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Impact of Bonding Capacity on Performance of Construction Contractors and Market

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Abstract

Bonding capacity is an important element in the construction competitive bidding environment. Despite numerous works dedicated to studying different aspects of construction bidding, the impact of bonding capacity on the performance of contractors and market is not explored yet. Using agent-based modelling, this paper aims to examine how bonding capacity affects the financial performance of contractors and market. Agent-based modelling is a powerful modelling tool for simulating the actions and interactions of autonomous agents with the aim of analysing their effects on the system as a whole. The results of this paper show that the extreme limitation of bonding capacity can make the market less efficient. Also, increase in the number of rational contractors as result of a proper bonding capacity limitation restricts the chance of irrational contractors winning from higher uncertainty in cost estimating.

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1. Introduction

Contractor default, being unable to complete the project according to the contractual obligations, can significantly affect the outcome of construction projects [1]. As a risk management strategy, construction owners usually protect themselves against the risk of contractor default by transferring this risk to surety companies by mandating the submission of the performance bond by contractors [2]. Performance bond involves three parties: surety company, owner (obligee), and contractor (principal). The bond guarantees to the owner that the contractor will perform the construction project in accordance with the provisions of the contract. If the contractor fails to perform the contract, the owner may call on the surety to step in and complete the project or correct project deficiencies. Because of the considerable consequences of the default, surety companies, owners, and other stakeholders are interested in predictive models that estimate the potential of contractors' default. As a result, several studies in the literature are dedicated to developing models that predict a contractor's default risk [3-9].

Bonding capacity is the maximum amount of surety credit a surety company will provide to a construction contractor. It is referred to as single job limit or aggregate limit and usually expressed in terms of the largest single construction project that the surety company would be willing to issue. In other words, it is the maximum amount of contract

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backlog a contractor can hold. Bonding capacity is also one of the decision parameters in the process of prequalification for determining financial status and stability of a contractor [10].

Despite the great contribution of the previous studies in the literature, the role of bonding capacity (as an internal element of contracting organizations) in the context of competitive bidding has not been explored thoroughly. This can be due to the lack of a high-fidelity model of the construction bidding environment that can incorporate the interrelationships between bonding capacity and other elements of contracting organizations and projects. In this paper, we use Agent-Based Modeling (ABM), as one of the central modeling and simulation tools in the field of computational economics and systems engineering, to examine the impact of bonding capacity on the financial performance of contractors and the market. ABM is a great tool for simulating the micro-behaviors of system components with the aim of analyzing their effects on the system as a whole. This makes ABM the right methodology to address the research question.

2. Methodology

2.1. Agent-Based Model of Construction Bidding

Agent-Based Modelling is recognized as a powerful computational tool for modelling and simulating complex systems in which a set of independent decision makers with different goals and behaviours interact with each other and the system. Due to its holistic approach and capability to deal with complex systems, ABM can be utilized for various research purposes including but not limited to prediction, proof, discovery, education and training [11].

In this paper, we use an agent-based model that reproduces the construction bidding environment with a focus on main decision points of contractors at the organization level. The mechanism of the simulation is that a set of contractors bid on a series of projects randomly generated and introduced into the market. Heterogeneity of contractors is limited to their mark-up decisions as they use different quantitative bidding methods. Similar to the real world contractors that try to learn about their competitors and market conditions and develop a bidding strategy, the simulated agent contractors collect the competitors' past bids and use quantitative bidding methods and determine their optimal bid price. We use a university package of a multimodal simulation software called "AnyLogic" in this paper. AnyLogic is a Java-based platform with the built-in capability to support Monte-Carlo, discrete event simulation, systems dynamics, and agent-based modelling [12].

Projects and Contractors are two main classes of objects in the simulation model. We define contractors as active objects in AnyLogic platform. Each contractor has a number of variables and parameters including bonding capacity, net worth, current work volume, and general & administrative costs. Each contractor also has a number of functions that defines its behaviours at decision or action points. Mark-up selection is the most crucial decision that each contractor has to make. For the purpose of this paper, contractors are set to be homogenous in all attributes except in their bidding methods.

While contractors are active agents due to their ability to learn and make decisions, we define projects as passive agents. Projects are generated consecutively over a simulation period of ten years (520 simulated time units) and are assigned a set of characteristics such as the project budget, the project duration, and uncertainty in cost estimate. Readers can find more details about the developed agent-based model of the construction competitive bidding using AnyLogic in [13-14]. The major assumptions of the paper are the following:

- The developed agent-base model simulates the low-bid lump-sum bidding process.
- Contractors in the market will remain the same throughout the simulation in the experiments.
- All contractors have the same size, initial working capital (which is zero), general and administrative (G&A) costs, cost estimating accuracy, and level of management capability and expertise.
- All contractors have access to their competitors' bidding history.

- All projects have the same budget of \$100M.
- To maintain market competition, having a minimum number of two participants is required for a bid to be valid. Otherwise, it will be cancelled.
- The estimated budget for upcoming projects is the same therefore bonding capacity sets a limitation on the maximum number of ongoing projects contractors are allowed to have at any time.

2.2. Quantitative Bidding Methods

In this subsection, we briefly explain the three quantitative bidding methods used in this study to create a heterogeneous market of rational bidders. The goal of a quantitative method is to use competitors' past bids to estimate the optimal mark-up for a contractor. In order to find the optimal mark-up, a contractor needs to maximize its expected profit through solving the following optimization problem:

$$\max E[Profit_{i,k}(x)] = [Pw_i(x) \cdot Profit_{i,k}(x)] \quad (1)$$

where x (markup) is the decision variable of the problem. The expected profit of contractor i for a given project k is defined as the product of the probability of winning ($Pw_i(x)$) and the profit given a chosen markup x . The bid ($B_{i,k}$), estimated cost ($ES_{i,k}$), markup (x), and profit have the following relationships for a given project k :

$$B_{i,k} = ES_{i,k}(1 + x_{i,k}) \quad (2)$$

$$Profit_{i,k} = ES_{i,k} \cdot x_{i,k} \quad (3)$$

The three quantitative bidding methods used in this paper use a competitor's past bids in order to characterize her bidding behavior with a probability distribution function of the bid ratio. The bid ratio ($BC_{k,i}$) for a given project (k) is defined as the ratio of the competitor j 's bid ($B_{j,k}$) to the contractor's own estimated cost ($ES_{i,k}$):

$$BC_{i,j,k} = \frac{B_{j,k}}{ES_{i,k}} \quad (4)$$

A stable distribution function ($F_X(x)$) of the bid ratio can be constructed if competitor j and contractor i have enough common and available past bids. Given the mean and variance of the distribution, the probability of beating competitor j ($P_{i,j}(x)$) with a given markup (x) can be simply calculated as follows:

$$P_{i,j}(x) = 1 - F_{X_{i,j}}(x) \quad (5)$$

The three quantitative bidding methods used in this paper are using different ways to estimate the probability of winning the bid for contractor i . Friedman [15] assumes the bid ratios of competitors are independent of each other. Hence, the probability of winning the bid (beating all competitors in a low-bid method), can be determined as follows:

$$Pw_i(x) = \prod_{i \in \text{Competitors}} P_{i,j}(x) \quad (6)$$

Based on his experience as a principal estimator, Gates [16] developed an empirical equation for determining the probability of winning the contract:

$$Pw_i(x) = \frac{1}{1 + \sum_{j \in \text{Competitors}} \left(\frac{1 - P_{i,j}(x)}{P_{i,j}(x)} \right)} \quad (7)$$

Finally, the *low-competitor model* [17-18] proposes that the only competitor the contractor aims to beat is the lowest competitor. Hence, the low-competitor model is based on collecting the historical data of the lowest bid, the winner, in each competition that contractor i participated in the past.

3. Description of the Simulation Experiments

3.1. Experiment Set A

The purpose of the first set of experiments (A) is to investigate the impact of different levels of bonding capacity on the performance of contractors with different bidding methods. In experiment set A, scenarios A1 to A7 cover a range of limitations on the number of ongoing projects contractors are allowed to have at any time during the simulation (See Table 1). This limitation simulates the bonding capacity of contractors in the real world bidding environment. Table 1 presents the number of ongoing projects allowed for contractors under scenarios A1 to A7. There are nine contractors competing with each other in the market. Contractors 1, 2, and 3 use Friedman model, contractors 4, 5, and 6 use Gates model, and contractors 7, 8, and 9 use Fine model. In the first set of experiments, projects are generated in the market one at a time unit under different scenarios.

3.2. Experiment Set B

The purpose of the second set of experiments is to investigate the impact of different levels of bonding capacity on the performance of both learning contractors and irrational contractors. Table 3 presents the number of ongoing projects allowed for contractors under scenarios B1 to B9. In experiment set B, the market includes a mix of contractors using three main learning algorithms and random markup. Contractors 1 and 2 use Friedman model, contractors 3 and 4 use Gates model, and contractors 5 and 6 use Fine model while contractor 7 and 8 choose their markup randomly from the range of [0% - 10%].

4. Results & Discussion

4.1. Results of the Experiment Set A

The results of the experiment set A are presented in Tables 1 and 2 and Figures 1 and 2. The number of contractors participating in biddings is one of the main factors influencing the level of competition in construction biddings. The higher the number of participants the fiercer the competition would be [19]. As Table 1 presents, the average and the minimum number of contractors in biddings have decreased from scenario A1 to scenario A7 due to imposing the limitation of bonding capacity. This limitation has also caused cancelation of 42 and 182 projects under scenarios A6 and A7 (respectively) where contractors have reached their quota and are not able to participate in some of the biddings, resulted in the cancelation.

One interesting observation presented in Table 2 is that the average markup of all contractors and volatility of the markup market have increased from scenario A1 to scenario A7. Observing Figure 1, the increasing trend of profit per project for all contractors in the market under scenarios A1 to A7 suggests that abundance of projects caused inflation in contractors' submitted markup and consequently their bids. As Figure 2 suggests, imposing the limitation of bonding capacity has decreased the winning rate of Friedman users and the market is divided almost equally among all contractors in scenario A7.

Fig. 1. Profit per Project of Contractors in Scenarios A1-A7

Fig. 2. Winning Rate of Contractors in Scenarios A1-A7

Table 1. Market information of scenarios A1-A7

Scenario	A1	A2	A3	A4	A5	A6	A7
Maximum number of ongoing projects allowed	8	7	6	5	4	3	2
Average number of contractors participating in the biddings	8.9	8.7	8.2	7.6	6.1	3.4	2.1
Minimum number of contractors participating in the biddings	7	7	6	5	3	1	1
Number of cancelled projects	0	0	0	0	0	42	182

Table 2. Average markup of contractors and volatility of the market in scenarios A1-A7

Scenario	A1	A2	A3	A4	A5	A6	A7
Average Markup of Friedman Users	0.81%	0.83%	0.90%	0.96%	1.26%	2.59%	4.43%
Average Markup of Gates Users	2.56%	2.74%	2.71%	2.77%	2.80%	4.07%	5.76%
Average Markup of Fine Users	1.50%	1.43%	1.63%	1.55%	1.53%	1.80%	1.91%
Average Markup of the Market	1.62%	1.66%	1.75%	1.76%	1.86%	2.82%	4.03%
One-Week Historical Volatility of Market Markup	0.82%	0.85%	0.85%	0.88%	0.90%	1.06%	1.18%
Annualized Historical Volatility of Market Markup	5.91%	6.15%	6.13%	6.35%	6.45%	7.63%	8.48%

4.2. Results of the Experiment Set B

The results of the experiment set A are presented in Tables 3 and 4 and Figures 3 and 4. With a few exceptions, trends and orders in the results of the experiment set B are consistent with the ones in the results of the experiment set A. As Table 3 shows, the average and the minimum number of contractors in the biddings has decreased from scenario B1 to scenario B9 due to imposing the limitation of bonding capacity. This limitation has also caused cancellation of 85 and 219 projects under scenarios B8 and B9 (respectively) where contractors have reached their quota and were not able to participate in some of the biddings, resulted in the cancellation.

As Table 8 shows the average markup of all contractors and volatility of the markup market have increased from scenario B1 to scenario B9. According to Figure 3, limiting the number of projects a contractor can have causes inflation in contractors' submitted markup and consequently their bids regardless of contractors' bidding methods. In other words, this limitation restricted the competition and lowered the market efficiency. Also, imposing the limitation of bonding capacity reduces the winning rate of Friedman users and the market is divided almost equally among all contractors as shown in Figure 4.

Finally, by comparing the results of experiment sets A and B, we can conclude that the with the increase in the number of rational contractors the benefits irrational contractors can get unpredictably from higher uncertainty in cost estimating will decrease.

Fig. 3. Profit per Project of Contractors in Scenarios B1-B9

Fig. 4. Winning Rate of Contractors in Scenarios B1-B9

Table 3. Market information of scenarios B1-B9

Scenario	B1	B2	B3	B4	B5	B6	B7	B8	B9
Maximum number of ongoing projects allowed	10	9	8	7	6	5	4	3	2
Average number of contractors participating in the biddings	7.96	7.92	7.79	7.62	7.22	6.25	4.57	2.84	1.88
Minimum number of contractors participating in the biddings	7	7	6	6	5	3	2	1	1
Number of cancelled project	0	0	0	0	0	0	0	85	219

Table 4. Average markup of contractors and volatility of the market in scenarios B1-B9

Scenario	B1	B2	B3	B4	B5	B6	B7	B8	B9
Average Mark-up of Friedman Users	1.10%	1.12%	1.07%	1.15%	1.20%	1.46%	2.18%	3.44%	5.10%
Average Mark-up of Gates Users	2.83%	2.72%	2.79%	2.81%	2.94%	2.95%	3.27%	5.40%	7.87%
Average Mark-up of Fine Users	1.59%	1.55%	1.60%	1.59%	1.52%	1.64%	1.67%	2.04%	1.84%
Average Mark-up of Random Users	5.04%	4.98%	5.19%	4.93%	5.02%	4.93%	4.85%	4.35%	4.41%

Average Mark-up of the Market		1.56%	1.51%	1.52%	1.51%	1.64%	1.93%	2.38%	2.86%	2.93%
One-Week Volatility of Mark-up	Historical of Market	1.08%	0.94%	0.95%	0.97%	1.07%	1.17%	1.55%	1.58%	1.82%
Annualized Volatility of Mark-up	Historical of Market	7.76%	6.80%	6.88%	7.00%	7.68%	8.43%	11.18%	11.64%	13.13%

5. Verification & Validation

For verifying the simulation model, we break down the model into several computation steps and verify the programming component of each step, which is easily doable due to AnyLogic's capability of collecting information on any parameter or process at any time through the simulation. We compute the corresponding calculations of all the process steps manually, compare and verify with the model calculations for some specific bidding cycles in several simulation runs.

For validating the simulation model, we use parameter variability (sensitivity analysis). We examine how uncertainty in the values of the key input parameters (such as project budget) can impact the model output and whether the outcomes are within a reasonable and expected range. Considering the capability of the developed agent-based model in AnyLogic, we employ different distributions for project budget, estimated duration, actual cost, and actual duration in addition to the fact that all experiments are conducted under different scenarios in order to make sure results are consistent. We also employ robustness analysis or extreme condition test in order to observe the response of the model to drastic changes such as complete failure in securing a project for a long period of the simulation or unexpected success in early bids. For example, the first 10 projects are given to a specific contractor and then the simulation was run as normal. We observe no significant change in the results.

6. Conclusion

Bonding capacity is an important element of construction contractors' organization as it is used for assessing financial status and stability of a contractor. Despite an extensive body of works in the area of construction bidding, the impact of bonding capacity on the financial performance of contractors in the bidding environment is not explored yet. In this paper, we use an agent-based model of construction bidding environment in order to investigate the impact of bonding capacity on contractors with different bidding strategies. Results indicate that in a market consisting of rational contractors imposing the limitation of bonding capacity can make the market less efficient: it decreases the gap between more effective and less effective contractors and increases average profit per project across the market. Also, an increase in the number of rational contractors would limit the chance of irrational contractors winning due to the variations of cost estimating among contractors.

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