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A Network Bidder Behavior Model in Online Auctions: A Case of Fine Art Auctions

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Abstract

The marketing literature provides a solid understanding of auctions regarding final sales prices and many aspects of the processes that unfold to result in those outcomes. This research complements those perspectives by first presenting a new bidder behavior model that shows the role of emergent network ties among bidders on the auction outcome. Dyadic ties are identified as the bid and counter-bid patterns of interactions between bidders that unfold throughout the duration of an auction. These structures are modeled using network analyses, which enables: (1) a richer understanding of detailed auction processes, both within auctions and across auctions of multiple lots, (2) a mapping of the processes to the forecast of prices and the trajectory toward final sales prices, (3) the clear and early identification of key bidders who are influential to the bidding action and who impact final auction sales prices, and (4) the results clearly show that the network exchange patterns are significant and contribute to an understanding of auction processes and outcomes above and beyond simple economic predictors such as the number of bids or bidders or the bidders' economic status. We conclude by providing some managerial implications for online auction houses and bidders.

Keywords: Online auctions; Dynamic pricing; Bidders; Networks

Introduction

Auctions are an important arm of retailing, along with shopping centers, department stores, big box stores, online outlets, and the like. Indeed, many contemporary auctions are quite large and therefore important, selling such diverse items as fish (cf., Tokyo's Tsukiji market, founded 1923, $5.5B annual, tsukiji-market.or.jp), real estate (f.1957, $.75B, williamsauction.com), antiques (f.1937, teppergalleries.com), thoroughbred horses (f.1935, $1B, keeneland.com), and so forth. Two of the best-known premier auction houses are Christie's (f.1766, $5B, christies.com) and Sotheby's (f.1744, $5B, sothebys.com), each of which made their names selling high-end works of art, and both of which now offer a much broader range of SKUs. Yet dominating them all, in size and scope, are online auctions such as eBay (f.1995, $12B), which sells an enormously wide variety of items, from paperclips to Ferraris. Online auctions warrant study, as attested by the presence of the topic in the *Journal of Retailing*.

In practice, the auction house manager's most important question has always been, "How do I achieve the most profitable sales prices?" Accordingly, there is a long-standing literature in marketing and economics on the auction outcomes of final sales prices. In addition, marketers have also begun to examine the processes that unfold during auctions that yield the final sales prices. Our research combines the two perspectives, in modeling the bidding processes as they develop and showing that doing so helps predict final outcome sales prices.

Our research models the structure of bids and counter-bids, representing the dynamic patterns of interactions as networks. As we describe in more detail shortly, network models are particularly applicable to bidding exchange data because bidders' behaviors are not independent. If a researcher is modeling final

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sales prices with auction items as the unit of analysis, it might be the case that those units of observation are independent (except perhaps in circumstances in which bidders cross-bid for comparable items across different auction slots, as described shortly), thus a standard general linear model may be used. However, the nature of the bid-counter-bid exchanges is that they are interdependent, rendering many statistical models inappropriate and requiring new and relevant modeling methodology. Network models were created to model structures of interconnections, for example, communications links among people, transportation links between city hubs, and so forth, thus addressing the concern of the bidder inter-dependence perfectly. Network models are also ideally suited to helping the auction house manager identify the most important bidders, so the managers know which bidders should be paid greater or lesser attention. We shall show that these important bidders are not necessarily simply the wealthiest patrons, for example, but they are those whose bid-counter-bid patterns are most influential.

We next review the literature and provide a context for our research. We examine both sales outcomes and auction processes. Extant research on auction processes tends to track aggregate activity over time, whereas we seek to understand auction processes at an even more precise, micro level, of what each bidder does and what the subsequent reactions of other bidders are to each action, thereby investigating what is occurring among the auction bidders to give rise to the aggregate processes, which in turn yield the sales outcomes.

Literature Review

Auctions have a long tradition as an important means of sales in the marketplace and as a focus of study in marketing and the *Journal of Retailing*, as researchers acknowledge the different channels of sales and distribution (cf., Brown and Dant 2009). For example, recent articles in the *Journal of Retailing* have examined the mechanism of "name your own price" auctions (Joo, Mazumdar, and Raj 2012), the effects of global markets for internationally sold products (Hu and Wang 2010), and online interfaces for eliciting and articulating bids and sales (Spann et al. 2012). However, before discussing current developments, let us begin with more fundamental research questions. We first consider the literature on auction outcomes, and then we turn to the literature on auction processes.

Auction Outcomes

The primary goal of an auction house is naturally to seek to maximize its profits. Not surprisingly, the academic literature has followed suit, traditionally focused on modeling auction outcomes. For example, Kamins, Drèze, and Folkes (2004) studied the effect of various referent price points as signals on the auctions' final sales prices. As anticipated, high signals (i.e., the seller's reserve price) yielded higher prices than low signals (i.e., minimum bid information). Perhaps more interesting was their finding that realized prices were maximized in the face of no anchoring information (no minimum or reserve mentioned, p. 625). When no referent signals were available, participants took the number of bidders as a cue to the desirability of the item sought, with more bidders driving prices upward.

The marketing and economics literature on auction outcomes is extensive. Final sales prices have been studied as a function of various reference prices (Dholakia and Simonson 2005; Kamins, Drèze, and Folkes 2004; Popkowski Leszczyc, Qiu, and He 2009). Bajari and Hortacsu (2003) found that sellers requesting higher minimum bids created auction environments that discouraged bidders from entering into the bid. As a result, fewer bidders participated, resulting in less competition. With no driving force toward higher sales prices, the auctions yielded lower expected profits, compared to the profits obtained when lower minimum bids were posted. Lower minimum bids provide lower barriers to entry, which encourages more participants to bid. Economists have always maintained that more bidding participants yield greater competition, which therefore result in relatively higher final sales prices (Levin and Smith 1996).

Sales outcomes have also been studied as a function of design elements of the auction formats themselves, such as whether bids are sealed or transparent (Cheema, Chakravarti, and Sinha 2012; Jap 2002; Klemperer 1998; Lucking-Reiley 1999). For example, English (ascending) auctions tend to generate larger surpluses than second-price auctions or Dutch (descending) auctions (Milgrom and Weber 1982), and auctions designated to raise money to benefit charities tend to yield higher bid prices, whether all proceeds or a lesser percentage of sales are donated (Haruvy and Popkowski Leszczyc 2009b; Popkowski Leszczyc and Rothkopf 2010).

Auction outcomes have also been studied as a function of characteristics of the products being sold. For example, higher prices and intentions toward willingness to pay higher prices occur when the risk of the purchase is reduced, such as when bidders can observe indicators of product quality and auction credibility via offers of money back guarantees or product authentication certification (Li, Srinivasan, and Sun 2009). Without objective information providing such assurances of quality, bidders make inferences from other cues, such as indicators regarding buyers' and sellers' reputations. For example, Cheema (2008) found that potential auction buyers took longer to make purchase decisions, paid more attention to and were less tolerant of surcharges (such as shipping costs) compared to shopping and bidding considerations for merchandize posted from higher reputation sellers. Subramaniam and Venkatesh (2009) also demonstrated that selling items separately, rather than bundling them together, yielded higher prices, as long as the number of bidders reached a critical mass.

Auction Processes

Researchers have also been interested in examining aspects of auction processes that give rise to final sales prices. Indeed, as Wang et al. (2008, p. 1100) state, obviously final prices matter, "but there is increasing evidence that what occurs during the auction also matters." For example, "name your price" auctions would seem like a generous pricing environment for the buyer—theoretically, it should result in price minimization for buyers, and therefore optimal prices from the buyer's perspective. Yet it is clear that bidders do not take advantage of the price naming and price minimizing as they might, because such auctions typically result in bidders posting and paying higher prices than normative decision making would predict (Spann and Tellis 2006). Chernev (2003) found that bidders preferred auction formats in which prices could be chosen (“select your price”) over auctions in which prices would need to be generated (“name your price”), even though the price generation format allows the bidder greater flexibility and precision. The dilemma seems to be that the “name your price” auction mechanism is not as buyer-friendly as it might at first seem, in part because price generation creates so much uncertainty and psychological discomfort that eliciting precise bids led to diminished decision confidence in the bidders.

Some research on auction processes emphasizes the economic concern for optimizing outcomes. For example, final sales prices can be predicted and even maximized as captured in real time forecasting (Dass, Jank, and Shmueli 2011; Dass and Reddy 2008). Sequences of online bids can help predict who will bid when (Park and Bradlow 2005), and the influence of bidders’ nearest neighbors can be modeled to enhance the accuracy in forecasting (Zhang, Jank, and Shmueli 2010). Such detailed sequential analyses of the auction process as it unfolds have even shown that bidders themselves are conscious and sensitive to the sequential auction environment, as when documenting demonstrably greater movement in price increases at the beginning and end of auctions, especially for expensive items (Bapna, Jank, and Shmueli 2008).

Other research on auction processes tends to emphasize the psychological concern regarding the bidders’ behaviors. For example, in studies of buyer–seller bidding dynamics, Jap (2002, 2007) watched price drops as they occurred throughout bidding periods. She found that when prices dropped a lot, bidders experienced diminished satisfaction, even though bidders should recognize the greater economic savings. The dissatisfaction was attributed to the implication that the early prices were too high.

Social psychological processes have also been shown to be important, perhaps explaining how it is that more bidders create greater competition, in turn raising sales prices. Simonsohn and Ariely (2008) demonstrated the signaling value that bidders obtained by simply observing others; essentially a virtuous cycle develops in that bidders were often attracted to bid on auction items in part due to the very popularity of that particular item’s auction attraction. Similarly, Ku, Malhotra, and Murnighan (2005) identified “auction fever,” where bidders engage in a fierce battle to win the item in an auction due to competitive arousal.

Bidder interactions have been shown to give rise to competitive responses among bidders even when those bidders are essentially anonymous (Ding et al. 2005; Fay and Laran 2009; Jap 2007; Jap and Haruvy 2008). The notion that a bidder responds to other bidders may be easier to understand in a traditional in-person auction (e.g., Christie’s), in which bidders identify each other in the audience by face or by a paddle number. Yet online auctions are less anonymous than one might think. Bidders become familiar with other bidders by their auction username, and competitor bidders are personified by the actions they take (e.g., as a bidder who seeks to win at any costs, etc.). Jap and Haruvy (2008) and Sinha and Greenleaf (2000) have found that bidders were quite adept at personifying others’ motives, for example, as being aggressive.

Given that auctions comprise bidders interacting with each other and responding to others’ bidding behaviors, a full understanding of an auction requires knowledge of these interactions. Our research models the bid-counter-bid exchanges as interdependent elements in a network. Bidders do not rationally post multiple bids simultaneously for the same item (and in many auctions are precluded from doing so); instead, bidders post bids in response subsequent to a competitor having posted a dominating bid. The fact that bids are submitted contingent upon other bids by other bidders indicates that bidders’ behaviors are interdependent (Chan, Kadiyali, and Park 2007; Spann et al. 2012; Suter and Hardesty 2005).

Auctions and the Potential Utility of Networks

Recognizing the social nature of auctions, Hinz and Spann (2008) investigated the extent to which social networks might be leveraged in the study of bids and sales prices. They note that the Internet promotes various forms of collaboration, such as information-sharing via social networks, and yet to date, “Previous research on . . .auctions has not examined the impact of information diffusion via digital and social networks on bidding behavior” (p. 352). They make the case that “bidders with many contacts are more likely to have access to a large amount of information” (p. 365) and they test their theorizing both in a lab study and by extracting the social actors and their links from a real online social network for those people who participated as bidders in the auction they studied. In our research, we do not have the luxury of an intact social network, online or otherwise, from which to draw links, nor would it be likely that auction managers could enact their use. Instead, we will use the actual behaviors of the exchanges, the bid-counter-bids themselves, to build the structure of bidding networks.

Wang and Chiu (2008) similarly investigated the collaborative nature of online information in their study of reputation systems and recommended sellers in online auctions. Their research used the relational ties between traders to improve the online system so that it would be less susceptible to manipulation and collusion to spuriously enhance a seller’s own ratings. Certainly such a service enhances the online auction experience for all involved, bidders and auction house managers. In our research, we will be modeling actual bidding behavior, which, while admittedly could be gamed, is less subjective than ratings of customer satisfaction.

We will use social networks to study the inter-connections among the bidders. Our links are not social in the classic sense—our bidders are not necessarily friends, they may not even know each other. They are connected by their bidding and counter-bidding exchanges. Their connection is essentially competitive.

Other research has examined different kinds of interconnections. For example, Anwar, McMillan, and Zheng (2006) note that much of the literature treats auctions as if they run independently of each other, with bidders participating in only one auction. Yet in many auctions, particularly online auctions like eBay, numerous substitutable goods are auctioned concurrently. They found that a significant portion (20–30%) of the bidders they studied bid across multiple auction lots, and these cross-bidders paid lower prices on average—almost a 10% discount. While they studied price reductions due to competing goods, characterizing eBay as an exemplar of a "clearinghouse for the sale of a large number of homogeneous goods" (p. 308), in our auction of relatively high-end art, the goods are more distinctive. There were several artists who had contributed more than one work of art, and to an art investor, one piece by a particular artist may be consumed as relatively homogeneous as another piece by that artist, however, the art community would presumably see the lots as unique and not commodity-like, and therefore in less competition with each other.

These results in Anwar, McMillan, and Zheng (2006) are consistent with those of Chan, Kadiyali, and Park (2007). While they did not study cross-bidding per se, they found that willingness to pay declined as more similar items were listed for bidding. When there was comparable quality available across homogeneous auction listings, there was less differential preference to any given lot item, reducing any perceived need to pay higher prices for an item that was attainable with some search at lower costs.

In another study of cross-bidding, Kayhan, McCart, and Bhattacherjee (2010) found that five percent of auction winners used such a cross-bidding strategy, and in doing so, realized a significant price discount (p. 329). The environment in which cross-bidding may occur and benefit the sellers include (p. 326): (1) that there is the "simultaneous occurrence of multiple auctions of the same product ending at approximately the same time," (2) that bidders "must be able to continually monitor these auctions and the standing bids at each auction, and decide on which auction to bid and for what amount," and (3) the bidder "must avoid multiple bids in different auctions at any given point in time, in order to avoid winning multiple items." Given that the price discounts for bidders "translate into lost revenues for sellers" (p. 331), the authors recommend that the auctions have different ending times, or that the auction house sell one-of-a-kind products. In our auction data, all lots are available for the same length of time, and as we mentioned, there were several lots available from each of several artists. However, the majority of the auction entries were unique and the items' price tags contribute to the characterization of the high-end art being somewhat exclusive.

The interdependencies among the bidders has also yielded some methodological concerns. For example, Li, Perrigne, and Vuong (2002) showed, using simulated bid data, how to obtain nonparametric estimates of bidders' value distributions under the assumption that the bidders' valuations are affiliated, roughly meaning correlated. We agree with the philosophy underlying their approach, namely that the as bidders reveal their intention to purchase auction lots, their revealed and emerging values affect and are affected by those of other bidders. Network modeling need not make the assumption that the bidders' valuations are known, even to themselves. We will track the bid-counter-bid patterns to see how those values arise and develop.

As we can see, auctions are inherently interdependent markets, and our research is intended to contribute to the literature by illuminating the specific dynamics of the interactive bidding patterns. Our research examines patterns of connections that give rise to an implicit network among bidders. Using network methods to model bidder interactions also provides us a way to identify the relatively small number of highly influential key bidders who play an important role in the auction process and outcomes. An important means of capturing network connections is to compute centrality indices for the actors (in our case, bidders) embedded in the network. In a standard social network, the relational ties may reflect friendships, so high scores reflect actors who are central or amidst many friends, and actors with lower indices are more on the periphery of the network (e.g., Freeman 1979). As we shall show, for our purposes, such indices may be interpreted as measures of the extent to which a bidder is key to the auction—deeply engaged in bid-counterbid actions and reactions. These central bidders are in the midst of the action in the network, in direct competition with other bidders, and naturally playing an influential role on other bidders (Bonacich 1987; Nieminen 1973).

Next, we describe our data and networks in greater detail. We then test our model.

The Auction Data

The data in this study are from second price simultaneous online auctions. The bidding has an ascending format; specifically, the rules posted on the site state as follows: "The closing bid for a lot is the highest bid at the time at which a particular lot's bidding has ended. No further bids can be made after the close of the bidding for that particular lot. The closing bid is considered a winning bid." It allows proxy bidding similar to that of eBay auctions (Roth and Ockenfels 2002). It is also a simultaneous auction, meaning simply that many items are available for bidding and sale at the same time. The company that organizes the auction specializes in a line of contemporary international art that is a leading emerging art market ($450mn, annual). In this particular art market, this online auction house sold more ($10.1mn) than Sotheby's ($5.2mn) or Christie's ($8.7mn).

Our source auction house organizes four to five annual sales events (like Christie's and Sotheby's) where 100–200 art items are bid upon in a three-day online auction. Prior to the auction, a catalog of available items is prepared (like Christie's and Sotheby's), with information about the items to be auctioned, including the title of the artwork, its size, media of the artwork, and the artist. In terms of value information, only pre-auction estimates are provided. The auction house consults with the consignor, seller, art experts, and professional art appraisers to derive this estimated value. There may be situations where a reserve price is set, but it is not disclosed to the buyers. The auction house contacts potential bidders via email and courier service, and sends them event invitations and catalogs. Further, the house organizes multiple viewing parties across the world, where potential bidders are invited to come and examine the art

Table 1
Summary data description.

	Mean	SD	Min.	Max.
No. of bidders per lot	6.35	2.47	2	14
No. of unique lots bid per bidder	4.93	7.95	1	65
No. of bids per lot	15.47	7.46	2	48
Opening bid	$19,343	$36,663	$650	$300,000
Pre-auction low estimates of the lots	$24,128	$45,747	$795	$375,000
Pre-auction high estimates of the lots	$31,065	$60,351	$1,025	$475,000
Realized sales value of the lots	$62,065	$133,198	$3,135	$1,486,100
Realized price of lots per sq. inch	$108.77	$225.49	$1.40	$1,865.42

works. Potential bidders register to pre-qualify, which includes a credit check and a selection of an online nickname to be used throughout the auction.

Bidding in these auctions starts with a value lower than the low estimate value. Bidders can bid only the incremental value that is preset by the auction house. If they decide on posting a higher bid than the pre-set value, an automated bidding system will place proxy bids on their behalf at the pre-set value. The auction has a fixed ending time and date set by the auction house, and the ending time for each lot is automatically extended until no new bid is submitted for three consecutive minutes so as to preclude sniping or last-minute frenetic bidding.

Auction houses evaluate their performance in part by comparing final realized sales prices with the lower bound pre-auction estimates, that is, predicted sales prices. Typically, the auction house manager and analysts use this ratio as a measure of the extent of successful performance of the items and the auctions. Accordingly, to maximize the utility of our findings and map directly onto practice, we use this ratio as an outcome variable and refer to it as *auction surplus*.[3]

During the three-day auction, 256 bidders competed against each other for 199 lots (paintings, drawings) by 70 artists (who presented an average of 2.8 lots per artist). A total of 3080 bids were placed. Most of the bidders did not use proxy bids (68%), and of those who did, 76% of these bidders used 8 or fewer proxy bids, and the mean number placed was 11. (We will say more about proxy bids shortly.) Table 1 contains the basic descriptive statistics: on average, 6.35 bidders bid on each lot, each bidder bid on 4.93 lots, each lot received 15.47 bids. The average realized lot price was $62,065.

Network Model of Bidder Interactions

One of the reasons for the absence from the literature of studies that focus on the micro patterns of bids and counterbids is that interdependent data render many traditional analytical techniques inappropriate. For example, while auction outcomes such as final sales price may be modeled using statistical techniques such as regression, the auction process data represent contingent interconnections. Many statistical methods assume independent observations and thus are less than optimal given that the very phenomena of interest are the interactions that violate assumptions of independence. Some other auctions researchers have identified this issue (cf., Dass, Jank, and Shmueli 2011) and in this paper, we study the viability and utility of network methods for studying the interconnected structures that arise from auctions.

To study the inter-connectivity, we use network analytical techniques, drawn from graph theory in mathematics and created for the express purpose of analyzing observations that are interdependent and for modeling patterns of interconnections (cf., Heider 1958; Iacobucci and Hopkins 1992; Knoke and Yang 2007; Marsden 1990). Networks are increasingly being acknowledged as an important paradigm for understanding a variety of marketing exchanges, such as business to business relationships, or customer exchanges in online social networks (Keeling, McGoldrick, and Sadhu 2013; Spralls, Hunt, and Wilcox 2011). Structurally, the dynamics of the auction process involve interactions among bidders, in the form of the bid-counterbid actions and responses. Bidders respond to bids in a developing sequence of bids, thereby also responding to other bidders. Such interactions and patterns of connections between bidders are intriguing theoretically and challenging analytically, thus making them one of the most important research priorities identified as yet understudied in the academic realm of auctions (Cheema et al. 2005). We examine the patterns of dyadic ties of bidders who compete against each other in the auction. A bid is posted in response to an updated current price, and effectively one bidder is responding to the actions of another, and as more bidders enter the auction, the pairwise interactions expand into a fuller bidding network. The dyads represent direct interactions between pairs of bidders, and as the broader network emerges, it becomes clearer that each bidder is reciprocally responding to many additional parties or bidders.

While many networks are social in nature, in our auction data, two bidders may not know each other (except through their online nicknames and observing their bidding behavior). However, there are at least two reasons that network models may be applicable, and if so, highly useful given their focus on interconnectivity. First, network analyses have been used to capture many contexts of interconnectivity that are not social, including

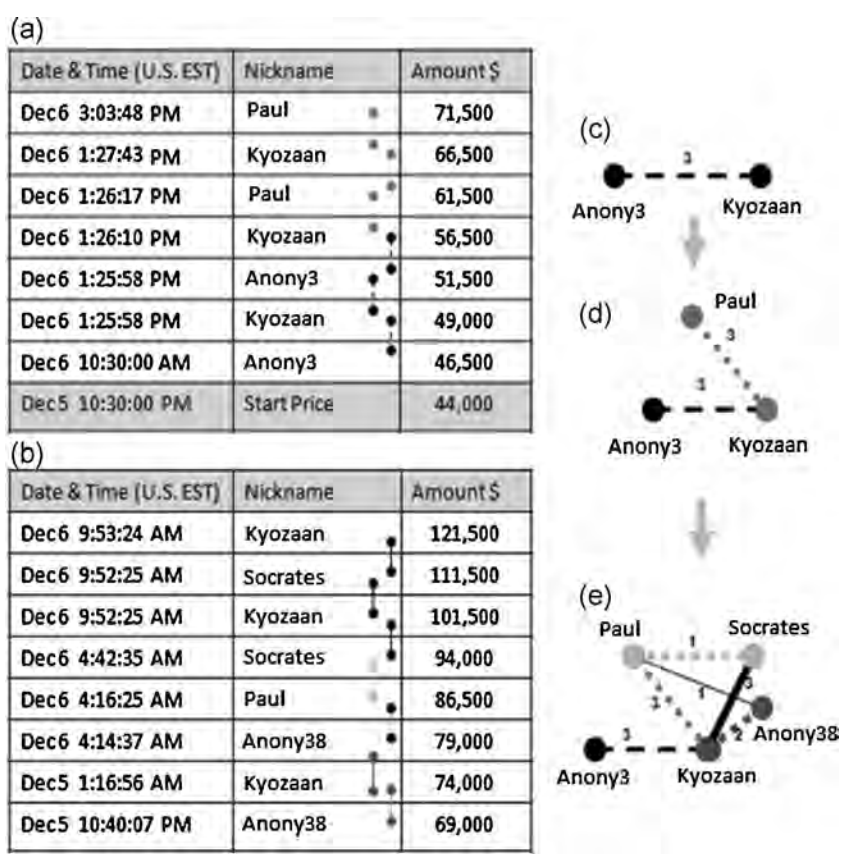
[3] Auction lots will obviously vary in their mean expected values (e.g., some paintings are expected to fetch more than others), so to test the sensitivity of the results (presented shortly), we also modeled the ratio of realized prices to pre-auction average estimates, rather than the lower (or higher) bounds. While the coefficient estimates were not numerically exactly identical, the pattern of results were the same, in terms of which effects were significant, and their signs and relative magnitudes. Given the similarities across the analyses, we opted to retain the surplus ratio measure that actual auction house managers use.

transportation routes, electrical circuits, business alliances, and so forth (Spralls, Hunt, and Wilcox 2011). Lovejoy and Sinha (2010) have noted that positing a tie between two nodes does not necessarily imply that the two actors know each other or communicate with each other. Network analysis is a class of analytical tools that may be applied to numerous substantive data, as any modeling technique; in the abstract, a network comprises nodes and the links that connect them. In our case, the nodes are bidders, and the links capture the patterns of bids and counterbids. The emergent network forms as bidders influence each other's behavior, in turn affecting both auction processes and outcomes. Second, it has been shown that in fact bidders do become familiar with each other and other bidders' bidding strategies (i.e., timing, frequency, bid increments, etc.), as they mutually bid on some common lots over the course of the auction, even if they do not communicate directly (Brusco and Lopomo 2002; Kwasnica and Sherstyuk 2007; Phillips, Menkhaus, and Coatney 2003).

Linkages between pairs of nodes are denoted in an adjacency matrix, whose form takes equal numbers of rows and columns, one each for each node. Even though the ties represent fundamental dyadic interactions (e.g., Krackhardt and Kilduff 2002), the matrices typically reveal concentrated groups of actors interacting with each other, certainly well beyond statistical randomness (Barabási and Albert 1999; Bonacich 1972). The challenge in network theory is to analyze the data properly, taking into account the inter-dependence among the nodes, vis-à-vis the linkages (Burt and Bittner 1981).

To illustrate the network concepts in the auction context, consider the bidding process depicted in Fig. 1. Fig. 1a (the first table) presents a portion of a bid history of sequential bids that unfold in real time, from December 5th at 10:30 p.m. through 3 a.m. the following morning. There are three bidders (in this excerpt) with online nicknames Paul, Kyozaan, and Anony3. The bidding begins (at the bottom of the first table) with a bid from Anony3, and a counterbid by Kyozaan, and back again, repeatedly bidding and counter-bidding three times, so in graph theory, we would link these bidder-nodes with a value of 3, very quickly building up a dyad that looks like Fig. 1c (to the right). The fifth bid in the auction comes from a new party, Paul, thus, a new node is added in Fig. 1d. Collecting all the bidding links results in the final Fig. 1e, showing how graph theory may be used to represent the bids and counterbids as a network tie between any pair of bidders who place a bid or react to another's bid.

Most bids were personally and intentionally posted, but some were posted via proxy bids; an authorization by the bidder to respond and increase the standing bid. For our purposes, the bid-counter-bid exchanges comprise the structure of the network, whether a bid was manually and willfully entered, or posted via the proxy system at the bidder's behest. We are using bidding


(a)

Date & Time (U.S. EST)	Nickname	Amount $
Dec6 3:03:48 PM	Paul	71,500
Dec6 1:27:43 PM	Kyozaan	66,500
Dec6 1:26:17 PM	Paul	61,500
Dec6 1:26:10 PM	Kyozaan	56,500
Dec6 1:25:58 PM	Anony3	51,500
Dec6 1:25:58 PM	Kyozaan	49,000
Dec6 10:30:00 AM	Anony3	46,500
Dec5 10:30:00 PM	Start Price	44,000

(b)

Date & Time (U.S. EST)	Nickname	Amount $
Dec6 9:53:24 AM	Kyozaan	121,500
Dec6 9:52:25 AM	Socrates	111,500
Dec6 9:52:25 AM	Kyozaan	101,500
Dec6 4:42:35 AM	Socrates	94,000
Dec6 4:16:25 AM	Paul	86,500
Dec6 4:14:37 AM	Anony38	79,000
Dec5 1:16:56 AM	Kyozaan	74,000
Dec5 10:40:07 PM	Anony38	69,000

Fig. 1. Formation of a bidder network. Figures (a) and (b) track the bids and counter bids of two different auction lot items. Each table is read from the bottom—an online nickname is identified for the bidder, as is the bid offered. The rows above illustrate the subsequent counter-bids and bidders. Taking each bid-to-counterbid link as a network connection, Figures (c)–(e) are graphical representations of the links that emerge from the bid-counterbid exchanges.

ties as the connective links in our network; we are not claiming that a pair of bidders are friends or have any other dyadic relationship. Furthermore, given the pre-sets in this auction, which are common among auctions, we chose to model the number of bids rather than bidding increments, but our results do not change if values are substituted. Finally, our results replicated whether we included the proxy bids or not.

For single-item auctions, the graph would be complete. However, our auction was a "simultaneous auction," which is simply a sales event in which many items are available for bidding at the same time. Each bidder can bid for several items at once, thus generating two types of bidder connections, one within an item and another across multiple items. Even aside from eBay, simultaneous auctions have long been a popular auction design, used for selling a wide range of objects, including FCC radio spectrum (McAfee and McMillan 1996; Milgrom 1998), U.S. treasury bills (Rothkopf, Pekec, and Harstad, 1998), timber, and cars (Kwasnica and Sherstyuk 2007). Researchers have identified simultaneous auctions as an important and understudied topic within the auctions literature (Jap and Naik 2008; Klemperer 1999), particularly given their greater complexity (Haruvy and Popkowski Leszczyc 2009a; Haruvy et al. 2008). For our purposes, a simultaneous online auction will allow us to understand interconnections among bidders for a single item, as well as among bidding between multiple items.

A simultaneous auction allows us to model the structure of interconnections formed by the bidding and counter-bidding for any given auction item, as well as the bidding patterns across different items. We might choose to create separate graphs, one for each item, particularly if our interest was focused on the items themselves. Our interest is more on the bidders, and how they bid and counterbid, to see how they compete for items, both within a lot as well as across auction lots. Network ties across items is represented in a second table, Fig. 1b, and in Fig. 1e, we aggregate the bid-counterbid exchanges collectively, resulting in the addition of more nodes and more links to represent the growing auction bidding patterns. Even the simple patterns depicted in Fig. 1e show distinct roles among the bidders. For example, compared to the others, Anony3 seems to be the least involved, whereas Kyozaan stands out because the greater frequencies of bids and counter-bids with others. Let us define the remaining network terms and notation, and then we will turn to the concept of central bidders, and how to measure and identify them in a network.

The bidder network is defined as a set of g bidders whose relationship is based on whether bidder n_j and bidder n_k bid sequentially on a lot where n_j, $n_k \in N$; $N = \{1, 2, \ldots, g\}$. The $g \times g$ symmetric matrix X contains elements $(X)_{jk} = p$, where p is the number of times bidders n_j and n_k bid sequentially on lots in the auction, and $p = \{0, 1, 2, \ldots, P\}$, where P is the maximum number of consecutive bids placed in the auction. Each data value represents each actor or bidder at one point in time for one auction item. With subsequent bid-counterbid interactions, the matrices build to aggregate networks that may be examined per auction item or per time point, and so forth, and these networks allow us to understand the unfolding patterns of bidding.

Key Bidders and Centrality

In addition to examining the interactions among participating bidders, researchers have long hypothesized that not all bidders are created equal. As Bapna et al. (2004) have suggested, it is not simply the number of bidders that contributes to the auction and accompanying pricing dynamics; instead, some bidders have more of an effect than others. For example, the auctions literature has contemplated and demonstrated the role of experienced bidders (Wilcox 2000). Even controlling for expertise, it would be theoretically interesting and managerially useful (to the auction manager, for example) if key bidders were identifiable during the auctions as a function of their engagement behavior. Once identified, such as by their early bidding entry or their intense bid-counterbid exchanges, their bidding activity would be expected to be very influential in terms of lot selections and values posted (Roth and Ockenfels 2002). Thus, while a simple economic prediction would forecast sales prices increasing as a function of the sheer number of bidders, due to the increase in competition (Wood et al. 2005), other researchers postulate that some bidders are special, and their presence in an auction determines or at least contributes to its results. We shall show that identifying such important bidders by their attributes such as wallet size is nowhere near as effective in understanding auctions, or predicting final sales outcomes, as identifying those key bidders as defined on the basis of their network of bidding activity.

Specifically, in our study, three bidder descriptors are computed for every time period to examine how the bidders' positions stabilize or change. The first is called degree centrality index C_{D}, which is computed and normalized as (Knoke and Yang 2007; Marsden 1990):

$$C_{\mathrm{D}}(n_i) = \frac{d(n_j)}{g-1} \qquad (1)$$

where $C_{\mathrm{D}}(n_i)$ is the degree centrality of bidder n_j, $d(n_j)$ is the total number of bidders that are connected to bidder n_j, and g is, as before, the total number of nodes in the network. The bidders with higher degrees are more central, and bidders with low degrees are those who reside on the social-periphery of the network or who are less intensely competitively posting bids.

Second, the average degree centrality index C_{AD} of the overall network at each time period is computed (Knoke and Yang 2007):

$$C_{\mathrm{AD}} = \frac{\sum_{j=1}^{g}[C_{\mathrm{D}}(n^*) - C_{\mathrm{D}}(n_j)]}{(g-1)(g-2)} \qquad (2)$$

$C_{\mathrm{D}}(n^*)$ is the largest observed degree centrality in the network, to normalize the degree measure, as a percentage of the network's maximum centrality.

The third index is a weighted form of centrality C_{W} (Bonacich 1987). Whereas degree centrality C_{D} and C_{AD} treat all of an actor's connections to others equally, weighted centrality C_{W} considers the connections of the others to whom the focal actor is connected. For example, two bidders, n_j and n_k, may have the same number of connections to other bidders, but if the bidders to whom n_j is connected are themselves highly central compared to bidder n_k's connections, then bidder n_j is more central according to the weighting captured in this index. Indices of weighted centralities capture averages of an actor's direct and indirect links (cf., Google's Page Rank algorithm). The weighted centrality for bidder n_j, $C_W(n_j)$ is derived by iteratively solving:

$$C_W(n_j) = \alpha(I - \beta X_m)^{-1} X_m 1 \tag{3}$$

where α normalizes the sum of squares of the indices to equal the number of ties in the network, $\beta > 0$ weighs higher scores for actors tied to other central actors, and I and 1 are the identity matrix and a vector of ones. Results across these three classes of indices were consistent, so the results that follow are based on degree centralities, unless otherwise noted.

Dyadic Bidder Ties—Within and Between Lots

Thus far, we have defined network patterns of connectivity as bid and counter-bids for a single item as the most direct network relational exchanges and then aggregated up for the auction-level analyses. Dyadic ties including within-lot and between-lot interactions further distinguishes the network patterns into two identifiable measures, thus allowing better scrutiny of the bidder network (cf., Boyd and Everett 1988).

At this point, we operationalize within-lot interactions between two bidders in a lot as the number of times the two bidders bid against each other sequentially. To capture the intensity of direct rivalry between two individual bidders for an item (Ku, Malhotra, and Murnighan 2005), we consider the *maximum* number of sequential bids between any bidder pairs within a lot. Formally, the within-lot interaction index for lot i is given by:

$$wl_i = \max(f_{jk}) \quad \text{for} \quad j = 1, \ldots, B_i - 1, \quad \text{and} \quad k = j + 1, \ldots, B_i, \tag{4}$$

where B_i is the number of bidders in lot i, and f_{jk} the number of bids between bidder n_j and bidder n_k.

Analogously, we operationalize between-lot dyadic interaction as the number of lots in which two individual bidders have both submitted bids (Brusco and Lopomo 2002). For all possible bidder pairs, we count the number of lots in which the pair has competed against each other. For a particular lot, we take the average of these pair-wise measures as an indicator of the item-specific between-lot bidder interaction (bl_i):

$$bl_i = \frac{1}{N_i} \sum_{j=1}^{B_i - 1} \sum_{k=j+1}^{B_i} cl_{jk} \tag{5}$$

where B_i denotes the number of bidders in lot i, cl_{jk} the number of common lots bid by bidders n_j and bidder n_k, and N_i the number of bidder pairs in lot i.

Economic Covariates and Statistical Controls

In addition, to statistically control for various extraneous heterogeneity, we include information on the artists (whether each was emerging, established, or other artists), lot characteristics (e.g., paper vs. canvas), and auction design characteristics (i.e., pre-auction low and high estimates, and opening bid). Artist categorization was identified as per Reddy and Dass (2006), and validated by the auction house managers. To control for unobserved artist heterogeneity, we include a random effect in our model to represent the individual artist who created the lot. Specifically, to isolate the effects of bidder interactions on auction surplus, we included several other covariates to control for still more potentially confounding variables:

- *Number of unique bidders participating in lot i*: per the basic economic element in the auctions literature, an often used aggregate measure to control for the overall competition level in single item auctions.
- *Number of bids per bidder in lot i*: also per a simple economic perspective from the auctions literature, another often used aggregate measure of competition in single item auctions, reflecting the overall activity level of bidders.
- *Average number of lots bid by bidders in lot i*: given that bidders can bid in multiple lots simultaneously, we were concerned that budget constraints could lower the average budget for each lot and affect the competition in the auction, hence this covariate.
- *Producer/Artist characteristics in lot i*: Artist reputation plays a crucial role in prices of art items (Mei and Moses 2002), providing the basis for bidders to estimate the value of the items. Three types of artists were identified, including "established," "emerging," and "others."
- *Product characteristics of lot i*: Reddy and Dass (2006) found that the medium of the art item (canvas or paper) can affect the price formation process. Similarly, Beggs and Graddy (1997) found that the size of art items is positively associated with bid prices. Accordingly, in our model we control for the (log) size of lot i and whether the art work is on paper.

Thus we model

$$\ell n(\text{Auction Surplus})_i = \beta_0 + \sum_{j=1}^{10} \beta_j x_{ji} + b_1 u_{1i} + e_i \tag{6}$$

for lots $i = 1, 2, \ldots, 199$, with these specific predictors:

- Network theory factors:
  - x_{1i} = within-lot dyadic bidder interaction and
  - x_{2i} = between-lot dyadic bidder interaction;
- Simple economic factors:
  - x_{3i} = number of bidders;
  - x_{4i} = number of bids per bidder;
  - x_{5i} = average number of lots bid by bidders;
- Control factors for this product category of auctions:
  - $x_{6i} = 1$ if the lot belonged to an established artist (=0 otherwise);
  - $x_{7i} = 1$ if the lot belonged to an emerging artist (=0 otherwise);
  - x_{8i} = dummy variable to indicate medium (=1 if paper, =0 if canvas);
  - x_{9i} = log(size of art work in square inches);

- u_{1i} = artist of lot i and $b_1 \sim N(0, \psi^2)$; ψ^2 is the variance of the random effect.

Results

Overall Network

We first present results on the overall network, and then results regarding the key bidders. As the auction progressed, the number of bidders increased from 61 at the beginning of the auction to 256 by the end of the auction. With more bidders arriving, more bid-counterbid links are naturally formed, from 309 at the beginning of the auction to 1463 by the end of the auction. The average degree centrality of the final bidder network is 2.914.

To statistically characterize the bidder network, it is significantly different from random, for which most of the bidders' centralities would be concentrated around the mean. Neither is the bidder network simplistic in being regular, for which all centralities of all bidders are equal. The bidder distribution depicts most bidders as having a low centrality and only a few bidders as having a large centrality. This result is significantly different from the centrality homogeneity that would be observed in a random network. Moreover, the distribution follows a power-law (Barabási and Albert 1999; Katz and Wilson 1956) implying that the bidder network is dominated by only a few highly central bidders.

The bidder network also exhibits the "small-world" property (Kleinberg 2000; Watts 1999). This quality is discerned by measuring the geodesic length (i.e., the average shortest distance) between bidders (l), and the clustering coefficient (τ) of the network, which is the average proportion of links between the vertices within a neighborhood over the total number of possible links in the network (where $\tau = [3k(k-1)]/[2k(2k-1) + 8pk^2 + 4p^2k^2]$, for k = the number of connected nodes, and $p = 0$ for regular networks and $p = 1$ for random networks). Small-world networks are graphs that are highly clustered like a regular graph ($\tau_{\text{real}} \gg \tau_{\text{random}}$), but possess small path lengths like a random graph ($l_{\text{real}} \approx l_{\text{random}}$). The bidder network has a high clustering coefficient ($\tau_{\text{bidder}} = 0.881$) compared to a random network with same number of bidders and bidder relationships (1463) ($\tau_{\text{random}} = 0.022$), but similar path length to a random network ($l_{\text{bidder}} = 3.097 \approx l_{\text{random}} = 3.391$). The properties of this bidder network suggest the fast spread of information compared to a random network. The small world property is reflected when actors are connected directly and independently connected indirectly such as through small clique clusters.

The network characteristics of average centrality decline as the auction progresses, indicating network fragmentation. Fig. 2 illustrates this steady decrease in the average centrality of the bidder network over the duration of the auction as more bidders enter the auction. This trend indicates that as the network becomes more heavily populated, a typical bidder plays a smaller role as competition is diffusing across more actors, a pattern that arises because in contrast, a few bidders emerge as key bidders given their greater levels of interactive activity, including with each other. We examine these key bidders in detail next.

Key Bidders

Auction house managers from Sotheby's, Christie's, Artnet, and our data source auction house unanimously agree that the identities of these bidders would be highly desirable information. Currently, these auction houses collect only some bidder information that includes the bidder's name, address, and verification of financial status. In some instances, auction managers may have personal knowledge about a particular bidder's preferences, especially if the bidder is well known, but in most cases, for most auction events and for most bidders, they have limited information. Auction managers rely solely on bidder activities during auctions for more information, which are typically limited to the items bid on and how much money the bidders are interested in paying for them. Willingness to pay is highly correlated with the number of lots on which a bidder bids ($r = 0.98$ for our data), but that number is not known until the end of the auction. Our weighted centrality index is nearly as highly correlated ($r = 0.89$), but its advantage is that it can be computed early in the auction event, and it can be traced to see if it changes and if new key bidders require greater attention.

Greenleaf, Rao, and Sinha (1993) showed the importance of the auction house, and the expectations and negotiations between buyers and sellers. Given the three-day duration of the auctions in this study, it is quite feasible and likely for auctioneers to target bidders during the event. Indeed, in our discussions with auction house managers, they acknowledge that they observe, albeit intuitively and not systematically, that a few bidders tend to emerge as central players, or key bidders. These bidders seem to have disproportionately large influence on price formation during an auction through their interactions with other bidders, both within and between-lots, even though they often win only a small fraction of the items sold in the end. The challenge in practice lies in how to systematically identify these key bidders from the observed bidding patterns.

In addition to studying networks holistically, many research inquiries focus on smaller subsets of actors in the network who are thought to be important in some manner. For example, diffusion of innovation is thought to occur through word of mouth, and marketers seek to identify opinion leaders who are particularly influential in their recommendations. Here too, models of the whole network can be complemented with analyses of the "key bidders" to see their impact on bids and prices.

Network centrality measures can be used to fill these managerial needs and their complementary theoretical gaps in the literature. Their application is readily used to identify key bidders based on the bidders' dyadic interactions, the depths of their pocket expenditures, and the intensity of their bidding activity. Thus, using networks, key bidders were identified based on their centrality scores. Recall the skewed distribution of bidder centrality and power, whereby most bidders have low scores and a few bidders have large scores. The five bidders with the highest centrality scores were the bidders named: *Kyozaan*, *Poker*, *Anonymous 3*, *Lord of the Rings*, and *Anonymous 118*.

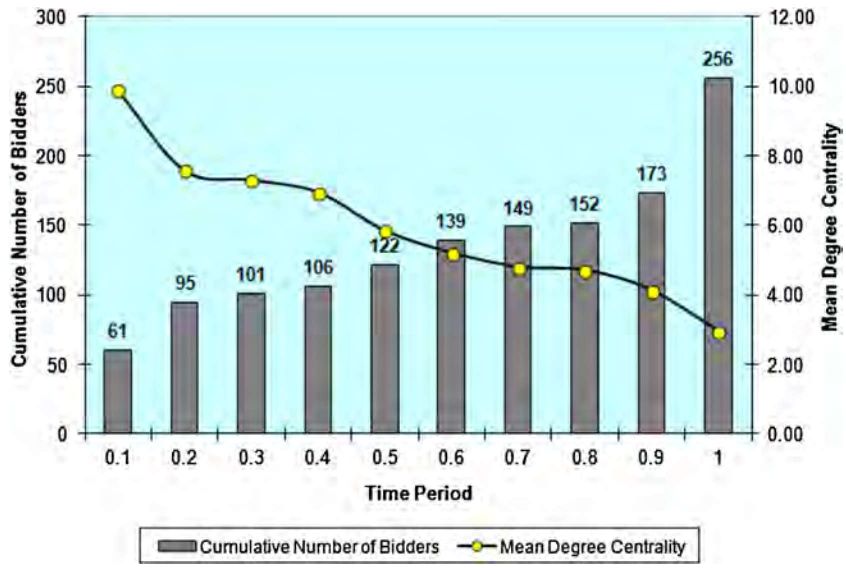


Fig. 2. Increasing cumulative number of bidders and declining centrality over auction duration. *Note*: This figure helps to explain the Pareto or power-law distribution—as auctions proceed, additional new bidders join, as represented in the growing heights of the bars in the bar chart. As a result, bids are spread among a larger number of competitors, in turn reducing the average index of overall actor centralities, as represented in the downward sloping mean centrality curve. As auctions develop, more bids are shared across more bidders, with a minority of exceptional, "key bidders" emerging who serve as the focus of the bidding activity in the network.

Table 2 provides a summary of these key bidders' behaviors. *Kyozaan* emerged as a highly central bidder in this auction. This bidder entered the auction event early, bid on many lots (56), and bid the most (182 bids). *Kyozaan* had the highest number of bidding relationships (59), also reflected in the high centrality measures. This bidder won four of the 56 lots bid on and spent $351,600.

Fig. 3 tracks the centrality statistics for the key bidders over time. For a conservative comparison, the five bidders with the next highest centrality indices are also plotted. It is clear that the key bidders distinguish themselves early in the auction and very clearly. The top five bidders' behaviors, as captured by the centrality scores, begin to differentiate themselves from the rest of the pack as soon as time point 1—that is, only 7 hr after the auction started. In addition, key bidders are not merely highly connected—they are important in their impact on auction prices, as we shall demonstrate in the set of results that follow on prices.

Impact of Key Bidders on Auction Prices

We modeled the effects of the potential influence of key bidders on the auction process in the following manner. We studied the final realized price as a percentage over the pre-auction low estimate from the auction house for the lots in which the key bidders participated. If, due to his or her participation, the key bidder were truly influential, then these lots should realize a higher price than the lots in which he or she did not participate.

Table 2
Key bidder comparison.

	Bidder				
	Kyozaan	Anonymous 3	Anonymous 118	Lord of the Rings	Poker
Total $ spent	$351,600	$263,423	$1,042,373	$1,011,746	$30,000
# Lots won	4	9	9	8	3
# Lots bid	56	58	18	37	65
Total # bids	182	128	104	137	152
Depth of pocket	$2,630,166	$2,524,497	$2,050,638	$3,325,247	$2,967,090
Total # bid relations	59	49	24	35	48
Centrality index	178	155	149	129	95
Avg. entry time (1st bid)	0.108	0.266	0.245	0.263	0.176
Avg. exit time (last bid)	0.412	0.565	0.8	0.645	0.336
Major artists' lots won	27, 68	10, 34, 38	42, 36, 18	50, 52, 69	41
Mean estimate lots bid	$45,327	$35,658	$40,301	$44,728	$33,457
Median lots bid	$15,912	$15,912	$22,165	$74,553	$37,845
# Agent bids	0	0	0	92	68

Note: These five bidders had the highest centrality scores, information that was not redundant with bidding activity (e.g., Total # bids), success (# Lots won), expenditure (Total $ spent).

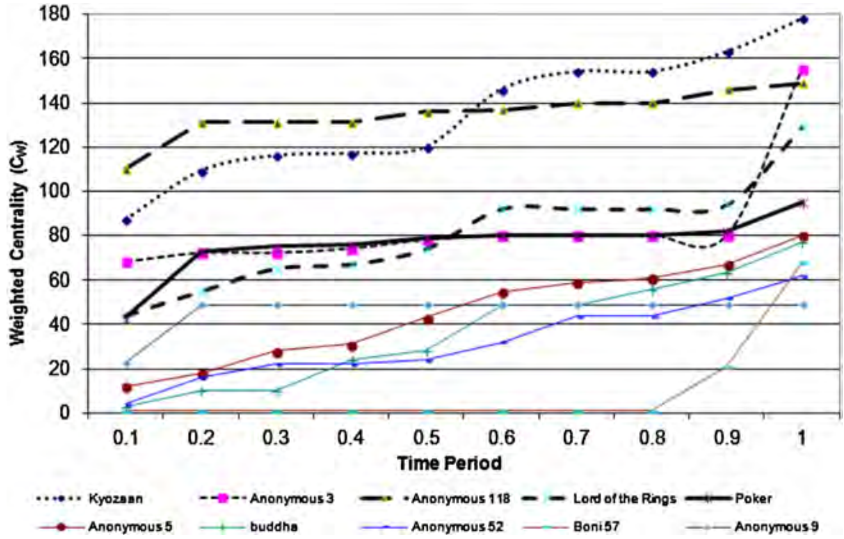


Fig. 3. Centralities of top 5 key bidders and next 5 competitors. *Note*: The top 5 key bidders (*Kyozaan*, *Poker*, *Anonymous 3*, *Lord of the Rings*, and *Anonymous 118*) begin to distinguish themselves in their interactions and influence even as early as the first time period. Their influence grows. As a conservative comparison, we also plot the next 5 scoring bidders, and it is clear that even as strong as they are, they are not as central to the auction's interactions or price outcomes as the top 5 key bidders we identified.

To tease apart characteristics of key bidders, we created three indices, the first based on bidder connectivity (i.e., network-based weighted centrality indices), the second based on bidder wealth (i.e., depth of pocket, or the maximum amount a bidder would need to pay at any given time if the bidder won all items currently bid upon), and the third based on bidder activity (i.e., the number of bids placed).

We also controlled for other determinants, including aggregate competitive measures (number of bidders, number of bids per bidder, and average number of lots bid by bidders); producer characteristics (indicators for established and emerging artist vs. others); product characteristics (indicator for works on paper and size of the art work); and unobserved heterogeneity due to different artists. Together, these data were analyzed using the following mixed effect model:

$$\ell n(\text{Auction Surplus})_i = \beta_0 + \sum_{j=1}^{13} \beta_j x_{ji} + b_1 u_{1i} + e_i \qquad (9)$$

for $i = 1, 2, \ldots, 199$ lots; x_{1i} = number of key bidders based on weighted centrality index; x_{2i} = number of key bidders based on depth of pocket; x_{3i} = number of key bidders based on bidding intensity; $x_{4i} = wl_i$, within-lot dyadic bidder interaction; $x_{5i} = bl_i$, between-lot dyadic bidder interaction; x_{6i} = number of bidders; x_{7i} = number of bids per bidder; x_{8i} = average number of lots bid by bidders; x_{9i} = dummy variable to indicate if lot belonged to an established artist; x_{10i} = dummy variable to indicate a lot by an emerging artist; x_{11i} = dummy variable for medium (=1 if paper, =0 if canvas); x_{12i} = log(size of art work in square inches); u_{1i} = artist of lot i; and $b_1 \sim N(0, \psi^2)$ where ψ^2 is the variance of the random effect.

The results in Table 3 show that it is more useful to identify "key bidders" as defined by their network measure of weighted centrality index than on the basis of their depth of pocket or their bidding intensity. The effect of key bidders based on network centrality is positive ($\beta = 0.084$) and significant ($p = 0.025$), and note that neither depth of pocket nor numbers of bids was significant. This finding is important in demonstrating the utility of networks in studying bidding and counterbidding behaviors

Table 3
Effect of key bidders on the auction outcome.

Variables	Standardized coefficient (standard error)	VIF	Replication study
Key bidders by dyadic interactions	0.084 (0.025)*	1.83	0.061 (0.024)*
Key bidders by depth of pocket	0.047 (0.026)	2.89	0.018 (0.043)
Key bidders by bidding intensity	−0.014 (0.034)	2.00	0.017 (0.027)
Within-lot dyadic interaction	0.137 (0.013)**	2.92	0.250 (0.009)**
Between-lot dyadic interaction	−0.105 (0.007)**	3.02	−0.066 (0.002)**
Covariates:			
Number of bidders	0.650 (0.006)**	1.78	0.678 (0.005)**
Number of bids per bidder	0.533 (0.020)**	2.78	0.334 (0.026)**
Average # lots bid by bidders	−0.019 (0.037)	3.57	−0.010 (0.029)
Established artist	−0.022 (0.028)	1.36	−0.016 (0.023)
Emerging artist	0.042 (0.031)	1.57	n.a.[a]
Works on paper	−0.014 (0.026)	1.35	0.058 (0.029)
Size of the artwork	0.017 (0.090)	1.58	0.048 (0.0001)
Adjusted R-square	0.92		0.91

Bidder interactions within-lots enhance final prices and bidders competing between-lots lower final prices (controlling for overall activity per #bidders and bids per bidder).

[a] The replication study featured only works by established artists.

* $p < .05$.

** $p < .01$.

Table 4
The effect of key bidders on price.

Artist	Lot	Medium	Opening bid	Low estimate	High estimate	Key bidder present?	Final price	Profit
Barwe	A	Drawing	$3,650	$4,545	$5,685	No	$7,150	57.32%
	B	Drawing	$3,650	$4,545	$5,685	Yes	$11,650	156.33%
Souza	A	Painting	$64,000	$80,000	$90,000	No	$151,500	89.4%
	B	Painting	$64,000	$80,000	$90,000	Yes	$265,000	231.1%

given that the results are distinctive apart from economic or financial descriptors of the bidders.

The positive and significant effect of network-based key bidders on auction surplus suggests that the presence of a key bidder enhances the auction surplus; additionally, across all lots, the more key bidders were bidding on more of the lots, the more realized surplus would be enhanced. Perhaps these key bidders were indeed the art experts referred to by Roth and Ockenfels (2002): participants who would be better informed about the items than others, such that their presence in a lot would signal a higher value of the item. On average, lots for which at least one key bidder was present ($n = 131$) realized a higher (3.12) auction surplus compared to lots where no key bidders participated (2.45; the difference between the surplus for lots that included key bidders and those that did not was significant; $t_{197} = 2.23$, $p = 0.026$). There were also dramatic differences between these key bidders and others with respect to the speed of the price formation. On average, prices of lots in which at least one key bidder participated exceeded the pre-auction high estimate value in one day, compared to nearly two days for lots with no key bidders bidding.

Finally, we tested whether the key bidders moderate the effects on other factors such as the number of bids. For instance, many papers have shown that the number of bids has a positive effect on price, but is the effect even stronger in the presence of key bidders? To test this idea, we examined the highest bids of non-key bidders who bid on items where key bidders participated and also on other similar items where the key bidders did not participate. In Table 4, we offer two examples where several variables are kept constant: the artist, the opening bids, the low and high estimates, and the medium of the art. The table shows the profits are greater when key bidders were involved (e.g., $11,650 vs. $7,150, and $265,000 vs. $151,500). In general, we found that these non-key bidders bid more ($t = 2.43$, $p < 0.05$) and paid higher prices (on average $14,488 more, $t = 2.02$, $p < 0.05$) on items where key bidders participated compared to items where key bidders did not participate (the difference between the surplus for lots that included key bidders and those that did not was significant; $t_{197} = 2.23$, $p = 0.026$). We conclude that key bidders drive up price (and surplus), and they also make others (non-key bidders) reach deeper into their wallets.

Thus, regarding key bidders, we note first that network centrality explained significantly more auction surplus variance than simple economic heuristics such as the number of bids and depth of pocket. Second, items on which at least one key bidder participated yielded significantly higher auction surplus than lots in which they did not participate. Third, non-key bidders tend to bid more and pay higher prices for items where key bidders participated than for items where the key bidders did not participate.

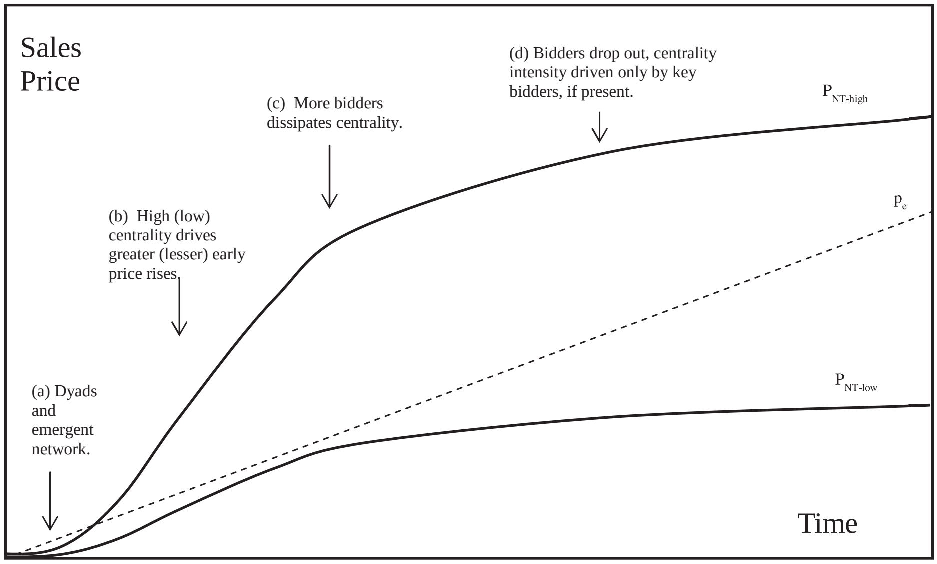
Fig. 4 organizes the theory testing we pursued in this paper. The dashed line represents a simple economic benchmark based on the prediction that more bidders over time create more competition and price increases. The network theorizing is comparatively richer. Where the linear-like economic prediction would forecast that the price continues to climb steadily, network structures begin to develop (e.g., point a in the figure) and create synergies (points b and c), accelerating prices upward. Similarly, toward the end of the auction, the economic prediction simply continues to rise in a steady state, whereas the network structure identifies that less concentrated bidders begin to fall away, with prices soon reaching their asymptotes. The figure also distinguishes the boost that key bidders provide, in that their presence surpasses the economic line, and their absence suppresses prices.

Within and Between Lots Bidder Interactions and Model Tests

Table 3 also presents the parameter estimates of the model testing the within- and between-lot effects on auction surplus. As anticipated, high intensity within-lot dyadic interactions (Eq. (4)) increased auction surplus ($\beta = 0.137$, $p < 0.0001$), and high intensity between-lot interactions (Eq. (5)) decreased auction surplus ($\beta = -0.105$, $p < 0.0001$). There may be several explanations for these results; one explanation for the decline in profits with greater between-lot bidding is probably most parsimoniously a budget constraint. Similar items may draw competition across the lots, but budget constraints would create the diminishing effect even when the lots involved are not particularly similar items.

The covariates of number of bidders ($\beta = 0.650$) and bids per bidder ($\beta = 0.533$) showed strong positive and statistically significant ($p < 0.0001$) effects. We also controlled for the possible effect of the average number of lots per bidder, in case budgets constrained prices. The adjusted $R^2 = 0.92$, suggesting a solid model fit.

To check the robustness of our model, we investigated issues of: (1) multicollinearity and (2) omission of other possible covariates in our analysis. Regarding multicollinearity, we computed the variance inflation factor for each of the variables and found no parameters to have values greater than 3.57 (see Table 3). Maruyama (1998, p. 64) suggests that any value below 6 indicates absence of multicollinearity. Second, we computed the condition index of the model (Belsley, Kuh, and Welsch 1980), which should not exceed 30, and ours did not.



$P_{NT\text{-}high}$ = network theory forecast for high centrality or presence of key bidders
p_e = baseline simple economic forecast function regarding competition from number of bidders
$P_{NT\text{-}low}$ = network theory forecast for low centrality or absence of key bidders

Fig. 4. Using networks to understand auction processes and prices. $P_{NT\text{-}high}$, network theory forecast for high centrality or presence of key bidders; p_e, baseline simple economic forecast function regarding competition from number of bidders. $P_{NT\text{-}low}$, network theory forecast for low centrality or absence of key bidders.

To test the soundness of our model, we considered five omitted variables whose effects we hoped would be minimal: (1) the number of bidder pairs present in a lot, (2) the number of latent bidders present in a lot, (3) the number of proxy bids in a lot, (4) starting bid, and (5) inter-bid time. The first, number of bidder pairs, is highly correlated (0.891) with the number of bidders placing bids in a lot, which is already represented in the model, thus, rendering the issue of omitted variables moot. As a measure of the second, latent bidders, we considered bidders from other items who are most likely to participate in the focal item, specifically those by the same artist (cf., Chan, Kadiyali, and Park 2007). For the third, we captured data from the auction house regarding bidders' maximum bids to serve as analogous to proxy bids. The fourth variable was directly recorded from the auction data, and the fifth variable was calculated from the bid history. Rerunning the model with these four additional covariates—the number of latent bidders, the number of proxy bids, starting bid, and inter-bid time—yielded non-significance for all of them, and our previous findings remained unchanged.

These results show that dyadic bidder interactions are significant in explaining variation in observed auction surplus across lots, offering clear empirical evidence that these interactions matter in simultaneous online auctions. Specifically, the results demonstrate that, everything else being equal: (1) in lots where bidder pairs bid on more lots together (i.e., higher "between-lot interaction"), auction surplus tends to be significantly lower; and (2) in lots where two bidders directly outbid each other more frequently (i.e., higher "within-lot interaction"), auction surplus tends to be significantly higher. The first of these results is presumably due to a limited share of wallet; that is, we have shown that the presence of key bidders in the auction of any single item enhances the profit realized for that item, yet having these bidders bid upon many items appears to push their limits against their financial constraints. To minimize between-lot competition and the resulting drop in profits, auction house managers might sell only one item from any given set of similar products as a time (e.g., during one auction event), so that the effect of substitution is diminished.

Measure Robustness

As a check on the operationalizations used in this study, we examined two other alternative explanations. First, while our bidder networks had deep pockets, one might argue that early bids are low and therefore can be outbid easily, compared to later, higher bids. Thus, we sought to examine whether the influence of a bidder was due to its being a relatively high bid or an early one. Therefore, we developed a new score for bidders termed "value influence" of bidder n_j, or vi_j, computed as the ratio of the final bid by a bidder for a lot over the final price of all the lots bid by the bidder. If a bidder bids early in the auction only, those bids will have less influence than if bid later in the auction. This index correlated with weighted centrality $r = 0.60$; that is, the value index is not completely redundant with the network measure we have been modeling, but the correlation is sufficiently substantial as to be indicative that our results are at least implicitly also capturing monetary dynamics of network interactions.

Second, one might alternatively argue that the bidders the auction houses should pay most attention to are not the key bidders—the people in the network who we have illustrated have an effect over other bidders, series of bids, build-ups of prices, and so forth—but instead those bidders who spend the most. It should not be surprising that the final amount bid by each bidder for different lots at the end of the auction is correlated with how much he or she spends in the first half of the auction ($\beta = 0.233$, $p < 0.0001$). However, if the auction hosts wish to identify those likely big spenders sooner, they can use the weighted centrality index, which may be computed in an ongoing manner. The network descriptors predict total expenditure even better than the first half sub-totals ($\beta = 0.310$, $p < 0.0001$). When both network centrality and first half sub-totals are in the same model predicting overall expenditure, the network predictor is still significant ($\beta = 0.390$, $p < 0.0001$), and the first half sub-totals are insignificant, a result not attributable to overwhelming multicollinearity, as these predictors themselves are correlated only by $r = 0.310$.

Finally, to assess whether any endogeneity may be a concern in our results, we conducted an alternative analyses. Specifically, we fit a pair of simultaneous equations, in which one equation is the model whose results are presented in Table 3, and another in which the number of bidders is modeled as a function of the variables that we have that can represent variability attributable to the artists (whether they are established or new), and the artwork product itself (its medium and its size). The findings in Table 3 were completely re-affirmed.

Validation and Replication Studies

The network analyses yielded interesting empirical results. To seek external validation regarding whether a network approach could be a meaningful framework within which to study auctions, we interviewed eight managers of major art auction houses and four known collectors of this class of art. We also conducted an online survey of contemporary art collectors and dealers who are regular bidders at this auction house. Forty-one respondents participated in the study in which they were asked about their bidding behavior. The items were 7-point Likert scales (7 = strongly agree). The survey results indicated that bidders indeed take notice of and identify their competitors in online auctions (e.g., through nicknames).

The results indicated that, in fact, most bidders (80%) browse through the web pages to investigate who is bidding on what items (mean = 5.54, $p < .01$ compared to the mid-point of 4.0). They (78%) also recognize nicknames of other bidders if they competed against each other for more than one item (mean = 5.29, $p < 01$). Regarding competitiveness, many of the respondents (54%) suggested that they are inclined to "win at all cost" when engaged in a head-to-head encounter with another bidder (mean = 4.61, $p < .05$). Thus, a network approach to studying auctions is relevant and could be quite fruitful, whether the network is truly social or a metaphor enabling the application of the models. While this study is small in scale, it seems to strengthen an argument for the external validity of this research.

To determine the generalizability of our results, we examined the replicability of the analysis of another sales event from the same online auction house run six months later. We found similar centrality distributions among the bidders, the bidder data showed properties of small world networks, and the key bidders had similar effects on the auction outcome. On average, the lots on which the key bidders (only three key bidders were identified) bid realized a higher price over the pre-auction low estimate, and the time taken to cross the pre-auction high estimate was significantly faster for these lots as compared to others. These results appear in the final column of Table 3 for comparative purposes.

Table 5
Study results and related theoretical framework.

Study results	Theoretical framework and references
Bid, counter-bid, bidder nodes	Graph theory: Marsden (1990)
Bidder interactions	Graph theory: Davis (1963), Heider (1958), Katz and Wilson (1956)
Network characteristics, power law	Network theory: Barabási and Albert (1999), Bonacich (1972)
Small world properties	Network theory: Kleinberg (2000), Watts (1999)
Identifying key bidders	Graph theory and network theory: Bonacich (1987), Freeman (1979), Knoke and Yang (2007), Nieminen (1973)
Within-lot interactions	Auction fever: Ku et al. (2005), Heyman, Orhun, and Ariely (2004)
Between-lot interactions	Dynamic price competition: Boyd and Everett (1988), Krackhardt (1988)
Price dynamics	Price evolution: Reddy and Dass (2006), Bapna et al. (2008), Borle, Boatwright, and Kadane (2006)
Importance of key bidders	Auction theory: Roth and Ockenfels (2002), Wilcox (2000)
Impact of key bidders on auction prices	Auction theory and price evolution: Reddy and Dass (2006), Bapna et al. (2008), Wilcox (2000)

Discussion

Auctions formats, bidder behavior, and the importance of bidder relations in auctions are well recognized in the academic community. The challenges to analyze such relations have always been the availability of desired data and the methodologies to analyze them. The current research contributes by introducing a network analysis approach to analyze these relationships and to develop ways to represent the bid-counterbid interactions among bidders and the resulting bidder networks that are formed.

Theoretical Contributions

This research offers contributions to both the auctions and networks literatures. Table 5 maps our findings onto the related theoretical frameworks in which they belong. In particular, the findings from the bidder connections and the resulting bidder networks are embedded in graph theory. Our research points network scholars in another direction in measuring sequences of interactions in a very meaningful setting. Just as the network element of this research afforded new insights into auctions, the auctions scenario may encourage networks researchers to relate their portfolio of structural indices to other measures on the actors or groups to establish convergent validity. This research also strengthens the stability of the network findings when the patterns of interaction are aggregated across auction bid items. For the auction researcher, this research shows how network methods may help auction modelers and auction managers achieve an even more detailed understanding of the micro moves, bid to bid to another answering bid, of how the eventual sought goal of sales prices are accumulated and derived.

This research also provides an endorsement of the importance of networks and incorporating relational ties into studies such as these auctions. When we compared different means of identifying key bidders, we found that classifying bidders on sheer economic grounds, such as their financial bases and qualifications, performed less well than identifying bidders using network analytical methods. This information is obviously important to auction house managers and thereby also to scholars building auction theories. Specifically, bids are not independently isolatable phenomena, and it would be best to model them using techniques suitable to such structured data, such as network models, as shown in this research.

This research results in a new bidder behavior model, which consists of the formation of bidder connectivity, localized dyadic competitions, and dominating roles of key bidders. Our research begins to map the dynamic nature of networks, how they are formed and evolve (e.g., Figs. 2 and 3), but we have just begun to tap a topic that should prove to be a fruitful line of inquiry for future research. Using network analysis, we show that bidders implicitly make connections with other bidders during bid-counterbid actions. After representing these connections in network form, we show that evolution of this network affects the auction outcome. In addition, we demonstrate that the role of those network-based "Key Bidders" has a positive impact on auction surplus and a positive effect on price dynamics at the beginning of auctions. The effectiveness of network theory is highlighted when recalling that the helpfulness of the presence of key bidders toward realizing higher prices is true only when key bidders were defined or identified using measures of network centralities, and not when using simple economic measures, such as depth of wallet.

This research should make clear that the use of network models and theories can contribute to the literature on auctions. In both the model and in the means of identifying the key bidders, the network approach contributed significantly, above and beyond existing, economic-based predictions. Network indicators regarding within-auction dyads, between-auction dyads, and key bidders were all important beyond sheer numbers of bids or bidders. We also believe that this study provides contributions to networks domains. Much of network theory and methods are as yet relatively new, and as a result, it is often perceived to be a sufficient contribution to simply describe a network structure. In this research, we have used network structures to understand and test important consequential dependent. Thus we have fortified networks theories and methods in this research in making clear that it is not just the case that networks exist or that they are interesting: they are important and can be used to explain other phenomena.

In terms of limitations, one concern that can arise with sequential bidding in online auctions is the possibility of shilling that is, having a confederate bidding enthusiastically to drive up prices, a practice that is illegal in most settings. Theoretically, shilling could have been present in the auctions from which our data are derived. However, given that the first bid is always above the reserve price, and that these items carry relatively high price tags, we expect that the presence of shilling in these auctions would be minimal.

Managerial Implications

Our research shows that key bidders may be identified very quickly after the opening of an auction (even after just a few hours). As a result, an auction house manager can be poised to quickly redirect resources and attention to these potentially influential bidders. Preferential treatment may seem antithetical to the democracy inherent to auctions, but it is naïve and poor business practice to not pay greater attention to more valuable customers (bidders). All passengers on a flight arrive en route, but frequent fliers may travel more comfortably; all gamblers have an equal chance in Vegas, but big spenders get free drinks. In our case, the key bidders as identified via our network methods, accounted for $3 million in purchases and the successful purchase of 33 lots (17% of the total lots auctioned).

Our research is also useful to the auction house manager after one auction in preparation for another. Prior to the opening of many auctions, auction houses arrange viewing events during which bidders can inspect items that will be put up for auction. Special invitations to these events are sent to potential prospects, primarily as a function of past purchases and registrations. The process is inefficient, with the invitations being cast with a wide net. Using our network modeling, an auction house manager could update their database by including a new set of potentially attractive bidders—our key bidders—based on characteristics different from the satisfaction of wealth criteria. Additional invitations would be issued to these key bidders (thus based on bidding performance at past auctions) to solicit another group of potentially profitable bidders. There would probably be some overlap between the two sets—the traditional pre-view bidders and those identified via their network activities, but the overlap is unlikely to be complete (for our study, $r^2 = 0.28$), so the first set would presumably be enhanced by the second. More information about potentially good bidders is better for the auction house manager in maintaining and purifying their customer management relationship systems. Our auction house contact has used our methods to revise their invite lists and have been highly satisfied with the results (recently featured in the *New York Times*, available from the authors).

From the perspective of the auction house manager, key bidders were helpful in driving up prices, even for lots the bidder did not ultimately purchase. The engagement of key bidders in bidding on these other lots generated additional bidding activity and the attention of other bidders, and of course, where there is more "bidding activity," prices rise. Auction house managers could offer incentives to these key bidders to bid on less popular lots, including price discounts, rebates, or other benefits to get the bidder interested in a lot that previously he or she had shown little interest in, to perhaps result in that bidder pursuing the art item, or perhaps simply to spark more action among other bidders who would observe the presence of a key bidder considering the item. These incentives could easily be issued in real time as the auction progresses, as it becomes clearer which lots are naturally drawing the attention of the key bidders, and which other lots could use some assistance.

Bidders can also watch for the presence of key bidders. Their bids provide positive signals about the desirability of an item, which may fortify the art collector's determination to achieve the purchase. At the same time, we showed that key bidders drives up sales prices, so the art investor may turn away from such lots, if they are seeking value purchases. Typically, auction houses such as the one studied here, post in real time during the auction the top 10 lots by activity (highest value lots, lots with most # of bids). We propose that in addition to the lot information, the auction house present real time information on bidders (bidders with most bids; bidders with highest bid, bidders with most lots). This makes it easy for potential bidders to identify and follow key bidders and the lots that they are bidding on. This will help the formation of the dyadic interactions and the bidder network which we have shown affects the auction outcomes.

Finally, on a more general note, while the focus in this paper has been on network models as being essential in applicability to interdependent data, networks also provide a different means of conceptualizing auctions, with their emphasis on capturing the bid-counter-bid exchanges as patterns of bidder connectivity. Given that bidders do not increase their activity independently, an auction house manager would benefit from sharing and making more explicit information about lots for which there seems to be heavy concentrations of bidding activities. Doing so may attract a key bidder to the auction, as well as other bidders with whom the key bidder would spar or compete, creating a flurry of bidding exchanges, obviously thereby increasing final sale prices.

Conclusions

In sum, we conducted this research to understand: the micro process of bidders interacting in an auction, the formation of bidder networks and their evolution by defining network ties as bid and counter-bid actions and reactions, the presence and identification of key bidders or bidders whose bidding behavior and apparent influence on the auction stand out, and complexities inherent to simultaneous auctions given the broad set of within-lot and between-lot connections. We believe that our research and this network approach provide insights on both the process and bidders which contributes to and complements the existing marketing literature on auctions.

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