AN AGENT BASED MODEL FOR EXPLORING THE EFFECTS OF OVERCONFIDENCE ON THE WINNER'S CURSE IN CONSTRUCTION PROJECTS

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ABSTRACT

AN AGENT BASED MODEL FOR EXPLORING THE EFFECTS OF OVERCONFIDENCE ON THE WINNER’S CURSE IN CONSTRUCTION PROJECTS

As a result of errors in cost estimation, the winning companies in competitive environments such as bids, auctions, etc. fail to achieve the anticipated profit or even incur losses. This phenomenon is labelled as the “winner’s curse.” Diverse causes led to the occurrence of this circumstance.

Until recently, technical errors were thought to cause most construction estimation errors. Behavioral economics has shown that certain biases in individual decision-making can also contribute to these undesirable situations. Overconfidence is common. This illusion is when a person thinks they are better at making decisions than they really are.

The agent-based modeling method was used to examine this bias. This method investigates the system pattern created by heterogeneous individuals with independent macro-level behavior. In this study, individuals can be considered as construction companies. The prevalent pattern in the sector is the phenomenon of the winner's curse.

However, focusing solely on the overconfidence effect may not yield meaningful results. Risk aversion is regarded as a protective behavior against the negative effects of the overconfidence. There may also be a correlation between the number of bidders and the winner's curse.

This study demonstrates that the phenomenon of the winner's curse exists in all dimensions of the overconfidence effect. When the number of bidders is small, overconfidence behavior has little impact on the winner's curse, but when the number of bidders is medium or large, the winner's curse increases slightly as the overconfidence effect decreases. Risk aversion does not provide any protection against the winner's curse phenomenon.

ÖZET

YAPIM PROJELERİNDE AŞIRI GÜVENİN KAZANANIN LANETİ ÜZERİNDEKİ ETKİLERİNİ ARAŞTIRMAK İÇİN ETMEN TABANLI BİR MODEL

Kazananın laneti petrol sanayisinde ortaya çıkmış olan bir kavramdır. Kısaca, maliyet tahminleri gerçekleştirilirken ortaya çıkan hatalar sonucunda ihale, açık arttırma vb. rekabetçi ortamlarda kazanan firmaların işin sonucunda bekledikleri kazancı elde edememesi, hatta zarar etmeleri durumu şeklinde tanımlanabilir. Bu durumun ortaya çıkmasının nedenleri oldukça çeşitlilik göstermektedir.

Yakın zamana kadar, yapım projelerinde ortaya çıkan tahmin hatalarının nedeni olarak teknik hatalar öncelikli olarak değerlendirilmekteydi. Ancak psikoloji ve davranışsal iktisat disiplinleri, bireylerin karar verme süreçlerindeki birtakım yanılsamaların da bu istenmeyen durumların yaşanmasına neden olabileceğini göstermektedir. Bu yanılsamaların sıklıkla bahsedilenlerinden birisi de "aşırı güven" yanılsaması olarak düşünülebilir. Bu davranışsal yanılsama, bireylerin kendi kabiliyetlerinin ya da karar verirken kullandıkları verilerin, gerçekte olduklarından daha iyi ya da kapsamlı olarak değerlendirilmesi olarak tanımlanabilir.

Bu yanılsama incelenirken, etmen tabanlı modelleme yönteminden faydalanılmıştır. Bu yöntem, kısaca birbirinden bağımsız davranabilen heterojen bireylerin mikro düzeyde davranışlarının, makro düzeyde ortaya çıkardığı sistem örüntüsünü araştıran bir yöntemdir. Bu çalışmada bireyler inşaat firmaları olarak düşünülebilir. Ortaya çıkan örüntü ise, sektörde hâkim olan kazananın laneti olgusudur.

Ancak, aşırı güven etkisinin tek başına incelenmesi; anlamlı sonuçlar elde edilmesini sağlamayabilir. Riskten kaçınma davranışı, bireyleri aşırı güven yanılsamasının olumsuz sonuçlarından koruyabilecek bir davranış tutumu olarak değerlendirilmektedir. İhalelere katılan isteklilerin sayısı da kazananın laneti üzerinde etkili olabilir.

Bu çalışma, kazananın laneti olgusunun, aşırı güven etkisinin tüm boyutlarında hüküm sürdüğünü göstermektedir. Katılımcı sayısının az olduğu durumlarda aşırı güven davranışı kazananın lanetini çok etkilemezken, sayısının orta ve çok olduğu durumlarda beklenenin aksine aşırı güven etkisi azaldıkça kazananın laneti az miktarda artış göstermektedir. Her durumda riskten kaçınma, kazananın laneti olgusundan bireyleri koruyamamaktadır.

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CHAPTER 1

INTRODUCTION

The "winner's curse" is a term coined in the oil industry to describe unanticipated negative outcomes resulting from uncertain oil-well drilling auctions (Thaler, 1988). The profitability of a well is jeopardized by uncertainty regarding the amount of oil remaining in each well. If the estimated amount of oil is greater than the actual amount, the oil company may be overly optimistic and prefer to make offers with excessively high operating rents for the oil well.

The construction industry's uncertainty and tendency to overestimate are not uncommon in the oil industry. Both the bidding processes for oil well operations and construction projects are highly competitive. Even though the causes may differ, uncertainty in both industries can make it difficult to make accurate forecasts. Consequently, the winner's curse is prevalent in construction projects.

There are numerous possible explanations for the causes and events that led to the curse on the winner. Researchers have claimed for a long time that incorrect calculations are the cause of the winner's curse. In addition to technical errors, behavioral biases and intentional deception play a growing role in studies attempting to explain estimation errors.

Deliberate deception is strategic misrepresentation perpetrated by individuals in order to realize impossible projects. Behavioral factors can also lead to inaccurate estimates during the decision-making phases of construction projects. According to decision theory, a decision is the selection of one alternative from two or more alternatives based on an evaluation of the optimal solution (Fellows & Liu, 2018). According to Fellows and Liu (2018), in order to make a decision, agents must gather information and make predictions about the future. In the literature, neoclassical and behavioral economic perspectives dominate the manner in which individuals' decision-making is explained. In this regard, the neoclassical economic perspective must be analyzed first in order to comprehend the dominant rationalist perspective in the literature.

The natural sciences and positivist epistemology had an impact on neoclassical economic theories. Also, for a considerable amount of time, theories in the field of economics were based on a rationalist perspective, which holds that agents are rational actors who make rational decisions. Homo economicus is the term used to describe the rational actor in the neoclassical perspective. During the decision-making process, these rationalist individuals aim to maximize their own happiness. Levitt and List (2008) characterize homo economicus as rational, self-centered, and capable of solving challenging optimization problems (p. 909). According to this theory, agents are able to make precise and testable decisions (Laibson & Zeckhauser, 1998). The goal of Homo economicus is to maximize satisfaction with limited resources. Edwards (1954) refers to the homo economicus as "economic man" and asserts that he possesses three essential characteristics: (1) access to all relevant information, (2) sensitivity, and (3) logic (p. 381). Likewise, Weintraub (2002) summarizes the neoclassical economists' assumptions in three points. First, the outcomes of various options can be correlated with values, and economic agents choose one of these options based on their values. Second, agents make decisions in an effort to maximize utility. Thirdly, agents are equipped with relevant and complete information to choose among the alternatives. This rationalist perspective on how individuals make economic decisions is based on mathematical explanations of how individuals make decisions (Laibson & Zeckhauser, 1998). The theory of expected utility is an example of a rationalist approach to decision-making. The theory of expected utility is based on mathematical formulas that calculate the expected values of states and decisions (Rabin, 2012). According to this perspective, each decision alternative has an expected value, and agents must make decisions based on the expected values.

However, behavioral economics has criticized this way of thinking about how the economy functions for some time. Behavioral explanations of how economic agents make decisions can be traced back to Adam Smith's classical economic ideas from the 1700s (Levitt & List, 2008). However, research conducted by individuals such as Herbert Simon, Daniel Kahneman, and Amos Tversky has altered current perspectives on behavioral economics. In 1979, Simon introduced the concept of "bounded rationality" (Simon, 1979). This is a way of considering how individuals make economic decisions. According to Gigerenzer and Selten (2002), an agent's rationality is constrained by the solvability of the decision problem, cognitive limitations, and the absence of sufficient time. The majority of the time, decision-makers lack sufficient data to make the best choice (Engström & Hedgren, 2012). To explain the actions of economic agents, Simon (1990) asserts that the concept of satisfaction must be examined. It is incorrect to view them solely as individuals seeking the most lucrative means of making money. This perspective evaluates decision-making agents as self-satisfiers rather than self-optimizers (Hartono & Yap, 2011). If a choice is acceptable to the agent, it need not be the best option.

In addition to Herbert Simon's concept of "bounded rationality," Daniel Kahneman and Amos Tversky developed the concept of "Prospect Theory," which explains how agents make risky decisions (Kahneman & Tversky, 1979, 1984). This article criticizes the descriptive application of the theory of expected utility by disproving it. According to the authors, the psychological value or pain of losses is more influential for a decision-making agent than the psychological value or utility of gains (Kahneman & Tversky, 1979). Individuals attempt to avoid losses by selecting the option with the highest degree of certainty, despite the fact that the expected utility of riskier alternatives is greater. This is in contrast to the mathematical models used in expected utility theory.

In addition to the concepts of bounded rationality and prospect theory, Kahneman and Tversky introduced the concept of "Two Systems" to the field of decision making (Kahneman, 2011). In this view, an agent's decision-making system consists of two systems, one of which is operated automatically, intensively, effortlessly, and continuously due to human evolution. This is System 1, which is capable of executing simple and automatic decision-making processes. System 2 is only used for complex decisions that require intensive computation (Kahneman 2011, pp. 21–22). System 1, which is constantly active and searching what occurs within the mind, is used for simple automatic tasks such as adding two and two, reading a road advertisement, or walking in a familiar park. System 2 is utilized for more complicated tasks, such as locating a woman with white hair in a crowd or reciting one's phone number.

System 1 decision makers are more likely to employ mental shortcuts, which Kahneman (2011) refers to as "heuristics" or "rules of thumb," when making decisions. Typically, heuristics simplify the cognitive processes of decision-making and reduce the time required to select a satisfactory solution. Likewise, Tversky and Kahneman (1974) state that heuristics are generally useful. They are derived from the past experiences of humans in comparable circumstances.

Heuristics are effective and efficient decision-making rules, especially for complex problems, that have evolved over the course of evolution (Gigerenzer, 1991). However, heuristics can occasionally result in systematic errors, which the literature refers to as "biases" (Gigerenzer, 1991). In some instances, System 1 changes the subject of the decision to a simpler one, leading to the application of an inappropriate heuristic in an inappropriate situation (Kahneman, 2011).

In one of their earliest studies, Tversky and Kahneman (1974) identified three decision-making shortcuts that lead to errors. These heuristics are: (1) "representativeness," which occurs when estimating an object's class membership; (2) "availability," which occurs when assessing the frequency or probability of an action or situation; and (3) "adjustment and anchoring," which occurs when making numerical estimates.

In the field of project management, according to Shore (2008), there are two perspectives on project managers. The first view considers project managers to be rational decision-makers, comparable to the neoclassical perspective in economics. The second perspective, which is based on the views of Kahneman and Tversky (1979) and Simon (1979), examines the behavioral perspective during project decision-making. Shore (2008) identified nine systematically occurring biases in project management. Likewise, Flyvbjerg (2021) listed the top ten effective behavioral biases in project management. Table 1.1 contains a summary of both reports.

Overconfidence is one of the most frequently cited biases in a variety of academic disciplines. Moore and Schatz (2017) define "overconfidence" as a broad concept denoting irrational behaviors characterized by excessive confidence that is incompatible with reality. It is typically the disunity between an individual's perceptions and reality. The causes of this deviation are diverse. There are various classifications and terms grouped under the term "overconfidence." This study examines miscalibration, a type of overprecision, under the umbrella term "overconfidence."

Overprecision (called miscalibration in some texts) is a type of overconfident behavior characterized by an overestimation of the precision of one's own data when compared to reality (Hoffrage, 2016; Lin & Bier, 2008). Overprecision, unlike other types of overconfident behavior, is an internally developed bias that is unrelated to the performance of other agents. For instance, a trader may disregard the volatility of a stock's historical return data and invest aggressively in that instrument based on its historical return mean. Similarly, contractor organizations may discover that the cost performance of previous projects did not match their estimates. Focusing intensely on the mean accuracy of the estimates and ignoring the volatility of the differences between estimates and actual costs may normally encourage contractors to participate in high-risk projects.

Table 1.1 Biases effective in the Project Management

Systematic-Bias	**Definition**	**Source**
Available data	Depending on readily available data.	Shore (2008)
Conservatism	Rejection of new information.	Shore (2008)
Escalation of commitment	Investing more in a project that will not succeed.	Shore (2008)
Groupthink	Motivation of group members to think similarly.	Shore (2008)
Illusion of control	Decision makers overestimation of own control on incidents.	Shore (2008)
Overconfidence	Unsupported level of high confidence.	Shore (2008)
Recency	Overtrust on the most recent data.	Shore (2008)
Selective perception	Differences between individual's perceptions of circumstances.	Shore (2008)
Sunk cost	Rejection of non-recovery of already invested costs and continue to investment.	Shore (2008)
Strategic misrepresentation	Deliberate distortion of information for strategic purposes.	Flyvbjerg (2021)
Optimism bias	Behaving over optimistic about outcomes of decisions.	Flyvbjerg (2021)
Uniqueness bias	Behavior of evaluating one's project as more singular than reality.	Flyvbjerg (2021)
Planning fallacy	Trend to underestimate costs and schedule of projects	Flyvbjerg (2021)
Overconfidence bias	Unsupported level of high confidence.	Flyvbjerg (2021)
Hindsight bias	Labeling past events as predictable when they occur.	Flyvbjerg (2021)
Availability bias	Unsupported trust to past data.	Flyvbjerg (2021)
Base rate fallacy	Ignoring generic base rate information and focusing on specific information.	Flyvbjerg (2021)
Anchoring	Depending too heavily to an anchor point of information.	Flyvbjerg (2021)
Escalation of commitment	Investing more in a project that will not succeed.	Flyvbjerg (2021)

When a contractor decides to submit proposals in response to bid announcements, he or she must first develop a cost estimate to forecast the costs necessary to complete the project. A contingency budget was added to the cost estimate to account for unforeseen expenses. Finally, a competitive and profitable profit margin is added to the cost. The assumption is that overconfident contractors will underestimate project risks and set the contingency cost too low in order to protect themselves from unforeseen expenses or damage. The most obvious effect of the inconsistent determination of the project contingency cost for contractors is a lower-than-anticipated profit or a loss. At the macro level, consistent overconfidence may hinder the competitiveness of rationally acting contractors, whose rivals submit inadequately low bids. As a result, it is anticipated that poor estimation decisions will have a negative impact on the quality of the products or other performance indicators of a project. For this reason, analyzing overconfident behavior and preventing its negative outcomes are crucial.

The risk-aversion bias is a possible mental shortcut that may protect organizations from the negative effects of overconfident behavior. Similar to the overconfidence bias, risk aversion is a common cognitive bias that influences the decisions of decision-makers. The emotional consequences of losses are more influential than the emotional consequences of gains, according to Kahneman and Tversky (1979). Individuals may favor safer options over riskier options, despite the fact that riskier options may provide more valuable benefits. As stated previously, the authors collected their data using the most well-known concept of "Prospect Theory" (Kahneman & Tversky, 1979). Prospect theory is among the earliest critics of the dominant "homo economicus" viewpoint. Individuals favor prospects with a lower utility in order to select more certain prospects. This contradicts the rational utility maximizers of the neoclassical economic perspective.

In order to explain and analyze the "Prospect Theory" and "risk aversion bias," the "Expected Utility Theory" must be described in depth. Both normative and descriptive applications of expected utility theory are possible. The normative aspects of the theory will not be investigated in this study. As previously stated, numerous behavioral economists have criticized the model's descriptive nature. However, both rationalist and behaviorist researchers (with some modifications) have used the mathematical model described in the theory to study how people make decisions. Individuals compute the expected utilities of alternative options by multiplying their probabilities by the option's value if realized. Moreover, the graph of this utility function should be a straight line for risk-neutral individuals. However, Kahneman and Tversky (1979) observed that this graph is convex (risk-averse) in gains and concave (risk-seeking) in losses for the majority of individuals.

In some instances, empirical research methods do not correspond precisely with the research topic. For instance, Fang, Kim, and Milliken (2014) state that concepts such as "sugarcoating" of data are inappropriate for empirical research methods such as surveys and interviews. Or, asking respondents how irrational they are when making decisions is not an easily accepted situation. In some cases, simulations are more suitable research methods for these reasons. In addition, Davis, Eisenhardt, and Bingham (2007) demonstrate the potential for applying virtual models to social phenomena. According to the authors, the use of simulations is beneficial for certain specialized interests, such as longitudinal studies, which require excessive use of resources such as time and money when empirical methods are employed.

In light of the aforementioned assertions, the primary objective of this study is to investigate the impact of overconfidence on the winner's curse in competitive construction bidding. A virtual model for analyzing the effects of overconfident behavior has been developed for the reasons already mentioned. To achieve this objective, an agent-based model involving interaction between contractor and client agents during the bidding process has been developed.

The selection of agent-based modeling is due to the fact that agent-based models enable the analysis of independently behaving agents. This research method employs a bottom-up approach. The behavior of individuals at the micro level generates a pattern (known as "emergent phenomena") at the macro level. For example, forest fires are modeled according to the actions of each tree agent (Niazi et al., 2010). In this study, independent contractor agents analyze the relationship between overconfidence and the winner's curse. In the construction industry, the intensity of the winner's curse is observed in the micro-level behaviors of construction agents. To achieve this objective, construction management adopts theories and tools derived from behavioral finance studies.

The second objective of the study is to determine whether risk aversion can shield agents and the entire industry from the negative effects of overconfident behavior. In some texts, overconfidence is described as a behavioral trait that reduces the impact of risk aversion (Kahneman & Tversky, 2012). Risk aversion can also be evaluated as a barrier to overconfident behavior. As a result, it seeks to analyze the effects of risk aversion on contractor agents' overconfidence. Here, models derived from research on behavioral finance are reapplied to the field of construction management.

For the purpose of describing the research, literature reviews on overconfidence and risk aversion are provided. In subsequent sections, the methodology employed, model design, findings, and discussion are elaborated.

CHAPTER 2

THE WINNER'S CURSE

It is commonly stated in the literature that engineers working for Atlantic Richfield, Capen, Clapp, and Campbell introduced the concept of "the winner's curse" in 1971. (Thaler, 1988). When estimating the amount of oil that will be extracted from a drill, the engineers were aware of the high degree of uncertainty. The business with the most optimistic estimate also submits the highest bid. If the most optimistic company's forecast is overly optimistic, it will incur losses. These engineers define this as the "winner's curse." According to Thaler (1988), a loss can occur in two ways: (1) a monetary loss as costs exceeds the budgeted amount, and (2) disappointment as the company earns a lower profit than anticipated.

Competitive selection processes, such as auctions or bids, depend on two evaluations: (1) the value of the bid to the bidder, and (2) the bidder's strategy and expectations if the bid is won. The first one relates to estimations of the bid award's value. For example, it can refer to the profit of a construction project or the monetary (or moral) value of a rare work of art. Here, technical errors, biases, or intentional distortions (such as Flyvbjerg's "strategic misrepresentation") are potential causes of inaccurate forecasts. The second issue is somewhat more complex. To defeat competitors, the bidder may choose an aggressive strategy consisting of a reduction in the profit margin. Or the bidder may maliciously intend to use change orders to make up for missing technical details in the contract documents. How the winner's curse affects the winner depends on the accuracy of the estimates and the objective of the strategy. Figure 2.1. illustrates the causes and effects of the winner's curse during each phase of the process.

In the majority of observed auctions or bids, the winner offers an irrationally optimistic bid that is lower than the possible profit from the bidding, and the mean of the bids is lower than the actual value of the bid object, according to (Thaler, 1988). This pattern, according to the author, results from two common systematic behaviors: (1) the winner's curse and (2) risk aversion. The majority of bidders are risk-averse, so they submit bids with extensive contingencies to prevent losses. In contrast, the bidder who overestimates the item's value will submit an inadequate contingency bid.

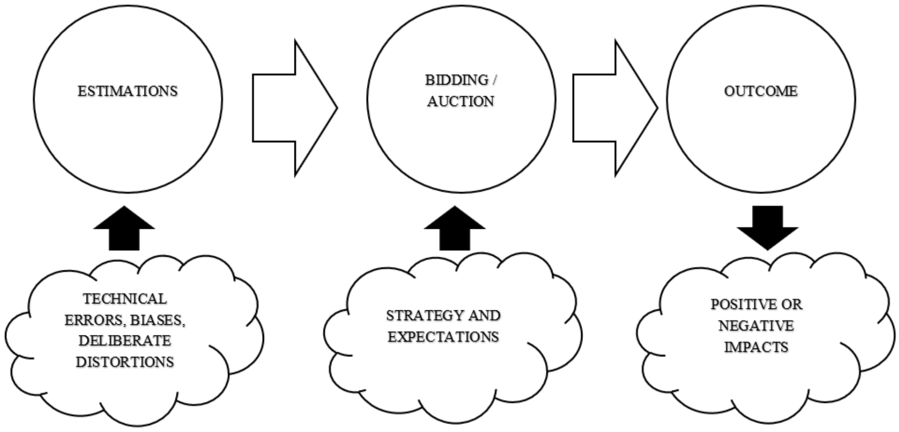

Figure 2.1 Causes and effects of the winner’s curse in phases of construction projects.

To protect themselves from the winner's curse, the construction organizations may opt to include a contingency budget in their bids. Conversely, larger contingency budgets indicate a diminished competitive advantage. Various indicators determine the degree of contingency. As mentioned previously, the organization's competitive strategy may impact the contingency. The determination of the competitive strategy can also be influenced by a number of other factors. For instance, Thaler (1988) states that the number of bidders influences competitive advantage. When there are numerous bidders at an auction and they are aware of this fact, bidders may choose to act aggressively in order to win the contract. Consequently, it is highly likely that bids with more participants will exhibit more severe levels of the winner's curse. The determination of contingency costs is also influenced by other variables, such as the degree of economic uncertainty and associated risks. Elsayegh, Dagli, and El-adaway (2020) demonstrate how difficult it is to choose between keeping contingency low to gain a competitive advantage and keeping it high to prevent losses.

Signor et al. (2020) list the uncertainty of the bid object's value, estimation errors, and the number of bidders as causes of the winner's curse. Similarly, the author adds some additional causes (or signals) of the winner's curse, including (1) asymmetric information, (2) supply/demand ratio, (3) discounts, (4) municipalities' legal guides and contracted prices, (5) number of bidders, (6) contractor's experience, (7) difference between the winning and second-best bid, and (8) social impact. In analyzing the causes of the winner's curse, the potential intentionality of the cause is also crucial. Typically, unintentional causes such as estimation errors or biases are held responsible for the winner's curse. In certain instances, however, deliberate causes are observed. Flvyberg's strategic misrepresentation is one of the most widely recognized deliberate causes. Similarly, unethical strategies are frequently employed in construction projects (Elsayegh et al., 2020), such as making technical contract documents appear insufficient in order to increase the contract price after the bidding process. Signor et al. (2020) focus on a distinct aspect of construction projects. When a contractor discovers that the winner's curse is present, lowering the quality of products may be a solution for mitigating its effects and dealing with it.

In public procurement processes, precautions are taken to prevent the winner’s curse. In the Turkish local public procurement system, for instance, threshold values are determined by the anticipated cost of the project prior to bidding. Elsayegh, Dagli, and El-adaway (2020) express identical sentiments concerning the Brazilian public procurement system. However, these measures are not sufficient in all situations. Similarly, Gunduz and Karacan (2009) assert that the preventive measures outlined in Law No. 4734 do not eliminate the winner's curse in the Turkish public procurement system.

As the organization loses profits, the winner's curse may be assessed as a loss for the contractor. However, it is also significantly more dangerous for other project participants. The winner's curse may result in the abandonment of projects without completion and even the bankruptcy of companies, which will have devastating effects on society and the economy Signor et al. (2020). Similarly, deteriorating product quality or delivery delays caused by financial issues are additional effects of the winner's curse on the various parties involved in a project (Gunduz & Karacan, 2009).

In construction project bidding, lump-sum contracts protect clients from the winner's curse more effectively. Nonetheless, the client's situation may become more complicated and risky if the contract is for a lump sum. As the project budget is fixed at the outset of a lump sum contract, the contractor is more susceptible to the winner's curse (Gunduz & Karacan, 2009). When the winner's curse is felt by the contractor, the contractor must consider a response. If the organization has sufficient funds, they may decide to respect the signed contract. In the event that the company is unable to eliminate the winner's curse, the client may experience unfavorable outcomes, such as the contractor abandoning the construction site.

CHAPTER 3

OVERCONFIDENCE

One of the prevalent biases in decision-making is overconfidence. Overconfidence is a general term for irrational behaviors characterized by excessive confidence that does not correspond to reality (Moore & Schatz, 2017). There are numerous instances of overconfident behavior in daily life. For instance, many believe they are superior drivers compared to the norm. Similarly, students attribute failure to instructors.

The "heuristics and biases program," initiated by Tversky and Kahneman in the 1970s and 1980s, influenced studies of decision-making and judgment. This is when overconfidence bias first began to manifest itself (Hoffrage, 2016). A concept describing irrational behavior in human judgment was conceived as a result of the fact that overconfidence was, at the time, a necessary premise for explaining deficiencies in individuals' information-processing capacities. This trend utilized the psychological concepts of adjustment, anchoring heuristics, and confirmation bias to demonstrate and explain overconfidence.

Overconfidence is a general term used to describe the disparity between a person's perception of reality and reality itself (Moore & Schatz, 2017). It is evident that this nonconformity has a variety of causes and effects. Similarly, Hoffrage (2016) asserts that the term "overconfidence" has multiple meanings. As a result, some academics define subheadings. The definition of overconfidence and the boundaries defining different types of overconfidence are not clearly defined. Variable methods are utilized to compare reality with overconfident beliefs. In the majority of instances, two types of work are performed: (1) estimation of the probability of correctness in statements and options, and (2) estimation of confidence intervals. Miscalibration of individuals indicates overconfidence bias for the first form. Individuals' confidence intervals are too small for the second form. In a similar vein, Glaser and Weber (2007) note that overconfidence manifests itself in the form of miscalibration, specifically the better-than-average effect and too narrow variance estimates.

Moore and Schatz (2017) provide a comprehensive summary of overconfident behavior types. According to the authors, overconfidence manifests itself in three ways in the judgments of individuals. The first type of overconfidence is overestimation, which is the belief that a person is better than his or her actual situation. The second belief is overplacement, which occurs when an individual believes he or she is superior to others, despite the fact that this is not true. Third, overprecision occurs when a person places an excessive amount of trust in his or her own knowledge of a subject. In addition, authors clarify the differences between optimism, self-esteem, self-efficacy, self-enhancement, and the overconfidence bias by emphasizing that these concepts do not correspond to reality. The erroneous comparison of beliefs with reality is a crucial element of overconfidence.

3.1. Types of Overconfident Behaviors

Researchers frequently employ the concept and term "overconfidence" to explain a vast array of irrational actions. However, overconfidence does not constitute a single instance of irrationality in decision-making processes (Moore & Schatz, 2017). There are numerous types of terminology for overconfident behaviors. Using "overconfidence" as a search term will result in the discovery of terms such as "better-than-average effect," "miscalibration," and "illusion of control." Moore and Schatz (2017) use the terms "overestimation," "overprecision," and "overprecision" to describe three types of overconfident behavior that assist individuals in avoiding confusion. Overestimation refers to individuals' erroneous perceptions of their own position as being superior to their actual status. Overplacement is an erroneous comparison between an individual and his or her competitors. In this relative evaluation, a person places themselves in a stronger position than rivals. The definition of overprecision is an unrealistic belief in one's own knowledge.

3.1.1. Overestimation

Overestimation is a cognitive bias associated with individuals' assessments of their own abilities. In the case of overestimation, an individual's self-capability is presented as being greater than the individual's actual capability. If you are experiencing overconfidence, you may believe you are more capable than you actually are. Overestimation disregards the performances of other individuals. Excessive optimism caused by overestimation may result in negative outcomes. For instance, if an athlete believes that his or her situation is sufficient for achieving their goals, despite the fact that this is not true, the need to practice may not be well understood. As a result, the athlete's performance may suffer. Similarly, students may prefer to study insufficiently to achieve satisfactory grades. Two research streams, according to Moore and Schatz (2017), observe persistent overestimation. The first is the "illusion of control," while the second is the "planning fallacy." Thompson (1999) defines the illusion of control as the mistaken belief that the individual making the decision has control over the outcome of the decision. The planning fallacy is what Buehler, Griffin, and Peetz (2010) refer to as the bias that leads individuals to believe they can complete a project with limited resources, such as time and money, despite the fact that similar projects require more.

In many instances, the propensity to believe that overestimation is common leads individuals to make bad choices. Moreover, in numerous instances, conditions are reversed (Moore & Schatz, 2017). Individuals in high-threat situations may exhibit behavior that is easily underestimated. For example, individuals perceive a greater threat to their health during epidemics. This demonstrates that overestimation is not a consistent, predictable behavior. In certain circumstances, decision-makers may anticipate negative outcomes as opposed to overestimation. The difficulty of tasks associated with the evaluated decision may influence the decision-self-evaluation maker in the opposite direction (Moore & Schatz, 2017). In situations involving simple tasks, individuals have a tendency to overestimate their abilities, believing they are superior to the actual situation. In contrast, difficult tasks induce "underestimation" of one's own capabilities. If a decision maker is confronted with a challenging task, he or she underestimates his or her own capabilities.

3.1.2. Overplacement

Like overestimation, overplacement is a distortion in the evaluation of an individual's self-capabilities. The distinction between the two concepts is whether or not the performance of others is considered. According to Moore and Schatz (2017), overplacement occurs when an individual's performance is rated higher than it is relative to the performance of other individuals. The phrase "above-average effect" is frequently used in the same manner (Beer & Hughes, 2010).

(Malmendier & Tate, 2005a) discovered that when people reflect on the good things they have, they begin to view themselves as superior to the norm. The better-than-average effect has an impact on the attribution of causality. As a result of their expectation that success will result from their actions, they take credit for the positive outcomes of their actions. On the other hand, bad luck is blamed for the results of actions when they fail. Similarly, when individuals choose the criteria used to evaluate them, they tend to view themselves as above average (Moore & Schatz, 2017).

On the other hand, critics argue that measuring overplacement in research studies makes it more difficult to discern the frequency of overplacement behavior. Moore and Schatz (2017) state that it is not a good idea to ask people where they are in relation to the mean because people's ability to judge does not work for this type of comparison. Similarly, the authors discuss critics of the studies who question the mean by asserting that the skewness of the distribution indicates that the majority of individuals are above the mean.

Aside from comparing your performance to that of others, another distinction between overestimation and overplacement is the effect of the difficulty of the task. Moore and Schatz (2017) state that comparing one's performance on a simple task to that of others leads to underestimation, not overestimation. According to Hoffrage (2016), overconfidence is proportional to the difficulty level. The more challenging the task, the greater the level of overconfidence. Similarly, a simpler task is associated with a lower level of overconfidence (Benoît & Dubra, 2011; Hoffrage, 2016; Moore & Cain, 2007). When decision-makers examine simple tasks that anyone can perform with ease, they believe their skills are inadequate for competition. However, the relationship between one's performance and that of one's competitors is unaffected by task difficulty. If an individual is superior or inferior to others in a particular action, he or she will likely maintain the compared position despite changes in task difficulty. Moore and Schatz (2017) state that underplacement is more prevalent than overplacement. This supports the aforementioned criticisms of overplacement's extensiveness.

In some instances, the concept of "egocentrism" may cause confusion with "overplacement." Overplacement and egocentrism are similar concepts with similar applications. According to (Moore & Cain, 2007), egocentric behavior is unawareness of the performance of competitors. When comparing performance to that of competitors, egocentrism causes individuals to disregard the likely performance of competitors. Individuals who are egocentric concentrate solely on their own abilities and disregard rivals. Camerer and Lovallo (1999) equate "reference group neglect" with "egocentrism." Egocentrism differs from overconfidence in that the decision-maker disregards the abilities of others rather than exaggerating his or her own.

3.1.3. Overprecision

Some experimental and empirical research (e.g., Lin and Bier (2008); Hoffrage (2016)) indicates that another type of overconfidence occurs when individuals overestimate the accuracy and relevance of their own data. Overprecision is an unwarranted reliance on one's own subject-matter expertise. In this instance, overconfidence manifests itself when we believe that the accuracy of our judgments, predictions, or inferences exceeds reality. This is referred to as "expert overconfidence" by Lin and Bier (2008), which means that the experts' estimates of confidence intervals are too small. Overprecision is characterized by overconfidence in one's own data (Moore & Schatz, 2017). Similar to overestimation, overprecision is a cognitive bias that influences the internal evaluations of decision-makers. As with other types of overconfidence, there are alternatives to overprecision that can be found in the literature. In the field of behavioral finance, one of the most prevalent terms is "miscalibration" (Lovric et al., 2010).

In some cases, decision-makers use historical data to make predictions regarding decision alternatives. A trader may examine the past performance of the stocks he or she owns or the past success of a company's new products, for instance. These are some data samples. Estimates and profits from previous bids and projects are also examples of historical data for construction companies. Looking at and considering historical data is extremely beneficial for decision-makers. However, there may be discrepancies between the past cases that generated their own records and the subject evaluated at the time of the decision-making process. Moreover, the desirability of the anticipated outcome(s) may cause decision-makers to undervalue the possibility of adverse outcomes. People may therefore place a great deal of emphasis on the mean of historical data while ignoring the variance when the mean is related to the desired outcome.

Moore and Schatz (2017) outline two phases for the potential method. First, it is a bad idea to ask individuals to estimate a phenomenon that they cannot know accurately. The second phase entails soliciting individuals' perspectives on their estimates, i.e., their level of confidence in their estimates. For instance, individuals may be asked to estimate the height of Mount Everest before being questioned on the likelihood of their estimate being accurate. From this perspective, respondents may also be asked to provide a confidence interval for their estimates. However, some authors criticize the confidence interval method because it is not how individuals determine whether or not their judgments are accurate.

In addition to empirical studies investigating overprecision, studies that are essentially experimental are also common. In mathematically modeled computer simulations, the effect of overprecision is demonstrated by modifying the standard deviation of the distributions of past records and reporting the observed results as simulation outcomes. This resembles manipulations of confidence intervals observed in empirically designed studies. Virtually modeled simulations make it possible to define and predict how biased decision-makers, such as those in the stock market, will influence the entire decision environment.

3.2. Negative And Positive Consequences of Overconfident Behaviors

In the field of business management, heuristics are frequently blamed for poor decisions and undesirable outcomes. Overconfidence is not ruled out. Moore and Healy (2008) state that current research demonstrates that overconfidence is required in certain circumstances, such as when creating a new product or launching a business. In the same way, some studies suggest that overconfidence can increase motivation, which can lead to successful decision-making. People may make irrational decisions if overconfident judgments result in illusory conclusions. The evolutionists Johnson and Fowler (2011), who criticize negative beliefs about gaining a competitive advantage, theorize that catastrophic events in history, such as world wars, may be linked to overconfidence.

Johnson and Fowler (2011) explain how overconfident behavior diminishes the effects of loss aversion. In the model, two competitors are competing for a scarce resource. One of the competitors is more competent than the other. One individual's capabilities are unknown to the other. Both individuals may decide to compete for the award in this circumstance. In this instance, the victor is the more competent competitor. If one of the competitors gives up, the other automatically receives the prize. In this situation, a rival does not need to be more competent than the other. If so, acting overly confidently will result in success, even if the other competitor is more skilled.

Another possible advantage of being overconfident is the ability to influence the outcome of a decision. When the decision-maker exhibits excessive confidence, he or she may attempt to improve the decision's outcome. This is supported by Flyvbjerg (2021), who argues that overconfident behavior leads to unrealistic optimism, which motivates managers to improve the outcomes of their decisions. In a similar vein, Hilary et al. (2016) demonstrate that overly optimistic (overestimated or overplaced) manager behaviors result in a greater number of managers attempting to meet the goals.

Malmendier and Tate (2005b) state that decision-makers are more optimistic when they believe they can influence the outcomes of their actions. But when you have less influence over events, you are less motivated to work diligently. In situations where there is little control over the outcomes of decisions, the most valuable option must be chosen because it is impossible to alter the outcome after the decision has been made. Consequently, the most frequently cited negative consequences of overconfident behavior may manifest in decisions made with little self-control.

CHAPTER 4

RISK AVERSION

4.1. Neoclassical Economic Views and Behavioral Economics

By the middle of the 19th century, the neoclassical school of economics, which asserts that rational individuals make decisions, consume in order to maximize their utility, and produce in order to maximize their profits, had become the dominant economic theory. The extensive use of mathematics to determine maximizations or measure utility has resulted in the alienation of psychological aspects in economics over time. However, research indicates that economic agents do not always make rational decisions. Consequently, rationalist perspectives on economic agents fail to adequately explain economic agents' behavior. Consequently, a relatively new research field is emerging: behavioral economics. Based on psychological foundations, behavioral economics is a policy that provides a theoretical perspective and better thinking when making better predictions of field events (Simon, 1990).

The origins of behavioral economics can be traced back to the critique of neoclassical economic assumptions, particularly the assumption of the rational man (homo economicus), which was prevalent until the 1980s. In behavioral economics, it is necessary to analyze people's economic behaviors and to incorporate psychological and sociological factors into economic data when theorizing. People may not act to maximize their benefits or profits for a variety of psychological reasons, such as asymmetric information, uncertainty, risk aversion, the desire to gain status and reputation, or the fear of losing them. These psychological factors may steer individuals away from maximization (Simon, 1990).

The origins of behavioral economics can be traced back to the publication of Adam Smith's "The Theory of Moral Sentiments" in 1759. Smith outlined the psychological principles of individual behavior in this work. A portion of Smith's body of work is concerned with individual preferences and choices. This article examines the phenomena of loss aversion, intertemporal choice, and overconfidence. Other portions of the discussion centered on preferences that emerge in social contexts. These include altruism, fairness, and market trust-building (Ashraf et al., 2005; Simon, 1990). The 1955 publication of "A Behavioral Model of Rational Choice" by H. Simon is considered a turning point in the field of behavioral economics. In his article, Simon asserts that the traditional economics assumption of the "economic man" requires a radical correction, and he will provide suggestions for its correction. According to Simon, global rationality is not possible due to the organization's own knowledge and capabilities, which will limit its rationality. Simon is not interested in "universal" models of rationality but rather "limited" models of rationality, in his own words (Simon, 1955, pp. 112–113).

4.1.1. Expected Utility Theory

Both rational economics and behavioral economics studies require a tool to explain and analyze why individuals choose one option over another. The utility function of expected utility theory provides a great opportunity for this purpose. In economics, the Expected Utility Theory (EUT) is the most prevalent explanation for how people behave in uncertain situations. EUT is a very convenient model for aggregation, especially due to its simplicity and mathematical ease (Şener, 2015). Its validity in describing individual behavior is debatable, however.

Before describing the EUT utility function, it is essential to define the concept of utility. The utility approach is predicated on the notion that when a person wants to purchase a good or service, he or she bases his or her decision on the amount of benefit he or she will receive from using the good or service. The expected utility approach, on the other hand, assumes that an individual makes a decision based on the benefits he or she will receive from a good or service in the future as opposed to the benefits he or she will receive at the time he or she intends to purchase that good or service. Specifically, the "expected utility" approach asserts that people choose which goods or services to purchase based on their expected usefulness. Consequently, modernists have transformed the utility function of traditionalists into an expected utility function (Şener, 2015). To explain the utility function, it is necessary to identify the historical development of the expected utility theory.

Bernoulli constructed the initial basis for the expected utility function. Daniel Bernoulli (1738) developed the expected utility theory to solve the problem known as the St. Petersburg paradox. The theory attempts to explain human behavior under conditions of uncertainty by beginning with a measurable utility function. The Petersburg Paradox, which his cousin Nicholas Bernoulli (1687–1759) proposed in a letter to Pierre Reymond de Montmort (1678–1713) in 1713, led Daniel Bernoulli (1700–1782) to develop this concept. The Petersburg Paradox poses the question of how much one must pay to participate in a coin-flipping game (Şener, 2015).

According to the rules of this game, you win two silver coins if you get heads on your first attempt, four silver coins if you get tails on your second attempt, eight silver coins if you get tails on your third attempt, sixteen silver coins if you get tails on your fourth attempt, and sixteen silver coins if you get tails on your fourth attempt. The game continues until the first head has been collected. There is a possibility that the payoff will increase indefinitely in the case of continuous heads (Şener, 2015). Since the sum of the series is infinite, the expected payoff of the game is also infinite. By introducing this game, Nicholas Bernoulli actually demonstrated that people do not always behave rationally. Even though the expected payoff of the game is infinite, people do not spend a great deal of money on it because they believe the low probability of receiving large payoffs will not occur. Therefore, they demonstrate irrational behavior by avoiding risk (Şener, 2015).

When attempting to explain the Petersburg Paradox, Daniel Bernoulli formulated the first definition of expected utility. He did so by introducing a novel method for assessing risk. According to Bernoulli's article's definition, "Specimen Theoriae Novae de Mensura Sortis," published in Latin in 1738, "the average benefit is obtained by multiplying the benefits of all possible profit expectations by the number of alternatives to these expectations and dividing the result by the total number of alternatives. The average utility corresponds to the problem's risk value." (Şener, 2015, p. 41).

Bernoulli argued that individuals maximize expected utility instead of expected income. Using a logarithmic function to describe the expected utility of the paradox, he suggested that a constant increase in income would result in a decrease in utility. However, he was unable to devise a logical study on how to measure utility. Daniel Bernoulli was the first to introduce the concept of expected utility to literature in the 1700s, as demonstrated by these explanations. Two centuries after Bernoulli, however, economists developed the expected utility approach based on this concept (Şener, 2015).

Von Neumann and Morgenstern first developed the cornerstone of EUT in 1947. The authors formalized Bernoulli's approach to expected utility by developing the axioms required for the existence of an expected utility function. Later, Herstein and Milnor

(1953), Savage (1972), Pratt, Raiffa, and Schlaifer (1964), and Fishburn (1970) formulated alternative axiom systems from which the Expected Utility theorem could be derived (Şener, 2015). Therefore, the Expected Utility model has enabled its use in a variety of contexts.

Von Neumann and Morgenstern assume that people base their purchasing decisions on the utility they will derive from the consumption of goods and services in the future. In addition, according to these economists, this utility can only be predicted using probabilities. Therefore, Von Neumann and Morgenstern concluded that the utility function is insufficient to explain how individuals decide what to purchase when there are risks, so they developed the expected utility function. This economist's work has taken its place in the literature as an important step in economics as a pioneer of modern demand theories based on the expected utility function, which replaced traditional demand theories based on the utility function (Şener, 2015).

The von Neumann and Morgenstern version of the Expected Utility theory is founded on a straightforward mathematical utility function of alternative choices. Each alternative has a variety of outcomes with differing values. And each outcome is associated with its own probability. To determine the expected utility of each option, the expected value of each potential outcome is multiplied by its anticipated likelihood. Then, the calculated values for each option are summed. The sum represents the expected utility of the option (equation 4.1). According to the EUT, a person selects a choice alternative when the utility of that prospect and the individual's assets surpasses the utility of the individual's assets alone (Kahneman & Tversky, 2012).

$$U(W) = \sum_0^n \quad p_n \cdot x_n \tag{4.1}$$

In the formula above, p is the probability of each alternative, x is the estimated utility of an alternative, and n is the number of all alternatives.

The expected utility approach of Von Neumann and Morgenstern differs from Daniel Bernoulli's expected utility. This is because von Neumann and Morgenstern demonstrated axiomatically for the first time that rational decisions can be made based on the maximization of expected utility. In other words, they obtained a practical utility function by proving that consumer expectations can be calculated using logic and reason.

Moreover, these economists extended Bernoulli's concept of expected utility for monetary returns to all possible outcomes (Şener, 2015).

Examining the history of the expected utility approach, it is possible to say that the first studies aimed to develop and validate this approach, whereas more recent studies seek to demonstrate systematic violations of the axiomatized model. The first group agreed with the statement that individuals always choose to purchase goods and services in a manner that maximizes expected utility. The second group, on the other hand, acknowledges that consumers may exhibit irrational behavior when risk, uncertainty, and other factors are considered and therefore may prefer options with lower expected utility (Şener, 2015).

The French mathematician Maurice Allais' examples of choice decisions, known as the Allais Paradox, are the first significant criticism of EUT. This important work by Maurice Allais demonstrates that consumers do not always maximize expected utility when making decisions. The Allais Paradox is a criticism of traditional approaches based on rational consumer behavior, as it is rational consumer behavior for an individual to choose the option with the highest expected utility. Similar criticisms were made by Kahneman and Tversky in their 1979 article, "Prospect Theory: An Analysis of Decisions Under Risk." In addition to their criticisms and after explaining the reasons for the deviations from the expected utility theory's decision-making processes, they propose the "prospect theory." The prospect theory assumes that when people make decisions under uncertainty, losses are more important than gains (Akyıldız, 2022; Kahneman & Tversky, 1979).

The Allais paradox demonstrates that a strict mathematical approach to rationality is not always the most effective way to explain decisions when there is considerable uncertainty. Cognitive biases may be more significant. The classic 1979 paper by Kahneman and Tversky, considered one of the pioneers of behavioral economics, proposed the "certainty effect" as a possible explanation for the Allais paradox. EUT states that people's preferences will not change even if the odds of comparing outcomes increase proportionally. Contrary to this prediction, however, are the experimental results. 78% of subjects prefer a game that guarantees a one-week vacation in England over one that offers a three-week European tour with a 50% chance of winning. However, when the probability of winning a 1-week tour is reduced to 10% and the probability of winning a 3-week tour is reduced to 5%, the majority of subjects (63%) prefer the 3-week tour. In other words, for options with a low probability of winning, the size of the prize becomes increasingly important, whereas as the probability of winning increases, options with a high probability of winning are preferred despite their less attractive prizes (Akyıldız, 2022).

The previously mentioned utility formula of EUT can be used as a normative decision-making tool, and the purpose of this text is not to debate its validity. In experimental studies, however, in addition to the Allais Paradox, several violations of the descriptive model are observed. As mentioned previously, Kahneman and Tversky (1979) discovered EUT violations in their seminal study. Individuals tend to disregard outcomes with a low probability in favor of more certain options ("certainty effect"), for instance. Similarly, one of the earliest critics of the rational perspective in economics is the "Bounded Rationality" theory of Herbert Simon. Two points distinguish the theory from rational perspectives. First, the theory emphasizes that individual access to information is restricted. Agents make decisions with limited information, which may result in the selection of a lesser-utility alternative. The second distinction is that economic agents have limited computational capabilities. The author concludes that economic agents do not make decisions that maximize utility. According to Simon (1990), agents make "satisfying enough" decisions.

Critics of EUT are not limited to Herbert Simon's "Bounded Rationality" and Kahneman and Tversky's "Prospect Theory." Several other criticisms of the neoclassical economic perspective have been developed. Studies such as "Regret Theory" (Loomes and Sudgen, 1982), "Prospect Theory" (Kahneman and Tversky, 1972), "Cumulative Prospect Theory" (Kahneman and Tversky, 1982), and "Rank Dependent Expected Utility Theory" reveal violations of the Expected Utility Theory, according to Levy, Levy, and Solomon (2000). Particularly, the experimental studies of Kahneman and Tversky reveal distortions in economic decisions.

4.1.2 Emergence of the Risk-Aversion

Individual decision-making analysis relies heavily on Kahneman and Tversky's Prospect Theory as a replacement for the utility function of EUT. Kahneman and Tversky (1979) highlight one of the primary distinctions between EUT and the Prospect Theory by diverting attention from the final stage of wealth to the changes in wealth. According to the authors, the asset prior to the decision serves as a reference point for the decision maker, who then highlights the change in wealth. According to the EUT, if a prospect values $1,000 and another option values $900, the first option demonstrates greater utility. In contrast, according to prospect theory, if option one is the result of a $2,000 asset investment and option two is the result of a $1,000 asset investment, decision makers are expected to find option two more desirable.

The utility function is depicted in the Prospect Theory as a plane with losses and gains. After the reference point, this "S"-shaped curve takes on a different appearance because individuals react differently to losses and gains. In other words, a break occurs at the citation. This curve, which is concave for gains and convex for losses, appears steeper for losses due to the loss aversion behavior of the individual. This indicates that the benefit obtained from the same unit of gain is less than the loss caused by the same unit of loss in absolute terms. According to Tversky and Kahneman, people experience almost twice as much pain when they lose as when they gain the same amount. This is known as risk-aversion behavior ((Tversky & Kahneman, 1974). Moreover, if the results are evaluated in the gain area according to the reference point, individuals exhibit a risk-averse outlook, whereas if they are evaluated in the loss area, individuals exhibit a risk-open outlook. The Reflection Effect was coined by Kahneman and Tversky. In contrast to the Prospect Theory developed by Kahneman and Tversky, these findings are founded on empirical observations and experiments as opposed to axioms derived from the rules of logic. From this perspective, Prospect Theory's purpose is to describe what actual behavior is or will be, as opposed to explaining the rational behavior approach.

Individuals are more concerned with the change in wealth relative to a reference point, according to Prospect Theory. Typically, the reference point is the initial level of wealth of the decision unit. Additionally, losses and gains are calculated relative to this point. Considering the reference point to be the goal of the individual, the decision will result in a gain for the portion above this point and a loss for the portion below it.

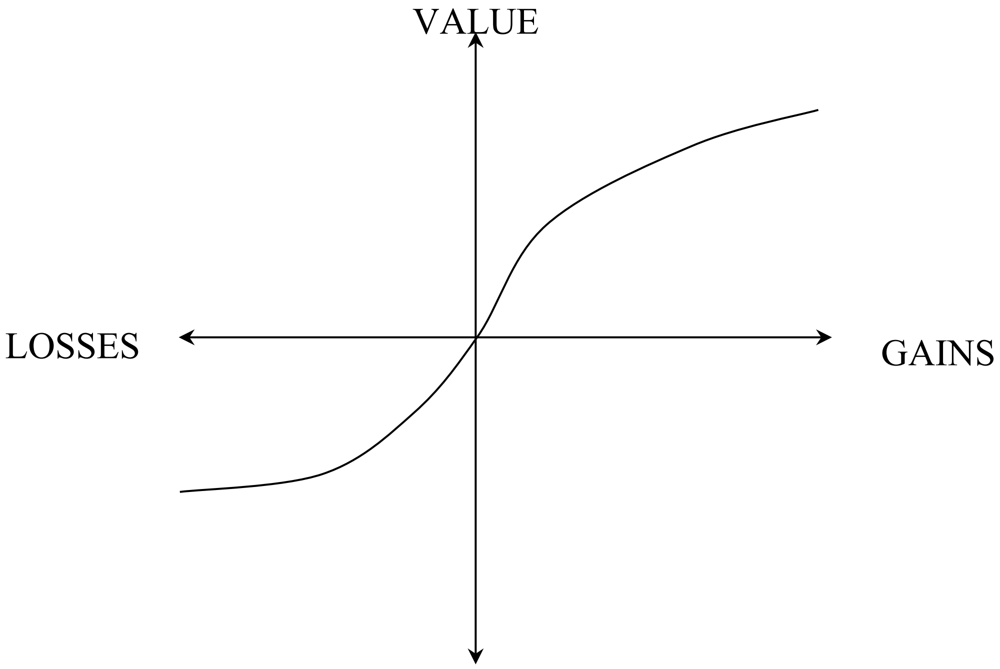

Figure 4.1 Effects of losses and gains according to behavior
(Source: Tversky and Kahneman 1991, 312)

4.1.3. Risk Averse Utility Functions

After stating the EUT violations, it is necessary to introduce risk-averse utility functions. According to Kahneman (2011), risk aversion refers to an individual's disposition toward risk. Risk aversion is, in its simplest form, an individual's preference for the less risky option when faced with alternatives with comparable payoffs. A correlation exists between risk aversion and the concavity of the EUT utility function. A person is risk averse when the function is strictly concave, risk neutral when the function is linear, and risk seeking when the function is strictly convex (Taşdemir, 2007).

In many cases, it is not sufficient to know that a person is risk averse. A metric is required to indicate the risk sensitivity of individuals. Arrow (1965) and Pratt (1978) proposed a wealth-dependent measure of risk aversion that is compatible with the EUT utility function, according to Levy, Levy, and Solomon (2000). Researchers suggest two methods for calculating risk premium: (1) relative, (2) absolute If u(w) is a continuously differentiable EUT utility function defined over wealth, then the Arrow-Pratt measure of absolute risk aversion is:

$$R_a(w) \equiv -u"(w)/u'(w) \text{ (absolute)} \quad (4.2)$$

$$R_a(w) \equiv -wu"(w)/u'(w) \text{ (relative)} \quad (4.3)$$

In this expression, u´(w) and u´´(w) are the first and second derivatives of the utility function, respectively. The sign of the value $R_a(w)$ indicates the individual's attitude towards risk (Taşdemir 2007, 311):

$R_a(w)$ < 0: risk averse,
$R_a(w)$ = 0: risk neutral,
$R_a(w)$ > 0: risk seeking.

The absolute risk aversion coefficient of Arrow-Pratt, Ra(w), is a local measure. Consequently, the degree of risk aversion can fluctuate or remain constant based on the level of wealth. Therefore, risk aversion behavior is categorized as decreasing absolute risk aversion (DARA), increasing absolute risk aversion (IARA), or constant absolute risk aversion (CARA). Absolute risk aversion is defined as decreasing if it decreases as wealth increases, increasing if it increases, and constant if it remains constant (Taşdemir, 2007).

Levy, Levy, and Solomon (2000) describe a selection of the risk-averse utility functions utilized in mathematical models of economic decision-making. According to the authors, the following utility functions were developed and used in the studies after the introduction of risk-averse behavior in individuals (Levy et al., 2000, p. 61):

Quadratic utility function: $U(W) = W - \alpha W^2$ (4.4)

The negative exponential function: $U(W) = -e^{-\alpha W}$ (4.5)

The negative exponential function: $U(W) = ln(W)$ (4.6)

The power function: $U(W) = W^{1-\alpha}/\ 1 - \alpha$ (4.7)

The adjusted logarithmic function: $U(W) = ln(W + A)$ (4.8)

The adjusted power function: $U(W) = (W + A)^{1-\alpha}/1 - \alpha$ (4.9)

In the above-mentioned functions, risk preference is determined by the value "α" and "A" is a constant value.

If the Arrow-Pratt risk aversion is applied to the above-mentioned utility functions, the relative risk aversion of the *"power function"* is calculated as "α" and the absolute risk aversion of the function is calculated as "α/W". Both values are positive, so the *"power function"* is risk-averse. As the absolute Arrow-Pratt measure is decreasing with wealth (α/W), it is identified as Decreasing Absolute Risk Aversion (DARA), and as the relative Arrow-Pratt measure (α) is not affected by the wealth, it is identified as Constant Relative Risk Aversion (CRRA). Levy, Levy, and Solomon (2000) state that empirical studies prove that decreasing absolute risk aversion - DARA exists and that there also are proofs (not as vigorous as DARA) for constant relative risk aversion-CRRA. 'The power function' fits this. Table 4.1 states Arrow-Pratt measures for all the above-mentioned functions (Levy et al., 2000).

Utilizing graphs is an efficient method for observing the risk aversion effect of the power function. As the value of risk aversion (α) increases, the calculated utility decreases in a nonlinear fashion. This trend is illustrated in Figure 4.2.

Table 4.1 Classification of utility functions according to Arrow-Pratt risk aversion functions (Source: Levy, Levy, and Solomon 2000, 62).

Utility function	Absolute risk aversion	Relative risk aversion
Quadratic	Increasing	Increasing
Negative exponential	Constant	Increasing
Logarithmic	Decreasing	Constant
Power	Decreasing	Constant
Adjusted logarithmic	Decreasing	Increasing
Adjusted power	Decreasing	Increasing

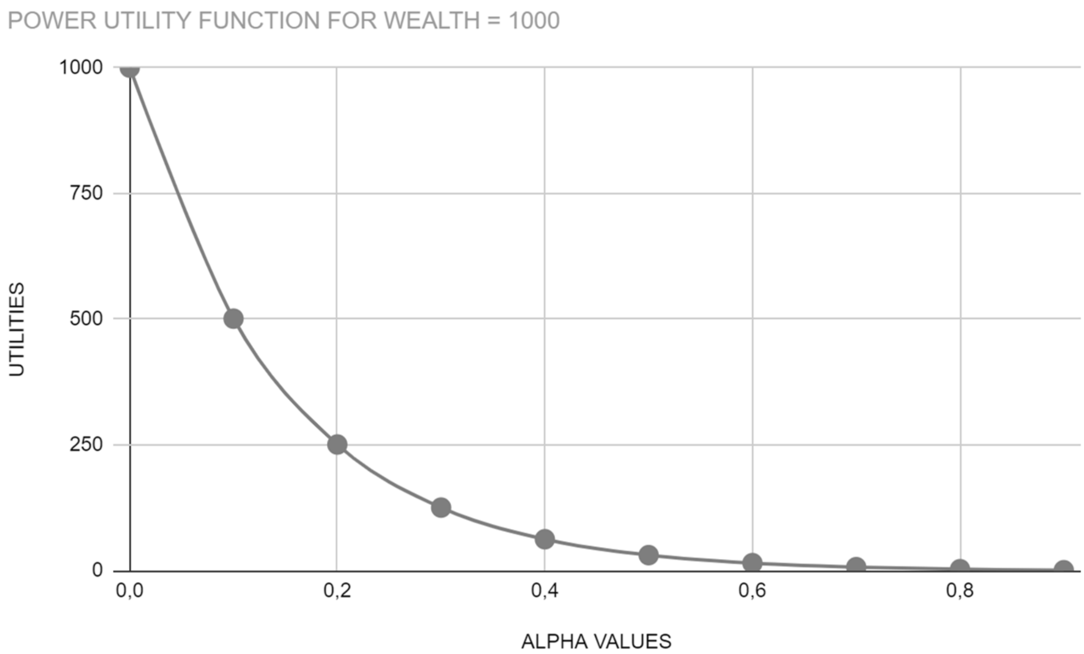

Figure 4.2 The impact of the risk aversion variable change on the calculated utility value (W: 1000)

CHAPTER 5

AGENT BASED MODELING

Similar to all research domains, advancements in computing technology and the diversity of research methods present opportunities for business management, economics, and project management. Agent Based Modeling (ABM) is one of the relatively recent innovations. Epstein (2012), Epstein and Axtell (1996), and Squazzoni (2012), among others, discuss the applicability of ABM in the social sciences.

Agent-based modeling (ABM) is a modeling technique that explicitly represents individual actors and their interactions. The actors may be individuals, corporations, industries, or states. They are animals or plants in biology and particles in physics. It is characteristic that they interact with other agents or environmental conditions in the model and follow distinct behavioral rules (Geisendorf, 2022).

ABM enables the representation of the variety of economic participants and the constraints of information, communication, and transactional opportunities. In addition, computer-based modeling enables us to draw conclusions from the model that would not be possible with mathematical modeling alone. More conventional approaches typically disregard the diversity of the model's participants, thus treating all market participants as identical (Troitzsch, 2012).

However, it can be important for decision-makers to understand which factors determine the development path of a complex social system and, more importantly, what the consequences of controlling interventions are. This is where ABM, which has enjoyed some popularity in the economic and social sciences for some time, comes into play, as it permits the modeling and simulation of the future development of complex systems on a (Gilbert, 2022). Other social science methods, such as case studies, participant observation, interviews, and attitude surveys based on questionnaires, provide valuable data for the development of agent-based models, as well as the scenarios in which ABM operates. Thus, one can speak of a complementary relationship between different research approaches, in which the ABM of socio-economic systems includes the four "Building Blocks" listed below Weyer and Roos (2017):

- The ABM enables a dynamic modeling of socioeconomic systems and, consequently, an analysis of economic and social change processes.
- ABM is predicated on the microfoundations of socioeconomic processes, i.e.., that agents are endowed with unique traits, preferences, and strategies.
- The interaction between micro-level (agents) and macro-level (socioeconomic systems) explains the emergence of emergent structures at the macro-level of socioeconomic systems.
- In addition, ABM is an experimental method that permits the targeted variation of parameters and the observation of their effects.

Therefore, ABM has evolved into a tool for economic and social science research that complements and extends the canon of qualitative and quantitative techniques (Van Dam et al., 2012).

5.1. Agent Based Modeling in Social Systems

ABMs begin with software-based models, i.e. abstract representations of real socio-technical or socio-economic systems in the computer, such as the economic or traffic system. In these systems, a large number of autonomous agents make decisions based on their own subjective preferences as they move around. Moreover, these agents interact with one another. Thus, one agent's decisions can influence the behavior of other agents. It is precisely these interactions and mutual behavioral adjustments that result in difficult-to-predict outcomes ex ante (Weyer & Roos, 2017).

ABM utilizes established theories of social and/or economic action when recreating complex systems on a computer, particularly when constructing the agents and the decision and interaction rules. There is an openness regarding which theories and models are utilized; they must only meet two requirements. First, they must contain assumptions about rules and mechanisms, such as the decision rules of actors, interaction mechanisms, and the micro-macro linkage. This includes the two questions of how the system influences the perceptions of the actors (macro-micro link) and how the system state emerges from the actions of the actors (micro-macro link) (Hedström & Ylikoski, 2010; Weyer & Roos, 2017).

On the other hand, they must be formalizable, meaning that the rules and mechanisms must be able to be translated into computer language. Agent-based models are a highly adaptable analysis tool that permits the combination of hypotheses from various theoretical traditions and can thus generate novel insights. By formalizing and implementing them in computer software, it is also possible to determine whether combining different theories without contradictions is possible (Weyer & Roos, 2017).

5.2. Structure of Agent Based Models

Agent-based models typically include three components: the agents, the environment in which they operate, and the rules governing the agents' interactions with other agents and the environment (Epstein, 2012).

5.2.1 Agents

Software-based agents are distinguished by their internal states, such as age, gender, etc., and by their behaviors (e.g., moving forward quickly or protecting the environment). Object-oriented programming makes it possible to encapsulate the properties of each individual agent in software so that each agent has unique characteristics; furthermore, the decision-making processes of a large number of agents can be handled almost simultaneously, allowing large populations of heterogeneous agents to be "bred" on the screen and their interactions to be observed (Epstein & Axtell, 1996; Resnick, 1997). Agents can be heterogeneous along numerous dimensions, with the dimensions taken into account depending on the purpose of the model. Their characteristics, such as place of residence, gender, education, knowledge, values, preferences, and attitudes, may differ.

5.2.2. Rules

These characteristics affect the decisions agents make, how they acquire and process information, the behavioral strategies or learning rules they employ, and the degree of rationality of their actions. Lastly, it can be demonstrated that agents have various networks within which they exchange information, for instance (Weyer & Roos, 2017).

Each agent bases its decisions on its own preferences and seeks the most optimal solution from its subjective perspective. The agents also interact with their environment as well as with other agents. (Therefore, the outcomes of the decisions can be very different: one agent rides a bicycle and the other drives a car.) By contributing to the development of a traffic jam, for instance, their actions alter the boundary conditions for the actions of other agents (Weyer & Roos, 2017).

5.2.3. Environment

In an agent-based model, one must also determine the environment, i.e., how the agents are interconnected and who interacts with whom. The space is frequently represented as a two-dimensional grid in the form of a chessboard when the models are spatial. Nonetheless, it is also possible to have a geodetically accurate representation of space with realistic traffic and communication routes. Alternately, the environment can be devoid of all spatial characteristics. In this case, it is conceivable that the agents in contact with one another are determined at random, or that only network-connected agents interact. This could be a kinship network, a professional network, or even the corporate network that represents their business relationships, depending on the application (Weyer & Roos, 2017).

5.2.4. Interactions

The interaction of the agents can be very simple - "Move to a random field in the immediate neighborhood. Fields occupied by other agents are excluded" - or very specific - "Search for a direct neighbor with the same income level and employment in the same industry. If such a person exists, there is a probability p to found a company together, if there is an excess demand for his products among the consumers of the simulated world" (Geisendorf, 2022).

5.3. Emergence

The interactions of the agents generate emergent effects - unexpected and unpredictable system states that cannot be derived from the properties of the system elements (i.e., the agents), but are the unintended result of the actions of a large number of autonomously acting agents (Epstein & Axtell, 1996; Weyer & Roos, 2017).

The traffic jam is a striking illustration of an emergent effect. No one intentionally causes it, yet it only develops because everyone contributes to its creation. In addition, it possesses properties not found in micro-level rules: The traffic participants move forward, whereas the traffic jam as a macro phenomenon moves at a constant speed in the opposite direction - with the traffic participants moving in a forward direction (Epstein & Axtell, 1996; Resnick, 1997; Weyer & Roos, 2017).

Agent-based modeling establishes a connection between the micro and macro levels, revealing the conditions under which macro states emerge and the path leading to them. Standard economic models attempt to represent the outcome - not the process - of assumed economic dynamics in a small number of highly aggregated equations (Geisendorf, 2022).

Without a social planner, the entire process is decentralized and self-organized through the interaction of micro- and macro-levels. The structural conditions (constraints) influence the choices of the agents, which in turn are the result of previous interactions between the agents and therefore change dynamically. Contrary to conventional mathematical models in economics, there is no coordination of individual behavior by a system's fixed point, such as a market equilibrium. Agents make decisions independently, without being required to conform to the decisions of other agents. This does not imply that equilibrium states are impossible in agent-based models. If they exist, they are the result of decentralized decisions made endogenously (Weyer & Roos, 2017).

Therefore, the system's dynamics, as well as its complexity, result from the interactions between the agents and their environment. Agents frequently follow simple rules (e.g., "take the shortest route"), but nonlinear interactions produce a surprisingly complex outcome at the system level. These nonlinear processes cannot be represented and studied by any other technique besides ABM (Epstein, 2012; Weyer & Roos, 2017).

In addition, it is possible to study controlling interventions in the system by executing intervention scenarios whose objective is, for instance, the prevention of traffic jams or blackouts in the power grid, i.e. which attempt to achieve a global optimum that is greater than the sum of the local optima of all agents, which results from decentralized (Weyer & Roos, 2017).

5.4. Representation of Reality

As with any modeling, it is impossible to represent a real system precisely. Always, an abstraction must be made that reduces the diverse reality to factors deemed relevant to the issue at hand. This makes it possible to focus on these partial aspects and select topics with precision. In contrast to purely mathematical models, computer modeling has a great deal more degrees of freedom because the restriction of the model's mathematical solvability is eliminated. This allows for more realistic models, which is an advantage of this method. In principle, it is possible to model arbitrarily complex ideas about facts, making a close approximation of reality plausible. The primary limitations of modeling are the computing power of the computer used, the availability of data for model initialization and parameterization, and the time available for model implementation and analysis. Simultaneously, this freedom poses a challenge for the modeler, as he or she must now actively decide which level of detail should be chosen in order to achieve the modeling and simulation objective with a reasonable amount of effort (Weyer & Roos, 2017).

5.5. Software

To implement an agent-based model, developers utilize a variety of software applications. Object-oriented programming languages such as C++, Java, and Python are suitable for this in principle. An object in a programming language is an element with functions, methods, procedures, and internal states that resembles an agent with its properties and behavior. Object-oriented programming languages are adaptable and, most importantly, quick, which is advantageous for large models containing numerous agents. However, programming languages are difficult to learn and are impractical for ABM because each step must be programmed "by hand." Therefore, dedicated ABM software is frequently preferable for users who lack programming expertise, despite the fact that such software is typically slower and less powerful than programming languages. There are currently numerous ABM software packages, with AnyLogic, Lsd, Repast, and Swarm being particularly well-known. NetLogo is widely used in the social sciences, in part because it permits intuitive input and is therefore conducive to education (Weyer & Roos, 2017).

Early ABM researchers began modeling software agents according to the KISS (Keep It Simple, Stupid) principle, which states that complex artificial societies emerge from simple agent rules (Epstein & Axtell, 1996). In ABM studies, the method of tracing back complex aggregate relationships to simple mechanisms and behavioral rules is still prevalent. Nevertheless, it is evident that very simple heuristics cannot adequately describe human behavior in situations involving conscious decisions. The rapid increase in computer power now enables the implementation of models based on social or economic theories of action and containing decision algorithms that approach the complexity of the actions and decisions made by actual decision-makers (Fink & Weyer, 2011).

CHAPTER 6

DESIGN OF SIMULATION

This section aims to describe the simulation's design objectives, constructs, functions, and iterative application process. The primary objective of this simulation is to observe virtually the effects of overconfident behavior on the winner's curse in the construction industry. Agent-Based Modeling (ABM) methodology is applied to the design of simulations in accordance with its guiding principles and instructions.

ABM is a tool for observing emergent phenomena that are formed by the micro behaviors of individuals in a society, as described in previous sections. The winner's curse is a negative idea resulting from various possible causes, such as the irrational behavior of contractor organizations. The overconfidence bias is a commonly observed behavior of decision-makers, including bidders. In prior sections, various forms of overconfidence were described. Overprecision is one of the effective forms of overconfidence (miscalibration in some texts). Overprecision is, in brief, an unfounded confidence in one's own knowledge that disregards the magnitude of the skewness of the distribution.

An opposing concept to overconfidence is risk aversion, which is also frequently discussed in behavioral studies. Risk aversion is the preference of individuals for choices with predictable outcomes over those with uncertain outcomes. This behavior is assumed to eliminate overconfidence's hazardous outcomes. However, it is not surprising to find research on topics such as cost overruns and other planning errors. Consequently, the relationship between overconfidence and risk aversion becomes essential when making bid decisions.

The above-mentioned circumstances demonstrate the need for a simulation measuring the effects of overconfidence on the winner's curse while accounting for risk aversion. The already established methods in behavioral finance are guided by a review of the pertinent literature. Individuals' investment strategies and tools for analyzing bubbles and other unfavorable macroeconomic outcomes are the subject of research. The model developed by Lovric, Kaymak, and Spronk (2010), which is based on the methods described by Levy, Levy, and Solomon (2000), enables simulations of the effects of overconfidence on the winner's curse at the industry level. Following sections will describe the agents, functions, iteration process, and recording tools used to simulate the construction industry's competitive bidding environment.

R version 4.2.1 is selected as the simulation software. The R Foundation is developing the R programming language as open source software. Scholars from around the globe are developing function libraries that can be easily downloaded from R project mirrors. The most practical aspect of the software is its design, which is suitable for object-oriented programming. Second, the software's comprehensive social computing library strengthens researchers.

6.1. Agents of the Model

The model's primary agent type is independent contractors. Contractors are implemented as R data frame objects. Data frame objects can store other types of data objects, including integers, doubles, and numeric vectors. In the designed model, contractor objects store information about completed projects. This information is utilized for evaluating bids. Past project information is stored as numeric vector objects gathered under contractor data frame objects. Figure 6.1 depicts a randomly generated contractor object.

The first vector contains past actual project costs incurred by contractors. In the model, it is labeled as "PastActualCosts." The second vector, "PastEstimates," contains cost estimates for previously completed projects. The third vector, "PastDifferences," is intended for recording variances between the estimated and actual costs of past organization projects. The fourth and final vector is "PastPercentageofDifferences," which records the ratio of differences to actual cost for the organization's historical project data.

```
> Contractors[[1]]
$PastActualCosts
 [1] 2258794 2258794 2258794 2258794 2258794 2258794 2258794 2258794 2258794 2258794 2258794 2258794 2258794 2258794 4508014

$PastEstimations
 [1] 2147813 2147813 2147813 2147813 2147813 2147813 2147813 2147813 2147813 2147813 2147813 2147813 2147813 2147813 4156840

$PastDifferences
 [1] -110980.67  299045.74  -85659.51  -89395.32 -198083.76 -309603.81  236726.85  154602.77 -401007.07  389087.43 -445600.87  426477.31 -203746.37
[14]  -73136.71 -297193.46

$PastPercentageofDifferences
 [1] -0.04913271  0.07021672 -0.02684855 -0.04150456 -0.06212532 -0.07933707  0.08954742  0.07141678 -0.08691952  0.08880443 -0.09817917  0.08571025
[13] -0.04294896 -0.05779257 -0.09901189
```

Figure 6.1 A contractor object defined in R simulation language

The simulation's second agent is project objects. Projects are simple numeric data generated randomly within the specified range at each simulation iteration. When a project is generated, it is assigned to three contractor agents for a competitive bidding process. Four additional objects in the model function as data holding vectors that grow with each iteration: (1) vector named “ActualCosts” used for recording actual costs of generated projects, (2) vector named “EstimatedCosts” used for recording estimated cost of winning bid for the project, (3) vector named “Iterate” used for recording number of the bid, and (4) vector named “DIFF” for recording differences between winner estimation and actual costs.

6.2. Functions Used in the Model

In ABM, autonomous agents behave according to rules that have been designed and developed. These rules are implemented in the model as functions. In R, the function() method is used to reveal required functions.

The name of the first function is "actualCostGenerator." It is utilized for randomly generating the actual cost of a project. The R library designed for uniform distributions is utilized for the function's development. The function requires two "minValue" and "maxValue" arguments. The first argument defines the minimum margin for project estimates, while the second argument defines the maximum margin for the project. This function generates a random value by applying uniform distribution to a specified range using the runif () function.

The "contractorInformer" is designed for the selection of contractors during the bidding function. This function generates a vector containing contractor numbers determined at random for the bidding process. "contractorSelector" is a similar simple function designed to select the winning contractor following competitive bidding. Simply, bid values serve as function arguments, and the function returns the lowest bid.

“EstimateGenerator” is the fourth function employed by the model. Contractor agents use this function to estimate the actual cost of bids. This function takes as its argument the project value minus the actual cost and a percentage value of the winner's curse. First, the function determines the estimation's minimum and maximum values. This range is computed by adding and multiplying the actual cost by a percentage value. The function then returns a value based on a uniform distribution that falls within the previously calculated range.

The "contractorGenerator" function is the next function. Before simulation iterations, this function is used to generate contractor agents. Two arguments are required for this function's application. Both are whole numbers. First is the number of contractors, and second is the memory size for previously recorded information. The first argument determines the number of contractors visible in the model. The second argument determines how many past projects are remembered by contractors as data.

The function returns a list object of R (defined in the model as "Contractors") containing contractor objects. When the function is executed, a loop iterates as many times as there are contractors. Each time the loop is executed, a new contractor object is created and added to the "Contractors" list. As mentioned previously, each contractor object stores past project data in vectors of past estimations ("PastEstimates"), past bids ("PastBids"), past actual costs of projects ("PastActualCosts"), and differences between actual costs and bids ("PastDifferences"). Initially, a loop is repeated for each contractor agent as many times as the memory length. In each repetition, the "actualCostGenerator" function is used to determine the actual costs incurred in the past. When the actual cost is determined, the previously described "estimateGenerator" function is used to generate an estimate value. These values are stored in the "PastActualCosts" and "PastEstimates" vectors of each contractor object. In addition, the difference between the actual cost and the estimate is computed and recorded in the "PastDifferences" vector. The function returns the list of "Contractors" whenever the loop for generating contractors has completed.

The "utilComputer" function is another function used in the model. It computes risk-averse utility values using the Power Utility Function described in earlier sections. The function is mathematically expressed in equation (6.1). To compute the utility value (U), the function requires the arguments wealth (W) and risk-aversion coefficient (α). After calculating, the function returns a value of utility.

$$U(W) \; = \; W^{1-\alpha}/1-\alpha. \tag{6.1}$$

A similar function to "utilComputer" is "certaintyCalculator." It is the reverse of the "utilComputer" function. When the utility value and the risk-aversion coefficient are sent to the function, the function returns the certainty equivalent value of the utility value.

One of the most critical functions designed for the model is the “submissionProcess” function. The function is used by contractor objects. A contractor agent uses this function when the agent is selected to submit a bid for a project. Briefly, the agent makes a cost estimation, computes possible variations from the estimation by using past data under the effect of overconfidence, determines the optimum level of contingency cost aiming both to be competitive and beneficiary, and by adding (or extracting in some cases) contingency cost to the estimation determines the submission amount.

The "submissionProcess" function requires the following arguments: (1) a contractor object, (2) the actual cost value, (3) the overconfidence coefficient value, (4) the value of the winner's curse, and (5) the risk aversion coefficient. In addition, this function uses some of the previously identified functions. At first, the "estimateGenerator" function is used by the contractor agent, which uses this function to create a cost estimate. The "actual cost" argument of the “estimateGenerator" function is transmitted to the "actual cost" argument of this function.

The “submissionProcess” function is the point where the contractor agent makes the decision to determine the amount of submission for the competitive bidding. When the agent is assigned to a bid, it initially computes the cost estimation. In order to determine the quantity of contingency costs, some prior steps are taken. The first is figuring out the average and standard deviation of differences from the past that the agent remembers. This is the point where the overconfidence bias is simulated. The standard deviation value is multiplied by the "overconfidence coefficient (OC)". If the OC value is between 0 and 1, this means an ungrounded trust in previous data and a decreasing amount of skewness in the distribution of the past data. This makes the agent overconfident. If the OC value is greater than one, then the agent underestimates the accuracy of the past data. This represents underconfidence. Figure 6.2 represents the relationship between OC and overconfidence and underconfidence.

In the “submissionProcess” function, five statistical ranges are developed for determination of the contingency cost. These ranges are relevant to the agent’s past bidding data. Estimations recorded in the past data are grouped under six sections: (1) estimation errors more than 10% on the negative side, (2) estimation errors between 10%

and 5% on the negative side, (3) estimation errors between 5% and 0% on the negative side, (4) estimation errors between 0% and 5% on the positive side, (5) estimation errors between 5% and 10% on the positive side, and (6) estimation errors more than 10% on the positive side. The agent computes the probabilities of each range by using the cumulative normal distribution function library of the R software. Whenever the cumulative probability of a range is computed, the cumulative probability of the previous section is extracted for obtaining the exact probability of the range. Following Figure 6.3. represents the distribution.

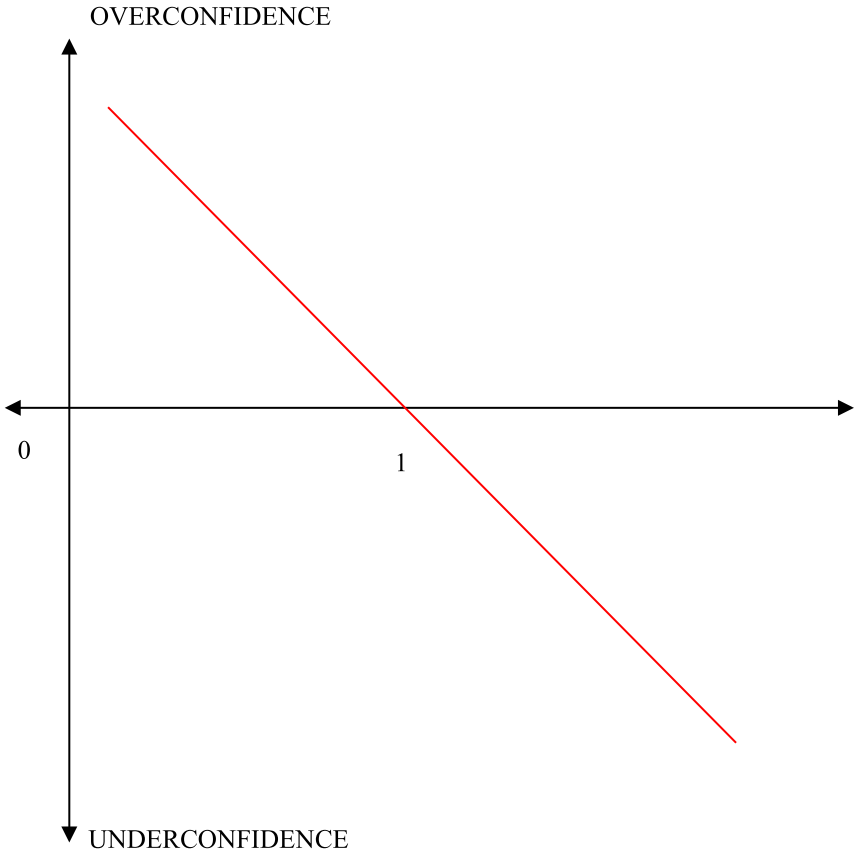

Figure 6.2 The relation between overconfidence coefficient and overconfidence - underconfidence.

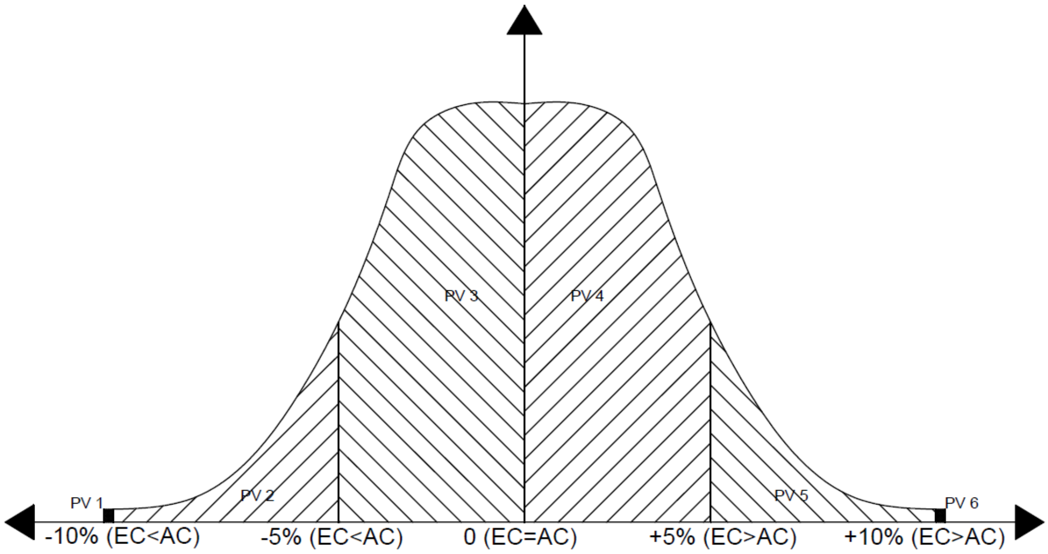

Figure 6.3 Statistical ranges defined for the “submissionProcess” function.

As stated previously, the "submissionProcess" function relies heavily on the contractor agent's historical bidding data. As the actual costs and estimated costs vary within a defined range in the simulation, the agent uses percentages of variations instead of monetary values. For this reason, the percentage values of the classes previously defined are multiplied by the estimated cost value in order to get the possible amount differences in each range. For instance, the possible difference in the second range (estimation errors between 10% and 5% on the negative side) and the fifth range (estimation errors between 5% and 10% on the positive side) are calculated by multiplying the estimated cost with 0.5. At the next step, each previously described value's utilities are calculated by the power utility function formula by using the “utilComputer” function. After determining the utilities, the potential contingency range with the highest utility is chosen.

After determining the most probable contingency range and the utility amount of it, the “submissionProcess” function calculates the certainty amount of the contingency. In order to calculate the certainty amount, the function uses the “certaintyCalculator” function. The result of this code is the amount of the contingency cost. The positivity or negativity of the contingency cost is dependent on the range. If the contingency is on a positive range the contingency is extracted from the estimated cost. In contrast, if the contingency is on a negative range the contingency is added to the estimation cost. The result of this final calculation is the amount the submit determined by the contractor agent.

The last function used in the simulation is the “pastDataUpdater” function. The function is used by the contractor agents who win the competitive bidding of the simulation. The function updates past data for the agent. Arguments of the functions are (1) actual cost, (2) estimated cost, (3) contractor object, and (4) length of the memory kept by contractor agents. As mentioned before, past data is recorded as vectors by contractor agents. Actual costs, The function replaces the oldest code record with the new one. For instance, the first record is replaced with the second one, and the second record is replaced with the third one. The last record is replaced with the new bidding data. The past data of the contractor agent is updated.

6.3. Iteration Process

6.3.1. Processes Executed Prior to Iterations

The simulation iterations are the repetitive actions where the actual simulation is realized. Before iterations can be executed, the definitions of previously described functions and variables must be finalized. The functions have already been described in detail in the preceding section, so they will not be explained again here. The previously defined variables are described in the following Table 6.1.

In addition to the definition of variables and functions, the generation of the contractor agents is executed prior to iteration. The contractor agents’ past data is generated randomly by the previously described “contractorGenerator” function. The function returns a list of contractors. The last process prior to iteration is the definition of the empty vectors "ActualCosts,” "EstimatedCosts,” “Iterate," and “DIFF." These vectors are updated at each iteration of the bidding process. The results of the simulations are developed from these updated vectors.

Table 6.1 Variables used in the simulation.

Variable Name in the Code	Definition
eValue	This value determines the amount of the winner’s curse. If the value is defined as 0.1, the estimations made by the contractors fall in a range between 10% higher and 10% lower than the actual cost.
contractorNumber	This integer determines the number of contractor agents in the simulation.
memoryLength	The length of vectors used for recording past data by the contractor objects.
OC	It is the abbreviation of the "overconfidence coefficient." It determines the level of overconfidence (and sometimes underconfidence) of the contractor agents.
alphaValue	This variable determines the level of risk-aversion of contractor agents.
iterations	This integer variable determines the number of repetitive iterations in a simulation.
minValue	This value is the lower limit of the actual costs of the projects in the simulation.
maxValue	This value is the upper limit of the actual costs of the projects in the simulation.
numberContractorInvited	This value determines the number of contractor agents participating in a bidding process.
projectNumber	This value is the number of projects that are bid on in an iteration of the simulation.

6.3.2. The Iteration Process

Iterations of the simulations happen in a loop that repeats itself as defined by the “iterations” variable. At the beginning of each iteration, the projects are generated by the “actualCostGenerator” function. At the next step, candidate contractors are selected by the “contractorInformer” function. The function determines the number of candidate contractors by using the “numberContractorInvited” variable.

In each iteration, a vector (“bids” in the code) for submitted bids is generated. The elements of the vectors are defined by the “submissionProcess” function. The function is used by the selected contractors. Then the lowest submission is labeled the "winning bid." Using the "pastDataUpdater" function, the contractor agent who created the winning bid updates its historical data in the subsequent step.

Whenever the bidding processes are complete and the past data of the winning contractor agents is updated, previously declared vectors of "ActualCosts," “EstimatedCosts” (cost estimations), “Iterate” (the number of the iteration), and “DIFF” (percentage values of differences between cost estimations and actual costs) are updated by the addition of data generated in the iteration. As the repetitive iteration loops finish, all of these vectors are collected under the data frame "Results." The data collected under the "Results" data frame are used for analysis, such as the correlation between the level of overconfidence and the winner's curse or the number of bidders and the winner's curse. The following Figure 6.4 is an example.

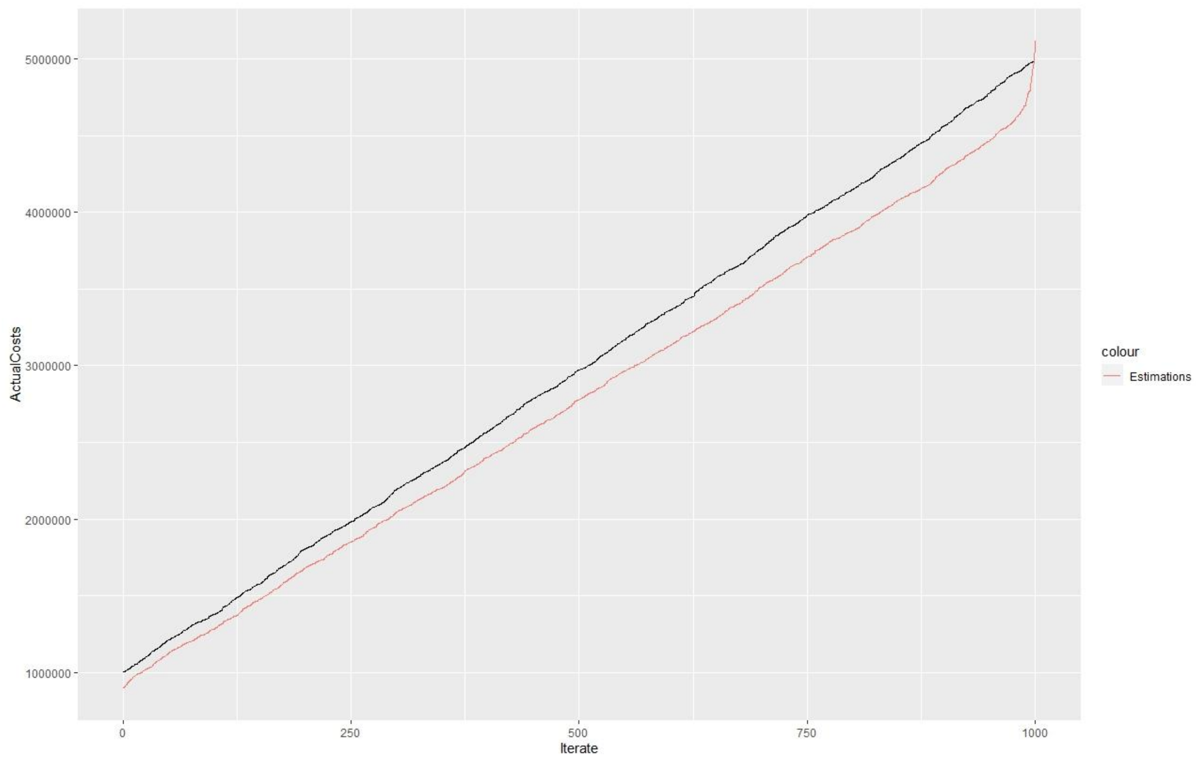

Figure 6.4 An example graph of the results of the simulation.

CHAPTER 7

RESULTS

The winner's curse effect is thought to be one of the best ways to look at how overconfidence affects the success of construction companies. The main reason for this idea is that construction companies are based on projects, and whether or not their expectations are met by the projects they take on shows how successful they are as a business. The winner's curse effect, which has been explained in depth in the previous sections of the study, is critical in terms of showing at what level organizations achieve their goals on a project basis.

It is important to consider the effects of other behavioral or technical phenomena when examining the effects of overconfidence as a result of the winner's curse. The first of these can be thought of as risk-averse behavior, which has already been discussed. It is believed that individuals who dislike taking risks are less likely to be overconfident. It can be assumed that risk aversion and overconfidence may have opposite consequences. Also, technical factors unrelated to the person making the decision, such as the number of bidders, may influence the winner's curse. As a result, they were included in the simulation described in the preceding section.

To design a virtual experiment that satisfies the stated objectives, it is necessary to ensure that the variables are set appropriately to produce meaningful results. Among the variables utilized in the simulation described in the preceding section, those that have a direct impact on the overconfidence effect are: (1) the overconfidence coefficient; (2) the risk aversion variable; and (3) the number of bidders entering the bidding process.

The overconfidence coefficient variable is quite critical for the purposes of the simulation. A value for the overconfidence coefficient between zero and one indicates that the decision maker is overconfident, whereas a value greater than one indicates that the decision maker is underconfident. In this study, the overconfidence coefficient is assigned values between 1.5 and 0.25 so that both overconfidence and underconfidence can be observed. In the power utility function, the risk aversion variable shows how risk-averse the person will be. In order for the values in the power function to be meaningful, this value must have a value between zero and one. While zero represents a riskinsensitive behavior, as the variable approaches one, the decision maker will be more risk-averse. In addition to these variables, the possible magnitude of the winner’s curse is identified by the winner’s curse variable. This variable determines the error margin for bidders' cost estimations. For instance, when this value is 0.2, the estimated cost can range from 20 percent above to 20 percent below the actual cost.

It is often emphasized that the number of bidders submitting a bid affects the bid price. One of the goals of this study is to determine how the number of bidders interacts with the overconfidence effect to influence the winner's curse. Or, in order to draw relevant conclusions, it may be necessary to observe the effects of the overconfidence effect on the winner's curse as the number of bidders varies.

To achieve the above-described objectives, it is considered reasonable to assign the initial values shown in the Table 7.1 below to the variables:

Table 7.1 Values assigned to variables for the initial simulation.

VARIABLE	APPEARANCE IN THE CODE	ASSIGNED VALUE AT THE STARTUP
The overconfidence coefficient	OC	0.25 - 1.50 (Varying)
The winner's curse variable	eValue	0.20 (20%)
Risk aversion variable	alpha	0.60
Number of bidders	BIDDERS	3

Once the simulation's variables and functions have been defined, as described in detail in the section describing the simulation's design, the simulation is executed a specified number of times. Before obtaining the results, it is necessary to determine the number of iterations. When determining the number of iterations, two goals were taken into account. As a result of the bidding processes, all of the contractor agents' past data, which is initially determined at random, is updated. The second requirement is that all contractors must participate in the bidding process. As a result of the preliminary experiments, it was determined that 10,000 iterations is the optimal number for achieving these goals.

In each experiment of the simulation, the winner's curse variable, the risk aversion variable, and the number of bidders variable take constant values. The overconfidence coefficient, however, takes values between 0.25 and 1.50 to determine whether the overconfidence effect causes the winner's curse in this instance. In order to determine the effects of variables on the winner's curse, variations are made to the experiments after the launch. The following are the steps involved in these variants (Please see Figure 7.1):

7.1. Startup Experiment

Below Figure 7.2 is the graph displaying the results of the startup experiment. Before interpreting the graph, it is important to make a few explaining comments. The winner's curse occurs when the associated value falls below zero. The further the value moves away from zero in the negative direction, the more intense the winner's curse becomes. The graph indicates that when the number of participants is relatively small and the level of risk aversion is moderate, changes in the overconfidence effect do not result in a significant shift in the winner's curse. However, the situation of the winner's curse occurs at all levels of overconfidence, and risk aversion is ineffective in preventing it.

7.2. Experiments with a Small Number of Bidders

To evaluate the effect of overconfidence on the winner's curse with a relatively small number of bidders, the following levels of risk aversion are planned for the experiments: (1) moderate risk aversion, (2) low risk aversion, (3) high risk aversion, and (4) absence of risk aversion.

The experiment with a moderate level of risk aversion was the one conducted at the startup. It is unnecessary to re-report its results. Determining how the effect of overconfidence on the winner's curse would be altered in the presence of low risk aversion is the purpose of the second experiment. All other variables remain unchanged as the simulation is regenerated with the risk aversion variable set to 0.1. The outcomes are displayed in the graph below (please see Figure 7.3).

EXPERIMENT 1 (STARTUP): SMALL NUMBER OF BIDDERS, MODERATE RISK AVERSION, VARYING OVERCONFIDENCE

EXPERIMENTS WITH A SMALL NUMBER OF BIDDERS

EXPERIMENT 2: SMALL NUMBER OF BIDDERS, LOW RISK AVERSION, VARYING OVERCONFIDENCE
EXPERIMENT 3: SMALL NUMBER OF BIDDERS, HIGH RISK AVERSION, VARYING OVERCONFIDENCE
EXPERIMENT 4: SMALL NUMBER OF BIDDERS, NO RISK AVERSION, VARYING OVERCONFIDENCE

EXPERIMENTS WITH A MODERATE NUMBER OF BIDDERS

EXPERIMENT 5: MODERATE NUMBER OF BIDDERS, MODERATE RISK AVERSION, VARYING OVERCONFIDENCE
EXPERIMENT 6: MODERATE NUMBER OF BIDDERS, LOW RISK AVERSION, VARYING OVERCONFIDENCE
EXPERIMENT 7: MODERATE NUMBER OF BIDDERS, HIGH RISK AVERSION, VARYING OVERCONFIDENCE
EXPERIMENT 8: MODERATE NUMBER OF BIDDERS, NO RISK AVERSION, VARYING OVERCONFIDENCE

EXPERIMENTS WITH A LARGE NUMBER OF BIDDERS

EXPERIMENT 9: LARGE NUMBER OF BIDDERS, MODERATE RISK AVERSION, VARYING OVERCONFIDENCE
EXPERIMENT 10: LARGE NUMBER OF BIDDERS, LOW RISK AVERSION, VARYING OVERCONFIDENCE
EXPERIMENT 11: LARGE NUMBER OF BIDDERS, HIGH RISK AVERSION, VARYING OVERCONFIDENCE
EXPERIMENT 12: LARGE NUMBER OF BIDDERS, NO RISK AVERSION, VARYING OVERCONFIDENCE

Figure 7.1 The steps of the experiments

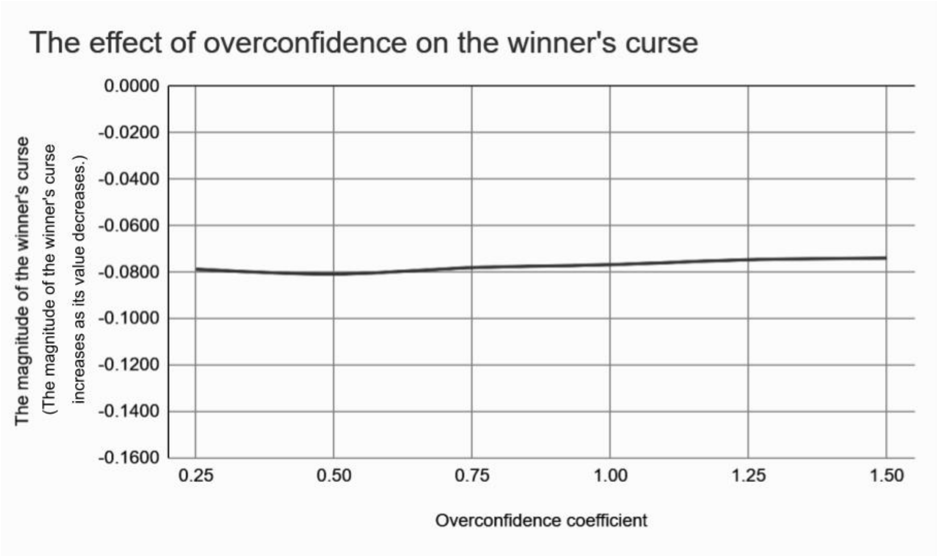

Figure 7.2 The effect of overconfidence on the winner's curse with a moderate level of risk aversion and relatively a small number of bidders (**α**=0.6, number of bidders: 3, the winner's curse range: 0.2)

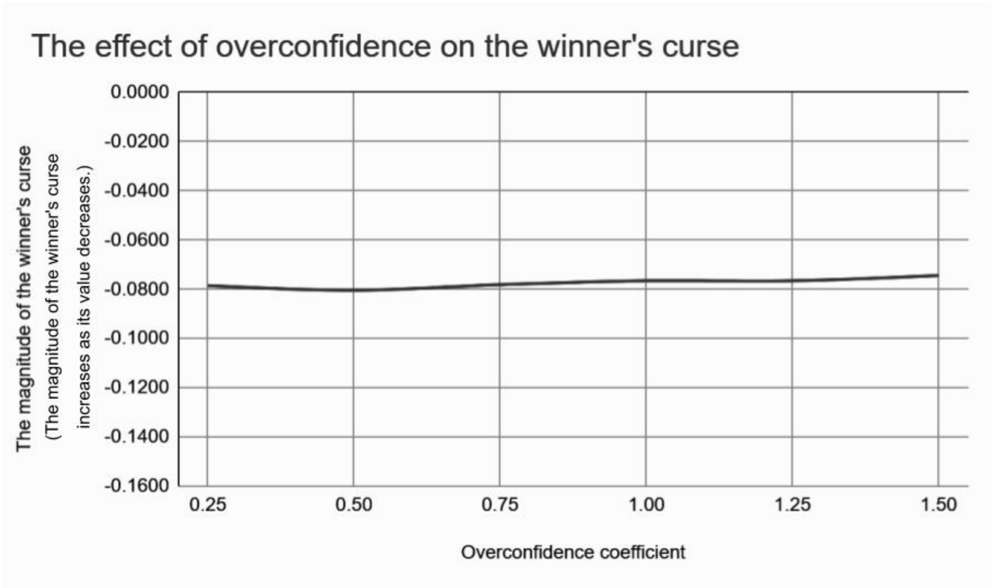

Figure 7.3 The effect of overconfidence on the winner's curse with a low level of risk aversion and relatively a small number of bidders (**α**=0.1, number of bidders: 3, the winner's curse range: 0.2)

The analysis of the preceding graph reveals that a reduction in risk aversion has no significant effect on the winner's curse. The result resembles this trend, which resembles the results of the initial experiment.

Conversely, the next experiment is selected to simulate the effects of overconfidence on the winner's curse with a high level of risk aversion and a relatively small number of bidders. In order to execute the simulation under these conditions, the risk aversion parameter is set to 0.9, and the number of bidders is set to 3. Similar to other cases, the winner's curse range is set to 0.2. Simulation reports that a high level of overconfidence is insufficient to prevent the winner's curse. Moreover, the high level of risk aversion yields similar results to the low level of risk aversion. The Figure 7.4 shows the relevant results.

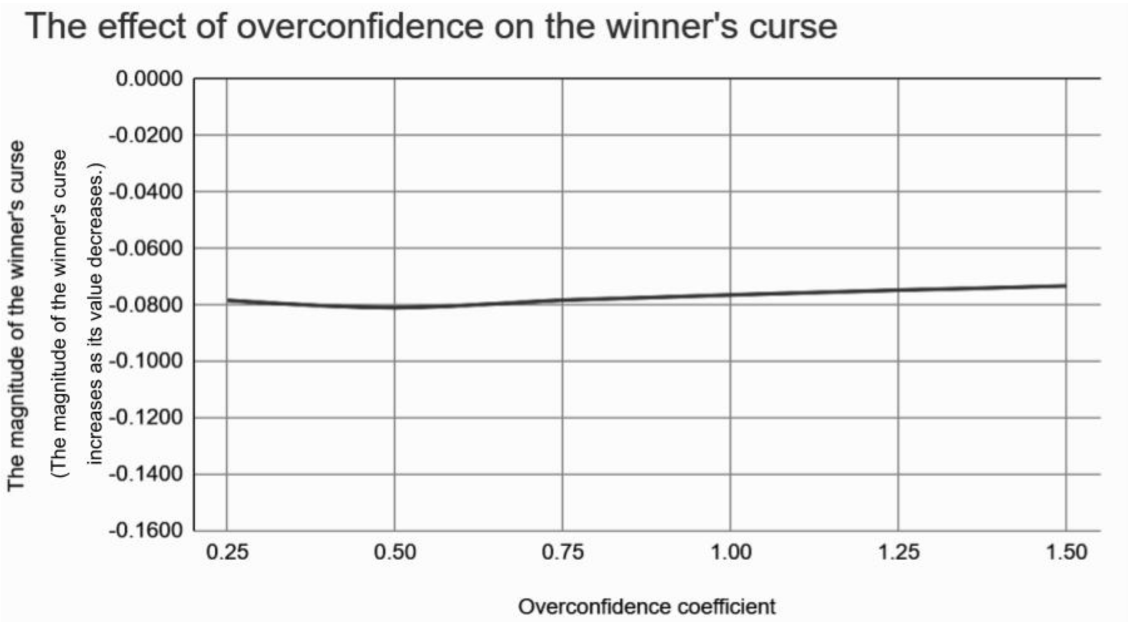

Figure 7.4 The effect of overconfidence on the winner's curse with a high level of risk aversion and relatively a small number of bidders (**α**=0.9, number of bidders: 3, the winner's curse range: 0.2)

Even if the situation is unrealistic, the case where there is no risk-aversion behavior is also analyzed. The risk aversion variable is set to zero in order to simulate this scenario. The following table displays the results. The graph at Figure 7.5 demonstrates that the winner's curse is more potent when risk aversion is completely disregarded. In a risk-neutral environment, variations in overconfidence have no effect on the winner's curse during the time period in which decision-makers are overconfident. In contrast, the winner's curse diminishes in the range where decision-makers are underconfident.

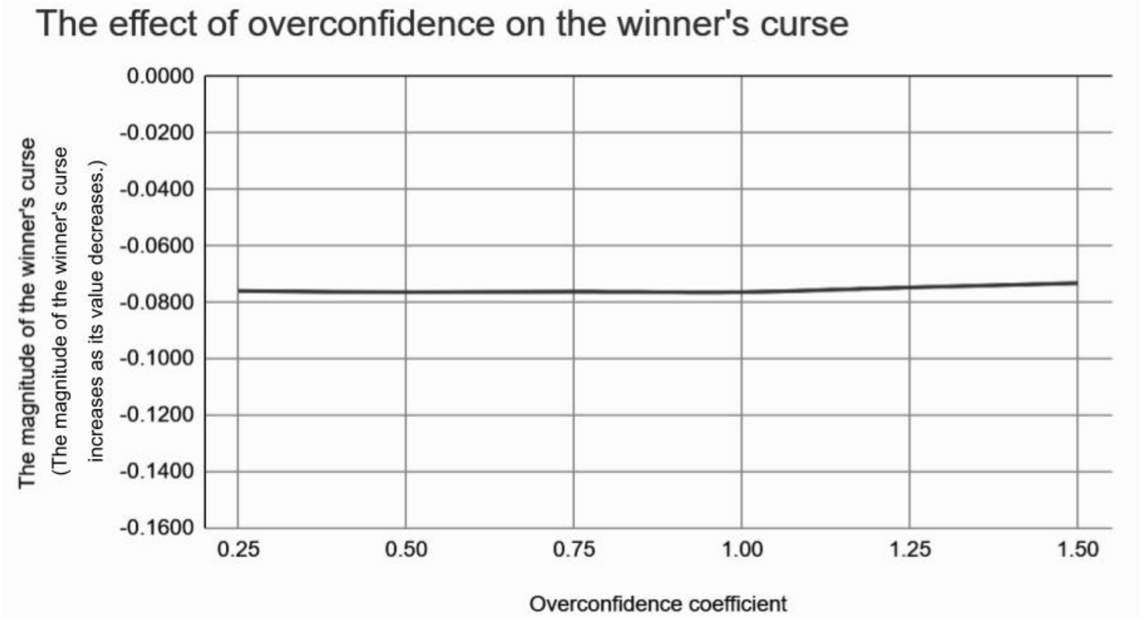

Figure 7.5 The effect of overconfidence on the winner's curse without risk aversion and relatively a small number of bidders (**α**=0, number of bidders: 3, the winner's curse range: 0.2)

7.3. Experiments with a Moderate Number of Bidders

For the following part of the experiments, the effect of the number of bidders is intended to be observed. In order to do this, previous experiments are repeated by a moderate number of bidders. Apart from the number of bidders, all other variables are varied in the same order. Figure 7.6 shows the result of the experiment executed with the variable overconfidence coefficient of 1.5, the risk aversion parameter of 0.6, and the number of bidders of 10.

Surprisingly, overconfidence has the opposite effect on the scale of the phenomenon known as the winner's curse. Thus, when overconfidence lessens, the winner's curse becomes more severe. Similar to earlier experiments, the winner's curse is observed in this observation, regardless of how much overconfidence varies.

At the subsequent stage of the experiment, the simulation is regenerated with a low level of risk aversion. As shown by the graph in Figure 7.7, the impacts of moderate risk aversion and low risk aversion on the phenomenon of the winner's curse are nearly identical.

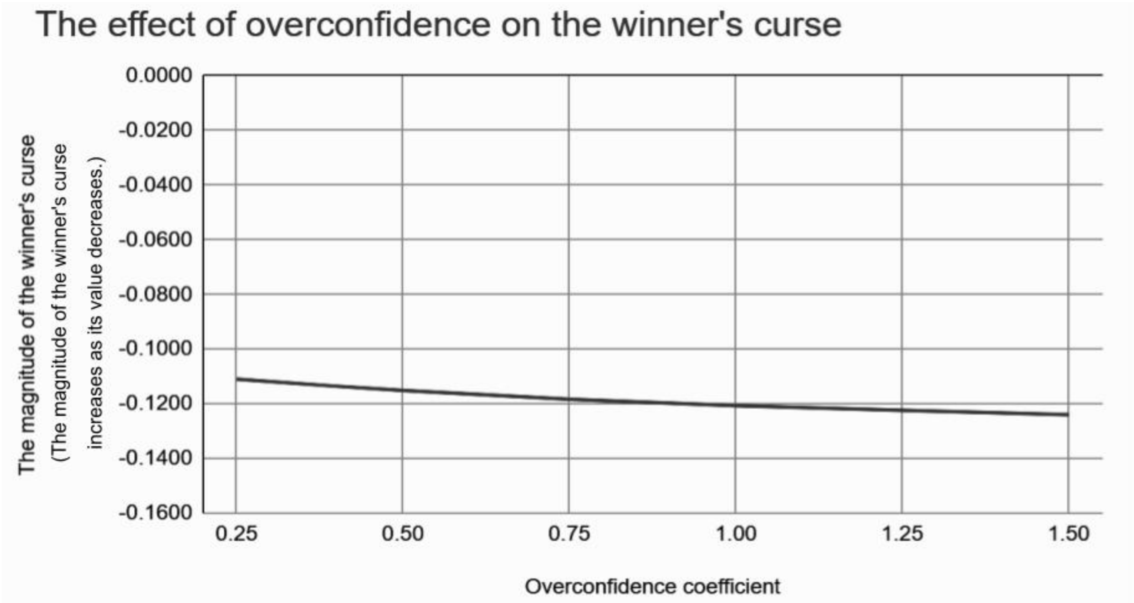

Figure 7.6 The effect of overconfidence on the winner's curse with a moderate level of risk aversion and a moderate number of bidders ($\boldsymbol{\alpha}$=0.6, number of bidders: 10, the winner's curse range: 0.2)

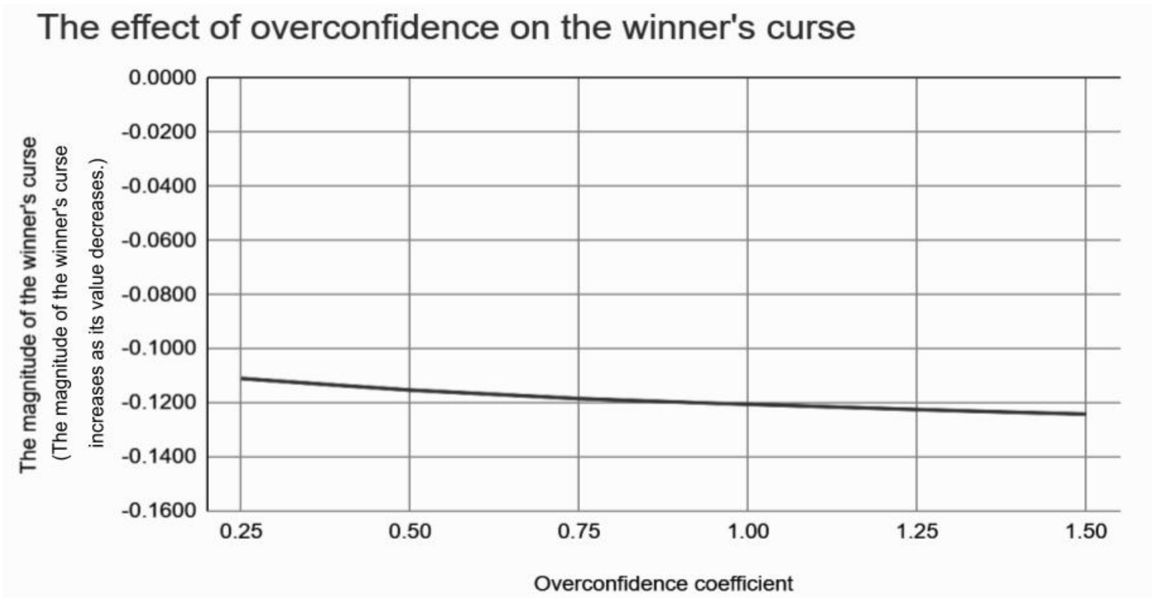

Figure 7.7 The effect of overconfidence on the winner's curse with a low level of risk aversion and a moderate number of bidders ($\boldsymbol{\alpha}$=0.1, number of bidders: 10, the winner's curse range: 0.2)

In the next phase of the study, it is determined how the winner's curse manifests in bidding with a moderate number of participants and high degrees of risk aversion. The outcomes closely resemble those of the preceding two experiments involving moderate risk aversion (Please see Figure 7.8).

In the final experiment, which is designed for auctions with a moderate number of participants, risk aversion is disregarded. In this situation, the outcome closely resembles those of earlier experiments with a moderate number of individuals (Please see Figure 7.9).

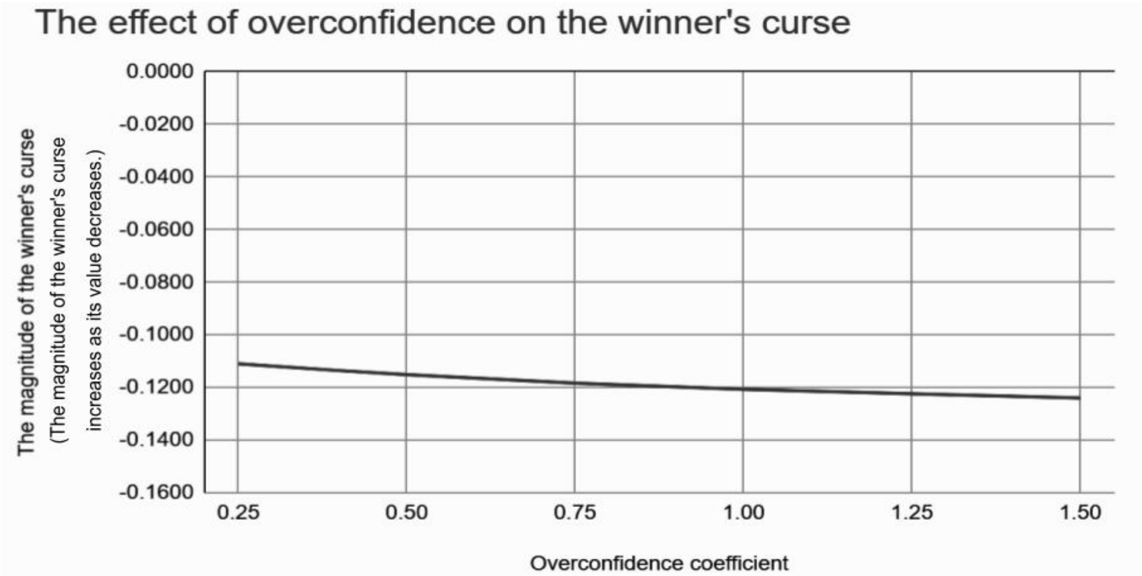

Figure 7.8 The effect of overconfidence on the winner’s curse with a high level of risk aversion and a moderate number of bidders ($\boldsymbol{\alpha}$=0.9, number of bidders: 10, the winner’s curse range: 0.2)

7.4. Experiments with a Large Number of Bidders

The virtual experiments presented in the preceding section demonstrate that raising the number of bidders has a minor impact on the winner's curse. Consequently, the objective of this section is to examine how a reasonably large number of participants influences the occurrence of the winner's curse. The number of participants in the virtual experiments conducted in this chapter was fixed at twenty for this reason.

In this section, similar to the preceding sections, moderate risk aversion is detected in the virtual experiment, whose results are presented first. Similar to the preceding section, surprisingly, the winner's curse phenomenon increases when overconfidence behavior decreases. As depicted in the graph in Figure 7.10 below, the curse of the winner grows increasingly obvious, albeit at a relatively low level in this instance.

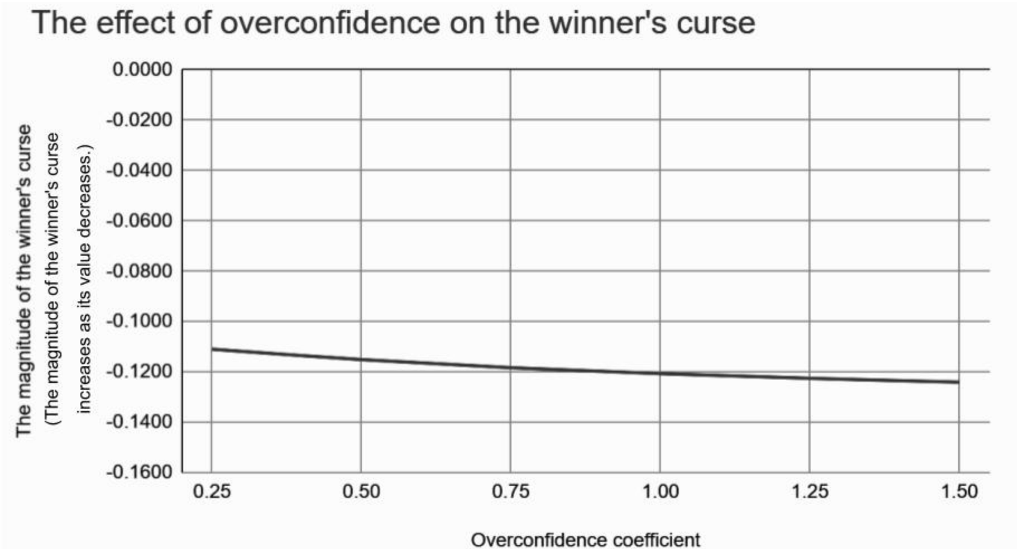

Figure 7.9 The effect of overconfidence on the winner's curse without risk aversion and a moderate number of bidders (**α**=0, number of bidders: 10, the winner's curse range: 0.2)

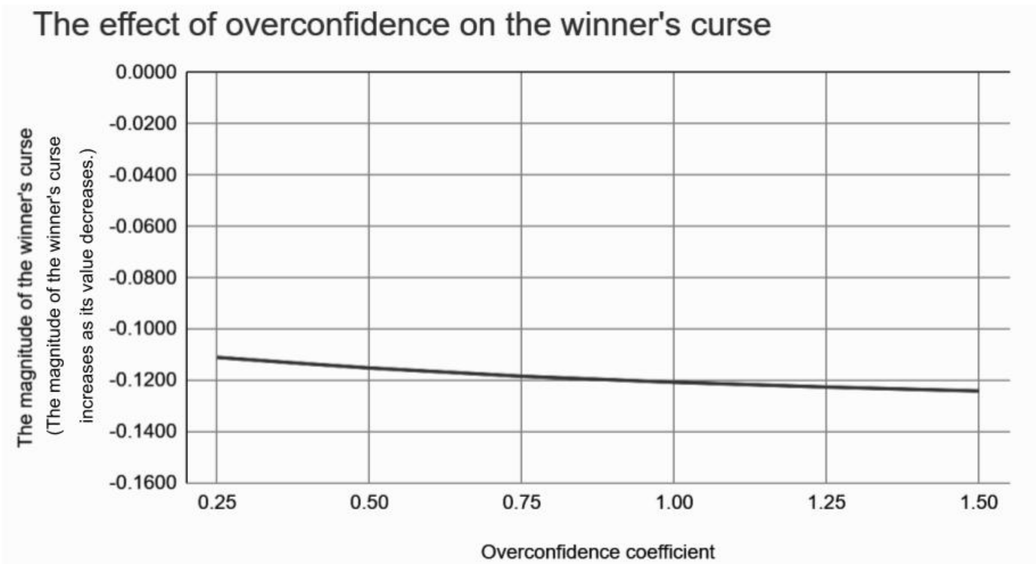

Figure 7.10 The effect of overconfidence on the winner's curse with a moderate level of risk aversion and a large number of bidders (**α**=0.6, number of bidders: 20, the winner's curse range: 0.2)

Next, it is determined how low risk aversion influences the winner's curse effect in construction bidding with a large number of participants. In order to accomplish this, the risk aversion determinant was set to 0.1 and the virtual experiment was repeated with the same variables. In multi-party auctions, there is no discernible change in the winner's curse phenomena when going from a medium level of risk aversion to a low level of risk aversion, as depicted in Figure 7.11 below.

In the next phase of the virtual experiments simulating construction bids with a large number of participants, the effect of strong risk aversion on the phenomenon of the winner's curse is examined. This virtual experiment shows very similar results to other experiments with a large number of participants and varying levels of risk aversion (Please see Figure 7.12).

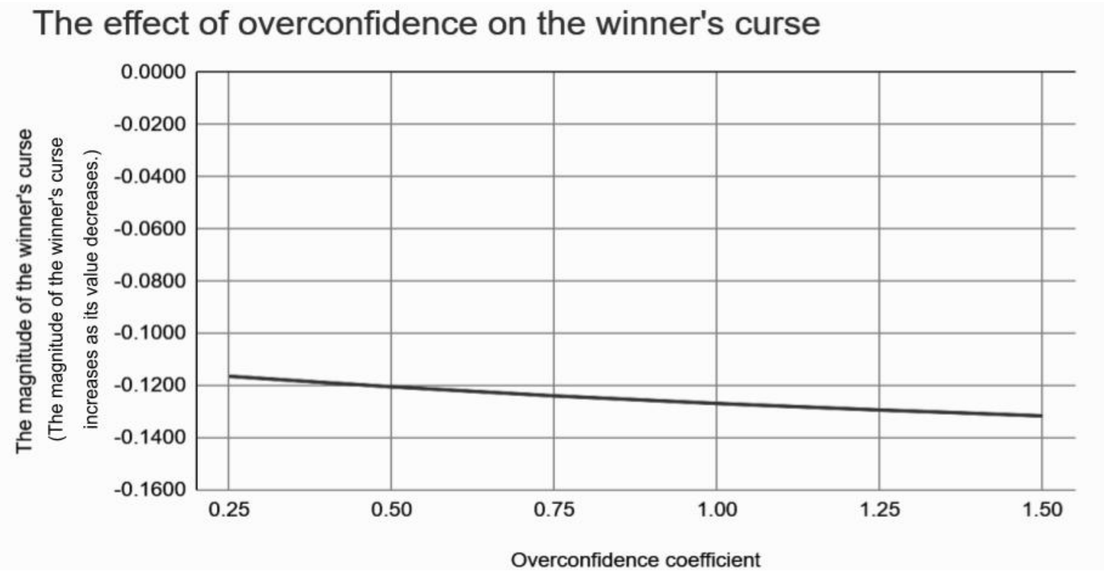

Figure 7.11 The effect of overconfidence on the winner's curse with a low level of risk aversion and a large number of bidders (α=0.1, number of bidders: 20, the winner's curse range: 0.2)

The case of risk aversion in multi-party auctions is finally modeled (Please see Figure 7.13). In contrast to other models with fewer participants, when risk aversion behavior is ignored in this virtual experiment, the outcomes are comparable to those of experiments involving risk aversion behavior. Risk aversion behavior has no effect on the winner's curse when the number of participants is relatively high.

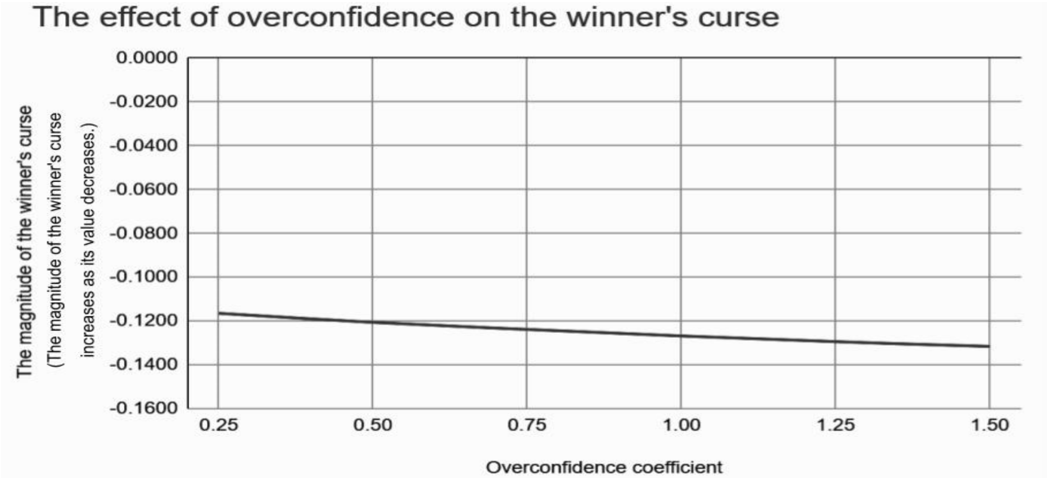

Figure 7.12 The effect of overconfidence on the winner's curse with a high level of risk aversion and a large number of bidders (**α**=0.9, number of bidders: 20, the winner's curse range: 0.2)

Figure 7.14 depicts a summary graph of the findings detailed in the preceding graphs. The graph demonstrates that the overconfidence effect is observed in all instances. Changes in overconfidence behavior have no effect on the winner's curse in auctions with a small number of bidders. When the number of participants reaches moderate or high levels, the overconfidence effect increases for all levels of overconfidence. In addition, individuals with low overconfidence are more susceptible to the winner's curse under these two circumstances.

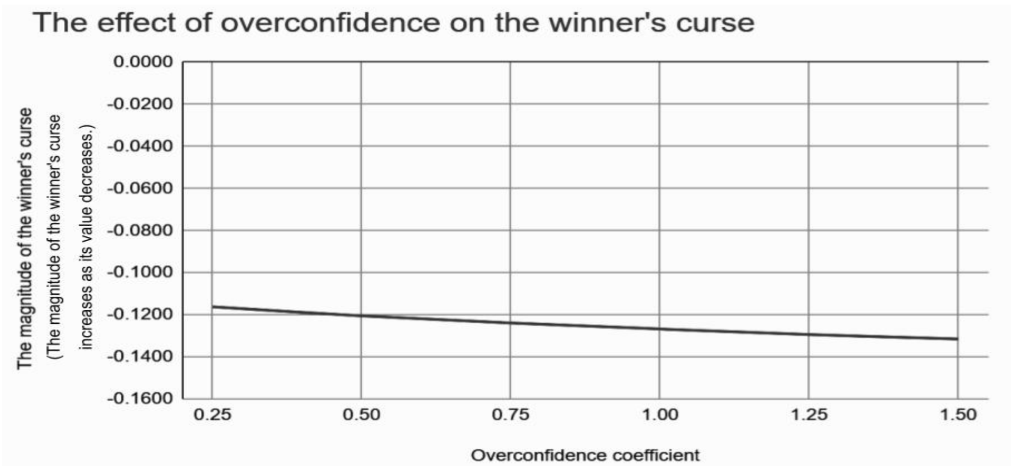

Figure 7.13 The effect of overconfidence on the winner's curse with absence of risk aversion and a large number of bidders (**α**=0, number of bidders: 20, the winner's curse range: 0.2)

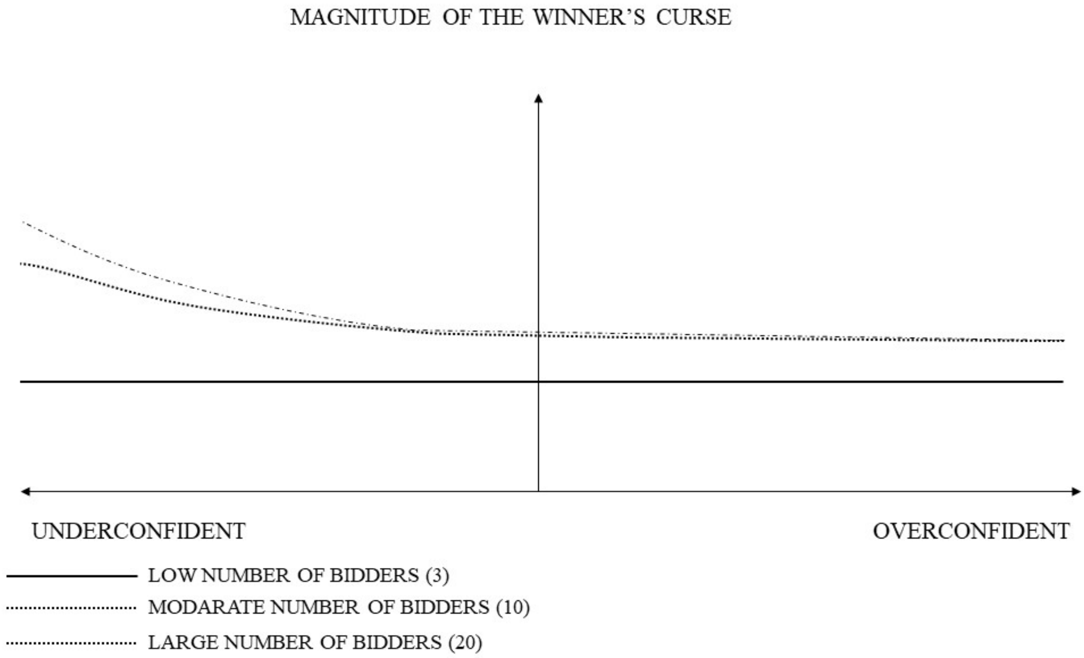

Figure 7.14 Graph illustrating the relation between the winner's curse, the number of bidders, and the overconfidence effect

CHAPTER 8

CONCLUSION

This paper's primary purpose is to investigate the effects of overconfidence in competitive construction bidding. As the overconfidence effect changes, we observe how the phenomenon known as the winner's curse manifests itself. In a nutshell, the overconfidence effect occurs when decision-makers consider themselves to be in a better position than they actually are. The phenomenon of the "winner's curse" is the failure to obtain the anticipated benefit from an auction due to technical errors or behavioral illusions that occur in a competitive auction environment.

However, it would be pointless to evaluate the overconfidence effect by itself. The frequently cited phenomenon of risk aversion in behavioral economics may mitigate the effects of overconfidence. In addition, it is frequently emphasized that the number of auction participants influences bid formation strategies. In designing the study's methodology, we have therefore attempted to account for these occurrences.

Decisions made by contractors acting independently and competing with one another shape the tendering process. In this regard, procurement processes are similar to a network of diverse individuals. To model this type of research virtually, the agent-based modeling technique has been developed. The agent-based model is intended to investigate the macro-level patterns that emerge from the micro-level decisions made by individuals.

Construction firms are project-based businesses. Each project procedure begins with cost estimation and concludes with project delivery, at which point the actual cost is determined. Therefore, it is essential that the initial cost estimate and the actual cost at the conclusion of the project are consistent. The winner's curse occurs if the cost estimate is overly optimistic, and the company does not make the expected profit or incurs losses.

In order to undertake projects, firms in the construction industry compete with one another during the tendering and negotiation firms. When a firm's competitors are highly influenced by the winner's curse, it will be unable to execute projects as desired. For this reason, the macro-scale pattern shown by the agent-based model developed for this study is the market's dominance of the winner's curse phenomenon. Other aims of the study include determining if risk aversion and the number of bidders engaging in the bidding process have an impact on this phenomenon, as well as observing how the winner's curse is affected by the increase and decrease of the overconfidence effect.

The model created for this purpose was applied iteratively to various configurations. The first objective was to determine how the overconfidence effect and variations in risk aversion in low-participant bids affect the winner's curse in the construction industry. One could claim that a consistent degree of the winner's curse emerges when the number of participants is small. A rise or fall in risk aversion does not protect decision-makers from loss or gain. In contrast, the winner's curse is marginally more effective in the model where risk-aversion behavior is ignored, and risk-neutral individuals are generated.

All virtual experiments done for auctions with a small number of participants were replicated for auctions with a medium number of participants in the subsequent phase. In contrast to tests with a small number of participants, the overconfidence effect was observed to have a minor effect on the winner's curse phenomenon in this instance. Contrary to predictions, the winner's curse tends to rise significantly when the overconfidence effect reduces. In the condition where the winner's curse is at its most intense, individuals are most underconfident. In this scenario, changes in risk aversion behavior, including complete disregard for risk aversion, have no effect on the winner's curse.

In the final phase of the research, the previously repeated trials were performed with a large sample size. This scenario yields findings that closely resemble those obtained with a moderate number of participants. As the effect of overconfidence diminished, a modest rise in the severity of the winner's curse was observed. In this particular instance, neglecting risk aversion had no effect on the winner's curse. In summary, risk aversion has no effect on the winner's curse when there are many participants.

In conclusion, the winner's curse is a frequent occurrence in competitive building bids. In auctions with a limited number of participants, the winner's curse is unaffected by the overconfidence effect, although the danger is somewhat enhanced for neutral bidders. The winner's curse is more effective in auctions with a medium or high number of participants. In some instances, an increase in the overconfidence effect results in a minor diminution of the winner's curse. Construction firms must evaluate their susceptibility to the winner's curse in all bidding processes. The greater the number of participants, the more susceptible contractors are to the winner's curse, which is characterized by underconfident behavior.

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