveness.

Finally, we propose that task complexity will enhance the effect of learning on bidding specialization. Complex tasks are generally unstructured and with a lower level of routinization, such as designing creative products and solving large-scale problems of system development. In complex tasks, freelancers who have accumulated deep knowledge and experience can effectively fulfill clients' requirements. Meanwhile, complex tasks involve fiercer competition that renders it difficult for freelancers. to win (Mo et al. 2018). Learning on task specialization denotes freelancers' absorption of winners' bidding experience in particular tasks. When the level of task complexity increases, freelancers are more likely to summarize prior winners' task category, expecting to gain related experience and enhance their bidding competitiveness. In contrast, freelancers may insist on their own pace of category focus when facing with simple tasks.

Hypothesis 6: Task complexity positively moderates the relationship between learning on bidding specialization and bidding competitiveness.

METHODOLOGY

Data Collection

Our data were collected from a leading crowdsourcing platform in China that incorporates a wide range of task categories such as LOGO design, software development, copywriting, and decoration. Since its inception in July 2010, the platform has attracted more than 23 million users. We developed a Python program to automatically collect objective data including all the pages of freelancers, tasks, and submitted bids. The dataset contained 1128 freelancers who participated in 1420 tasks and submitted 8400 bids. On the whole, each freelancer submitted more than three bids, which met the prerequisite of using linear growth modeling as our analytical approach (i.e., at least three waves of time-series data).

Variable Operationalization

For the dependent variable, we measured **bidding competitiveness** based on the concept of Euclidean distance, which has been used to measure the technological distance of patent portfolio (Hohberger et al. 2015) and the distance of freelancers' problem-solving abilities (Pollok et al. 2019). TextRank algorithm was used to extract keywords from task descriptions and bidding proposals, which represented clients' requirements and freelancers' supplies respectively. Those supplies corresponding to requirements were marked as responsive supplies, while others were marked as additional supplies. Assuming that the number of rivals in the current task was k (k≥1). The number of focal freelancer's responsive supplies that were not overlapped with other rivals' was fr_i (i∈[1,k]); the number of focal freelancer's additional supplies that were not overlapped with other rivals' was fa_i (i ∈ [1,k]). Similarly, the number of the winner's unique responsive and additional supplies was wr_i (i∈[1,k]) and wa_i (i∈[1,k]). Bidding competitiveness was measured as:

$$\frac{\sum_{i=1}^{k}\sqrt{{fr_i}^2+{fa_i}^2}}{\sum_{i=1}^{k}\sqrt{{wr_i}^2+{wa_i}^2}}$$

With regards to independent variables, we measured learning on bidding strategies in the way that freelancer learned from the last task's winner strategies. This was because focal freelancer could not ascertain the winner when submitting bids in the current task. We adopted the **freelancer's order of submitting the bid** and **proposed price for delivering required products** as a proxy for **bidding sequence** and **bidding pricing**. The following formula was used to calculate **bidding specialization**:

$$\frac{n/m}{(\sum_{i=1}^{k}\frac{n_i}{m_i})\,/k}$$

where m was the total number of tasks focal freelancer had participated (m≥3); n was the number of participated tasks belonging to the same category as the m^{th} task (n≥1); k was the number of rivals in the current task (k≥1).

Assuming that focal freelancer's bidding sequence, bidding pricing, or bidding specialization in last task was fs; the winner's bidding sequence, bidding pricing, or bidding specialization in last task was ws. **Learning on bidding sequence, pricing and specialization** was measured as:

$$\frac{\text{fs}\,/\text{ws}}{[\sum_{i=1}^{m-1}\left(\frac{fs_i}{ws_i}\right)]/(m-1)}$$

Concerning our moderator, we used the level of task reward as a proxy for **task complexity**. Task reward has been leveraged to measure task complexity in extant research (Hong et al. 2020). The current platform set 7 different ranges of task reward, which we coded as 1 to 7 from low to high. Assuming that task reward in the current task was tr. The number of tasks focal freelancer has participated was m. Task complexity was measured as:

$$\frac{tr}{(\sum_{i=1}^{m}tr_i)/m}$$

Regarding control variables, we considered three types of attributive differences related to winner, task, and other rivals. On the winner side, we controlled for the difference between focal freelancer and winner in work duration (number of working days proposed in their bids), proposal length (number of characters within bidding proposals), and bidding interval (temporal distance of submission time to the task's starting time). On the task side, we controlled for the difference between the current task and previous tasks in description length (number of characters within task descriptions) and task duration (number of days the task had lasted). On the rival side, we controlled for the difference between focal freelancer and other rivals in professionalism, authentication, qualification, and experience.

Data Analysis

Linear growth modeling (LGM) is a useful approach of depicting, measuring, and analyzing longitudinal changes and dynamic phenomenon (Williams et al. 2003). Specifically, LGM allows us to model freelancers' strategic changes over time and links such growth trajectories with related variables. We used Stata to dissect the relationship between learning on bidding strategies and bidding competitiveness.

Analytical results were reported in Table 1. Due to the space limit, this manuscript does not present the results of control variables. Model 1 showed that learning on bidding sequence (β=0.008, $p<0.05$) and learning on bidding pricing (β=0.007, $p<0.05$) were positively associated with bidding competitiveness, supporting Hypothesis 1 and Hypothesis 2. However, learning on bidding specialization (β=-0.007, $p<0.05$) was negatively associated with bidding competitiveness, thus rejecting Hypothesis 3. We failed to find a significant interaction effect (β=0.001, $p>0.1$) from Model 3. Hence, Hypothesis 4 was not supported. Model 4 and Model 5 revealed that task complexity positively moderated the effect of learning on bidding pricing (β=0.004, $p<0.1$) and learning on bidding specialization (β=0.005, $p<0.05$) on bidding competitiveness, therefore supporting Hypothesis 5 and Hypothesis 6.

	DV = Bidding Competitiveness				
	M1	**M2**	**M3**	**M4**	**M5**
Constant	3.233** (0.016)	3.225** (0.016)	3.231** (0.016)	3.230** (0.016)	3.231** (0.016)
Independent Variables					
LBS	0.008** (0.003)	0.008** (0.004)	0.008** (0.003)	0.007** (0.003)	0.008** (0.003)
LPC	0.007** (0.003)	0.007** (0.003)	0.008** (0.003)	0.010** (0.003)	0.008** (0.003)
LSP	-0.007** (0.003)	-0.007** (0.003)	-0.007** (0.003)	-0.007** (0.003)	-0.006* (0.003)
Moderator					

TC		0.016** (0.003)	0.016** (0.003)	0.016** (0.003)	0.017** (0.003)
Interactions					
LSQ×TC			0.001 (0.003)	0.001 (0.003)	0.001 (0.003)
LPC×TC				0.004* (0.002)	0.004* (0.002)
LSP×TC					0.005** (0.002)
Wald chi-square	19.96**	22.60**	0.05	3.22*	3.70*

Notes: Standard errors for model coefficient estimates are shown in parentheses. Coefficient significance level: **p* <0.05, ** *p* <0.01. LBS=Learning on Bidding Sequence; LPC=Learning on Pricing; LSP=Learning on Specialization; TC=Task Complexity.

Table 1. LGM Results

EXPECTED CONTRIBUTIONS

Our contributions are expected to be threefold. First, we synthesize the evidence from the auction literature together with crowdsourcing characteristics to validate a series of bidding strategies, on which freelancers can learn to enhance their bidding competitiveness. Although previous scholars have uncovered several streams of bidding strategies for submitting competitive bids in crowdsourcing tasks (Hong et al. 2016; Hwang et al. 2019; Ke et al. 2021), none of them have considered the issue of strategic learning as freelancers participate in multiple tasks. Essentially, the competition among freelancers is a long haul in which temporal failures do not mean freelancers are kicked out from crowdsourcing platforms. This study furnishes a timely investigation on freelancers' strategic learning for improving bidding competitiveness.

Second, we extend vicarious learning by expounding winners as the target for freelancers' learning on bidding strategies. Despite extant research has clarified the importance of learning for freelancers (Riedl et al. 2018; Ye 2022), these studies regarded a group of peers as the learning object. Crowdsourcing tasks involve many candidates who employ varied bidding strategies. In this arena, observing and learning every rival's bidding strategy is not a wise choice for freelancers. Instead, we contend that freelancers should concentrate on learning from winners because winning experience has confirmed the validity of winners' bidding strategies. From this respect, our research opens up an avenue to promote the efficiency of strategic learning for freelancers.

Third, even though some studies have investigated the moderating effect on vicarious learning in crowdsourcing tasks (Riedl et al. 2018; Ye 2022), we shed light on task complexity as the boundary condition of learning on bidding strategies. Notably, strategic learning pertains to a dynamic process that may be contingent on the features of each task. In other words, different tasks involve different environments that may influence the effectiveness of learning on bidding strategies. More recently, Ye (2022) acknowledged that environmental features of crowdsourcing tasks were likely to affect freelancers' vicarious learning. Our study responses to this call and provides fine-grained suggestions for freelancers to learn on bidding strategies in both complicated and simple tasks.

DIRECTIONS OF FUTURE RESEARCH

This study can be enriched in the following directions. First, although we validate the effectiveness of learning on bidding strategies through linear growth modeling, our samples include few freelancers from other countries. Given that freelancers with different cultural backgrounds may have different behavioral tendency and learning patterns, cross-cultural examinations are supposed to be conducted in the future to corroborate our findings. Second, previous literature suggests that learning pertains to a subjective process (Aranda et al. 2017), in which psychological and cognitive factors should not be neglected. Despite the objective data used in this study can showcase freelancers' authentic strategic behaviors, we believe experiment or survey can complement our method to yield more interesting findings. Third, it should be acknowledged that this study does not consider the impact of learning period. Thus, comparing the difference between short-term and long-term strategic learning is also a valuable attempt in the future.

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