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The Disappearing Winners: An MAS Study of Community-Type Rivalry in Construction Markets

Keda Chen [1,*], Xiaowei Wang [2], Zhenhua Guo [3] and Weidan Liu [3]

[1] School of Civil Engineering and Architecture, Jishou University, Jishou 416000, China
[2] Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, MI 48109, USA; xiaowei.xw.wang@outlook.com
[3] School of Management Science and Real Estate, Chongqing University, Chongqing 400044, China; zhenhuaguo@cqu.edu.cn (Z.G.); liuweidan@cqu.edu.cn (W.L.)
* Correspondence: chenkeda@jsu.edu.cn

Abstract: Business communities in the construction market are becoming increasingly diverse, with a deepening impact on industrial development and enterprise competition. Despite many existing empirical studies on communities, they weaken competitive interactions and have limited applicability to the dynamic issues of community formation and evolution. To address the gaps identified in the literature on bidding competition dynamics, this study constructs a multi-agent system (MAS) model. This model is designed to simulate the formation of community-type rivalry in the construction market by incorporating key variables identified from empirical observations of bidding behavior. It also designs and runs two experiments focusing on the impact of overall market factors and enterprises' own factors on the formation of an equilibrium state of community-type rivalry to explore the mechanism behind its formation. We find that the density of community networks and the process of community formation are significantly affected by the number of enterprises, the scope of competition among enterprises, and the lifespan of the link, while they are not significantly affected by the size of the market or the exit thresholds of enterprises. In addition, this study finds that, under the bidding competition rule, the number of times that an enterprise bids is closely related to its network location advantage. However, larger and more mature enterprises have difficulty in maintaining a central position in a competitive network. This study provides different perspectives for an understanding of corporate community formation and offers valuable insights into the governance of community phenomena in the construction market.

Keywords: community-type rivalry; construction market; multi-agent simulation; social network

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1. Introduction

The pandemic, the volatile international environment, inflation, and other external issues have led to a negative outlook among construction businesses. It is linked to the increasing urbanization and environmental awareness of the current period, while the updating of consumer attitudes and the influx of new technologies continue to broaden the competitive scope of the industry, which is increasingly aggravating the risk of fluctuations in the construction market. Competition is essential in facilitating resource reallocation, fostering innovation and efficiency, and addressing market needs. Commercial competition is dynamic and multifaceted, with communities of competitive interactions embedded beneath the surface [1]. Compared to the broader commodity market, the business communities in the construction market are more numerous and diverse, with bid-rigging enterprises, business groups, and bidding consortia, all of which are observable networks of communities in the construction market [2]. When examined on a broader scale, whether from the perspective of nations such as the United States [3] or Jordan [4] or more comprehensively from the global construction market [5], empirical evidence exists that can elucidate the presence of community networks.

These communities, whether strategic collaborations or transient interests, are crucial to improving inter-organizational interactions and project performance [6,7]. Communities serve as a mechanism for resource aggregation to achieve a competitive advantage and align with individual profit-oriented actions [8]. Distinct forms of communities have distinct purposes. Although the pursuit of short-term benefits by some communities may hinder the development of a sustainable competitive advantage [9] or even lead to unfair competition, communities are still an effective means of improving the competitiveness of construction enterprises [10] and can help enterprises to deal with intense competition and market uncertainty and even maintain a delicate balance between competition and cooperation [11].

Community-type rivalry (CTR) is a specific form of business interaction through which enterprises acquire resources, share information, and determine their competitive positions [12]. Understanding the underlying mechanism of CTR formation in the construction market is of practical significance in guiding the competitive practices of construction enterprises; however, this is not an easy task. First, a great number of studies connected to business communities focus on efficiency improvements, and these beneficial studies may focus excessively on the ex post effects of communities, which can easily lead to causality misinterpretation in association with formation problems. Focusing on enterprises' interactions with customers, rather than with competitors, may downplay the role of competition in community formation [13]. Furthermore, the results of related studies at different levels imply that communities play an important role in competition in the construction market; however, there are few paths to a unified understanding of how communities affect competition in the construction market. In terms of market concentration, the construction industry suffers from intense competition and low profitability [14], in contrast to enterprise-level competition, which reduces enterprise turnover but increases profits [15]. A potential explanation for this discrepancy is that the building business operates under imperfect competition, with construction enterprises depending on substantial rent to generate profits [16]. However, for the construction industry, which lacks technological barriers, enterprises are theoretically required to devote more effort to creating and protecting their competitive positions [17], which suggests that the competitive environment for construction enterprises is closely related to their autonomous decision-making.

Competitors constitute the fundamental elements of a competitive network environment and are crucial to the competitive decisions of construction enterprises. Horizontally, established enterprises can benefit from the perceptions of competitors and prefer strong rivals to weak ones [18], whereas new entrants to the construction market focus on enhancing their competence and subordinating their perceptions of competitors. From a longitudinal perspective, the formation and evolution of enterprises' competitive relationships are not independent of each other; community-based competitive relationships among enterprises trigger, interfere with, and transform one another [19].

Although there is considerable evidence that competitive relationships between construction enterprises underlie community formation, few studies have focused on the community formation process from a competitive perspective. Research findings have mostly focused on the mutual benefits of cooperation resulting from the aggregation of construction enterprises in a certain dimension; however, its sustainability has been questioned, arguing that the industry's prevailing supply arrangements may limit the potential for cooperation between construction enterprises to rise beyond the project level to a strategic level [20]. It is perhaps for this reason that, when confronted with the issue of communities in the construction market, scholars have drawn on experiences from areas such as industrial organization theory, lacking a unique understanding of the construction industry. Studies have found that an enterprise's competitive advantage is reflected in the number, centrality, and connectivity of its network ties [21]. The network location is directly related to the number of winning bids of construction enterprises [1]. Relational networks have a positive impact on enterprises' performance and sustainable competitive advantage [22]. These studies are mostly based on static cross-sectional data, which are valuable in assisting enterprises at a particular stage in formulating their competitive strategies. However, without an abstract, generalized modeling tool, the impact of these studies on construction enterprises' understanding of the laws of competition and the formulation of long-term strategies is limited. To fill this gap, this study explores the complex systematic laws of community-based competition formation in the context of the bidding competition model in the construction market. In the construction market, CTR involves a complex network of relationships among multiple players, and these complexities can be better modeled and understood through a multi-agent system (MAS), revealing potential nonlinearities and dynamics. To translate our findings into actionable strategies, we propose specific policy interventions to enhance the market stability and competition. Additionally, we outline a framework for enterprises to leverage their network positions for a competitive advantage, drawing directly from our model's insights.

2. Literature Review

2.1. The Formation of Communities in the Construction Market

Competition and cooperation are fundamental drivers of business community formation, with competition being more critical and important. Existing studies have attributed the formation of enterprise communities to resources and information. Related studies on industrial cluster theory and resource dependence theory have concluded that the competitiveness of construction enterprises is the main driving force behind their clustering in geographic or social relationship networks [11]. These clusters facilitate the integration of resources, information exchange, and the development of a single business strategy, thereby improving the manageability and effectiveness of the construction complex [23]. Owing to their unique production methods, construction enterprises have difficulties in significant geographic clustering but tend to adopt different strategies based on the market and project characteristics and utilize resources, such as social networks, to further form business collaboration networks [11]. This network of construction enterprises with small-world characteristics exhibits an island effect around large construction enterprises [1], with more attention being paid to large enterprises (LEs) than to small and medium-sized enterprises (SMEs) [24]. Although large enterprises have a greater influence within the network, they maintain their market positions by influencing government policies [11]. A study of Turkish contractors indicated that the clustering of enterprises facilitates market entry for newcomers while simultaneously heightening the competitiveness within the community [25]. Communities are networks of relationships with the explicit purpose of acquiring resources or information and are based on competitiveness.

The formation of corporate communities is an iterative, self-organizing process, and the state of the community during the formation process has a direct or indirect impact on the subsequent competitive and cooperative behaviors of construction enterprises [26,27]. When constructing competitive cooperative behaviors, construction enterprises first exhibit role orientation and then combine other factors to predict behavioral outcomes [28]. Under repeated bidding competition interactions, to cater to the owner's needs, the characteristics of construction enterprise communities are manifested in terms of the geographical and technical division of labor [1]. Research related to game theory demonstrates that frequent competitive contact between participants can foster cooperation, which may emerge either as a weakly binding trade community or a strongly binding bid-rigging network based on embedded social links [29]. Regardless of the nature of the community network, competitive relationships remain the foundation and underlying logic that forms these communities. Resource dependence theory generally focuses on high-power enterprises when studying similar issues; however, some empirical studies have argued that low-power enterprises are indirectly threatening high-power enterprises by shaping their survival and growth opportunities through their influence on the regulatory environment [30]. This implies that CTR, while starting with competition, has a positive impact on the generation of weak competition such as bid rigging [31], which is likely to be generated through the evolution of the community network structure [21].

The structure of a community network in which an enterprise is embedded is critical to its competitive position and outcomes. Case studies have shown that enterprises benefit from network centrality and that the community network structure plays a crucial role in the flow of knowledge and information between enterprises [32]. This is even more evident in enterprises' competition for innovation, where the network structures of enterprises are influenced by their existing social networks, which in turn affect their ability to exchange knowledge and innovate through an iterative process [33]. In "community-type" rivalry, competitors are an enterprise's unique competitive advantage, and the competitive network formed by competitors can help enterprises to update their resources and perceive the market [18]; moreover, especially for small and medium-sized startup enterprises in the United States, the benefits from competitors are obvious [34]. When parsing the CTR problem, we cannot avoid the competitive relationships among construction enterprises, which are the cornerstones of communities.

2.2. Competitive Relationships Among Construction Enterprises

Competitive relationships in construction enterprises are defined as direct or indirect competitive interactions that shape an enterprise's competitive behavior and strategies. The creation of each competitive relationship is a small step in the formation of associational competition, and the reconstruction of communities is based on the definition of an asymmetric binary competitive relationship between two enterprises [35]. In industry studies, such as those involving the airline industry and iron ore mining, the competitive dynamics among enterprises are characterized by the extent of market overlap or commonality [36,37]. The advantage of this approach is that it can quantitatively reflect a competitive relationship through market data; however, as a descriptive approach, it is difficult to reproduce its evolution. There is also the category of definitional approaches based on resource similarity, such as patents, suppliers, and other resources, which may ignore the roles of many non-technical factors. To explore the mechanism of CTR in the construction market, it is necessary to combine the consciousness–motivation–ability and social network perspectives [38]. The former theorizes about the binary competition relationship between enterprises, whereas the latter considers the influence of network relationships and structures on enterprise behavior.

Competitive behavior is strong evidence of the emergence and existence of competitive relationships. Enterprises' competitive behavior affects other competitors. This affective relationship is characterized by asymmetry [35], which extends to the level of the market structure, reflected in the level of agglomeration and the competitive positions of enterprises in different sectors [5]. Although the likelihood of a competitive relationship between two enterprises is affected by several factors, such as the geographic distance [35], open bidding and competition in the construction industry facilitate the identification of competitive relationships between construction enterprises [1]. Competitive relationships are dynamic and evolve in response to both internal and external situations. For example, in the United States, a recession may cause more construction enterprises to compete for low-margin or small-scale projects and develop aggressive pricing strategies and make community rivalries denser when it is more difficult to move resources across communities [39]. Competitive relationships may potentially cease to exist, and, under specific circumstances, competitive communities may gradually transform into cartels, characterized by fixed prices and allocated markets, as exemplified by the cement market in South Africa [40].

In summary, the origin of CTR in the construction market lies in the pursuit of competitiveness among enterprises. To attain this objective, construction enterprises fully use and cultivate diverse social networks that are interwoven and mutually influential, with a competitive relationship network serving as the foundation. Although data such as patents, market shares, and bidding records can provide a valuable static perspective on associational competition, they have greater limitations in defining competitive relationships and studying the formation of associational competition because of their inability to capture the dynamics of competitive behaviors. These are affected by issues such as the type of data, which makes it difficult to explore in depth the effects of multiple competitive environmental factors, such as the market size and rivalry, on the formation of associational competition. It is thus difficult to explore the influence of the market size, rivals, and other competitive environmental factors on CTR formation. Ex post facto studies can provide valuable empirical references for policymakers, but they are insufficient in predicting or evaluating key factors and their degrees of influence; therefore, it is necessary to further explore the formation mechanism of organized competition from a modeling perspective.

Differential equations, cellular automata, and multi-agent simulation (MAS) have been successively applied to various types of enterprise competition modeling, and these models are becoming increasingly complex and close to the real world. MAS can adeptly characterize individuals' heterogeneity and their positions within the network, offering a more intricate representation than the preceding two models, and is proficient in simulating self-organized complex networks. MAS provides "levers" for the understanding of complex system phenomena by bridging the gap between the micro and macro [41,42]. Therefore, this study uses MAS to construct a CTR formation model for both bidders and tenders and describes the formation process of association-based competition by defining the attributes and behavioral rules of the participants.

3. Model Construction

3.1. Attribute and Variable Settings

Although the competition in the construction market is complex, bidding decisions at the construction enterprise level are considered much clearer. From the enterprise's viewpoint, it is essential to evaluate their competitiveness and external risks prior to submitting a bid [43]. However, under limited resource conditions, construction enterprises can only pursue a balance between risk management costs and quotation advantages [44]. Bidding serves as a mechanism that illustrates the competitiveness of enterprises. In this process, they assess their own strengths and risks from the perspectives of resources, relationships, and the industry structure [45]. Based on Ahmed [43] and Hanak [46], this study assumes that, when a bidding project arises within the market, each construction enterprise in the market makes bid/no-bid decisions by combining its own competitiveness, the requirements of the bidding project, and the rivals with whom it has a historically competitive relationship, as well as estimating its own bidding win rate and comparing its own risk preferences. The contractor centrality measure derived from the two-way network model is more strongly correlated with the bidding performance than the traditional assessment based solely on the number of bidders [3]. Therefore, after the bidders are determined, the three most competitive bidders form a triangular competitive network, from which one is randomly selected as the winning bidder. With the emergence of randomized bidding projects, the interactive process of bidding is repeated, and the evolution of association-based competition is advanced, with construction enterprises continuously updating their competitiveness and competitive networks based on the results of the bidding process.

This model simulates competition through a three-stage process: bid/no-bid (BNB) decision making, forming competitive relationships, and determining the winner. Although there are numerous aspects that affect bidders' bidding decisions [43], the factors that affect BNB decisions can be characterized as the inherent qualities of construction businesses and the competitive interactions between them [47]. The inherent qualities of construction enterprises include competitiveness and competitive risk preferences [46,47]. Risk-averse contractors seek to avoid and mitigate potential losses. In contrast, risk-tolerant contractors are more inclined to accept the risk of losses to enhance their likelihood of securing the bid [48]. Contractors' risk attitudes determine their competitive strategies and influence the market dynamics [49]. However, risk assessment is inherently uncertain and subjective, so it is simplified to a random variable to explore its impact on competitive dynamics. The simulation modeling of the operation of association-based competition, variable settings, and value ranges are shown in Table 1.

Table 1. Variable settings for MAS experiment on CTR.

Object	Variable	Definition of Variable	Description of Variable
Construction enterprise	BNB decision $I_i = \{a, b\}$	a denotes a bidder; b denotes a non-bidder.	
	Competitiveness E_i	The overall strength of the construction enterprise, which influences the BNB decision and whether it can win the bid.	$E_i \in [0, \infty]$. The larger the value of E, the stronger the overall strength of the enterprise.
	Risk appetite R	Factors affecting the range of bidding intentions of construction enterprises in BNB decision making.	$R \in [0, 1]$. A higher R value increases the range of bidding intentions and the likelihood of participating in the tender process.
	Estimated winning percentage P_i'	When a bidding project emerges, the construction enterprise ⊐ estimates the winning rate based on the size of the project, the number of connected competitors, and the competitiveness of the competitors.	$p_i' \in [0, 1]$. The smaller the value of p_i', the smaller the estimated winning rate and the less likely it is to participate in the bidding.
	Acceptable winning rate P_i	The lowest acceptable bid winning rate for construction enterprises.	$P_i \in [0.05, 0.2]$, The smaller the value of this indicator, the lower the expected winning rate that construction enterprises can accept, and the more likely they are to become bidders.
Overall market indicators	Exit_threshold	Construction enterprises exit the market when their competitiveness is below this indicator.	Exit_threshold $\in \{5, 10, 15\}$
	Num_turtles	Total number of enterprises in the market.	Num_turtles $\in \{40, 80\}$
Tender	Scale of bidding project B	The scale of the bidding project requires the competitiveness of the construction enterprise to match it.	$B \in [5, B_{\max}]$. Indicator B is evenly distributed within the range $[5, B_{\max}]$. Considering the actual engineering situation, we set the minimum project size to a non-zero value.
Competitive relationship	Edge weight $\omega_{i,j}$	The number of repeated competitions between enterprise ⊐ and enterprise j.	$\omega_{i,j} \in [0, \infty)$ and it is an integer. The larger the value of this indicator, the more times the two enterprises meet during bidding.
	Age of competitive relationship $A_{i,j}$	$A_{i,j}$ represents the unrenewed time of the competitive relationship between two enterprises.	$A_{i,j} \in N$. If it is greater than a certain value, the connection will disappear.
	Node degree k_i	The number of competitors currently competing with the construction enterprise i.	$k_i \in N$

3.2. Agent's Rules of Behavior

Relationship formation and disconnection in CTR are affected by many factors, and simulation modeling cannot completely replicate a real situation. To analyze the process of the operation and evolution of CTR with limited resources, this study simplifies and sets the following behavioral rules for agents.

Rule 1. *The smaller the gap between the size of the project and the competitiveness of the construction enterprise, the greater the likelihood of bidding.*

Construction enterprises' BNB decisions are significantly influenced by the project size [43,50]. Small- and medium-sized contractors cannot afford the costs and financial risks associated with large projects and prefer projects with conservative future returns and profitability in the short term [51]. In contrast, large contractors favor larger projects and more stable client types [52], seek to avoid unnecessary competition, and pursue long-term benefits [53]. Enterprises are dominated by economies of scale [54], contractors of different sizes have a preferred range of contract sizes [55], and projects that are too large or small are not optimal for construction enterprises. Based on this, this study proposes behavioral Rule 1: the smaller the gap between the size of the bidding project and the competitiveness of the construction enterprise, the higher the likelihood of participating in the bidding.

Rule 2. *The more connected opponents (m_i), the closer the predicted bid win rate (P_i') is to the theoretical winning rate.*

Business managers need to help to build a competitive advantage by obtaining competitive intelligence from both the internal and external environments of the organization [56]. Competitor identification is an important part of competitive intelligence, and construction enterprises generally achieve the goal of rival identification through factor or product competition [43]. Research in the Hong Kong construction industry suggests that large construction enterprises with more competitive opportunities can obtain more accurate competitive intelligence [57]. A similar view is found in a study of the Australian infrastructure industry, which suggests that maintaining good relationships with local peers and differential competitive advantages are necessary to compete [58]. In some markets with asymmetric information, sophisticated enterprises can distinguish customers with more profitable mining values and transform them into information advantages to avoid competing with newcomers for low-margin customers, which affects the competitive landscape of the entire market [59]. Based on this, this study proposes Rule 2: the more connected rivals, the closer the predicted bid win rate is to the theoretical winning rate considering all potential bidders.

Rule 3. *When the competitors are fixed, the greater the competitiveness of a bidder (E_i), the higher its bidding success rate.*

The success of a construction enterprise's bidding depends largely on the accuracy and competitiveness of its tender offers [60]. Johnen [59] argued that the competitive advantage of a seasoned enterprise can be derived from an informational advantage that accumulates over time from contact with a variety of customer segments, enabling them to avoid some low-margin customers and unwanted competition, which is essentially competitiveness in the marketplace. In other words, the bidding success of seasoned enterprises in markets with asymmetric information is likely higher. In addition, market research in Nigeria proves that material availability and labor productivity are important factors affecting the success rate of competitive bidding, and government policies external to enterprises do not have a significant effect on the success rate in terms of winning bids [61]. The bidding success rate is affected by the number of bidders and their competitiveness [57]. Some scholars have pointed out that the number of bidders acts as a mediating variable between the "project (competitiveness) requirements" and the "intensity of competition" [62]—that is, the competitiveness of the construction enterprises participating in the bidding process is negatively correlated with the competitive intensity of the bidding project. Accordingly, this study proposes behavioral Rule 3: when the competitors are fixed, the greater the competitiveness of a bidder, the higher its bidding success rate.

Rule 4. *The competitiveness of bidders (E_i) decreases at an accelerated rate when the number of failed bids increases.*

Obtaining contracts is a prerequisite for the survival of construction enterprises. However, the construction industry has one of the lowest five-year survival rates for businesses compared to other industries [63]. Within the initial five years of operation, 80% of the small and medium-sized enterprises (SMEs) and contractors in South Africa's construction sector will be eliminated from market competition [64]. Although there are many reasons that construction enterprises fail, their inability to gain sufficient business and market shares remains significant. The various risk factors that lead to the failure of a construction enterprise are higher in the early stages of growth and decrease in risk as the enterprise ages [65]. In short, the initial rate of decline in viability or competitiveness is faster if a construction enterprise cannot win bids. To simplify the multi-subject simulation model, this study proposes behavioral Rule 4: construction enterprises' competitiveness decreases exponentially as the number of failed bids increases.

3.3. Agent's Interaction Rules

1. The proliferation and renewal of the network

The competitive landscape in the construction business is constantly shifting and being redefined [66]. To closely reflect reality, the competitive relationship in the model is designed to emerge or disappear under certain conditions. When enterprise i and enterprise j appear in a bidding competition simultaneously and both occupy the top three positions in competitiveness, if there is no connection between them, a new link will be added. The new link will arise with an initial edge weight $\omega_{ij} = 1$ and the age of the competitive relationship $a_{ij} = 1$. If a connection already exists between them, then we set $\omega_{i,j} = \omega_{i,j} + 1,\ a_{ij} = 1$.

The attribute information of l_{ij} includes the edge weight and age, which is expressed as follows:

$$l_{ij} = (\omega_{ij}, a_{ij}) \tag{1}$$

2. E_{ij}: The awareness of enterprise i towards the competitiveness of enterprise j

Competitive isomorphism posits that companies in competition increasingly mirror one another, leading to heightened parallels in strategy, structure, and behavior [67]. Understanding competitors' strengths is an important part of BNB decisions. Although it is very difficult to clearly perceive each other's capabilities, familiarity between competing enterprises increases as the number of times that they compete increases. If, after the end of a round of bidding, the marginal power of the connection between enterprise i and enterprise j increases, the range of fluctuations in the degree of awareness of enterprise i regarding the competitiveness of enterprise j will decrease, enterprise i will be able to judge the competitiveness of enterprise j with greater probability, and the extent of the increase will be directly proportional to the degree of awareness. If there is no change in marginal power, it means that the two enterprises have not produced a new competitive relationship between them, and the judgment of the competitiveness of enterprise i on enterprise j will remain unchanged. If there is no connection between enterprise i and enterprise j, or if the original connection has disappeared owing to a lack of new additions for a long time, enterprise i is unable to consider enterprise j when estimating the bid-winning rate. According to an empirical study [1], the awareness of competitors will have singularity after six joint bids by construction enterprises, according to which the competitiveness awareness degree is designed as

$$\begin{array}{c}\text{If } \omega_{i,j} \leqslant 6\ E_{ij} = E_j\left[1 + 30\%.Random\left(-\frac{1}{\omega_{ij}}, \frac{1}{\omega_{ij}}\right)\right] \\ \text{If } \omega_{i,j} > 6\ E_{ij} = E_j[1 + Random(-5\%,5\%)]\end{array} \tag{2}$$

4. Research Methodology and Process

4.1. Research Methodology

This study constructs an MAS model of "CTR in the construction market" based on the behavior and interaction rules of agents. In this study, the "maximum project size", "number of enterprises", "exit threshold", "acceptable range of projects", and age of competitive relationship" are set as independent variables. We observe the changes in the network characteristics of market communities using two indicators: the global clustering coefficient and the number of communities (Figure 1). To fully demonstrate the formation of CTR, the simulation model must be run for a sufficiently long time to ensure that the communities are stabilized. The simulation and statistics are mainly implemented in the Netlogo software version 6.0, and the detection of communities and calculation of network metrics are performed using the Social Network Extension toolkit in Netlogo.

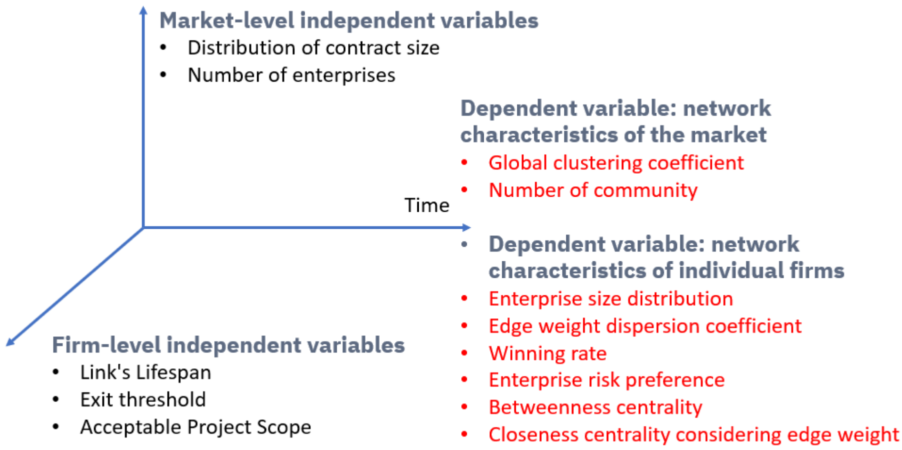

Figure 1. Three variable dimensions for community competition simulation experiments.

4.2. Experimental Design

4.2.1. Experimental Steps

The experiment is conducted in two steps. Experiment 1: We set up 8 scenarios (Table 2) corresponding to the 4 independent variables (excluding "link lifespan") and compare the changes in the indicators of the characteristics of the association network and the final equilibrium state under the 8 scenarios, so as to judge the influence of each variable on the formation of CTR. In reality, the number of competitors generally changes in tandem with the size of the market, and the "maximum project size" and "number of enterprises" in the eight scenarios are set to increase or decrease simultaneously. Experiment 2: Using the behavioral space function of Netlogo, we collect the changes in the "global clustering coefficient" and "number of communities" under the given experimental scenarios and perform a correlation analysis with the five independent variables. The relationship between the performance data of individual enterprises in the final equilibrium state and the indicators of the characteristics of the individual association network is then determined and analyzed.

Table 2. Parameter settings for various scenarios in simulation experiments.

	Max Project Scale	Number of Enterprises	Acceptable Project Scope	Exit Threshold
Scenario 1	40	40	10	5
Scenario 2	80	80	10	5
Scenario 3	80	80	30	5
Scenario 4	40	40	10	15
Scenario 5	40	40	30	5
Scenario 6	80	80	30	15
Scenario 7	80	80	10	15
Scenario 8	40	40	30	15

4.2.2. Assignment of Parameters

In the experiments, the randomness parameter is set as a uniform distribution within $[-1, 1]$ or $[0, 1]$. For the construction enterprise's estimated bid winning rate, acceptable winning rate, profitability, competitiveness, etc., the values are taken in different ranges, influenced by other conditions. The specific parameter assignments are as follows.

- Assignment of common attributes to groups of construction enterprises

The starting value of the total number of construction businesses, N, in the model space was established at 50, subject to modification via the input box. Second, the decay coefficient was assumed to be an exponential function with base a. Studies have shown that, while the first five-year elimination rate for startups in general industries may be 50% [68], the five-year elimination rate for construction startups reaches 80% [64]. The initial value of a was set to 0.95.

$$E_{it+1} = E_{it} \cdot a = E_{i0} \cdot a^t a \subset (0, 1) \tag{3}$$

In the above equation, E_t is the competitiveness of the construction enterprise at moment t, and t is the length of time for which the construction enterprise continues to fail.

- Assignment of individual states to construction enterprises

According to agent's behavioral Rule 1, one of the necessary conditions for enterprise i to bid is that the scale of bidding project B is within its own scope of concern L_i. L_i is determined by its own competitiveness E_i and risk preferences R_i. The value of E_i is within [5,50], the value R_i is within [0, 1], and L_i can be defined as

$$L_i \in [E_i - \alpha.R_i, E_i + \alpha.R_i] \tag{4}$$

An important condition that affects the BNB decision is the acceptable win rate. The actual average win rate in the construction market is between 11.8% and 15.1% [4]. Accordingly, this value was assigned as $P_i \in [0.087, 0.15]$. The smaller the value, the lower the expected bid win rate that a construction enterprise can accept; additionally, the more it can accept the result of failure, the more likely it is to participate in bidding. The acceptable win rate is influenced by an enterprise's risk appetite. Construction enterprises that are relatively small and less competitive are more inclined to accept high risks [69], whereas enterprises that are more profitable and viable are more risk-averse [49]. In short, the greater the risk appetite, the smaller the acceptable win rate, which is expressed by the following formula:

$$P_i = 5\% + e^{-R_i}.10\% P_i \in [0.087, 0.15] \tag{5}$$

- Assignment of project size for tendered projects

The sizes of the tendered projects B_t were set to obey a uniform distribution of [10, max_project_scale]. In the actual construction market, the distribution of individual project scales may obey the Pareto distribution, the Gamma distribution, or the special form of the exponential distribution. However, considering the widespread subcontracting behavior in construction contracting, the experiments conservatively set the project scale B_t to a uniform distribution.

5. Simulation Results

5.1. Results

Table 3 presents the final stabilized state of the association network of the model in different contexts. Table 4 shows the results of the correlation analysis between the two dependent variables, the "global clustering coefficient" and the "number of communities", and the five independent variables based on the statistics obtained from the behavioral space experiment. Table 5 shows the correlation between the enterprise's network indicators and its competitive performance in Scenario 1. Owing to the large number of scenarios and variables, a comparison of the scenarios would not only consume a large amount of space but also easily overlook key core issues. Therefore, based on the three tables of experimental results, the following section analyzes the characteristics of CTR formation under different competitive scenarios and discusses the significance of the results in guiding real market competition.

Table 3. Evolutionary results for CTR networks under different situations.

	Global Clustering Coefficient	Time Required to Stabilize Global Clustering Coefficients	Number of Communities	Time Required to Stabilize Number of Communities	Sum of Edge Weights	Sum of Degrees
Scenario 1	0.27	60	4~6	100	410	220
Scenario 2	0.17	140	6~8	200	460	270
Scenario 3	0.33	100	4~6	100	430	200
Scenario 4	0.27	30	4~6	100	310	180
Scenario 5	0.21	200	6~8	200	690	387
Scenario 6	0.18	180	5~7	200	620	400
Scenario 7	0.18	160	5~7	200	470	280
Scenario 8	0.28	60	4~6	100	420	220

Table 4. Correlation of overall market competitive performance under various scenarios.

	Global Clustering Coefficient	Number of Communities
Maximum Project Size	−0.042 (0.776)	0.100 (0.497)
Number of Enterprises	−0.803 (0.000 ***)	0.731 (0.000 ***)
Acceptable Project Scope	0.358 (0.013 **)	−0.079 (0.594)
Exit Threshold	−0.226 (0.123)	−0.127 (0.391)
Link's Lifespan	0.072 (0.628)	−0.407 (0.004 ***)

Note: ***, ** represent 1%, 5% significance, respectively.

Table 5. Correlations between enterprises' network indicators and competitive performance (S1).

	Enterprise Size	Discrete Coefficients of Edge Weights	Number of Bids	Rate of Winning	Enterprise Risk Preference	Betweenness Centrality	Closeness Centrality Considering Edge Weight
Enterprise size	1.000 (0.000 ***)	−0.035 (0.832)	0.219 (0.175)	0.344 (0.030 **)	−0.089 (0.585)	0.024 (0.883)	0.054 (0.743)
Discrete coefficients of edge weights	−0.035 (0.832)	1.000 (0.000 ***)	−0.576 (0.000 ***)	0.077 (0.636)	−0.485 (0.002 ***)	−0.892 (0.000 ***)	−0.717 (0.000 ***)
Number of bids	0.219 (0.175)	−0.576 (0.000 ***)	1.000 (0.000 ***)	0.184 (0.256)	0.283 (0.076 *)	0.440 (0.004 ***)	0.322 (0.043 **)
Rate of winning	0.344 (0.030 **)	0.077 (0.636)	0.184 (0.256)	1.000 (0.000 ***)	0.080 (0.622)	−0.203 (0.209)	−0.022 (0.893)
Enterprise risk preference	−0.089 (0.585)	−0.485 (0.002 ***)	0.283 (0.076 *)	0.080 (0.622)	1.000 (0.000 ***)	0.364 (0.021 **)	0.296 (0.064 *)
Betweenness centrality	0.024 (0.883)	−0.892 (0.000 ***)	0.440 (0.004 ***)	−0.203 (0.209)	0.364 (0.021 **)	1.000 (0.000 ***)	0.694 (0.000 ***)
Closeness centrality considering edge weight	0.054 (0.743)	−0.717 (0.000 ***)	0.322 (0.043 **)	−0.022 (0.893)	0.296 (0.064 *)	0.694 (0.000 ***)	1.000 (0.000 ***)

Note: ***, **, * represent 1%, 5%, 10% significance, respectively.

5.2. Effect of Market Size and Number of Enterprises on Formation of CTR

Table 3 demonstrates that, assuming that the other variables are held constant, changes in the "maximum project size" and "number of enterprises" result in the following comparisons (S1→S2, S5→S3, S4→S7, S8→S6): as the market size increases and the number of enterprises rises, the number of probabilistic communities increases, the global clustering coefficient declines, the network density is diminished, and the time needed for the stabilization of the CTR network is escalated significantly. The correlation analysis results regarding the time-series data from the behavioral space experiment are presented in Table 4. The number of enterprises exhibits a significant correlation with both the number of communities and the global clustering coefficient, whereas no correlation exists between the market size and these two indicators. Thus, the behavioral space experiments demonstrate that the number of enterprises exerts a more substantial influence on the formation of CTR.

Do swings in market demand impact the structure of CTR networks? Standard economic models informing competition strategies indicate that growth in demand should result in an increase in the number of enterprises applicable solely to industries with low technological barriers [70]. Certain academics contend that network effects [71] and interdependence among competitors [72] can prevent new entrants from establishing their presence in emerging markets. This analysis illustrates that, assuming that enterprises retain some recollection of their competitive ties, fluctuations in market demand do not substantially modify the structural characteristics of the CTR network but merely induce variations within its distribution range. The CTR network has notable resistance to market demand variations. The findings of the behavioral space experiment presented in Table 4 further corroborate this perspective.

The number of communities is determined by the degree of modularity; thus, it is closely associated with the global clustering coefficient, indicating that a reduced number of communities correlates with greater network cohesion. These experimental findings further corroborate this inference. However, two aspects of the number of communities need to be emphasized. First, the number of communities, network tightness, and communities' stabilization time are substantially associated. A decreased number of communities and a more unified network are associated with a shorter stabilization period. Moreover, although the number of enterprises significantly affects the number of communities, Scenarios 1 and 3 indicate that the increased probability of competition may alleviate the influence of the enterprise quantity on CTR formation, leading to extended durations of market volatility. This shows that, in addition to the number of enterprises, an "acceptable project scope" is also an essential element shaping the organization of communities.

5.3. Effect of Enterprise-Level Independent Variables on Formation of CTR

The term "acceptable project scope" denotes the competencies of construction enterprises within the actual market. A broader "acceptable project scope" correlates with an expanded actual bidding scope for the enterprise, increasing the likelihood of engaging with competitors of varying sizes. Table 4 demonstrates that there is a substantial positive association between the "acceptable project scope" and the "global clustering coefficient", but no link with the "number of communities". The "acceptable project scope" significantly affects the density of the CTR network; a higher number is associated with a more compact network. Table 3 also supports this hypothesis. For instance, when comparing Scenario 2 to Scenario 3, an increase in the "acceptable project scope", while keeping all other variables constant, results in the maximum global clustering coefficient and the minimum number of communities. Nonetheless, a comparison of Scenarios 1 and 5 reveals that identical modifications in the "maximum project size" and "number of enterprises" yield a diminished impact; at this juncture, the convergence rate of the CTR network markedly declines, suggesting that the expansion of the "maximum project size" and "number of enterprises" undermines the robustness of the CTR network.

The "link lifespan" is a specific variable in this study that quantifies the duration for which a competitive relationship between enterprises can persist without renewal. This trait is challenging to define and assess in reality; however, experimental findings can be illuminating. Table 4 indicates a substantial negative correlation between the "link lifespan" and "number of communities", whereas no correlation exists with the "global clustering coefficient". This suggests that prolonged competitive engagement among enterprises is associated with a larger average size of the acknowledged communities, leading to a diminished number of communities without improving the network's cohesion. The "acceptable project scope" substantially influences the density of the CTR network; a greater value correlates with a more condensed network. A plausible reason for this outcome is that the adjusting effect of the "link lifespan" is global and homogenous. The augmentation of the "link lifespan" results in the greater retention of links, thus diminishing enterprises' anticipated win rates and prompting less risk-averse enterprises to be more willing to forgo bids.

5.4. Correlation Between Enterprises' Competitive Performance and the Location of Networks

Table 5 shows the association between enterprises' CTR network parameters and their competitive performance once communities are stabilized, which helps us to understand the impact of CTR on enterprises' performance. First, Table 5 is interpreted based on the "enterprise size", which is related to the "winning rate" but not correlated with the "number of bids" or network characteristics. There is no correlation between the "enterprise size" and "win rate" or between the "number of bids" and network characteristics. Empirical studies have shown that the competitive network formed by the external expansion of the market can bring more competitive advantages to large construction enterprises [73], and small and medium-sized construction enterprises are more focused on improving their competitiveness through internal management [74]. Industrial economics indicates that most sectors feature the simultaneous presence of a limited number of major enterprises alongside numerous minor enterprises. The competitive network in the construction industry is a multi-community, multi-center network structure [1]. However, in the simulation, experienced enterprises do not occupy the most beneficial places in the network. Established enterprises that ought to occupy a central position in the network appear to have vanished, necessitating further discourse predicated on the "number of bids" from these enterprises.

Simulation studies reveal that an enterprise's bidding frequency is strongly correlated with its risk acceptance, the number of competitors, and the proximity to the CTR network hub. It may be extrapolated that, on the one hand, in a stabilized market, new entrants have a limited impact on the CTR network, and the process of the CTR network attaining a steady state is mainly a process of competition, expansion, and solidification among enterprises. Conversely, a rise in the "number of bids" may stimulate greater collaborative activity among enterprises, but the willingness of enterprises to cooperate is contingent upon their maturity and the competitive dynamics among partners [75]. Nonetheless, an increase in the volume of bids will not facilitate the sustained expansion of the enterprise size, because there exists a constraint on the market demand inside the model. If the large enterprises in this stage continue to keep their competitive strategy unchanged and stick to the regional market, as in the model, the result is that these enterprises gradually move away from the center of the association network, the winning rate decreases, and the scale of the enterprise stabilizes. In practice, large construction enterprises encountering growth impediments typically pursue geographic expansion, whereas their existing markets are characterized by significant competitive limitations, frequently featuring only a limited number of bidders.

6. Conclusions and Implications

This study developed an MAS model of CTR in the construction market using the Netlogo platform to simulate the establishment of CTR relationships among construction enterprises and their effects on competitive outcomes under varying conditions. This study yields the following conclusions: (1) the number of enterprises in the market and their competitive scope are the primary determinants of the CTR network's structure, and the influencing factors include the number of communities, network tightness, and robustness; (2) increases in market demand variables and enterprise numbers diminish the convergence rate of the CTR network; (3) within CTR, enterprises exhibiting high risk tolerance are more likely to engage in competitive behavior and secure advantageous network positions; however, the various factors examined do not ensure that robust enterprises can sustain a large scale and success rate.

This study's primary theoretical contribution enhances the enterprise competition model through a social network lens and offers a referential theoretical framework for the comprehension of CTR in the construction sector. These findings underscore the significance of competitive networks in fostering enterprise competitiveness. The micro-analysis conducted herein more accurately elucidates the impact of competitive relationships on the association phenomenon than empirical studies. The experimental outcomes reveal the presence of the "winner's curse" phenomenon within the CTR context. During the intermediate and later phases of the experiment, as the community's network structure increased in density, enterprises positioned centrally within the network initially gained short-term market advantages. However, these enterprises subsequently encountered difficulties owing to the depletion of their competitive resources or excessive exposure. The simulation results mirror the phenomena observed in the real world [76], offering validation for the model's applicability. This congruence between our theoretical findings and empirical evidence underscores the model's ability to capture essential competitive dynamics. Furthermore, our model contributes by revealing the underlying mechanisms at the micro level, which empirical studies often leave unexplored. This provides a nuanced perspective on the formation and evolution of competitive relationships in construction markets.

As digital technologies such as building information modeling (BIM), artificial intelligence, and big data analytics continue to transform the construction industry, policymakers should encourage the widespread adoption of these innovations to enhance the transparency and efficiency within competitive networks. On one hand, these technologies can facilitate real-time data exchange and collaborative decision-making, allowing enterprises to better navigate the complexities of community-type rivalry. On the other hand, the results of the model experiments show that a clearer competitive relationship between competitors can make the market's stabilization process smoother when facing fluctuations, leaving companies and the market with more time to digest.

For newcomers and construction enterprises with development bottlenecks, this study is informative in formulating their competitive strategies. First, this study advises every enterprise to retain the capacity to recognize and recall their competitors. This can assist enterprises in reducing their competition resource consumption, enhancing their bidding success rates, and preserving their core positions in the network. Another commonly neglected point is that this can assist enterprises in earning an extended survival time when the market is prohibitive. Second, CTR networks can function as both obstacles and avenues for the entry of newcomers. For seller markets, such as the construction industry, where the target market is defined and heavily reliant on the owner, or for regional markets, where the market demand is low and competition is intense, the earlier that an enterprise enters the market, the better. For latecomers, selecting a tighter network of communities as an entry point is a prudent strategy, or opting for a market with increasing demand may enhance the likelihood of survival. Finally, administrators must recognize that CTR is a two-edged sword: the tighter the CTR network, the more advantageous it is to establish a pre-existing advantage, but the more likely it is to draw competitors from outside the community. Consequently, when an enterprise attains a specific degree of pre-accumulation, it must be prepared to confront the "winner's curse", recognize structural holes within the CTR network, and venture into novel fields.

7. Shortcomings and Prospects

To explore the formation of CTR, this study considered only the key components, with limited reflection on the complexity of competition in the real market. The dimensions of the enterprise, the scale of the project, and the risk tolerances within the model are simplifications of bidding behaviors, and the model may encounter more complex estimation challenges in real-world applications. Subsequent research could incorporate novel model perspectives, influencing factors, and subjects of action. For instance, utilizing chance-constrained programming [77] to integrate uncertainties into existing models could enhance the models' adaptability and realism. Additionally, this model can be improved to examine the stability and resilience of existing communities with diverse backgrounds who are facing disruptive technological changes in the market. It is also possible to explore the stochastic bi-level problem [78] of interests between associations and enterprises under drastic market fluctuations. Furthermore, future work may address how economic strategies should be formulated to guide industrial transformation. Moreover, supplementary empirical data must be used to validate and improve the model, thereby increasing its accuracy in practical simulations and forecasts.

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