Two Essays on Bidder Behavior in Simultaneous Online Auctions

by

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(Under the direction of Srinivas K. Reddy)

Abstract

The growing popularity of online auctions and the availability of rich and detailed bidding data have spawned many new empirical researches in auctions that were not possible to explore earlier. Particularly, more information is now known about bidder behavior in auctions than ever before. Still, there are certain auction characteristics that desire for more research. One such area is bidder competition in auctions. Current view on this topic considers each bidder to compete against all the other bidders as a whole, without distinguishing one competitor from another. This consideration is inadequate in explaining the effects of different levels of rivalry between bidder pairs. To overcome this limitation, this dissertation presents an innovative approach of looking at bidder competition at a dyadic bidder level. The context of the study is simultaneous online auctions selling modern Indian art. Simultaneous auction, a popular online auction format for selling highly complementary products is ideal for such study as bidders in these auctions typically compete for more than one lot (item) simultaneously, thus engaging in both within-lot and between-lot interaction (competition). This dissertation consists of two essays. The first essay shows that after controlling for aggregate level of competition, dyadic bidder interactions have significant effect on the auction outcome. Extending on these findings, a new approach of representing bidding data is presented. Each bidder is connected based on the dyadic interactions between them and a "bidder network" is formed. Using the analytical tools from Social Network Analysis, the key or important bidders in the network are identified and their effect on the auction outcome is analyzed. In the second essay, dyadic bidder interactions are used to analyze situations where bidders reevaluate or update their reservation value for the item. Using choice models, it is established that high level of between-lot interaction has a significant effect on the propensity of this behavior. The notion of dyadic interaction is further extended to analyze characteristics of bidders (termed here as Reactors) who change their pre-set reservation value for the item.

INDEX WORDS: Simultaneous Online Auctions, Dyadic Bidder Competition, Key Bidders, Bidder Networks, Value Updating Bidders, Random Effect Model

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Dedication

To My Parents and Ani

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Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

Internet has greatly popularized auctions in recent years. It has transformed the way auctions are traditionally held, eliminated borders, and created new ways in which consumers and businesses realize values for items. Although many predicted their death with the "burst of the internet bubble," in the later 90ties, online auctions have grown even popular since. The public nature of all these auctions has also opened new opportunities for empirical researchers to gather and analyze huge amount of bidding data that were not available earlier. Since online auctions are fundamentally similar to their offline, brick-and-mortar counterparts, many theoretical results founded in economics and psychology, and derived from the offline auctions, have often proven to hold in the online environment (winner's curse [2], revenue equilibrium [3, 9, 17] and so on). There are also other findings that are distinct to online auction (bidder dynamics [4, 21], reference points [7, 13], auction fever [16],seller reputation [18], last-minute bidding [22], and forward-looking bidding [25]). Possible reasons for such uniqueness are the world-wide reach of the internet, anonymity of its users, longer auction time, transparency, constant availability and continuous change.

Most of this popularity is attributed to the success of online auction site, eBay, where anything from hairclips to private jet planes gets sold. For this reason, almost all prior studies on online auctions have used eBay or eBay like auctions as their data source. Recently, there has been increasing interest in an alternative auction format, commonly known as *Simultaneous Online Auction* (SOA), which has become very popular for selling high-priced complementary items such as fine art and collectables. These auctions sell multiple items simultaneously, meaning that auctions start and end at the same time for all items. This is different as compared to eBay where items are sold independently, meaning that their auction beginning and end time are not related. Since many items are highly complementary, bidders in these auctions typically desire to purchase more than one item at a time. As a result, bidders frequently compete against each other simultaneously, not only within the same auction (i.e. for the same item), but also across other auctions that sell complementary items. This leads to a unique bidding dynamics [23] and bidder competition that is exclusive to SOAs. This dissertation presents two essays examining the effect of such bidder competition on the auction outcome and on value updating behavior of bidders.

SOAs are different from the auctions held on popular auction sites such as eBay, both in terms of the auction design and the types of items they sell. SOAs are held by specialized online auction houses dedicated to selling only one type of item (e.g., SaffronArt.com sells only Modern Indian Art, Attinghouse.com sells only Chinese Art and Southeast Asian Art) and with a price tag ranging from a few thousands to a few millions of dollars. Unlike eBay where auctions are held for 3-7 days, SOAs have shorter (typically 2-3 days) auction period. SOAs sell multiple objects simultaneously in a first-price ascending auction format. In contrast, eBay sells items in a variant of the second-price sealed-bid auction [15]. Another difference between eBay auctions and SOAs is the type of closing rule. While eBay has mostly fixed hard-close times, SOAs tend to have soft-closing times where the time automatically extends after a late bid. A soft-close auction format not only encourages bidders to bid early [22], but also discourages *sniping*[1] in the last moment. SOAs are also organized by only one seller, i.e. the auction house (similar to the Christie's and Sotheby's auctions), whereas eBay provides an auction platform for many different sellers. Finally, on eBay bidders are rarely observed to consciously compete against each other across different auctions that take place simultaneously, as it is unlikely that bidders will have similar product demand and even if they do, it is highly implausible that they will compete for the same item at the same

[1]Sniping is a strategic bidding activity where bids are submitted in the last moments of the auction to allow minimal time to other bidders to react to this bid. Such behavior is prominent in eBay auctions as the auction closes promptly at a specific time.

time as products in eBay typically have multiple listings. Moreover, eBay now masks bidder identities thereby eliminating the ability of bidders to identify competitors across auctions.

With high stakes and unique bidding environment, research in SOAs is crucial to the auction house managers. Particularly, investigating how bidder competition and influence lead to different bidder phenomenon is a topic of great importance. Unfortunately, no prior work has been done on SOAs in the online setting and all earlier studies in offline setting are theoretical and analytical in nature and have mainly looked at optimal bidding strategy [24] and revenue equilibrium [5, 19, 8]. In this dissertation, I intend to fill this gap by empirically investigating bidder competition in simultaneous online auctions of Modern Indian Art.

Studies on bidder competition in single-item auctions are also limited. They have mostly considered the aggregate measures of competition in the auction such as number of bidders and number of bids per bidder. For examples, the number of bidders as a proxy for auction competitiveness has been used to examine auction dynamics [4, 21]; herding behavior [6]; tradeoff between auction formats [14], and the number of bids per bidder is used as a proxy for the level of bidder interaction [1, 10]. Overall, all these studies share the same basic perspective on bidder interaction, wherein a bidder is viewed as competing against all the other bidders as a whole, without distinguishing one competitor from another. Although the number of bidders and the number of bids per bidder capture the general intensity of competition in the auction, they are inadequate in explaining the effects of different levels of rivalry between bidder pairs. To overcome this limitation, both essays presented here consider bidder competition at a dyadic level, particularly focusing on the interactions between bidder pairs. This consideration effectively advances the current understanding of bidder competition by looking beyond aggregate competition measures and examining its effect on the auction outcome (essay 1) and on the value updating behavior of bidders (essay 2). Ariely and Simonson [1] suggested online auctions as a three-stage process (The details of each stage are given in Table 1.1). In the same lines, the contribution of this dissertation is essentially at the second and third stage of the auction process. Essay 1 examines the

Table 1.1: Online Bidding Behavior

Auction Stage	*Value Assessments*	*Decision Dynamics*
Auction choice/ entry	Type of product	N/A
	Auction Info (starting price etc.)	
	Availability of comparisons	
	Previous bidding activity	
	Concurrent (observed) auctions of related items	
	Planned vs. impulse bidding	
Middle phase of the auction	Bids submitted by others	Escalation
	Biased sample of others	Self perception
	Local context focus	Endowment
	Involvement	Attribute weights
	Dyadic bidder interactions (Essay 2)	Utility of bidding & competing
End of auction	**Dyadic bidder interactions (Essay 1)**	Winner's vs. loser's curse
		End rules
		Strategic late bidding

*Taken from "Buying, Bidding, Playing, or Competing? Value Assessment and Decision Dynamics in Online Auctions," Dan Ariely and Itamar Simonson, Journal of Consumer Psychology, 13(1&2), 113-123

effect of dyadic bidder interactions as a value assessment factor at the end of the auction and essay 2 examines the effect at the middle phase of the auction when bidders reconsider their valuation and decide whether to increase their reservation price for the item. Both these notions are shown in Table 1.1 in bold. In details, the first essay (presented in Chapter 3) examines the effect of bidder competition in SOAs. Particularly, this essay takes a closer look at bidder interaction (repeated outbidding) at dyadic bidder level and examines its effect on the auction outcome, which is defined as the realized price in excess of what was expected by the auction house before the auction started, or, simply, *seller profit*. The results show that measures based on dyadic bidder interactions are significant in explaining the variation in seller profit across lots, offering empirical support for the argument that dyadic bidder interactions matter in simultaneous online auctions. Specifically, I find that 1) in lots where bidders bid in more lots together (i.e., higher "between-lot interaction"), seller profit tends to be significantly lower; and 2) in lots where two bidders directly outbid each other more frequently (i.e., higher "within-lot interaction"), seller profit tends to be significantly higher. Given the empirical evidence for the effects of dyadic bidder interactions on seller profit, I "connect" any two individual bidders with each other (based on the level of interactions between them) and use the resulting "*bidder network*" to identify "key" bidders based on their positions in the network. I borrow analytical tools from Social Network Analysis, which has long been applied to identify central figures in various forms of communities, virtual or real. In the context of simultaneous online auction, by analogy, each bidder can be viewed as a "node," and the dyadic bidder interactions form the "tie" between the corresponding nodes. Mapping out the nodes and ties leads to a virtual network of bidders, which allows one to conduct network analysis to identify key bidders. Three findings on the impacts of key bidders are of particular note. First, compared to key bidder identification measures based on simple heuristics such as the number of bids and depth of pocket, my measure of key bidder explains significantly more variance in *seller profit*. Second, lots with key bidders' participation yield significantly higher *seller profit* than lots without their presence. Finally, the presence of key bidders speeds up the price increase in the first half of the auction, but slows down the rate of price increase in the second half.

In sum, the intended contribution of my first essay is of three-fold. First, I introduce simultaneous auction to the online auction literature, wherein bidders compete against each other for multiple items simultaneously. Second, in the context of simultaneous auction, I examine bidder competition at the dyadic level, including between- as well as within-lot interaction. Finally, I investigate bidder interactions through the lens of a network structure, which enables me to identify key bidders based on their central positions in the network, and examine their impacts on the auction. A flowchart showing the outlines of the two essays is shown in Figure 1.1.

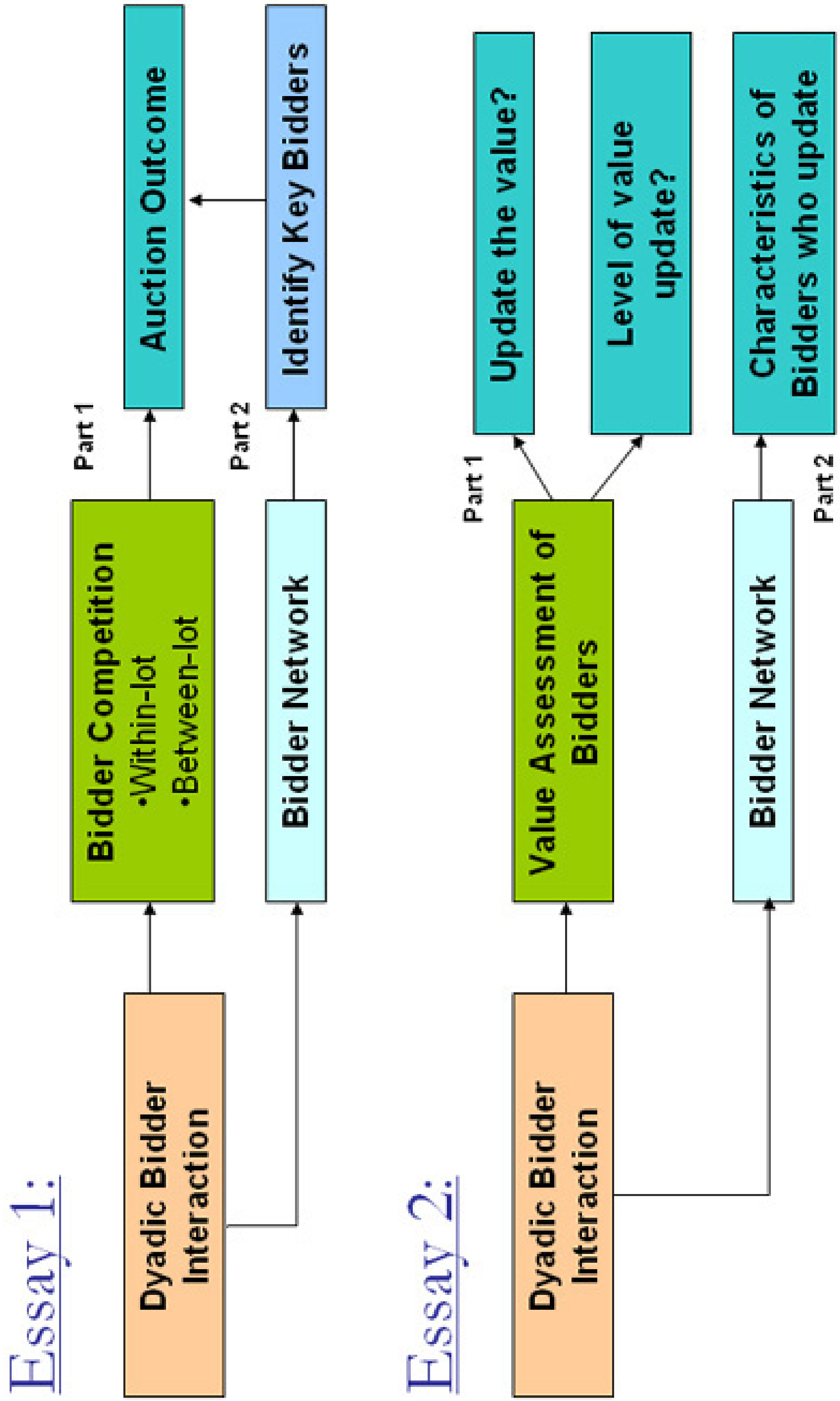

Figure 1.1: Outline of the Dissertation

In these auctions, (like any other affiliated private value[2] auction), some bidders will consult the bid amount of other bidders during the auction and update their pre-set valuation and their "willingness to pay" for the items they are interested in (affiliation theory [20]). Particularly, if the bidders have limited information about the art items, they will consult bids of other bidders as additional item information [11, 12]. Furthermore, in simultaneous auctions, bidders frequently encounter each other in more than one item. Therefore, it is possible for bidders to get "familiar" with other bidders and their bidding strategy and get influenced by them. In the second essay (presented in Chapter 4), I investigate the effect of such influences on the value-updating bidders (termed as *Reactors*).

In this essay, I assume that bidders do update their value during auctions and such behavior is revealed when bidders place a higher bid value after using a proxy bidding system earlier in the auction. Proxy bidding is a commonly available feature in most online auction houses where bidders set a maximum amount they are willing to pay, and then let the auction house place proxy bids on their behalf until the proxy price. Along these lines, Ku, Malhotra and Murnighan [16] performed a survey of bidders and found that most of them use proxies to set their maxima. Taking such an approach to identify value-updating behavior in auctions, first I investigate the effect of "familiar bidders" on the propensity of such bidder phenomenon. Next, I analyze the characteristics of *Reactors* in the presence of influencing bidders (termed here as *Influencers*) by considering the data as a sociomatrix and build a random effect model. I examine three important questions pertaining to the *Reactors*: In what type of lots (art items) do bidders update their value? Do they bid more in the first half or in the second half of the auction? Are they selective in the lots on which they bid, or do they bid on many lots?

Results suggest that high level of "bidder familiarity" or between-lot bidder interaction has a negative effect on the bidder's propensity to update their value and on the level of

[2]Bidders' valuations have some dependence with each other (loosely speaking, one bidder's high value signal makes it more likely that other bidders will exhibit high values), implying that bidders can change valuation if others' bidding behaviors are observable as in open bid format [20].

value update. Further, I find that *Reactors* typically bid on fewer items, suggesting that they might be the collectors and not the art dealers [22]. They also bid on high value items and bid more in the second half of the auction than in the first half. Interestingly, *Reactors* and *Influencers* rarely alter their role during the auction, and there is more possibility for *Reactors* to encounter the same *Influencers* over other items than the opposite. In addition, I also show that my random effect model of value updating bidder (*Reactors*) analysis performs better than a competing logistic model, thus reaffirming the role of the "bidder familiarity" in the auctions.

In sum, the contribution of my second essay is of three-fold. First, I examine the effect of bidder competition on the propensity of value-updating behavior of bidders. Second, from the technical standpoint, I demonstrate an application of a random effect dyadic relation model for complex human behavior and emphasize the importance of new and advanced statistical techniques available to the social science field. And third, I use an innovative and rich network framework to examine the inter-bidder influence in the auction and analyze characteristics of value-updating bidders.

The rest of the dissertation is presented as follows. In the second chapter, I introduce Simultaneous Auctions and provide an overview of the extant literature on it. In the third chapter, I discuss the first essay in details along with all the results. In the fourth chapter, I present the second essay along with the findings. Finally, the fifth chapter presents the concluding remarks on the two studies and discuss future directions.

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Chapter 2

Literature Review

For decades, simultaneous auctions have been a very popular auction design for selling complementary high priced items in offline auctions. Prior to 1990's, these auctions were in a sealed-bid format where bidders were required to submit sealed bids simultaneously [29, 31]. This form of simultaneous auctions was, and still is, very popular for assigning government procurements. In 1994, the Federal Communications Commission (FCC) organized a new form of simultaneous auction, i.e. Simultaneous Multiple-Round (SMR) Auctions to sell licenses for electromagnetic spectrum. It was one of the first auctions in the world that was held on a browser-based system. Nowadays, simultaneous auctions are commonly used to sell timber, cars [17], U.S. treasury bills [30], oil drilling rights and so on. Recently, it has also become popular as an online auction format, selling fine arts and collectables. In this dissertation, I present two essays on bidder behavior in simultaneous online auctions. Both these essays (Chapter 3 and Chapter 4) have their own literature review section that discusses studies relevant to the respective context. Therefore, in this chapter, I will only provide an overview of the extant literature on simultaneous auctions and online auctions.

2.1 Simultaneous Auctions

Most researches in simultaneous auctions are focused either on studying optimal bidding strategy and revenue equilibrium or on comparing simultaneous auctions with other auction designs. The general trend of these studies has mainly focused on the underlying bidding process in different simultaneous auction formats. For example, Rothkopf [29] showed that Lagrangian approach is the best way to determine a profit maximizing set of sealed bids in a sealed-bid simultaneous auction, Smith and Rothkopf [31] examined simultaneous auctions that carry a single fixed charge, which incurs if and only if one or more auctions are won, and Baye and his colleague [1] investigated auctions where all bidders forfeit their bid values if they lose the auction. With the introduction of Simultaneous Multiple-Round (SMR) Auctions in 1994, some newer studies have investigates the auction process [18], auction efficiency [25] and revenue-superior versions [22] of SMR.

Studies focused on revenue equilibrium have mainly looked at the effect of bidder competition in these auctions. Many studies [2, 11, 17] concluded that there exists a low-revenue equilibrium in these auctions. Two possible reasons have been suggested for this phenomenon. One suggests that during simultaneous auctions, bidders engage in some kind of signaling mechanism [2] where they implicitly agree to divide the items among themselves without engaging in any form of conflict (tacit collusion). Another set of literature [11] suggests that this low-equilibrium may be a natural outcome and not based on any signaling mechanism among bidders. They explain it as a sub-game with excess bidders dropping out at an intermediate stage and thus, the remaining bidders divide the objects among themselves at a lower price.

Other researches on simultaneous auctions have focused on comparing the auction format with other popular auction designs. Holt [14] compared it with sequential descending auctions based on the effect of changes in procurement procedures and the number of bidders on expected procurement cost. He found that if the bidders are risk averse, the expected procurement will be lower in simultaneous auctions as compared to sequential descending auctions. Hausch [12] examined the question, when to use simultanoeus auctions and when to use sequential auctions for selling multiple items. He concluded that there exist two types of effect, namely information effect and deception effect[1]. Information effect increase the seller's expected revenue and deception effect reduces expected revenue. Thus, sellers' auction design preference should be dependent on the expected effect in the auction. The two

[1]Deception effect is predominantly develops in sequential auctions where bidders strategically underbid in order to avoid revealing information about his value for later objects

essays presented in this dissertation extend this literature by examining the effect of dyadic bidder competition in the online version of simultaneous auctions. Therefore, in the next section, I summarize the major studies on online auction.

2.2 Online Auctions

With the growing popularity and availability of abundant bidding data, online auctions have become a popular research topic in recent years. Most of these studies have advanced our understanding of bidder behavior in auctions that were not possible to explore earlier. For example, Dholakia and Simonson [10] and Kamins and his colleagues [15] investigated the effect of reference points in online auctions, Dholakia et. al [9] examined herding behavior in these auctions, Zeithammer [33] examined the forward-looking behavior of bidders where bidders adjust their current bid value based on the presence of other auctions of similar items, and Bapna and his colleagues [4] looked at bidder surplus in these auctions.

Another research trend has focused on examining different auction characteristics that are unique to online auctions. For example, [8, 21] investigated the effect of buyer and seller reputation in online auctions. In the same lines, Wilcox [32] and Borle and his colleagues [6] looked at the effect of experienced bidders' (based on the eBay rating) behavior on the auction outcome. Roth and Ockenfels [28] investigated the last-minute bidding behavior of bidders and also investigated how bidders with more experience behave as compared to bidders with less experience. Finally, Bapna and his colleagues [3] categorized bidders based on their behavior and developed an online bidder topology.

Finally, another reserach stream on online auction focuses on its bidding process and price formation. For example, Bapna and his colleagues [5] and Reddy and Dass [27] used Functional Data Analysis [26] to investigate the effect of different auction characteristics on the price dynamics during auctions, and Park and Bradlow [24] and Chan and his colleagues [7] examined bidders' willingness to pay in the auction. Interestingly, all the above studies have focused on single-item auctions. This dissertation contributes to the online auction literature by introducing simultaneous online auctions and examining two interesting bidder phenomenon, i.e. key bidders and value-updating bidders by focusing on dyadic bidder competition.

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Chapter 3

Essay One: Dyadic Bidder Interactions and Key Bidders in Simultaneous Online Auctions

3.1 Introduction

The growing popularity of online auctions and the availability of bid history data have spawned a large number of empirical studies, addressing a wide range of topics including, for example, price dynamics [6, 30], bidder surplus [5], reference points [18, 33], buyer and seller reputation [16, 46], auction formats [43, 35], reverse-auctions [31, 32], name-your-own price auctions [64], herding behavior [17], experience of bidders [12], forward-looking behavior of bidders [68], bidders' willingness to pay [52, 14], bidder heterogeneity and auction design [4], etc.

All these studies have focused exclusively on single-item auctions, where bidders compete for one item at a time. Meanwhile, another auction format, commonly known as simultaneous auction [63], has recently become popular in online settings where multiple heterogeneous items are sold *concurrently* to the same group of bidders over an extended period of time [58]. Unlike auctions held on eBay and Amazon, simultaneous auctions give rise to a competitive environment that is quite different from single-item auctions, because in simultaneous auctions bidders compete against each other not only within a lot (for an item), but also across lots. In addition, simultaneous auction has become one of the most popular auction formats in selling a wide range of objects including, for example, FCC radio spectrum [48], U.S. treasury bills [60], timber and cars [40].

There have been a few analytical [13, 63] and experimental studies [40, 53] on the competitive dynamics of simultaneous auctions. This chapter, however, is the first empirical investigation (to the best of our knowledge) into bidder competition in the context of simultaneous online auction. As a starting point, we are interested in examining the impacts on auction outcome of two frequently observed forms of dyadic bidder interactions[1]:a pair of bidders repeatedly outbid each other for an item (termed hereinafter within-lot interaction), and a pair of bidders bid for multiple items simultaneously (termed hereinafter between-lot interaction). Furthermore, through our interviews with auction house managers who have run many simultaneous online auctions, we learned that in these auctions a few bidders tend to emerge as the dominant players (termed hereinafter "key bidders"), who seem to have disproportionately large influence on price formation during a auction, even though they win only a small fraction of the items auctioned together. The challenge is how to systematically identify these bidders based on the pattern they place their bids within as well as across multiple lots, and quantify their impacts. In this chapter, we set out to address these two closely related (as we shall illustrate later) issues in the context of a simultaneous online auction where 199 fine-art items were open for bidding simultaneously for a group of 256 invited bidders during a three-day period.

Understanding how individual bidders compete against and interact with each other is important for designing auctions [49]. Studies on single-item online auctions have modeled the intensity of bidder competition using mainly two measures: the number of bidders as a proxy for auction competitiveness [6, 58, 19, 35, 1, 23, 39, 53], and the number of bids per bidder as a proxy for the level of bidder interaction [1, 25, 39]. All these studies share the same basic perspective on bidder interaction, wherein a bidder is viewed as competing against all the other bidders as a whole, without distinguishing one competitor from another. Although the number of bidders and the number of bids per bidder can capture the general intensity of bidder competition, they are inadequate in explaining the effects of dyadic bidder interactions, because they fail to reflect the fact that some bidder pairs may engage in more

[1]The term "bidder interaction" has been used to indicate repeated bids and counter-bids between bidders [53, 23].

aggressive competitive bidding than others, and bidders may respond to bids from different competitors differently.

To overcome this limitation, we look at bidder competition at a dyadic level, focusing on the interactions between bidder pairs and how these dyadic interactions affect auction outcome, which is defined as the realized price in excess of what was expected by the auction house before the auction started, or, simply, *seller profit*. Our results show that measures based on dyadic bidder interactions are significant in explaining the variation in seller profit across lots, offering empirical support for the argument that dyadic bidder interactions matter in simultaneous online auctions. Specifically, we find that 1) in lots where bidders bid in more lots together (i.e., higher "between-lot interaction"), seller profit tends to be significantly lower; and 2) in lots where two bidders directly outbid each other more frequently (i.e., higher "within-lot interaction"), seller profit tends to be significantly higher.

Given the empirical evidence we find for the effects of dyadic bidder interactions on seller profit, we "connect" any two individual bidders with each other based on the level of interactions between them and use the resulting "*bidder network*" to identify "key" bidders based on their positions in the network. We borrow analytical tools from Social Network Analysis, which has long been applied to identify central figures in various forms of communities, virtual or real. For example, social network analysis has been used to find out which websites play a central role in directing online traffic [34, 51], or which researchers are gatekeepers of new ideas [7]. Particularly, in Marketing, it has been used to model various dyadic interactions [26, 29], buyer-seller interactions [27], brand-switching behavior [28] and interpersonal influence processes in market diffusion [66]. In the context of simultaneous online auction, by analogy, each bidder can be viewed as a "node", and the between- and within-lot interactions between any two bidders form the "tie" between the corresponding nodes. Mapping out the nodes and ties leads to a virtual network of bidders, which allows us to conduct network analysis to identify key bidders.

Three findings on the impacts of key bidders are of particular note. First, compared to key bidder identification measures based on simple heuristics such as the number of bids and depth of pocket, our measure of key bidder explains significantly more variance in *seller profit*. Second, lots with key bidders' participation yield significantly higher *seller profit* than lots without their presence. Finally, the presence of key bidders speeds up the price increase in the first half of the auction, but slows down the rate of price increase in the second half.

In sum, the intended contributions of our study are threefold. First, we introduce simultaneous auction to the online auction literature, wherein bidders compete against each other for multiple items simultaneously. Second, in the context of simultaneous auction, we examine bidder competition at the dyadic level, including between- as well as within-lot interaction. Finally, we investigate bidder interactions through the lens of a network structure, which enables us to identify key bidders based on their central positions in the network, and examine their impacts on the auction.

The rest of the chapter proceeds as follows. First, we briefly review the related online auction literature. Second, we present the setting of our study and describe the data. Third, we present our investigation of the effects of bidder interactions on seller profits. Fourth, we illustrate how bidder interactions may be represented in the form of a network, and introduce the associated network analysis we conduct to identify the key bidders. Fifth, we present the results from our investigation of key bidders' influences on seller profits and price formation. Finally, we conclude by discussing managerial implications of our work and directions for future research.

3.2 Literature Review

There are also a few studies that suggest the presence of a dominant bidder or a group of bidders who have strong influence on other bidders in auctions [36, 62]. Prior literature has identified influential bidders based on their experience. Considering bidder feedback ratings available from eBay, these papers [59, 67] have investigated the influence of these dominant bidders over others. Unfortunately such a buyer rating system is not in place in other online auction houses, and most bidders do not have a bidding history which may be useful for managers. In this chapter, we take an innovative approach of creating a bidder network, which is fundamentally based on dyadic bidder interactions, and then use centrality measures (such as Bonacich Power) derived from network analysis to identify the key bidders and analyze their roles in a heterogeneous multiple-item online auction.

3.3 Data

Our data were collected from a 3-day simultaneous online auction held by SaffronArt.com in December 2005. SaffronArt.com sells modern Indian art[2] exclusively through its online auctions. Online fine art auctions and specifically this auction house provide an interesting setting to analyze bidder networks. The auction house prepares a catalog of items to be sold during the auction and informs the potential bidders ahead of time (through an email notification and a link to the online catalog or a printed catalog). Bidders pre-register and are qualified (bank references and credit checked) by the auction house to participate online in a given auction. The auction is held over a multi-day period (typically three days). The characteristics of such an auction, where a set of interested and informed bidders participate actively on a focused set of objects over a relatively short period and where one can track and capture all bidding activity, will be the ideal setting for our analysis, because such transparency of information is vital for our study.

The data for this study are the bid histories of 199 art lots (each lot is a unique piece of art - namely a painting, a drawing or a sculpture) from an online auction conducted in December 2005. This auction uses an ascending-bid format with a fixed ending-time and date

[2]Modern Indian art, with over $100 million in auction sales in 2006, is now one of the leading emerging art markets. In 2005, online auction sales of modern Indian art from SaffronArt.com ($18.06 million), a leading online auction house, were more (of modern Indian art) than those from the traditional auction houses like Sotheby's ($10.49 million) and Christie's ($14.89 million). Further, SaffronArt.com sold more art items (390) than Sotheby's (276) and Christie's (248) in 2005.

set by the auction house. Furthermore, the items are grouped together with 20-40 paintings in a set and the sets have staggered endings with 30 minutes difference between them. Only bidders registered in advance for the specific auction may bid on the lots.

In addition to the bid histories of the 199 lots, information on artist characteristics (e.g., emerging vs. established artists) and lot characteristics (e.g., pre-auction low and high estimates, opening bid) was also collected. The works of 70 artists were auctioned in this event, with an average of 2.8 lots per artist. The realized prices averaged $62,065 per lot and ranged from $3,135 to $1,486,100. Overall, 256 bidders participated in this online auction and placed 3,080 bids. The number of bids averaged 15.5 per lot and ranged from 2 to 48. The number of bidders averaged 6 per lot and ranged from 2 to 14 across the lots. Bidders on average bid on 4.93 lots with a range of 1 to 65. Some of the key descriptive information about the auction is presented in Table 3.1.

3.4 Dyadic Bidder Interactions

One of the most prominent features of online auctions is their ability to provide bidder transparency and easy access to all the bidding activities. During auction registration, each bidder is provided with an identification name, similar to a paddle number in live auctions. Bidder ID is helpful in identifying the bidders' preferences and purchase intent in the auction. More importantly, repeated interactions among bidders, even without direct communication, allow them to learn each other's bidding strategies [40, 53]. Our focus is on the effects of two types of dyadic bidder interactions frequently observed in multi-item simultaneous online auctions. The first type of dyadic bidder interaction captures the intensity of competition between two specific bidders for an item, and thus is termed *within-lot interaction*. The second type of dyadic bidder interaction measures the spread of the competition between bidders, i.e. the number of items in which two particular bidders are competing together and termed as *between-lot interaction*.

Table 3.1: Summary Data Description

	Mean (SD)	Median	Min.	Max
No. of Unique Bidders Lot	6.35 (2.46)	6	2	14
No. of Unique Lots Bid Bidder	4.93 (7.95)	3	1	65
No. of Bids Lot	15.47 (7.46)	15	2	48
Opening Bid in $	$19,343 ($36,663)	$6,400	$650	$300,000
Pre-Auction Low Estimates of the Lots	$24,128 (45,747)	$8,000	$795	$375,000
Pre-Auction High Estimates of the Lots	$31,065 (60,351)	$10,230	$1,025	$475,000
Realized Value of the Lots in USD($)	$62,065 (133,198)	$22,000	$3,135	$1,486,100
Realized Sq. Inch Price of the Lots in USD($)/Sq. Inch	$108.77 (225.49)	$45.12	$1.40	$1,865.42

3.4.1 Within-lot Interactions

We define within-lot interactions between two bidders in a lot as the total number of times the two bidders have bid sequentially. For every item auctioned, we first consider the unique pairs of bidders participating. Then for each of these bidder pairs, we count the number of times the bidders have bid sequentially (i.e. $A \rightarrow B \rightarrow A$). Since our goal is to determine the extent of such interactions for each lot, we consider the maximum interaction value among the bidder pairs. Thus, within-lot interactions (wl) is computed as

$$wl_k = \max_k \sum_{i=1}^{B_k} \sum_{j=1}^{B_k - 1} n_{i,j} \tag{3.1}$$

where B_k is the total number of bidders in lot i, B_k is the total number of bidders in lot k, and $n_{i,j}$ is the total number of sequential bids between bidder i and bidder j.

In most online auctions such as ours, bidders are encouraged to post the highest possible value they are willing to spend for the item, thus allowing them to place a higher value than the next incremental price level. In such cases, the auction house places a proxy bid on behalf of the bidder until the item price reaches the bidder's reservation value. To outbid this bidder, other bidders can either bid higher value incrementally or place a higher proxy bid. Interestingly, we did not find any instance of the second approach in our auction data. Therefore, we considered all sequential bids between the proxy bids for the within-lot interaction measure.

Prior studies [1, 25, 41] suggest that rivalry between bidders will lead to competitive arousal, which in turn will lead to auction fever and overbidding [39] by bidders. We posit that such overbidding will lead to higher auction outcome and thus we hypothesize,

H1: All else equal, high intensity of within-lot dyadic interactions among bidders in a lot will lead to higher auction outcome.

3.4.2 Between-lot Interactions

Between-lot interactions indicate the competitive span between a bidder pair. Like the previous measure, for every item auctioned, we first determine the unique bidder pairs. Second, for all the bidder pairs, we count the number of items in which the pair is competing simultaneously. Finally, we take the average of these pair-specific measures as the intensity of the between-lot interaction for the item. Thus, between-lot interactions (bl) is computed as

$$bl_k = \sum_{i=1}^{B_k} \sum_{j=1}^{B_k-1} l_{i,j}/N_k \tag{3.2}$$

where $l_{i,j}$ indicates the total number of common items bids by bidder i, B_k is the total number of bidders in lot k, and bidder j and N_k is the total number of bidder pairs in auction k.

Prior analytical study by Brusco and Lopomo [13] suggests that when bidders compete on multiple items in simultaneous auctions, they tend to engage in a tacit collusion. Such collusive equilibria will dampen bidder competition, thus leading to a lower price [40, 53]. Furthermore, Kwasnica and Sherstyuk [40] also provide evidence of such collusion in auctions without communication among bidders such as our online auction. Therefore, we hypothesize,

H2: All else equal, high intensity of between-lot dyadic interactions among bidders in a lot will lead to lower lot auction outcome.

3.4.3 Auction Outcome

We consider the auction outcome as the ratio of the final realized price to the pre-auction low estimate of the items. The pre-auction estimates are provided by the art experts consisting of econometricians, art curators and art historians and are available to the bidders before the auction starts. This value estimate contains a lower bound and an upper bound value where the lower bound indicates the minimum expected value of the item by the auction houses. Our measure, which we term as *Seller's Profit*, indicates the value in excess of the expected value realized by the item. Thus,

$$Seller's\ Profit = \frac{FinalRealizedPrice}{Pre-AuctionLowEstimate} \tag{3.3}$$

To normalize the distribution of the measure, we log transform it for the analysis.

3.4.4 Impact of Bidder Interactions on Auction Outcome

In order to determine the effect of dyadic bidder interactions on the seller's profit, we control for other influential covariates such as the aggregate competition components, producer characteristics of the art work, and product characteristic of the artwork. Based on the aggregate competition measures used in earlier studies, we control for the number of bidders competing for the lot [1, 23, 39, 53], number of bids per bidder [1, 25], and a between-lot competitor index [22, 23]. This index (BLCI) is a ratio of two numbers. The numerator is the number of distinct bidders that bidder A competes with on all common items during the auction. The denominator is the total number of bids on those common items minus the bids of bidder A in those items. Therefore,

$$(BLCI)_i = \frac{\sum_{j=1}^{B_i} \frac{(nc)_j}{\sum_{l=1}^{Lj}[(nb)_l - (nb)_{jl}]}}{B_i} \tag{3.4}$$

where $(nc)_j$ is the total number of unique competitors of bidder j, $(nb)_l$ is the total number of bids in lot l, $(nb)_{jl}$ is the total number of bids by bidder j in lot l, $= 1, 2, \ldots, B_i$ are the bidders in lot i, $l = 1, 2, \ldots, L_j$ are the lots bid by bidder j

Recent studies on art market [45, 58] suggest that type of artist plays a big role in the auction prices. Therefore, we include producer characteristics such as type of artists in the art market, which is categorized into established artists, emerging artists and others. Such artist information is readily available along with other item specific provenance to the bidders prior to the auction. Prior studies on art prices also suggest product characteristics such as size [8] and type of artworks (works on paper versus others) [58] to affect the auction price. Therefore, we include these product-specific factors in our model.

3.4.5 Control for Artist Heterogeneity

In art markets, works of individual artists differ distinctively from each other. This uniqueness of their artistic approach, style, and ideas introduces artist specific unobserved heterogeneity in the bidding process. Failure to adjust for such heterogeneity will lead to biased error terms and serial correlation in the residuals and less efficient estimates [55]. Therefore, we include a random parameter component in our model to represent the individual artist who created the lot. Thus, our complete model is as follows:

$$(Seller\ Profit)_i = \beta_0 + \sum_{j=1}^{9} \beta_j x_{ji} + b_1 u_{1i} + e_i \tag{3.5}$$

Where x_{1i} = Within-lot intensity of lot i.

x_{2i} = Between-lot intensity of lot i.

x_{3i} = No. of Bidders in lot i.

x_{4i} = No. of Bids per Bidder in lot i.

x_{5i} = Between-lot competitive index of lot i.

x_{6i} = Indicator variable for Established Artist for lot i.

x_{7i} = Indicator variable for Emerging Artist for lot i.

x_{8i} = Indicator variable for Paper work for lot i.

x_{9i} = Size of lot i.

u_{1i} = Artist of lot i.

and $i = 1, 2, \ldots, 199$ lots and $b_i \sim N(0, \psi^2)$

More details on these covariates are provided in Table 3.2.

Results (Table 3.3) show that both within-lot interactions and between-lot interactions have a significant effect on Seller Profit. We find that all else equal, within-lot dyadic bidder interactions have a positive effect on the Seller Profit with a standard coefficient of 0.149, thus supporting our first hypothesis H_1. We also find that between-lot dyadic bidder interactions have a negative effect on Seller Profit with a standard coefficient of -0.064, thus supporting our second hypothesis H_2.

3.4.6 Model Robustness

To test model robustness, we investigate issues of (1) Multicollinearity and (2) Omission of other possible covariates in our analysis.

Table 3.2: Model Parameters

	Covariates	**Definition**	**Supporting Literature**
Dyadic Competitive Bidding	$(wl)_i$	Maximum number of times two bidders bid sequentially in the lot.	Competition Arousal (Heyman et. al. 2004; Ku el. al 2005)
	$(bl)_i$	Average number of common lots bid by any two bidders pair in the lot.	Tacit Collusion (Kwasnica and Sherstyuk 2007; Phillips el. al 2005)
Aggregate Competition Component	$(NB)_i$	No. of bidders participating	Ariely and Simonson 2003, Heyman et. al 2004
	$(NBB)_i$	No. of Bids Bidder	
	$(BLCI)_i$	Between-lot Competitor Index	Feinstein et. al 1986; Gupta (2002)
Producer Characteristics	$(ESTA)_i$	Indicator for Established Artist	Mei and Moses 2002, Reddy and Dass 2006
	$(EMERG)_i$	Indicator for Emerging Artist	
Product Characteristics	$(PAPER)_i$	Type of Art Work (Indicator for Paper)	Reddy and Dass 2006
	$(SIZE)_i$	Size of the art work	Beggs and Grady 1997

Table 3.3: Effect of Dyadic Bidder Interaction on Auction Outcome

Covariates	**Standard Coefficient (Standard Error)**	**T-value**	**P-value**
Within-lot Interaction	0.149 (0.035)	4.20	$< .0001$
Between-lot Interaction	-0.064 (0.027)	-2.35	0.0204
Number of Bidders	0.711 (0.029)	24.69	$< .0001$
Number of Bids/ Bidder	0.521 (0.036)	14.37	$< .0001$
Between-lot Competition Index	-0.059 (0.034)	-1.73	0.0853
Emerging Artist	0.021 (0.025)	0.81	0.4174
Established Artist	-0.028 (0.024)	-1.14	0.2581
Works on Paper	-0.022 (0.026)	-0.92	0.3574
Size of Artwork	0.026 (0.026)	0.99	0.3224

Table 3.4: Correlation Matrix of the Covariates

	(wl_i)	(bl_i)	(NB_i)	(NBB_i)	$(BLCI_i)$	$(EMERG_i)$	$(ESTA_i)$	$(PAPER_i)$	$(SIZE_i)$
(wl_i)	1								
(bl_i)	.061	1							
(NB_i)	.238*	−.304*	1						
(NBB_i)	.743*	.231*	−.069	1					
$(BLCI_i)$	−.124	−.602*	.584*	−.396*	1				
$(EMERG_i)$	−.045	−.108*	.128	−.029	.159*	1			
$(ESTA_i)$	.274	.292*	−.173*	.069	−.277*	−.395*	1		
PAPER(x_i)	.104	−.104	.059	.017	.011	−.073	−.054	1	
SIZE(x_i)	−.096	.122*	−.060	−.056	−.068	.411*	−.149*	−.431*	1

*Correlation is significant at the 0.05 level (2-tailed)

Multicollinearity

In order to make sure that our analysis is not subject to any multicollinearity issues, we first analyze the correlation table of the covariates (Table 3.4).

The correlation table shows that only the variable "no. of bidders per bidder" has a high correlation (0.7425) with "within-lot interaction." In order to determine whether this has any serious effect on the estimates of the model parameters, we performed two sets of multicollinearity diagnostics. First, we computed the variance inflation factor (VIF) for each of the variables and found no parameters to have values more than 2.92. Maruyama [44] (page 64) suggests that any value below 6 indicates absence of multicollinearity. In our second diagnostic approach, we computed the condition index of the model [9]. The condition index shown in Table 3.5 does not contain any value greater than 30. Therefore, we can safely conclude that no multicollinearity is present in our analysis.

Table 3.5: Condition Index Table

Number	Eigen Value	Condition Index
1	6.62	1.00
2	1.17	2.38
3	0.87	2.77
4	0.42	3.99
5	0.36	4.28
6	0.27	4.97
7	0.19	5.92
8	0.06	10.19
9	0.03	14.00
10	0.02	20.45

Other Possible Covariates

The effectiveness of the results is frequently affected by the omission of other possible covariates in the model. We identify two such covariates in our case, including (1) number of bidder pairs present in the lot, (2) number of latent bidders present in the auction of each item, and (3) total number of proxy bids in the lot. In our analysis of correlation between "number of bidder pairs" and other covariates, we find that the variable is highly correlated (0.8907) with the number of bidders placed a bid in the lot. Therefore, we decided not to include the variable in our model.

Presence of latent bidders posits a bias to our estimates of the parameters in our model. Prior studies [2, 14, 42] have extensively looked at various approaches to determine the number of latent bidders in the auction. Among the approaches, the method by Chan et. al[14] to include bidders from other items who are most likely to participate in the focal item is the most reasonable in our case. Therefore, we computed the latent bidders based on their participation of items by the same artist. Since, the latent number of bidders was highly correlated with the observed number of bidders in the auction, we decided against its inclusion in our model.

In online auctions, such as ours, bidders are encouraged to bid the maximum they are willing to pay for the items. To facilitate such behavior, auction houses provide an automated system which allows bidders to enter the maximum amount they are willing to spend and then place proxy bids on behalf of the bidders until that value. In order to control for such proxy bids which may create artificial competition in the auction, we ran the above equation (i) with another covariate to indicate the total number of proxy bids in lot i. This variable came out to be insignificant and there was no difference in the results.

3.5 Key Bidders

Given the empirical support we find for the effect of dyadic bidder interactions on the auction outcome, we focus on the question "Whom to specifically invite to these auctions?" One suggestion is to invite "key" or influential bidders for future auctions. Presence of influential bidders and their effect in live auctions is well documented [24, 36] in the auction literature. In the art auctions, these bidders are reputed collectors or dealers who are well recognized by others. Their preferences and bidding activities provide a lot of information regarding the value of the art items, and thus influence others during the auction process. In online auctions, without the physical presence of the bidders, it is difficult to identify these market experts. Studies on key bidders based on eBay auctions [12, 59, 67] have utilized the bidder feedback rating to identify them. This measure has two limitations; first, most other online auction houses such as *SaffronArt.com, uBid.com, Shopgoodwill.com, Aspireauctions.com* do not have a bidder rating system in place. And second, most bidders in these auctions are relatively new. Art has recently become a mainstream investment opportunity and thus has started attracting bidders who have no known bidding experience. Therefore, there is a need to come up with a new influence measure to identify key bidders in an online auction. From the managerial perspective, identifying these bidders is important, as managers can cultivate a stronger relationship with them and invite them to future auctions.

To fulfill our goal, we first attempted to identify key bidders based on simpler heuristic measures such as depth of pocket and the number of bids placed which are readily available to managers. The first measure is computed as the maximum amount to be spent by a bidder at any given time during the auction if the bidder would have won all the items he or she is concurrently winning. The second measure, i.e. the total number of bids placed, indicates the bidders' level of participation.

We also created a third influence measure of bidders based on the dyadic bidder interactions in the auctions. We take a novel approach of representing bidder interactions as a network (we call it as "bidder network") with nodes representing the bidders and the value of inter-node ties indicating the level of sequential bidder interactions between them. The network structure of bidders also provides a suitable platform for applying Social Network Analysis to compute centrality indices of bidders such as Bonacich Power. The power measure for each bidder indicates the level of influence a bidder may have over others during the auction. Considering the top 1% bidders based on the power measure as our Key Bidders, we analyzed how their presence affects the *Seller Profit* of the items. We also compare our novel measure with the ones based on the simpler heuristics. Finally, using sophisticated modeling techniques such as Functional Data Analysis, we determine the effect of key bidders (based on our network approach) on the price and price dynamics (such as rate of change in price).

3.5.1 Identification of Key Bidders

At a fundamental level, we define the bidder network as a set of g bidders whose relationship is based on whether bidder i and bidder j bid sequentially on a lot where $i, j \in N$. We define $N = 1, 2, \ldots, g$ as the set of g bidders and Y as a set of ordered pairs recording the extent of interaction between pairs of bidders. In this case, we define the extent of the dyadic interactions as the number of times p, bidder i and bidder j bid sequentially on the lots in the auction. Y is represented as a $g \times g$ matrix, where $(Y)_{ij} = p$; $p = 0, 1, 2, \ldots, P$ where P is the maximum number of consecutive bids placed in the auction. We create this non-directional[3], symmetric matrix Y for $g = G$ bidders in the online auction which forms the basis for the network analysis[4].

Let us illustrate the network building process with an example. Consider the bid histories taken from an online art auction shown in Figure 3.1a and Figure 3.1b. The first two sequential bids in Figure 3.1a is posted by bidders *Anonymous 3* and *Kyozaan*. We posit that this indicates a dyadic bidder interaction between the bidders. Therefore, in our bidder network, we consider two nodes, one representing *Anonymous 3* and another representing *Kyozaan* and the value of the link between them as 3 (Figure 3.1c) (since they bid three times sequentially). Further, in the same bid history, we find another bidder, *Poker* to bid sequentially against *Kyozaan* three times. Therefore, we include another node in our network to represent *Poker* and link it with *Kyozaan* with a dyadic bidder interaction intensity of 3 (Figure 3.1d). Then, we consider the second bid history (Figure 3.1b) where we find *Anonymous 38* and *socrates* have bid sequentially against *Poker* and *Kyozaan* multiple times. Therefore, we include two more nodes in our bidder network, and provide value to the links based on the number of times they bid sequentially against others (Figure 3.1e). Following this process of identifying each bidder as a node and assigning a value equal to the total number of consecutive bids placed by him or her in all the 199 lots auctioned, we create the bidder network. Like the dyadic interactions analysis, we consider all sequential bids between a proxy bid and new incremental bids of other bidders in the bidder network[5]. Furthermore, it is possible for an active bidder (large number of bids) to have high number of adjacent bidders and thus, higher power. To control for this bidder characteristics, we developed a directional bidder network where the strength between the bidders is proportion to the number of bids of the

[3]In our earlier approach, we created a directional bidder network, capturing who follows whom in the auction. The key bidders identified using the directional network are same as the ones obtained using a non-directional network. We presented only the results using a non-directional network in this chapter. Results from a directional network may be obtained from the authors.

[4]We also consider other measures such as the proportion of times any pair of bidders appeared (bid) together across all lots in the auction. This measure, which does not capture the sequential nature of bids, yielded similar results.

[5]We also developed a bidder network after excluding the proxy bids in the auction. We did not find any difference in the key bidder analysis with this network formulation.

initiative bidder. Results of the key bidders do not differ with that approach. Hence, we only present findings based on our initial approach. Figure 3.2 illustrates the evolution of the bidder network during the auction.

To identify the key bidders, we investigate the bidder network using a popular social network analysis tool. Network analysis is a very useful and powerful tool to study real-world networks such as the bidder network described above. Researchers in social sciences probably have the longest history of quantitative study of real-world social networks. Milgram Stanley [47] was the first to conduct a small-world experiment to determine connectivity of people in U.S. The concept of social network [65] and its analysis have found a wide variety of applications in sociology, marketing and statistics. Social Network Analysis (SNA) has also made its mark in other applications such as national security as demonstrated by Krebs [37], who maps the terrorists participating in the 9-11 attack in a network and determines the central players of the attack. Currently, the U.S. government is using this technique to scan through large telephone databases for suspected terrorists [20].

At a very fundamental level, SNA focuses on implications of relationships among entities [65] such as the dyadic interactions among bidders in the auction. To apply SNA to our bidder network, we assume that bidders are interdependent units and the ties among bidders represent the level of dyadic interaction between them. We used centrality index called *Bonacich Power* [11] to identify key bidders in the auction. Such an index indicates the strength of the social entities (bidders) and their ties in the network [28]. *Bonacich Power* is an unique influence which not only considers direct interactions, but also consider links of the adjacent nodes to measure influence. Consider the bidder network shown in Figure 3.3. Both *doc* and *Anon 8* are central bidders and seem to be well connected to other bidders. But who is more powerful in terms of influencing other bidders? If we look closely, we find that neighbors of doc are isolated, whereas the neighbors of *Anon 8* are fairly well connected. Therefore, *Anon 8's* influence on his/her neighbors will be less strong than *doc's* influence on his/her neighbors. This is the argument that Bonacich [11] makes. He argued

Rank	Nick Name	Amount($)	Amount(Rs)	Date & Time (US EST)
Current Highest Bid 1	Poker	71,500	3,146,000	Dec 6 2005 3:03:48 AM
2	Kyozaan	66,500	2,926,000	Dec 6 2005 1:27:43 AM
3	Poker	61,500	2,706,000	Dec 6 2005 1:26:17 AM
4	Kyozaan	56,500	2,486,000	Dec 6 2005 1:26:10 AM
5	Anonymous 3	51,500	2,266,000	Dec 6 2005 1:25:58 AM
6	Kyozaan	49,000	2,156,000	Dec 6 2005 1:25:58 AM
7	Anonymous 3	46,500	2,046,000	Dec 5 2005 10:30:00 PM
	Start price	44,000	1,936,000	Dec 5 2005 10:30:00 PM

Figure 3.1 (a)

Rank	Nick Name	Amount($)	Amount(Rs)	Date & Time (US EST)
Current Highest Bid 1	Kyozaan	121,500	5,346,000	Dec 6 2005 9:53:24 AM
2	socrates	111,500	4,906,000	Dec 6 2005 9:52:25 AM
3	Kyozaan	101,500	4,466,000	Dec 6 2005 9:52:25 AM
4	socrates	94,000	4,136,000	Dec 6 2005 4:42:35 AM
5	Poker	86,500	3,806,000	Dec 6 2005 4:16:25 AM
6	Anonymous 38	79,000	3,476,000	Dec 6 2005 4:14:37 AM
7	Kyozaan	74,000	3,256,000	Dec 6 2005 1:16:56 AM
8	Anonymous 38	69,000	3,036,000	Dec 5 2005 10:40:07 PM

Figure 3.1 (b)

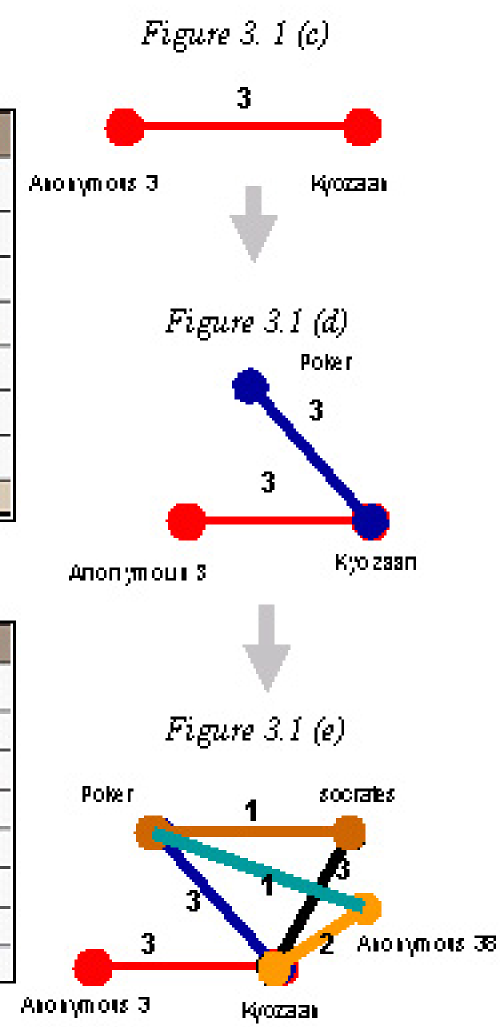

Figure 3.1: Formation of a Bidder Network

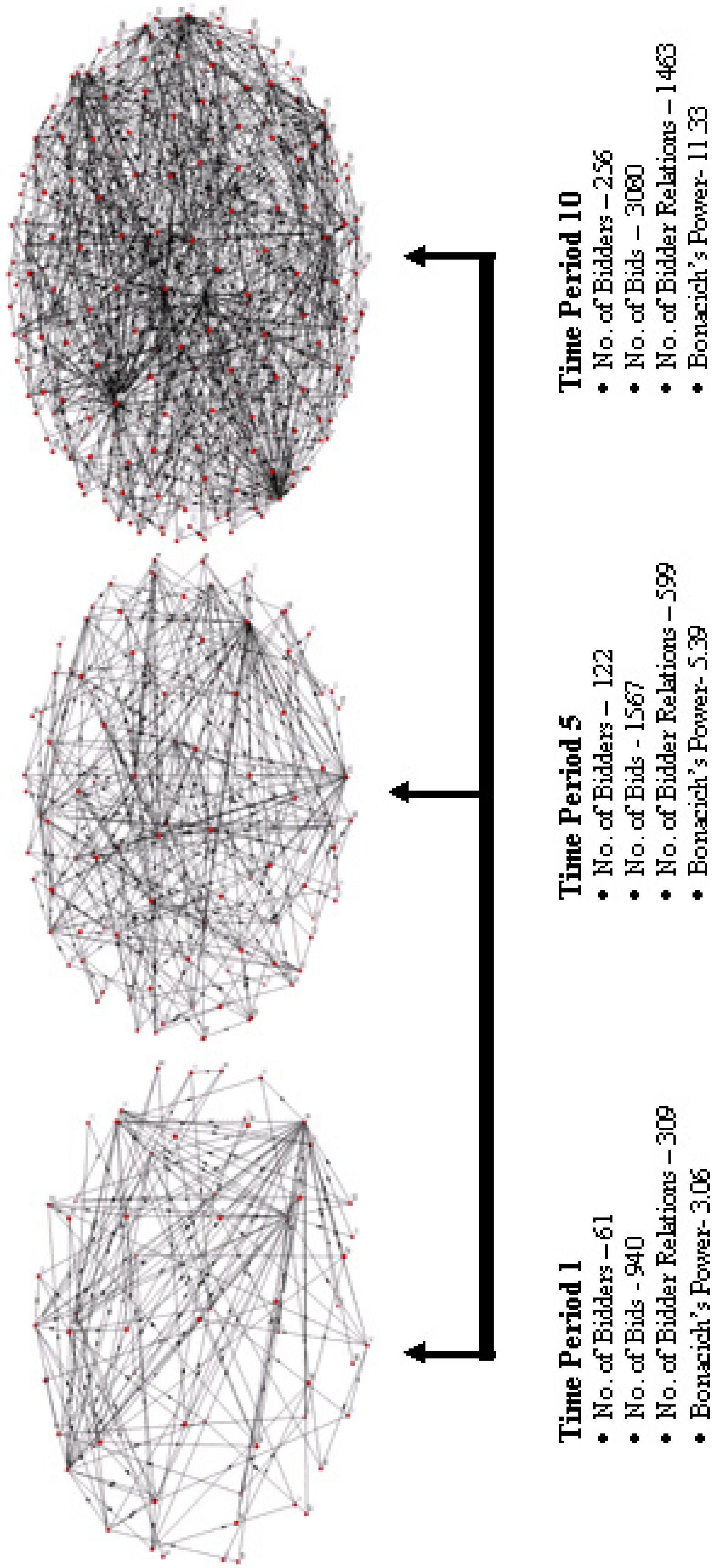

Figure 3.2: Bidder Network Evolution over the Auction Duration

that although a node's connection to other nodes makes that node central, this does not necessarily makes him/ her powerful. He shows that being connected to other actors that are minimally connected makes one more influential as these actors are dependent on you - whereas well-connected actors are not[6]. Similarly, a bidder will have more influence on a minimally connected bidder than on well-connected bidder.

Investigating the distribution of the network characteristics, we find that most bidders have low power centrality, while a few bidders have large power centrality. We consider top 1% bidders[7] as the key bidders based on their Bonacich's Power measure and thus identify *Kyozaan*, *Anonymous 3* and *Anonymous 118* as the key bidders in the auction[8]. Table 3.6 provides a summary of the bidding behavior and the centrality measures of these key bidders.

We also identify key bidders based on simpler heuristics such as number of bids placed and depth of pocket. For these naive measures, we also consider the top 1% bidders as the key bidders. We find that *Kyozaan*, *buddha* and *Anonymous 38* are the key bidders based on the number of bids placed and *Speed*, *Lord of the Rings* and *Kyozaan* are the key bidders based on the depth of pocket measures. *Kyozaan* by all network measures emerges as a central and influential bidder in this auction. She entered the auction early, bid on many lots (56) and bid the most (182 bids). She has the highest number of bidding relationships (59) and plays a key communicative role in the auction. She won four (two of which are by major established artists) of the 56 lots that she bids on and spent $351,600. In contrast, *Speed*, who is the top bidder based on the depth of pocket, had bid on only 3 lots and won two of them, spending a total of $1.56 million.

To categorize the bidding strategies of these influential bidders, we analyze their bidding activity including their average time of entry, average time of exit and extent of using

[6]See Bonacich [11] for details on how Bonacich's Power of individual bidders in a network is estimated.

[7]For robustness of our analysis, we also defined key bidders as the top 5% and top 10% bidders of the measures. The results obtained from those analyses were found similar to those of top 1%. Therefore, we only present top 1% bidder results. Other results can be obtained from the authors.

[8]This assessment was confirmed by the eigenvector centrality scores computed by using the Factoring method suggested by Bonacich [10]

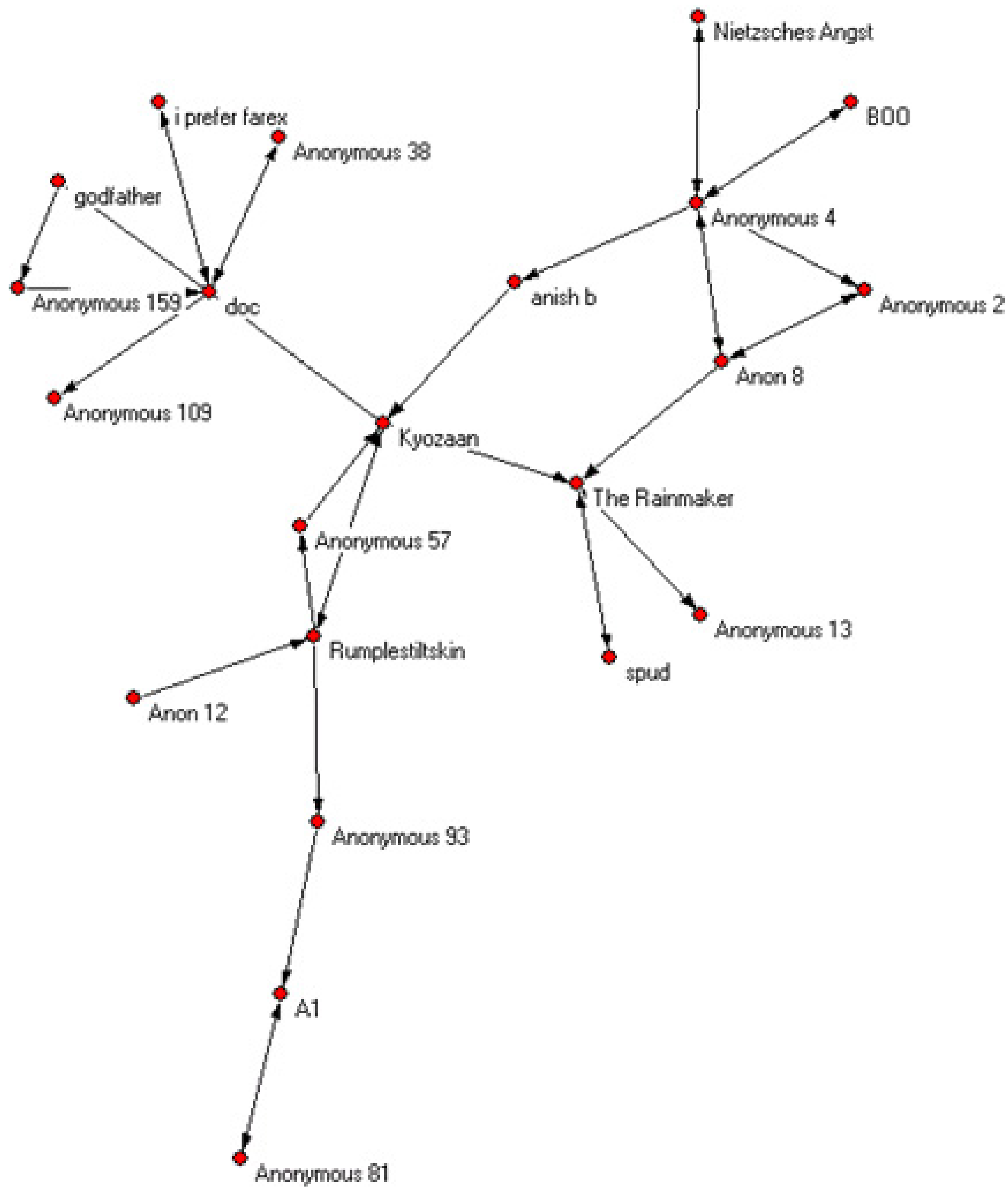

Figure 3.3: Example of a Bidder Network

Table 3.6: Key Bidder Comparison

	Bidder: Kyozaan	**Bidder: Anon. 3**	**Bidder: Anon. 118**	**Bidder: Buddha**	**Bidder: Anon. 38**	**Bidder: Lord of the Rings**	**Bidder: Speed**
Total $ Spent	$351,000	$263,423	$1,042,373	$379,205	$41,350	$1,011,746	$1,563,000
No. of Lots Won	4	9	9	9	1	8	2
No. of Lots Bid	56	58	18	44	29	37	3
Total No. of Bids	182	128	104	165	158	137	14
Depth of Pocket	$1,403,867	$700,200	$1,214,683	$1,062,584	$658,000	$1,202,651	$1,563,000
Total No. of Bidding Relations	59	49	24	32	27	35	5
Bonacich's Power	178	155	149	74	48	129	8
Average Entry (First Bid) Time (Std. Dev)	0.108 (0.222)	0.266 (0.439)	0.245 (0.076)	0.638 (0.158)	0.107 (0.339)	0.263 (0.292)	0.787 (0.268)
Average Exit (Last Bid) Time (Std. Dev)	0.412 (0.321)	0.565 (0.466)	0.800 (0.310)	0.772 (0.207)	0.447 (0.331)	0.645 (0.376)	0.998 (0.0003)
Lots Won of Major Established Artists	2	3	3	3	0	3	2
Average Estimate of Lots Bid (Median)	$45,327 ($15,912)	$35,658 ($15,912)	$40,301 ($22,165)	$22,186 ($9,947)	$94,053 ($60,000)	$44,728 ($74,553)	$225,000 ($125,000)
No. of Automated* Agent Bid	0	0	0	6	8	92	0
Bapna et. al Taxonomy	Part.	Part.	Part.	Part.	Early Evaluator	Agent Bidder	Opp.

*Bidders are labeled as Agent Bidder when they use automated agent to bid 50% or more of their total bids.

Part. −Participator Opp,. −Opportunist

automated bidding agents. Comparing these bidder characteristics with Bapna's bidder taxonomy[9] (Bapna et al. 2004), we classify the influential bidders, *Kyozaan*, *Anonymous 118* and *Anonymous 3*, as *Participators*.

3.5.2 Impact of Key Bidders

We perform two level of analysis to determine the impact of key bidders in the auction. First, we compare the effect of the key bidders on *seller profit* based on the three measures discussed earlier and second, we examine the effect of the key bidders on price and price dynamics (price curve $f_j(t)$, $f_j'(t)$ (velocity), $f_j''(t)$ (acceleration)) during the auction using Functional Data Analysis.

Comparison of Key Bidder Measures

To compare the effect of three key bidder measures on *Seller's Profit*, first we create three new variables to represent the total number of key bidders based on bidder influence, depth of pocket, and bidding intensity in a lot. We also control for other determinants such as the two dyadic bidder interactions (within-lot interaction and between-lot interaction), aggregate competitive measures (number of bidders, number of bids/ bidder and average between-lot competitor index, producer characteristics (indicator for established artist and indicator for emerging artist), product characteristics (indicator for works on paper and size of the art work) and heterogeneity due to different artists. The following mixed effect model is tested in the process.

$$(Seller\ Profit)_i = \beta_0 + \sum_{j=1}^{12} \beta_j x_{ji} + b_1 u_{1i} + e_i \tag{3.6}$$

[9]Bapna et al. (2004) identified several bidder types in their analysis of multi-unit online auctions of computer hardware and consumer electronic products. They classify them as *Early Evaluators*, who place bids at early stages of the auction, *Middle Evaluators*, whose maximum bid is submitted at the middle of the auction, *Opportunists*, who bid near the end of the auction, *Sip-and-Dippers*, who typically place 2 bids, one early and one at the end of the auction, *Participators*, who illustrate early entrance and late exit, and *Agent Bidders*, who extensively used automated bidding agents provided by the auctioneer.

Where x_{1i} = No. of Key Bidder based on dyadic interactions in lot i.

x_{2i} = No. of Key Bidder based on depth of pocket in lot i.

x_{3i} = No. of Key Bidder based on no. of bids of bidders in lot i.

x_{4i} = Within-lot intensity of lot i.

x_{5i} = Between-lot intensity of lot i.

x_{6i} = No. of Bidders in lot i.

x_{7i} = No. of Bids per Bidder in lot i.

x_{8i} = Between-lot competitive index of lot i.

x_{9i} = Indicator variable for Established Artist for lot i.

x_{10i} = Indicator variable for Emerging Artist for lot i.

x_{11i} = Indicator variable for Paper work for lot i.

x_{12i} = Size of lot i.

u_{1i} = Artist of lot i.

and $i = 1, 2, \ldots, 199$ lots and $b_i \sim N(0, \psi^2)$

Results (Table 3.7) show that our measure of identifying key bidders based on the bidder network analysis has outperformed other competing measures. The impact of key bidders based on network analysis on Seller Profit is positive (standard coefficient=0.082) and significant (p-value = 0.0354). On the other hand, the impact of key bidders based on depth of pocket is positive (standard coefficient=0.054) but non-significant (p-value = 0.2229) and the impact of key bidders based on the bidder's number of bids is negative (standard coefficient = -0.023) and non-significant (p-value= 0.6643). It is also important to note that the effects of dyadic bidder interactions are similar to what was found earlier.

Table 3.7: Effect of Key Bidders on the Auction Outcome

Covariates	**Standard Coefficient (Standard Error)**	**T-value**	**P-value**
Key Bidder by Dyadic Interactions	0.082 (0.037)	2.19	0.0303
Key Bidder by Depth of Pocket	0.054 (0.042)	1.26	0.2084
Key Bidder by Bidding Intensity	−0.023 (0.052)	−0.45	0.6538
Within-lot Interaction	0.135 (0.035)	3.81	0.0002
Between-lot Interaction	0.115 (0.034)	−3.42	0.0009
Number of Bidders	0.665 (0.033)	20.08	$< .0001$
Number of Bids/ Bidder	0.531 (0.036)	14.83	$< .0001$
Between-lot Competition Index	−0.016 (0.036)	−0.44	0.6630
Emerging Artist	0.039 (0.026)	1.49	0.1376
Established Artist	−0.023 (0.025)	−0.90	0.3677
Works on Paper	−0.010 (0.024)	−0.42	0.6755
Size of Artwork	0.021 (0.026)	0.81	0.4186

These key bidders have a significant effect on the auction process. On average, lots (n=131), where at least one bidder was present, fetched a higher (3.45) Seller Profit (Figure 3.4) as compared to lots where no key bidders participated (Seller Profit=2.84). We also found significant effects of these key bidders on the speed (Figure 3.5)of price formation in the auction. Prices of lots where at least one key bidder has participated on average crossed the pre-auction high estimate value provided by the auction house in one day, but it took nearly two days for lots without key bidders to cross the pre-auction high estimate.

Impact of Key Bidders on Price and Its Dynamics Using Functional Data Analysis

To determine the effect of the key bidders on the price dynamics during the auction, we utilized the newly emerging literature on analysis of online auction price dynamics using Functional Data Analysis [6, 30, 58]. This involves (i) recovering the price curves of the individual lots in the online auction using smoothing techniques such as a monotone smoothing

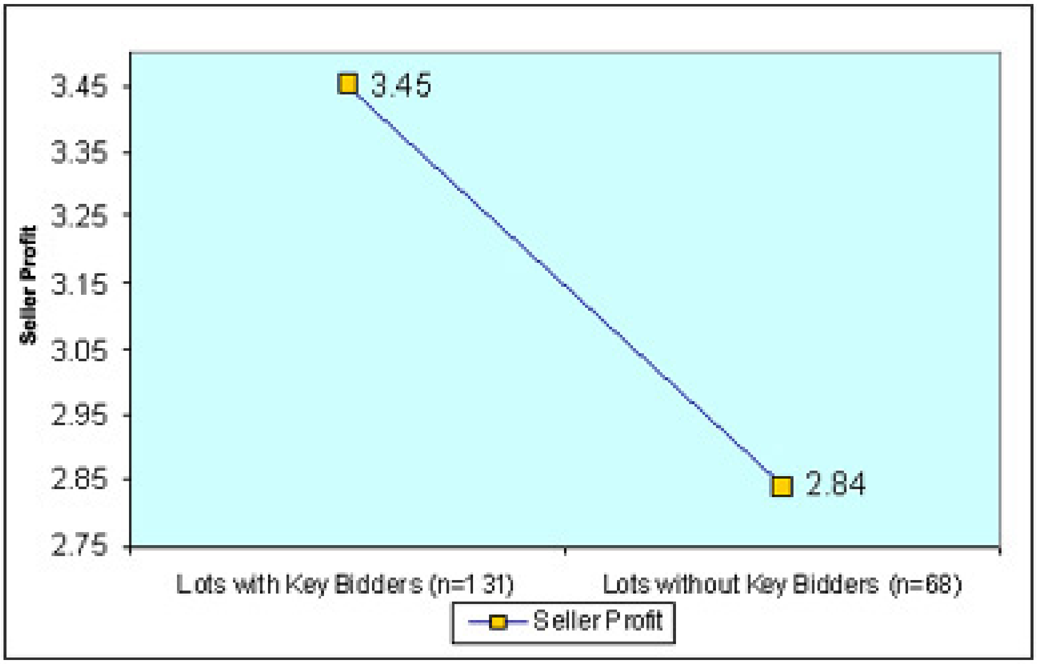

Figure 3.4: Impact of Key Bidders on Seller's Profit

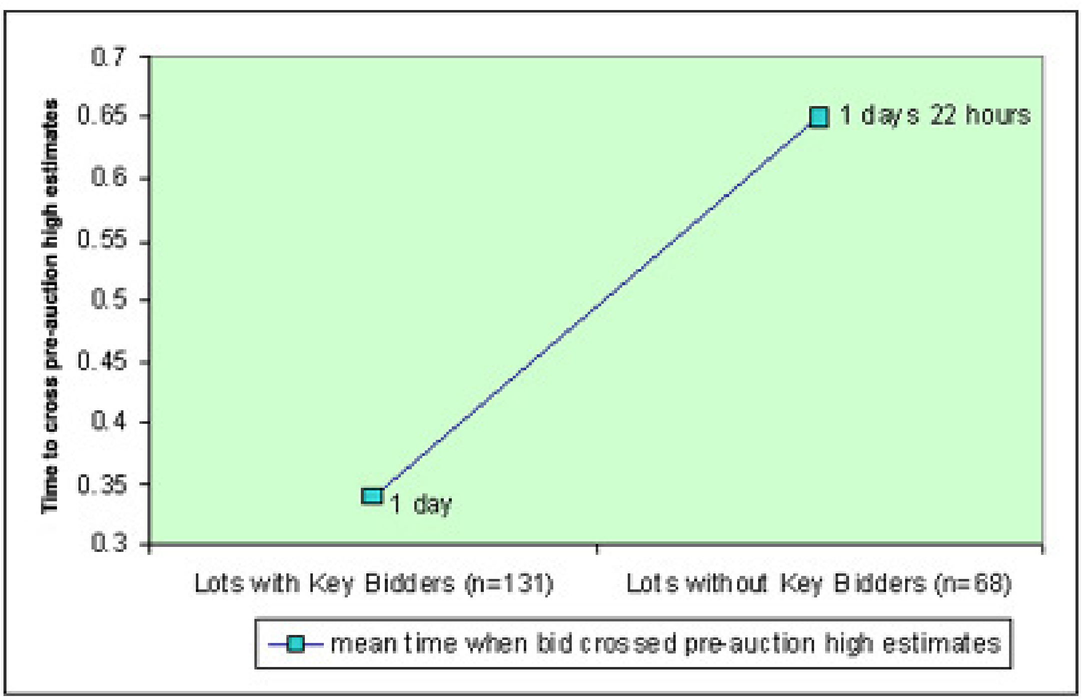

Figure 3.5: Impact of Key Bidders on Speed on Price Formation

spline [57] and (ii) modeling (using functional regression) the heterogeneity of these price paths using covariates (presence of key bidders, dyadic bidder interactions, aggregate competitive measures, producer characteristic and product characteristics) to provide insights on the relationship of these covariates and the price dynamics during the auction. In our case, we are only interested in the changing effects of the key bidder presence in a lot on its price dynamics.

As a part of our analysis, we estimate the price curve ($f_j(t)$ for lot j) for each lot in the auction using splines and compute derivatives of the price curve such as rate of change of price (price velocity-first derivative $f_j'(t)$) and rate of change of price velocity (price acceleration-second derivative $f_j''(t)$). Since different lots have different realized prices, we scaled the price curves between 0 and 1, where each data point represents the current value of the item as a ratio of its final realized value. We then use functional regression to investigate how the presence of key bidders has affected the price dynamics during the auction. Unlike standard regression models, where predictor and explanatory variables are scalars or vectors, functional regression allows variables to take on a functional form (see Appendix). For example, in our case, the response variables are the price curve $f_j(t)$, $f_j'(t)$ (velocity), $f_j''(t)$ (acceleration) that capture the price formation process during the auction. Please see Appendix for more details on the smoothing techniques and functional regression.

The results of the functional regression are displayed in the form of estimated parameter curves (solid lines) in Figure 3.6. A plot of the confidence bands (gray lines) around this curve is also displayed to allow us to draw a statistical inference (at the 95% confidence level) about the significance of the estimated curve.

Results show that although the presence of these key bidders has no significant effect on the current auction price, it has a significant relationship with the price velocity. The confidence bounds (at 95% confidence levels) indicated by the gray lines signify that the parameter is positive and significant at the beginning of the auction, which later becomes negative as the auction progresses. This indicates that presence/absence of key bidders con-

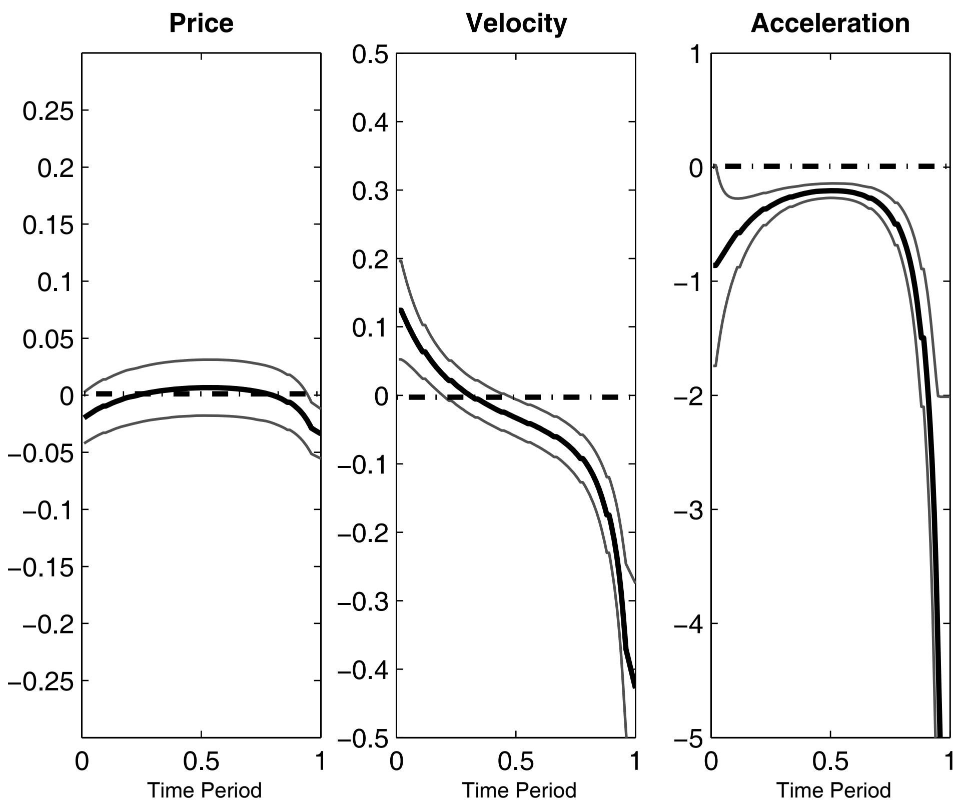

Figure 3.6: Estimted Parameter Curves for the Presence of Key Bidders

tributes to faster/ slower price-velocity at the beginning of the auction and slower/ faster price-velocity near the end of the auction. The parameter curve associated with price acceleration is significant and negative throughout the auction. This implies that lots where key bidders are present experience a slowdown in the price acceleration throughout the auction, with it being the slowest at the end of the auction.

3.6 Conclusions and Future Directions

Although the importance of bidder interactions in auctions is well recognized in the academic community [15], prior studies have mainly focused on the aggregate measures of competition (Bidder "A" versus all other bidders). In this chapter, we contribute to this end by focusing on dyadic bidder interactions between two specific bidders within a lot and across lots that are auctioned simultaneously. Using a unique dataset from a simultaneous online art auction, we found that these two types of bidder interactions affect the auction outcome differently. Within-lot interactions were found to have a positive influence over *Seller Profit*, whereas between-lot interactions were found to have a negative effect on the *Seller Profit*. Given the nature of the data and absence of a cognitive model, we are in no position to prove any of the theoretical arguments we provide for the hypothesis. We acknowledge this limitation and hope that our study will encourage future studies to investigate the cause of such bidder phenomenon.

As a part of identifying key bidders in the auction, we used a rich network framework to formulate the dyadic bidder interactions across the auction and created a *Bidder Network*. This allowed us to determine the key bidders based on the positions and connectivity of the bidders in the network. Using social network analysis, we identify key bidders and found it to outperform other simpler measures in explaining *seller's profit*. We also investigated the effect of these key bidders on the price dynamics during the auction and found that they have a positive and significant effect on the rate of change of price at the beginning of the auction, but that the effect becomes negative as the auction progresses.

From the managerial perspective, the results reflect various auction management implications worth mentioning. First, results from within-lot and between-lot interactions provide insights regarding which items to sell simultaneously in these auctions that will encourage more within-lot interactions and discourage between-lot interactions. Next, our rich network-based identification of key bidders provides a new managerial tool to identify influential bidders and invite them to future auction events. Not only did the three key bidders identified account for $1.66 million in purchases and 22 lots (11% of the total lots auctioned), but their presence in the auction has a significant effect on the Seller Profit. This suggests that auction houses should also consider inviting bidders based on their competitive bidding activity and not just based on their depth of pocket and experience. More specifically, they should try inviting pairs of bidders who have the same taste and may engage in intense dyadic bidder interactions. Further, using the results from the effect of key bidders on price dynamics, auction house managers should be able to estimate the marginal effect of inviting these bidders during the auction.

In this study, we show that there's dyadic bidder effect beyond the aggregate competitive in auctions. This will encourage future analytical and experimental studies to understand in-depth characteristics of these interactions and develop more effective price forecasting models. Our rich approach of representing bid history as a network also opens a wide range of new future researches. For example, one can create a network by treating the lots (art objects) as nodes. This may help us to understand the market structure of art objects and artists and could shed light on complementarities and substitutability in art markets.

Although there are design differences between popular online auction such as eBay and simultaneous online auctions such as ours, we expect similar results with eBay data if the starting and ending time of multiple objects are same or very close to each other and each object attracts the same group of bidders intend to purchase more than one object. Identifying such auction events from eBay, one can compare the effect hard closing time (like eBay) and soft closing time (like our auction) on bidder behavior. Furthermore, the paintings sold in the simultaneous auctions are grouped in 20-40 item sets. Since the closing times of these sets are staggered with a 30 minute difference, it creates an unusual auction dynamics where some paintings end at the same time and others end at different times. Future study on how such auction rules affect bidding dynamics will be useful.

Our study provides a framework to advance our knowledge on bidder behavior in online auctions. Particularly, our conceptualization of dyadic bidder interactions may further support ways to model bidder learning and competitive rivalry occurring during an online auction. Specific questions, such as how losing (not winning) a lot early in the auction affects bidding behavior later in the auction, may also be examined by analyzing bidder influence at different time-periods of the auction. In this chapter, we considered a one-mode non-directional network to conceptualize dyadic bidder interactions. Other approaches like using a two-mode directional network (hierarchical structure with bidder relations nested inside the auctioned lots) may also be explored in future researches to investigate influence of auctioned item characteristics on formation of bidder interactions.

In this research, we looked at online auctions of modern Indian art, an emerging art market that has seen an explosive growth of 2000% in the last two years[10]. Will the bidder behavior and the impact of bidder recognition be different when the market reaches a more mature stage? Will the key bidders have such a significant impact on the auction price dynamics? As the same band of collectors moves from one auction to the next over time, will the same key bidders emerge influencing the auction? As we follow the trend of this art market and gather more data on online auctions, such important questions can be addressed in the future.

Newman [50] indicates that the study of complex networks is in its infancy, as we are just beginning to understand the patterns and statistical regularities of real-world networks. He suggests the study of the impact of the network structural properties on behavioral processes as the most important direction for future study. We have contributed to this end by not only

[10]For more information on Modern Indian Art, please visit http://www.modernindianart.net

identifying and analyzing an interesting real-world network, namely the bidder network in an online auction, but also using the structural properties of bidders to identify key bidders and determine their effect on the price dynamics.

The dyadic and network view of bidder behavior shifts the focus from atomistic explanations of bidder behavior (independent bidder behavior assumption) to relationships among them. We hope that our conceptualization will motivate other researchers to advance our knowledge on bidder behavior and bidder strategies in online auctions.

3.7 Appendix

3.7.1 Smoothing Splines

To recover the underlying price curves, we used penalized smoothing splines [57, 61], which provide both small local variation and overall smoothness. They also readily yield higher-ordered derivatives of the target price curve as desired in our case. For every lot auctioned, we fit a polynomial spline of degree p

$$f(t) = \beta_0 + \beta_1 \times t + \beta_2 \times t^2 + \beta_3 \times t^3 + \ldots + \beta_p \times t^p + \sum^L \beta_{pl}[(t - \tau_l)_+]^p.$$

where τ_1, τ_2, $\ldots \tau_L$ is a set of L knots and $u_+ = uI_{[u \geq 0]}$. The choice of L and p determines the departure of the fitted function from a straight line with higher values resulting in a rougher f, which may result in a potentially a better fit but a poorer recovery of the underlying trend. A roughness penalty function of the following may be imposed to measure the degree of departure from the straight line

$$PEN_m = \int [D^m f(t)]^2 dt.$$

where $D^m f, m = 1, 2, 3 \ldots$, is the m^{th} derivative of the function f. The goal is to find a function $f^{(j)}$ that minimizes the penalized residual sum of squares

$$PENSS^{(j)}_{\lambda,m} = \sum^n (y_i^{(j)} - f^{(j)}(t_i))^2 + \lambda \times PEN^j_m.$$

where the smoothing parameter λ provides the trade-off between fit $[(y_i^{(j)} - f^{(j)}(t_i))^2]$ and variability of the function (roughness) as measured by PEN_m[11]. We used the b-spline module developed by [56] for minimizing $PENSS_{\lambda,m}^{(j)}$.

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3.7.2 Functional Regression

Unlike standard regression models where predictor and explanatory variables are scalars or vectors, functional regression allows one to have these variables take on a functional form. For example, the response variable in our case is the price curve $f_j(t)$, $f_j'(t)$ (velocity) and $f_j''(t)$ (acceleration) that capture the price formation process during the auction. Potential explanatory variables are the presence of key bidders, and other characteristics of the lot such as the type of artists (established, emerging or other), medium of the painting (canvas or paper), and size of the painting (area in square inches).

The dependent variable $Y(t)$ is a $J \times 1$ vector of functional variables where J is the number of lots. If we want to model the current price, then $y_j(t) = f_j(t)$. We set $y_j(t)= f_j'(t)$ if we are modeling bid velocity. A linear model is considered where the design matrix X is typically a matrix of observed covariates or explanatory variables,ϵ is an error vector with mean zero and $Y(t)$ is as defined above and $\beta(t)$ is the vector of parameters which measures the influence of the covariates at every point in time. Functional regression models then allow us to understand the influence of covariates on price dynamics over time. As Ramsay and Silverman [57] point out, this is achieved by estimating $\beta(t_i)$ for a finite number of points

[11]Sensitivity tests were performed with different values of p (4, 5, 6 were used) and λ (14 different values between 0.001 to 100 were used). We found the model fit to be insensitive to different values of p and λ. However, the RMSE for the model was the lowest with p=4 and $\lambda = 0.1$. Thus, we use these smoothing parameters in recovering the price curves.

in time t (in our case t=100) and constructing a continuous parameter curve by simply interpolating between the estimated values.

To capture the effects of the explanatory variables on each of the price dynamic variables $f_j(t)$, $f_j'(t)$ (velocity) and $f_j''(t)$ (acceleration), we run a regression for each time period (1-100) for data from all the lots (n=199). The parameter estimates associated with each explanatory variable are then plotted along with confidence bands to indicate the impact and its significance over the entire auction.

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Chapter 4

Essay Two: An Investigation of Value Updating Bidders in Simultaneous Online Art Auctions

4.1 Introduction

For the last three decades, simultaneous auctions have become one of the most popular auction settings for selling high-priced affiliated private value items, including FCC radio bandwidth spectrum [26], U.S. treasury bills [32], timber [21] and so on. Recently, this auction format has become popular in online auctions to sell collectables and fine arts [8]. In these auctions, all the items are sold simultaneously, meaning that their auctions start at the same time and end at the same time. The set of bidders who attend these auctions remain the same throughout the auction event. Such an auction setting is particularly successful in situations where the items are highly complementary and the buyers have a demand for more than one item. For example, broadcasting companies typically need to purchase more than one bandwidth of the radio spectrum; art collectors buy more than one item of their favorite artist and so on. This results in a unique competitive scenario where same bidders are frequently observed to compete on more than one item at the same time, thus leading to two types of bidder competition, i.e. within-lot interaction and between-lot interaction.

Ariely and Simonson [1] suggest that during online auctions, bids submitted by other bidders play a significant role in the bidders' value assessment process. Particularly, in affiliated private value auctions[1] such as fine art auctions, bidders have limited information about the items. Therefore, they consider other bidders' valuation (bid value) as additional information

[1]Bidders' valuations are dependent on other bidders' bid value (loosely speaking, one bidder's high value signal makes it more likely that other bidders will exhibit higher values), implying that bidders update item valuation based on the bids posted by other bidders[25].

[17, 18] during auctions. In simultaneous auctions, bidders frequently encounter each other in more than one item. Therefore, it is possible for value-updating bidders to encounter the same bidder more than once. How does the presence of "known" bidders affect the propensity of value-updating behavior? In this paper, I intend to answer this question. In particular, I analyze the characteristics of such value-updating bidders (termed here as *Reactors*) in the presence of influencing bidders (termed here as *Influencers*). I examine three important questions pertaining to the *Reactors*: In what type of lots (items with high estimates or low estimates, paper or canvas work, type of artist) do bidders update their value? Do they bid more in the first half or in the second half of the auction? Are they selective in the lots on which they bid, or do they bid on many lots?

Recent studies on this issue [1, 12, 20] have focused on the underlying psychological factors that result in value updating behavior. They identified factors like bidder rivalry, social effects, and escalation of commitment that lead to a "win at any cost"' mentality of the *Reactors* (when they start bidding irrationally in order to win the item [20][2]). They used aggregate competition information such as the number of bidders and number of bids per bidder in the auction. In this chapter, I take a closer look at this phenomenon. Particularly, I focus on bidder competition at a dyadic level (i.e. between a pair of bidders) in the auction and examine how it affects the value updating behavior of bidders after controlling for aggregate level of competition. I assume that bidders do update their value during auctions and such behavior is revealed when bidders place a high bid value after using a proxy bidding system earlier in the auction. Proxy bidding is a commonly available feature in most online auction houses where bidders set a maximum amount they are willing to pay, and then let the auction house place proxy bids on their behalf until that price[3]

From the auction house manager's perspective, understanding the behavior of bidders is important. Since the rivalry among auction houses has intensified in recent years, much

[2]This emotional phenomenon is commonly known as "auction fever"

[3]Ku, Malhotra and Murnighan [20] performed a survey of bidders and found that most of them use proxies to set their maxima.

more attention is now given to strengthen relationships with bidders. The underlying quest for all the managers is now to cultivate and promote a strong relationship with bidders and encourage them to participate more in future auctions. Thus, *Reactors* play a pivotal role in the success of the auction house. Their value updating behavior typically leads to overbidding and higher price [20] paid for the item, thus playing a critical part in the price formation process in the auction. Therefore, managers are interested in learning[4] on what and when these bidders bid. To this end, this chapter attempts to investigate their characteristics in these simultaneous auctions.

Another contribution of this chapter from all other online auction research is the context of the study, i.e. auctions of high-end fine arts. Selling high-priced art items through online auctions has become a recent trend in the art market. As the demand for fine art has reached its all-time high [2], auction houses and art dealers have found Internet-based auctions as one of the most reliable ways to sell art items to a wider group of art lovers. Established online auction houses such as SaffronArt.com, Attinghouse.com, AspireArt.com and so on, use the simultaneous auction setting in their auctions. Simultaneous online auctions are different from eBay auctions, which are frequently analyzed in academic research. In a simultaneous auction, all the items up for sale are sold *concurrently* to the same group of bidders over a certain period of time. This gives rise to a complex competitive environment, where there is a great level of interdependence between bidders leading to value-updating behavior by some of them. With the art market so hot and with so much at stake for the auction house managers, this chapter is well focused in helping these managers develop a better relationship with their customers.

In this chapter, I accomplish two tasks. First, I investigate the effect of "known" bidders at the dyadic bidder level (bidder familiarity) on the value-updating propensity of bidders. This is in effect an extension of the prior studies [12, 20] that have only looked at the effect of aggregate competition in the auction. I model the propensity of value-updating bidders

[4]Auction house managers from multiple auction houses were interviewed during our investigation.

using a logistic model and found that that high level of between-lot bidder interaction has a negative effect on the bidder's propensity to update their value. This indicates that on average, the more the proxy-bidders competing with the participants in other lots, the less likely that they will update their value. I further extend this study by investigating the effect of bidder familiarity on the level of value-update for those who have decided to update. Once again, I found this effect to be negative, indicating that even though a bidder updates his value, his update value level will be low in the presence of familiar bidders.

In the second task, considering the above empirical evidence, I include the aspect of bidder dependency/ familiarity in the modeling of value-updating bidders. Traditional approaches using linear models and logistic regressions are capable of fulfilling this goal, but lack the capacity to capture the bidder dependency that exists in simultaneous auctions. Particularly, with bidders competing for multiple items simultaneously, bidders "recognize" each other and engage in anti-competitive practices such as bidder collusion [8, 21]. To some degree, this limitation is due to the data structure available from the auction houses. To overcome this issue, I represent the auction data in the form of a network X_{ij} of bidders where bidder j (the *Reactor*) has updated his valuation in presence of "known" bidders i (*Influencer*). Using this rich and innovative framework, I examine the characteristics of *Reactors* using a random effect dyadic relation model [13]. This is based on a generalized regression framework and is capable of handling covariates of both bidder types. It builds on the social relations model [34, 36] and is capable of specifying random effects between subsequent bidders. It is proficient in simultaneously considering regressor variables; as well as correlation between *Reactors* having the same *Influencers*, between *Reactors* bidding on the same item, and reciprocity between *Reactors* and *Influencers*. In other words, this approach analyzes the bidder characterisics in consideration with the bidder dependence in these simultaneous auctions. Further, I find that *Reactors* typically bid on fewer items, suggesting that they might be the collectors and not the art dealers [31]. They also bid on high value items and bid more in the second half of the auction than in the first half. Interestingly, *Reactors* and *Influencers* rarely alter their roles during the auction, and there is more possibility for *Reactors* to encounter the same *Influencers* over other items than the opposite. In addition, I also show that our random effect model of value updating bidder (*Reactors*) analysis performs better than a competing logistic model, thus reaffirming the role of the "bidder familiarity" in the auctions.

In sum, the contribution of this chapter is of three-fold. First, I examine the effect of bidder competition on the propensity of value-updating behavior of bidders. Second, from the technical standpoint, I demonstrate an application of a random effect dyadic relation model for complex human behavior and emphasize the importance of new and advanced statistical techniques available to the social science field. And third, I use an innovative and rich network framework to examine the inter-bidder influence in the auction and analyze characteristics of value-updating bidders. The rest of the chapter is presented as follows. First, I describe the auction data of the research. Second, I discuss the analysis of the effect of between-lot bidder competition on the occurrence of value-updating bidders in the auction. Third, I present the random effect dyadic relation model and explain how I use it to determine the characteristics of *Reactors*. Fourth, I present the results of the investigation. Finally, I discuss the implications of this work and present directions for future research.

4.2 Auction Data

Online auctions[5] have become a hot research topic in economics, marketing, management and statistics. Particularly, with the availability of detailed bidding data from online auctions, we are now able to investigate bidder behavior and auction characteristics in details that were not possible to explore earlier. For example, in the last decade, a wide range of new

[5]Laudon and Traver [22] estimate that online auction sales (C2C and B2C) will top $36 billion by 2007. Revenue exceeded $6 billion in 2006 at eBay, the pioneering online auction firm where everything from paperclips to private jets get sold. Even traditional auction houses like Christie's (whose annual revenues are expected to top $4 billion in 2006) are adopting the online model. (http://www.iht.com/articles/2006/07/12/news/auction.php) (http://internet.seekingalpha.com/article/25034)

studies have looked at interesting auction issues such as price dynamics [6, 16], bidder surplus [5], importance of reference points in auctions [10, 19], herding behavior [9], and forward-looking behavior of bidders [37]. Interestingly, all these studies have focused exclusively on single-item auctions such as eBay, where bidders compete for one item at a time.

Unlike prior studies, this chapter investigates simultaneous online auctions where multiple items are sold *concurrently* to a same group of bidders over a certain period of time. We have collected the data from an online auction house called *SaffronArt.com*. This auction house sells only Modern Indian Art and has become a prominent distribution channel of that genre in recent years. More specifically, the data come from a three-day auction where 199 art lots (a unique piece of art such as a painting, a drawing or a sculpture) were sold. Unlike eBay auctions, these auctions are in simultaneous first-price ascending format. The lots are open at a specific date and time, and they close simultaneously at a specific time. Moreover, to allow bidders to compete for multiple items, the lots are closed sequentially in a group of 20 to 25 lots. For example, lots 1-25 may close at 9:00am and lots 26-50 will close at 9:30am. Further, to discourage devious online bidder behavior such as *sniping*[6], the auction has a soft closing time: the closing time extends by three minutes whenever a bid comes during the last three minutes of the auction. This time extension continues until no one bids during a span of three minutes.

4.2.1 Modern Indian Art

Modern Indian Art, with over $100 million in auction sales in 2006, is now one of the leading emerging art markets in the world. Although traditional auctions for Modern Indian Art have existed since 1995, it is only since 2000 that the market has exploded, with values realized at auctions growing at a brisk 68.7% annually (coincidentally, this is when *SaffronArt.com*, the source of our data, started its online auctions of Modern Indian Art). In 2006, online

[6]Sniping is a strategic bidding activity where bids are submitted in the last moments of the auction to allow minimal time to other bidders to react to this bid. Such behavior is prominent in eBay auctions as the auction closes promptly at a specific time.

auction sales of Modern Indian Art from SaffronArt.com ($36.76 million) had more sales (of Modern Indian Art) than the traditional auction houses like Sotheby's ($35.29 million) and Christie's ($33.08 million). Further, *SaffronArt.com* sold more art items (537) compared to Sotheby's (484) and Christie's (329) in that year[7]. The top ten Indian artists sold 31% of the lots and contributed to 57% of the total value realized at auctions since 1995. Two of these artists are now ranked in the top 100 artists in the world based on their auction sales in 2005. A new set of emerging artists (the new trendsetters, typically born after 1955) have contributed 2% in value and 3% in lots and are becoming increasingly popular, commanding ever higher prices.

4.3 Impact of Dyadic Bidder Interaction on Value-Updating Behavior

Identifying *Reactors* in an auction is challenging. First of all, no prior information is available about the private-value distribution of the bidders. These bidders do not reveal the maximum amount they are willing to spend, nor do they explicitly announce that they have updated their value at the end of the auction. Luckily, in online auctions, the auction house provides a proxy bidding service to the participants. Proxy bidding is a commonly available feature in most online auctions where bidders set the maximum amount they are willing to pay for the auctioned item, and then let the auction house place proxy bids on their behalf until that price. Bidders using this facility have a pre-determined value for the item and use proxy bidding to stay within that value limit [4]. Ku and his colleagues [20] performed a survey of the bidders and found that most of them use proxies to set their maxima. The respondents used terms such as *"maximum personal limit", "what we were willing to spend", "the most I was willing to bid",* and *"by how I valued it"* to explain their proxy bids. In the same lines, we considered a bidder to be updating his value if he re-enters the bidding process and places a normal (non-proxy) bid that is higher than his earlier proxy bid.

[7] In 2005, online auction sales of Modern Indian Art by SaffronArt.com were $18.06 million, more than that of Sotheby's ($10.49 million) and Christie's ($14.89 million). *SaffronArt.com* also sold more art items (390) compared to Sotheby's (276) and Christie's (248) in 2005.

Earlier studies [1, 12] suggest that bidder competition in auctions, as indicated by the number of bidders participating and the number of bids per bidder, plays a positive role on the value updating behavior of bidders. Ku and his colleagues [20] further added that such competition ultimately leads to “auction fever”, which in turn results in overbidding by bidders. This chapter contributes to this literature by extending our view of bidder competition from aggregate level to the dyadic level. In simultaneous auctions, bidders are frequently observed to bid on more than one item at the same time. This creates a unique competitive environment where the same bidders compete on multiple items simultaneously. In this context, the crucial question is, how does the presence of “familiar” bidder (high between-lot bidder interaction) affects the propensity for the proxy-bidders to update their value? Will they be more inclined to update their value or will they avoid doing so? Further, even if they update their value, what will be the level of the value update? Empirical findings from Chapter 3 suggest that high between-lot bidder interaction leads to lower *auction outcome*. This is possibly due to the formation of bid rings among bidders [29] where bidders make implicit arrangement to divide the objects among them and thus, leading to tacit collusion [21]. Therefore, high between-lot interaction may reduce the propensity for proxy-bidders to update their value. Thus, we hypothesize:

H1: All else equal, high intensity of between-lot dyadic interactions between the proxy-bidder and other bidders will lead to a lower propensity for the proxy-bidder to update his value.

In the same lines, we hypothesize that even if the proxy-bidder updates his value during the auction, he will be reluctant to place a higher bid. They may be eager to indicate their continued interest on the item to intimidate other bidders, but they may not be willing to expose more information about their private value. Therefore, we hypothesize:

H2: All else equal, high intensity of between-lot dyadic interactions between the proxy-bidder and other bidders will lead to a lower level of value-update for the proxy-bidder.

In order to test the first hypothesis (H_1), we model the propensity of value-updating behavior in the auction with a logistic model. For each item, we identify whether the any of the initial proxy-bidders has changed their value during the course of the auction and has placed a higher non-proxy bid. We identify each item as 1 if a bidder has updated his value after placing a proxy bid and 0, if a bidder placed an initial proxy bid at the beginning of the auction, but did not place any non-proxy updated bid. Next, we consider p_i as the probability that a proxy-bidder has updated his value in item i and model the logit of the probability as a linear function of the item covariates of i. Since we are investigating the level of bidder "familiarity" of the proxy bidder, we compute the between-lot intensity of these bidders based on the bids posted between their proxy and non-proxy bids. If the proxy bidder did not update his value during the auction, we compute his between-lot competition intensity for the complete auction time. Other covariates included in the model are competition characteristics (within-lot competition, number of bidders, number of bids per bidder), artist characteristics (artist reputation, artist's previous year's auction value), and item characteristics (media of the item, size of the item and pre-auction estimate of the item). We further log transform between-lot intensity, artist's previous year's auction value, pre-auction low estimate and size of the lot to offset the skewness of their distribution. Thus,

$$logit(p_i) = ln(\frac{p_i}{1-p_i}) = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \ldots + \beta_k x_{k,i} \tag{4.1}$$

Where x_{1i} = Log(Between-lot intensity of the Proxy Bidder in lot i.)

x_{2i} = Within-lot intensity in lot i.

x_{3i} = Indicator variable for Established Artist for lot i.

x_{4i} = Indicator variable for Emerging Artist for lot i.

Table 4.1: Effect of Dyadic Bidder Interactions on the Value Updating Behavior

Covariates	**Estimate (Standard Error)**	**Wald (Chi−Square)**	**Pr>Chisq.**
Between-lot Interaction of Proxy Bidder	−2.290 (0.556)	16.969	< .0001
Within-lot Interaction	0.042 (0.340)	0.015	0.9030
Established Artist	0.011 (0.915)	0.0001	0.9905
Emerging Artist	0.785 (0.993)	0.625	0.4292
Number of Bidders	0.399 (0.219)	3.327	0.0681
Number of Bids/ Bidder	1.202 (0.588)	4.183	0.0408
Artist's Previous Year's Auction Value	0.799 (0.816)	0.961	0.3269
Pre-auction Low Estimate	−0.038 (0.685)	0.003	0.9561
Works on Paper	2.037(0.962)	4.487	0.0342
Size of Artwork	1.209 (0.718)	2.8308	0.0925

x_{5i} = No. of Bidders in lot i.

x_{6i} = No. of Bids per Bidder in lot i.

x_{7i} = Log(Artist's previous year's auction value in lot i.)

x_{8i} = Log(Low Estimates of the lot i.)

x_{9i} = Indicator variable for Paper work for lot i.

x_{10i} =Log(Size of lot i.)

and $i = 1, 2, \ldots, 199$ lots

Results (shown in Table 4.1) suggest that between-lot competition of the proxy bidder has a significant negative effect (coefficient=−2.290) on the propensity of their value-updating behavior, thus supporting our hypothesis H_1. We also found that both aggregate competitive measures of the item (i.e. number of bidders and number of bids/ bidder) are significant and positive as previously suggested by [12, 20]. Indicator for work on paper (coefficient=2.037) is also found to be significant and positive, suggesting that bidders tend to update values more in works of paper. In our dataset, some lots have more than one bidder placing an initial proxy bid. Among these bidders, some of them update their values and others do not. In these cases, we indicate the item with 1 if atleast one of the proxy bidders have updated their value[8].

In order to test the second hypothesis H_2, we now focus our attention to bidders who have already updated their values. Here we analyze how between-lot intensity affects the level of value update of these bidders. We regress the % value update of these bidders on the same set of covariates used in the logistic model (Equation 4.1). We consider the following linear model:

$$(\%\, Value\, Update)_i = \beta_0 + \sum_{j=1}^{10} \beta_j x_{ji} + e_i \tag{4.2}$$

Where x_{1i} = Log(Between-lot intensity of the Proxy Bidder in lot i.)

x_{2i} = Within-lot intensity in lot i.

x_{3i} = Indicator variable for Established Artist for lot i.

x_{4i} = Indicator variable for Emerging Artist for lot i.

x_{5i} = No. of Bidders in lot i.

x_{6i} = No. of Bids per Bidder in lot i.

x_{7i} = Log(Artist's previous year's auction value in lot i.)

x_{8i} = Log(Low Estimates of the lot i.)

[8]As a separate analysis, we analyzed the percentage of bidders who update their value in each item and then model it against the same covariates as we did in the logistic regression, with a Generalized Linear Model (GLM). Results from the GLM analysis are found to be same as the ones obtained from the Logistic Regression.

Table 4.2: Effect of Dyadic Bidder Interactions on the Level of Value Update

Covariates	**Standard Coefficient (Standard Error)**	**T-value**	**P-value**
Between-lot Interaction of Proxy Bidder	−0.490 (0.043)	−2.75	0.0088
Within-lot Interaction	−0.037 (0.043)	−0.16	0.8738
Established Artist	−0.166 (0.095)	−0.88	0.3864
Emerging Artist	0.069 (0.110)	0.32	0.7534
Number of Bidders	0.050 (0.024)	2.22	0.0318
Number of Bids/ Bidder	0.331 (0.057)	1.50	0.1421
Artist's Previous Year's Auction Value	−0.261 (0.084)	−0.66	0.5152
Pre-auction Low Estimate	0.520 (0.079)	1.33	0.1894
Works on Paper	0.296(0.085)	1.71	0.0947
Area of the Artwork	−0.119 (0.069)	−0.38	0.7075

x_{9i} = Indicator variable for Paper work for lot i.

x_{10i} =Log(Size of lot i.)

and $i = 1, 2, \ldots, 199$ lots

Results shown in Table 4.2 confirms our hypothesis (H_2) regarding the effect of high between-lot interaction on the level of value update. We find that between-lot bidder interaction of the value-updating bidder (i.e. Reactors) has a significant negative effect (coefficient=−0.490) on the level of his value update. Therefore, more the Reactors are familiar with other participants; smaller will be their level of value update. We also found that the number of bidders participating has a significant positive effect (coefficient = 0.050) on the level of value change. Although this result is in accordance with the earlier findings [20], high negative coefficient of between-lot bidder interaction as compared to the positive coefficient of number of bidders will finally result into an overall negative effect of bidder competition on the level of value update. In other words, the above result validates our assertion that consideration of bidder competition at dyadic level is essential in understanding bidder phenomenon in online auction.

4.4 Bidder Influence Network

One of the greatest challenges with the available auction data (see Figure 4.1) is how we capture the inter-bidder dependence during an auction. Particularly, we want to somehow transform the bid history to something that will represent the between-lot competition of the bidders. That is, we should consider the influence of the *Influencers* over the *Reactors* in our modeling effort of their characteristics. In order to consider the inter-bidder dependencies, proper representation of the bidding data is necessary. We transform the bid history into an $N \times N$ bidder influence matrix where N denotes the number of bidders participating in the auction. The value $y_{i,j}$ in each cell of the influence matrix indicates the influence of bidder i over bidder j. We considered the influence measure $y_{i,j}$ as the total number of items in which the *Influencer* (bidder i) has bid between the proxy and non-proxy bid of the *Reactor* (bidder j). Since the auctions are held simultaneously, prior auction studies [8, 21] suggest that bidder-pair with multiple engagements tend to influence each other. Dass and his colleagues [8] also showed that such engagements lead to dyadic-level bidder effect, which has significant effect on the seller's profit even after controlling for the aggregate competition in the auction. Figure 4.2 illustrates the network data structure with *Reactors* and *Influencers* as nodes. Here $x_{1,2}$ indicates the number of items in which bidder 1 (an *Influencer*) has placed a bid between the proxy and non-proxy bid of bidder 2 (a *Reactor*).

We also considered two other possible measures of influence for our bidder network $Y_{i,j}$. The first approach considers the order in which the *Influencers* have placed their bids. We assumed that the bidders whose bid is close to that of the non-proxy bid of the *Reactor* will provide more value information than the bidders who have placed a bid earlier than that. We captured this notion by computing the difference between the bid ranks (order of the

110
Jagannath Panda

High-rise- Bee-rise

Signed and dated in English (verso)
2006
Oil, acrylic and fabric on canvas
78 x 156 in (198.1 x 396.2 cm)

$58,140 - 69,770
Rs 2,500,000 - 3,000,000

Next Valid Bid : $ 106,600 (Rs 4,583,800)

Rank	Nick Name	Amount($)	Amount(Rs)	Bid Type	Date & Time (US EST)
Current Highest Bid 1	Anonymous 3	99,100	4,261,300		Mar 8 2007 10:47:06 AM
2	Anonymous 25	91,600	3,938,800		Mar 8 2007 10:21:57 AM
3	racoon	84,100	3,616,300		Mar 8 2007 6:19:29 AM
4	Anonymous 138	76,600	3,293,800		Mar 8 2007 12:54:47 AM
5	racoon	71,600	3,078,800		Mar 7 2007 8:57:15 AM
6	Anonymous 47	66,600	2,863,800		Mar 7 2007 1:39:24 AM
7	Anonymous 25	61,600	2,648,800		Mar 6 2007 11:51:47 PM
8	Anonymous 3	56,600	2,433,800	Proxy	Mar 6 2007 11:10:21 PM
9	Anonymous 25	51,600	2,218,800		Mar 6 2007 11:10:21 PM
10	Anonymous 3	49,100	2,111,300	Proxy	Mar 6 2007 10:30:00 PM
	Start price	46,600	2,003,800		Mar 6 2007 10:30:00 PM

Figure 4.1: Bid History from an Online Auction of Modern Indian Art.

Reactors

Influencer	Bidder 1	Bidder 2	Bidder 3	.... Bidder 80
Bidder 1	0	x_{12}	x_{13}	
Bidder 2	x_{21}	0	x_{23}	
Bidder 3 . . Bidder 80	x_{31}	x_{32}	0	

Figure 4.2: SocioMatrix of Influencers and Reactors

bids) of the *Reactor* and his *Influencers*. The second approach considers the reaction time of the *Reactors*. In other words, it considers the difference between the bids of the *Influencers* and the *Reactor's* normal bid. The shorter the time difference, the larger is the influence. The longer the time difference, weaker is the influence as the *Reactor* may have used other resources to update his value of the item. Both approaches yielded the same results as our first approach, and thus their results are excluded from this chapter[9].

4.5 Bidder Characteristics of Reactors

This study assumes that the characteristics of *Influencers* and *Reactors* are homogeneous within the bidder types. Since the bidder influence data is represented in the form of a socio-matrix $Y = [y_{i,j}]$, there are certain modeling constraints that need to be addressed. First, the model needs to accommodate bidder level covariates. The main goal of this chapter is to characterize bidders who update their value during a simultaneous auction. Therefore, our

[9]The results from these approaches can be obtained from the auctions.

modeling framework should be capable of investigating the characteristics that define a *Reactors*. And second, the model should allow second order dependencies (such as reciprocity and common bidder effect in auctions where two interdependent bidders have common *Influencers* or common *Reactors*). Second order dependencies are essential in identifying the stability of the bidder characteristics. For example, reciprocity will tell us whether bidders exchange their role as *Reactors* or *Influencers* during the auction. The effect of common *Influencers* and *Reactors* will emphasize how repeated encounters with the same bidders affect bidder decisions. In this chapter, we develop a random effect dyadic relational model to investigate the characteristics of the bidders.

4.5.1 Random Effects Dyadic Relation Model

This modeling approach is based on the earlier works of Hoff [15, 13] that specify and analyze random effects for the originator (*Influencer*) and the recipient (*Reactors*) in a social relations setting. It starts with the description of a simple linear model and builds the complexities around it sequentially. Consider modeling the dyadic influence data with a linear regression model of the following form:

$$y_{i,j} = \beta' x_{i,j} + \epsilon_{i,j} \tag{4.3}$$

where $y_{i,j}$ represents the influence of bidder i over bidder j, and $x_{i,j}$ represent the dyadic level covariates. Since we also want to take into account the second order dependencies, we assume the error component to have a covariance structure that is exchangeable under identical permutations of the indices i,j of the *Influencers* and *Reactors*, respectively. In our case, the influence of bidder i over bidder j is distinct from the influence of bidder j over bidder i (i.e. $y_{i,j}$ and i,j are different from $y_{j,i}$ and j,i) so we can represent the joint distribution of the *i,j's* or the residuals in terms of a linear random-effect model

$$\epsilon_{i,j} = a_i + b_j + \gamma_{i,j} \tag{4.4}$$

where a_i represents the effect of an *Influencer*, b_j represents the effect of a *Reactor* and $(a_i, b_j)' \sim$ multivariate normal $[MVN](0, \sum_{ab})$. Thus,

$$\begin{bmatrix} a_i \\ b_j \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ba} & \sigma_b^2 \end{bmatrix}\right)$$

Further, we also consider $(\gamma_{i,j}, \gamma_{j,i})' \sim MVN(0, \sum_\gamma)$. Therefore,

$$\begin{bmatrix} \gamma_{i,j} \\ \gamma_{j,i} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\gamma^2 & \rho\sigma_\gamma^2 \\ \rho\sigma_\gamma^2 & \sigma_\gamma^2 \end{bmatrix}\right)$$

This leads to a covariance structure of the error given by

$$\begin{aligned} &E(\epsilon_{i,j}^2) = \sigma_a^2 + \sigma_b^2 + \sigma_\gamma^2 && E(\epsilon_{i,j}\epsilon_{i,k}) = \sigma_a^2 \\ &E(\epsilon_{i,j}\epsilon_{j,i}) = \rho\sigma_\gamma^2 + 2\sigma_{ab} && E(\epsilon_{i,j}\epsilon_{k,j}) = \sigma_b^2 \\ &E(\epsilon_{i,j}\epsilon_{k,l}) = 0 && E(\epsilon_{i,j}\epsilon_{k,i}) = \sigma_{ab}^2 \end{aligned}$$

where σ_a^2 represents the variance in the observations due to the presence of common *Influencers*, σ_b^2 represents the variance in the observations due to the presence of common *Reactors* and ρ represents the correlation of observations within a *influencer-reactor* pair, and serves as a measure of reciprocity or mutuality[10] in the bidder influence data [13]. Since the goal is to analyze the characteristics of *Reactors*, only the bidder specific covariates are considered in the model. Thus,

$$\theta_{i,j} = a_i + b_j + \gamma_{i,j} \tag{4.5}$$

The above Equation (4.5) is modeled such that the dyadic data are unconditionally dependent, but conditionally independent; given the random effects of *Influencers* and *Reactors*. Therefore, $E(y_{i,j}|\theta_{i,j}) = g(\theta_{i,j})$, and $p(y_{12}, y_{13}, \ldots y_{n,n-1}|\theta_{12}, \theta_{13}, \ldots \theta_{n,n-1}) = \prod_{i\neq j} p(y_{i,j}|\theta_{i,j})$

[10]This model is also known as the "round-robin" model [34, 36].

In our case, a Poisson model with log-link is appropriate, given that we measure the level of influence $y_{i,j}$ as the number of items where bidder i has presumably influenced bidder j to update his value. Thus,

$$g(\theta_{i,j}) = \epsilon^{\theta}_{i,j} \tag{4.6}$$

$$p(y_{i,j}|\theta_{i,j}) \sim Poisson(e^{\theta_{i,j}}) \tag{4.7}$$

4.5.2 Modeling the Effect of Second-Order Dependence

In auctions, there are possibilities that the effect of intense rivalry initiated between two bidders in the early part of the auction may spillover to the later part of the auction and influence the *Reactors* to update their value. Consider a hypothetical scenario: say bidder A and bidder B have engaged in a bidding-war in the auction. This bidding phenomenon may influence the proxy bidder, say C to update his private value and place a higher non-proxy bid. Such second order effects are common in art auctions [30, 31, 8]. To capture the effect of these second order dependencies in the context of the regression setting, a latent K-dimensional vector z_i for each bidder is constructed and the inner product $z_i'z_j$ is added to the error model Equation 4.4 as suggested by Hoff [13]. Thus,

$$\epsilon_{i,j} = a_i + b_j + \gamma_{i,j} + z_i'z_j \tag{4.8}$$

Based on the magnitude and direction of the latent vectors, the inner product $z_i'z_j$ will capture different second-order dependence through the expectation of the second order moment[11]. Further, the incorporation of $z_i'z_j$ into the linear predictor allows additional moments of $\epsilon_{i,j}$. Thus,

[11]For more information on how the values and directions of z_i represent various third-order dependencies, please refer to [13, 15, 27].

$$E(\epsilon_{i,j}^2) = \sigma_a^2 + \sigma_b^2 + \sigma_\gamma^2 + K\sigma_z^4$$
$$E(\epsilon_{i,j}\epsilon_{j,i}) = \rho\sigma_\gamma^2 + 2\sigma_{ab} + K\sigma_z^4$$
$$E(\epsilon_{i,j}\epsilon_{k,i}) = K\sigma_z^6$$

Since the inner-product term is a fixed effect, it can be considered as a reduced-rank interaction term. This is termed as the *bilinear effect* or *multiplicative interaction*.

To include this inner product of the bidder's latent characteristics in the random effect model, Equation (4.5) is re-parameterized as

$$\theta_{i,j} = \beta'_{inf} x_{inf,i} + a_i + \beta'_{rea} x_{rea,i} + b_j + \gamma_{i,j} + z'_i z_j \tag{4.9}$$

where $x_{rea,i}$ are the *Reactor* specific covariates and $x_{inf,i}$ are the *Influencer* specific covariates in the model.

Bayesian estimation is performed to estimate the model shown in Equation 4.9. A Markov Chain Monte Carlo (MCMC) algorithm is used to sample values of the *Influencer* and *Reactor* specific parameters from their posterior distribution. Like any MCMC process, the estimation of the bilinear model is done by using a three-step process of sampling from the desired target posterior distribution $p(\beta_{inf}, \beta_{rea}, \sum_{ab}, Z, \sigma_z^2, \sum_\gamma |Y)$. The three steps are:

1. Sampling of linear effects in the model:
   (a) Sample $\beta_{inf}, \beta_{rea}|\beta'_{inf}, beta'_{rea}, \sum_{ab}, Z, \theta, \sum_\gamma$
   (b) Sample $\sum_{ab}, \sum_\gamma$ from their full conditionals
2. Sampling of bilinear effects:
   (a) For each bidder $i = 1, 2, \ldots n$, sample $z_i|\{z_j : j \neq i\}, \theta, \beta, s, r, \sum_z, \sum_\gamma$
   (b) Sample $\sum_z$ from its full conditionals
3. Update $\{\theta_{i,j}, \theta_{j,i}\}$ using Metropolis-Hastings step:

(a) Propose $\begin{pmatrix} \theta^*_{i,j} \\ \theta^*_{j,i} \end{pmatrix} \sim MVN\left(\begin{pmatrix} a_i + b_j + z_i' z_j \\ a_j + b_i + z_j' z_i \end{pmatrix}, \Sigma_\gamma\right)$

(b) Accept $\begin{pmatrix} \theta^*_{i,j} \\ \theta^*_{j,i} \end{pmatrix}$ with probability $\frac{p(y_{i,j}|\theta^*_{i,j})p(y_{j,i}|\theta^*_{j,i})}{p(y_{i,j}|\theta_{i,j})p(y_{j,i}|\theta_{j,i})} \wedge 1$

The 'gbme' function[12], written in R [14] is used to perform the above estimation process and to determine the characteristics of auction participants who overbid (*Reactors*). The prior distributions of the parameters are taken as [14]:

- $\beta \sim MVN(0, 80 \times I_{4\times 4})$
- $\Sigma_{ab} \sim$ inverse Wishart$(I_{2\times 2}, 4)$
- $\sigma^2_u, \sigma^2_v \sim$ iid inverse gamma(1,1), $\sigma^2_\gamma = (\sigma^2_u + \sigma^2_v)/4, \rho = (\sigma^2_u - \sigma^2_v)/(\sigma^2_u + \sigma^2_v)$

We used K=2 (latent dimensions) in our analysis. Five different values of K, ranging from 0 to 4, were tested with a four-fold cross-validation procedue as described by Hoff in his seminal paper [13]. The predictive performance for all the K values were roughly the same. The biggest improvement in the marginal likelihood criterion was from K=1 to K=2. Therefore, K=2 was selected. Table 4.3 illustrates our findings.

4.5.3 Base Model

We compared our random effect model with a competing base model such as a logistic regression which can also be used to determine the characteristics of the *Reactors*. We first identify the bidders who are updating their value based on their proxy and non-proxy bidding and assign a value of 1 for a *Reactor* and 0 for not a *Reactor*. Next, we consider p_i as the probability that a bidder i is a *Reactor* and model the logit of the probability as a linear function of the bidder covariates. Thus,

[12] http://www.stat.washington.edu/hoff/Code/GBME/

Table 4.3: Evaluation of K-Latent Dimensions

K	log p($Y|\hat{\beta}, \hat{a}, \hat{b}, \hat{Z}, \Sigma_\epsilon$)
0	-399.45
1	-397.14
2	-392.71
3	-394.33
4	-398.98

$$logit(p_i) = ln(\frac{p_i}{1-p_i}) = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \ldots + \beta_k x_{k,i} \tag{4.10}$$

We used the same bidder covariates in Equation (4.9) as were used in Equation (4.10). Performance of our random effect model is compared to this one using their negative log likelihood value.

4.6 Bidder Covariates

Reactors are examined in the context of three types of characteristics: lot (item) characteristics, auction characteristics and bidder behavior characteristics.

4.6.1 Lot Characteristics

Prior work on auctions of fine arts [3, 30] found that both the pre-auction estimates of the items provided by the auction house and the art type (paper or non-paper work) to be significant drivers of auction prices. Before the auction starts, potential bidders are exposed to various types of information about the lots. Lot information and provenance provided by the auction house (in their printed catalogs and in their websites), and comments and suggestions of the art experts (in personal blogs, art magazines, etc.), provide information on the value of the art items such as the estimated price, artist information, and previous auction price history of similar paintings by the artists. The price estimates indicate the value of the items as suggested by the auction house experts (like curators, art specialists, etc.). Mei and Moses [24] found these value estimates to have high correlation with the final realized prices of the art items. Therefore, the higher the pre-auction estimates, the greater is the tendency for the item to fetch a higher price, and so higher stakes are associated with it. Such high stakes lead to higher bidder propensity to clarify and justify their future bids. Therefore, bidders look for other value signals from different sources and are inclined to change their value belief during the auction of these lots. Thus, we hypothesize that the bidders who act as *Reactors* tend to bid on lots that have high pre-auction estimates.

The media on which the art item is painted plays an important role in its maintenance and longevity [30]. For example, works on paper are typically of low price as compared to that of works on canvas since paper tends to be more fragile than canvas. Therefore, low financial risk is associated with the purchase of non-paper items and thus, we hypothesize that the *Reactors* will tend to update values more on non-paper items.

4.6.2 Artist Characteristics

Artist characteristics such as reputation and previous auction history of the artists also play an important role in the valuation of the art items. Established artists are highly reputed and their works are well recognized in the art market. Most of their works have been resold many times in the market and, thus, their value commonly known to all. Therefore, the works of established artists present a low risk purchase opportunity for the bidders [30]. On the other hand, emerging artists are new to the art market and their works are not well known. Further, not enough works of these artists are sold in the marketplace in order to estimate their values confidently. Therefore, the values of the works of these artists are highly uncertain, making them high-risk purchases. Thus, *Reactors* are hypothesized to react and change their values in lots created by the emerging artists as they tend to seek more information from other bidders.

Like artist reputation, historical market information such as the average price per square inch of the artists' art works or the total number of items sold in the previous year provide a signal to the bidders about the market value of the artist [30]. If the value realized by the works of an artist is low in the previous year, stakes will be high for their art work. Since evaluators are unaware of how the market will react to the works of these artists, they are high-risk purchases for the bidders. Similarly, if fewer items of the artist are sold in the previous year's auctions, less information is available about the artist's present market value. Therefore, it is highly probable for bidders to rely upon other value signals in these lots. Thus, it is hypothesized that *Reactors* will tend to change their values in these lots.

4.6.3 Bidding Characteristics

During auctions, *Reactors* are assumed to wait and consult bids of others participants (*Influencers*) to reduce any uncertainty they may have about the value of a lot. Thus, we conjecture that *Reactors* will bid more in the second half of the auction than in the first half. Further, these bidders by the virtue of their behavior tend to be selective in the types of lots on which they bid. Their attachment to a particular item is an integral reason for them to update their private value for the lot [12]. Therefore, we hypothesize that they will participate in auctions of fewer lots than other bidders will.

4.7 Results

The description of the bid data is presented in Table 4.4. In this particular auction, 199 lots were sold, and 42 bidders were observed to change their value belief for 63 lots during a Modern Indian Art auction held in December 2005. Eighty bidders participated in the auctions of these 63 lots creating 947 bid instances. Thus, an 80×80 bidder matrix is created and only the influences on those forty-two bidders who changed their value belief are considered.

Table 4.4: Data Description

No. of Lots Sold	199
No. of Bids	3080
Average No. of Bids per Lot[Range]	15.47 [2, 48]
Average Value of the Lots [Range]	$56,282 [$2,850, $1,351,000]
Average First Bid of the Lots	$19,343 [$650, $300,000]
Average No. of Bidders per Lot [Range]	6.35 [2, 14]
Average Time of Bids (Scaled 0-1)	0.4998
Average Time of Entry to the Auction	0.5386
Average Time of Exit to the Auction	0.8397

Bidder level covariates are used in the model to determine the characteristics of those who overbid. Table 4.5 presents the correlation between the bidder level covariates.

A Markov Chain Monte Carlo algorithm was run for the influence data. Each chain was run for 200,000 iterations. However, since a large number of parameters (*Influencer* and *Reactor* specific covariates, and terms capturing higher order dependencies) is analyzed in the model, only every 50th iteration is stored in order to keep the output file to a reasonable size, as suggested by MacEachern and Berliner [23]. Outputs from the first 20,000 iterations were considered burn-in and were not recorded. The posterior means and quantile-based 95% confidence intervals are presented in Table 4.6 and Table 4.7. Log transformations of the covariates were used in the analysis. The plots of marginal mixings are presented in Figures 4.3, 4.4 and 4.5. The plots of the posterior densities are also illustrated in Figures 4.6 and 4.7. The variables order for the results is same as the correlation table. For example, $bs_1 = br_1 =$ *Total no. of lots won*, $bs_2 = br_2 =$ *Low Pre-Auction Estimates of the Lots Bid* and so on.

The parameter estimates (Table 4.6) illustrate that the effect of a pre-auction estimate is positive and significant at 95% C.I. for the *Reactors*. This suggests that bidders who typically change their value belief have bid on lots with high estimated values. Positive but

Table 4.5: Correlation Matrix of the Bidder Covariates

	(x_1)	(x_2)	(x_3)	(x_4)	(x_5)	(x_6)	(x_7)	(x_8)
Low pre-auction estimates of the Lots Bid (x_1)	1							
No. of Lots sold by the Artists in the previous year's auction (x_2)	.551**	1						
No. of Lots by Emerging Artist (x_3)	-.183	-.182	1					
No. of Lots by Established Artist (x_4)	.584**	.655**	.210	1				
No. of Paper Works (x_5)	.127	.201	.474**	.399**	1			
No. of Bids Placed in the First Half of the Auction(x_6)	.107	.158	.359**	.431**	.515**	1		
No. of Bids Placed in the Second Half of the Auctions(x_7)	.204	-.089	.291**	.264*	.116	-.201	1	
Total No. of Unique Lots Bid (x_8)	.239*	.243*	.666**	.673**	.693**	.606**	.304**	1

** Correlation is significant at the 0.01 level (2-tailed)
* Correlation is significant at the 0.05 level (2-tailed)

Table 4.6: Posteror Means and Quantile-Based 95% Confidence Interval for Influencer and Reactor Level Covariates

Covariates	Influencers	Reactors
Low Pre-Auction Estimates of the Lots Bid	−0.3861	5.3660
	0.2545	**9.2870**
	0.9042	13.1774
No. of Lots Sold by the Artists in the Previous Year's Auction	−0.5961	−5.8831
	−0.1460	**−3.2870**
	0.3120	−0.6054
No. of Lots by Emerging Artists	−0.1371	−1.6351
	0.2415	**0.8290**
	0.6323	3.0512
No. of Lots by Established Artists	−0.1492	−3.7290
	0.2350	**−1.3695**
	0.6120	0.9690
No. of Paper Works	−0.4022	−0.6831
	−0.0295	**1.3795**
	0.3471	3.5781
No. of Bids Placed in the First Half of the Auction	0.1229	−0.4751
	0.5240	**1.8985**
	0.9260	4.7242
No. of Bids Placed in the Second Half of the Auction	−0.7030	8.2930
	−0.2420	**11.0610**
	0.2515	7.3632
Total Number of Unique Lots Bid	−0.7850	−10.1655
	−0.2305	**−6.4200**
	0.3080	−3.2234

Table 4.7: Posteror Means and Quantile-Based 95% Confidence Interval for Major Parameter of the Bilinear-Effects Model

Parameters	Posterior Mean and C.I.
Common Influencer Variance	1.4927
	1.9965
	2.7062
Common Reactor Variance	67.9891
	91.5990
	128.6762
Influencer-Reactor Covariance	-5.1890
	$\mathbf{-2.4560}$
	0.1013
Error Variance	0.0720
	0.1160
	0.1970
Reciprocity	-0.7680
	$\mathbf{-0.4960}$
	-0.0399
Variance of Latent Dimensions	0.0610
	0.1320
	0.3330
Variance of Inner Dimensions	0.0490
	0.0970
	0.2120
Negative Log Likelihood of $Y_{i,j}, Y_{j,i}$ Modeling Effects	$\mathbf{-448.324}$

non-significant estimates for the number of paper works sought by the bidders indicate that the *Reactors* tend not to bid on paper art items. Further, none of the artist related covariates were found to be significant at 95% C.I. in explaining the behavior of the *Reactors*.

We also examined the bidder characteristics of the *Influencers* and *Reactors* by comparing their bidding frequency during each half of the auction. Results show that the coeffient for the number of second half bids for the *Reactors* is positive and significant at 95% C.I., but the coefficient for the first half bid frequency is not significant. This suggests that *Reactors* tend to bid more in the second half of the auction than the first half. We also found that *Influencers* significantly bid more in the first half as compared to the second half of the auction. In addition, we examined the coefficient for the total number of unique lots bid by the two types of bidder. We found that the coefficient for the *Reactors* is negative and significant at 95% C.I. (coefficient$= -6.4200$) and the effect for *Influencers* is non significant. This suggests that that *Reactors* participate in auctions of fewer lots as compared to the *Influencers*. A summary of the results is presented in Table 4.8.

Estimates of other major parameters (Table 4.7) suggest that the common influence variance is smaller than the common *Reactor* variance, meaning that the *Influencers* maintain their role throughout the auction. Since these influencing bidders are frequently observed to bid on more lots, they tend to be the art dealers [31]. On the other hand, the common *Reactor* variance is large. This also supports the findings that the *Reactors* bid on fewer items and thus, the same *Reactor* is seldom encountered by the *Influencers*. Error variance was found to be small, suggesting a good fit our model. Finally, we find that the reciprocity is negative. This further supports the notion that the *Reactors* and *Influencers* rarely switch roles during the auction.

Table 4.8: Summary of the Findings

COVARIATES	**INFLUENCERS**	**REACTORS**
Low Pre-Auction Estimates of the Lots Bid	Not significant	Positive, significant effect suggesting that *Reactors* tend to update values on lots with high pre-auction estimates.
Artist's Reputation	Not significant	Negative, significant effect suggesting that *Reactors* tend to update value on works of artists who have sold fewer works in recent years
No. of Paper Works	Not significant	Not significant
Bid Frequency at Each Half of the Auction	The posterior mean shows a positive significant effect of the first half bid freq. and non-significant effect of the second half bid freq. This indicates that *Influencers* bid more in the first half as compared to the second half of the auction	The posterior mean shows a positive and significant effect of second half bid freq. and non-significant effect of the first half bid freq. This indicates that the *Reactors* tend to bid more in the second half as compared to the first half of the auction.
Total No. of Unique Lots Bid	Not significant	The posterior mean indicates a negative, significant effect, suggesting that *Reactors* tend to bid on small number of lots.

Table 4.9: Output from the Competing Logistic Model

Covariates	Estimate	p-value
Low Pre-Auction Estimates of the Lots Bid	0.1739	0.5716
No. of Lots Sold by the Artists in the Previous Year's Auction	−0.4450	0.1275
No. of Lots by Emerging Artists	−0.0222	0.9160
No. of Lots by Established Artists	0.2169	0.2150
No. of Paper Works	−0.1234	0.4680
No. of Bids Placed in the First Half of the Auction	0.0954	0.0111
No. of Bids Placed in the Second Half of the Auction	0.1378	0.0166
Total Number of Unique Lots Bid	−0.2644	0.0779

4.8 Performance of the Model

We compared our random effect model with a competing base model as shown in Equation (4.10). We fit this base model using the same dataset, with the *Reactors* already identified based on their proxy values and indicated with an indicator variable. The results from the base model (Table 4.9) also confirm our findings from the random effect model. We further find that the negative log likelihood of this model is −96.975. Since we want to select a model with minimum negative log likelihood, we select the random effect model, which not only provides more information about the auction processes that lead to the value updating behavior of the bidders, also has a lower negative log likelihood (−448.324) than the base model.

4.9 Implications and Future Directions

This chapter investigates the effect of dyadic bidder competition on the value updating behavior of bidders. We also extend our study to analyze the characteristics of bidders (termed here as *Reactors*) who update their private value of the items in the presence of

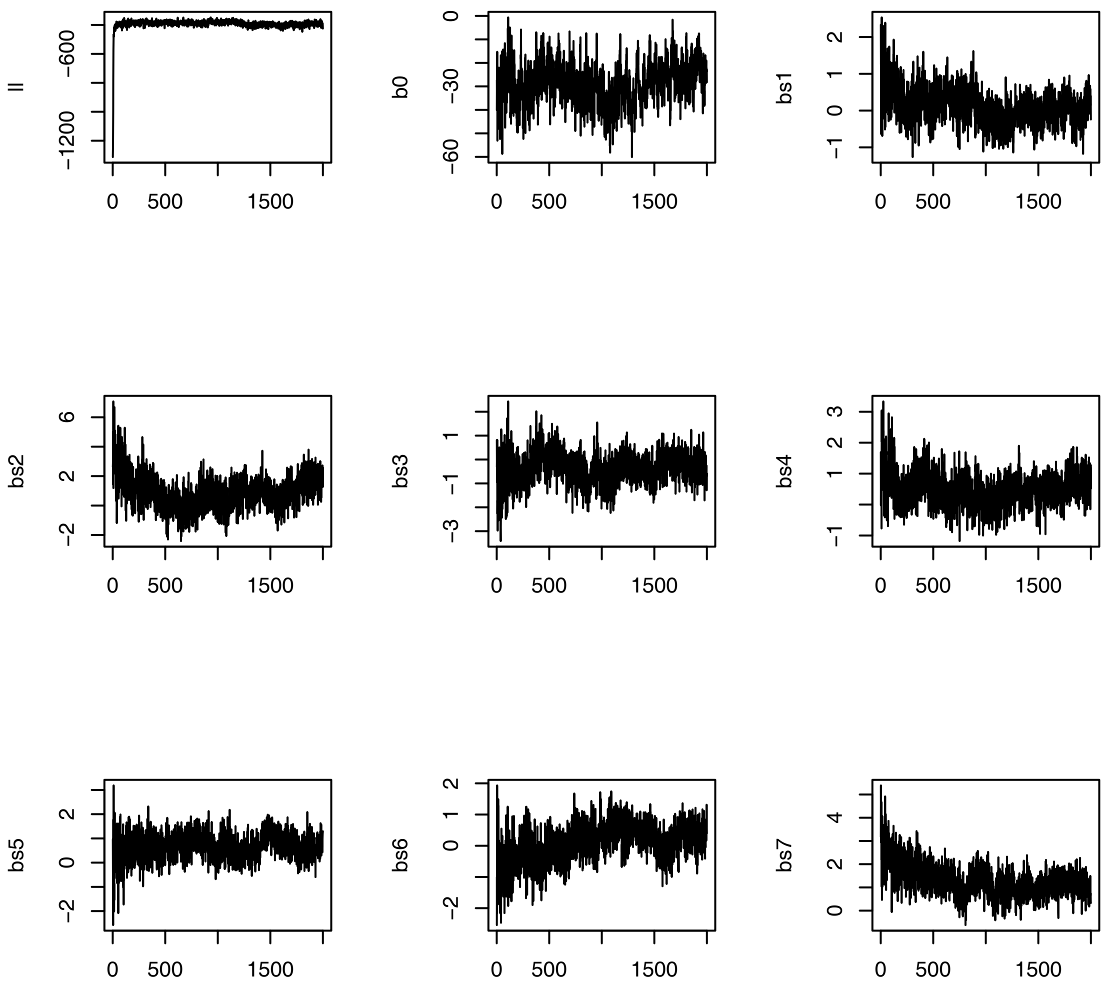

Figure 4.3: Plots of Marginal Mixing -1

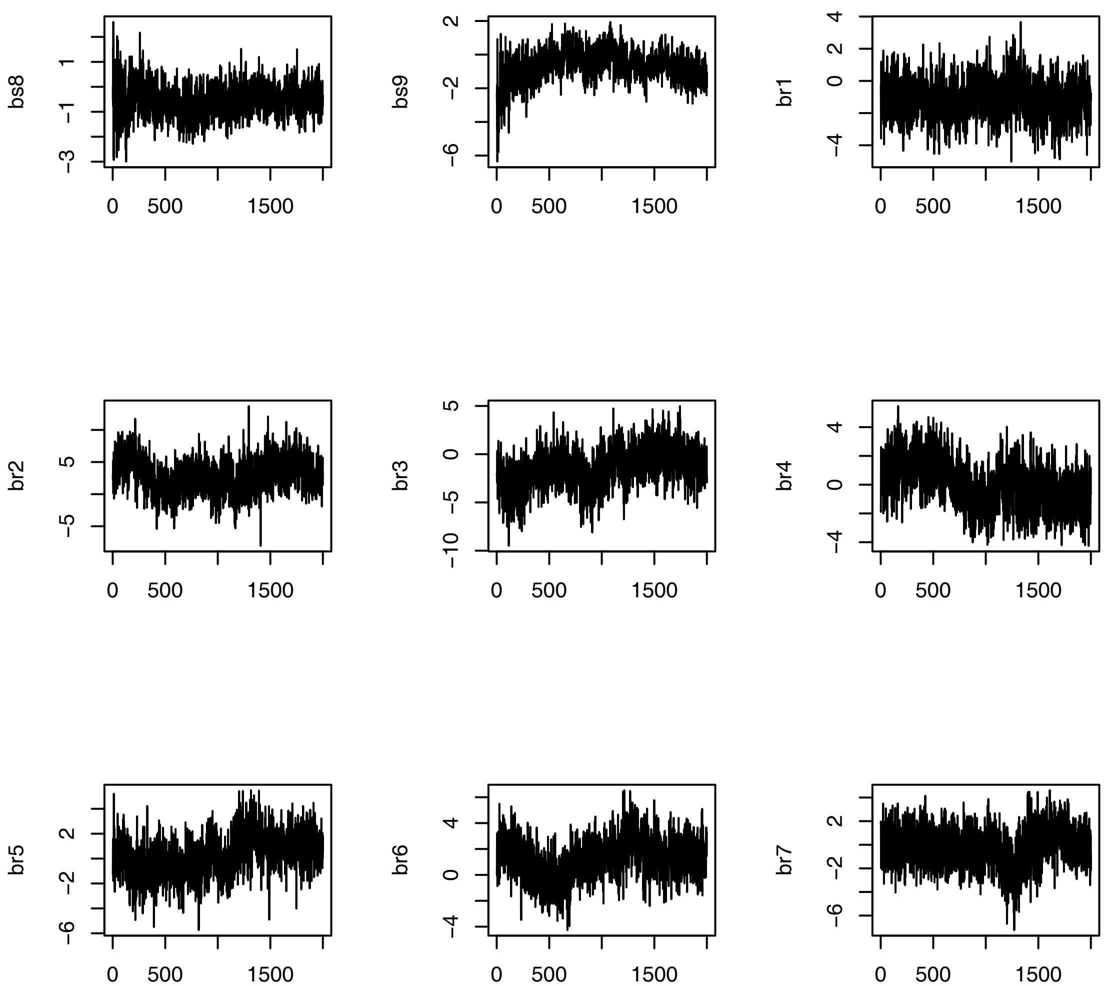

Figure 4.4: Plots of Marginal Mixing -2

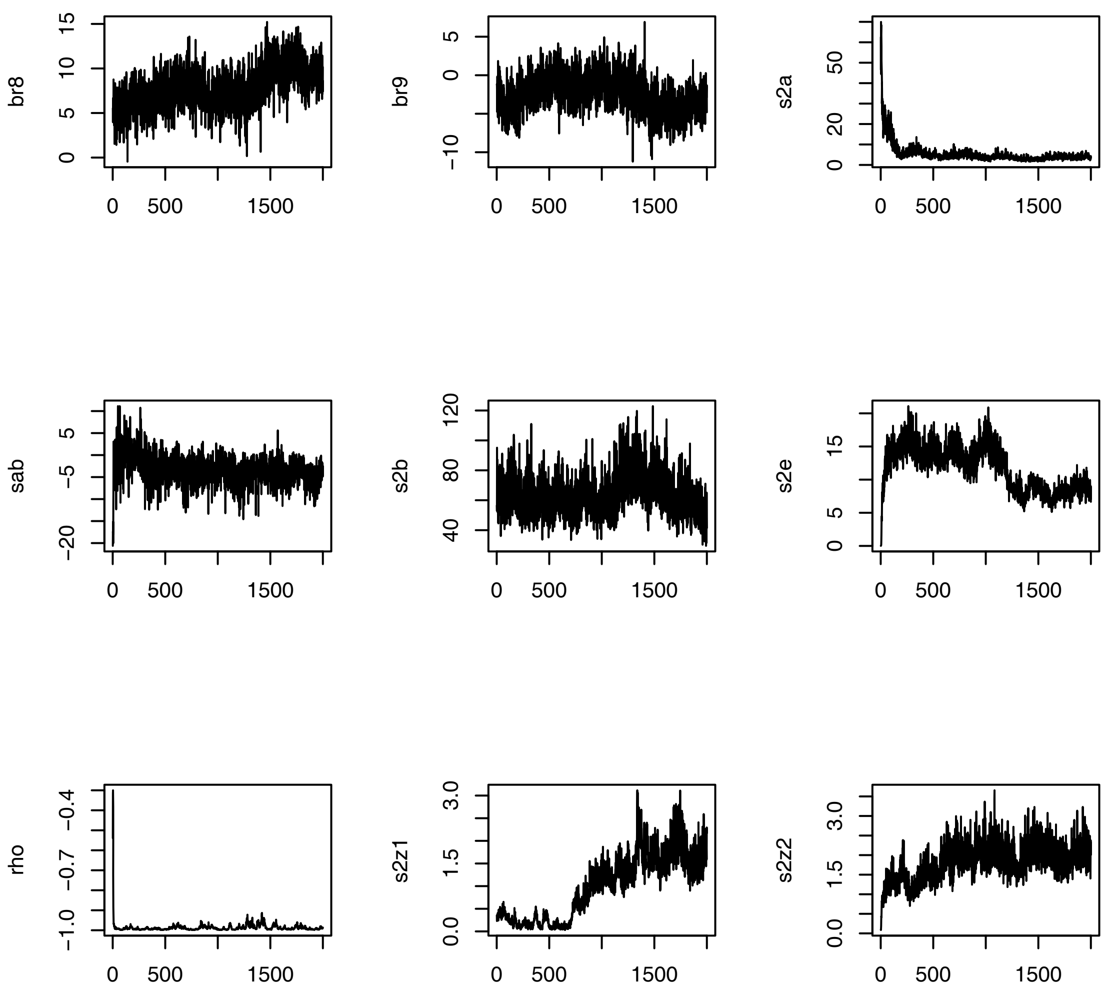

Figure 4.5: Plots of Marginal Mixing -3

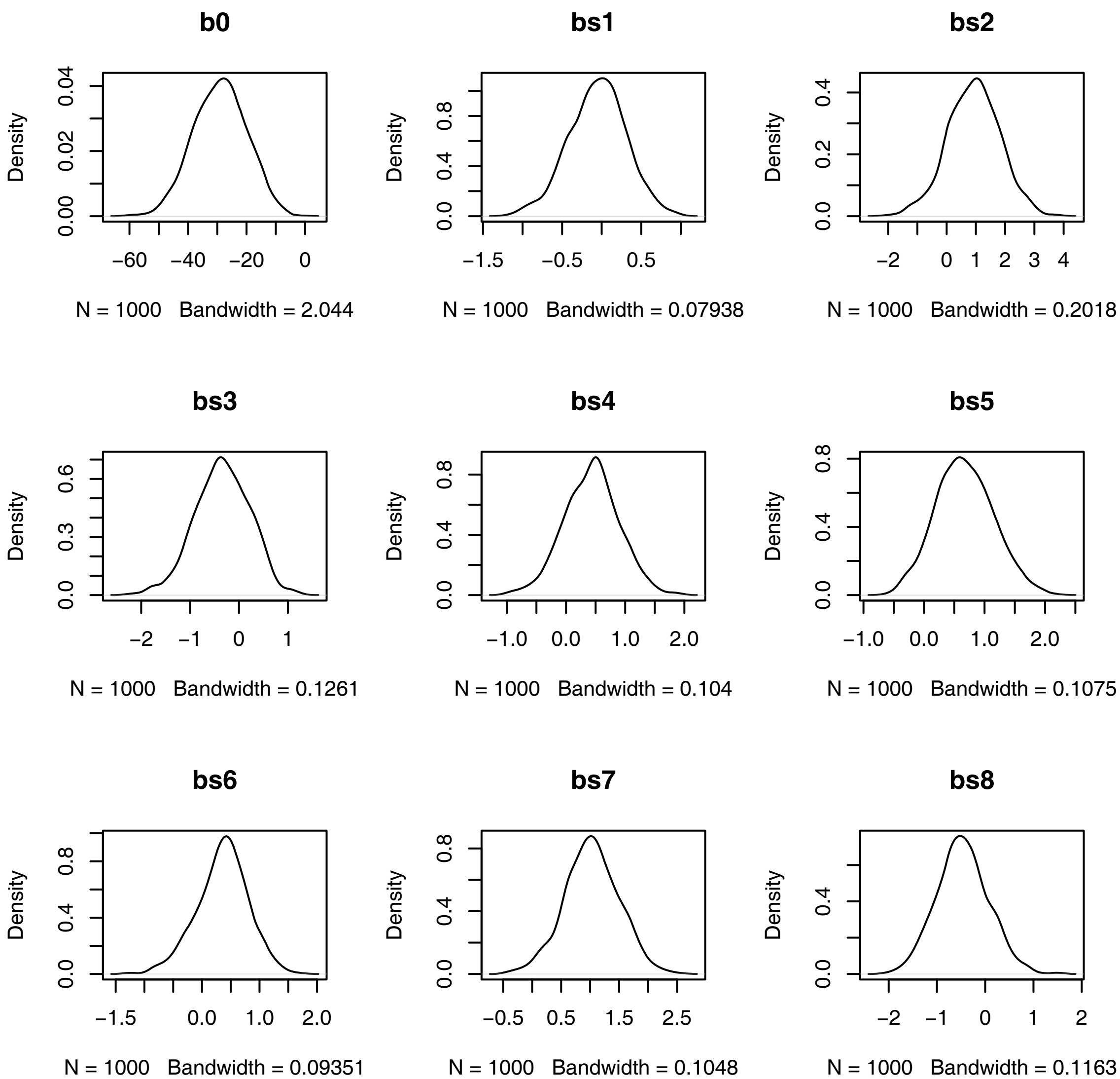

Figure 4.6: Plots of Posterior Densities-1

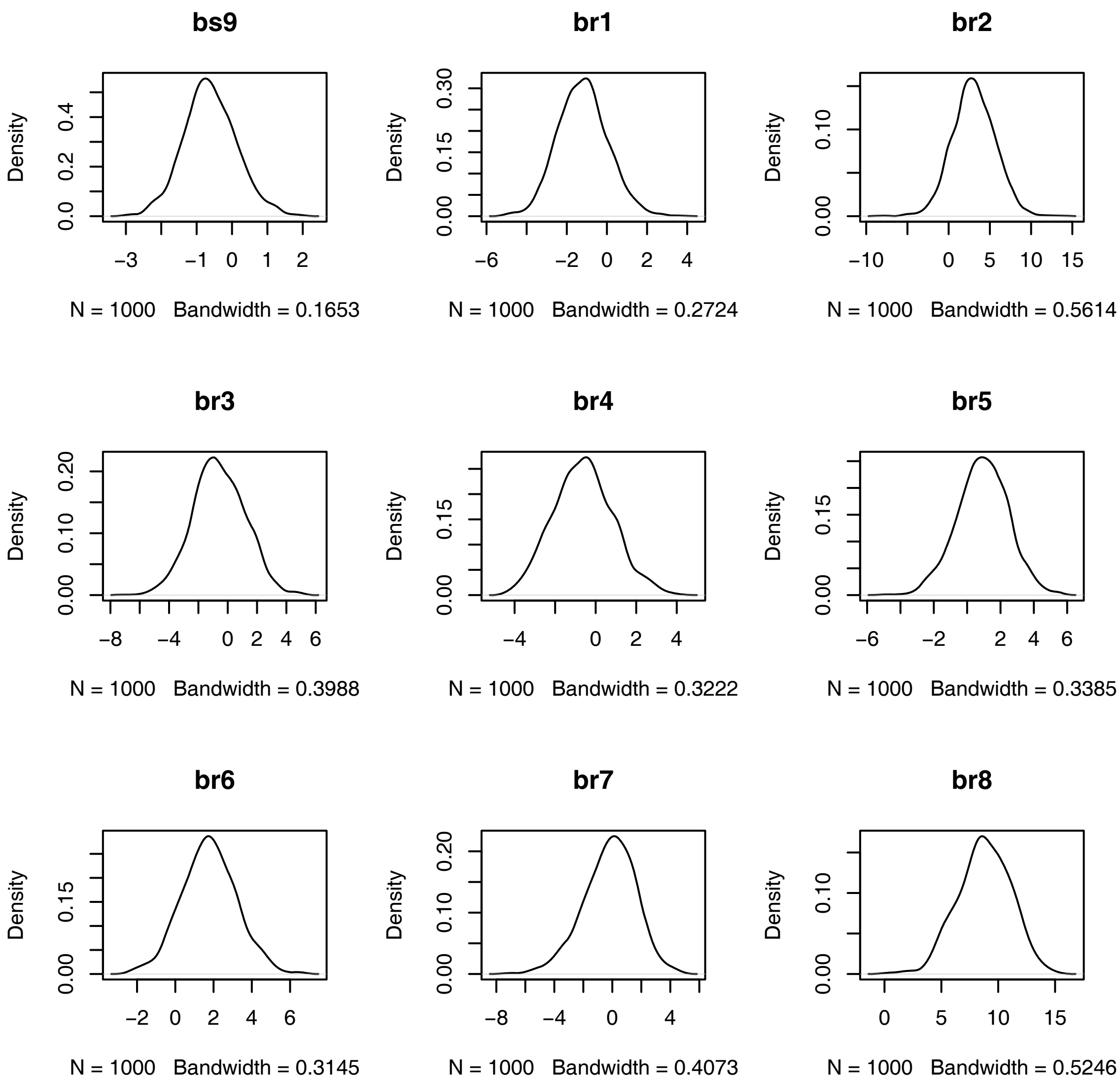

Figure 4.7: Plots of Posterior Densities-2

the influencing bidders (termed here as *Influencers*). Traditional approaches such as linear models or logistic regressions, although useful in our context, lack the capacity to analyze *Reactors* and *Influencers* concurrently. Particularly, they are unable to capture complete information of bidder competition in their analysis. To overcome this issue, we represent the auction data as a network of bidders where the nodes represent the bidders participating in the auction and the ties between them represent an *Influencer−Reactor* relationship. We further develop a random effect model capable of handling the covariates of both bidder types at the same time and show that this model outperforms a traditional logistic model based on its negative log-likelihood.

From the auction house manager's perspective, this study provides a way to identify different types of bidders. Such information is vital in strengthening their relationship with different groups of bidders. For example, our analysis suggest that *Reactors* mostly bid on fewer items, indicating that they might be the art collectors, who unlike the art dealers, are very selective on the items they desire to purchase [31]. Therefore, there is great possibility and opportunity for the auction house managers to create a stronger relationship with these bidders by taking various strategic decisions during the auction. Suggestive decisions are shown in Table 4.10 to support the auction house managers.

As with most research work, this study also has some limitations that need to be acknowledged. First, it is difficult to determine *Reactors* if they have not used a proxy bidding system. We used an identification system in the lines of work done by Ku and his colleagues [20] which is tested and proved using a bidder survey. Work by Bapna and his colleagues [4]) found that certain types of bidders in online auctions use proxy bidding as a part of their bidding strategy (referred to as *Agent Bidders*). They suggested that these bidders place more than 60% of their bids as proxy bids. *Reactors* in our study had less than 20% of their total bids as proxy bids, and thus can be assumed not to be *Agent Bidders*. We tried three different approaches to identify the level of influence of an *Influencer* over a *Reactor*.

Table 4.10: Managerial Implications

FINDINGS	MANAGERIAL IMPLICATIONS
Reactors bid on fewer items and mostly on high-priced items	– Provide more potable information about the artist and the artwork such as price trend, performance of other items of the artist in the auction. – Provide customized support through account managers.
Reactors bid more in the second half than in the first half of the auction	– Managers have time (1-2 days in a 3 day auction) to offer consulting products to these bidders.

Although, our measures seem to be adhoc in nature, it is grounded on the auction theory. Still, further study is needed to develop a better influence measure.

A bidder's value change during an auction should be a strategic element in designing auctions that are more effective. Therefore, sophisticated models may be developed in the future to predict which lots will attract such behavior and which will not. This may help in optimizing lot orders in future auctions. Our study contributes to strategy refinement by investigating competition among bidders from the dyadic bidder level. Further studies on this topic are essential to understand the underlying bidding dynamics in auctions. Although it was not possible in this study, one may effectively identify value change of bidders by taking a survey of bidders prior to the auction and record their pre-auction valuation for the items on which they intend to bid. This will specifically indicate whether a particular bidder has changed his valuation or not.

We hope that this chapter will encourage other researchers to investigate the process of a bidder's value change more closely using other statistical techniques. We also hope that this will promote future applications of bilinear effects models and other advanced techniques in other areas of social sciences.

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Chapter 5

Conclusion and Future Directions

In the past decade, the growing popularity of online auctions has spurred many new bidder behavior researches that were not possible earlier. Unfortunately, almost all of these researches have focused on sequential auctions that are independent of each other. In this dissertation, I present two essays that focus on another popular online auction format known as simultaneous online auctions. Particularly, I investigate the effect of bidder competition on different bidder phenomenon. Prior research on bidder competition share the same basic perspective on bidder interaction, wherein a bidder is viewed as competing against all the other bidders as a whole, without distinguishing one competitor from another. Although the number of bidders and the number of bids per bidder capture the general intensity of competition in the auction, they are inadequate in explaining the effects of different levels of rivalry between bidder pairs. To overcome this limitation, both essays presented here consider bidder competition at a dyadic level, particularly focusing on the interactions between bidder pairs. This consideration effectively advances the current understanding of bidder competition by looking beyond aggregate competition measures and examining its effect on the auction outcome (essay 1) and on the value updating behavior of bidders (essay 2).

From the first essay, I find that the two dyadic bidder interactions (i.e. within-lot and between-lot) affect the auction outcome differently. Within-lot dyadic interaction was found to have a positive effect and the between-lot interaction was found to have a negative effect. I also find that the key bidders identified using the competition information performs better than the key bidders identified using depth of pocket and experience of bidders. From the managerial perspective, these findings provide insights on which bidders to invite and when to invite. For example, the results suggest that the auction house managers should encourage more within-lot interactions and less between-lot interactions in order to get higher revenue. This can be achieved by carefully considering items that are less complementary and will attract lesser between-lot competition. Managers are also encouraged to invite pairs of bidders who have the same taste and may engage in intense within-lot interaction. Results from the key bidder analysis suggest that managers should invite bidders based on their competitive activity in prior auctions and not just based on their depth of pocket and experience. Effect of key bidders on the price dynamic also provides an opportunity for the managers to estimate the marginal effect of inviting these bidders during the auction on revenue .

In the second essay, I find that high intensity of between-lot dyadic interactions between the proxy bidder and other bidders leads to a lower propensity for the proxy bidder to update his value. I also find that high intensity of between-lot interactions also reduces the level of value-update for the proxy bidders. These findings further support the prior conclusion that managers should discourage between-lot interactions. This essay presents a way to identify value-updating bidders and bidders who influence them to do so in the auction. Managers can utilize this process to classify their customers and strengthen their relationship with them more effectively. Analyzing the characteristics of value-updating bidders, I find that they bid on fewer items and on high priced items. I also find that they bid more in the second half than in the first half of the auction. This suggests that mangers may consider having account managers for these bidders who can help them making satisfying bidding decisions. A summary of the findings and the managerial implications are presented in table 5.1.

In this dissertation, I show that there is dyadic bidder effect beyond the aggregate competitive in auctions. I further consider a rich approach of representing bid history as a network. I firmly believe that this dissertation will encourage future analytical and experimental studies to understand in-depth characteristics of these interactions and develop more effective price forecasting models. The dyadic and network view of bidder behavior shifts the focus from atomistic explanations of bidder behavior (independent bidder behavior assumption) to relationships among them. I hope that this conceptualization will motivate other researchers to advance our knowledge on bidder behavior and bidder strategies in online auctions.

Table 5.1: Summary of the Essays

Essays	Findings	Managerial Implications
Essay One: Dyadic Bidder Interactions and Key Bidders in Simultaneous Online Auctions	– High intensity of within-lot dyadic interactions among bidders in a lot leads to higher auction outcome. – High intensity of between-lot dyadic interactions among bidders in a lot leads to lower lot auction outcome.	– Encourage more within-lot interactions and less between-lot interactions. – Invite pairs of bidders who have the same taste and will engage in intense within-lot interactions.
	– Key bidders identified using competition information performs better than bidders identified by depth of pocket and experience.	– Invite bidders based on their competitive bidding activity in prior auctions and not just based on their depth of pocket and experience.
Essay Two: An Investigation of Value Updating Bidders in Simultaneous Online Art Auctions	– High intensity of between-lot dyadic interactions between the proxy-bidder and other bidders leads to a lower propensity for the proxy bidder to update his value. – High intensity of between-lot dyadic interactions between the proxy-bidder and other bidders leads to a lower level of value-update for the proxy bidder.	– Discourage between-lot interactions in auctions so that it encourages bidders to update their value and results into higher revenue.
	– Reactors bid on fewer items and mostly on high-priced items.	– Provide more potable information about the artist and the artwork such as price trend, performance of other items of the artist in the auction. – Provide customized support through account managers.
	– Reactors bid more in the second half than in the first half of the auction.	– Managers have time (1-2 days in a 3 day auction) to offer consulting products to these bidders.