A REVERSE AUCTION BIDDING STUDY OF RETURNS FROM GUARDIAN PERSONALITY TYPES

A Thesis

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

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August 2018

Major Subject: Construction Management

ABSTRACT

Traditionally in construction, procurement of products and/or services has been conducted via a sealed bidding format, termed in the United States as a hard bid. With changing technology and time, newer methods are being accepted and applied to the process of awarding contracts for the supply of building construction services. One of these systems is the Reverse Auction Bidding system. The purpose of this research is to study the results of an academic game play using a Reverse Auction Bidding (RAB) site conducted with graduate students in a Construction Management program at Texas A&M University. This research continues a long running investigation into how Game Theory and Personality types impact on the returns from the game.

Nash developed the basic theory that forms the foundation for any study of a game, one of the issues that Nash briefly discussed is personality impact on game play. This research work investigates the link between personality type and returns. Construction contracts are negotiated often by teams, although often a single person has the final call on the price. Earlier studies into RAB showed that the normalized profit results were approximately fitted by a Beta distribution, which is consistent with other studies of auctions. However, a "secondary underlying" distribution appears to provide a linear addition to the Beta distribution for the normalized profit range greater than 0.75. The objective of this study is twofold, to study the game play returns for Guardian personality types and to investigate the underlying game play cause for the linear addition to the beta distribution, which is thought to be of Gaussian form. Three games were played using the RAB web site. The results showed a trend toward the Beta and Normal distributions and the impact of personality was observed in the game results, although the expected dominance of the Guardian personality was destroyed by the profit destroying play of another personality type, who

rushed everyone to the bottom of the distribution. The conclusions are that personality has an impact on results and that the linear addition to the Beta distribution is the result of intelligent playing by some players, who impose a secondary Gaussian distribution on the average returns shown by the Beta distribution. Further work is suggested on the Gaussian distribution and the profit destroying play of another personality type.

DEDICATION

This is dedicated to my Father, Vinod Wadhwani, who had immense trust in me when I started any venture into life. This is surely guided by him while drawing logical explanations on behavior of people. My family kept pushing me to go far and beyond my limits, and to constantly produce quality work. This research is dedicated to all those who always believed in me.

ACKNOWLEDGEMENTS

I wish to acknowledge all the people who helped me in this time at Texas A&M University. My advisor Dr. John M. Nichols, Dr. Phil Lewis, and Liz smith. I would also like to acknowledge my friends who kept me motivated through the time I was writing this thesis.

CONTRIBUTORS AND FUNDING SOURCES

This work was supported by a dissertation committee consisting of Associate Professor John M. Nichols and Associate Professor John A. Bryant of the Department of Construction Science and Stephen Caffey Assistant Professor of the Department of Architecture.

Some of the data analyzed for Chapter 3 and Chapter 4 was provided by Associate Professor John M. Nichols from previous RAB studies completed at TAMU.

All other work conducted for the dissertation was completed by the student independently. There are no outside funding contributors to acknowledge related to the research and compilation of this document.

NOMENCLATURE

The required definitions, based on previous research work on RAB, which commenced with the study by van Vleet van Vleet (2004), are:

Definitions

- **Reverse Auction Bidding:** Reverse auction bidding is a type of auction in which the roles of buyers and sellers are reversed. In a regular auction (also known as a forward auction), buyers compete to obtain a good or service, and the price typically increases over time. In a reverse auction, sellers compete to obtain business and price decrease over time (Machado, 2009).
- **Game Theory:** A formal analysis of conflict and cooperation among intelligent and rational decision makers (van Vleet, 2004)
- **Bidders Personality:** "The dictionary defines personality in several ways. One definition emphasizes the public, social stimulus, or behavioral characteristics of a person that are visible to other people and make an impression on them. Another definition stresses a person's private, central, inner core. Included within this private core are the motives, attitudes, interests, believes, fantasies, cognitive styles, and other mental processes of an individual. Some definitions of personality emphasize its "person" quality, personal existence, or identity features. Other meanings of personality are associated with specific disciplines or professions" (Panchal, 2007).
- **Responsive Bidder:** A bidder whose bid satisfies all the terms and conditions of bidding, delivery requirements, detailed specifications is called a responsive bidder (Machado, 2009).

- **Aggressive Bidder:** Aggressive bidders are the bidders who attain highest overall returns in the entire bidding process (Chouhan, 2009).
- **Average Bidder:** Average bidders are bidders who attain average distribution of returns in the entire bidding process. (Chouhan, 2009)
- **Poor Bidder:** Poor bidders are bidders who attain below average distribution of returns in the entire bidding process.
- **Economically effective bidder-** The bidder who attains highest overall returns in the form of profits from the entire bidding process (Machado, 2009).
- **Economically ineffective bidder-** The bidder who attains lowest overall returns in the form of profits from the entire bidding process (Machado, 2009).
- **Economic Winner**-An individual who generated the highest average returns. Panchal (2007)coined this term to indicate a more successful player in the game. An economic winner makes no direct difference to the game for the player where the player has an objective of minimizing the average bid for the game. The player sees the average price for purchases and a distribution of prices (Guhya, 2010).
- **Economic Loser**- An individual who generated the lowest average returns. Panchal (2007) coined this term to indicate a less successful player in the game. An economic loser makes no direct difference to the game for the player where the player has an objective of minimizing the average bid for the game (Guhya, 2010).
- **Game-** a series of jobs for the construction of a reinforced concrete floor slab, each game lasts approximately 8 to 10 weeks in game play time, with each round of the game modelling a week and occurring in a 20 minute period, with 15 minutes of bid time and 5 minutes of build time (Guhya, 2010).
- **Traditional bidding-** In this type of auction all bidders simultaneously submit bids in such a way that no bidder knows the bid of any other participant. The highest/lowest bidder is assumed to be awarded at the price submitted provided no other contracts opened on the decision process (Boser, 2000).

- **Bid arrival-** a record when bid activity occurs and creates a bid track on online bidding system. This record includes bidding information like price, bidder information, bid time, etc., (Yuan, 2013)
- **bestResponsebidding (BR)-** this strategy is also known as myopic bidding, straightforward bidding or, bidding gradient. bestResponsebidding bid ‘straightforwardly’, offering the package that has the highest expected surplus, which is measured as the gap between the actual cost of the package and its computed value at current (feedback) prices. (Iftekhar, Hailu, & Lindner, 2012)
- **PowerSet bidding (PS) -** PowerSet bidder evaluates all possible packages in each round, and submits bids for all packages with positive expected surplus. PowerSet bidding is also known as limited straightforward bidding. (Iftekhar et al., 2012)
- **Constrained PowerSet bidding (CPS) -** In constrained PowerSet bidding, the bidder anchors on the bestResponse package to identify other suitable packages, say, within 50% range of the value of the expected surplus of the anchored package. This strategy will allow bidders to reduce their bidding costs by focusing on a fewer number of packages compared with PowerSet bidders. (Iftekhar et al., 2012)
- **Heuristic PowerSet bidding (HPS) -** HPS bidders randomly select around half of the PowerSet bids. Therefore, while CPS bidders would select a subset of PowerSet bids with the highest expected surplus, HPS bidders might select bids with a low expected surplus. The strategy is appropriate when bidders are either not fully confident about the current market information or are motivated by factors other than profit maximization. (Iftekhar et al., 2012)
- **Naïve bidding (NV) -** A naïve bidder submits bids on all possible combinations of items, regardless of expected surplus. Performances of different bundling strategies

are often compared against the efficiency achieved by naïve bidders. (Iftekhar et al., 2012)

Game Definitions

The following list contains terms associated with the reverse auction bidding game. These terms were defined by van Vleet (2004), Chaudhari (2000), Panchal (1995) and Guhya (2010).

λ player	this represents the bidder group, treated as a single entity for game analysis.
λ_i player	the i^{th} bidder in the bidding group.
υ player	the purchaser.
α game	the postulated sub-game played between bidders in seeking economic advantage over the remaining bidders. This game almost always disadvantages the υ player, but the υ player created the system and so is responsible for the υ player's economic losses as a result.
ω game	the postulated sub-game played within the Reverse Auction Bidding game between the purchaser and the bidders. In terms of this analysis, it effectively reduces to a two-player game, with competition implications for all players. The υ player sees only the average of all won bids.
τ	bid time allowed for each round of play in the game.
δ	period between bid time τ that represents the work time in the game.

B_j	i^{th} bid
B_v	accepted bid for each job.
K	this variable is a fixed dollar sum, representing the υ player's base price, although in this game K is a vector of costs.
Γ	this variable is a fixed dollar sum, representing the υ player's maximum incremental price above K
Ξ	this variable is defined by the set of numbers $\{\Xi \mid 0 < \Xi \leq 1\}$, although negative values of Ξ are permitted by the Reverse Auction Bidding system. Ξ normalizes the profit data. A negative Ξ_j represents a loss on direct costs to the λ_i player who makes this type of bid, and enough of these bids will lead to a bankrupt player. This type of play is discouraged as the assumption in the game is steady state economic conditions in the outside economy. Future studies may look at a failing market, but that is beyond this study.
Type ξ	a stronger player
Type ζ	a weaker player
Type ϕ	Exists and who is within the middle of the profit range

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CHAPTER 1

INTRODUCTION

Background

Reverse auction bidding (RAB) is an innovative procurement method. Its name indicates its distinct feature, the reversed roles of buyers and sellers. It was used in materials and services of commercial as well as construction procurement. Moreover, many private and government agencies in construction industry are utilizing RAB as one method of procurement. This thesis presents a study of three Reverse Auction bidding games played at Texas A&M University in May 2018. The purpose of the study was twofold, to further consider the impact of the Guardian personality type on the overall results <Get a reference for Keirsey> and to determine the likely source of the Gaussian bump in an otherwise Beta distribution of profits

Online auctions are widely used in commerce and industry for trade. However, the concept of online bidding in construction industry is novel. Reverse auctions utilize secure internet technology to enable contractors in the tendering process. "In the UK, the office of Government Commerce is championing the use of reverse auctions to improve procurement efficiency and save project costs. Use of auctions in bidding for construction is however the subject of current debate"(Abu-Shaaban, 2005). In reverse auctions, the auctioneer sets the starting bid and the bidders compete in multiple rounds successively to offer the most desired offer on the product specified in the Request for Quotation (RFQ).

Increased transparency & reduced costs, advanced user (bidder) monitoring, healthier competition, recognition of new contractors/suppliers, easy bid comparison, reduced clerical work, multi-supplier coordination, and multiple bidding opportunities are a few advantages of the postulated online reverse auctions.

Communication quality between the auctioneer and bidders before, during, and after bid is crucial. “Research conducted on reverse auctions from a consumer’s point of view shows significant difference in both mean and final sale prices which is due to varying information synergies in online auction and physical auction.”(J. & M., 2000) “Reverse auctions could lead to cost savings up to and order of 20%. However, sustainability of these numbers is a matter of future research.”(Andrew, Paul, & C., 2003) Reverse auction was recognized to bring new sellers who could offer lower price, while making current seller annoyed at losing the hard-won long-term business.” (Emiliani, 2005) “Due to its price-oriented characteristics, RAB could lead to profit margin erosion.” (C. & M.L., 2007)

van Vleet noted in 2004 that, “In order to accurately assess the implications of reverse auctions, it was essential to know and understand the behaviors of those who engage in the bidding process. Without a method of evaluating the process, it is impossible to clearly understand whether RAB is a success or not.” Bidders are required to make two decisions, first, that of quoting a price for a product/service. Second, the right time in the bidding session to quote that price.

“To truly determine the success or detriment of a method introduced into a system, a clear understanding and full appreciation its functions and relationships is required” (Piper, 2013) Studies have been conducted by Machado (2009), Guhya (2010) and Siagaonkar (2010), at TAMU to analyze how the bidders’ personality affects RAB. “It has been observed that when Guardians play against other personality type they outperform but when Guardians play against each other the profit drops significantly”.(Agrawal, 2014).

This section of the thesis outlines the research objective, the limitations of the study and the significance of the study.

Research Objective

This study seeks to understand:

1. the performance of Guardians relative to the remainder of the population
2. The overall objective is to understand how communication occurs within RAB and human games using statistical inference
3. In the analysis, the differences created by guardians that appear in their performance using Beta distribution and postulate that they follow a Normal distribution are sought
4. The first statistical question is the secondary underlying distribution a Normal distribution?
5. The second statistical question is underlying distribution is caused by Guardians, during the game play?

Limitations

The use of electronic business methods is becoming increasingly important. There has been a very long-running and loudly argued division in the construction discourse group of the ethical aspects associated with Reverse Auction Bidding (RAB). van Vleet in an IRB approved study, in 2004 showed that the game was not directly collusive, but the free flow of information provided "canny" players with a sense of play that allowed them to perform better than the average.

After 25 studies conducted at Texas A&M University (TAMU), it is thought that guardian personality types tend to perform better than the "average" human, with the provisos:

1. the test population in the previous 25 studies on RAB conducted at TAMU, which represented by the other 15 personality types, there is a total of 16 personality types per the Keirsey Temperament Theory
2. that there is no more than one guardian in one game
3. and each game is generally played with four players and new players in each game

Game Limitations

The game limitations are:

1. The participants of this study are Masters Students in the Department of Construction Science at TAMU.
2. The participants will be asked to volunteer and selection will be made randomly.
3. To maintain the Herfindahl index, each team will have only four members (one guardian and other three non-guardians)
4. No more than eight to ten (8-10) games will be played for a cumulative period of four hours (4 hours)
5. The RAB game is designed to operate in a steady state condition, thus eliminating any economic market pressure.
6. No legal consequences have been added to the RAB game simulation.

Scope Limitations

The limitations for the scope of play are:

1. Industry professionals will not form a part of this study

2. This study will not identify sub-type guardian personality leading to a bump in RAB normalized profit data
3. This study can be taken further by analyzing the patterns of the players to determine what causes them to gain or lose profits

Significance of the Study

The twenty-five previous studies conducted at TAMU show a Beta Probability Distribution for the overall population, but, there is a "secondary underlying" distribution that appears to arise from some of the bidding patterns. This secondary underlying distribution is a bump in the overall Beta Probability Distribution, shifted to the right of the curve with greater bid numbers.

The goal of the study is to provide:

1. a better understanding whether the "secondary underlying" distribution is a Normal Probability Distribution
2. Guidance as to if, the guardians cause the secondary distribution bump

CHAPTER 2

REVIEW OF LITERATURE

Introduction

This section of the thesis outlines the relevant review of the literature related to Game Theory, Reverse Auction Bidding and Personality Types that impact on the work.

Game Development

van Vleet (2004) developed the original game with the purpose of studying tacit collusion in Reverse Auction Bidding. One of the many concerns raised about RAB is that it is another form and bid shopping, is anathema to the average contractor in the construction industry (Harbert, 2003). Van Vleet was interested in whether in a game developed to study RAB if tacit collusion could be observed.

The game was developed to provide a simple tool to study the impact of bidding methods on the results. The basic theory for the game is that a contractor in Houston is looking to have house slabs constructed in each of six new residential development areas. Figure 1 shows the six theoretical sites in Houston. As with any game, the six sites are just a useful method for introducing some randomness into the game play, with the point of making it impossible for a player to develop a single strategy for each site. As is usual for a production homebuilder the work is repetitive, which simplifies the production process. The production builder builds only one type of home and hence requires each contractor to pour only one type of slab. The key assumption is that each Monday, the υ player, posts the jobs that they are going to start that week. The data included is where each job is located. All λ_i players have been prequalified and only price matters, as is normal in this type of bidding system.

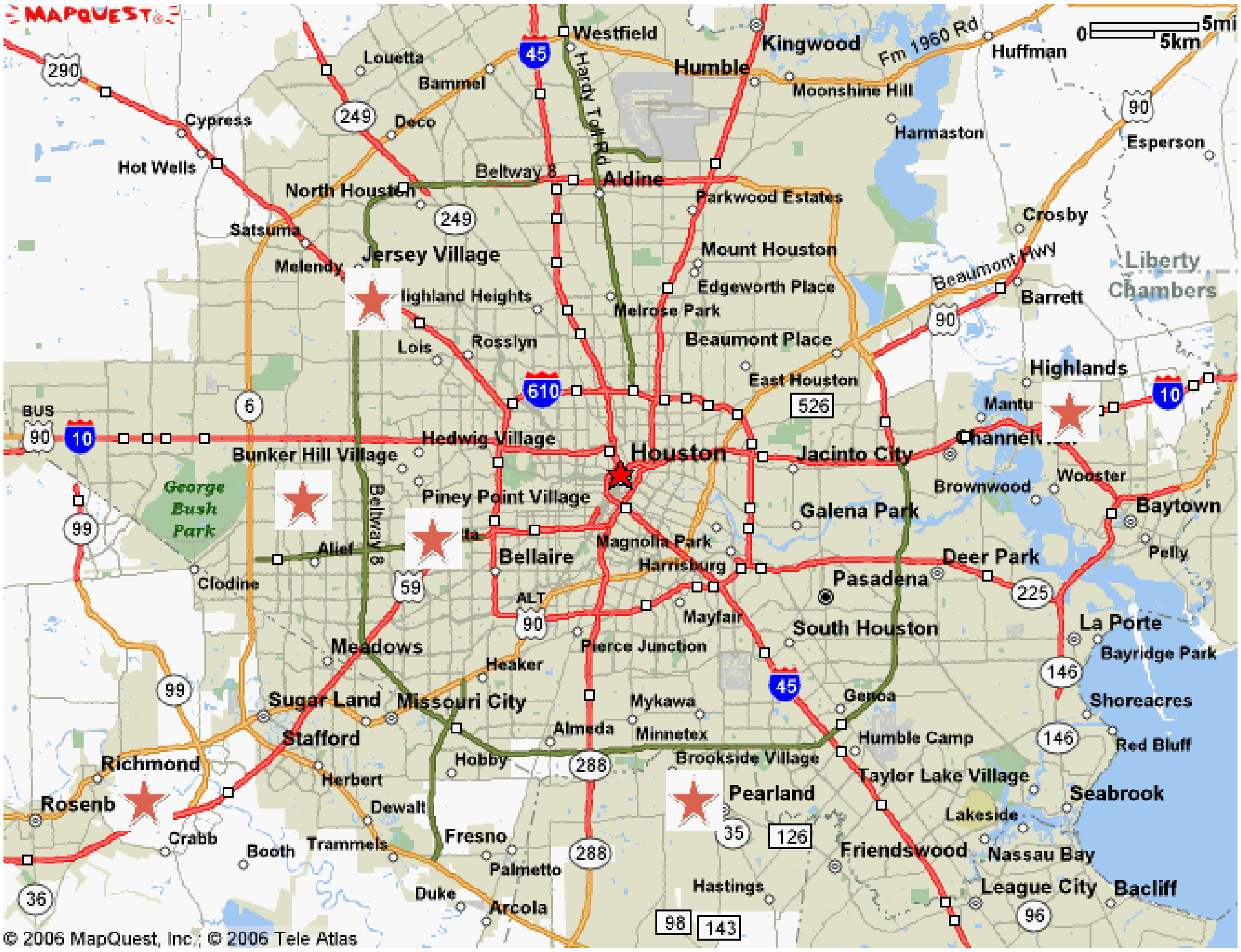


Figure 1: Construction Site Locations in Houston (Reprinted from MapQuest, 2006)

The game ignores the reality that a canny contractor would negotiate long term contracts with the main sub-contractors.

Nash Equilibrium and Game Theory

Reverse auctions are an excellent platform to study game theory. Game theory has four elements which are; (1) players; (2) actions that the players might take; (3) timing of interaction of actions taken; and (4) result of the interaction. Nash developed game theory and the strategies or actions used by players, and defined *Nash Equilibrium* (Nash Jr., 1950a, 1950b, 1951, 1996). Jackson notes "Nash Equilibrium is a profile of strategies such that each player's strategy is a best response (i.e. results in highest available payoff) against the equilibrium strategies of other players. (Jackson)" ***N*** defines the number of players in equation (1)

$$N = (1, 2, 3, \ldots n) \tag{1}$$

Further, ***a*** defines the set of pure Nash strategies of each player as shown in equation(2);

$$a = (a_1 \times a_2 \times a_3 \ldots \times a_n) \tag{2}$$

Further to while not all games have a pure strategy, Nash equilibrium, every game with a finite set of actions has at least one mixed strategy. These mixed strategies generate what is called a, *Mixed Strategy Nash Equilibrium*. For a player ***i,*** a Mixed Strategy is a distribution s_i on a_i where; *s* is a profile of mixed strategies for n players as shown in equation (3)

$$s = (s_1 \times s_2 \square s_3 \ldots \times s_n) \tag{3}$$

Note that an equilibrium provides a prediction about how each player will move in each contingency and this makes a prediction about the path to be taken. This predictive path is called *equilibrium path*."

Nash equilibrium is an important concept for reverse auction bidding simulation game in trying to understand player behavior, it predicts why some decisions may be individually attractive, but can be a terrible idea for groups as in the classis Prisoner Dilemma. In a Nash equilibrium, every person in a group makes the best decision for themselves, based on what the person thinks the others will do. And no-one can do better by changing the strategy since it is assumed that every member of the group is doing as well as they possibly can.

Unfortunately, Nash also discusses the concept of a group action that may swamp individual play in a fast-moving game, such as this RAB study and player personality can impact on "rational play methods" with players making moves that are not in their best economic interest, either individually or for the group.

Personality Types

Table 1 shows the Keirsey Temperament Sorter Test Summary (Chouhan, 2009).

Table 1: Keirsey Temperaments

	Temperament	Role	Role Variant
Introspective (N)	Idealist (NF) *Diplomatic*	Mentor (NFJ) *Developing*	Teacher (ENFJ): *Educating*
			Counselor (INFJ): *Guiding*
		Advocate (NFP) *Mediating*	Champion (ENFP): *Motivating*
			Healer (INFP): *Conciliating*
	Rational (NT) *Strategic*	Coordinator (NTJ) *Arranging*	Field marshal (ENTJ): *Mobilizing*
			Mastermind (INTJ): *Entailing*
		Engineer (NTP) *Constructing*	Inventor (ENTP): *Devising*
			Architect (INTP): *Designing*
Observant (S)	Guardian (SJ) *Logistical*	Administrator (STJ) *Regulating*	Supervisor (ESTJ): *Enforcing*
			Inspector (ISTJ): *Certifying*
		Conservator (SFJ) *Supporting*	Provider (ESFJ): *Supplying*
			Protector (ISFJ): *Securing*
	Artisan (SP) *Tactical*	Operator (STP) *Expediting*	Promoter (ESTP): *Persuading*
			Crafter (ISTP): *Instrumenting*
		Entertainer (SFP) *Improvising*	Performer (ESFP): *Demonstrating*
			Composer (ISFP): *Synthesizing*

Significant work in this group of studies has shown that the Guardian tends under most favorable circumstances to perform better than others. This is of course not completely true as other factors impede the play.

Reverse Auctions background

If one considers an apple, the supply is huge and the individual has no ability to change the overall supply price as explained by Perloff (2004), but in the case of this set of subcontractors, each subcontractor has a set capacity of three slabs, albeit with the ability to acquire, for a fee, additional capacity. The first bidder therefore in essence reduces their capacity to bid further jobs with the first bid, providing a clue to the other bidders as to the willingness to bid, their initial price range, but more importantly reduces the overall capacity for the remaining bid set. This is the essential feature of RAB, the purchaser is providing the sellers with near perfect and real time information, the game is then between the sellers to maximize their individual profits within the vagaries of play, where there are probably 100 million bid points and humans make very "non-rational" decisions under these circumstances as explained by Nichols (2017). The purchaser is acting irrationally in their desire to drive down prices and creating a perfect market for the canny seller, of course the poor seller is swamped and generally makes remorseful decisions.

Reverse auction runs on a simple principle of dynamic pricing (DP). Dynamic pricing is the price associated with products or services when price changes dynamically with respect to (w.r.t.) demand, and other situation specific parameters. DP can come in various formats and online auction is one of them, with the ability to attract larger audiences.

Figure 2 shows the difference between profit margins of fixed pricing vs. dynamic pricing, although this applies, the seller is watching up to twelve bids at once, the pricing is highly dynamic and controlled by many decisions.

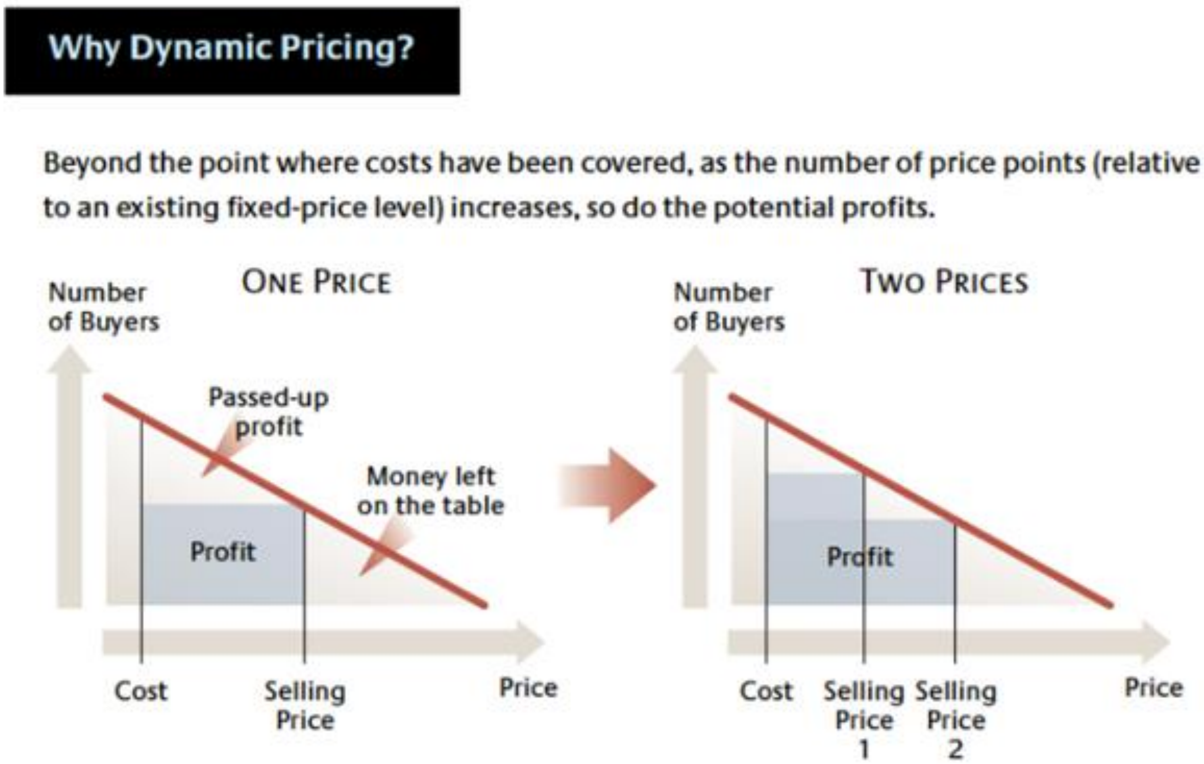


Figure 2: *Reaping Higher Profits – dynamic pricing – Reprinted from Sahay (2007)*

Sahay (2007) notes "There are two categories of DP: (1) posted prices that customers/suppliers can see; and (2) price discovery mechanisms, in which they determine prices through their own actions during the transaction." The first category would be better for the slab purchaser, but this desire for lowest cost plays into the hands of the sellers who now know bid capacity and price ranges, which is not known in a hard bid.

Latitude of price acceptance (LPA) is defines as a range of price possibilities which have little or no impact on purchase decisions. “A McKinsey and Co. study shows that LPAs can range widely, up to 10% for engineered industrial components”(Sahay, 2007). Dynamic pricing is used in reverse auction bidding (RAB) allowing dynamic information exchange which helps alleviate the problems arising due to hard bid by introducing transparency of bidding, multiple bid submissions, and price visibility to all players. The purchaser pays a penalty for providing this information to the sellers and it does not necessarily result in price minimization.

Online technologies are an effective method for transmitting information based on their quality of providing instant feedback throughout the bidding process. Any gap in knowledge can be immediately fixed, provided, that both the auctioneer and supplier have a response team set-up on their ends. Compared to physical auctions, online auctions are easier to organize, and facilitate participation from different geographical locations. As Jap (2012) notes “The technology behind an auction format is not complex; hence, many firms can offer such a format as a part of their sourcing solutions or software (e.g. *B2emarkets, Commerce One, Oracle*). The technology also enables unprecedented temporal and geographical efficiencies, making it easier than ever to organize and host an online auction.”

Reverse auction bidding as a procurement method

RAB plays the role of a purchasing and supply management (PSM) method in construction. Saranga and Moser (2010) observed, “An effective and efficient management of PSM activities allowed many global companies to become a leader in their business”. A significant role-shift of PSM from a merely source management to an operational and financial contributor has been observed in the recent years due to price surges, economic crisis, and demand for cost-savings.”

Since a major portion of production process is decided in the preliminary part of the design processes, PSM methods can be applied more effectively then as shown in Figure 3.

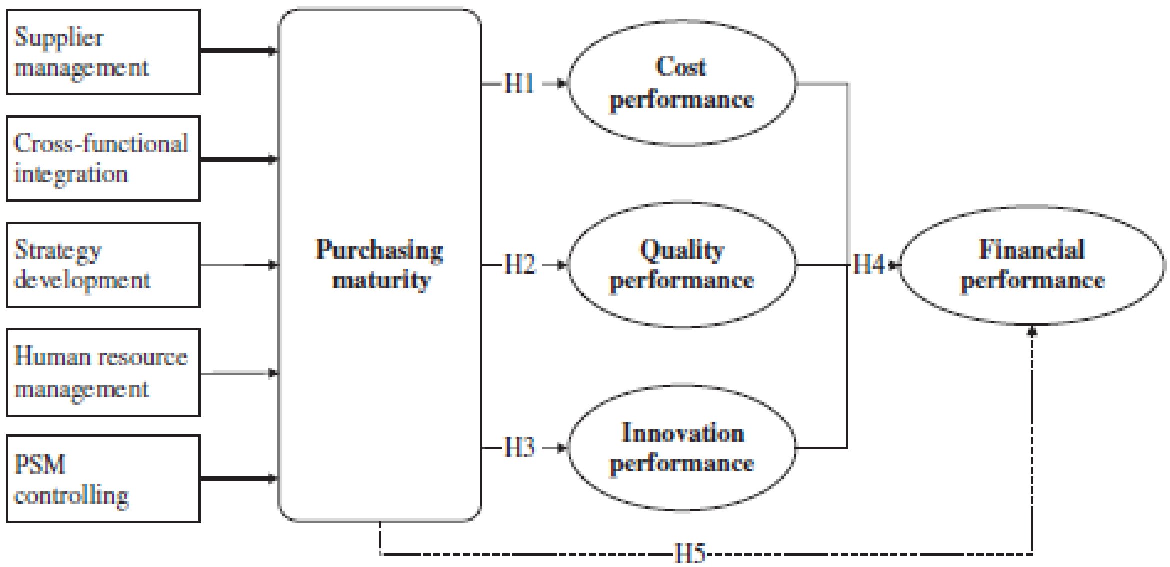


Figure 3: *PSM Methods – Reprinted from Evi Hartman (2012)*

Hartman, Kerkfeld, and Henke (2012) note, "Empirical research to-date confirm an expected positive relationship between PSM activities and performance improvements while the narrow scopes of the surveys limit the generalizability of the results." Beneficiaries of RAB have been purchasers seeking:

1. Reliable communication with bidders,
2. Consistency & accuracy of information exchange,
3. A reduction in bid preparation & distribution costs,
4. An increase in the number of potential suppliers, to adjust the Herfindahl Index to their benefit

5. A platform for electronic submission.

Buyer-supplier relationships in reverse auction bidding

Caniels and van Raaji (2009) suggest from their study on supplier's perspective of electronic reverse auctions (ERA) that most suppliers have a negative opinion on reverse auctions, except the small suppliers, since they see it as an opportunity to enhance competitiveness. Of course, the authors suggest that level of ERA expertise is instrumental in ERA success. Wilcox (2000) observes, "In aggregate, more experienced bidders are more likely than less experienced bidders to place their bids during the final minute of the auctions" A supplier's economic state, and size of supplier base (firms) is inversely proportional to having a positive outlook towards RAB. Whereas, change in market competition is directly proportional towards an RAB's success. "Based on respondents from one country, there are limited possibilities for generalization from suppliers from other countries, especially developing economies" (Caniels & van Raaji, 2009).

Jap and Haruvy (2008) suggest that both economic and non-economic relational factors, whether to assess current or potential relationships are a systematic part of the bargaining effort, both before and after the auction. The supplier's trade-off their pricing strategy with these factors. The authors also point out that the suppliers with rapid bid changes had a negative price-haggling process, affecting long term relationships. Losch and Lambert (2007) opine that buyer's relationships improve when they have a quality background check on the suppliers before the biding happens. While, the supplier's relationships improve on high valuation of non-price factors like cost management, delivery performance, and prior quality of work.

Human factor in reverse auction bidding

Organizations these days have become more people-oriented as they have identified that human potential is of utmost importance. How people interact and network has given rise to organizational hierarchy and research. "There is a need to explore factors that bind team members and understand the elements that promise effective team performance (Omar, Syed-Abdullah, & Hussin, 2010)." Homogenous teams (members of same personality), and heterogeneous teams (members of different personalities), affect team performance in distinct manner. While homogenous teams experience more positive reaction, excessive coercion leads to slow performance. On the other hand, heterogeneous team members need time to understand and strategize a plan to reach their goals. There is still uncertainty involved in the survival of new electronic markets. Ding, Eliashberg, Huber, and Saini (2005) used economic analysis as a formal representation of the emotions evoked by the auction process, thus developing and testing a new analytical model for economic and behavioral constructs. The results of the study pointed out;

(1) The bidder usually changes their bid after each round, irrespective of any learning offered.
(2) The bid change depends on the outcome of the previous one;
(3) Emotions are an integral part of a bidder's decision state and bidding strategy;
(4) As predicted in the model described by the paper, a bidder in a relatively favorable environment emphasized more amount of gain, but gradually puts emphasis on the probability of winning.

“In the case of online reverse auctions for construction projects, the ethical issues involved in the bidding technique directly reflects on the owner’s ethical and social responsibilities to their shareholders (Hatipkarasulu & Gill Jr., 2003).”

Recent Research trends in reverse auction bidding till date

Carr (2003) notes that at equilibrium, “The bids tendered by higher-quality vendors will be preferable to the buyer.” This can be considered a problem as one seeks to define high quality and avoid the beauty contest issues of bidding. “Van Vleet, while starting the RAB gameplay noted in 2004 that, “In order to accurately assess the implications of reverse auctions, it was essential to know and understand the behaviors of those who engage in the bidding process. Without a method of evaluating the process, it is impossible to clearly understand whether RAB is a success or not.”(van Vleet, 2004). Shankar (2005) pointed out that the issue of tacit collusion was obvious in the gameplay. “As the game progresses, the participants started using winner’s curse against participants set who were underbidding projects, thus freeing up the remainder projects for higher returns.” “Horlen, Eldin, and Ajinkya (2005), discuss procedures involved in reverse auction practices, their advantages, and disadvantages.” These authors are generally dismissive of the process as being akin to bid shopping. The perspective of bid shopping depends as to whether one has contractor’s or an economist’s viewpoint. The contractor is what is best for me and the economist is what is best for the system. These are different viewpoints.

Emiliani (2005) examined efficacy of rationale behind creating codes of conduct, and guidelines behind online reverse auctions. “The results show that they have negligible impact on expanding use of reverse auctions.”

Zeng, Davis, and Abott (2007) studied the application of artificial intelligence (AI) in RAB study at TAMU for the first time, by introducing a single algorithm AI player. The key finding here is that the algorithm was easily detected by the players, as the AI player bid on three jobs, just two seconds after each human bid. The players made a strategy to outbid the AI player until AI's loss, and then resumed their competitive play.

Nichols (2017) has postulated that an AI program can be created that passes the Turing test as it clearly did not for Zeng et al. (2007). As part of the work on the development of the AI program Yuan (2013), studied the statistical properties of bid arrival timings. First, the results fit the distribution of the bid arrival times to be Gaussian and Poissionian, wherein the best fit of bid arrival time was modelled by non-homogeneous Poisson process (NHPP). Second, controlling the Poissionian process has a square root factor. These findings also hold true for the findings from the eBay online auction bid arrivals data "(Shmueli, Russo, & Jank, 2007).

Volk (2007), articulated, "Not all auctions are same. That, a single set of rules cannot optimally govern all auctions in a dynamically changing procurement landscape. Well-articulated principles, on the other hand, can guide every competition design."

Giampietro and Emiliani (2007), through their research investigated if reverse auctions were coercive. The main findings of this work "are;

(1) Reverse auctions aggressively bring new buyers into play, which potentially harms long-term buyer-supplier relationships, and cuts down into the ones whose mere objective is short-term cost reduction;

(2) Coercion in auctions occurs through threats of loss of future business;

(3) Reverse auctions are inconsistent with US federal procurement standards."

The point of the previous work is that purchasers often have preferred sellers, the classic economic beauty contest and that canny bidders will play to this failure in ethics.

Sikora and Sachdev (2008) studied the efficacy of using automated agents for learning bidding strategies in contexts of strategic interaction involving multiple sellers in reverse auctions. Results from the experiment show, "The evolutionary and reinforcement learning agents, with incomplete information displayed the desirable properties of rational behavior and convergence even on the absence of stable equilibrium."

Chaudhari (2009) carried out his research with participation of six players, thus, with a lower market concentration, to primarily observe owner's interference in an RAB scenario, where participants were oblivious about this interference. The primary finding was the observation of price drop on the account of owner's interference, although when the players became aware of the interference they objected verbally.

Huh and Park (2009) fill in the gap of knowledge between post auction supplier selection by using an auction-bargaining model. The major finding of this research is that a post-auction negotiation provides the buyer and supplier with an opportunity to learn more about project costs, knowledge, and performance.

Bedekar (2010) showed that there is an observable pattern in the bidding strategy of first time bidders during participation in RAB bidding game developed at TAMU. The important finding here is that the first-time bidders are highly competitive throughout the bidding, thereby reducing overall normalized profit levels, and profit gain started at later game stages. Also, guardians formed bid maximum number of bids during the game."

Guhya (2010) reviewed van Vleet's results on RAB game, using a lower market concentration with the participation of five players. Guhya suggested that in an alpha (α) game, higher than average returns are made by some bidders. Critically, the number of bids matched anecdotal evidence of real reverse auction bidding systems. Billing (2010) study attempted to analyze the process of RAB using modern graph theory. This work has potential to develop the strategy for the AI player, but the standard Auction Graph models failed to identify the critical issue of bid differential statistics.

The simplest box graph for the Billing study is shown in Figure 11. The real issue for the Turing test (Abelson, Sussman, & Sussman, 1987) is the bid differential amounts and average timings, this will be developed from Graph Theory over the next few years.

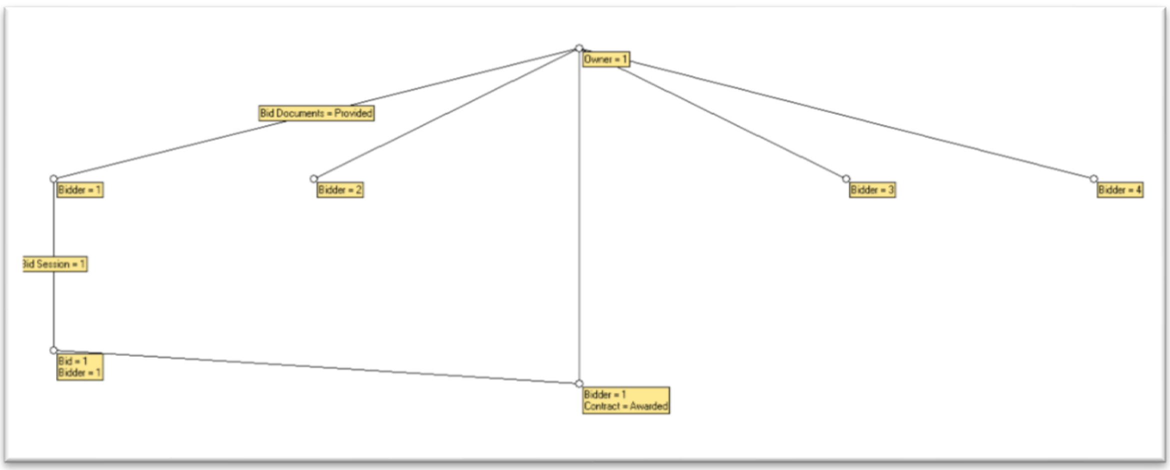


Figure 4:Sample graph Theory Model for a single RAB bid – Reprinted from Billing (2010)

Puro, Teich, Wallenius, and Wallenius (2010), in their study show that bidding is heterogeneous among bidders, unlike what traditional auction theory suggests. Moreover, learning and bidders' consistency over time in different auctions is studied. Three main strategies appear above all; (1) Evaluator strategy; (2) Late bidding; and (3) Multi-bidding. The RAB study detailed here suggests that personality, and personality conflicts during the bidding have an impact on the overall group returns.

Bhalerao (2011) pointed out to the use of differential bid data (i.e. the difference between the winning bid and the second last bid) as a key performance indicator. The author noted that bidders overlook the concept of slowly decreasing the bid price, where the difference could also be in decimals. This is a good strategy to make profits.

Yeniyurt, Watson, Carter, and Stevens (2011) looked at drivers of bidding behavior in electronic reverse auctions. First, personal characteristics of the decision maker, bidding history and experience, auction characteristics and timing affect the bid aggressiveness. Thus, understanding these factors influences intense bidding activity in electronic reverse auctions (ERAs), to strategically improve market value. Second, from a supplier's perspective, selecting representatives (bidders) with a high NFC (i.e. a variable that reflects tendency to spontaneously engage in, and enjoy cognitive efforts) may decrease risk of profit loss in ERAs.

Dashnyam, Liu, Hsu, and Tsai (2011) developed a method for real-time prediction of closing price and duration of English auctions in business to business (B2B) marketplace. This methodology offers an accuracy of 84.60% and 71.90% for closing price and duration after first four bids respectively.

Joo, Mazumdar, and Raj (2011) as a group investigates strategies of successful bidders and its influence on savings derived from a name your own price (NYOP) retailer, relative to buying the same product from a retailer posting prices. The important finding of this research is that the magnitude of bid increments is an important determinant of consumer savings. The author suggests that NYOP retailers should explore mechanisms to shape bid increments or counter offers at successive bidding stages rather than manipulating frictional costs.

Zhou (2012) was a multi-comparison study between different number of bidders with one, two, and three games having different Herfindahl index. The main findings were; (1) There was a significant impact on individual returns on varying the number of players, due to different competitive environment; (2) In a ten-bidder game, there was a missing learning period; (3) The best performing personalities for three, four, and ten-bidder games are artisan, guardian, and rational respectively. Among these, the guardian had highest returns.

Iftekhar et al. (2012), in their paper studied performance of several price feedback computation algorithms for three distinct stages of competition, and for a set of package selection strategies potentially used by bidders. The primary findings of this research are;

(1) Performance of an auction design depends on the package selection strategies adopted by bidders, implying that an auctioneer can promote these recognized bidding strategies, to promote more number of bids are submitted;
(2) Auction performance can be improved by using pricing-feedback mechanisms and rules set against bidding strategies during the bid."

Gwebu, Hu, and Shanker (2012), in their experiment point out that bid-takers can enable bidders to submit higher quality bids by reducing information asymmetry in multi-attribute reverse auctions (MRA).

Piper (2013) studied experienced participants from the industry thus confirming that the personality affect bidding more when compared to the experience of players. Piper's research also pointed out the discrepancy of his study that idealists made more profit than guardians, against the long-standing study at TAMU suggesting guardians making maximum profit. Piper's research also confirmed to the bidding trends where profits are low at beginning and increase with time, maximizing during mid-game, and decreased further on.

Agrawal (2014) research was focused on games with a predominance of guardian personality types. The study pointed out that overall percentages for the participants on game completion were very low when the players were all competitive. This result was because guardians over perform when pitted against each other. Agrawal also pointed out that bank credit is a key performance indicator, especially because as there was absence of linearity between loan and profits, as is usually observed. Finally, the study is an exception as it is the only one showing that idealists perform better than guardians, when there are multiple guardians.

Kumar (2014) study aimed to verify that bid timing fitted non-homogeneous Poisson process model (NHPP). The results indicated that cost distribution is non-Gaussian, meaning that buyer's objective is not achieved for all bidders. The second sub-game is between the bidders, they utilize the non-Gaussian component of the profit distribution to amplify individual returns.

Li (2014) studied the statistical differences between the return data of economically efficient and economically inefficient bidders. Li's research also proved the hypothesis that economically efficient bidders earned on an average more than USD 180,000 per game, of 8 weeks, and economically inefficient players earned on average less than USD 80,000 per game, of 8 weeks duration.

The concept of economically efficient and inefficient in RAB was developed by Peterson (2010), several studies since that time have attempted to place economic numbers on the definitions for this game.

Karl (2014) contributes to the potential use of business games to study the results of auction behavior in a construction business environment and to investigate the winner's curse and its effects for a company and a whole market. The primary finding of this research is pointing out three causes behind winner's curse during construction auctions, which are;

(1) "Unknown events contributing to increased project costs;

(2) Strong competition influencing player's bidding strategy;

(3) Underestimated project costs."

Fugger, Katok, and Wambach (2014) show that in buyer-determined auctions, this format leads to collusion, and non-competitive pricing.

Dass, Reddy, and Iacobucci (2014) used network analysis to show that bidders implicitly make connections with other bidders during bid encountered auctions, such that once these are represented as networks, their evolution can be seen. The effectiveness of network theory is highlighted on realizing higher prices with, "Key-Bidders", those who positively impact auction surplus at the beginning of the auction."

Pham, Teich, Wallenius, and Wallenius (2015), review decision and game theoretic research, experimental studies, information disclosure policies, and research on integrating and comparing negotiations and auctions. The takeaway is that multi-attribute online reverse auctions (MAORA) rectify the price-based approach of reverse auctions by contributing weightage to non-price attributes such as quality, quantity, etc. and can also be implemented for multi-unit and multi-item auctions."

Liu, Zhu, and Hu (2016), through their research suggest that optimal procurement condition for a retailer is when a suppliers' Bayesian-Nash equilibrium strategy is (q (.), Q (.)), which depends on suppliers' marginal production costs and so is stochastic for the retailer."

Zhang and Li (2006) used survey data from eBay users, and applied a probit model to investigate the choice of payment methods in online auctions. The important findings are;

(1) Seller's sales volume affects payment choice;

(2) Product characteristics affect payment choices more than traders

(3) Seller's reputation affects availability of choices in payment methods

Drawbacks of reverse auctions

Three major issues with online auctions are cultural differences, ethical behavior, and long-term cost savings.(Jap, 2012). For continuous success in online auctions, it is necessary to communicate effectively about the auction setting, outcomes, and decision milestones. There exist many online auction formats which in turn provides a plethora of data, but, there is a dearth of studies providing insights on cost savings or supplier performance variances. “There is a lack of knowledge on performance behavior of professional bidders and its effect on the marketplace. (Wilcox, 2000)”. “Much research on electronic reverse auction bidding has been conducted in a laboratory environment, which renders minimal risks, in which the subjects have much less to lose or gain. (Koppius, Mithas, Jank, Shmueli, & Jones).”

“The five most common myths associated with RAB are: (1) price is the most important objective and non-price factors can be easily complemented with it; (2) both commodity and non-commodity items can be successfully bid through reverse auctions; (3) when using RAB as a way of business, buyer-supplier relationships can be balanced; (4) continued cost savings are possible even after first time bidding event; and (5) reverse auctions will serve a potential future business tool (Schoenherr & Mabert, 2007).”

RAB also has a risk of dilution of bidders, which happens when multiple auctions run simultaneously, thus resulting in a lower final ending price.

Summary

To summarize the literature review, it is now evident that research done to date at TAMU has explored various personality and behavioral attributes of bidders while playing a simulated game play like an auction process. The data so collected till now has contributed to developing an overall range of statistical sets where bidders tend to pick their profit margins from. A bin of ranges developed for normalized profit are necessary to generalize the profit limits for statistical inference. The data so collected is unique for its kind as such bidding data is not available from auctions conducted in real-life. The results collectively from the data show a presence of beta distribution and some secondary underlying bump starting at 0.7 normalized profit level. This research will look for the possibility of a secondary distribution, and if it is normal in its statistical nature.

Further, the economists tend to see reverse auction in terms of rational and non-rational play as defined by Nash equilibrium, and its theories. Inferences drawn from research from an economics perspective helps to understand effects on buyer-supplier relationships. Authors suggest that reverse auctions render long-term buyer-supplier relationships void if non-price attributes are not accounted and valued for on bid contracting.

Finally, from a behavior and organizational perspective, trend of organizations to becoming people-centric demands that organizations be vary of the strengths and weaknesses of their employees both, individually, and as a group. People / players while bidding tend to form a network, and the group decision process depends on the path followed by these networks of people.

CHAPTER 3

METHODOLOGY

Introduction

This chapter of the thesis summarizes the methodology used for the game play. Reverse Auction bidding (RAB) has been documented in a number of existing studies (Chouhan, 2009; van Vleet, 2004). This chapter outlines the control features for the games. The Figure 5 , below shows an overview of the methodology used.

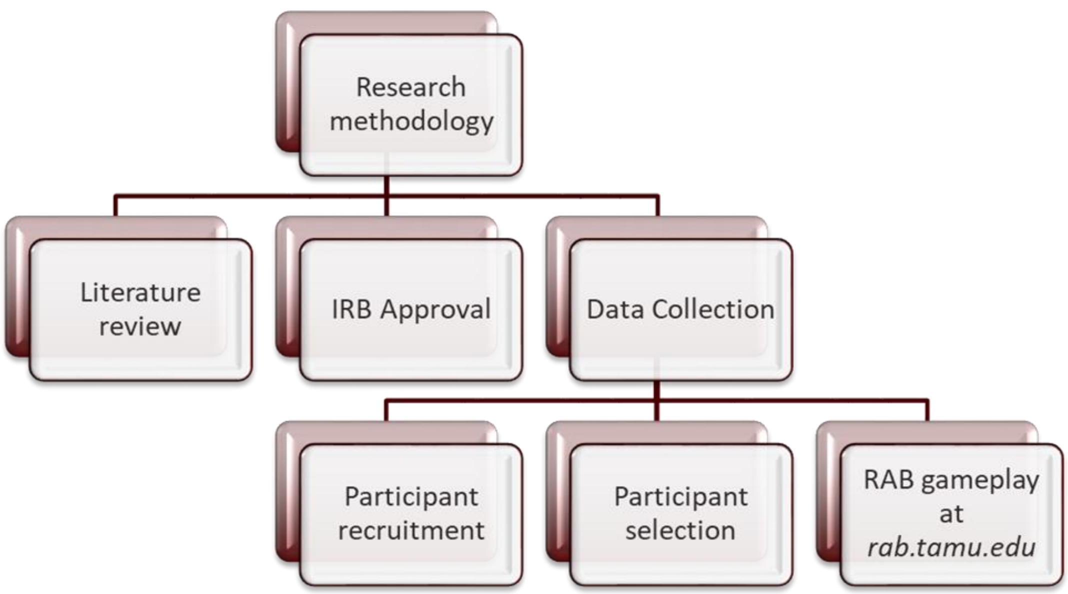


Figure 5: Overview of the methodology

IRB Application

Before continuing with the study, an IRB approval was obtained on April 4, 2018. The research study conducted uses human participation, and does not have any risks than minimal risks encountered in daily life. Thus, necessitating an IRB approval.

Control Features for the Games

The game is played on internet using a specially developed website at TAMU. A game typically has four players, who have not played the game before, as the study team attempts to understand the basic findings for new players and their personality types. The original game has been modified slightly to align the game rules with a real bidding situation with reasonable economic controls.

The key control features for the game are summarized in Table 2. Each bidder starts with a bank account balance of $40,000 to provide working capital, considering that the game models a small subcontractor pouring and finishing concrete slabs this is considered reasonable. Each bidder has the capacity to pour three slabs per week, and there are four bidders so the theoretical capacity is 12 slabs per week. A mechanism was introduced to vary the capacity of each bidder, using a bank loan that cost $500 to increase the bid capacity by one job for a week. This mechanism is actually a very strong indicator of performance in the game and demonstrates the utility of the Herfindahl index measure.

The games typically last for nine theoretical weeks, where each bidding week is represented by 15 minutes of play time and 5 minute of data collection (total of 20 minutes). A random procedure is used to determine the number of slabs per week to mimic a real sales market, a rain impact is introduced, again a random function. Bidders are assigned unique login names which are not shared with other participants.

Table 2: Van Vleet's default variables for Game

Component	Unit	Amount
Bank account of each contractor at start of the game	$	40,000
Job cost	$	10,000 for the slab cost travel costs delivery charges
Total time of competition	Weeks	8
Maximum work capacity at outset of the game	Jobs	3
Loan amount for adding bid capacity	$	500
Each job contract time	Days	5
Work week	Days	6 (Monday to Saturday)
Chances of rain delay	Percent	30
Construction cost accrued	-	Daily
Payment for work	Day	5^{th}
Bidding time	Minutes	15

The work is assumed to occur in May in Houston, Texas. Figure 5 depicts the rain distribution for this area.

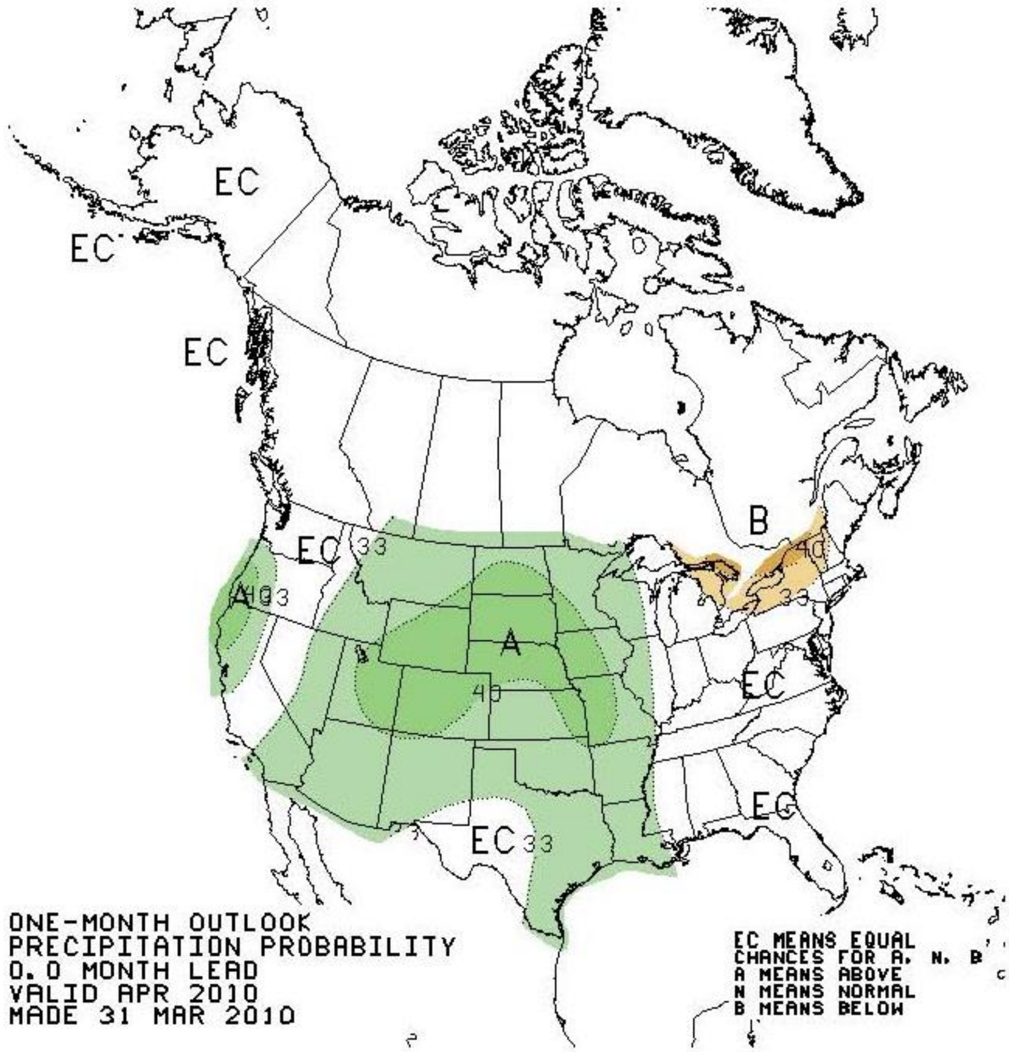


Figure 6:*Rain Probability in USA (Reprinted from NOAA, 2010)*

Table 3 presents the rain delay data for the first week of the Reverse Auction Bidding game. A one (1) indicates rain on a particular day at a particular site, resulting in a delay to the contract completion. There will be no additional charges for any delays, nor is the contractor penalized for the delay in cost terms as the contractor is assumed to make reasonable arrangements with the workforce for rain delays, which are assumed to be covered in each player's bids.

Table 3: Rain Delay Data for First Week

Day	**Site 1**	**Site 2**	**Site 3**	**Site 4**	**Site 5**	**Site 6**
Monday	1	0	0	0	1	0
Tuesday	0	1	1	0	0	0
Wednesday	0	0	0	0	0	0
Thursday	0	0	1	0	0	1
Friday	1	0	0	0	1	1
Saturday	0	0	0	0	0	0

Each bidder had a nominal capacity for three jobs per week. Rain delays could reduce this capacity, theoretically to zero, although statistically this is improbable. A bank loan mechanism was provided for each bidder to increase their capacity to bid as shown in Figure 6. This bank loan mechanism changes the Herfindahl index, by giving leverage for risk-efficient bidders to take charge and bid on more number of jobs, which increases their chances of winning.

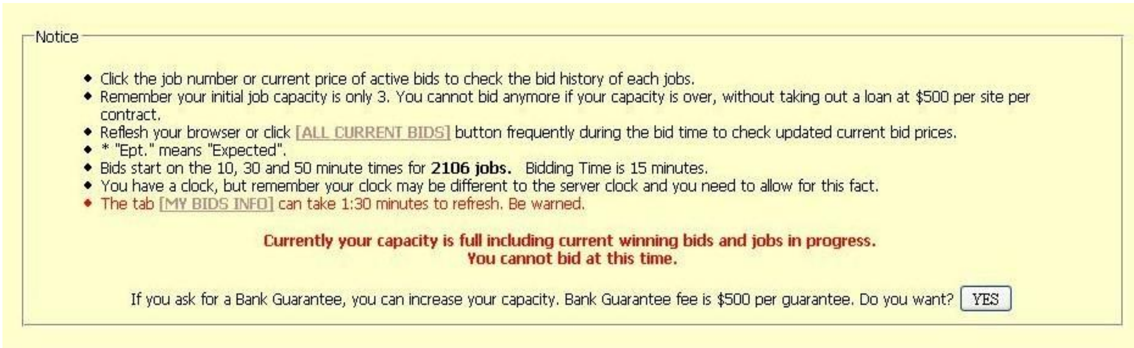


Figure 7:*Bank Guarantee Screen – Reprinted from Guhya (2010)*

Each participant was provided a unique login-credential set based on their personalities as determined by KTS-II. In the design of the web page, allowances were made such that the bidding process minimized the irrelevant information given to the bidders. The significant information includes the job cost, current bids and the bidder's name in addition, before the bidding time commences or after bidding is closed, no bids can be placed. Bidding is set to occur for a 15-minute time span, then the system is closed for 5 minutes. It is usually considered a break time for participants.

After starting a session, the participants are taken to "All Current Bids" screen as shown in Figure 8 below. This screen provided bid information including location of the site and related cost for each job. This was the identical information provided for all participants.

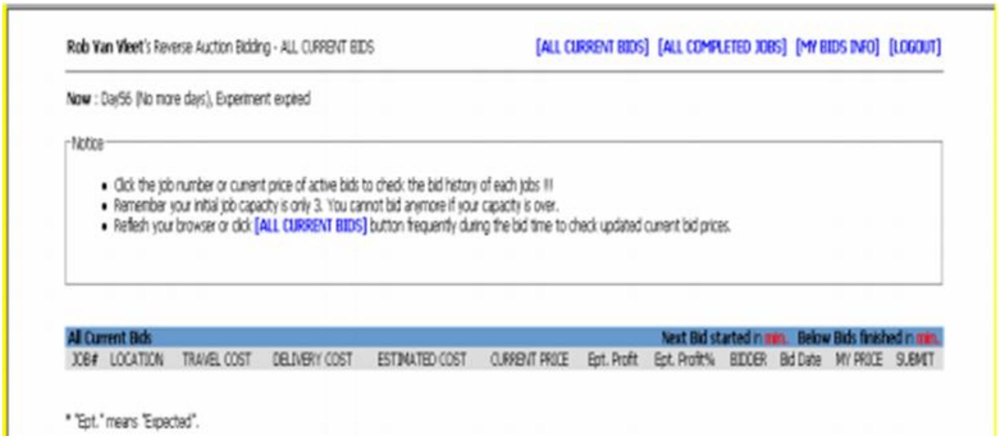


Figure 8: *All current bids screen from RAB website at TAMU – Reprinted from (Guhya, 2010)*

There are some strict protocols established, which control the bidder for the maximum and minimum allowable bid amount. Figure 9, below shows a web statement during the game which stops the bidder to go beyond the maximum allowable bid amount.

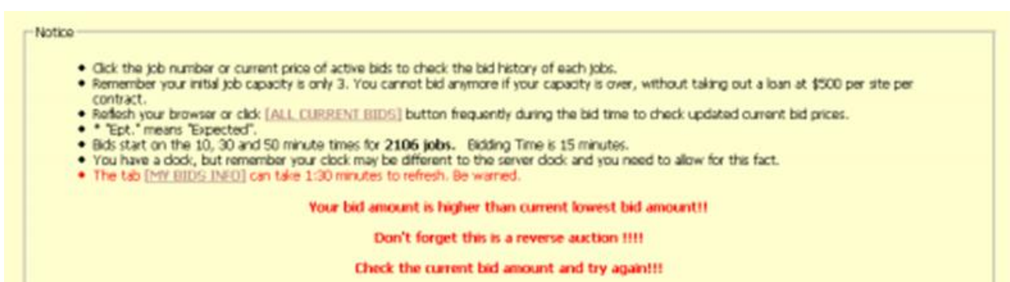


Figure 9: *Higher than acceptable bid-web statement – Reprinted from (Guhya, 2010)*

A page during the game constantly shows the participants about the real-time change of bids and rank or change of the company leading the auction bid amount for a given bid. Further, the bidder can gather information about his/her progress and develop a strategy accordingly. A web page, such as shown in the Figure 10, shows the current standing of the bidders and bid win details.

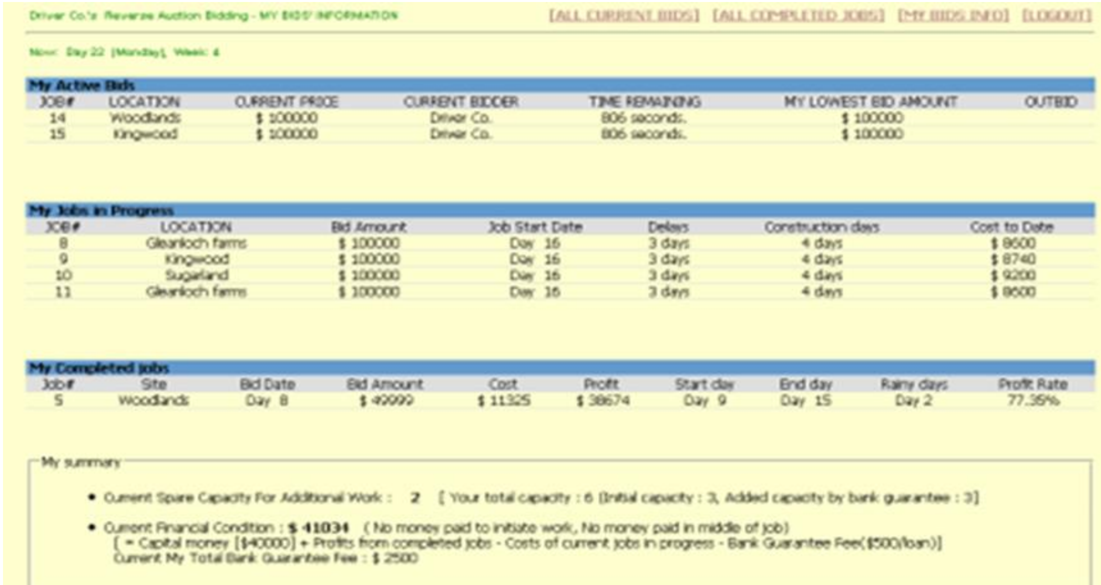


Figure 10: *My bids information webpage displayed during the gameplay*

This screen also shows the financial state of the participant, which helps the bidder in framing a future strategy such as how many jobs a bidder could bid for, and if the bidder is already lagging due to his uncompleted jobs, how much money a bidder would have to borrow from bank and other financial institutions to bid for a job in the following week. This financial information is provided under the category My Summary. The information is:

- Current calculated cash assets
- Capacity for additional works including jobs with bank guarantees
- Cumulative loan charges till date 24 Current financial condition provides the working capital information to the participants as shown on Fig. 10. It is calculated by deducting costs of current jobs and bank loans from the profits of completed jobs. The initial capital is $40,000 and the bank guarantee is $500 per loan.

The formula used is:

Current Financial Condition = (Capital + Profits) – (Costs of Current Jobs + Bank Costs)

Participant selection and team formation

As suggested in the IRB application, the participants are approached through a classroom setting at TAMU's Department of Construction Science. They are Master's students in the department with a knowledge of architecture or civil engineering as their basis and are considered a perfect batch to do the game study. The interested candidates were then informed about their time and efforts requirement and given a voluntary participation option. The ones who volunteered went on to the next step of the selection process conducted on May 11, 2018. This was personality determination using KTS-II (Keirsey Temperament Sorter Test). The participants were asked to logon to www.keirsey.com and take the test. This test usually lasts around 15 minutes.

Further the participants were given a random number and an accompanying information sheet where they choose the times slots suitable for them to conduct the gameplay, along with their personality types. There were fifteen participants at this stage.

The participants whose time slots were a good match, keeping in mind the requirement that each team should have exactly one guardian personality type, and other could be non-guardians. A total of twelve (12) participants were chosen to continue the study further and with the formation of three teams. Figure 11, below shows the team concentration for the gameplay.

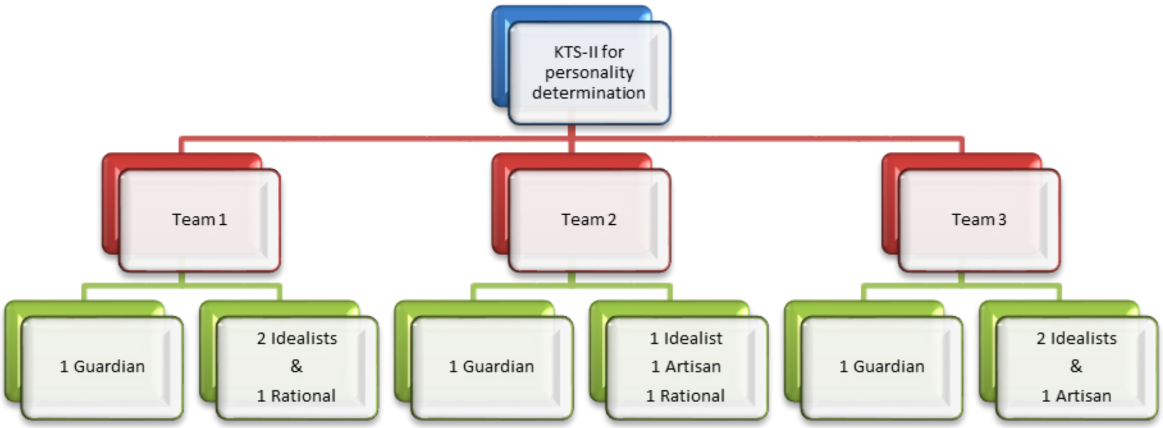


Figure 11: *Team formation for RAB gameplay*

RAB Gameplay at rab.tamu.edu

After team formation, the players came to the Francis Hall, at their designated timings for a cumulative period of three (3) hours to participate in the gameplay.

CHAPTER 4

RESULTS

Introduction

This chapter summarizes the results for the study. The key results are game setup, jobs per week,

Game Setup

Three games were played for this study with three teams. Each game had four players. The game features and the player types are summarized in Table 4. Note that since the number of participants for this study were higher than expected, for ease a group of four participants is called a team, followed by the number in the order of time in which they participated. Each team was given time slots of a cumulative period of three hours after the teams were set-up for the gameplay.

Table 4: *Game Features and Player Types*

Component	**Unit**	**Amount**
Bank account of each contractor at start of the game	$	40,000
Job cost	$	10,000 for the slab cost travel costs delivery charges
Total time of competition	Weeks	8
Maximum work capacity at outset of the game	Jobs	3
Loan amount for adding bid capacity	$	500

In game 1 and 3, the common personality types were treated as a single entity for play and analysis purposes.

Number of jobs per week for each game

A set of dice were used to establish the random number of jobs per week in the range of two to twelve. As can be expected from dice statistics, the middle numbers are more commonly represented for the usual statistical reasons (Johnson, 2000). Figure 12 shows the number of jobs per week for the first game.

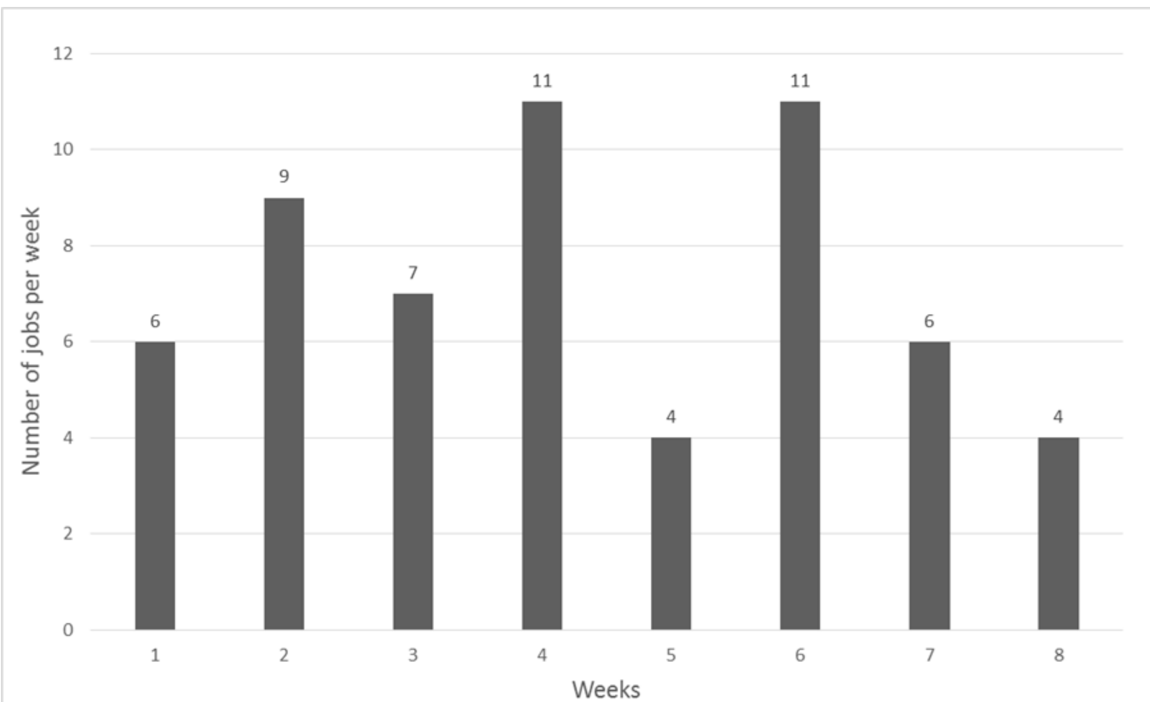


Figure 12: *Gameplay 1 – Number of jobs per week*

The average number of jobs per week is about 7 and so there are usually 2 jobs per player on average available. If each player takes the 2 jobs per week at about the maximum profit the 8 weeks return per player should be about USD480, 000 dollars. As observed by Peterson (2010) the economically efficient player make in the order of USD150,000 dollars. Figure 13 shows the number of jobs per week for gameplay 2.

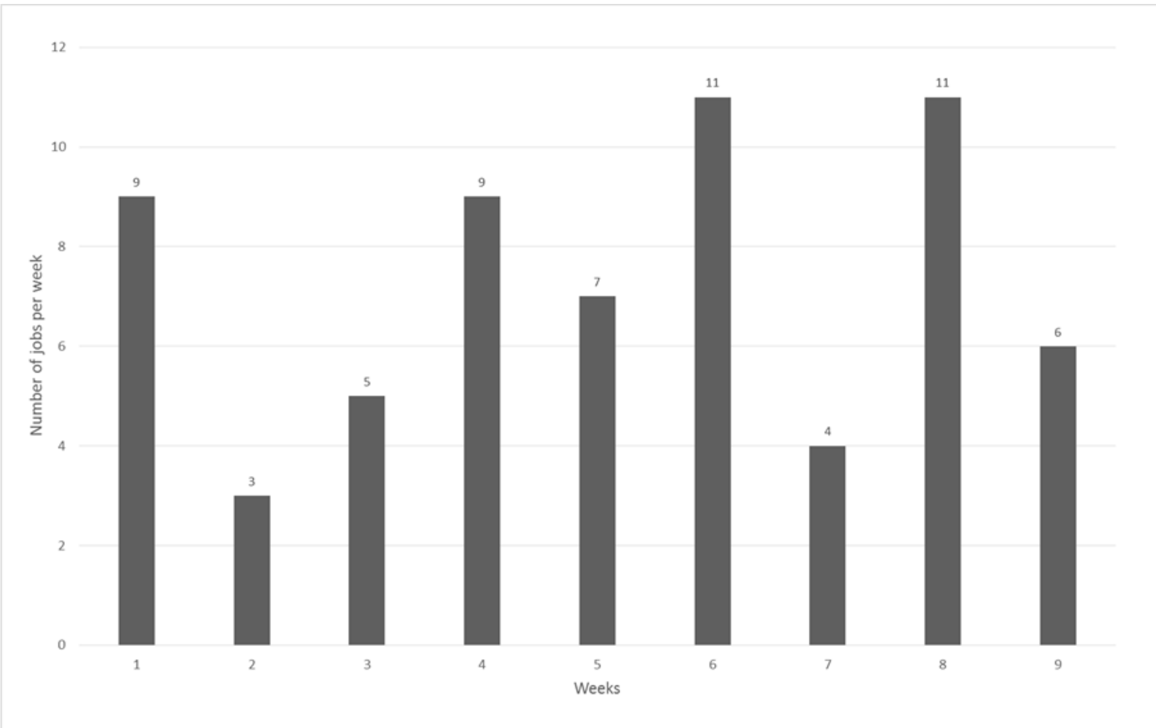


Figure 13: *Gameplay 2 Number of Jobs per week*

Figure 14, below shows number of jobs per week for gameplay 3.

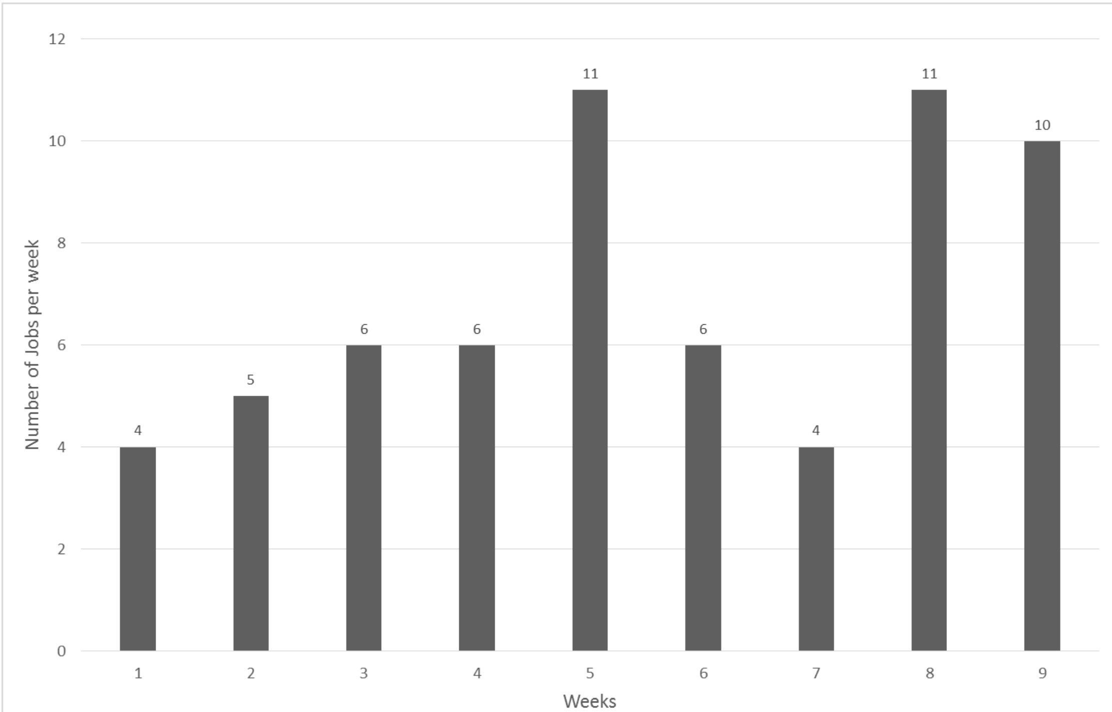


Figure 14: *Gameplay 3 Number of jobs per week*

Maximum profit per week per team

The graphs below represent the maximum profit per week for each team. Figure 15 shows the maximum profit per week for the first gameplay in each week. The pattern of competition, followed by better play and then competition is evident in the figure.

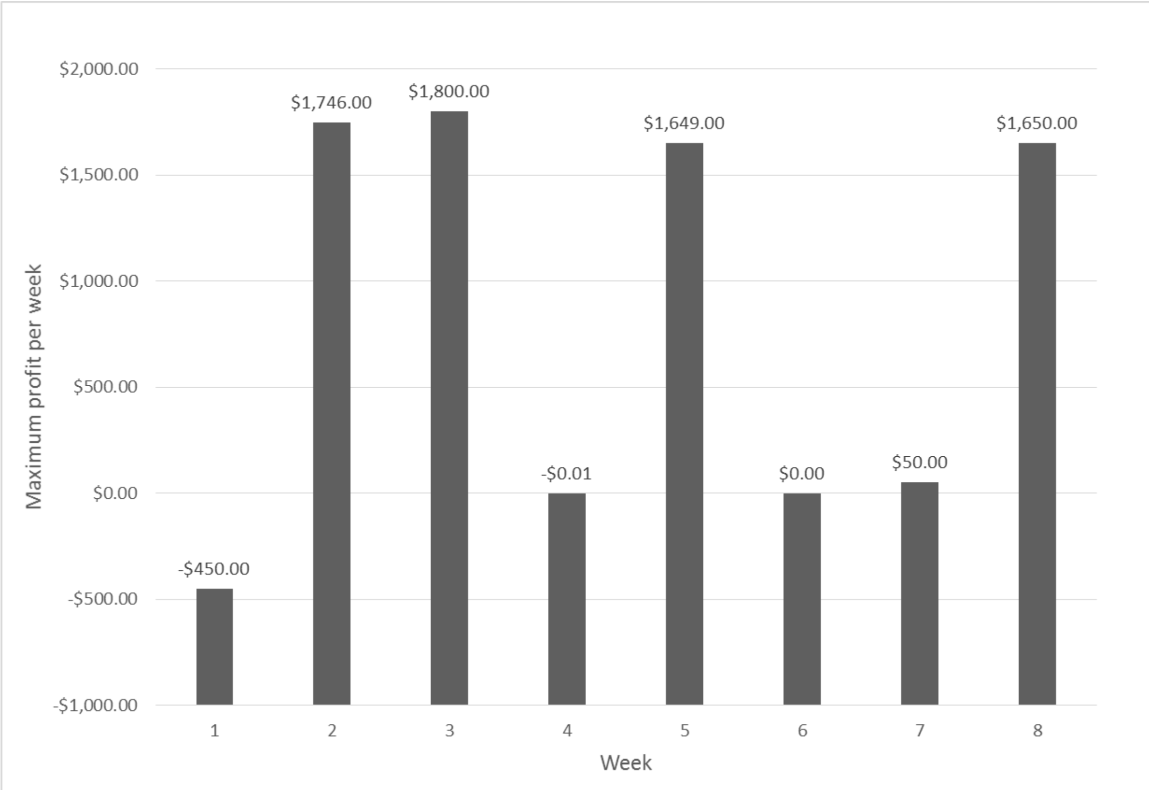


Figure 15: *Gameplay 1 - Maximum profit per week*

Figure 16 shows the maximum profit per week for the second gameplay in each week. The results indicate that the canny players are starting to develop better returns in the later weeks.

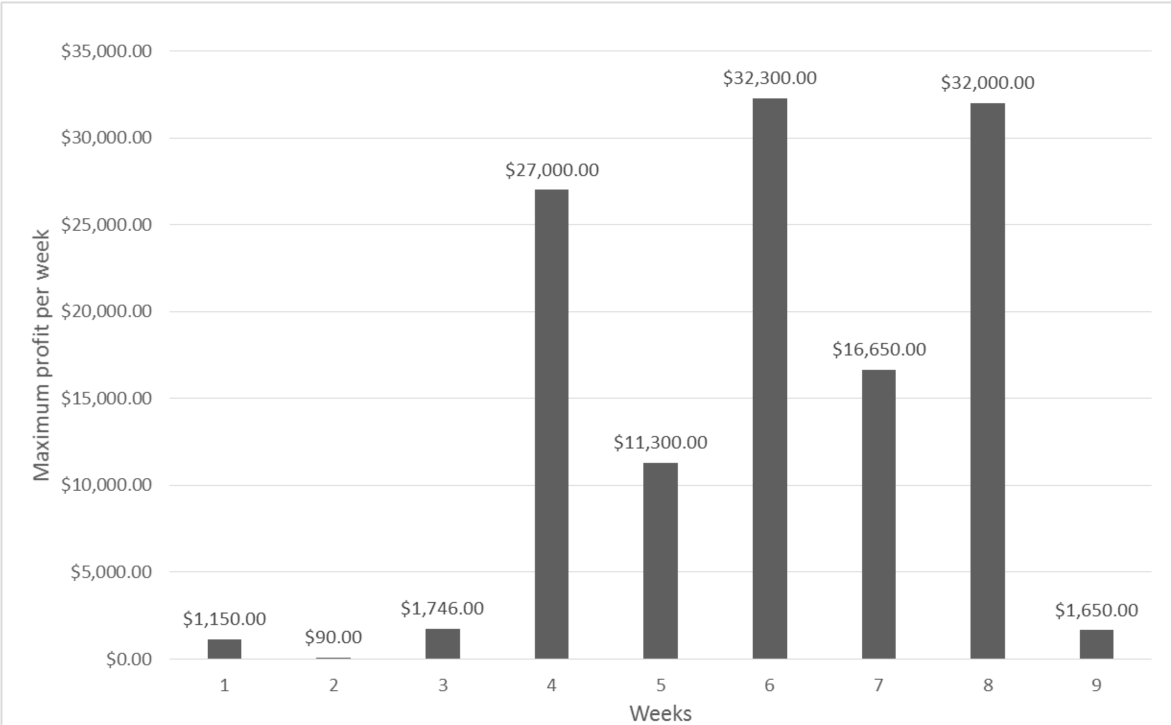


Figure 16: *Gameplay 2 Maximum profit per week*

Figure 17, shows maximum profit for gameplay 3 for each week. This gameplay has particularly high returns on maximum profit on comparison with other two teams. Essentially, the players in this team, joined the gameplay slot when the players from gameplay 2 were present in the game room at Francis Hall. They were interacting with each other and hence understood better the knowledge passed on from the players who played this game before. Although still they were new players who did not play the game earlier, they were advised by the other players in the gameplay 2 from their experiences. This, is a point to note.

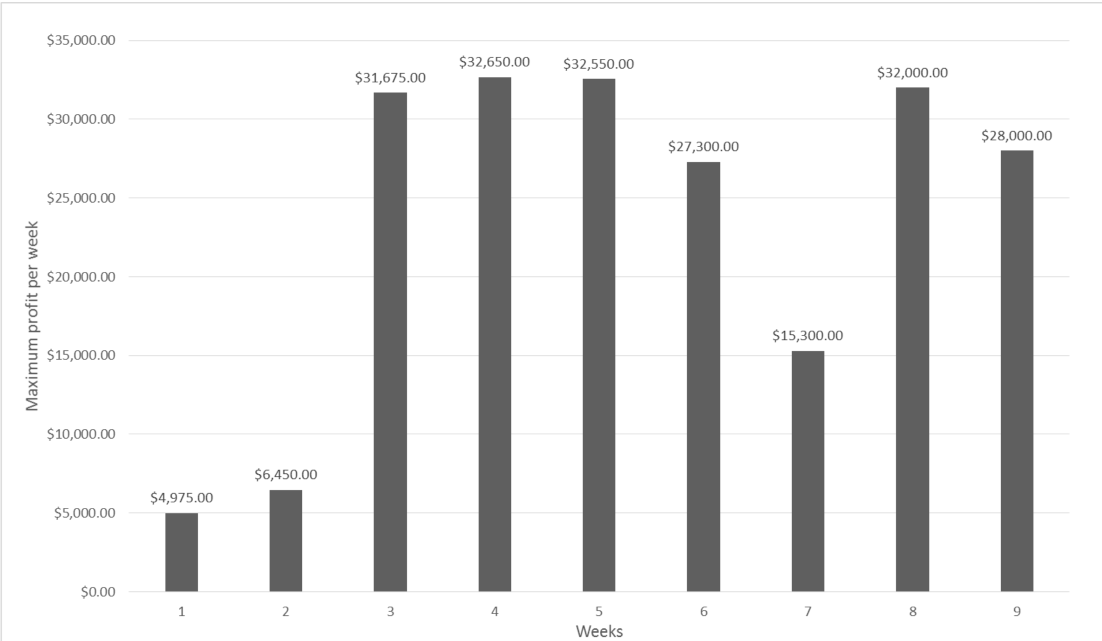


Figure 17: *Gameplay 3 Maximum profit per week*

Minimum profit per week per team

The graphs below represent the minimum profit per week for each team for each of the gameplay slots. To summarize the findings from this parameter of minimum profit each week, look at the clear differences in the numbers for each gameplay and each week. For the players in gameplay 1 and gameplay 2, their minimum profits for each week have a negative value, meaning that overall, there was a loss. But, for gameplay 3, there is only one negative entry, others are as high as in the range of $11,000 to $26,000 to be minimum. Clearly these players understood the game really well and performed exceptionally.

Common among players in gameplay 1 and gameplay 2 is the presence of a rational personality type. From the observation it seems that players of this personality type tend to lower the profit levels. Hence, they pick from a set of numbers which is highly in a Beta distribution range. Figure 18, shows the minimum profit for gameplay 1 for each week.

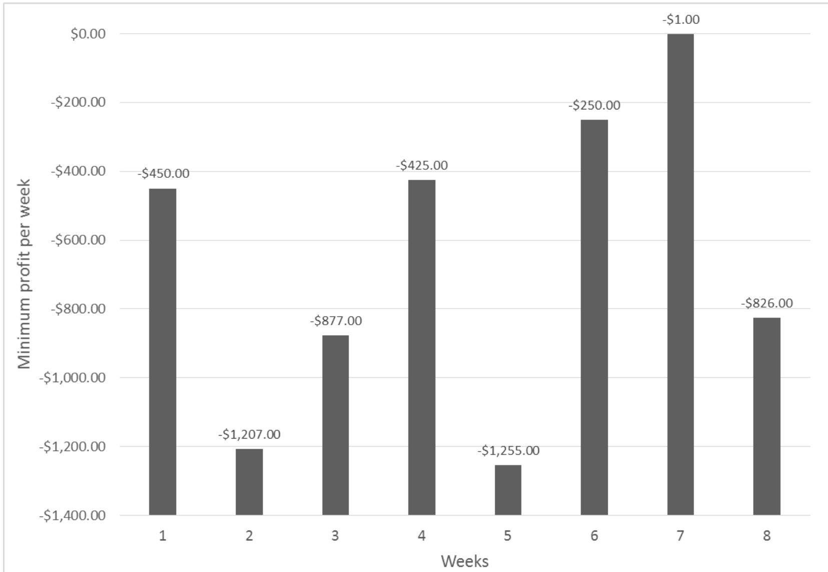


Figure 18: *Gameplay 1 Minimum profit per week*

Figure 19, shows the minimum profit for gameplay 2 for each week.

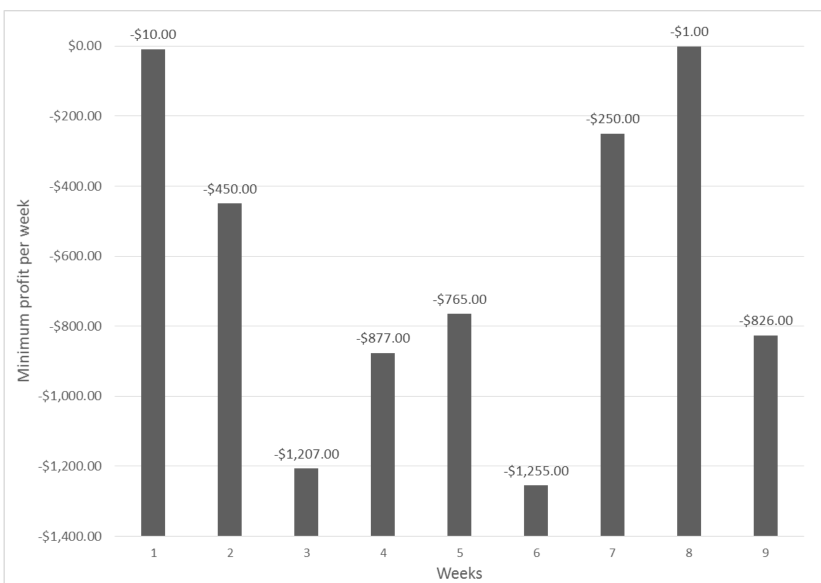


Figure 19: *Gameplay 2 Minimum profit per week*

Figure 17, shows minimum profit for gameplay 3 for each week.

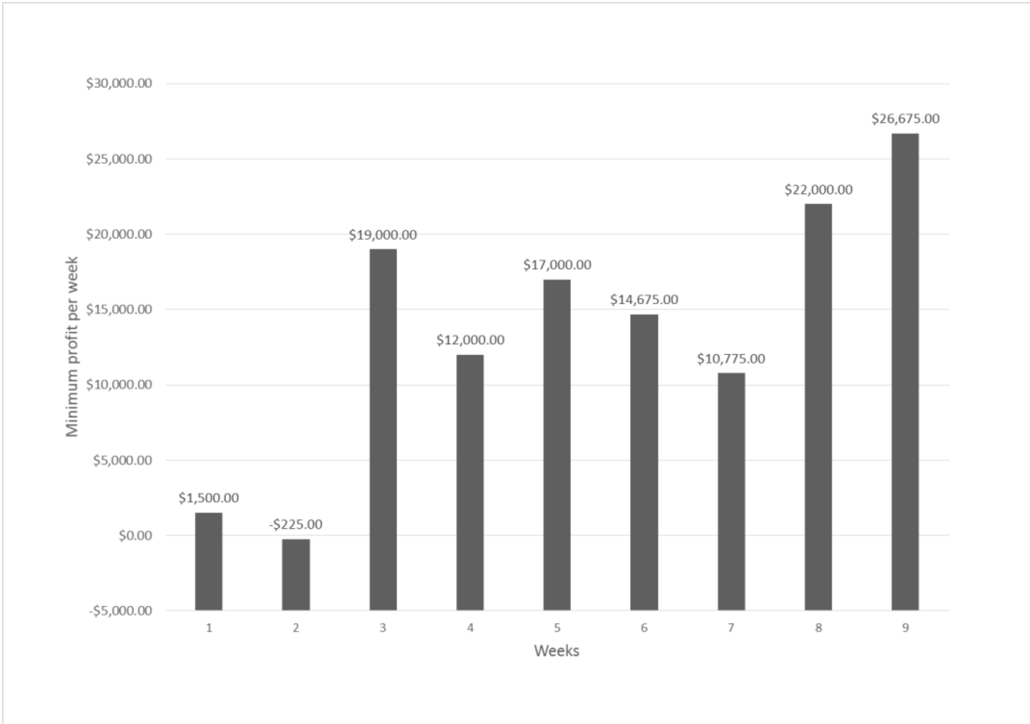


Figure 20: *Gameplay 3 Minimum profit per week*

Gross profit of players in all teams

The graphs below show a comparative analysis of gross profit of each player in each gameplay. Except for gameplay 1, where rational personality type player makes the maximum profit amounting to a gross of $7,000; in gameplay 2, and gameplay 3, the highest profit is made by the guardian personality type players which is $387,823, and $547,600 respectively. Note that the gross profit in gameplay 3 is the highest, and lowest for gameplay 1. Also note that artisan personality type players have made the second highest gross profit for each gameplay session. There is an absence of artisan personality type in gameplay 1, which is interesting and may be a cause of such low margins of profit. It can however be a future research topic. Figure 21, shows the gross profit for gameplay 1.

Figure 22, shows gross profit of players in gameplay 2

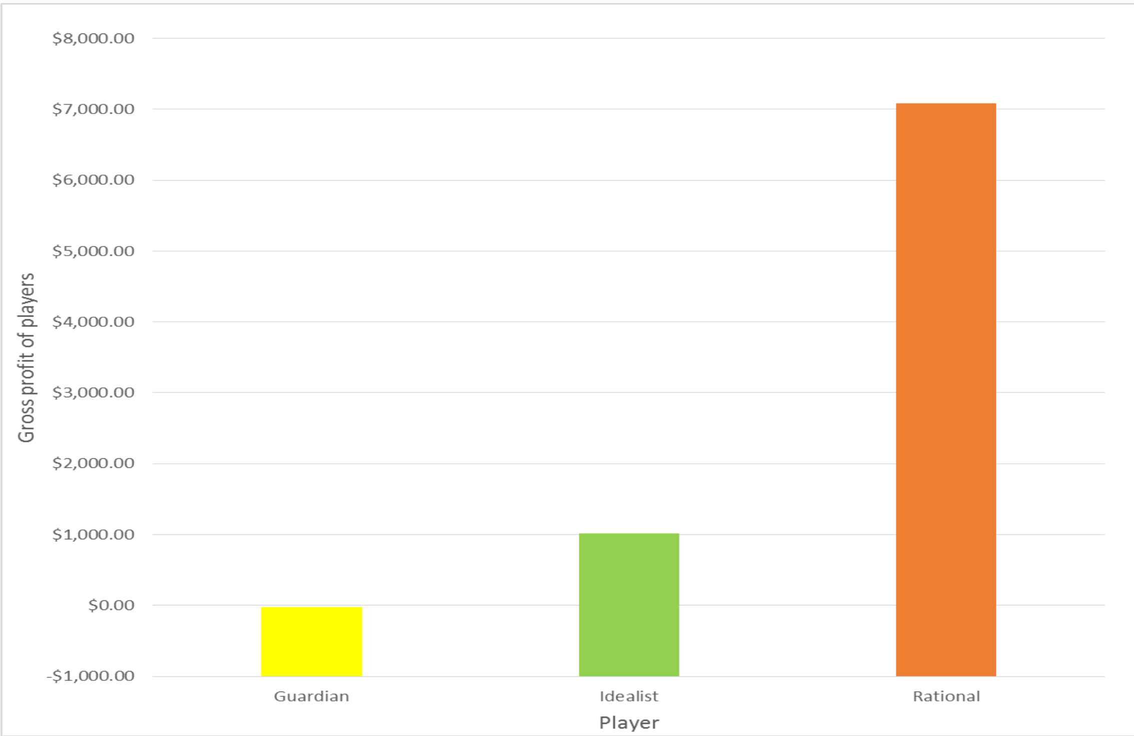


Figure 21: *Gameplay 1 Gross Player profit*

Figure 22, represents the gross profit made by players in gameplay 2.

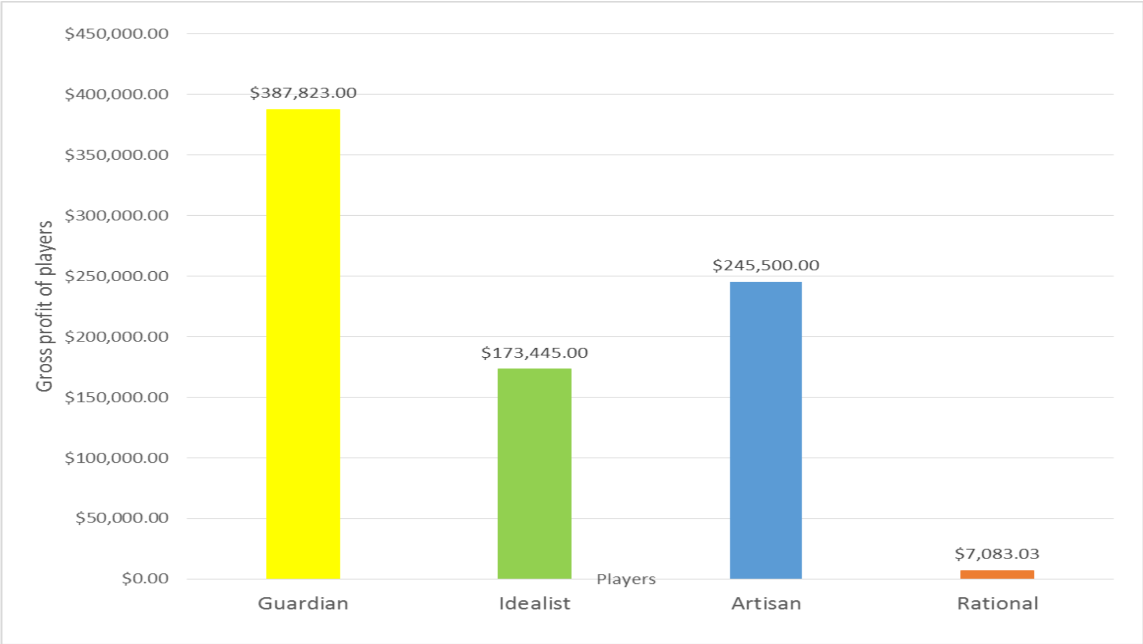


Figure 22: *Gameplay 2 Gross Player profit*

Figure 23, shows the gross profit made by players in gameplay 3.

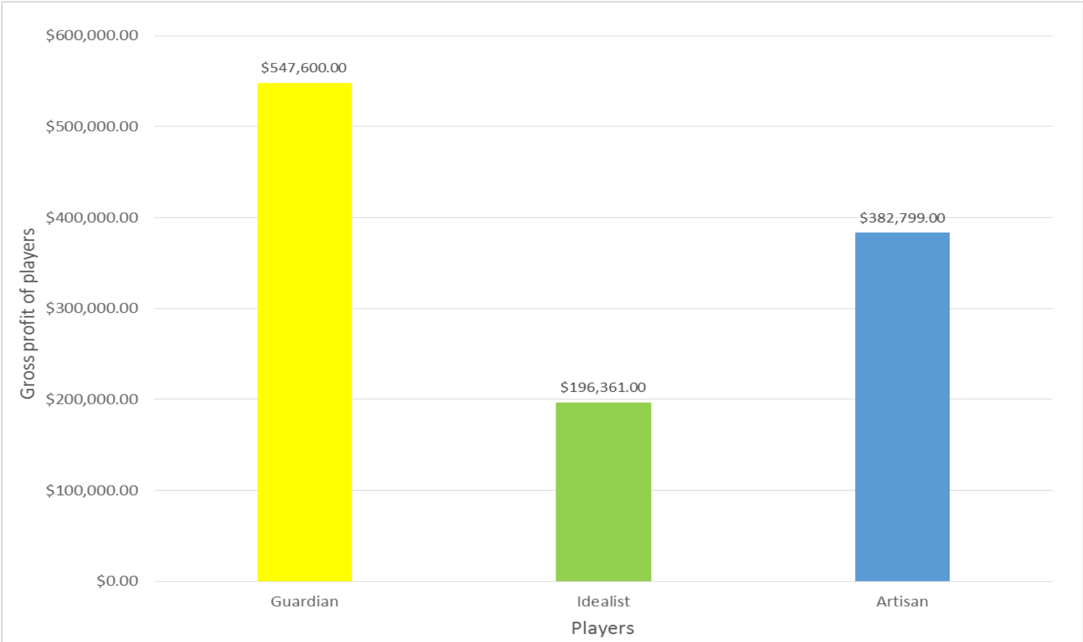


Figure 23: *Gameplay 3 Gross player profits*

Bid efficiency of players in each team

The following graphs represent the bid efficiency of each player in each team. Bid efficiency is the ratio of wins to the total number of bids bid. These are expressed as a percentage. Using this variable, it is evident that rational personality type players have the highest bid efficiency. The highest bid efficiency is observed for the rational personality player in gameplay 2, with a bid efficiency of 60%. Despite having the lowest bid efficiency, the highest profits are made by guardians, and artisans. This means, that they pick their bids from the higher profit regions. Figure 24, shows the bid efficiency of players in gameplay 1.

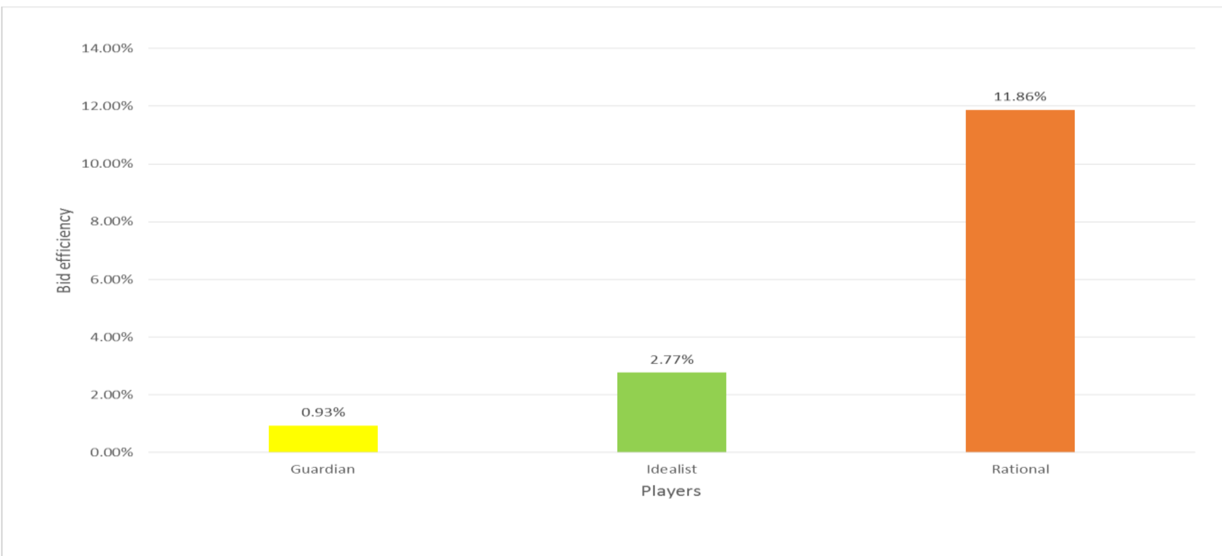


Figure 24: *Gameplay 1 Player bid efficiency*

Figure 25, shows the bid efficiency of players in gameplay 2

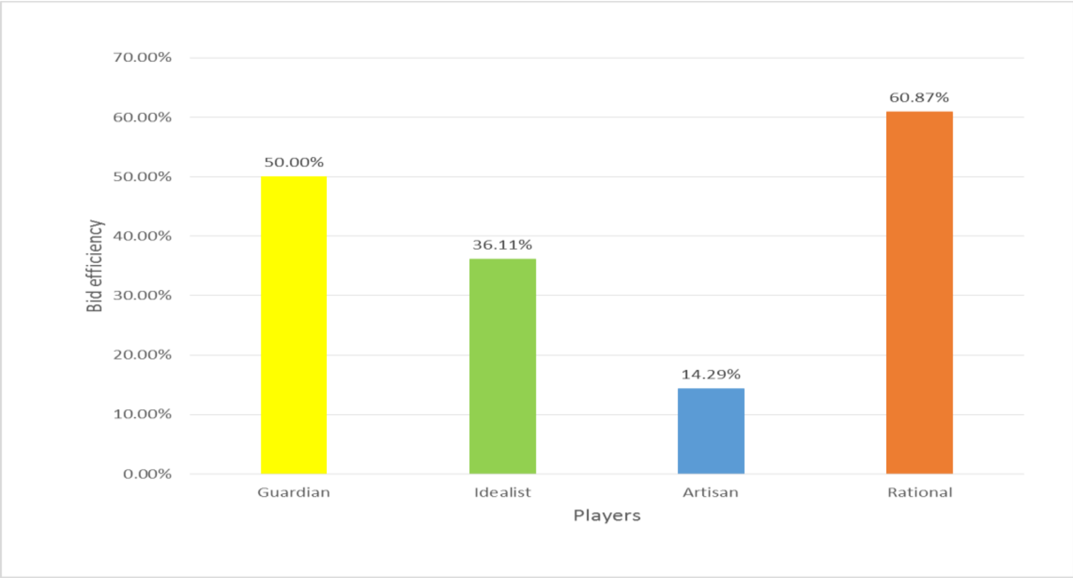


Figure 25: *Gameplay 2 Player bid efficiency*

Figure 26, shows the bid efficiency of players in gameplay 3.

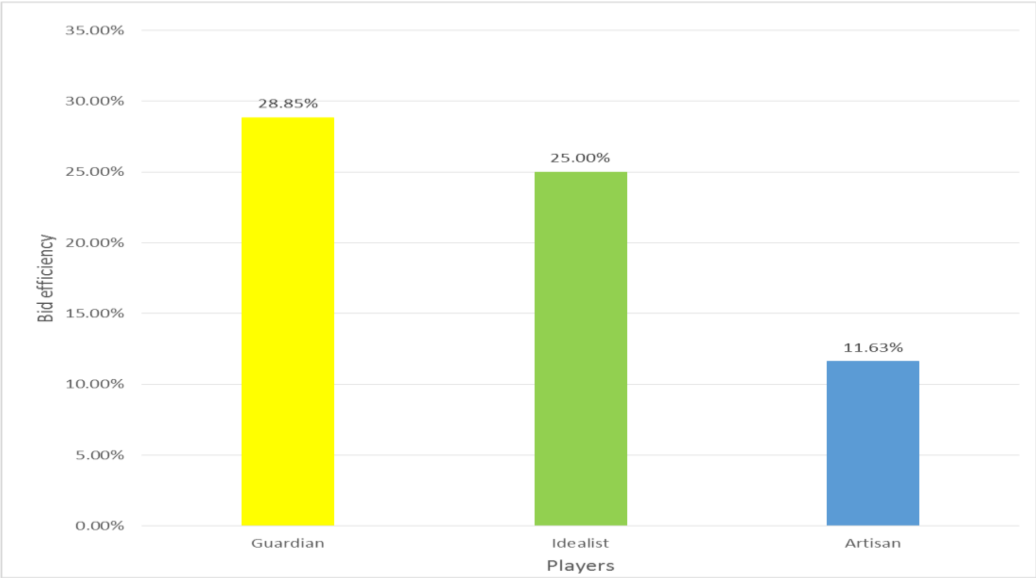


Figure 26: *Gameplay 3 Player bid efficiency*

Contract price or accepted bid prices per team for each player

The following graphs represent the contract price or the cost of job or lowest bid accepted for each job that the players could bid on. This is cumulative for all the games during the gameplay. Note that irrespective of the price point, these numbers rise and reach maximum during the mid-game time. However, they start decreasing again at the end of the game when all the players proficiently understand the game. This confirms the presence of stages of four game stages during the gameplay, which are learning, discovering, competitive, and profit making. It is clearly indicated in the gameplay 1 and gameplay 2 that the rational personality players in the game bring the total price down, and they play only to win the number of jobs or win the bids. They take the whole gameplay as a video game, disregarding the fact that these simulations would be any effective in reality. In gameplay 2 and gameplay 3, the highest bid amount winning job is by an artisan and guardian respectively.

Figure 27, shows the contract price for all players in gameplay 1. Note that there is only a learning, discovering, and competitive stage for gameplay 1. The profit-making stage is missing here. With the rational player winning many bids, and lowering the total profit margin, there is no room to make a bid below a certain profit level to win it.

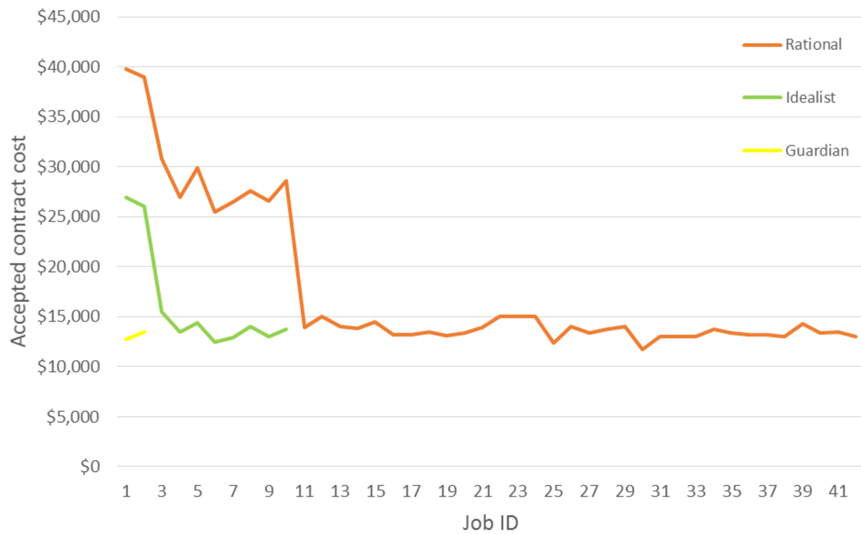


Figure 27: *Gameplay 1 Contract price per player for each job*

Figure 28, shows the contract price per player for gameplay 2.

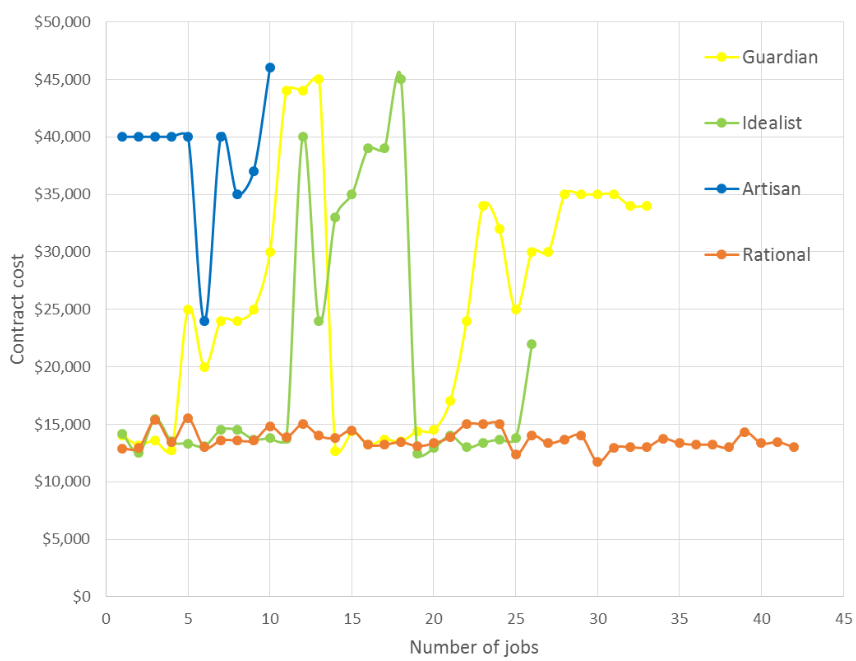


Figure 28: *Gameplay 2 Contract price per player for each job*

Figure 29, shows the contract price per player for gameplay 3.

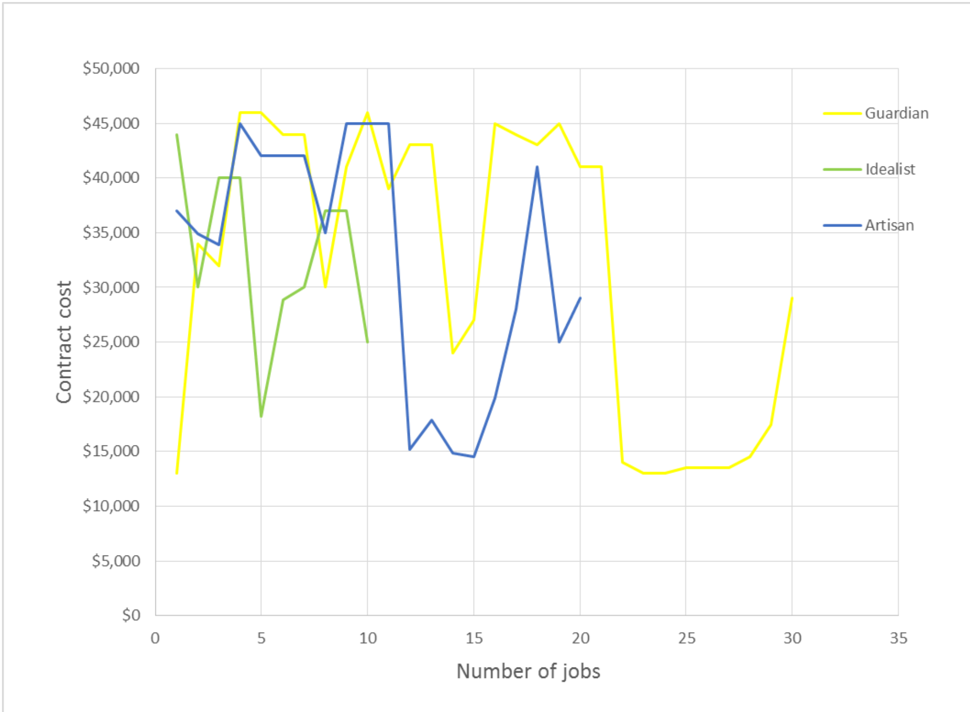


Figure 29: *Gameplay 3 Contract price per player for each job*

Profit percentage per job won for all teams

The following graphs represent profit expressed in percentage per job won. There are graphs per team, subdivided into number of players in each gameplay and the profit percentages of the jobs won by them. This trend similar to the contract price per gameplay. Figure 30, shows the profit percentage for all players in gameplay 1.

Figure 30: *Gameplay 1 Comparative profit percentage per player*

Figure 31, shows profit percentage for all players in gameplay 2.

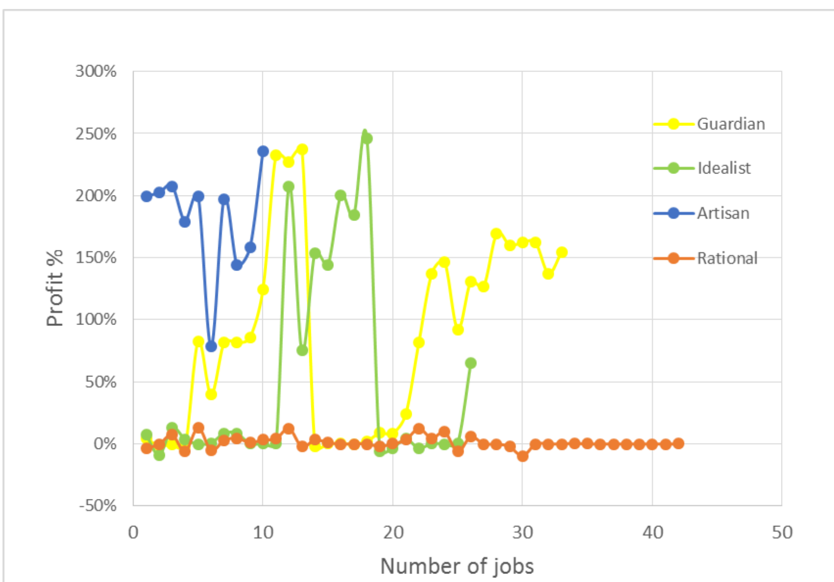


Figure 31: *Gameplay 2 Comparative profit percentage per player*

Figure 32, shows the profit percentage for all players in gameplay 3.

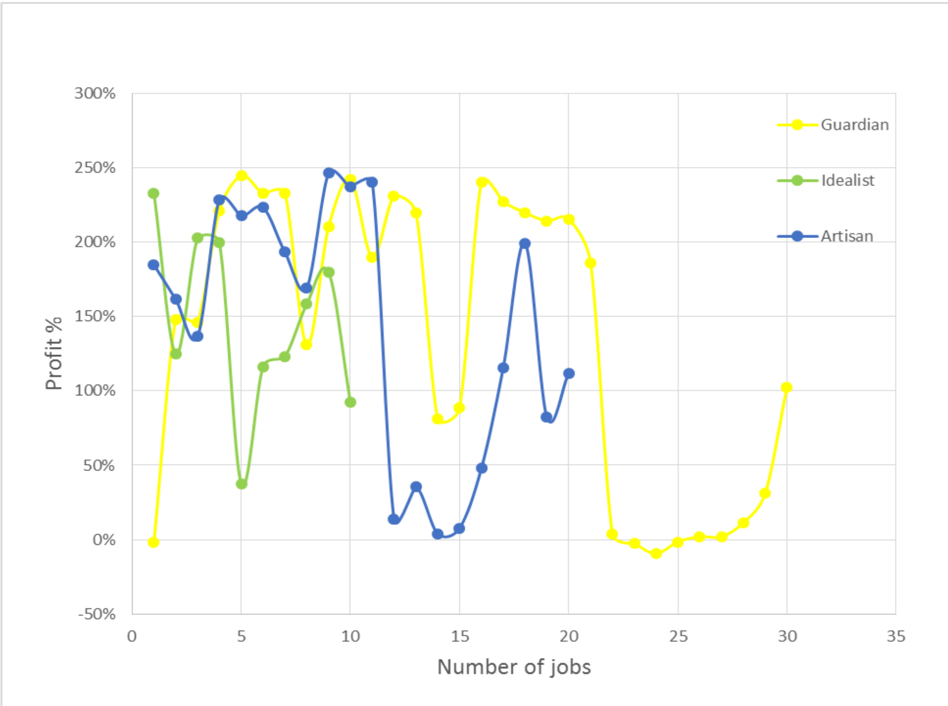


Figure 32: *Gameplay 3 Comparative profit percentages per player*

Cumulative profit per team

The graphs below represent a comparative analysis of cumulative profit per number of jobs. The important takeaway from this variable and its results from all gameplays is that the cumulative profit increases for all players in gameplay 1, gameplay2, and gameplay 3. With the exception that in gameplay 2, the cumulative profit for rational personality player is nearly constant through the game. Inferencing from it, we suggest that the rational player just won bids and did not benefit from it, while other took advantage of it and took bids with much more profit. Figure 33, shows the cumulative profit per player for gameplay 1.

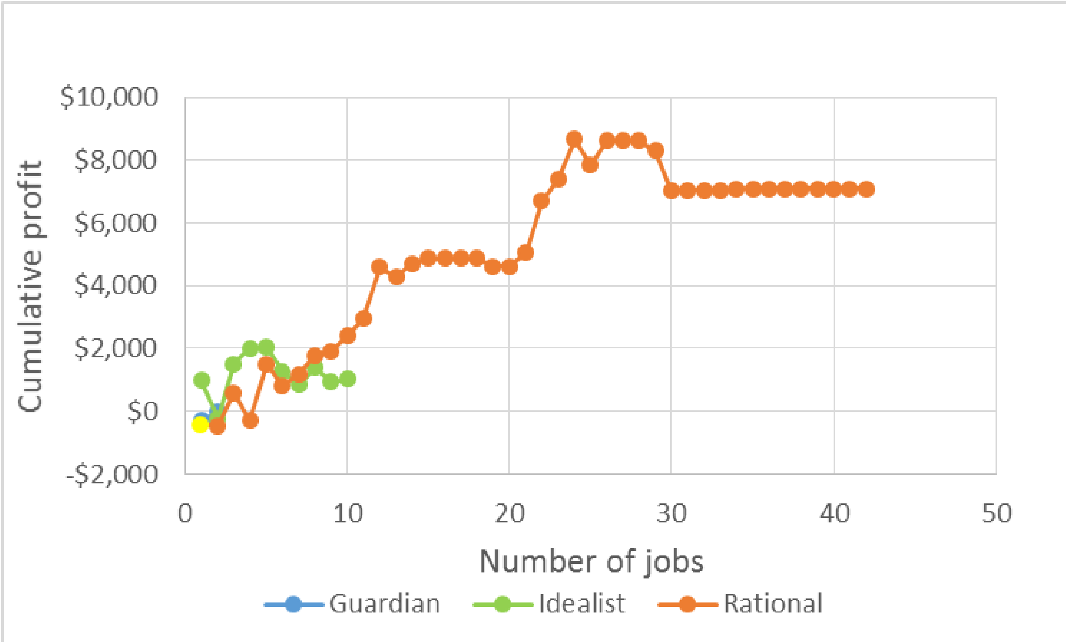


Figure 33: *Team 1 - Cumulative profit per player*

Figure 34, shows the cumulative profit per player in gameplay 2.

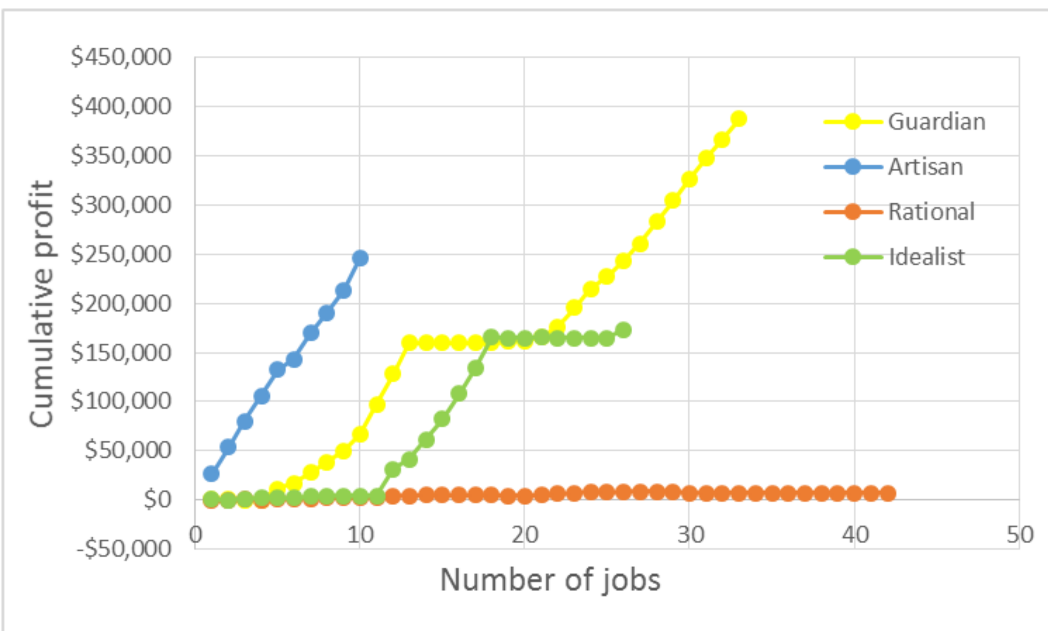


Figure 34: *Game 2 Cumulative profit per player*

Figure 35, shows cumulative profit for all players in gameplay 3.

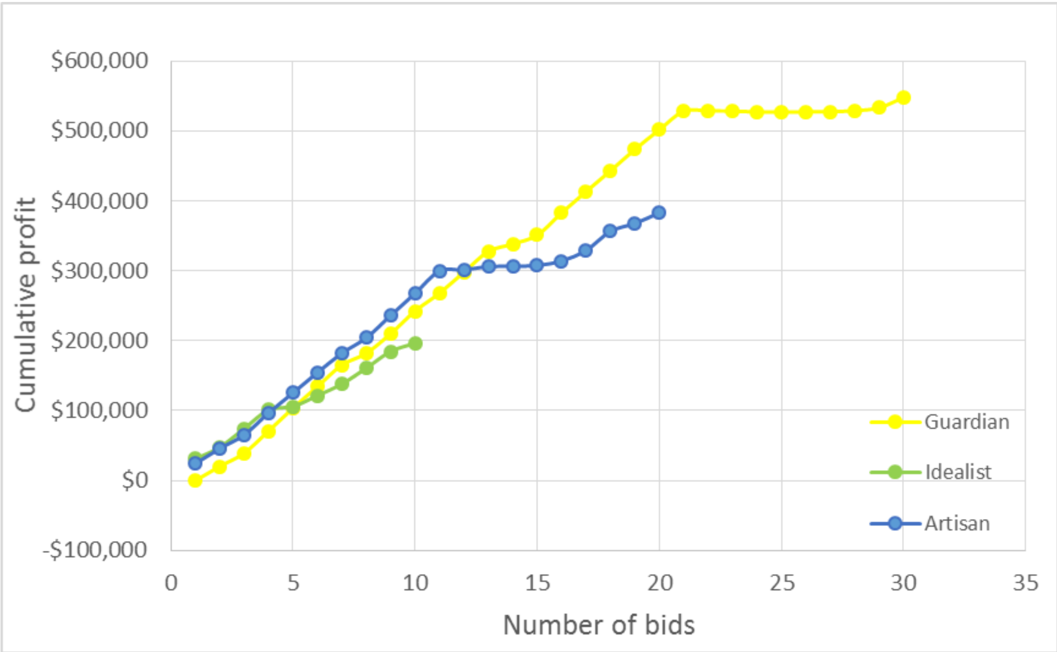


Figure 35: *Game 3 Cumulative profit per player*

Comparison of Student T-test results within games

Student T-test results for Gameplay 1

The standard test for comparing the performance of the players is the Student's t Test. Here, the comparison is between the profit sets for each player in each game.

Table 5, shows the T-test results for gameplay 1 between Guardian and Idealist.

Table 5: *Comparison of Results for Gameplay 1 Players – Player 1 to Player 2*

Description	***Number***	***Comment***
Player 1 Mean Profit per job	$983	Poor performance
Player 2 Mean Profit per job	$129	Poor performance
Students t Test comparison of profit set t value	1.68	
Degrees of Freedom	4.21	
p-value	0.179	
Conclusion	No statistical acceptable difference	
Player 1 Total jobs won	4	
Player 2 Total jobs won	26	
Player 1 Total jobs won in normalization range > 0.75	1	
Player 2 Total jobs won in normalization range > 0.75	0	
Comment	Player one performed better	

Table 6: *Comparison of Results for Gameplay 1 Players – Player 1 to Player 4*

Description	***Number***	***Comment***
Player 1 Mean Profit per job	$983	Poor performance
Player 4 Mean Profit per job	$93	Poor performance
Students t Test comparison of profit set t value ::	1.646	
Degrees of Freedom	4.599	
p-value	0.167	
Conclusion	No statistical acceptable difference	
Player 1 Total jobs won	4	
Player 2 Total jobs won	25	
Player 1 Total jobs won in normalization range > 0.75	1	
Player 2 Total jobs won in normalization range > 0.75	0	
Comment	Player one performed better	

Table 7, shows the T-test results for gameplay 1 between Idealists and Rationals.

Table 7: *Comparison of Results for Gameplay 1 Players – Player 2 to Player 4*

Description	***Number***	***Comment***
Player 1 Mean Profit per job	$129	Poor performance
Player 4 Mean Profit per job	$93	Poor performance
Students t Test comparison of profit set t value ::	0.2268	
Degrees of Freedom	40.84	
p-value	0.8217	
Conclusion	No statistical acceptable difference	
Player 1 Total jobs won	26	
Player 2 Total jobs won	25	
Player 1 Total jobs won in normalization range > 0.75	0	
Player 2 Total jobs won in normalization range > 0.75	0	
Comment	Player one just performed better	

The overall results from Gameplay 1 show very low performance by all players. A Student's t Test score greater than 2 is generally considered to be significantly distinct, in these three cases the first player performed marginally better, but it is not statistically acceptable conclusion at the standard 5% level.

Only player 1 managed one profit score in the normalized range above 0.75, so this game was competitive and the fourth player destroyed the profits with a lot of wins at low prices.

Student T-test results from Gameplay 2

Table 8**,** shows the T-test results for gameplay 2 between guardians and idealists.

Table 8: *Comparison of Results for Gameplay 2 Players – Player 1 to Player 2*

Description	***Number***	***Comment***
Player 1 Mean Profit per job	$10555	Good performance
Player 2 Mean Profit per job	$12326	Good performance
Students t Test comparison of profit set t value:	0.463	
Degrees of Freedom	35.92	
p-value	0.645	
Conclusion	No statistical acceptable difference	
Player 1 Total jobs won	17	
Player 2 Total jobs won	20	
Player 1 Total jobs won in normalization range > 0.75	3	
Player 2 Total jobs won in normalization range > 0.75	4	
Comment	Player one performed better	

Table 9, shows the T-test results for gameplay 2 between guardians and artisans

Table 9: *Comparison of Results for Gameplay 2 Players – Player 1 to Player 3*

Description	**Number**	**Comment**
Player 1 Mean Profit per job	$10555	Good performance
Player 3 Mean Profit per job	$18752	Excellent performance
Students t Test comparison of profit set t value ::	-2.04	
Degrees of Freedom	30.68	
p-value	0.049	
Conclusion	statistical acceptable difference	
Player 1 Total jobs won	17	
Player 2 Total jobs won	14	
Player 1 Total jobs won in normalization range > 0.75	3	
Player 2 Total jobs won in normalization range > 0.75	7	
Comment	Player two performed better	

Table 10, shows the T-test results for gameplay 2 between guardians and rationals

Table 10: *Comparison of Results for Gameplay 2 Players – Player 1 to Player 4*

Description	***Number***	***Comment***
Player 1 Mean Profit per job	$10555	Poor performance
Player 4 Mean Profit per job	$6809	Poor performance
Students t Test comparison of profit set t value ::	1.05	
Degrees of Freedom	26.995	
p-value	0.29	
Conclusion	No statistical acceptable difference	
Player 1 Total jobs won	17	
Player 2 Total jobs won	10	
Player 1 Total jobs won in normalization range > 0.75	3	
Player 2 Total jobs won in normalization range > 0.75	0	
Comment	Player one just performed better	

Table 11, shows the T-test results for gameplay 2 between idealists and artisans

Table 11: *Comparison of Results for Gameplay 2 Players – Player 2 to Player 3*

Description	***Number***	***Comment***
Player 2 Mean Profit per job	$12326	Good performance
Player 3 Mean Profit per job	$18752	Good performance
Students t Test comparison of profit set t value::	-1.67	
Degrees of Freedom	31.54	
p-value	0.103	
Conclusion	Statistical acceptable difference at 10% level	Noticeable
Player 1 Total jobs won	20	
Player 2 Total jobs won	14	
Player 1 Total jobs won in normalization range > 0.75	4	
Player 2 Total jobs won in normalization range > 0.75	7	
Comment	Player three performed better	

Table 12, shows the T-test results for gameplay 2 between idealists and rationals

Table 12: *Comparison of Results for Gameplay 2 Players – Player 2 to Player 4*

Description	***Number***	***Comment***
Player 1 Mean Profit per job	$12366	Good performance
Player 3 Mean Profit per job	$6809	Acceptable performance
Students t Test comparison of profit set t value ::	1.65	
Degrees of Freedom	29.2	
p-value	0.11	
Conclusion	statistical acceptable difference at 10%	
Player 1 Total jobs won	17	
Player 2 Total jobs won	14	
Player 1 Total jobs won in normalization range > 0.75	3	
Player 2 Total jobs won in normalization range > 0.75	7	
Comment	Player two performed better	

Table 13, shows T-test results for gameplay 2 between artisans and rationals

Table 13: *Comparison of Results for Gameplay 2 Players – Player 3 to Player 4*

Description	***Number***	***Comment***
Player 1 Mean Profit per job	$18752	Poor performance
Player 4 Mean Profit per job	$6809	Poor performance
Students t Test comparison of profit set t value ::	3.36	
Degrees of Freedom	23.07	
p-value	0.002	
Conclusion	Very statistical acceptable difference	
Player 1 Total jobs won	14	
Player 2 Total jobs won	10	
Player 1 Total jobs won in normalization range > 0.75	7	
Player 2 Total jobs won in normalization range > 0.75	0	
Comment	Player three seriously performed better	

The overall results from Gameplay 2 show very good performance by all players. A Student's t Test score greater than 2 is generally considered to be significantly distinct, in these three cases the first player performed marginally better, but it is not statistically acceptable conclusion at the standard 5% level.

Player 3 was exceptionally better than the other players in both this game and game 1. Player 3 is an artisan, which is interesting.

Student T-test results from Gameplay 3

Table 14, shows the T-test results for gameplay 3 between guardians and idealists

Table 14: *Comparison of Results for Gameplay 3 Players - Player 1 to Player 2*

Description	***Number***	***Comment***
Player 1 Mean Profit per job	$21868	Exceptional performance
Player 2 Mean Profit per job	$22159	Poor performance
Students t Test comparison of profit set t value	0.09	
Degrees of Freedom	31.53	
p-value	0.92	
Conclusion	No statistical acceptable difference	
Player 1 Total jobs won	18	
Player 2 Total jobs won	15	
Player 1 Total jobs won in normalization range > 0.75	11	
Player 2 Total jobs won in normalization range > 0.75	8	
Comment	Player two performed better	

Table 15, shows T-test results for gameplay 3 for guardians and artisans

Table 15: *Comparison of Results for Gameplay 3 Players - Player 1 to Player 3*

Description	***Number***	***Comment***
Player 1 Mean Profit per job	$21868	Excellent performance
Player 4 Mean Profit per job	$21169	Excellent performance
Students t Test comparison of profit set t value ::	0.212	
Degrees of Freedom	36.09	
p-value	0.83	
Conclusion	No statistical acceptable difference	
Player 1 Total jobs won	18	
Player 2 Total jobs won	27	
Player 1 Total jobs won in normalization range > 0.75	11	
Player 2 Total jobs won in normalization range > 0.75	15	
Comment	Player one performed better	

Table 16, shows T-test results for gameplay 3 between idealists and artisans

Table 16: *Comparison of Results for Gameplay 3 Players - Player 2 to Player 3*

Description	***Number***	***Comment***
Player 1 Mean Profit per job	$22159	Excellent performance
Player 4 Mean Profit per job	$21169	Poor performance
Students t Test comparison of profit set t value ::	0.3659	
Degrees of Freedom	38.94	
p-value	0.716	
Conclusion	No statistical acceptable difference	
Player 1 Total jobs won	15	
Player 2 Total jobs won	27	
Player 1 Total jobs won in normalization range > 0.75	8	
Player 2 Total jobs won in normalization range > 0.75	15	
Comment	Player two just performed better	

The overall results from Gameplay 3 show very high performance by all players. A Student's t Test score greater than 2 is generally considered to be significantly distinct, in these three cases the first player performed marginally better, but it is not statistically acceptable conclusion at the standard 5% level.

Clearly tacit collusion is occurring in the bidding and the game would cause heartache for the purchaser.

To summarize the takeaway from the results obtained after conducting the Student T-test analysis is given in Figure 36.

Student T-test results for all teams					
Team	**A**	**B**	**p-value**	**Result**	**Comment**
Team 1	Guardian	Rational	0.167	Not statistically acceptable	Overall results from team 1 are at a very low profit level. In both the t-test analysis, there was only a marginally better performance, but it is not acceptable at 5% significance level. Only the guardian managed one profit score entry in the normalized range above 0.75. So, this game was competitive and the rational player destroyed all profit margins, due to winner's curse.
	Guardian	Idealist	0.8217	Not statistically acceptable	
Team 2	Guardian	Idealist	0.645	Not statistically acceptable	Overall results from team 2 show a very competitive and profitable performance by all players. In all the cases, the guardian performed marginally better, but is not statistically acceptable at a 5% significance level. However, the artisan player performed exceptionally better that the other players.
	Guardian	Artisan	0.049	Statistically accpetable	
	Idealist	Artisan	0.103	Statistically accpetable at 10%	
	Idealist	Rational	0.11	Statistically accpetable at 10%	
	Artisan	Rational	0.002	Very statistically acceptable	
Team 3	Guardian	Idealist	0.92	Not statistically acceptable	Overall results from team 3 show a very high performance by all players. A student's t-test score here was not statistically significant here at 5% significance level. Players performed only marginally better than each other. Thus, there was clear case of tacit collusion and would be an eyesore for the purchaser of such high paying sevices, with exceptionally high profit margins observed upto 200 % in this game.
	Guardian	Artisan	0.83	Not statistically acceptable	
	Idealist	Artisan	0.716	Not statistically acceptable	

Figure 36: *Summary of Student's T-test results*

Comparison of normalized bid amount for all gameplays and all players

This section contains analysis on the normalized bid amount during each gameplay for all players. It is necessary to study this analysis because it helps understand the current standing of all players of the bid amount they pick from standardized bins.

Gameplay 1

Figure 37, below gives a comparative analysis of normalized bid amount for all players in gameplay 1. Note that all players have at least one bid from each standardized bin of normalized bid amount range. There is a high concentration of bid amounts picked from the range of 0.2-0.4. This is essentially the beta distribution or economically inefficient range of values to pick the bids from.

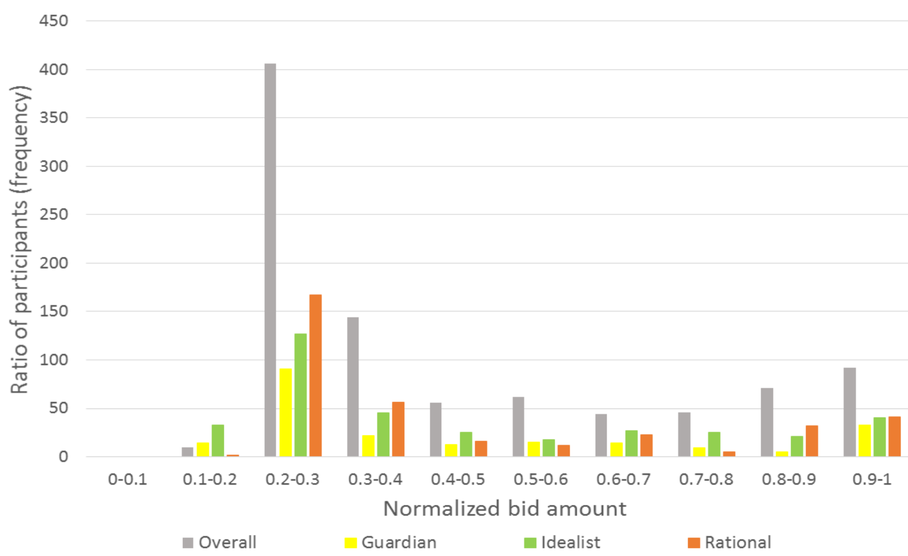


Figure 37: *Comparison of normalized bid amount for all players in Gameplay 1*

Gameplay 2

Figure 38, below gives a comparative analysis of normalized bid amount for all players in gameplay 2. Note that all players have at least one bid from each standardized bin of normalized bid amount range. There is a high concentration of bid amounts picked from range of 0.1-0.2, and 0.6 – 0.9. The first range type is economically inefficient range, however the second one is where the higher bids are placed. Note that the artisan and guardian personality players have higher number of bids from this region. While, the rational personality player has maximum bids from the economically inefficient or beta distribution zone.

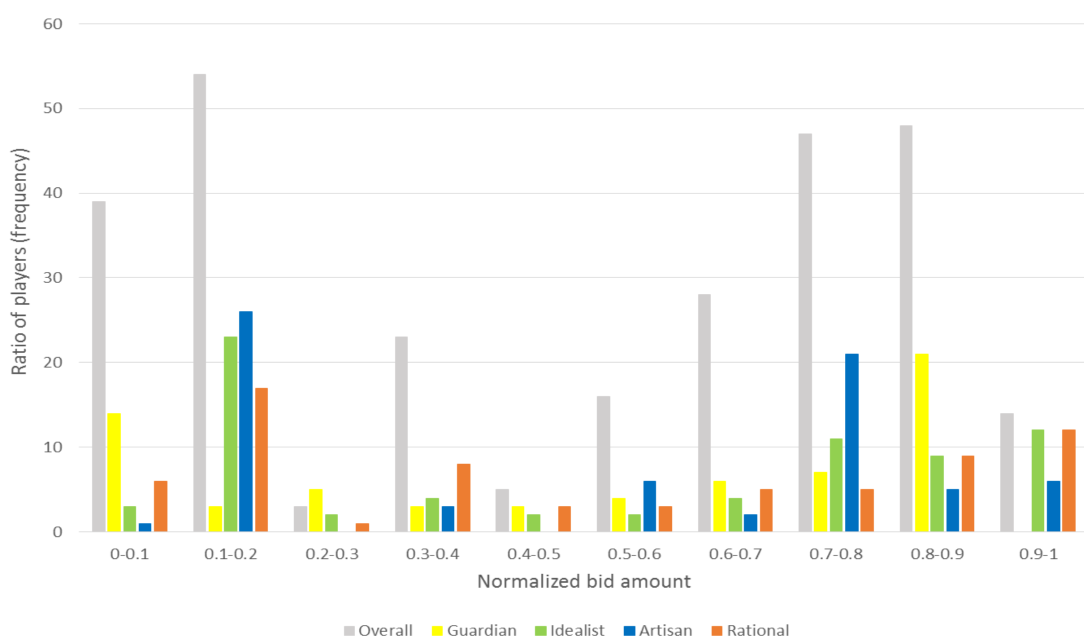


Figure 38: *Comparison of normalized bid amount for Gameplay 2 for all players*

Gameplay 3

Figure 39, below gives a comparative analysis of normalized bid amount. Note that the idealist players do not draw bid amounts from the normalized ranges of 0.1 – 0.2; 0.4 – 0.5; and 0.9 – 1.0. The highest number of bids drawn from the economically efficient range of 0.6 – 1.0, is from the artisan and guardian personality types.

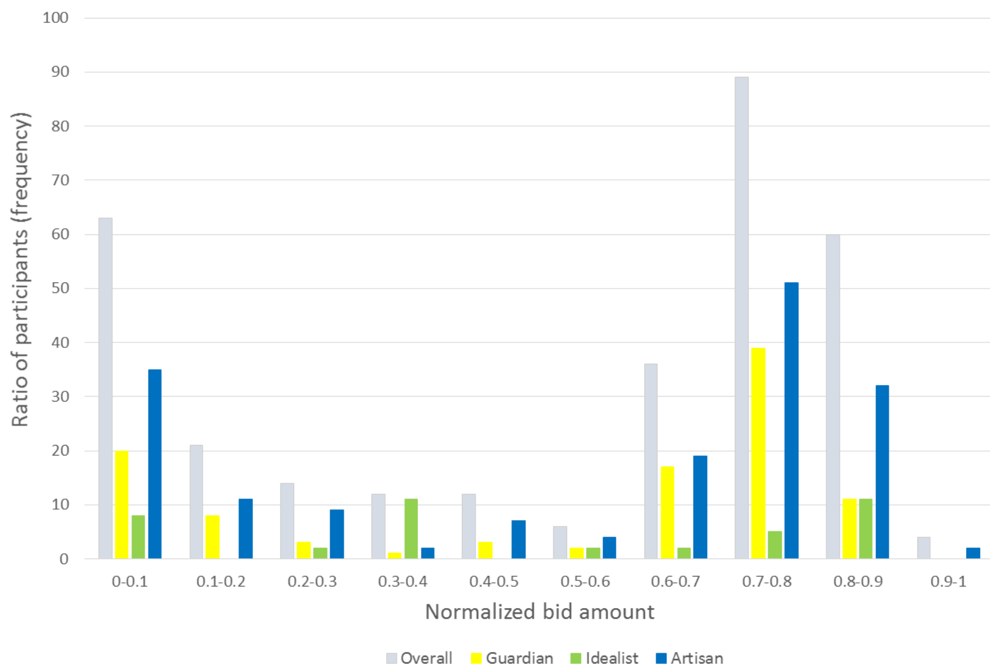


Figure 39: *Comparison of normalized bid amount for Gameplay 3 for all players*

Comparison of normalized profit for all gameplays and all players

This section contains analysis on the normalized profit during each gameplay for all players. It is necessary to study this analysis because it helps understand the current standing of all players of the profit they aim for, from standardized bins. This is an important variable, based on which this research started out. The hypothesis is that there is a secondary underlying distribution or bump in normalized profit range starting at 0.7.

Gameplay 1

Figure 40, below shows the normalized profit frequency distribution for all players in gameplay 1. Note that here highest profits are made in the range 0.3-0.4, by rational personality player. Whereas the idealist player has profit ranges drawn from all range except from 0.7-0.8. There is no secondary distribution visible here because it was highly dominated by the rational personality player who constantly pulled all the players to a very marginal profit, where all players gave up bidding because it did not make sense for them to work on a project with such low profits. Sometimes these profits were also negative.

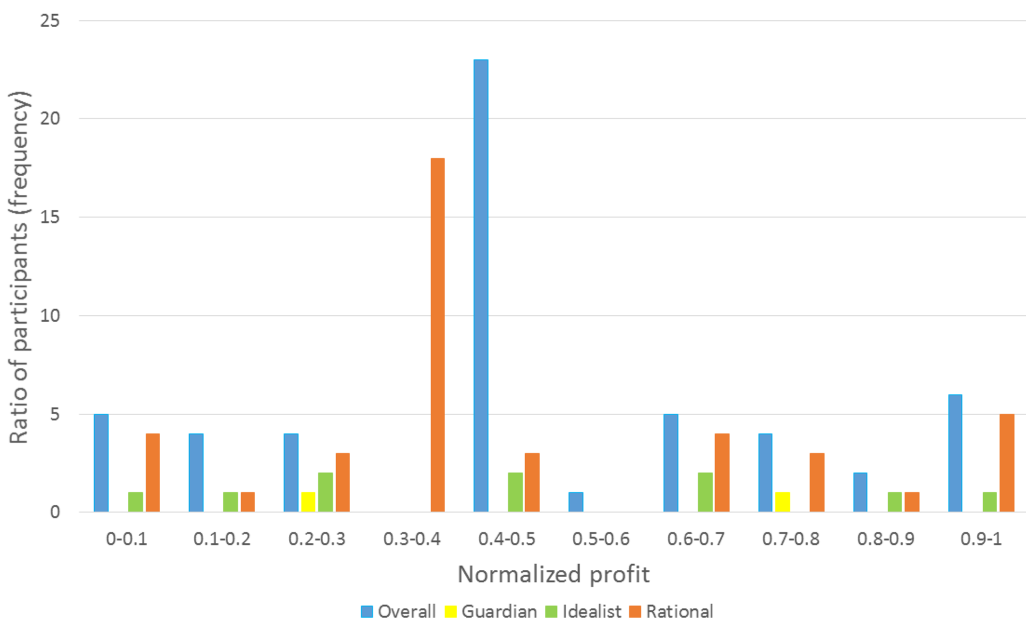


Figure 40: *Comparison of normalized profit for Gameplay 1 for all players*

Gameplay 2

Figure 41, below shows normalized profit for gameplay 2. Note that the rational personality player draws maximum profits in the range of 0.3-0.4. The idealist draws maximum profits from 0.2-0.3 range, the guardian from 0.1-0.2; and 0.9-0.1, but has at least one entry in each profit range. Observe that the artisan does not draw from the bin ranges of 0.1-0.2; 0.4-0.5; 0.7-0.8; and 0.8-0.9.

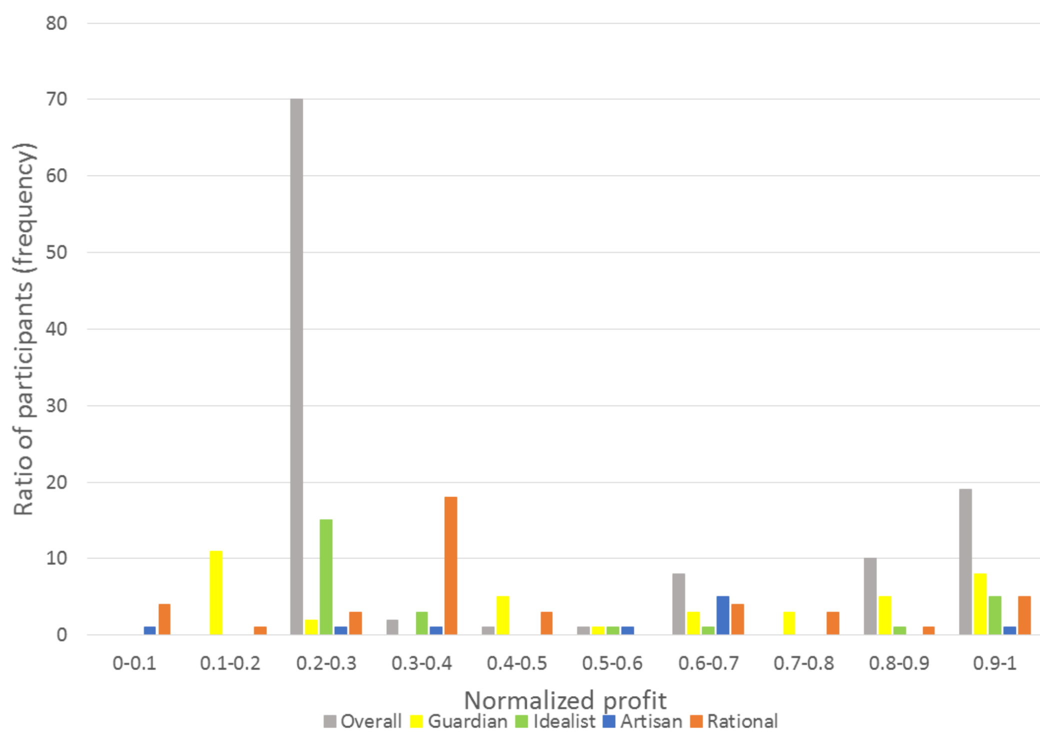


Figure 41: *Comparison of normalized profit for Gameplay 2 for all players*

Gameplay 3

Figure 42, below shows the normalized profit for all players in gameplay 3. All players have profit entries in the range 0 – 0.9, except for the idealist player who also has entries in 0.0-1.0

range. Here, highest number of entries are observed in 0.8-0.9 range. This gameplay in particular was interesting, as players seem to have tacitly colluded. But, in this gameplay there is very distinctively a secondary distribution. It shape is normal or not is however questionable, with the data that we have. However, it surely cannot be ruled out as there is an observable trend of a normal distribution. We are unsure about it because the results were not repeatable across all games.

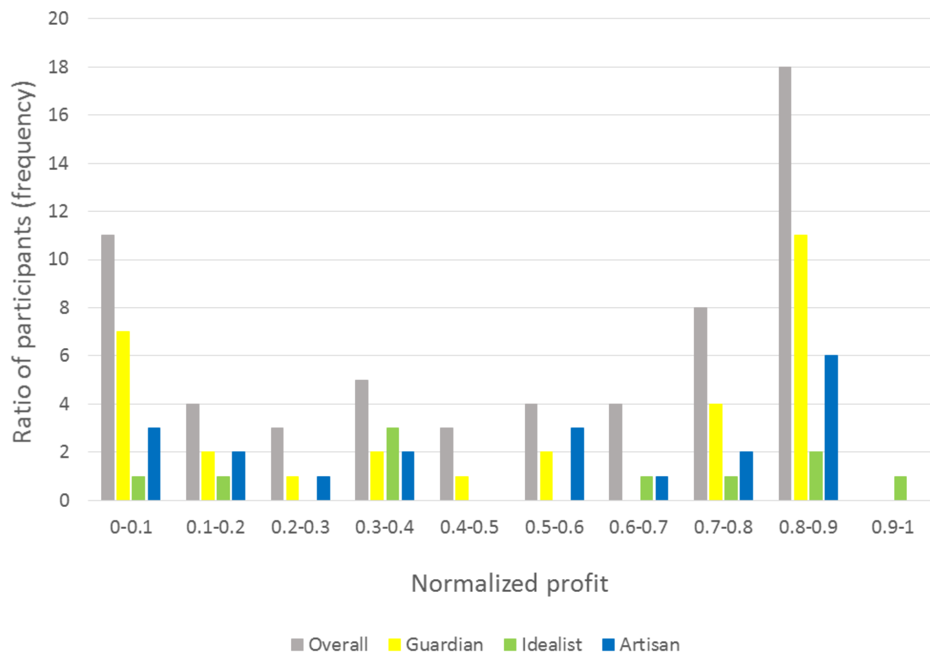


Figure 42: *Comparison of normalized profit for Gameplay 3 for all players*

Normal distribution fitting of normalized bid amount for all gameplays

This section contains analysis on the distribution fitting of normalized bid during each gameplay for all players. It is necessary to study this analysis since the distribution fitting used shows the fit of the data. Interestingly, most results favour the movement of bids towards a Gaussian distribution for economically efficient players. Also, for economically inefficient players, the distribution shows with high confidence interval to be Non-Gaussian. But, the data is not enough to place a definitive answer to the fit of the model.

Gameplay 1

Figure 43, below shows the normal distribution fitting of normalized bids from gameplay 1 for all players and the overall gameplay. It is clearly indicated that the bids in gameplay 1 are not normally distributed for any player.

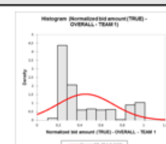
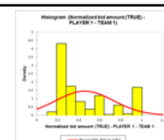
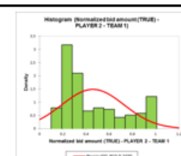
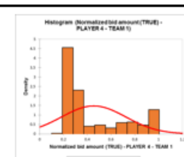
	Distribution fitting of normal bid amount per team for all players			
	H0: The sample follows a Normal distribution			
	Ha: The sample does not follow a Normal distribution			
Teams	Descriptive data	Test Interpretation 1	Test Interpretation 2	Graph
Team 1	Overall	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.	
	Guardian	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.	
	Idealist	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.	
	Rational	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.	

Figure 43: *Normal distribution fitting of normalized bid amount for Gameplay 1 for all players*

Gameplay 2

Figure 44, below shows the normal distribution fitting of normalized bids from gameplay 2 for all players and the overall gameplay. It is clearly indicated that the bids in gameplay 2 are not normally distributed for any player.

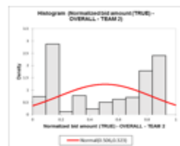
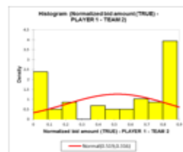
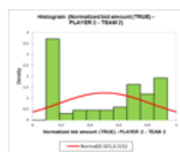
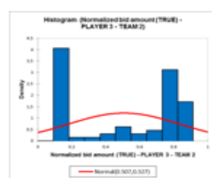
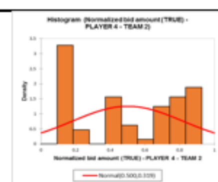
	Distribution fitting of normal bid amount per team for all players			
	H0: The sample follows a Normal distribution			
	Ha: The sample does not follow a Normal distribution			
Teams	**Descriptive data**	**Test Interpretation 1**	**Test Interpretation 2**	**Graph**
Team 2	**Overall**	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.	
	Guardian	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 1.00%.	
	Idealist	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.70%.	
	Artisan	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.04%.	
	Rational	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 3.42%.	

Figure 44: *Normal distribution fitting of normalized bid amount for Gameplay 2 for all players*

Gameplay 3

Figure 45, below shows normal distribution fitting of normalized bid amount for all players in gameplay 3. Note that only for the idealist and artisan players, the results are fitting statistically to a normal distribution.

To summarize for all teams, it cannot be definitively said that artisan and idealist players follow a normal distribution while picking bid amount entries. But, it can be observed that some players playing efficiently for higher profits do tend to pick sets from a normal distribution.

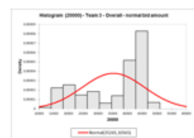
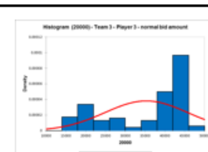
	Distribution fitting of normal bid amount per team for all players			
	H0: The sample follows a Normal distribution			
	Ha: The sample does not follow a Normal distribution			
Teams	**Descriptive data**	**Test Interpretation 1**	**Test Interpretation 2**	**Graph**
Team 3	**Overall**	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.	
	Guardian	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.	
	Idealist	As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	The risk to reject the null hypothesis H0 while it is true is 27.20%.	
	Artisan	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.	

Figure 45: *Normal distribution fitting of normalized bid amount for Gameplay 3 for all players*

Normal distribution fitting of normalized profit for all gameplays

This section contains analysis on the distribution fitting of normalized profit during each gameplay for all players. It is necessary to study this analysis since the distribution fitting used shows the fit of the data. Interestingly, most results favour the movement of bids towards a Gaussian distribution for economically efficient players. Also, for economically inefficient players, the distribution shows with high confidence interval to be Non-Gaussian. But, the data is not enough to place a definitive answer to the fit of the model.

Gameplay 1

Figure 46, shows the summary for normal distribution fitting of normalized profit for gameplay 1. Note that the overall distribution, guardian's distribution, and idealist's distribution is normally distributed. It clearly indicates that rational player's distribution is not normal.

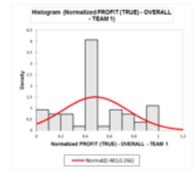
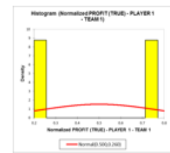
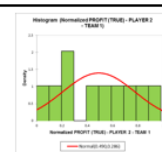
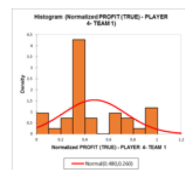
	Distribution fitting of normal profit amount of jobs per team for all players			
	Distribution fitting of normal profit amount of jobs per team for all players			
	H0: The sample follows a Normal distribution			
	Ha: The sample does not follow a Normal distribution			
Teams	Descriptive data	Test Interpretation 1	Test Interpretation 2	Graph
Team 1	Overall	As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	The risk to reject the null hypothesis H0 while it is true is 5.53%.	
	Guardian	As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	The risk to reject the null hypothesis H0 while it is true is 93.28%.	
	Idealist	As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	The risk to reject the null hypothesis H0 while it is true is 86.75%.	
	Rational	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 1.05%.	

Figure 46: *Normal distribution fitting for normalized profit for Gameplay 1 for all players*

Gameplay 2

Figure 47, below shows the normal distribution fitting of normalized profit for gameplay 2. Note that the overall distribution, and idealist's distribution is not normal in its statistical distribution. But, for the guardians and artisans, the distribution fitting seems to fit the normal distribution.

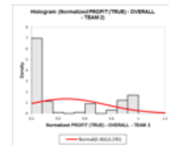
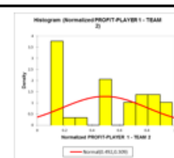
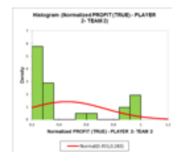
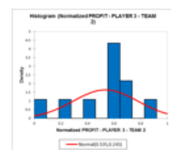
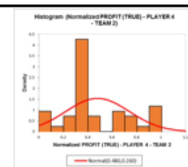
	Distribution fitting of normal profit amount of jobs per team for all players			
	Distribution fitting of normal profit amount of jobs per team for all players			
	H0: The sample follows a Normal distribution			
	Ha: The sample does not follow a Normal distribution			
Teams	Descriptive data	Test Interpretation 1	Test Interpretation 2	Graph
Team 2	Overall	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.01%.	
	Guardian	As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	The risk to reject the null hypothesis H0 while it is true is 13.40%.	
	Idealist	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 0.11%.	
	Artisan	As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	The risk to reject the null hypothesis H0 while it is true is 39.54%.	
	Rational	As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.	The risk to reject the null hypothesis H0 while it is true is lower than 1.05%.	

Figure 47: *Normal distribution fitting of normalized profit for Gameplay 2 for all players*

Gameplay 3

This is an exceptional gameplay. All the data distributions, for overall all players, guardians, idealists, and artisans fit the normal distribution statistical fitting. Looking at this game solely, it cannot be concluded distinctively which players follow or not a normal distribution because the game results are not repeatable in all the gameplays. There must be more data present to make sure of the distribution type in the secondary underlying distribution.

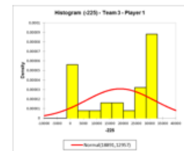
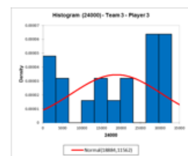
	Distribution fitting of normal profit amount of jobs per team for all players			
	Distribution fitting of normal profit amount of jobs per team for all players			
	H0: The sample follows a Normal distribution			
	Ha: The sample does not follow a Normal distribution			
Teams	Descriptive data	Test Interpretation 1	Test Interpretation 2	Graph
Team 3	Overall	As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	The risk to reject the null hypothesis H0 while it is true is 6.44%.	
	Guardian	As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	The risk to reject the null hypothesis H0 while it is true is 12.20%.	
	Idealist	As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	The risk to reject the null hypothesis H0 while it is true is 93.05%.	
	Artisan	As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.	The risk to reject the null hypothesis H0 while it is true is 45.96%.	

Figure 48: *Normal distribution fitting of normalized profit for Gameplay 3 for all players*

Comparative analysis of previous studies v. this study

Figure 49, below shows a comparative analysis of normalized profit from previous studies done at TAMU, in comparison to the results obtained from this research. This figure and analysis was conducted to see a slight presence of the secondary underlying distribution, as well as to see if the results from previous studies are comparable to the current. There is clearly a secondary distribution, but more data is needed to find its statistical fit.

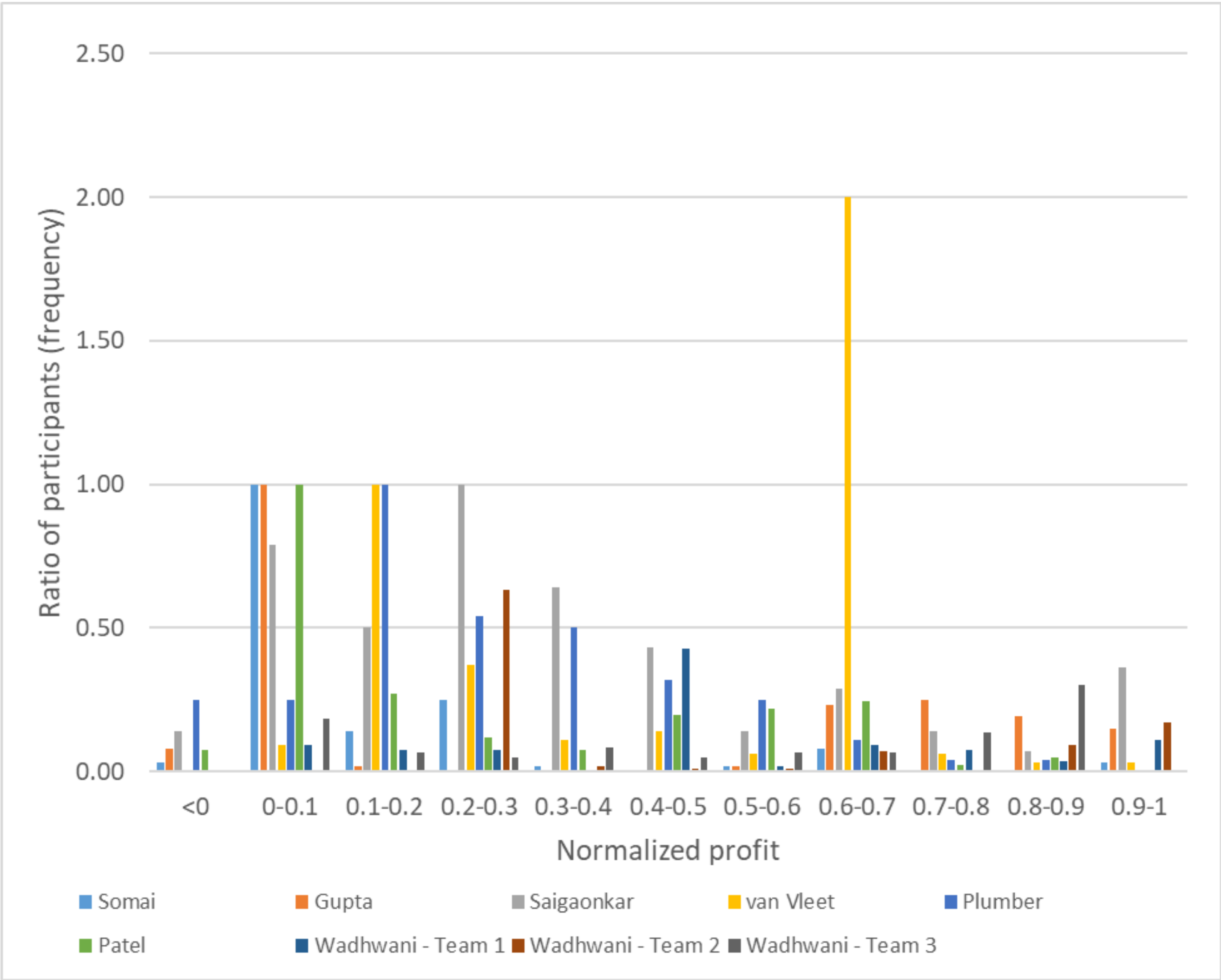


Figure 49: *Comparative analysis of previous studies v. this study*

CHAPTER 5

CONCLUSIONS

Points to make:

- The student's t Test clearly shows that a driven player can destroy the profit margins for all as shown in Game 1.
- The student's t Test clearly shows that a very good player can decent the profit margins even in the face of competition as shown by the Artisan in Game 2.
- Game 3 is tacit collusion and is interesting but anomalous. Three good players are a problem for the purchaser here.
- Rationals are poor performers and profit destroyers

Two new methods have been added to the standard methods to investigate the performance of the players, the first is a round robin of Student's t test comparisons across many games and the second is the determination of the sources for the high profit margins. These high profit margins are not generated uniformly by the players, but there are selective players who generate all the observed high profits and they are not rationals.

- The first hypothesis, that guardians are economically efficient players is true, however it is not exclusive to the guardian personality only. Others too tend to be economically efficient. Thus, the first hypothesis that guardians are economically efficient players is true.
- The second hypothesis, that a bump in the distribution of normalized profit entries occurs at or beyond 0.75 normalized profit range visible, however, the hypothesis that this bump is caused because of the guardians only, is false. In fact, in the first team, there was only one entry in that region for guardian personality. In the second and third teams, both

idealists and artisans performed exceptionally well, so much so that the difference in normalized profit range, using a student T-test was not highly significant when concerned with guardians only.

- The third hypothesis, that the bump so caused it normal in its statistical distribution properties is still a topic of debate. There is a clear trend of two distributions being present in the statistical plotting of normalized profits. One of them is majorly Beta. While, the other is supposedly Gaussian, because human being are involved. More data is required to ascertain that second distribution.
- From the analysis, rational personality type players have been the worst performers. It was a clear observation that these players tend to pick their bids from the bets distribution sample set and can potentially drive the whole process into a loss for both the buyer and supplier, because prices on contracts with unrealistically low profit margins., thus rendering the auction futile. The winner's curse situation was clearly a trait observed in the rational players.
- Furthermore, a distribution fitting to fit a normal distribution was run on normalized profits, and normalized bids for each team and each player in the team. There is a clear movement towards a normal distribution sample space for artisans, guardians, and idealists and this economically efficient. Clearly, rational players are driven to pick their samples from the bets distribution, thus decreasing overall profits, and thus economically inefficient.
- Also, tacit collusion is not a myth when it comes to reverse auctions. Team 3's play is a classic example of collusion. The players performed exceptionally well with no statistically observable results in the student T-test analysis.

- Finally, the student T-test is a good is added as a standard method to investigate the performance of the players. The first is the round of student’s T-test comparisons across many games and the second is the determination of the sources for high profit margins. These high profit margins are not generated uniformly by the player, but there are selective players who generate overall high profit, but they are not rational players.

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