REVERSE AUCTION BIDDING

FURTHER ELEMENTS TO THE GAME THEORY

A Thesis

by

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ABSTRACT

Reverse Auction Bidding systems are increasingly used by some large corporations for the supply of buildings, an example is the major firm Target. The belief is that the Reverse Auction Bidding system improves the efficiency of the bidding system and leads to cost savings during the construction process. Neither statement has been shown to be correct at this time. A game theory was developed for the Reverse Auction Bidding system; this theory postulated that two sub-games exist within the overall Reverse Auction Bidding game. The first sub-game is between the purchaser and the set of bidders. The purchaser is presented with a group of lowest prices that under the rules of the game must be accepted. This group of prices has been shown to have a non-normal distribution in prior research at TAMU. If economic efficiency was to be maintained by the bidding system, one would expect a normal distribution with a tight range on the standard deviation, which does not occur. The second sub-game is between the bidders, who make use of the non-normal aspects of price group to maximize individual returns. All things being equal and given the intent of the game, the purchaser would expect the bidders return to be normally distributed with a small standard deviation representing a tight control on price, which has never been observed in game play. Three types of bidders have been postulated for the set, the first is an economically efficient bidder, an economically inefficient bidder, and a middle of the road bidder.

This study aims to compare statistically the difference between economically efficient bidders, Type ξ bidder, and economically inefficient bidders, Type ζ bidder, in

terms of the statistical properties of the return data. The central hypothesis is that a statistically evident bias exists between the average return generated by the Type ξ bidder and the Type ζ bidder. The addition of the two distributions along with the average return generated by a Type ϕ bidder results in the observed distribution for the group, L. The secondary hypothesis is that Type ξ bidders minimize the price reduction for each bid. The first hypothesis is true, the Type ξ bidder earn on average twice the returns of the Type ζ bidder. The second hypothesis is not true, the Type ξ bidder as a set do not attempt to minimize the bid differentials. Further research is suggested on the statistical properties of the bid differentials as more games are played at TAMU.

DEDICATION

In memory of my grandmother, Ruiyun Ren.

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NOMENCLATURE

Definitions

The following list contains terms associated with the reverse auction bidding game. These terms were defined by the previous RAB researchers at TAMU:

RAB	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).
RAB Game	a standard game is eight rounds of twenty minutes
Round	a single twenty minute period played usually with four players, fifteen minutes is the bid period and five minutes for rest and to allow the computer system to model the actual work week
Game Theory	a formal analysis of conflict and cooperation among intelligent and rational decision makers (van Vleet, 2004)
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).

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.

KTS — a self-assessed personality questionnaire designed to help people better understand themselves and others. It was first introduced in the book Please Understand Me. It is one of the most widely used personality assessments in the world, and its user base consists of major employers including Bank of America, Allstate, the U.S. Air Force, IBM, 7-Eleven, Safeco, AT&T, and Coca-Cola.

SQL — a special-purpose programming language designed for managing data held in a relational database management system. Originally based upon relational algebra and tuple relational calculus, SQL consists of a data definition language and a data manipulation language. The scope of SQL includes data insert, query, update and delete, schema creation and modification, and data access control. Although SQL is often described as, and to a great extent is, a declarative language (4GL), it also includes procedural elements.

Defined Variables in the Game Theory

The defined variables are:

λ player — this represents the bidder group, treated as a single entity for the purpose of game analysis

λ_i player	the i^{th} bidder in the bidding group
υ player	this represents the purchaser
α game	The 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 is deemed to effectively reduce to a two player game, with competition implications
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
i	Site number, $[1 \le i \le 6]$
j	Bid number counter, $[1 \le j \le n]$, a game is not valid without at least one valid bid
n	total number of bids in the game
B_j	j^{th} winning bid, where $\mathrm{B}_v = \sum_{j=1}^{n} \mathrm{B}_j$
k	bidder number $[1, 2, 3 \ldots m]$
m	maximum number of bidders, typically 3, 4, 5 or 10
M_l^k	bidder k, bid set $\{l : 0 \le l \le p\}$
p^k	bidder k, number of bids

$B^i_{\max}$ represents the maximum allowable price for each site i

B_υ is the set of all winning bids, summed to the total cost for the game

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 normally 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 is used to normalize 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.

Δ^k_l Set of price reduction or lost profit for each bid

δ^i_j Element of each set Δ

Type ξ A more economically effective bidder.

Type ζ A less economically effective bidder

Type ϕ Bidder who is within the middle of the range

L	set of all bids for the game, this is a finite closed set, it may be the Φ, but this is improbable unless all players declined to participate. But there may be zero bids for one site during a game, but generally $\{\forall L_{\xi}, L_{\phi}, L_{\zeta} : \mathrm{L}_{\xi} \cup L_{\phi} \cup L_{\zeta} = L\}$ Clearly $B_{\upsilon} \subset L$.
L_{ξ}	set of bids for Type ξ bidders, this is a finite closed set, it may be the $\varnothing$, but this would only occur if all four players had identical returns, improbable but not impossible or where $L \subseteq \varnothing$, generally $\forall L_{\xi} : L_{\xi} \subset L$. It is true that $\sum_{1}^{p^{\zeta}} L_{\zeta} < \sum_{1}^{p^{\xi}} L_{\xi}$, it is true that $\sum_{1}^{p^{\zeta}} L_{\zeta} < \sum_{1}^{p^{\phi}} L_{\phi}$, but it is false that $\sum_{1}^{p^{\phi}} L_{\phi} < \sum_{1}^{p^{\xi}} L_{\xi}$, it may be true but it is not necessary in order for these sets to define the three bidder types.
L_{ϕ}	set of bids for Type ϕ bidders, generally $\forall L_{\phi} : L_{\phi} \subset L$
L_{ζ}	set of bids for Type ζ bidders, generally $\forall L_{\zeta} : L_{\zeta} \subset L$
$\varnothing$	empty set

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CHAPTER I

INTRODUCTION

Introduction and Study Purpose

This thesis summarizes an investigation into a number of Reverse Auction Bidding studies completed at TAMU. This thesis presents the literature review for related to the current research, the study methodology, provides an outline of the results and the analysis and provides conclusions on the research. This chapter outlines the background to the study, summarizes the objectives of the study, develops the hypothesis and outlines the limitations of the study research.

This thesis includes details of the game developed by van Vleet (2004) and as such some the game description material and figures in this report is common to this study and others. It is suggested that a manual should be developed for the game, although this is beyond the scope of this research work.

Background

A reverse auction is a type of auction in which the roles of buyer and seller are reversed. Specifically the bidders compete to obtain business from the purchaser and the fundamental hypothesis is that prices will decrease as the bidders undercut each other. Vleet (2004) initiated the ongoing study of Reverse Auction Bidding at Texas A&M University.

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. And a number of private and government agencies in construction industry are utilizing RAB as their method of procurement. This study continues a long running study into the process and features of Reverse Auction Bidding at TAMU. Van Vleet (2004) initiated the ongoing study of Reverse Auction Bidding at Texas A&M University. The work now includes twenty studies that have developed the game theory associated (Maschler, Solan, & Zamir, 2013) with this game and the statistical techniques used in the analysis of the results for each game (Guhya, 2010).

RAB as a bidding system is distinct from the sealed hard bid, the traditional procurement method used in construction up until the early 1990s. In the traditional sealed hard bid, the lowest price is still the major criterion for awarding bid. However, all sellers only have one time to bid the project almost always anonymously and all bid prices are sealed in the bid package prior to the opening of the tenders. This is a simple game, with one bite of the cherry so to speak. Of course there are variations related to bidder capability, capacity and prior relationship to the purchaser, but provided one uses a pre-registration and review this remains the most economically effective method for purchasing construction related activities and goods (Reinisch, 2011).

The purpose of this study is to investigate the statistical properties of three subsets of the bidding set, L. The bidding set is the set that contains all of the individual bids, essentially an integer set of numbers constrained by the game to the range of 10,000 to 35,000. The three subsets, postulated from earlier work, (Yuan, 2013), are the set of bids for the better bidders, termed Type ξ bidder, and this bidding set, termed L_{ξ} and the poorer bidder, termed the Type ζ bidder, and this bidding set, termed L_ζ, and the average or Type ϕ bidder, with a bidding set termed, L_ϕ.

The set L is then defined as the complete set, $\{L_\phi, L_\xi, L_\zeta\}$. The use of set theory, (Borowski & Borwein, 1989), provides a mathematical formalism for describing the game.

The central hypothesis for this research is based on the observation in early work that some bidders performed significantly better than other bidders. Variable names have been assigned to the three types of bidders identified in previous research, as defined in Nomenclature.

Objective of the Study

The purpose of this study is to compare statistically the difference between the good or type ξ bidders and the poor or type ζ bidders in terms of the statistical properties of the bid differential or Δ sets. In addition, this study also analyzes the statistic property of the profit loss of type ξ bidders and type ζ bidders, defined from the analysis of the Δ sets.

Hypotheses

<u>The central hypothesis in mathematical terms states that:</u>

A statistically evident bias exists between the average return generated by the Type ξ bidder and the Type ζ bidder.

This hypothesis is based on the observation that the returns in the previously studied games are not normally distributed, but show a distribution with two distinct peaks for the normalized profit data (Saigaonkar, 2010) . Normalization in this sense is the transformation of profits into a range from zero to one. Hence, the addition of the two distributions along with the average return generated by a Type ϕ bidder results in the observed distribution for the group, L.

The second hypothesis is that:

Type ξ bidders minimize the price reduction for each bid.

This aspect of game play has not previously been investigated using the existing Reverse Auction Bidding data sets. The theoretical idea is that the better bidders limit their losses on each bid.

Significance

The ultimate goal is to produce a conceptual Turing Machine (Church, 1941) that matches and beats a human bidder without the human bidder being aware that they are playing a machine. There are very many aspects to this problem, not the least of which is determining the strategy for an economically efficient bidder. In game theory, one is interested in the outcomes, which can be difficult to quantify, but for this game the simple outcome for the bidding sub-game is the greatest return. This research will help the further understanding game play methods of the characteristics of economically efficient bidders in Reverse Auction Bidding.

Mikael (2014) postulated that human players will compensate for the actions of a Turing Machine type player and will ultimately beat the machine, if it attempts to play at human speeds. The long term goal would be to develop a flash bidder, although there are ethical issues with this type of future development.

Limitations

The data collected in this study will be the result of TAMU simulated bidding process. In the bidding process, all games will be limited to four players. The bidding process will be based on a concept phase, in which the bidders' only emphasis is the price, however, economic and all the other conditions that may have side effects on the bidding process are assumed steady throughout the period of the bidding process. In addition, there are no professionals from industry participating in this process. All the participants are faculties or students from Construction Science Department of Texas A&M University, the sample size is relatively small and lacking diversity in the background and age.

CHAPTER II

LITERATURE REVIEW

Introduction

This literature review provides a summary of the main elements of the research into Reverse Auction Bidding to this time. An increasing number of construction industry corporations are engaged into application of reverse auctions, which it is postulated can improve market efficiency, procurement process efficiency, and access to larger supplier base to achieve considerable savings in purchase cost. This brief review considers some of these aspects related to RAB.

Texas A&M Studies

Extent literature surveys exist in the prior work completed at TAMU in the period 2004 to 2013 (Chaudary, 2009; Gregory, 2006; Guhya, 2010; Gujarathi, 2008; Gupta, 2010; Machado, 2009; Panchal, 2007; Piper, 2013; Plumber, 2010; Saigaonkar, 2010; Shankar, 2005; van Vleet, 2004; Zhou, 2012). This work initially looked at the development of the web based system, followed by consideration of personality types and its impact on bidding and recently on the development of the game theory related to reverse auction bidding.

Other Auction Types

This section presents a summary of other auction types and issues associated with the system including:

- Traditional Types of Auctions
  - English Auctions

    - Dutch Auctions
    - Sealed First Price Auctions
    - Vickrey Auction
    - Other Types of Auctions
    - Reverse Auction Bidding
- Reverse Auction Bidding in Construction Industry
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- Mathematical Theory of the Reverse Auction Bidding
- Bid Arrival Timing and Other Game Issues
- Summary

Traditional Types of Auctions

An auction is that one can procure goods and services through the use of a bidding mechanism. There are different kinds of traditional auctions and Klemperer (1999) classified four main types of auctions. These four auctions are English auctions, Dutch auctions, sealed first price auctions and the Vickrey auctions. There are also other types of auctions, including the Japanese auctions, the Take-it-or-leave-it auctions, and the Candle auctions, to list some of the variants.

English Auctions

English auction, also known as forward auctions or ascending auction is the most commonly used form of auction. It is suitable for limited supplied goods or unique sold items (Sam Wamuziri, 2009). In English auctions, the bidding process was started with the lowest acceptable price for seller, usually the reserve price. Each bid after that point must exceed this price. As a result, a seller could keep the item from selling for less than this reserve price, where it has been set at the beginning of the auction. Bidders then begin bidding over the items against each other by placing higher price than the last bid. The auction terminates when no more bidders are willing to offer a higher price. Moreover, the item sells at the highest bid. A seller will hold the items, if the final bid price does not exceed the reverse price. The notable characteristic of English auction is that each bidder knows the level of the current best bid during the whole auction process (McAfee & McMillan, 1987).

This type of auction is used to sell antiques or artworks. The point is to maximize returns by allowing the market to establish the price points (Hartford, 2005). As you would expect for these types of auctions for topline artwork the market has developed to a few centralized locations in England and New York.

Dutch Auctions

Dutch auction, also called multiple items auctions or open descending price auction (Krishna, 2009), is named for the Dutch tulip auctions. It is a converse type of auction when compared to the English auction. The seller initially calls a very high price. Seller will constantly lower the price through each round of bid until a bidder is finally willing to accept this price. The Dutch auction relates the price paid to the time of the auction. Namely, the longer the auction goes on, the lower the price.

In a Dutch auction, rational bidders always have their own clearly acceptable valuation of the item for sale. The auction begins with a price, which is inevitably over this valuation, while the bidder keeps waiting. Once the successively lowered sale price comes down and reaches this amount, a buyer may accept this offer but obtain a zero profit. Waiting longer to bid a lower price will increase the bidder's profit. However, this behavior provides the economic risk that the bidder may end up losing the item to another bidder (Sam Wamuziri, 2009).

So Dutch auctions force bidders to think about their own valuation of the item before the auction and act decisively while bidding. This type of auctions is often used for perishable items (McAfee & McMillan, 1987) like flowers in the Netherland, fish in Israel, tobacco in Canada, and used furniture. These items are used locally, in contrast to the art auctions, where the product may end up at any location in the world that a major art collector chooses to live.

Sealed First Price Auctions

Sealed first price auction is a first price sealed bid auction (FPSB). Different from English auction, all bidders just simultaneously submit only one bid (Krishna, 2009). Like the English auction, the item goes to the highest bidder. Sometimes, a seller will choose the winner randomly from those who name the same highest bid, if there is a tie. The fundamental rule of sealed first price auction is that all bidders could not know the bid information of other competitors before the end of the auction and also couldn't adjust their own bids according to other's bids (McAfee & McMillan, 1987).

In sealed first price auction, the bidder gets three options. They are:

- to bid his/her full valuation
- to bid a shaded value of the full valuation
- to bid considerably under the valuation(Sam Wamuziri, 2009).

Options 3 may lead the bidder to losing the bid to their competitors, while option 1 could gain the bidder no profit if their bid was successful. As a result, rational bidding strategy for sealed first price auction should be bidding with a shaded value of the full valuation. With this approach, the bidder could make a profit and win the bid at the same time. The bidder gains more profit with higher shaded value held. Too much shaded value may increase the risk of losing the bid.

So, this kind of auction forces bidders to guess the valuation of others' and bid a little more than this amount (S. Wamuziri & Abu-Shaaban, 2005). Some UK construction procurement uses this type of auctions. UK construction is often based on the work by the Quantity Surveyor who provides an estimate of the construction costs to the purchaser (RICS, 2000); this system has a number of economic advantages for the purchaser in having:

- a pre-bid estimate from an estimating expert
- a consistent set of quantity take offs guaranteed by an independent expert
- a standard for the quantity methods that is agreed across the industry

- a document that has been tested in the courts

Vickrey Auction

Sealed second price auction is similar to sealed first price auction, where all bid will be sealed and revealed at the same time. What makes them different is that the winner of this kind of auction only needs to pay the second highest price bid other than the highest one. It is also called Vickrey auction to commemorate the economist who first put forward that this type of action as it pushes each bidders to bid their true valuations (Sam Wamuziri, 2009). Overall, the best strategy of sealed second price auction is to bid the true value, which is identical to English auction. However, they have different information transparency (Sam Wamuziri, 2009), since sealed second price auction needs information transparency.

In addition, each bidder is in a passive condition. As a result, sealed second price auction is seldom used in practice. A sealed second price auction is a very good tool to model bidder‘s behavior, since bidder needs to bid their true value. Vijay (Krishna, 2009) pointed out that sealed second price auction is in some ways similar to proxy bidding system, which is used by Internet auction site like eBay. In eBay, a bidder who bided the highest is awarded the bid by actually paying the current highest bid plus the current bidding increment (Krishna, 2009).

Other Types of Auctions

Besides those four types of auction mentioned above, there are still some other types, like Japanese auction, Take-it-or-leave-leave-it auction and Candle auction. In a Japanese auction, the price rises up through each round of bid. Each bidder shows if they are willing to stay at the current price level for each round. Once a bidder quits, the bidder will not reenter the auction. In Take-it-or-leave-it auction, the seller announces the price of each project, and bidder can choose accept ("take"), which leads the end of auction, or reject ("leave") the bid, after which seller goes to the next. The clear advantage of this type of auction is that protect the private valuation information (Sam Wamuziri, 2009). In Candle auction, the bid is awarded to the last bid price before a candle burns out (S. Wamuziri & Abu-Shaaban, 2005). This is similar to the RAB where a timer runs out.

Reverse Auction Bidding

Reverse Auction Bidding is a relatively new type of procurement method, which has the roles of the bidder and seller reversed, which has been studied for about 20 years. It is also regarded as an internet-based system. This new type of auction that was known in the mid-1990s as Business-to-Business (B2B) online Reverse Auction (Schoenherr & Mabert, 2007). The establishment of Web auctions as a tool to facilitate exchanges between buyers and suppliers is emerging as a new business paradigm. After this experiment a part of the Naval Supply Systems Command, in May 2000, tried Reverse Auction Bidding (Mabert & Skeels, 2002).

At the same time, many Fortune 1000 companied began tasting the benefits this new method of procurement (Emiliani & Stec, 2001). Web auctions of products like service or commodities are using sophisticated advertisement techniques to display the product being offered for sale. United Airline has started an online auction system for first class upgrade, this system has two similarities with Reverse Auction Bidding, the first one is that a group of bidders make offers for a special seat, the other one is the United Airline will select the best offer to maximize their returns, which is also the market driven for Reverse Auction Bidding. The overall expectation from this published research is that the overall average price for bids obtained using the Reverse Auction Bidding Process would be lower than a hard bid system.

This statement has not been shown to be correct at this time, nor is ever likely to be provable.

Reverse Auction Bidding in Construction Industry

In construction, the use of Reverse Auction Bidding is increasing. At a scheduled time, the owners open a bidding site with a “game” and bidders who are interested in the project submit their price to the web-based system. Then the web-based system posts the prices on the site for all bidders to compete. Contractors can lower the price to win the bid in a certain period of time. Compared to traditional sealed bidding, in which all bids from other bidders are kept confidentially, Reverse auction bidding provide opportunities for subsequent bidding after prices are open (Shankar, 2005)

Some corporations use the Reverse Auction Bidding method to buy their construction materials. For instance, the Minnesota Department of Administration procure the construction products with the RAB method. In addition to the purchase of commodities, in a recent case, Pennsylvania’s Department of General Services also use the RAB technique procure construction services.

Several private companies, such as Target have used Reverse Auction Bidding systems (Shankar, 2005; Yuan, 2013).

Posited Savings for RAB

One study indicated that a properly executed reverse auction has the potential to save an additional 8 percent to 20 percent cost for an organization below its current price (Guillemaud, Farris, & Hooper, 2002). The Minnesota Department of Administration benefited from the use of RAB, which enable the Minnesota Department of Administration drop the price of the aluminum it purchased from $1.555 per pound $1.029 in 45 minutes. The state achieved a saving of $150,000 for taxpayers about over the course of five years. As summarized by the state, “A reverse auction gets to the absolute lowest price a vendor will offer, as opposed to a bid price [under the traditional sealed bid approach] that might not be the bottom line price” (Shankar, 2005)

RAB has its own flaws or challenges to not only sellers but also buyers, everything has two sides. Strategic relationships and partnership between buyers and sellers might be impaired. “Because of excessively focusing on price, the online reverse auction has caused a move away from the close partnerships that were once successfully working for both buyers and sellers. An empirical study concluded that high emphasis on two main benefits of reverse auctions, purchase price reduction and time savings (procurement process efficiency), negatively impact the buyer-seller cooperation and sellers’ strategic relationships” (Pearcy & Larry, 2007). In order to win the bid, a seller has to lower its margin to a bare minimum. With such a low margin, there is no room for any adjusting and adapting to unforeseen situations. It can jeopardize long term buyer-supplier relationships; reduce the suppliers’ trust and cooperation. Ultimately, it can even lead to the erosion of the supply base and result in less competition and higher prices.

Figure 1 clearly shows the problems with these claims. Results from earlier studies showed that the bidding set L has a distinct non-normal distribution when the data is normalized.

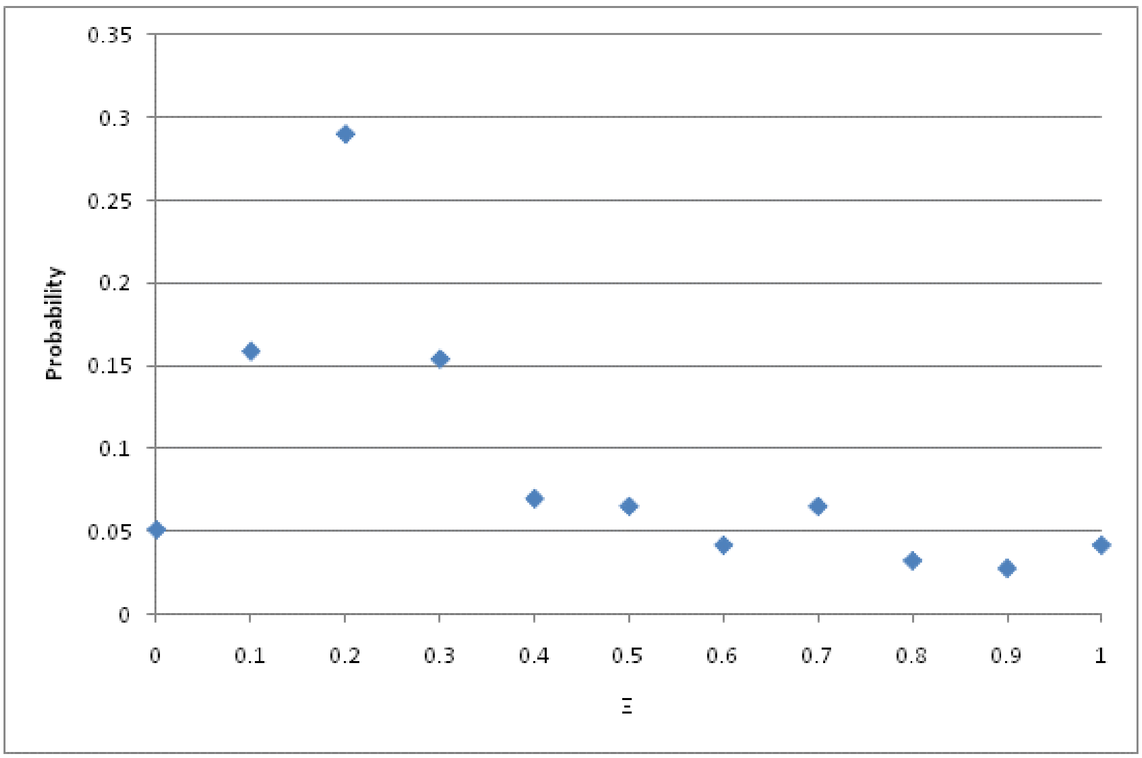

Figure 1. Normalized profit data for two earlier studies, after Saigaonkar (2010)

A good game strategy can provide some players with returns higher than the average. Anecdotal evidence on Reverse Auction bidding shows that this happens in real systems. In terms of game theory, an auction can be considered a game between players.

One player, υ, has a good for sale in a traditional auction and a good to purchase in a reverse auction.

The other player, λ , is typically a group that is bidding to purchase the item in a traditional auction or sell the item in a reverse auction. The λ player derives from the concepts put forward by Church (1941). The λ player sees a different statistical distribution set for each player in the λ group, but the υ merely observes one statistical distribution set. These statistical distribution differences form the basic element to this research work, as the point is to develop a machine bidder that outbids all human bidders, but is humanlike (Abelson, Sussman, & Sussman, 1987; Winston & Horn, 1989).

Procured Items

The discussion, which questioned the feasibility of Reverse Auction Bidding of all kinds of products, has never stopped. Some researchers (Mabert & Skeels, 2002) studied some cases and concluded that Reverse Auction Bidding could not be suitable for every purchasing contract. Products, like strategic items and direct inputs, are not that accessible to Reverse Auction Bidding due to their long-term contract requirement or oligopoly among sellers, (Schoenherr & Mabert, 2007). The suitable ones included complex and highly-engineered items (Wagner & Schwab, 2004) or standard projects. Jap (2002) put forward that the only suitable products should be commoditized products.

Schoenherr & Mabert (2007) explore this myths that Reverse Auction Bidding is commodities-products-only auction. They suggested having Reverse Auction Bidding for non-commodities products by refining the RFQ order, conducting market research and analysis, defining detailed and specific attributes of projects, and using specialized third-party consultant.

Legal Issues

As a new modern method of procurement, Reverse Auction Bidding attracted more and more attention from manufacturing and service sector business and government agencies. Its popularity also raised the concern of its legal and contractual issues. Research dealing with legal issue indicated that there was some unfair trade practice (Engel & Emiliani, 2007) during Reverse Auction Bidding. The unfairness came from the unequal positions of buyer and sellers.

Sellers were facing sort of coercion in Reverse Auction Bidding. Horlen, Eldin, & Ajinkya (2005) analyzed the future legal challenges of Reverse Auction Bidding in terms of some legal grounds, like Federal Trade Commission, Anti-Dumping Act of 1916, Robinson-Patman Act, Clayton Antitrust Act and Business Method Patents.

Reverse auction was banned by the Federal Acquisition Regulation (48 CFR 245.610 and 48 CFR 15.610), because some flaws in legal performance (Merson, 2000), however, the prohibition was later removed. Though legal challenges existed in Reverse Auction Bidding awarded contract, Reverse Auction Bidding is still appealing to public buyer, like large international companies and government. The state of Texas, Pennsylvania, Kansas, New York State, Missouri, Minnesota, and Wisconsin (Horlen et al., 2005) had approved the legislation to allow Reverse Auction Bidding.

Economically the system is transparent and one could argue fair for all parties, provided that a coercive relationship does not exist or the game is not rigged, (Giampietro & Emiliani, 2007).

Buyer to Seller Relationship

Since price became the relatively decisive element in Reverse Auction Bidding process, the expected side effect is the negative impact Reverse Auction Bidding might bring to the buyer-supplier relationship. It is possible that buyer may omit the non-price elements like reputation, quality and previous partnership etc. This may result in deterioration of previous seller-buyer partnership. People question whether Reverse Auction Bidding can be used in procurement, which requires long-term seller-buyer relationship. Reversed auction was recognized to bring new business to new sellers who could offer lower price, while making current seller annoyed at losing the hard-won long-term business (Emiliani & Stec, 2005). Due to its price oriented characteristic, Reverse Auction Bidding could lead to profit margin erosion (Emiliani & Stec, 2004) and coercion to sellers. In construction industry, seller-buyer partnership could be impaired when contractors, who won the contract with lowest price in Reverse Auction Bidding, would charge higher prices for change orders and extra work if client ordered, in order to keep their profit margin (Sam Wamuziri, 2009).

While some researchers tried to refute by putting forward the idea that Reverse Auction Bidding could potentially benefit both sellers and buyers at the same time. Some researchers suggested that buyers, who need collaborative and long-term relationship sellers, can use Reverse Auction Bidding as a process improvement tools to check market price instead using it as a price weapon (Smart & Harrison, 2003). Also, the buyer-seller relationship can be kept fair to all by prequalifying bidders with non-price elements, detailing RFQ, providing education, training and assistance to bidders during Reverse Auction Bidding process (Schoenherr & Mabert, 2007).

An important economic observation is when all things are equal the prices should be the determining factor (Hartford, 2005) for projects funded by shared equity. Reinisch (2011) showed the problems with alternative bidding systems.

Reverse Auction Bidding Myths and Reality

Schoenherr and Mabert (2007) studied 30 case studies for companies that had participated in RAB systems, which enable them investigate the most common myths related with Reverse Auction Bidding. They discussed myths for Reverse Auction Bidding:

- Reverse Auctions are only about the price;
- Reverse Auctions are only suitable for commodities;
- Reverse Auctions damage the buyer-supplier relationship;
- Savings in Reverse Auctions will decrease;
- Reverse Auctions are passing fad.

Figure 2 shows the current myths about reverse auction in the industry. Schoenherr and Mabert (2007) studied the reality vesus the myths based on their study of 30 companies.

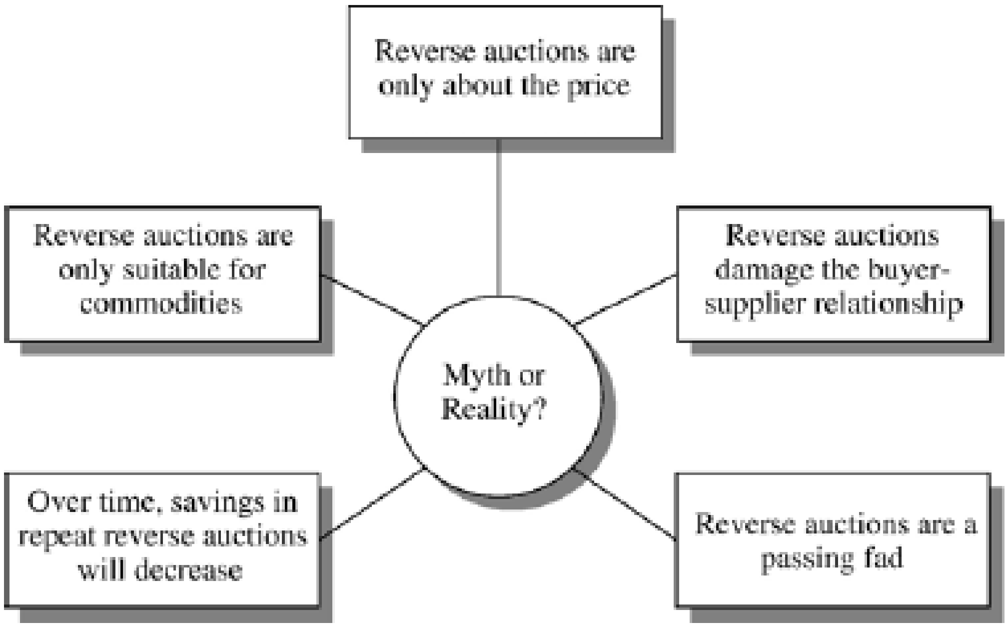

Figure 2. Common RAB myths after Schoenherr and Mabert (2007)

The findings are:

- While a lower price is one objective in reverse auctions, it is often not the most important one, and can be easily complemented with non-price attributes
- While commodities are usually easier candidates for reverse auctions, non-commodity items can also be put up for bid successfully
- While reverse auctions can hurt buyer–supplier relationships, there are many ways to prevent that from happening
- While first-time bidding events likely result in higher savings, continued cost advantages are possible

- While reverse auctions will not be used as much as in the past, they are here for the long-run

Influence of Personality Types to Reverse Auction Bidding Outcome

Students from Texas A&M University have conducted studies on RAB for the last decade. The research was commenced by van Vleet (2004), the theoretical basis of the study is the simulated bidding process which reflected the project of supply of slabs in Houston. In the following year, Shankar (2005) tested the methods from van Vleet's study and showed that the results could be replicated. Rogers (2010) suggested that personality may have an impact on returns.

Further studies have been conducted by Machado (2009) and Saigaonkar (2010) at TAMU to analyze the bidders' personality impacts on the results. The work is based on the Keirsey Temperament Sorter test. Keirsey Temperament Sorter is a self-assessed personality questionnaire designed to help people better understand themselves and others. The test and scoring method are presented in Appendix A and B respectively.

The Keirsey Temperament Sorter test has seventy-one questions, and identifies sixteen types of personalities that fit into four groups SJ - The Guardians, SP - The Artisans, NT – The Rationals, and NF - The Idealists.

Table 1 shows the Keirsey Temperament Sorter Test categories.

Table 1
Keirsey Temperament Sorter Matrix

	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):
			Mastermind (INTJ): *Entailing*
		Engineer (NTP) *Constructing*	Inventor (ENTP): *Devising*
			Architect (INTP): *Designing*
Observant (S)	Guardian (SJ) *Logistical*	Administrator (STJ)	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):
			Composer (ISFP): *Synthesizing*

Table 2 shows the categories in the KTS system.

Table 2
Summary of the Individual Components of the Different Personality Types

#	Name	Meaning
E	Extraversion	Feel motivated by interaction with people. Tend to enjoy a wide circle of acquaintances, and *gain* energy in social situations
N	Intuition	More abstract than concrete. Focus attention on the big picture rather than the details, and on future possibilities
F	Feeling	Value personal considerations above objective criteria. In making decisions, often give more weight to social implications than to logic
J	Judgment	Plan activities and make decisions early. Derive a sense of control through predictability
I	Introversion	Quiet and reserved. Generally prefer interacting with a few close friends rather than a wide circle of acquaintances, and *expend* energy in social situations
P	Perception	Withhold judgment and delay important decisions, preferring to "keep their options open" should circumstances change
T	Thinking	Value objective criteria above personal preference. When making decisions, generally give more weight to logic than to social considerations
S	Sensing	More concrete than abstract. Focus attention on the details rather than the big picture, and on immediate realities rather than future

This research has shown tentatively that the major personality type of Guardian always gives best performance in comparison to the other personality types. But in the recent study conducted by (Piper, 2013), three guardians are beaten by an idealist. This requires further studies and demonstrates the complexity of the personality problems. A significant amount of work has been completed on personality impact at TAMU, clearly personality is one factor that affects performance.

Mathematical Theory of the Reverse Auction Bidding

The earliest research was interested in the ethical issues associated with Reverse Auction bidding systems. The main conclusion is that a purchaser is free to use a RAB system to purchase good, there are however several issues:

- If only a single bid is submitted it is not likely to be at the lowest cost
- Single bids occur frequently even in competitive games
- humans make mistakes and miss things

This mathematical theory has been used to review a number of case studies completed at TAMU, both with graduate students and now a set of four professional estimators (Piper, 2013). (Guhya, 2010) defined the bidders as Type ξ to represent a more economically effective bidder and as Type ζ to represent a less economically effective. Nichols (2010) defined Type ϕ Bidder as bidders who is within the middle of the range for complete the set L. Type ϕ have not yet been formally and statistically observed (Nichols, 2010).

(Guhya, 2010) also discussed the Mathematical Theory of the Reverse Auction Bidding. Consider a Reverse Auction Bidding game where the υ player is willing to accept bids of the type shown in equation (1):

$$\mathrm{B}_j = \mathrm{K} + \Xi_j \Gamma, \tag{1}$$

Γ represents the upper limit the υ player is prepared to pay in the game above the nominal minimum bid amount K. A negative Ξ 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. The concept of Γ can be attributed to Professor Feigenbaum (Guhya, 2010), who considered there had to be an upper limit everyone was prepared to pay for a service or good.

The bidding period for each game lasts for a set time, τ, in this case it is 15 minutes. The total cost for υ player is shown in equation (2):

$$\mathrm{B}_v = \sum_{j=1}^{n} \mathrm{B}_j, \tag{2}$$

This total cost is based on the accepted lowest bid for each job, where a valid bid was submitted by the λ player. Each λ_i player then has a unique set of bids and a unique set of jobs, with a total return to the λ_i player defined by a simple summation.

The results of this statistical analysis using equation (1) and (2).

Figure 3 shows the normalized profit levels for the four player game

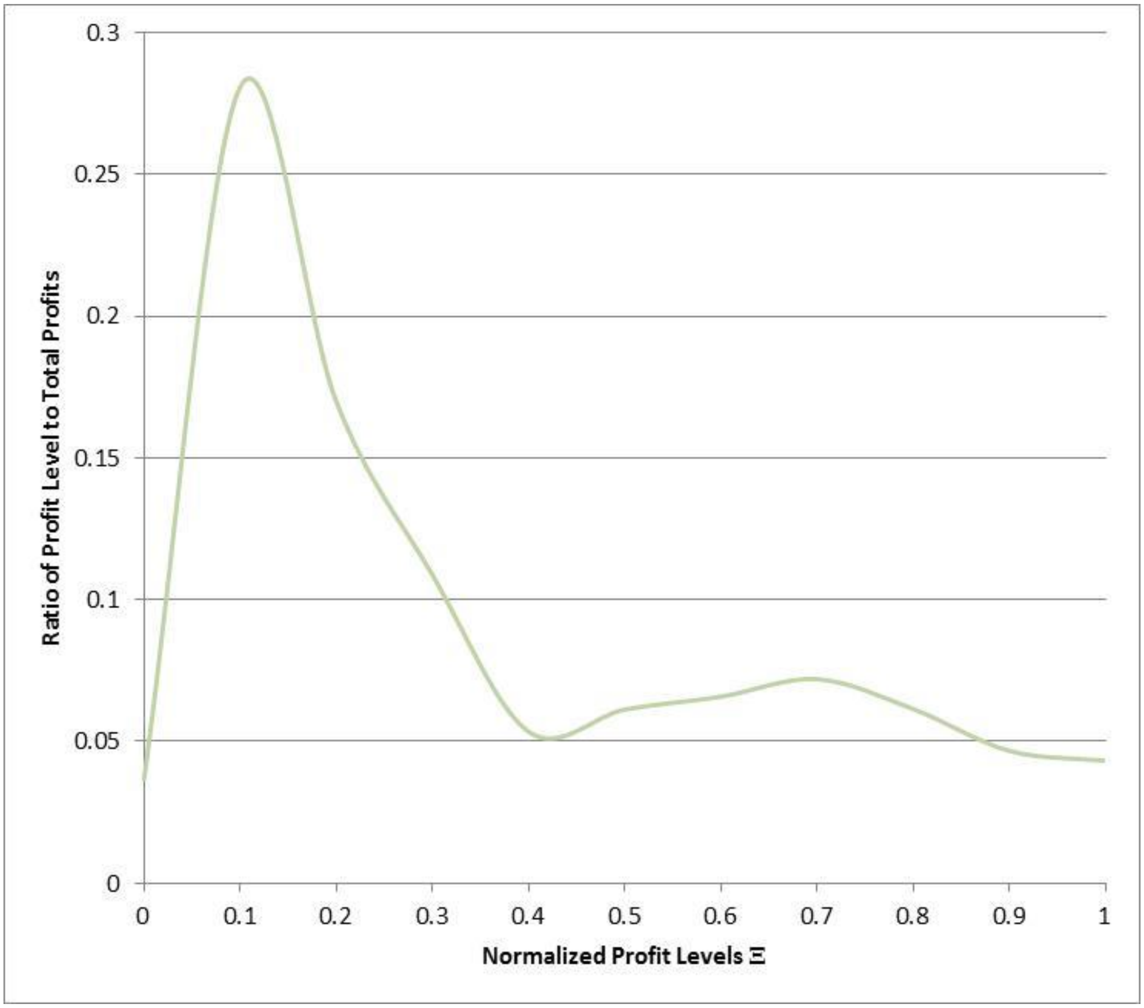

Figure 3. Normalized profit levels for the four player game

There are clearly two elements to the distribution, which has been consistent across game play from the earliest studies.

Current Analysis

The current stage in the analysis is to analyze the statistical properties of the profit drop on each bid, where the lost profit on a bid is defined as Δ_L^k . It is postulated that the statistical analysis of the sets of lost profit, Δ_L^k , data will provide an indicator of the quality of the players. The data set of interest is shown in equation 3:

$$\mathrm{B}_j^i = B_{j-1}^i - \delta_j^i \, , \tag{3}$$

Bid Arrivals

A research group has studied the arrival time of eBay bidding (Shmueli, Russo, & Jank, 2007). They stated that the arrival time of eBay bidding will fit the BARISTA model. The BARISTA (Bid ARrivals In STAges) is a three-stage nonhomogeneous Poisson process. The first stage is “espresso stage” (short and intense), in which the biding start. The second stage is called macchiato stage” (stained), which is during the mid-auction period with increasing intensity. The third stage is last moment of bidding, called “ristretto stage” (extra intense). In this stage, there are extremely intensive activities. This study gives instructions about the best time to bid. A Poisson process is a special type of Markov process that happens in a fixed consecutive time period (Boxma & Yechiali, 2007). As a continuous-time process, it is a mathematical model of a completely random series of events (Cox & Lewis, 1966).

Yuan (2013) analyzed 6674 reverse auction bidding bid arrival times for nine previous TAMU reverse auction bidding case studies. Table 3 shows the individual Reverse Auction bidding games used by Yuan.

A Poisson process counts the numbers of occurring events along the timeline and the time of the occurred events in a certain time interval. According to its characteristics, it is also a type of point process of the real half line. Yuan found that the results show that the Poisson process model for the arrival times fits the non-homogeneous Poisson process

(NHPP) model. The results from her study have the similar heterogeneity in RAB bidding dynamics to the situations of eBay online auction that were studied by others (Russo, Shyamalkumar, Shmueli, & Jank, 2004; Shmueli, Russo, & Jank, 2004; Shmueli et al., 2007).

Table 3
Reverse Auction Games studied by Yuan

Experiment Date	Researcher ID	No. of Contractors	No. of Section	No. of Projects	No. of Bids
5/4/2004	1	5	8	86	773
5/29/2006	2	4	25	118	192
6/4/2006	3	9	13	156	1077
11/5/2007	4	4	5	43	346
4/6/2010	5	5	8	54	804
4/3/2010	6	37	10	179	776
6/8/2010	7	4	10	97	865
6/10/2010	8	4	9	92	759
6/11/2010	9	4	9	91	1082
TOTAL	9	76	97	916	6674

Figure 4 shows a plot of the bid arrival times for the ninth case study, completed in November 2010. The data shows the bids pack into the higher end of the bidding time of 900 seconds, with most bids in the period 700 to 900 seconds.

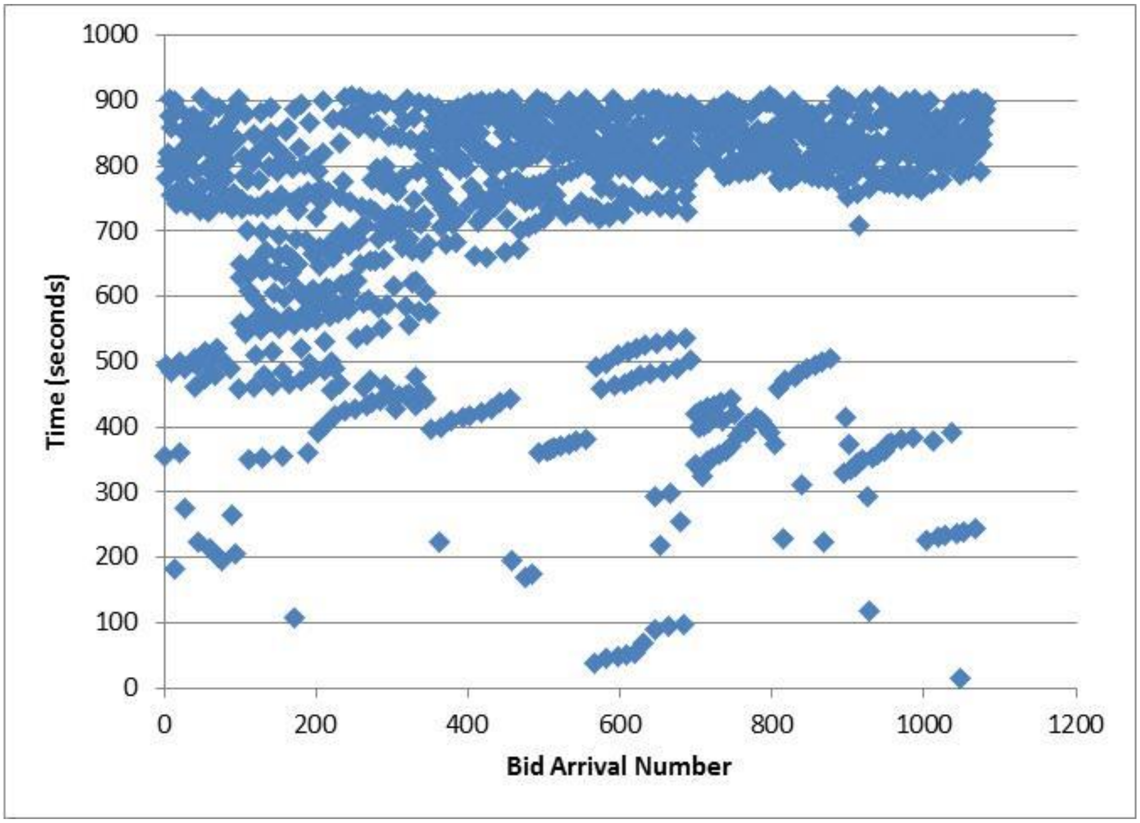

Figure 4. Bid arrival time data for case study nine

Yuan divided the 900 seconds of game play into 180 intervals of five seconds each. She counted the arrival times for each 5 second interval for the complete data set. The results are plotted in Figure 5. The process has a theoretical upper limit of infinity, but one is constrained by the speed of human typing. Yuan in a simple study showed that a cutoff number of bids per second existed and determined this value. She showed that the upper limit of 140 matches the value reasonably.

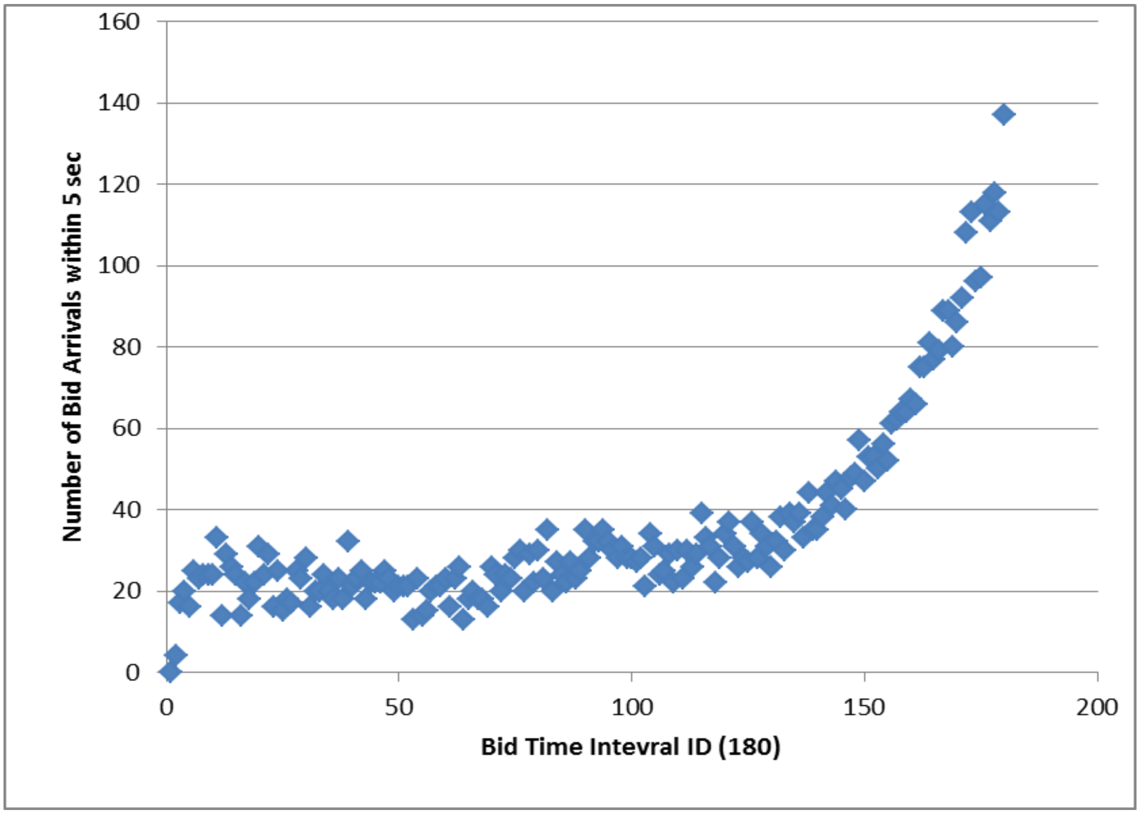

Figure 5. Bid arrivals for complete set

The author concluded from the analysis that reverse auction bidding bid arrival times follows a Poisson process, as for the eBay data (Shmueli et al., 2007).

One of the main issues over the last decade, relates to the issue of timing. The game is played on the internet, the clock time on the various devices may be different and most likely are, causing issues on determining “finish time” for each game. This is not a trivial issue, and one that should be of concern to all involved in such games.

Summary

As an innovative procurement method, the application of RAB is increasing and developed. This literature review introduces existing procumbent methods and their characteristics. Previous researched mainly studied on its external effects of RAB, such as potential savings, the applicable industry, related legal issues and effects for the relation between buyers and seller. Further studied discussed the advantages of Reverse Auction Bidding, which mainly discusses the cost savings; while, the some researchers also imply that Reverse Auction Bidding has its flaws, such as impairing the long-term seller-buyer relationship.

The published article studying RAB dynamics (biding strategies and bidders' performance) is rare, while some researchers studied the eBay auction performance. Because the eBay online auction and the Reverse Auction Bidding have significant similarities in bidding process, this literature review referred some studies on eBay online auction. Russo (2010) has studied the arrival time of eBay bidding. She stated that the arrival time of eBay bidding will fit the BARISTA model. The BARISTA (Bid ARrivals In STAges) is a three-stage nonhomogeneous Poisson process. The first stage is "espresso stage" (short and intense), in which the biding start. The second stage is called macchiato stage" (stained), which is during the mid-auction period with increasing intensity. The third stage is last moment of bidding, called "ristretto stage" (extra intense). In this stage, there are extremely intensive activities. This study give instructions about the best time to bid. Yuan (2013) analyzed the bidding data of Reverse Auction Bidding from previous 9 experiments from TAMU, and the results have the similar heterogeneity in RAB bidding dynamics to the situations of eBay online auction that were studied by other Russo (2010).

van Vleet (2004) started the ongoing study of Reverse Auction Bidding at Texas A&M University. This research continues today with twenty-four studies completed to date. The theoretical basis of the RAB study is the simulated bidding process, using the supply of house slabs in Houston. The work is repetitive and simple, the participant is assumed to have a work capacity of three slabs per week, a rain element is introduced to provide a random element to the ability to complete work and the bank is willing to increase additional capacity for a fee, although for historical reasons the fee is termed a loan.

Not all of the studies are suitable for use in this study, because of constraints introduced by the research question of interest to a particular study, such as owner's interference. Nine studies had data suited to this study.

Studies have been conducted by Machado (2009), Guhya (2010) and Saigaonkar (2010) at TAMU to analyze the bidders' personality impacts on the RAB returns. The studies are based on the Keirsey Temperament Sorter test. There have been studies in the areas of game theory, tacit collusion among bidders, the significance of personality, the RAB game for the role variants of guardians in different types of industrial and some specific cases studies.

CHAPTER III

METHODOLOGY

Introduction

This chapter outlines the methodology used for the Reverse Auction Bidding game site and the specific features applicable to this research study. The chapter contains a presentation on the game description, data structure and data analysis methods.

Game Description

van Vleet (2004) was interested in the ethical aspects of Reverse Auction bidding. He developed a simple game to study aspects of RAB (Kim, 2004). The simplicity introduced by van Vleet has allowed for significant exploration of personality, bid timing and now bid differentials. In the real world, prior to a RAB round, all sellers might have gone through a prequalification selection stage, so that final bid selection is based solely on submitted price. The assumption in this study is that only those who are prequalified can be involved in RAB bidding. During the auction process, prequalified sellers can bid multiple times anonymously. The TAMU web based system uses anonymous login names for each bidder to ensure a fair system, but participant selection is from students who have some construction industry experience.

Guhya (2010) in his review of the first case study outlined the RAB game as played at TAMU as an algorithm. The algorithm is shown in Figure 6. All the data is stored in the SQL dataset first and transferred in Microsoft EXCEL for analysis. Recently the site has been redeveloped as an ASP.NET MVC 4 site to provide a modern interface to the Microsoft SQL Server database (Paz, 2013).

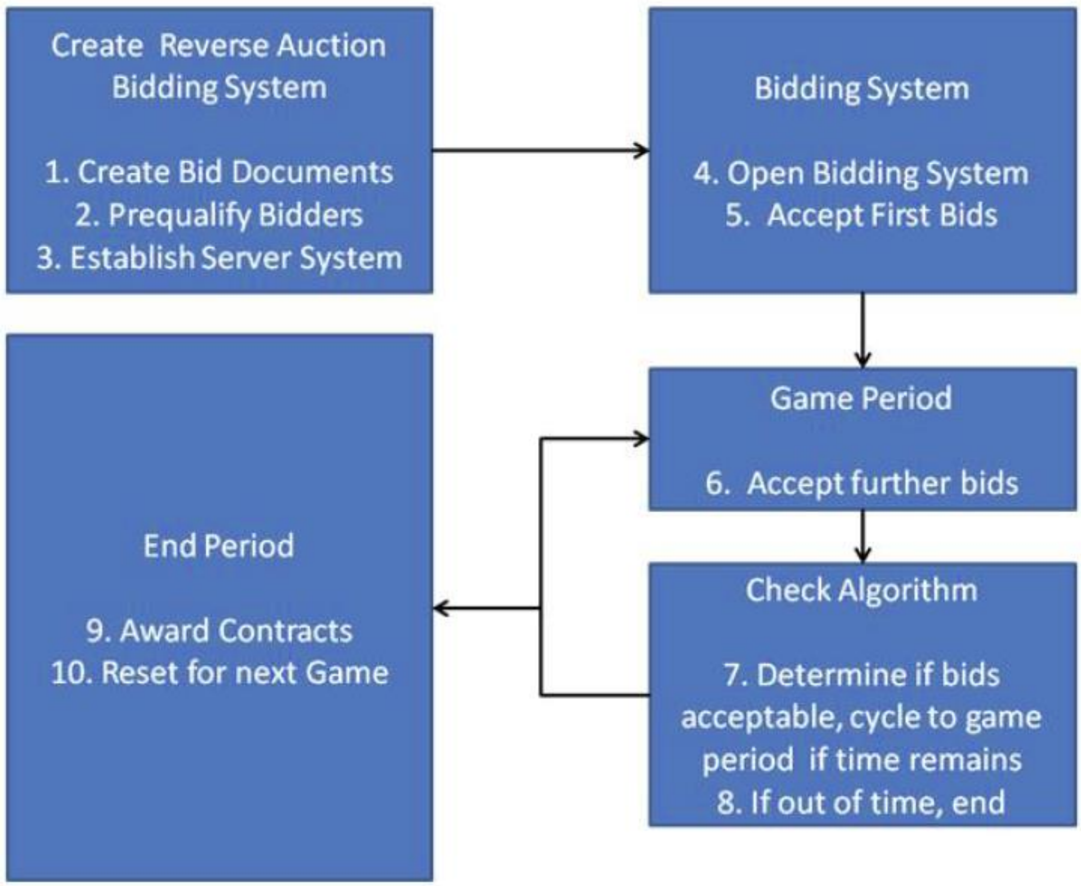

Figure 6. Reverse Auction Bidding general algorithm after Guhya (2010)

The idea is to develop some differences in the construction costs so that a single player could not follow a simple pattern to play the game. This system has been maintained in all games.

van Vleet selected six sites in Houston for the game play. Figure 7 shows a map of the six sites used in all games since 2004. He assumed that all costs are based on the distance from Sugarland as the contractors would be near the purchaser. This is a reasonable assumption for this game study, providing some differentiation in costs for each site.

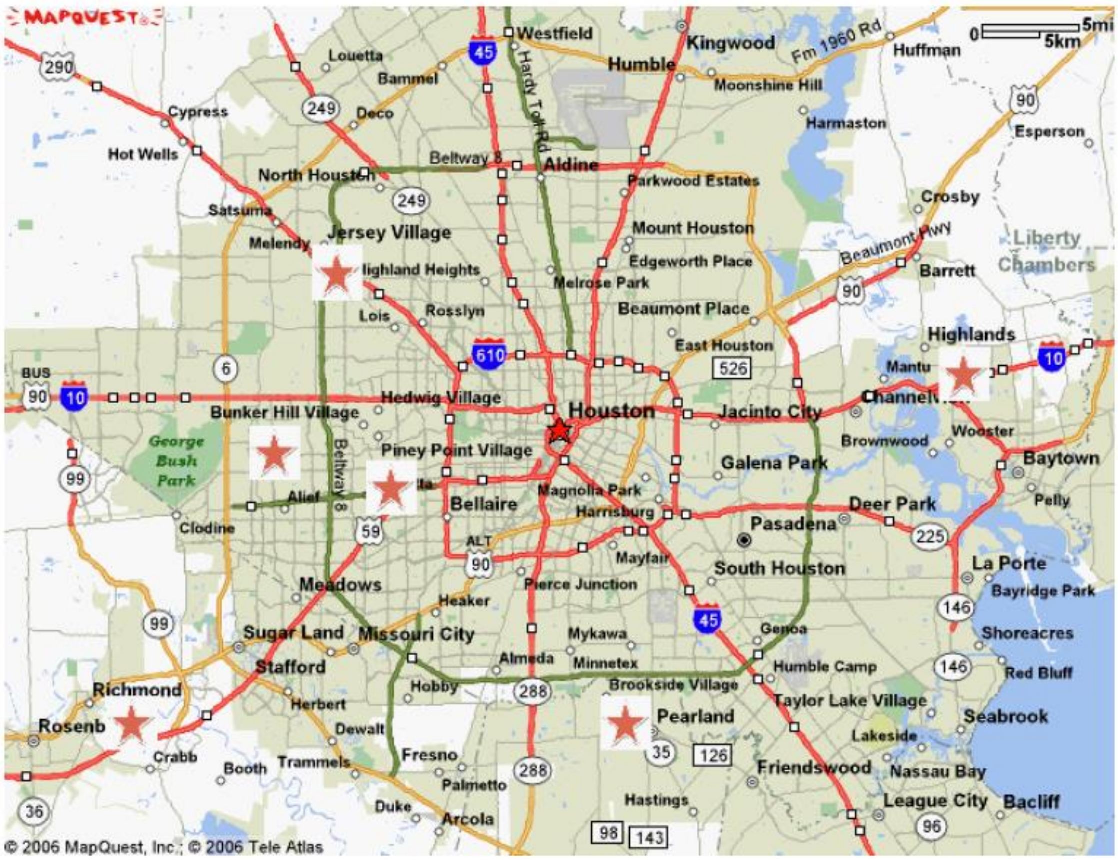

Figure 7. Construction site locations in Houston

The basic scenario developed by van Vleet. Significant advances have occurred with the web site; however, van Vleet established all of the critical factors for the game. The timing of each round of the game, representing a week, was set at 20 minutes, with 15 minutes of bid time and 5 minutes of construction time. One subsequent game modelled on a ten-minute week proved to be a disaster to play as a game and this idea was abandoned. Stable economic conditions are assumed to exist for the duration of the work. A game generally takes from three to four hours. Each game has eight to nine rounds of play, each round model a week in a real world scenario, but for efficient play is modelled as a twenty minute interval. The interval has fifteen minutes of play or bidding time and five minutes for recovery.

Table 4 shows the location names for the six sites and the distance from the purchaser's main office location in Sugarland.

Table 4
Location of the Construction Sites in Houston

Site #	*Location of Development*	*Distance from Sugarland (kilometres)*
1	Brookside Village	41.6
2	Piney Point Village	24
3	Highlands	70.4
4	Jersey Village	40
5	Bunker Hill Village	27.2
6	Richmond	14.4

Table 5 shows the site development costs for each of the locations. The base cost for the slab is $10,000.

Table 5
Site Development Costs for Each Slab

Site #	*Travel Cost ($)*	*Delivery Cost ($)*	*Total Cost($)*
1	858	624	1482
2	495	360	855
3	1452	1056	2508
4	825	600	1425
5	561	408	969
6	297	216	513

As Guhya (2010) noted the work is repetitive, as is usual for a production homebuilder, which simplifies the production process. In almost all of the research work to date, new players have been introduced for each game, as the research has focussed on the development of the player's ability in the early stages of the game.

The key assumption is that each Monday, the owner, termed the υ player, posts the jobs that they are going to start that week. The data included is where each job is located. In the game play, the owners post the job offers and all the related information (like the location of the jobs, estimated cost of the jobs, etc) on the ASP based website (Kingsley-Hughes, Kingsley-Hughes, & Read, 2004) every Monday, and then all the bidders log on to the web site and starting bidding for the jobs.

Table 6 lists the default variables for the Reverse Auction Bidding web site.

Table 6
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 production builder builds only one type of home and hence requires each contractor to pour only one type of slab. All λ_i players have been prequalified and only price matters, as is normal in this type of bidding system. An upper limit of 3.5 times the base cost is set as the maximum allowed by the game. This derives from a study of the base and range of sales prices for soft drink. A lower limit of 0.9 times the base cost is set as a minimum allowed by the game, unless the bidder elects to bid lower and confirms the bid. This rule was introduced to catch typing mistakes, such as a bidder bid offer of $1,500 instead of $15,000, as the purchaser does not want bankrupt subcontractors. The rule is also to enforce the bank's requirements of a reasonable return in a stable economic environment. Bidding period is 15 minutes per game, so there is a limit to the number of bids in the period (Yuan, 2013).

One of the variables used in the game is rainfall. Rain on to many days on a working site during a week can delay completion and reduce the bidder's capacity in the following week. Houston has relatively high rainfall from May to July every year. The game was assumed to played during this period, as this is when the first game occurred. Delay caused by rainfall was taken into accounted in this game. National Oceanic and Atmospheric Administration (NOAA, 2010) provides the data on the statistical information for the probability of rain in Houston for the months of May, June and July. Figure 8 depicts the rain distribution for this area.

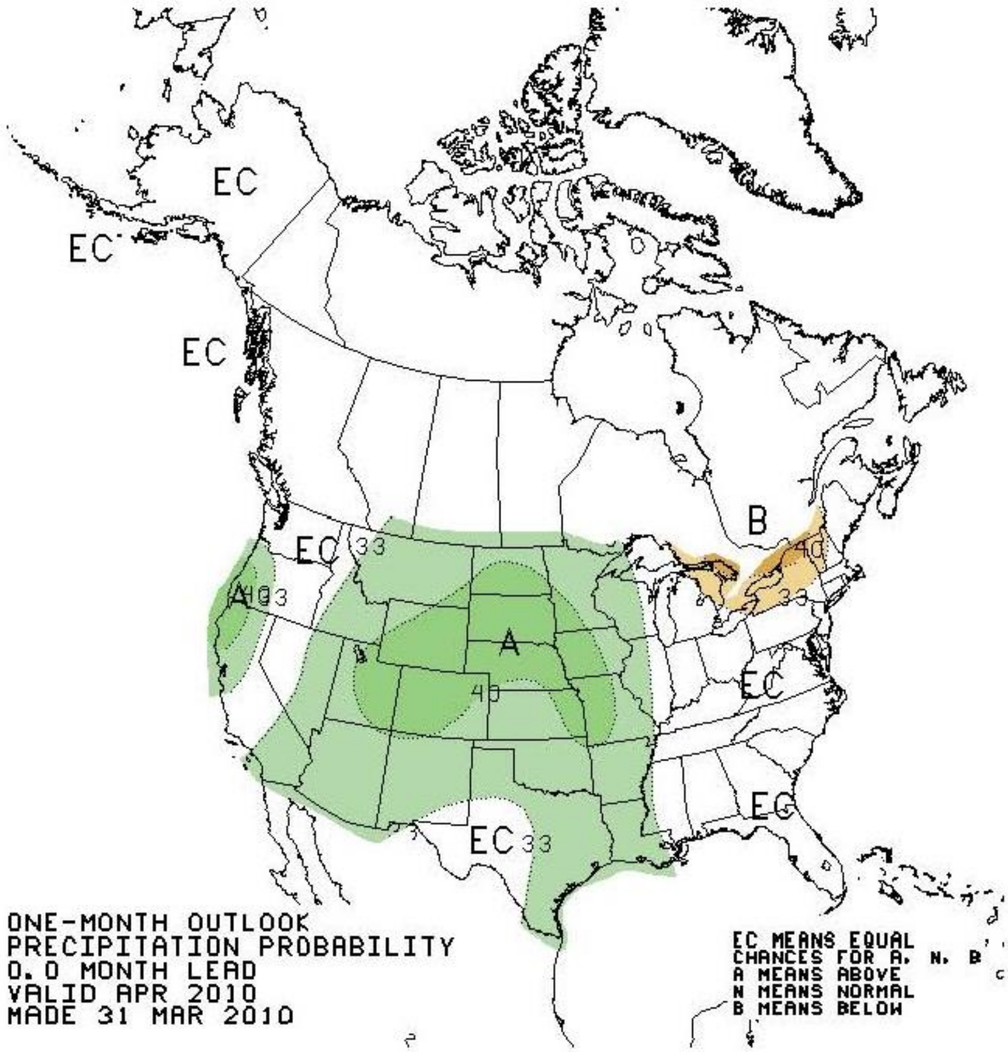

Figure 8. Rain probability in USA after NOAA (2010)

The point is to introduce a random element to the game. If rain occurs on two days of the week on one of the awarded contracts sites for the week, then the contractor's capacity in the following week is reduced by one. Table 7 represents the form of the rain delay matrix on each of the site location used in the case studies. "1" denotes enough rainfall to cause a delay in construction, whereas “0” denotes no rainfall. Currently there is no correlation between the site locations and the amount of rainfall in that vicinity.

Table 7
Rain Delays for Week One

Day	Site					
	One	Two	Three	Four	Five	Six
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

Figure 9 shows the login page of TAMU Reverse Auction Bidding system, each participants will have their own username and password to login. Figure 10 shows a sample data collection screen. The screen shows that the participant at week 4 with one completed jobs and four jobs in process. The participant also holds the lowest price for two bids ongoing now.

If the bidding on this round is not over, then all other bidders have the opportunity to bid at lower price to win the job.

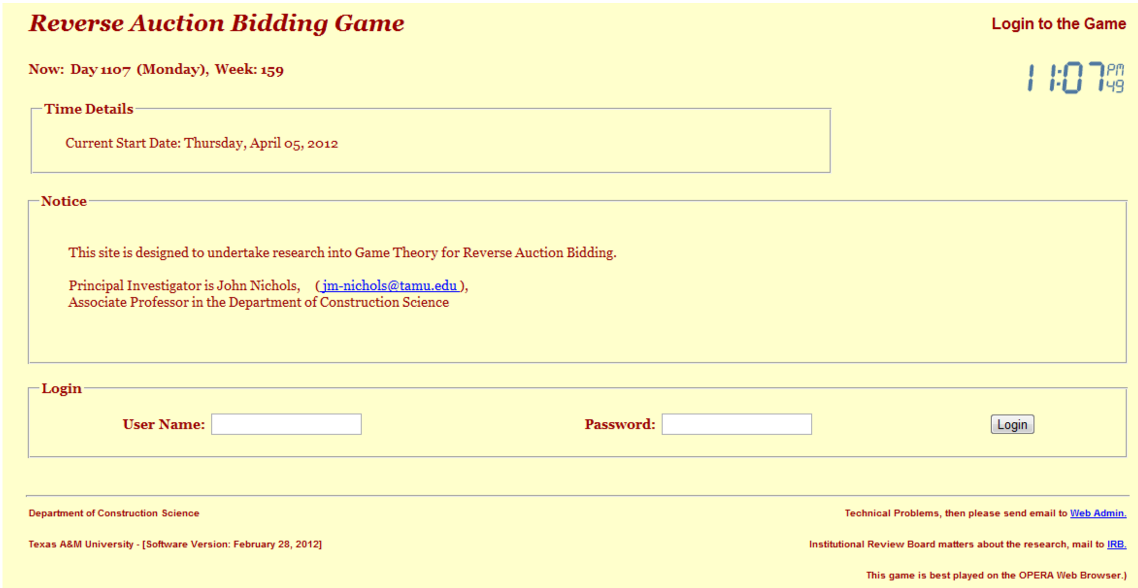

Figure 9. Reverse Auction Bidding login screen

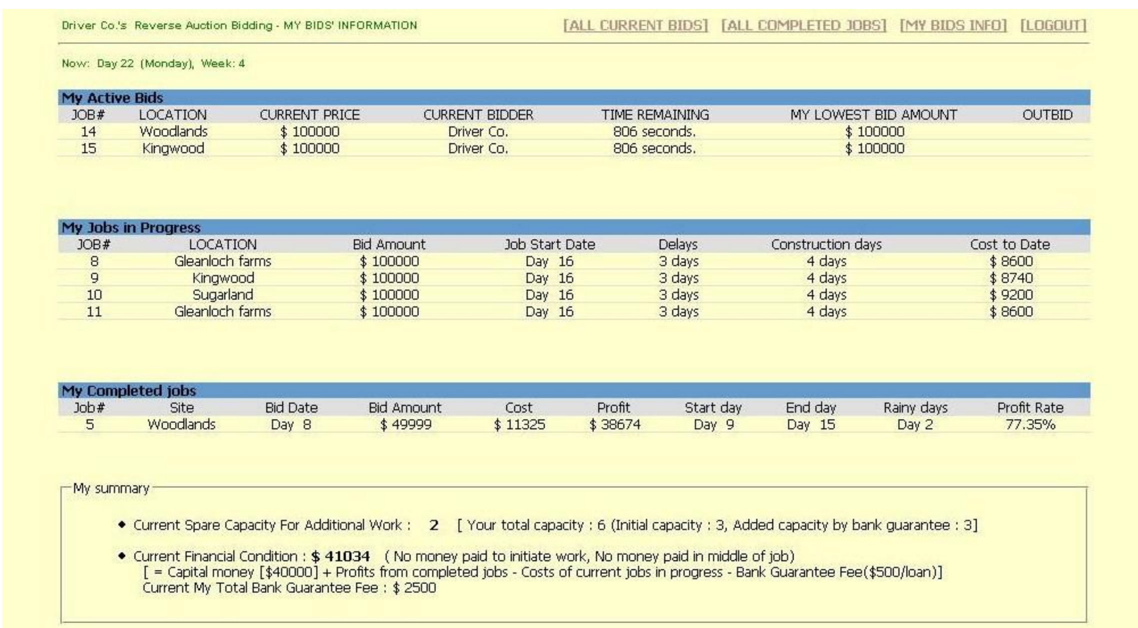

Figure 10. Reverse Auction Bidding - sample data screen

A mechanism was provided for each bidder to increase their capacity to bid as shown in Figure 11.

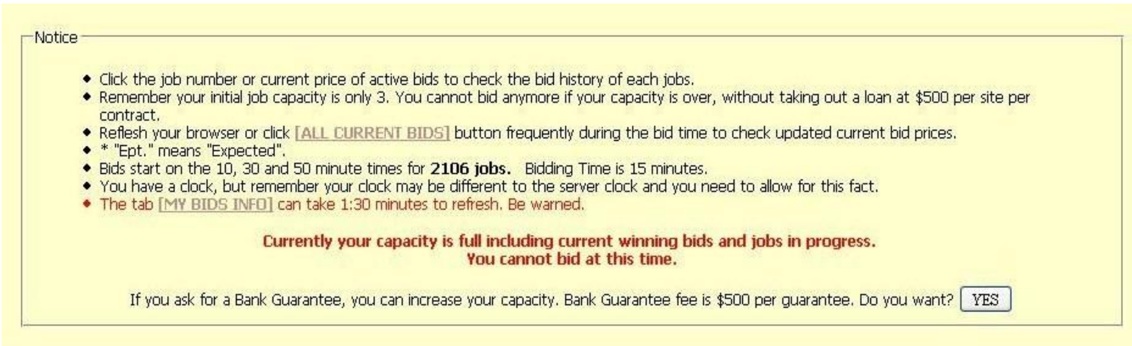

Figure 11. Bank loan screen

The point of the game is to watch the development and the forms of competition in the game. Competition is introduced in two forms, the first by the purchaser providing a different number of jobs per week. Each participant has a capacity to pour three slabs per week, provided there is no rain. This means that the four players each have 25% of the market share. The corresponding Herfindahl index is 2500. The players compete for jobs.

The players do have a mechanism to amend their capacity; the term used is a bank loan and this term is used for historical reasons. A payment of a fee of $500 to the bank increases the capacity of the bidder for one week by one job. Previous research has shown this is a powerful tool for winning more work (Gupta, 2010). A simple analysis based on the Herfindahl Index equation shows the relative change in the market strength of the players who take out bank loans.

Figure 12 shows the change in the calculations for the Herfindahl Index for a change in capacity of one player from three to four and then five jobs per week. The Index changes from 2500 to 2653, but the market strength as measured by the index moves from 625 to 1275 for the peak bidder and from 625 to 459 for the others.

The change explains some of the benefits of taking out bank loans.

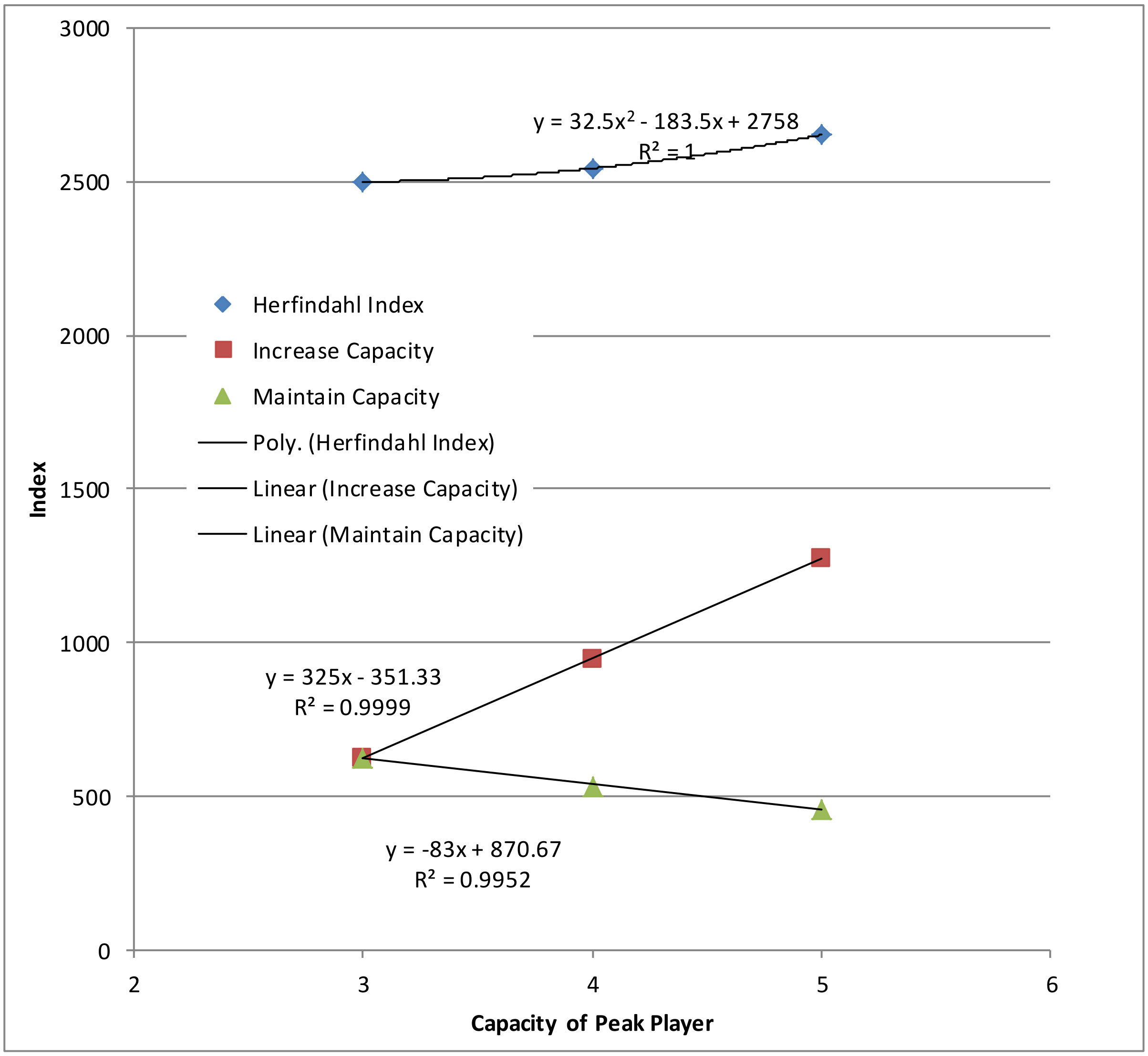

Figure 12. Herfindahl Index changes for capacity change

Data Structure

There are nineteen research studies completed by previous master's students at TAMU. Eight high quality data sets were used for this analysis. Table 8 summarizes the detailed information about the data sets used in this analysis.

Table 8
Study List

Study No	Student Name	Participants
1	Van Vleet	5
4	Gujarathi	4
9	Saigaonkar	4
11	Gupta	4
12	Patel	4
14	Plumber	4
15	Bedekar	4
16	Katakam	4

Table 9 shows a sample of the bid data taken from the first study. The data is stored during the game in a SQL Server database. There are a total of six tables in the database. SQL-Table 1 holds the log data for the people logged onto the computer system. SQL-Table 2 holds the company names and login details. A company name is given to each player so that their confidentially is maintained during the game. SQL-Table 3 holds the job data, including start and end times. The numbers of jobs per week are determined using a set of die. SQL-Table 4 holds the bid data as shown below on Table 9. SQL-Table 5 holds the weather delay data and SQL-Table 6 holds the summary of the construction details. A number of integer flags are used to control data flow because a web site is essentially stateless (Paz, 2013).

Table 9
Bid Data - Sample after van Vleet (2004)

Bid ID	Job ID	Ctr ID	Bid Amount	Bid Date	Bid Time	Bid Status
1	1	9	$15,000.00	1	7:00:20 PM	0
2	1	8	$13,000.00	1	7:00:22 PM	0
3	3	9	$12,000.00	1	7:00:31 PM	0
4	2	8	$14,000.00	1	7:00:53 PM	0
5	1	4	$12,999.00	1	7:01:02 PM	0
6	4	4	$20,000.00	1	7:01:25 PM	0
7	12	6	$12,825.00	1	7:01:28 PM	0
8	2	7	$13,500.00	1	7:01:29 PM	0
9	5	9	$12,000.00	1	7:01:34 PM	0
10	4	7	$15,000.00	1	7:01:36 PM	0
11	1	8	$12,500.00	1	7:01:39 PM	0
12	4	7	$14,000.00	1	7:01:48 PM	0
13	7	8	$16,000.00	1	7:01:50 PM	0
14	2	7	$13,000.00	1	7:01:54 PM	0
15	11	4	$12,700.00	1	7:01:58 PM	0
16	1	4	$12,400.00	1	7:02:21 PM	0

The stored data is:

- Bid Id consecutive integer
- Job Id Job number applied to a particular site and day
- Ctr Id Bidder Identity number used for the program
- Bid Amount Offer
- Bid Date Each week is numbered, 1, 2, 3 etc…
- Bid Time Time that the bid is offered by the bidder
- Bid Status Reserved for program use

Table 10 shows a sample of the control data used for the game. The data is in four groups:

- Identity Number used to record all details in the SQL Server database as the key identity. Five is reserved for system use
- Name, Logon Name and Password. The logon name is usually a simple name such as shown here and does not link to the actual player
- Capacity current weekly capacity
- Loan amount and the amount taken in bank loans

It is suggested for future research purposes that the loan data include the timing of the loan data, so that the impact during particular rounds of the games can be studied effectively. The weekly capacity is recalculated at the end of each week to allow for rain and non-completion of some jobs and at the time of taking out a bank loan.

Table 10
Reverse Auction Bidding Control Data

ID	Name	Username	Password	Capacity	Loan
1	Doc	Beith	Butcher	3	$0.00
2	Grumpy	Coll	WillGrimm	3	$0.00
3	Happy	Duir	HalfPint	3	$0.00
4	Sleepy	Gort	Napoleon	3	$4,000.00
5			Reserved for system use		
6	Bashful	Muir	Grub	3	$2,500.00
7	Sneezy	Nion	Chuck	3	$8,500.00
8	Dopey	Quert	Wolf	3	$2,000.00
9	Stealthy	Gus	Lenny	3	$11,000.00

Table 11 shows an example of the job and profit details. The data columns are:

- Control ID the contract number to identify each unique job
- ID player identity number, if 5 then not awarded
- Job ID the job identity number in the job list, some jobs may not be awarded
- Cost for the job including base, travel, delivery and site costs
- Profit for the job as a gross profit
- Delay number of days of delay in the job due to rain
- UC reserved for system use

- Begin Date are numbered 1, 2, 3, etc. so a week is seven days, commencing with Day 1 as a Monday, Sunday is observed as a day of rest as is common in the construction industry
- End Date at the end of the contract, if equation 4 is true then there has been no impact on the capacity due to rain

$$EndDate - BeginDate = 4 \tag{4}$$

Table 11

Profit and Job Data

Control ID	ID	Job ID	Cost	Profit	Delay	UC	Begin Date	End Date
1	4	1	$10,350.00	$1,650.00	0	5	2	6
2	4	5	$10,350.00	$1,400.00	0	5	2	6
3	9	13	$10,000.00	$900.00	0	5	2	6
4	7	2	$10,450.00	$1,650.00	1	5	2	7
5	4	3	$10,450.00	$1,549.00	1	5	2	7
6	6	4	$10,450.00	$1,550.00	1	5	2	7
7	7	7	$10,700.00	$1,600.00	2	5	2	8

Petersen (2010) studied the performance of ξ bidders. The bid amounts for this game are shown on Figure 13.

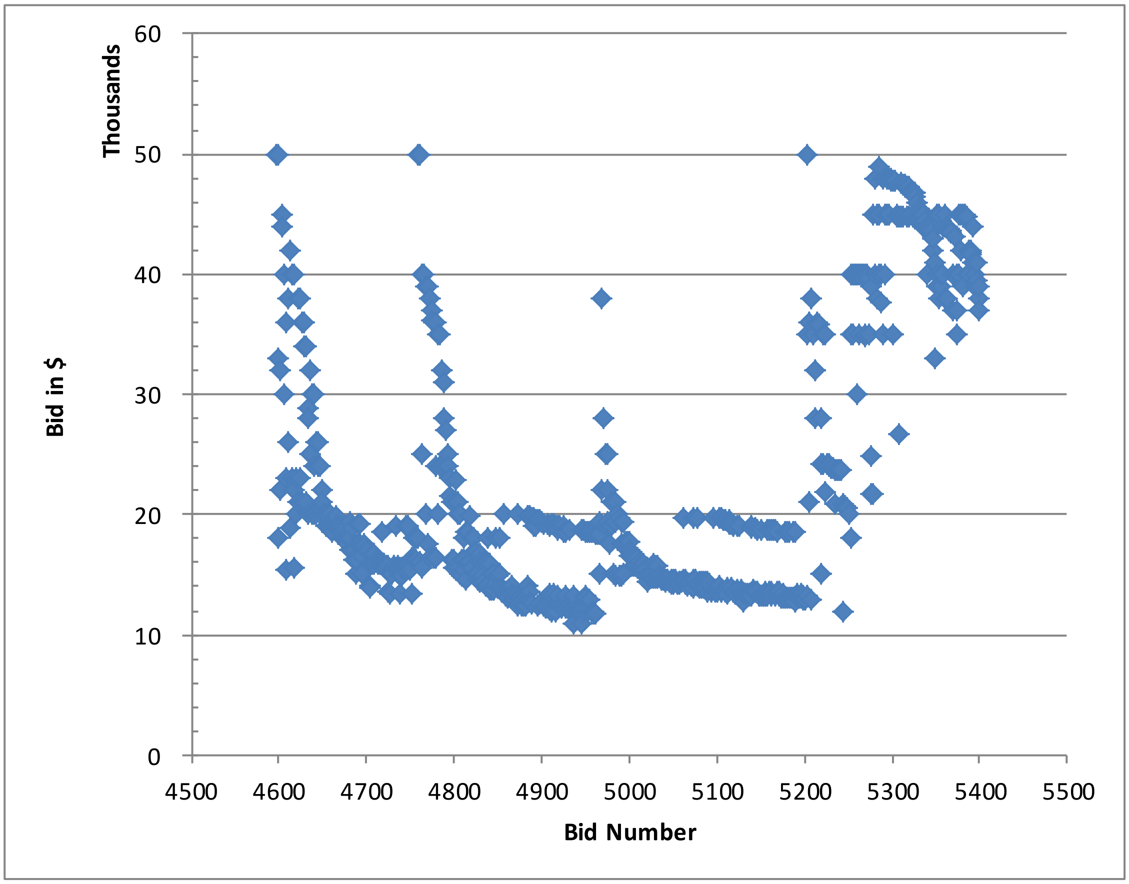

Figure 13. Bid distribution from RAB Study Ten after Petersen (2010)

Data Analysis

Researchers developed a number of the techniques used for the analysis of the Reverse Auction Bidding data, based on the work of the earlier researchers. The first stage in the data analysis is to sort the bid data for each different bidder. Table 12 shows a sample of the bid data from RAB Study Number 10 (Petersen, 2010).

The data of interest is the bid reduction at each step of the play. This data can be collected from a sorted data set.

Table 12
Game 10 Bid Data Sample

Bid Number	Job Number	Participant	Bid Amount
4750	1368	4	15450
4741	1368	2	15550
4733	1368	4	15582
4730	1368	2	15600
4713	1368	4	15850
4710	1368	2	16000
4708	1368	4	16750
4707	1368	2	16800
4701	1368	4	16890
4700	1368	1	17000
4698	1368	4	17400
4696	1368	2	17500
4691	1368	4	17520
4675	1368	2	18000
4661	1368	4	18500
4653	1368	2	19000
4643	1368	6	19999
4619	1368	2	20000

The price reduction data is collected and then sorted into different bin range: between 1 and 10, between 10 and 100, between 100 and 1000, between 1000 and 10,000, and 10,000 above. Figure 14 shows the counts of the number of bid drops made by Participant 1 in RAB Research Number Four.

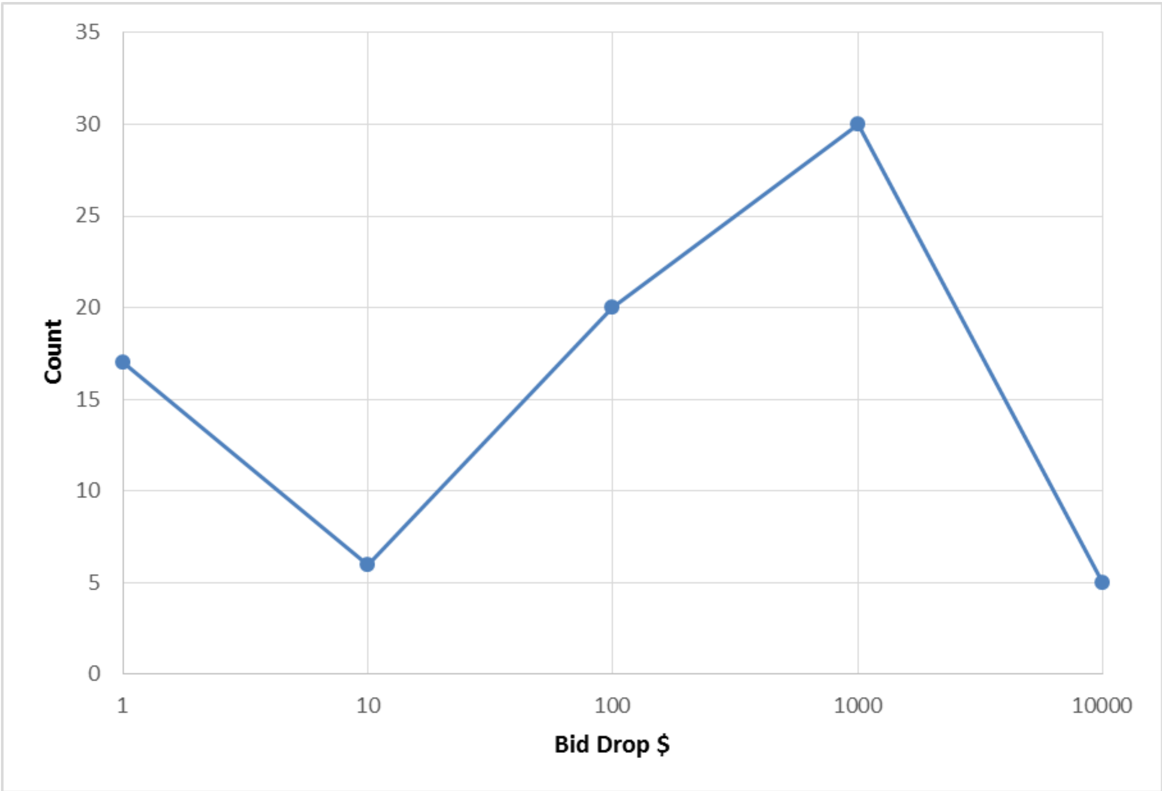

Figure 14. Frequency of Different Profit Loss Level

The figure shows that the bidder reduced the total bid group by $82,077. This represents a significant portion of the available profits.

CHAPTER IV

RESULTS

Introduction

This chapter provides a summary of the results for the analysis of the several games used for this study. The sections of the chapter are:

- Summary of the Study Data
- Analysis of the δ Data
- Findings

Summary of the Study Data

The research work is based on a group of the Reverse Auction bidding games completed at Texas A&M University since 2004. Table 13 lists the studies used in this work.

Table 13
Study Results Summary

Study No	Participants	Number of Bids	Maximum Bid	Minimum Bid	Winning Bidder ID
1	5	698	$1,200,000	$2,000	9
4	4	347	$300,000	$133,335	3
9	4	903	$60,000	$12,898	12
11	4	865	$62,000	$11,700	2
12	4	759	$64,000	$12,499	1
14	4	1282	$60,416	$12,000	4
15	4	708	$35,000	$11,800	1
16	4	403	$64,000	$11,900	1

Table 13 shows the study number, which relates to the order of the studies in the overall research work, the number of participants, the number of bids, the maximum bid and the minimum bid. These games are played by new bidders in each game, although a player was once used twice. Figure 15 shows a plot of the bid data for the original study by van Vleet (2004).

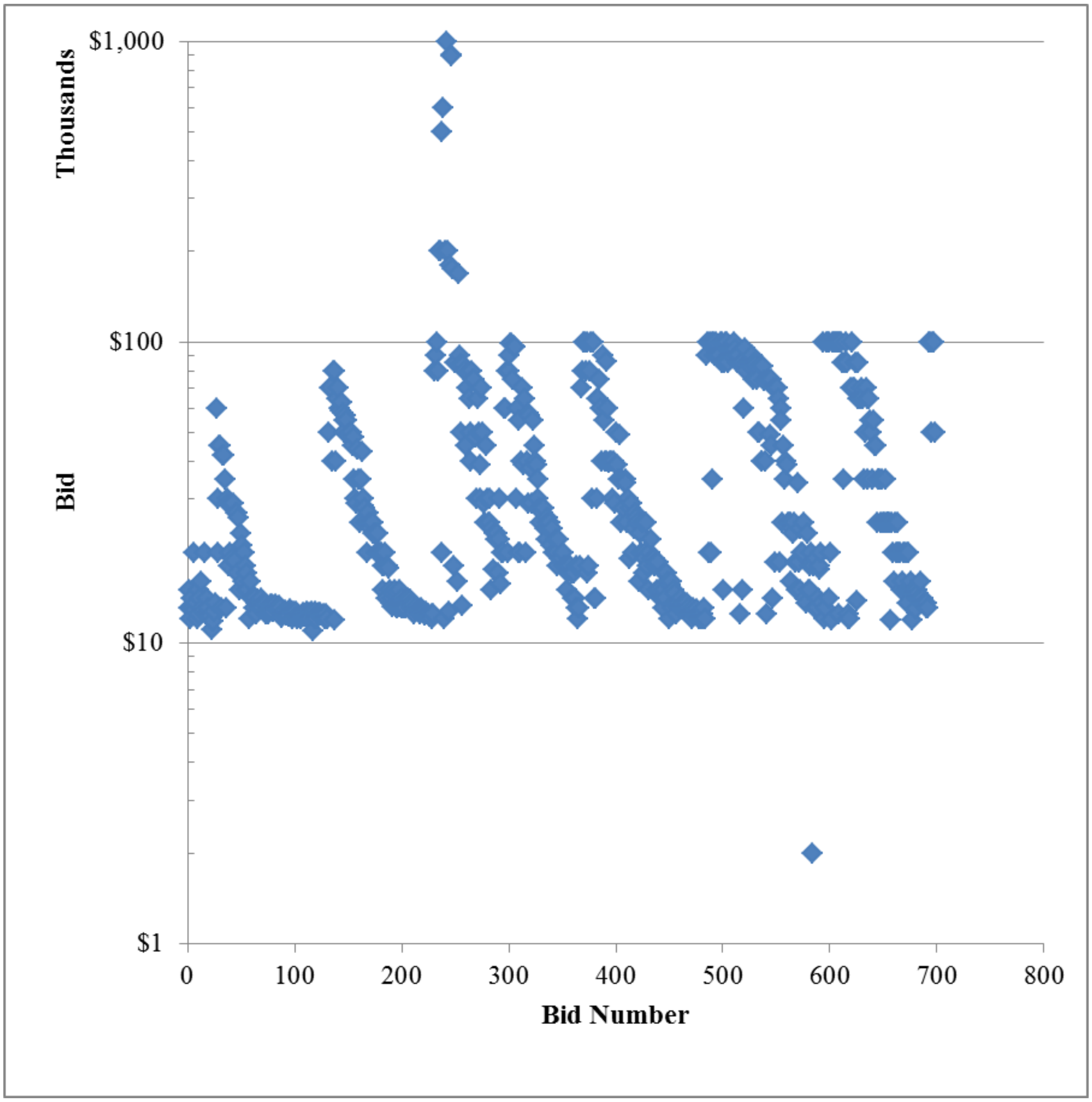

Figure 15. Study number 1 - bid data

The other observation of importance in Table 13 is the variation in the bid maximums. The results point to the need for the conceptual development of the upper limit to the bid price. An upper bid limit was introduced by Gujarathi (2008) to provide an upper limit price point to match the real world linits. The limit is 3.5 times the base price including the travelling and delivery costs. The travelling and delivery costs were recently adjusted upward to reflect current cost conditions. This idea stems from the reasonable concept that the purchaser has the economic sense to understand values that are economically excessive (Hartford, 2005).

Figure 15 shows the early stage of low bids, which was studied and formalized by Chouhan (2009). The $2000 bid at a time when the average bid is $20,000 shows the problem of typing errors, this is the type of error that will lead to a court case or a broken relationship as most small contractors cannot absorb such a loss. This issue was fixed with the introduction of the check on low prices. There is also a bid limit of 0.9 times the base costs; this is in place to catch typing errors that would otherwise spoil the game data. Occasionally bid data includes losses instead of profits. Dharamshi (2014) recently completed a three game study; the 24th study in this research set. The third game in Dharamshi's study shows atypical results including a number of losses and unusal profit levels. This game will be discarded for future analysis.

Figure 16 shows the number of bids per job for each of the jobs.

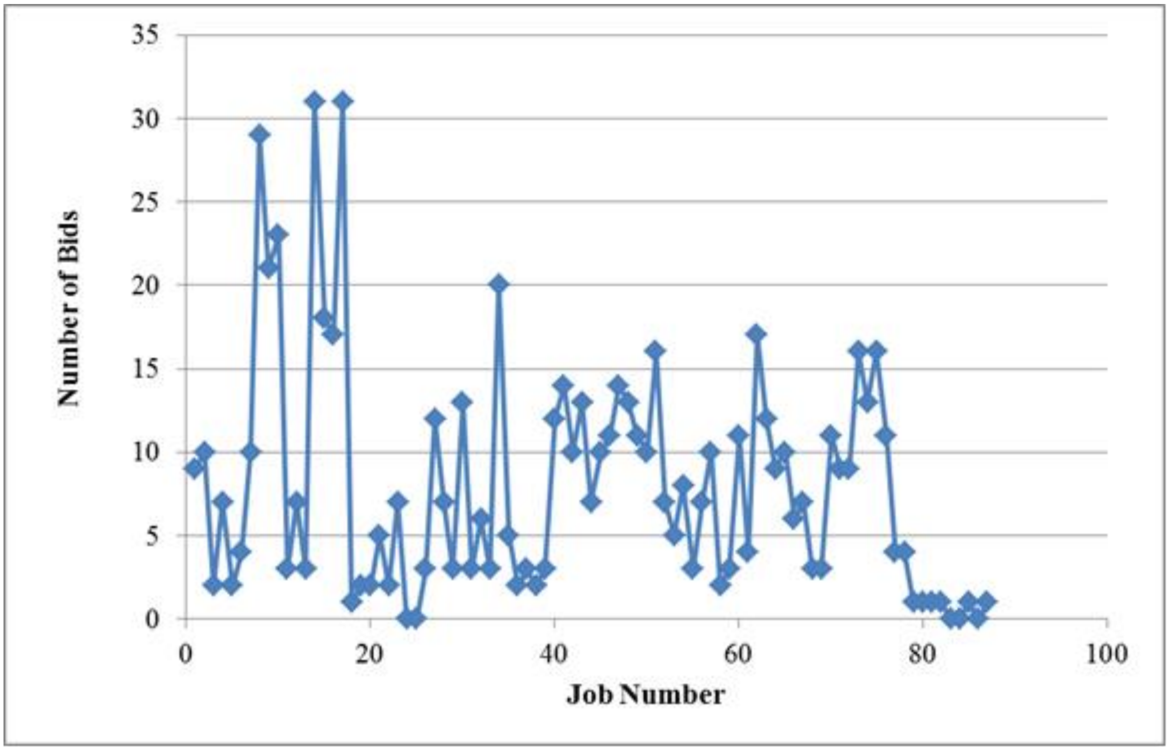

Figure 16. Number of bids per job

The key observations are the issue of flagging interest after job number 80, the high number of bids in the early game play, which leads to an erosion of profit. This observation on flagging interest has led to the standard eight round game, which based on an average of 7 to 8 jobs per game yields about 50 to 60 jobs in each game.

In studying the profits levels between games, the method developed by Guhya (2010) was to normalize the profit using equation (1). Guhya's method is applied to the profit on each job.

Dharamshi (2014) studied the total profits obtained by each participant in three games to establish a more formal definition for the Type ξ, Type ζ and Type ϕ bidders. He used a standard 8 round game to define a Type ξ, as one who averaged 18% of the available profit, a Type ζ player as one who averaged 2% of the available profit and a Type ϕ player as one who averaged about 9% of the total profit. One of the suggested indicators for poor performance is making significant reductions in the offered price, the rules of the game only require a reduction of one cent to make a valid bid, and anything more is essentially wasted profit in terms of the λ player. The λ player is a symbolic assignment, but poor average performance ultimately affects all bidders.

The variable of interest is then moved to the bid drop or reduction in the price. Figure 17 shows a histogram plot of the binned bid reductions for the fourth study (Gujarathi, 2008).

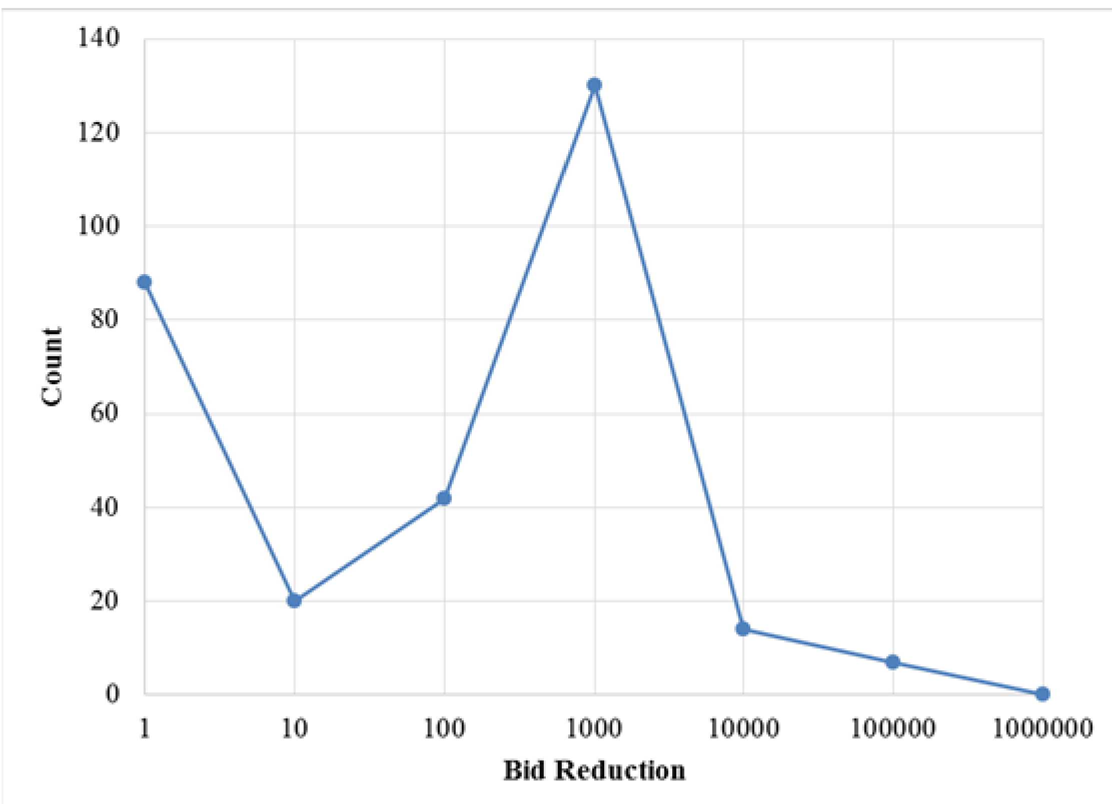

Figure 17. RAB Study 4 – bid reduction binned amounts

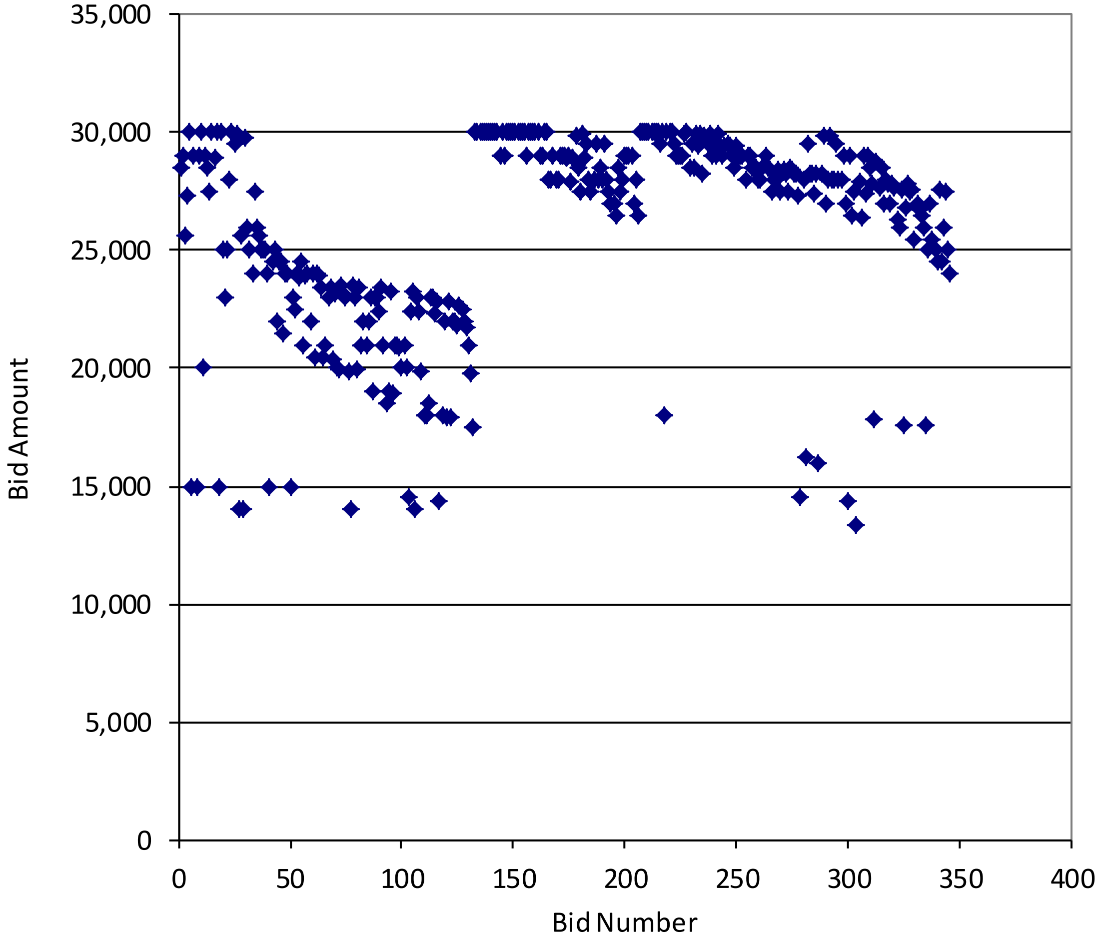

Figure 18. RAB Study 4 - bid amounts

Figure 18 shows the issue with the binning procedure, the maximum drop in price is 18,000, which does not fit into the 10,000 bin, but is included in the 100,000 bin. Figure 19 shows the complete bid drop data plotted as a histogram for the set of studies used in this research.

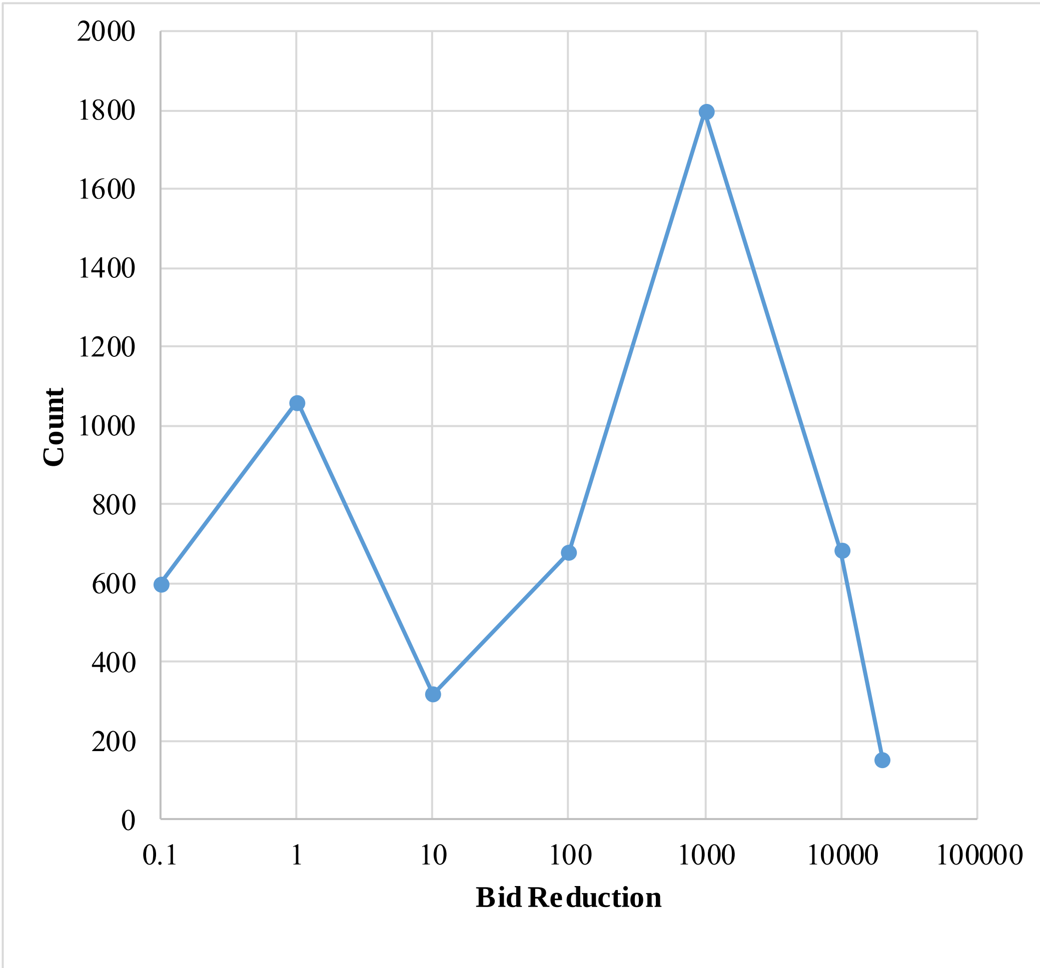

Figure 19. Study Set: Bid drop count

As for the normalized total profit graph, this distribution is bi modal in nature (Borowski & Borwein, 1989). The next step is to normalize the data into fractions with the total fraction summing to one. The reduction of 0.1 represents the zero or opening bid that has no "theoretical drop" as a zero value will not plot on a logarithmic graph.

Figure 20 shows the bid reduction count data for all of the studies included in this research presented as a fraction of the total of 5286 bids.

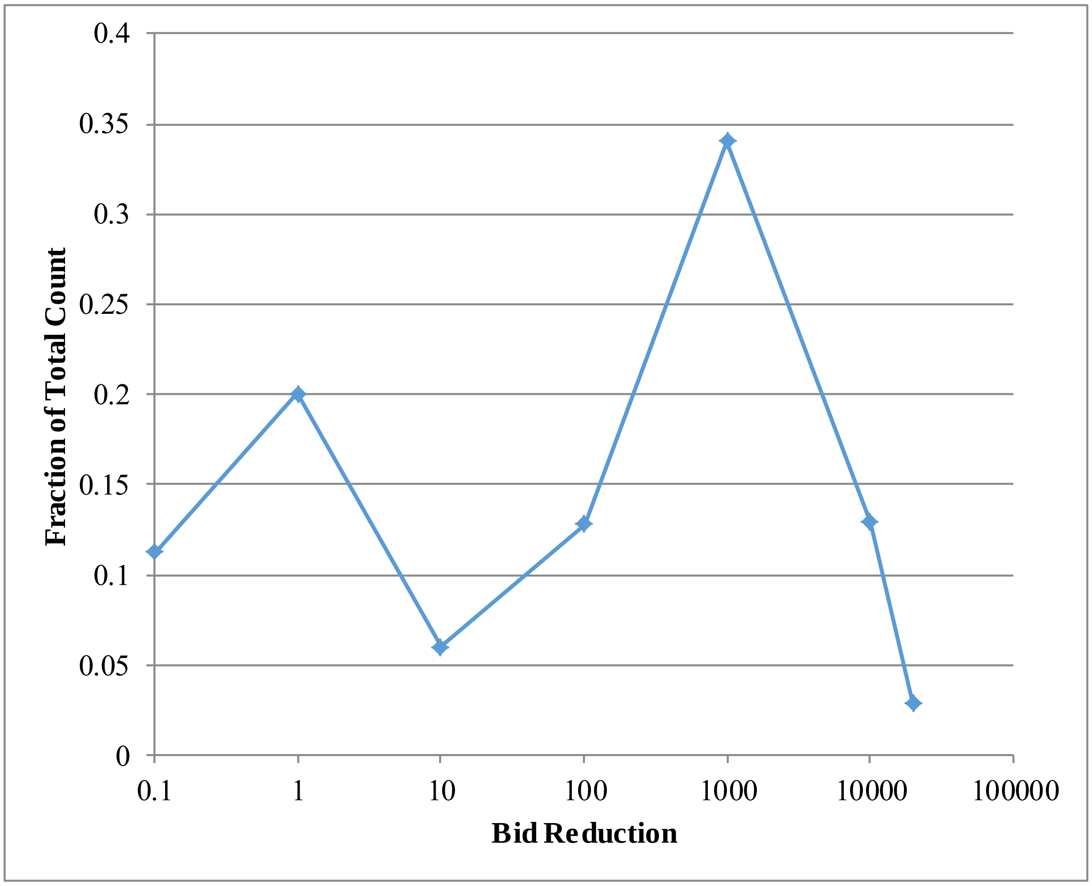

Figure 20. Study Set: Bid drop count – fractions of total count

The simplest assumption is that it easiest to type 28000 to bid below 29,000 than any other number. It is illustrative to look at the bid drop data for a single job, with a group of bids. Figure 21 shows a sample of the δ data, this represents the price drop per bid for this job.

Table 14 shows the mean value and standard deviation for each bidder or participant for job 10. The results from the table suggest that participant 4 is a better bidder than the others.

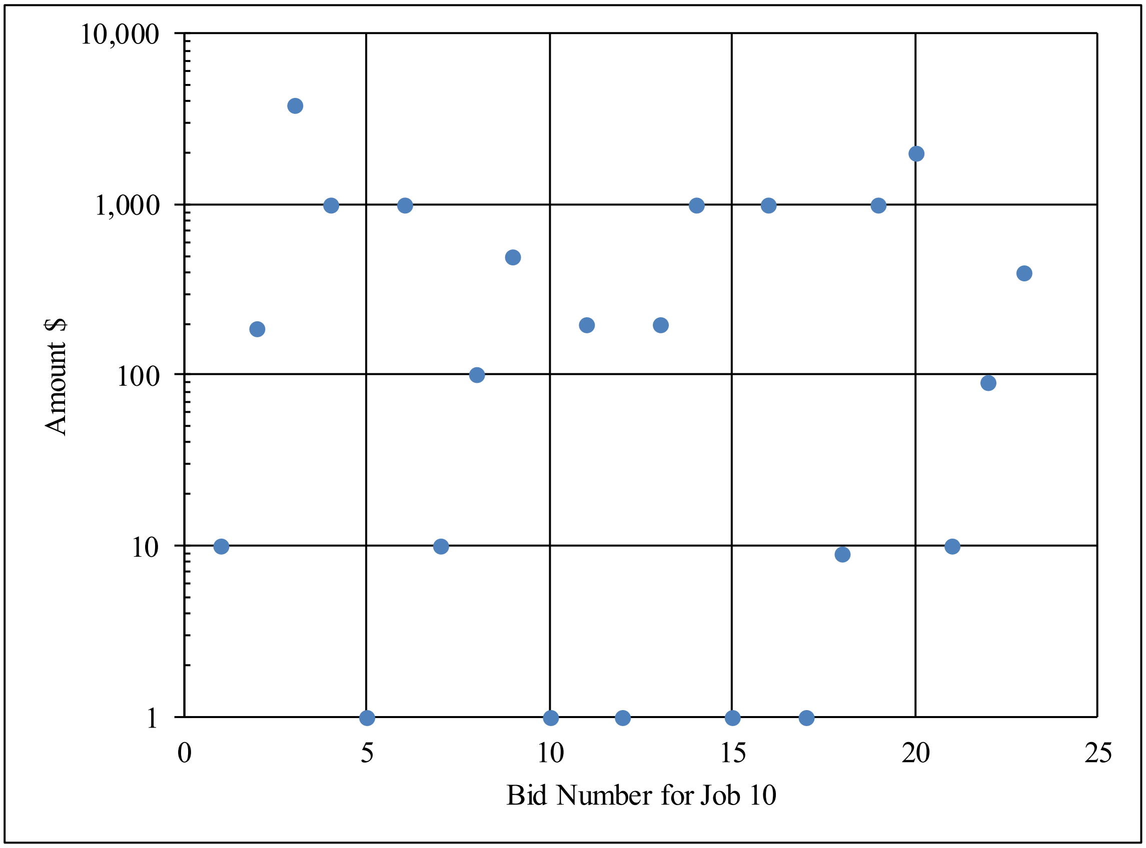

Figure 21. Study Number 4 – Job number 10 bid data

Table 14
Study Number 4: Job Number 10 Bid Data

Participant	Mean Value of Bid δ Data	Standard Deviation
1	918	1400
2	680	460
3	550	800
4	42	75

Figure 22 shows the bid data plotted in bid order. The drop of 3,500 at bid number 4 is significant in the overall loss on the job, representing 1 bid in 24, but 25% of the profit loss.

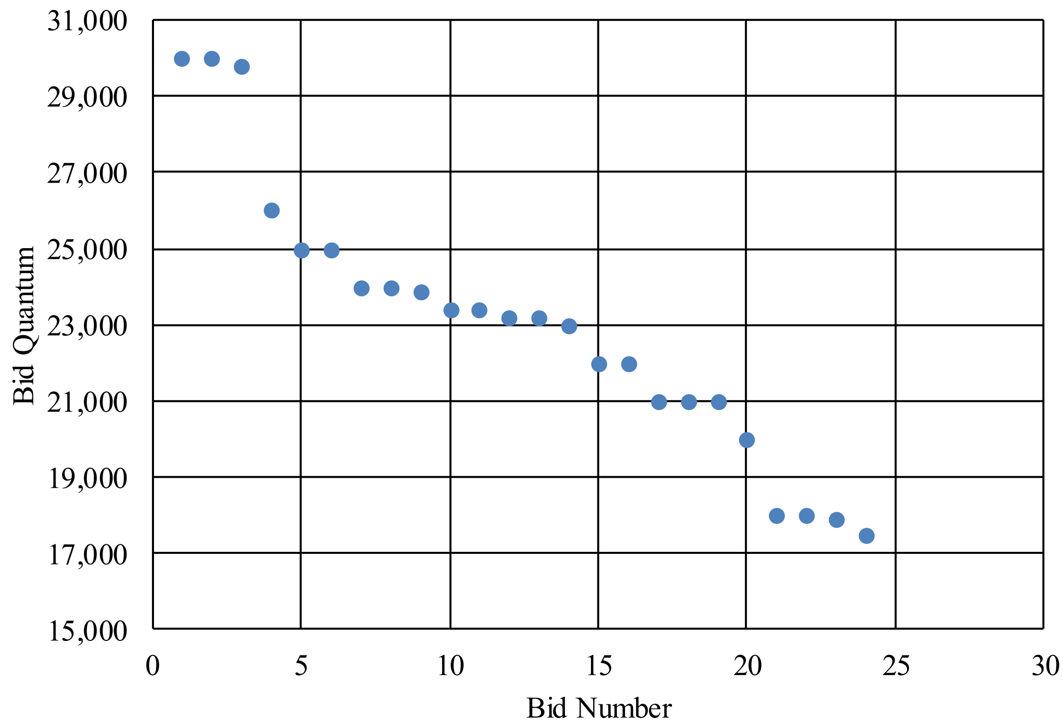

Figure 22. Study Number 4 - job number 10 bid data plot

A linear regression analysis of the bid data on Figure 22 yields an equation of the traditional form shown in equation (5):

$$y = mx + b \tag{5}$$

The regression equation results are presented in Table 15. One measure of reliability of data is the variation in the ratio of the standard error to the value, in this case the slope variation is 6.7%. This is a good fit for human based data. The secondary measures in the linear regression are the normal probability plot and the residual plot.

Table 15
Regression Analysis Results

Component	Value	Standard Error	t-Stat
m	29044	455	64
b	-482	32	15

Figure 23 shows the normal probability plot for the bid data. The data is clearly normally distributed except for the large drop on the 3-4th bids.

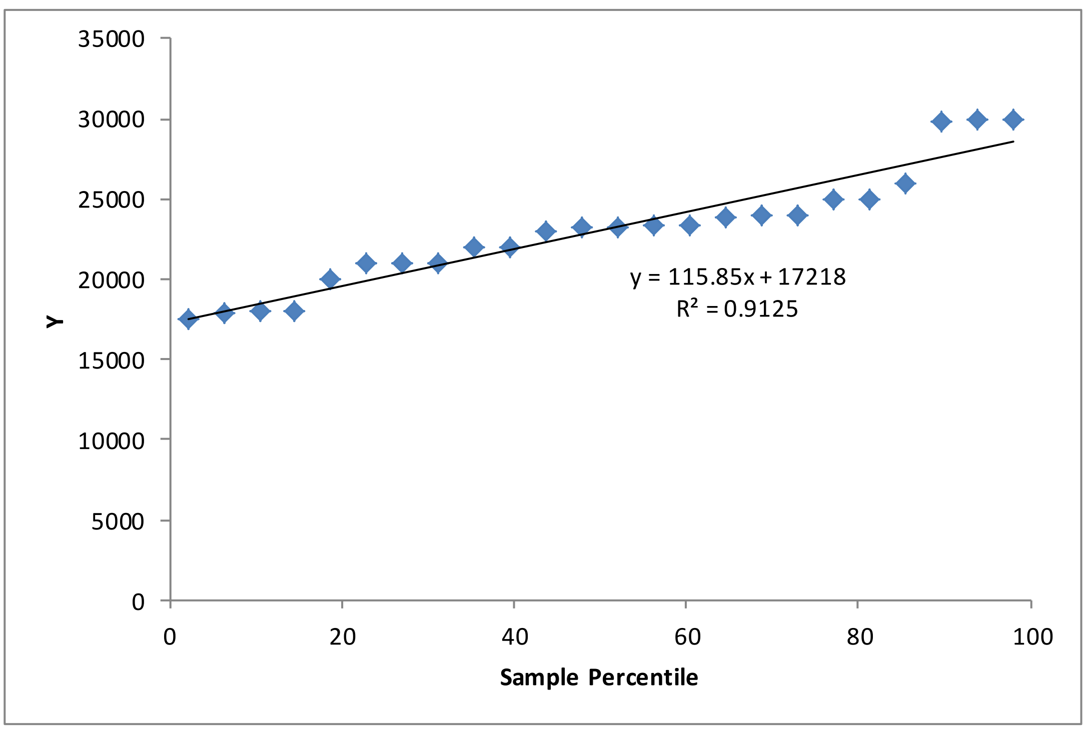

Figure 23. Study Number 4 - job number 10 normal probability plot

Figure 24 shows the issue of the large drop in the bidding and the apparent cyclic pattern in the bid data.

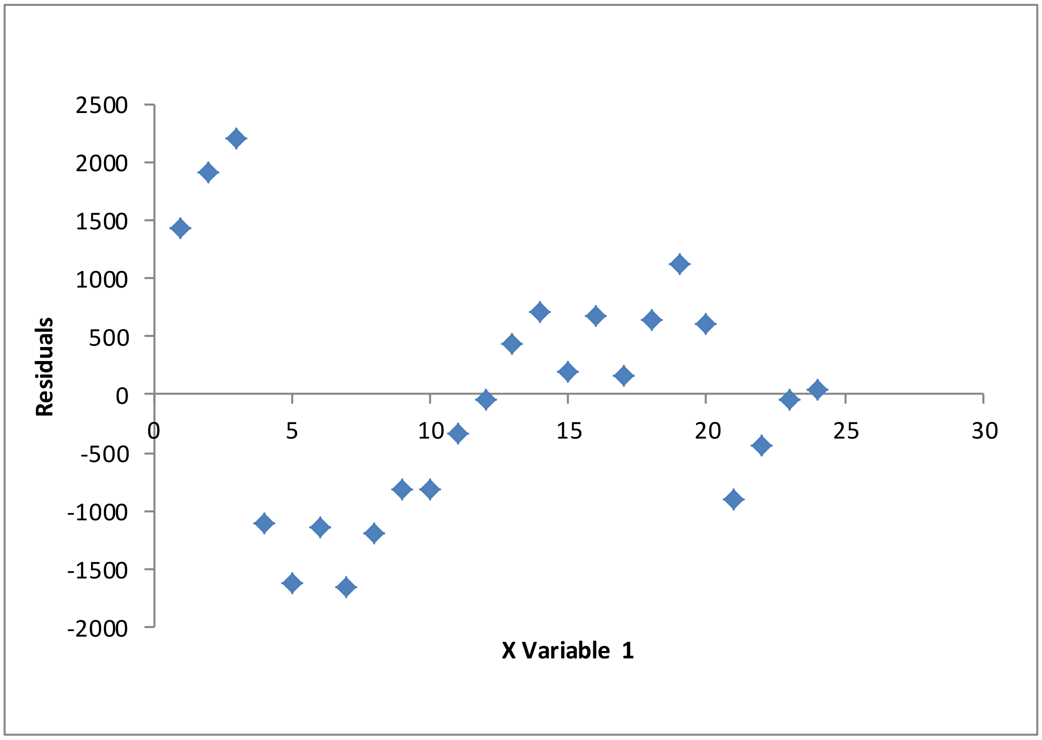

Figure 24. Study Number 4 - job number 10 residual plot

In summary, the bid drops in excess of $2000 are not within the normal or Gaussian estimates of the distribution of bids. The issues with this bidding are:

- the fourth bidder brings in an initial price of $30,000, which is approximately $20,000 below the upper limit
- although the bidders were consistent in the number of bids, the scatter on each bid differential is significant

Figure 25 shows the pattern of the δ data for the tenth job in study number 4.

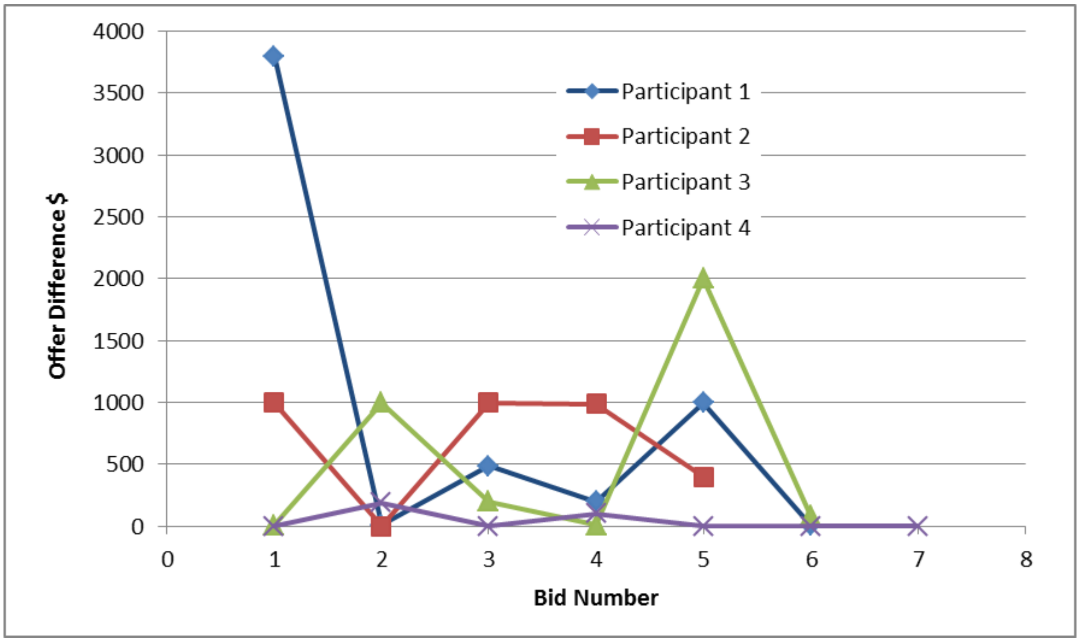

Figure 25. Study Number 4: job number 10: bid δ data

Participant 4 is clearly an economically efficient bidder in terms of reducing the amount given away with each bid. The interesting observation is that this study developed the concept of the upper limit on price, but these bidders did not exceed $30,000 on any offer.

This analysis however points to the difficulty of identifying an economically efficient bidder, is the efficiency in the bid process or merely the total profit made at the end of the game.

Analysis of the δ Data

A summary of the δ data for each of the studies is given in Table 16. The critical observation with this data is the preponderance of bid amount drops in the $1000 range.

This could be due to the ease of typing 29,000 in place of 29,999 if bidding against a $30,000 bid.

Table 16
Summary of the δ Data

Study No	Bid Differential δ Data						
	0	1	10	100	1,000	10,000	10,000+
1	78	88	8	89	511	2	0
4	39	88	20	42	130	14	7
9	64	132	18	77	58	5	0
11	96	139	102	156	251	93	28
12	93	334	65	48	108	62	48
14	92	151	5	43	455	286	50
15	71	98	98	214	149	71	7
16	63	30	2	9	136	150	13

Figure 26 shows the data in a graphical form to highlight the peak points at $1 and $1000.

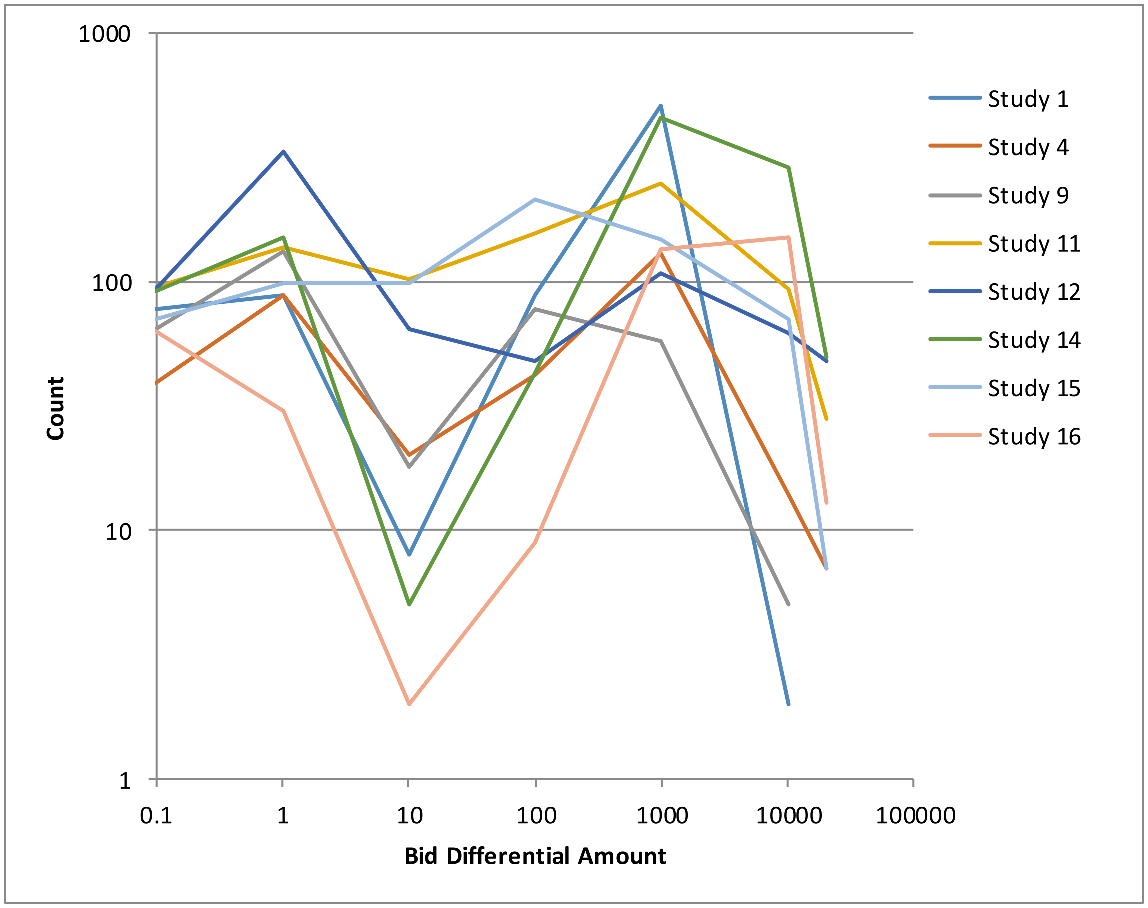

Figure 26. Bid differential data - all studies

Appendix A contains a detailed analysis of each study in terms of bid differentials and an inter-game comparison of the results. The results in Appendix A show:

- a strategy can be observed in the bid differential play, it does not always result in the highest returns, but it is significant and discernable statistically in the data
- the range of profits, and bid differentials is significant given that the only bidding pressure in the game is from the λ player
- some people are very poor bidders and do poorly in the game

Some researchers opined that a strategy existed to beat the bidders who lowered by only a low amount, such as one dollar. The strategy is to make a bid that is significantly lower, so as to signal that the bidder is aggressive and the strategic bidder seeks profits elsewhere. This pattern search is a separate study.

The first hypothesis is:

A statistically evident bias exists between the average return generated by the Type ξ bidder and the Type ζ bidder.

Figure 27 shows that there is a statistically significant difference in the average returns generated by the players based on their rank in the profit sum for each game. The Type ξ or efficient bidders won on average in excess of 180,000 per game, whereas the Type ζ or inefficient bidders won on average less than 80,000 per game. These results are in line with the observations by Dharamshi (2014), who studied three separate game results.

The second hypothesis is:

Type ξ bidders minimize the price reduction for each bid.

The data shows that some players do attempt to minimize the bid differentials, but this is not the group generally defined as Type ξ bidders. Some opinions suggest why this hypothesis was not true for this study data.

CHAPTER V

CONCLUSION

In an economic system, the reward comes in the form of profit. There is no getting away from the observation that economically efficient participants in the Reverse Auction bidding game are perceived to be those participants who make the most money under standard game conditions. There are other forms of economic efficiency, reducing costs whilst maintaining prices increases profit, but this game the reliance is on a sound strategy for bidding.

The Reverse Auction Bidding game was developed at TAMU by Mr. van Vleet in 2014 as part of the work for a Master's paper. Since that time, twenty four further studies have been completed using the game system or in doing advanced statistical analysis of aspects of the game or game theory. One of the theories advanced was that an economically efficient bidder could be identified from the set of all bidders; this bidder was termed the Type ξ bidder, to avoid the term economically efficient. Conversely the economically inefficient bidder could be identified and termed the Type ζ bidder.

This research looked at two aspects of the game and the statistical data. The first aspect was based on the theory that the Type ξ bidder and the Type ζ bidder could be defined by the quantum of the returns. This is stated in hypothesis one. The hypothesis is true, a rank order analysis of the returns showed that the rank one bidders earned on average more than 180,000 per game and the low rank bidders, rank four or five earned on average less than 80,000 per game. The results are statistically significant at the 5%

level. The second hypothesis is that the Type ξ bidder would use a strategy of minimizing the bid differentials to increase their returns. A set of bidders exist who appear to minimize the bid differentials, but the set does not contain all of the Type ξ bidders, nor is it exclusive of Type ξ bidders. This hypothesis is not true.

The economically efficient bidders are not the ones who win the most awards, nor come in first in the game under all circumstances as we have defined now the Type ξ bidder by an average return instead of just first place in a game. A further study is suggested to combine a bid arrivals study and profit strategy to look for the strategies for optimum price and most awards.

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APPENDIX A

ANALYSIS OF THE BID DATA

Introduction

The stages of the bid data analysis are:

- determine the rank order and profit amounts of the participants in each of the games
- determine the bid drop data, rank order and descriptive statistics for this data

Games – Profit and Rank Order of Participants

Table 17 summarizes the rank order of the participants for total profit in each of the games. The participant number matches the number assigned in the SQL database for each study. Table 18 shows the profit numbers for each game in rank order.

Table 17
Participant Rank Order for Profit

Study	Participant Rank Order for Profit				
	1	2	3	4	5
1	9	7	4	8	6
4	1	3	2	4	-
9	12	1	3	4	-
11	1	4	2	12	-
12	1	2	4	3	-
14	3	4	1	2	
15	4	3	1	2	-
16	1	3	2	4	-

Table 18
Profit Rank Order

Study	Profit in Rank Order				
	1	2	3	4	5
1	68950	68122	43033	42225	18825
4	107424	91571	50103	28980	-
9	231104	123474	61240	45203	-
11	393965	368126	310565	297881	-
12	159074	157268	150114	125084	-
14	433434	334706	302232	252181	
15	45212	18193	17755	14833	-
16	269321	99846	53873	35098	-

Figure 27 shows the average profit for each rank order. Whilst there is some statistical debate about taking a regression on rank order data, the results are shown on the figure. The averaged data shows a relationship that is not evident in the complete data set using an analysis of profit against bid drop.

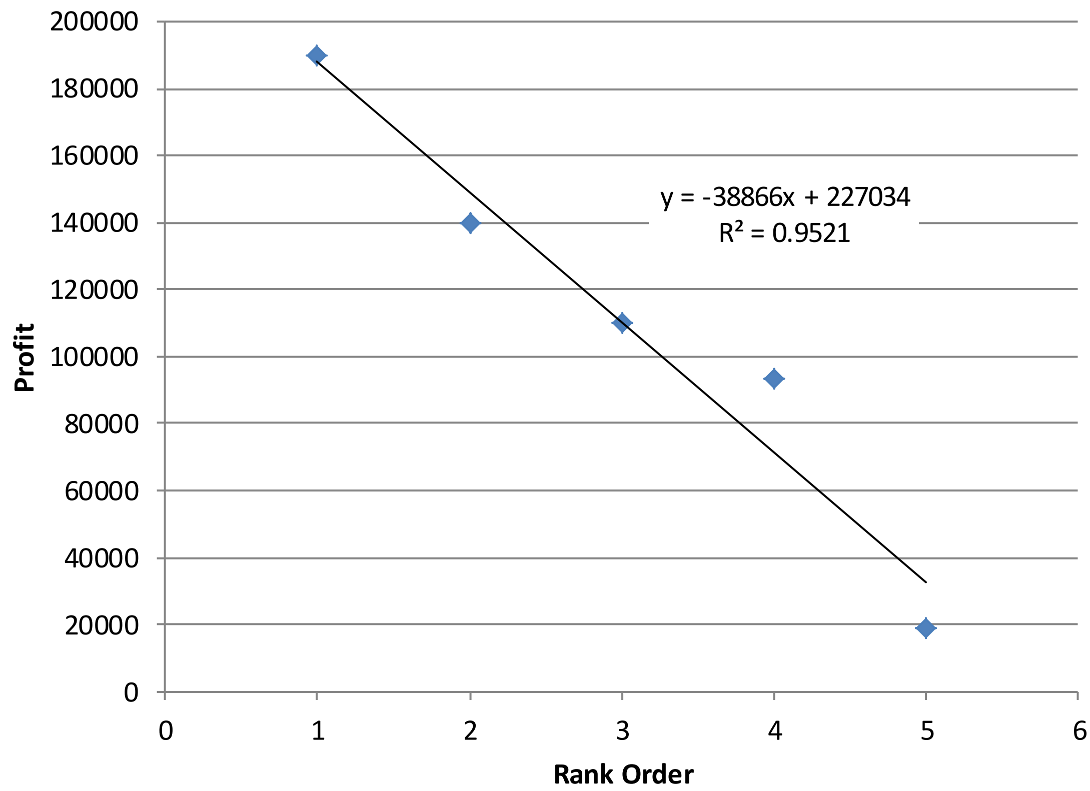

Figure 27. Profit average for each rank

Games – Bid Drop – Mean Data in Logarithmic Form

The bid drop data shows a wide distribution from 1 cent to 20,000 dollars. The data can be binned into logarithmic sets to mitigate the dominance of a few large bids. The bid drops means are shown in Table 19. The average results have been determined for each of the data sets based on order in the SQL Server participant number ranking.

Table 19
Logarithmic Mean of the Bid Drops

Study	Logarithmic Mean of the Bid Drops				
	1	2	3	4	5
1	2.61	3.73	2.71	3.38	2.36
4	1.91	2.27	0.99	1.63	-
9	2.01	2.08	2.54	1.52	-
11	2.20	1.05	2.04	1.84	-
12	0.76	0.96	1.82	2.02	-
14	3.03	2.87	3.00	0.89	-
15	2.23	1.65	1.40	1.85	-
16	1.79	3.22	3.18	3.11	-
Average	2.1	2.2	2.2	2.0	-

The results shown in Table 19 has a mean value of 2.14 ±0.77. Table 20 shows a Student's t Test analysis for the unordered bid drop data. The data for the first listed participant in the SQL database is compared to the second column. The analysis is repeated for each combination of columns. The simple hypothesis being tested is that there is no statistical differences in the column data as it should be randomly assigned. The results show that the all of the separate column data is drawn from a similar set to the other column data.

Table 20

Student t Test results for Participants Columns for Bid Data Drops

		2		
1	0.37	0.39	0.1	NC
2		0.04	0.44	NC
3			0.45	NC

Games – Bid Drop -Rank Order

The next step in the analysis is to place the bid drop data in increasing numerical order of the bid drop data in logarithmic form is shown in Table 21. The mean value for each rank order from 1 to 5 is also shown in the table.

Table 21
Numerical Increasing Order of the Bid Drop Data in Logarithmic Form

Study	Participant				
	1	2	3	4	5
1	2.36	2.61	2.71	3.38	3.73
4	0.99	1.63	1.91	2.27	
9	1.52	2.01	2.08	2.54	
11	1.05	1.84	2.04	2.2	
12	0.76	0.96	1.82	2.02	
14	0.89	2.87	3	3.03	
15	1.4	1.65	1.85	2.23	
16	1.79	3.11	3.18	3.22	
Average	1.345	2.085	2.32375	2.61125	3.73

A regression analysis for the average data compared to the rank order was completed using standard regression techniques. Figure 28 shows the results of the linear regression analysis and the fitted line.

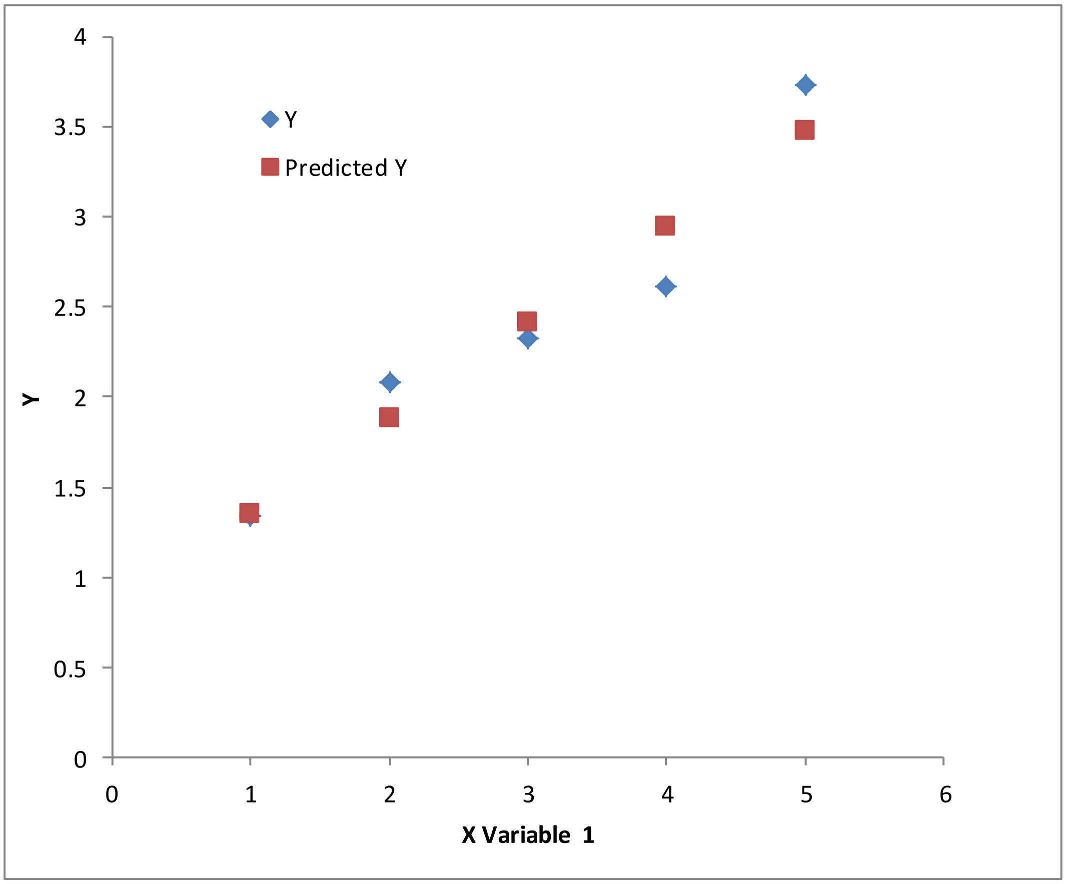

Figure 28. Regression plot for the bid drop results against rank order

The results show that the bid drop amounts are related in a linear fashion to the rank order for the data. Figure 29 shows the normal probability plot from the residual analysis. The plot shows the data is normally distributed. Figure 30 shows the residual data, the number of points is too limited to draw firm conclusions, but the results do not show a discernable pattern.

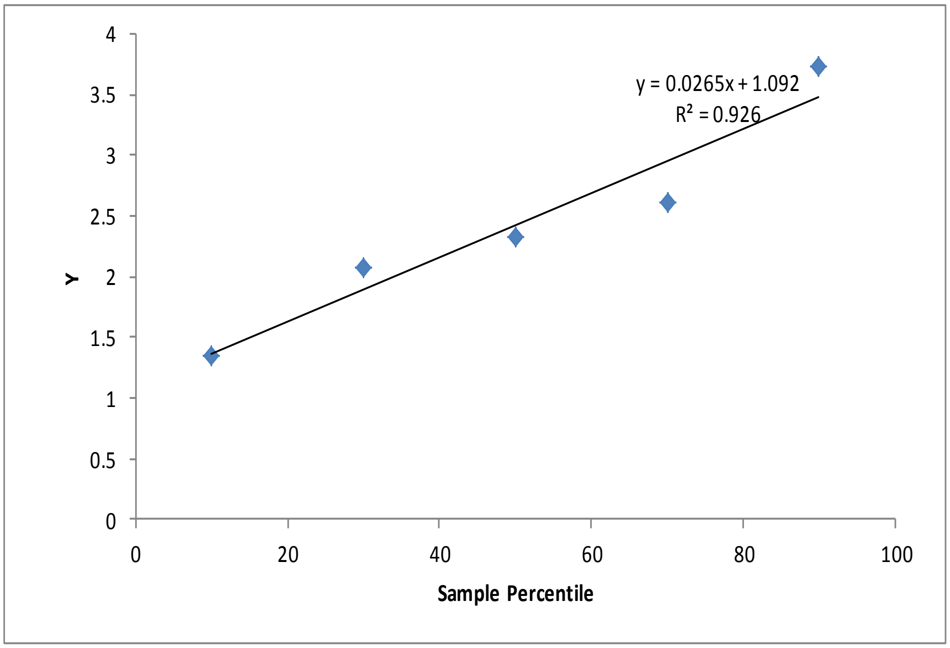

Figure 29. Normal probability plot for the bid drop results against rank order

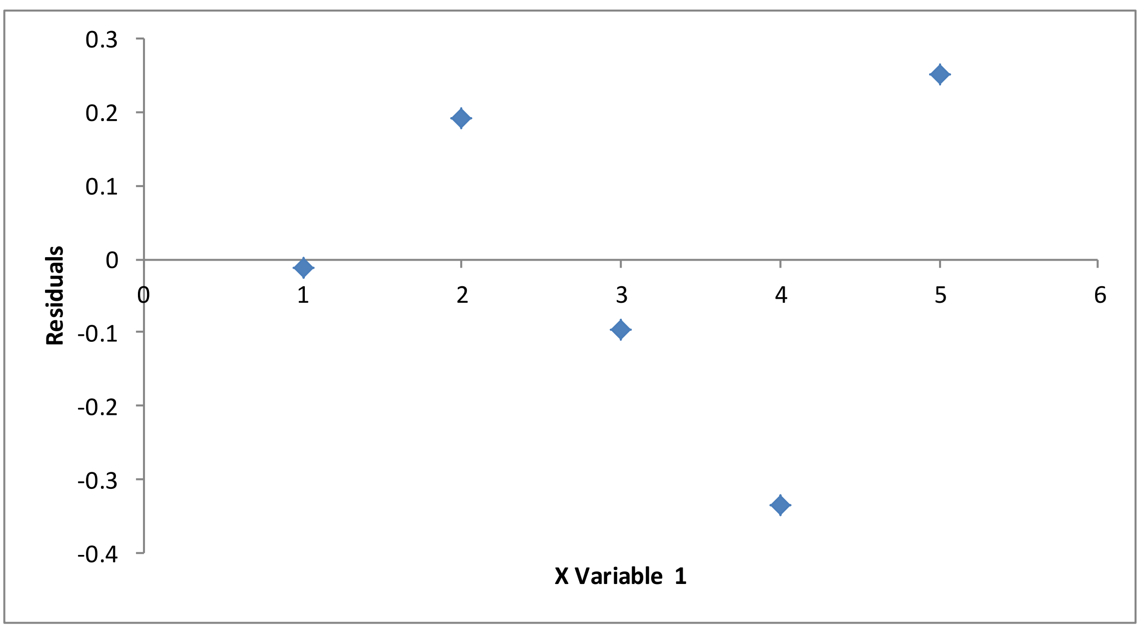

Figure 30. Residual data plot for the bid drop results against rank order

Games Descriptive Data

The descriptive data for each game is presented in the following figures. The data is the bidder id, the mean value for the profit lost in the bid differentials, the logarithmic means of this data, the percentage of the awards for each bidder, the rank order in terms of the number of bids won, the rank order for bid drop differentials and the difference in the two ranks.

Table 22 shows the descriptive data. The interesting player in this set is participant 001-7, who won 30% of the awards, ranked third on the bid differentials and had the second highest profit.

Table 22
Game 1 Summary of the Descriptive Data

Bidder ID	Profit Loss Mean	Logarithmic Mean	Awards Number/ Total Awards	Rank for Awards	Rank for Saving	Award Rank – Saving Rank
001-4	415.05	2.618104	20.0%	3	2	1
001-6	5442.7	3.735818	12.0%	5	5	0
001-7	521.33	2.717116	29.3%	1	3	-2
001-8	2403.9	3.380924	16.0%	4	4	0
001-9	230.6	2.362861	22.7%	2	1	1

Table 23 shows the descriptive data for game 4. The interesting player here is number 2, the player came in third in the profit level, but had the greatest number of awards. This appears to indicate an overly aggressive player who is not thinking strategically.

Table 23
Game 4 Summary of the Descriptive Data

Bidder ID	Profit Loss Mean	Logarithmic Mean	Awards Number/ Total Awards	Rank for Awards	Rank for Saving	Award Rank – Saving Rank
004-1	81.15976	1.9093408	12.1%	4	3	1
004-2	185.8186	2.2690893	45.5%	1	4	-3
004-3	9.780366	0.9903551	27.3%	2	1	1
004-4	42.49147	1.6283017	15.2%	3	2	1

Table 24 shows the descriptive data for game 9. Participant 009-12 showed that a good performance in winning awards, getting the highest profit in this game and reducing the amount lost on bid differentials is possible.

Table 24

Game 9 Summary of the Descriptive Data

Bidder ID	Profit Loss Mean	Logarithmic Mean	Awards Number/ Total Awards	Rank for Awards	Rank for Saving	Award Rank – Saving Rank
009-1	102.4	2.010281	20.3%	3	2	1
009-3	121.7	2.085293	18.6%	4	3	1
009-4	348.41	2.542095	35.6%	1	4	-3
009-12	33.441	1.524283	25.4%	2	1	1

Table 25 shows the descriptive data for game 11. Participant 1 made the greatest profit, but did not play very strategically.

Table 25
Game 11 Summary of the Descriptive Data

Bidder ID	Profit Loss Mean	Logarithmic Mean	Awards Number/ Total Awards	Rank for Awards	Rank for Saving	Award Rank – Saving Rank
011-1	158.44	2.1998524	21.7%	3	4	-1
011-2	11.382	1.0562159	21.7%	3	1	2
011-4	111.16	2.0459382	22.7%	2	3	-1
011-12	70.556	1.8485368	34.0%	1	2	-1

but the overall profit was low.

Table 26 shows the descriptive data for game 12. Participant 012-1 performed well in all measures, but the overall profit was low.

Table 26
Game 12 Summary of the Descriptive Data

Bidder ID	Profit Loss Mean	Logarithmic Mean	Awards Number/	Rank for Awards	Rank for Saving	Award Rank –

			Total Awards			Saving Rank
012-1	5.7593	0.7603668	36.3%	1	1	0
012-2	9.2558	0.9664162	20.9%	3	2	1
012-3	66.107	1.8202459	18.7%	4	3	1
012-4	107	2.0293956	24.2%	2	4	-2

r than expected for this player.

Table 27 shows the descriptive data for game 14. This game had exceptionally high profits for all players, all would be classified as Type ξ players. Participant 014-3 led in two of the three measures, the bid differential was higher than expected for this player.

Table 27
Game 14 Summary of the Descriptive Data

Bidder ID	Profit Loss Mean	Logarithmic Mean	Awards Number/ Total Awards	Rank for Awards	Rank for Saving	Award Rank – Saving Rank
014-1	1082.7	3.034511	22.0%	3	4	-1
014-2	755.89	2.878457	20.9%	4	2	2
014-3	1009.4	3.0040495	33.0%	1	3	-2
014-4	7.8126	0.8927939	24.2%	2	1	1

Table 28 shows the descriptive data for game 15. Participant 014-4 made the greatest profit, but all participants performed poorly and would be classified as Type ζ bidders for all intents and purposes.

Table 28
Game 15 Summary of the Descriptive Data

Bidder ID	Profit Loss Mean	Logarithmic Mean	Awards Number/ Total Awards	Rank for Awards	Rank for Saving	Award Rank – Saving Rank
015-1	171.13	2.2333277	30.0%	1	1	0
015-2	44.702	1.6503266	30.0%	1	3	-2
015-3	25.165	1.4007969	22.9%	3	4	-1
015-4	78.641	1.8956502	17.1%	4	2	2

Table 29 shows the descriptive data for game 16. Participant 016-1 performed well on all measures, made a significant profit and would be classified as a Type ξ player.

Table 29
Game 16 Summary of the Descriptive Data

Bidder ID	Profit Loss Mean	Logarithmic Mean	Awards Number/ Total Awards	Rank for Awards	Rank for Saving	Award Rank – Saving Rank
016-1	61.86	1.7914066	35.5%	1	1	0
016-2	1686.1	3.2268785	24.2%	2	4	-2
016-3	1542.7	3.1882837	21.0%	3	3	0
016-4	1290.3	3.1106805	19.4%	4	2	1

Summary

The results show a linear relationship between the participant rank order to the bid drop differentials.

APPENDIX B

THE KEIRSEY TEMPERAMENT SORTER

For each question, decide on answer a or b and put a check mark in the proper column of the answer sheet. Scoring directions are provided. There is no right or wrong answers since about half the population agrees with whatever answer you choose.

1. When the phone rings do you
   a. hurry to get to it first
   b. hope someone will answer
2. Are you more
   a. observant than introspective
   b. introspective than observant
3. Is it worse to
   a. have your head in the clouds
   b. be in a rut
4. With people are you usually more
   a. firm than gentle
   b. gentle than firm
5. Are you more comfortable in making
   a. critical judgments
   b. value judgments
6. Is clutter in the workplace something you
   a. take time to straighten up
   b. tolerate pretty well
7. Is it your way to
   a. make up your mind quickly
   b. pick and choose at some length
8. Waiting in line, do you often
   a. chat with others
   b. b. stick to business
9. Are you more
   a. sensible than ideational
   b. ideational than sensible
10. Are you more interested in
    a. what is actual
    b. what is possible
11. In making up your mind are you more likely
    a. to go by data
    b. to go by desires
12. In sizing up others do you tend to be
    a. objective and impersonal
    b. friendly and personal
13. Do you prefer contracts to be
    a. signed, sealed, and delivered
    b. settled on a handshake
14. Are you more satisfied having

a. a finished product

b. work in progress

15. At a party, do you

a. interact with many, even strangers

b. interact with a few friends

16. Do you tend to be more

a. factual than speculative

b. speculative than factual

17. Do you like writers who

a. say what they mean

b. use metaphors and symbolism

18. Which appeals to you more:

a. consistency of thought

b. harmonious relationships

19. If you must disappoint someone are you

a. usually frank and straightforward

b. warm and considerate

20. On the job do you want your activities

a. scheduled

b. unscheduled

21. Do you more often prefer

a. final, unalterable statements

b. tentative, preliminary statements

22. Does interacting with strangers

a. energize you

b. tax your reserves

23. Facts

a. speak for themselves

b. illustrate principles

24. Do you find visionaries and theorists

a. somewhat annoying

b. rather fascinating

25. In a heated discussion, do you

a. stick to your guns

b. look for common ground

26. Is it better to be

a. Just

b. merciful

27. At work, is it more natural for you to

a. point out mistakes

b. try to please others

28. Are you more comfortable

a. after a decision

b. before a decision

29. Do you tend to

a. say right out what's on your mind

b. keep your ears open

30. Common sense is

    a. usually reliable

    b. frequently questionable

31. Children often do not

    a. make themselves useful enough

    b. exercise their fantasy enough

32. When in charge of others do you tend to be

    a. firm and unbending

    b. forgiving and lenient

33. Are you more often

    a. a cool-headed person

    b. a warm-hearted person

34. Are you prone to

    a. nailing things down

    b. exploring the possibilities

35. In most situations are you more

    a. deliberate than spontaneous

    b. spontaneous than deliberate

36. Do you think of yourself as

    a. an outgoing person

    b. a private person

37. Are you more frequently

    a. a practical sort of person

    b. a fanciful sort of person

38. Do you speak more in

    a. particulars than generalities

    b. generalities than particular

39. Which is more of a compliment:

    a. "There's a logical person"

    b. "There's a sentimental person"

40. Which rules you more

    a. your thoughts

    b. your feelings

41. When finishing a job, do you like to

    a. tie up all the loose ends

    b. move on to something else

42. Do you prefer to work

    a. to deadlines

    b. just whenever

43. Are you the kind of person who

    a. is rather talkative

    b. doesn't miss much

44. Are you inclined to take what is said

    a. more literally

    b. more figuratively

45. Do you more often see

    a. what's right in front of you

    b. what can only be imagined

46. Is it worse to be

    a. softy

b. hard-nosed

47. In trying circumstances are you sometimes

    a. too unsympathetic

    b. too sympathetic

48. Do you tend to choose

    a. rather carefully

    b. somewhat impulsively

49. Are you inclined to be more

    a. hurried than leisurely

    b. leisurely than hurried

50. At work do you tend to

    a. be sociable with your colleagues

    b. keep more to yourself

51. Are you more likely to trust

    a. your experiences

    b. your conceptions

52. Are you more inclined to feel

    a. down to earth

    b. somewhat removed

53. Do you think of yourself as a

    a. tough-minded person

    b. tender-hearted person

54. Do you value in yourself more that you are

    a. reasonable

    b. devoted

55. Do you usually want things

    a. settled and decided

    b. just penciled in

56. Would you say you are more

    a. serious and determined

    b. easy going

57. Do you consider yourself

    a. a good conversationalist

    b. a good listener

58. Do you prize in yourself

    a. a strong hold on reality

    b. a vivid imagination

59. Are you drawn more to

    a. fundamentals

    b. overtones

60. Which seems the greater fault

    a. to be too compassionate

    b. to be too dispassionate

61. Are you swayed more by

    a. convincing evidence

    b. a touching appeal

62. Do you feel better about

    a. coming to closure

    b. keeping your options open

63. Is it preferable mostly to

a. make sure things are arranged

b. just let things happen naturally

64. Are you inclined to be

a. easy to approach

b. somewhat reserved

65. In stories do you prefer

a. action and adventure

b. fantasy and heroism

66. Is it easier for you to

a. put others to good use

b. identify with others

67. Which do you wish more for yourself:

a. strength of will

b. strength of emotion

68. Do you see yourself as basically

a. thick-skinned

b. thin-skinned

69. Do you tend to notice

a. disorderliness

b. opportunities for change

70. Are you more

a. routinized than whimsical

b. whimsical than routinized

APPENDIX C

KIERSEY TEMPERAMENT SORTER SCORING

Introduction

Table 30 shows a sample of the KTS Scoring sheet.

Table 30

KTS Scoring Sheet

Enter a check for each answer in the column for a or b.

	a	b		a	b		a	b		a	b		a	b		a	b		a	b
1			2			3			4			5			6			7		
8			9			10			11			12			13			14		
15			16			17			18			19			20			21		
22			23			24			25			26			27			28		
29			30			31			32			33			34			35		
36			37			38			39			40			41			42		
43			44			45			46			47			48			49		
+50			51			52			53			54			55			56		
57			58			59			60			61			62			63		
64			65			66			67			68			69			70		
1			23			43			45			65			67			87		

1			2	3			4	5			6
	E	I			S	N			T	F	

7			
	J	P	

Directions for Scoring

The directions for scoring the test are:

1. **Add down** so that the total number of a answers is written in the box at the bottom of each column. Do the same for the b answers you have checked. Each of the 14 boxes should have a number it.
2. **Transfer the number** in box #1 of the answer grid to box #1 below the answer grid. Do this for box # 2 as well. Note, however, that you have two numbers for boxes 3 through 8. Bring down the first number for each box beneath the second, as indicated by the arrows. Now add all the pairs of numbers and enter the total in the boxes below the answer grid, so each box has only one number.
3. **Now you have** four pairs of numbers. Circle the letter below the larger numbers of each pair. If the two numbers of any pair are equal, then circle neither, but put a large X below them and circle it.

APPENDIX D

IRB APPROVAL

TEXAS A&M UNIVERSITY

DIVISION OF RESEARCH AND GRADUATE STUDIES - OFFICE OF RESEARCH COMPLIANCE

1186 TAMU, General Services Complex
College Station, TX 77843-1186
750 Agronomy Road, #3500

979.458.1467
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http://researchcompliance.tamu.edu

Human Subjects Protection Program

Institutional Review Board

DATE:	10-April-2014
MEMORANDUM TO:	LI, JIAXING 77843-3578
FROM:	Office of Research Compliance Institutional Review Board
SUBJECT:	Initial Review

Protocol Number:	IRB2014-0176M
Title:	Reverse Auction Bidding
Review Category:	Expedited

Approval Period: 10-April-2014 **To** 01-April-2011

Approval determination was based on the following Code of Federal Regulations:

45 CFR 46.110(b)(1) - Some or all of the research appearing on the list and found by the reviewer(s) to involve no more than minimal risk.
----
(7) Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation or quality assurance methodologies.

(Note: Some research in this category may be exempt from the HHS regulations for the protection of human subjects. 45 CFR 46.101(b)(2) and (b) (3). This listing refers only to research that is not exempt.)

Provisions:

This research project has been approved for one (1) year. As principal investigator, you assume the following responsibilities

1. **Continuing Review:** The protocol must be renewed each year in order to continue with the research project. A Continuing Review along with required documents must be submitted 30 days before the end of the approval period. Failure to do so may result in processing delays and/or non-renewal.
2. **Completion Report:** Upon completion of the research project (including data analysis and final written papers), a Completion Report must be submitted to the IRB Office.
3. **Adverse Events:** Adverse events must be reported to the IRB Office immediately.

4. **Amendments:** Changes to the protocol must be requested by submitting an Amendment to the IRB Office for review. The Amendment must be approved by the IRB before being implemented.
5. **Informed Consent:** Information must be presented to enable persons to voluntarily decide whether or not to participate in the research project.

This electronic document provides notification of the review results by the Institutional Review Board.