6

AN ANALYSIS OF PRICE DYNAMICS, BIDDER NETWORKS, AND MARKET STRUCTURE IN ONLINE ART AUCTIONS

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6.1 INTRODUCTION

One of the greatest contributions of e-commerce and online auctions is their ability to provide detailed bidding records in the form of a bid history. These data sources not only furnish dynamic information regarding the status of auctions, but also capture the essence of auction activities that was not accessible from live auctions. In this chapter, we explore three broad online auction issues from these bidding data: the effects of various factors on price dynamics, effects of inter-bidder interactions on bidder dynamics, and underlying relationships of auctioned objects. From the auction house manager's perspective, insights from issues like how price formation takes place, how competitive bidding among bidders evolves, and which items are perceived as similar and dissimilar by the bidders are vital in setting up future auctions. Here we present results of the above investigations using data from online auctions of fine arts.
Fine art auctions present a unique context to our study. Unlike most functional products such as computers and electronic devices, whose auction data are used in prior studies, art objects are more hedonic. Their consumption is driven more by affective experience such as the aesthetic pleasure that one derives from them than by their utilitarian or functional benefits (Reddy and Dass 2006). Furthermore, the prices of artworks sold in these auction houses range from a few thousand to a few million dollars, resulting in higher stakes on the auction outcome. Therefore, crucial information on price dynamics, bidder dynamics, and market structure is greatly valued by both auctioneers and bidders.

Prior research on fine arts and art markets has mostly focused on the price realization of artworks in auctions and on their potential as an investment (Baumol 1986; Ashenfelter 1989; Pesando 1993; Mei and Moses 2002; Ashenfelter and Graddy 2003). However, very little is known about the issues frequently faced by art auction house managers. In this chapter, we present some new approaches and investigate the relevant issues.

To help us understand how bid history can facilitate our studies, we consider a bid history snapshot (Figure 6.1) taken from an online auction of fine arts. Like any typical bid history, it consists of three important elements: bidder information, bid amount, and bid time (the time at which the bid is placed). Such information constitutes the fundamental basis for online auction research, which can be represented in a three-dimensional data cube (Figure 6.2). This data cube illustration streamlines the information available from the bid history. The x-axis of the plot represents the lots (auctioned items), the y-axis represents the bid time, and the z-axis represents the

Figure 6.1 Bid history snapshot of an online art auction.

1For example, in their analysis of 15 studies, Ashenfelter and Graddy (2003) report an estimated average real return of art as investment of 2.6%, with a range of 0.55% to 5%.
bidders who participated in the auction. Such an illustration is vital to determine
which characteristics of the bid history to use for which analysis. For example, if
we focus only on the auctioned lots (x-axis) and the bid time (y-axis), we study
price dynamics research (Bapna et al. 2008; Reddy and Dass 2006). If we focus
on individual bidders (z-axis) across all the auctioned lots (x-axis), we study bidder
dynamics research (Dass et al. 2007a).

We also present some innovative and state-of-the-art approaches in some of the
analysis. First, we use functional data analysis to investigate price dynamics.
Second, we examine bidder dynamics by considering a network framework among
the bidders. In particular, we create a network among bidders and then use social
network analysis to fulfill our goal. Finally, we develop an artist network between
the artists whose artwork is auctioned and then use the purchase intent of the
bidders to determine the underlying art market structure.

This chapter is organized as follows. First, we discuss the context of our study, i.e.,
a contemporary Indian art auction, and describe the online auction data used in our
studies. We used two different datasets, one for the price and bidder dynamics and
another for market structure analysis. We discuss each of them in Section 6.3.
Second, in Section 6.4, we explain our work on price dynamics of online art auctions
and discuss the findings. In Section 6.5, we present our methods and the results of the
bidder dynamics analysis. In Section 6.6, we explain our approach to studying the art
market structure and discuss the results. Finally, in Section 6.7, we discuss the man­
gerial implications and future research opportunities.

6.2 CONTEMPORARY INDIAN ART

The fine arts market is one of the fastest-growing markets in the world. In 2005, the
turnover for fine arts sales in auctions exceeded over $4 billion (up from $3.6 billion
in 2004, a growth rate of 10%), and the total world art market is estimated to be over
Two esteemed auction houses, Christie’s and Sotheby’s, have dominated the art market since the eighteenth century, but due to the recent popularity of the Internet, they are facing fierce competition from some newly established auction houses that have only online operations. One example is the emerging market for contemporary Indian art. With over $100 million in auction sales in 2006, contemporary Indian art is now one of the leading emerging art markets in the world. Although Christie’s and Sotheby’s started auctioning this art in 1995, in 2000 the market exploded, with 68.7% annual revenue growth (coincidentally, this is when SaffronArt.com, the source of our data, started its operations). In 2006, online auction sales of contemporary Indian art by SaffronArt.com ($20.80 million) were comparable to those of traditional auction houses like Sotheby’s ($35.29 million) and Christie’s ($33.08 million). Further, SaffronArt.com sold 390 art items, whereas Sotheby’s and Christie’s sold 484 and 329 items respectively in that year. The top 10 Indian artists sold 31% of the lots and contributed to 57% of the total value realized at the auctions since 1995. Two of these artists are now ranked among 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.

6.3 ONLINE AUCTION DATA

SaffronArt.com data are ideal for our study, as this auction comparable with house in the mainstream auction houses, provides rich auction data, and gives a good representation of the contemporary Indian art market. The auctions are held over a multi-day period (typically three days). Bid histories of the auctioned items are available from the auction house’s website during the auction. Figure 6.1 is a snapshot of a bid history from the auction website. This auction uses an ascending-bid format with a fixed ending time and date set by the auction house. Further, to discourage sniping behavior by the bidders, the auction adds three more minutes to the time clock if the last bid is placed in the last three minutes of the auction (Roth and Ockenfels 2002). The auction also uses a proxy-bid system similar to the one used by eBay, where the bids are automatically updated on behalf of the bidders. Proxy bidding is a common feature in most online auction houses, where bidders set the maximum amount they are willing to pay for the auctioned item and let the auction house place proxy bids on their behalf until that price is reached. Bidders using this facility have a predetermined value for the item and use it to stay within

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2Total sales of contemporary Indian art in both online and offline auctions in 2006 were $136 million.
3In 2005, online auction sales of contemporary Indian art by SaffronArt.com were $18.06 million, more than those of Sotheby’s ($10.49 million) and Christie’s ($14.89 million). SaffronArt.com also sold more art items (390) than Sotheby’s (276) and Christie’s (248) in 2005.
4For more information on the contemporary Indian art market, visit http://www.modernindianart.net.
5Roth and Ockenfels (2002) examined the difference in the last-minute bidding strategies of bidders in these types of auctions and in eBay auctions, where the auction ends exactly at a particular time.
that limit (Bapna et al. 2004). We also collected other item-specific information for our analysis. A complete list of these items will be discussed later.

For our analysis, we use two different datasets. The first dataset is taken from an online auction where 199 lots (each lot typically is a unique piece of art—namely, a painting, a drawing, or a sculpture) were auctioned in December 2005. In this particular auction, works of 70 artists were auctioned, with an average of three lots per artist. The average realized price per lot was $62,065 and ranged from a low of $3,135 to a high of $1,486,100. Overall, 256 bidders participated in this online auction and placed 3080 bids. The number of bids per lot averaged 15.47 and ranged from 2 to 48. On average, 6 bidders participated in each lot, ranging from 2 to 14 bidders across the auction. The mean number of bids per bidder was 4.93, with a range from 1 to 65. Some of the key descriptive information about the auction is presented in Table 6.1. We used this dataset to investigate the price dynamics and bidder dynamics issues.

For our art market structure study, we used a dataset from another auction held in March 2005. Only 44 lots from nine artists were auctioned, and 66 bidders participated. As one of our primary goals in this study is to illustrate the process of determining the underlying market structure, we decided to use this smaller dataset.

### Table 6.1 Summary Description of Dataset 1

<table>
<thead>
<tr>
<th></th>
<th>Mean (SD)</th>
<th>Median</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of unique bidders/lot</td>
<td>6.35 (2.47)</td>
<td>6</td>
<td>2</td>
<td>14</td>
</tr>
<tr>
<td>No. of unique lots bid/bidder</td>
<td>4.93 (7.95)</td>
<td>3</td>
<td>1</td>
<td>65</td>
</tr>
<tr>
<td>No. of bids/lot</td>
<td>15.47 (7.46)</td>
<td>15</td>
<td>2</td>
<td>48</td>
</tr>
<tr>
<td>Opening bid in $</td>
<td>$19,343 ($36,663)</td>
<td>$6400</td>
<td>$650</td>
<td>$300,000</td>
</tr>
<tr>
<td>Preauction low estimates of the lots</td>
<td>$24,128 (45,747)</td>
<td>$8000</td>
<td>$795</td>
<td>$375,000</td>
</tr>
<tr>
<td>Preauction high estimates of the lots</td>
<td>$31,065 (60,351)</td>
<td>$10,230</td>
<td>$1025</td>
<td>$475,000</td>
</tr>
<tr>
<td>Realized value of the lots in USD($)</td>
<td>$62,065 (133,198)</td>
<td>$22,000</td>
<td>$3135</td>
<td>$1,486,100</td>
</tr>
<tr>
<td>Realized sq. inch price of the lots in USD($)</td>
<td>$108.77 (225.49)</td>
<td>$45.12</td>
<td>$1.40</td>
<td>$1865.42</td>
</tr>
</tbody>
</table>

### Table 6.2 Summary Description of Dataset 2

<table>
<thead>
<tr>
<th></th>
<th>Mean (SD)</th>
<th>Median</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of unique bidders/lot</td>
<td>4.25 (1.50)</td>
<td>4</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>No. of unique lots bid/bidder</td>
<td>2.83 (3.14)</td>
<td>2</td>
<td>1</td>
<td>17</td>
</tr>
<tr>
<td>No. of bids/lot</td>
<td>8.66 (3.58)</td>
<td>9</td>
<td>3</td>
<td>18</td>
</tr>
<tr>
<td>Opening bid in $</td>
<td>$23,308 (20,346)</td>
<td>$18,000</td>
<td>$3040</td>
<td>$91,230</td>
</tr>
<tr>
<td>Preauction low estimates of the lots</td>
<td>$27,563 (23,939)</td>
<td>$23,260</td>
<td>$3490</td>
<td>$104,660</td>
</tr>
<tr>
<td>Preauction high estimates of the lots</td>
<td>$33,536 (28,993)</td>
<td>$27,910</td>
<td>$4500</td>
<td>$127,910</td>
</tr>
<tr>
<td>Realized value of the lots in USD($)</td>
<td>$44,397 (39,703)</td>
<td>$35,750</td>
<td>$4125</td>
<td>$176,000</td>
</tr>
<tr>
<td>Realized sq. inch price of the lots in USD($)</td>
<td>$55.25 (48.00)</td>
<td>$38.24</td>
<td>$13.22</td>
<td>$225.64</td>
</tr>
</tbody>
</table>
(the works of only 9 artists were auctioned compared to 70 in the first dataset) based solely on its size. Sixty-six bidders posted 381 bids with 8.66 bids/lot. The average value of the lots auctioned was $44,397 (min = $4125, max = $176,000). The average number of bidders per lot was 4.25, with an average time of auction entry of 0.0861 minute. Some of the key descriptive information about the auction is presented in Table 6.2.

6.4 PRICE DYNAMICS

Investigation of price formation dynamics provides vital information regarding the factors contributing to the evolution of the bid dynamics. Such information is vital for auction house managers, as it provides a basis to determine how prices change during the auction. The factors whose effect on price dynamics we explore are artist characteristics (established or emerging artist; prior sales history), art characteristics (size; painting medium—canvas or paper), auction design characteristics (opening bids, preauction estimates; position of the lot in the auction), and competitive characteristics (number of bidders; number of bids). In this section, we will first discuss our modeling process and then present the results.

Price formation analysis of online auctions of hedonic heterogeneous products is both complex and challenging. The uniqueness and scarcity of the art objects and the genre differences among the artists result in high variability among the lots, making the development of a generalized model for estimating price dynamics a challenging task. Prior studies by Jank, Shmueli, and their associates (Shmueli et al. 2004; Bapna et al. 2008; Shmueli and Jank 2005a, 2005b) have developed sophisticated statistical methods to visualize and analyze the dynamics of online auctions. Recently, Wang and her colleagues (2006) explored ways to apply such dynamics to forecast the final prices of the auctioned items on an ongoing basis. These studies form the methodological background for our approach to analyze price dynamics in online auctions of fine arts.

From the modeling perspective, online auction data present challenges that make applying traditional econometric/regression methods difficult. The data consist of records of bid sequences placed at evenly spaced intervals, thus precluding the use of traditional time series methods in our analysis. Moreover, as in eBay auctions, a bidding frenzy is observed toward the beginning and near the end of the auction. Functional data analysis (FDA) (Ramsay and Silverman 2005), which at its core is the analysis of curves rather than points, is well suited to analyze this type of data. Using this technique, we analyze the price dynamics (velocity and acceleration) in online auctions after recovering the underlying price curves using a nonparametric curve-fitting technique such as splines (Simonoff 1996). Whereas the traditional regression methods are useful in modeling the final price points in the auctions, FDA provides the required tool to model the price dynamics and determine their relationship with the strategic variables during the entire auction. In this process, we first smooth the bid data for each lot and recover the underlying price curves. Then we model the heterogeneity of these price paths using the above-mentioned
characteristics to provide insights into the relationship of these covariates in the price dynamics during the auction.

6.4.1 Method

As the first step toward our goal, we must smooth the given data. This involves some preprocessing steps. First, we standardize the auction time by scaling it within 0 to 1; thus, 0 ≤ t_{ij} ≤ 1, where t_{ij} represents the jth bid in lot i. Then we accommodate the irregular spacing of the bid arrivals by linearly interpolating the raw data and sampling them at a common set of time points t_i, 0 ≤ t_i ≤ 100, i = 1, 2 ... total number of lots. For each of the bid times, we compute the corresponding log-transformed bid values to reduce the skewness of its distribution.

As part of the second stage in our analysis, we use penalized smoothing splines (Simonoff 1996; Ramsay and Silverman 2005) to recover the underlying price curves. These splines effectively capture the local variation in the dataset and readily provide different derivatives of the smoothed price curves. This functionality allows us to analyze higher-order functions of the auction price, namely, price velocity (first-order derivative) and price acceleration (second-order derivative). To recover the underlying price curve, we consider a polynomial spline of degree p.

\[
f(t) = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 \ldots + \beta_p t^p + \sum_{l=1}^{L} \beta_{pl}(t - \tau_l)^{P}
\]

where \(\tau_1, \tau_2 \ldots \tau_L\) is a set of L knots and \(u_{ik} = u_l[l_k \geq 0]\). The choice of L and p determines the departure of the fitted function from a straight line, with higher values resulting in a rougher \(f\). This may result in a better fit but a poorer recovery of the underlying trend, as it has a tendency to overfit the given data. To avoid this problem, the following a roughness penalty function (PEN) is 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 mth derivative of the function \(f\). The goal is to find a function \(f^{(j)}(t)\) (the jth bid in lot i) that minimizes the penalized residual sum of squares (PENSS)

\[
PENSS_{\lambda,m}^{(j)} = \sum_{i=1}^{n} [y_i - f^{(j)}(t_i)]^2 + \lambda \times PEN_m^{(j)}
\]

where the smoothing parameter \(\lambda\) provides the trade-off between the fit \([(y_i - f^{(j)}(t_i))^2]\) and variability of the function (roughness) as measured by \(PEN_m\). We used the b-spline module developed by Ramsay (2003) for minimizing \(PENSS_{\lambda,m}^{(j)}\).

Finally, to analyze the effects of different covariates on price dynamics, we apply functional regression with the price functions as our response variable and the determinants such as artist characteristics (established or emerging artist; prior sales history), art characteristics (size; painting medium—canvas or paper), auction design characteristics (opening bids, preauction estimates; position of the lot in the
auction), and competitive characteristics (number of bidders; number of bids) as our explanatory variables. Functional regression is ideal for our case, as unlike a typical regression setting, it allows the functional form of variables in the analysis. For example, the response variables in our case are the price curve \( f(t) \) and the price-velocity curve \( f'(t) \) that capture the price formation process during the auction. Functional regression models allow us to understand the influence of covariates on price dynamics over time. As Ramsay and Silverman (2005) point out, this is achieved by estimating \( \beta(t) \) for a finite number of points in time \( t \) (in our case, \( t = 100 \)) and constructing a continuous parameter curve by simply interpolating between the estimated values \( \beta(t_1) \ldots \beta(t_n) \). To capture the effects of the explanatory variables on each of the price dynamic variables, we run a regression for each time period (1–100) for data from all the lots (\( n = 199 \)). The parameter estimates

\footnote{For an auction house manager, practical use of price dynamics is limited to price velocity. Therefore, we did not perform any analysis on price acceleration.}
associated with each explanatory variable are plotted along with confidence bands to indicate the impact and its significance over the entire auction. Figures 6.3a–d illustrate the results of our analysis.

6.4.2 Results

We find auction design characteristics such as opening bid for the lots, to have a positive effect on price formation throughout the auction, with its effect decreasing toward the end of the auction. Its effect on price velocity is also positive at the beginning of the auction but becomes negative by the end. This indicates that lots with higher opening bids show less price velocity at the end of the auction or, alternatively,
that lots with lower opening bids show greater price velocity at the end of the auction. We also find that lots auctioned later in the auction exhibit lower price levels during the auction. Such items have less price velocity during the early stages of the auction, but it increases toward the end of the auction. The results are illustrated in Figure 6.3a.

Interestingly, the current number of bids and the number of bidders during the auction are found to have no significant effect on price formation but considerable effect on price velocity. It is high at the beginning and near the end of the auction, with an increasing number of bids and bidders, but low during the middle of the auction. The results are illustrated in Figure 6.3b.

Results of the historical auction activities of artists (the price realized and the number of lots sold in the previous year) show that their effect on price velocity diminishes as the auction progress (Figure 6.3c). Price level is also found to be positively affected by the artist's historical price records, with the effect being strongest during the middle of the auction. Comparing the price dynamics of emerging and established artists, we find that the price levels of lots painted by emerging artists are lower throughout the auction, whereas those of lots painted by established artists are high throughout the auction. Furthermore, price velocity is low for emerging artists early in the auction but high near the end. The opposite is true for established artists. No significant effects of art characteristics (size; painting medium—canvas or paper) are found in our study. The results are illustrated in Figure 6.3d.

A complete summary of the results is shown in Table 6.3.

### TABLE 6.3 Summary of Findings

<table>
<thead>
<tr>
<th>Auction Design Characteristics</th>
<th>Price Level</th>
<th>Price Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opening Bid</td>
<td>Opening bid has positive effect on price level throughout the auction, with the effect decreasing toward the end of the auction.</td>
<td>The impact of the opening bid on price velocity is positive at the beginning of the auction. This effect is negative by the end of the auction, indicating that lots with higher opening bids show less price velocity at the end of the auction. Alternatively, lots with lower opening bids show greater price velocity at the end of the auction.</td>
</tr>
<tr>
<td>Lot Position</td>
<td>Lots auctioned later in the auction have lower price levels during the auction.</td>
<td>Change in price is slow for lots having a higher lot position during the early stages of the auction. Price velocity is rapid at the end of the auction.</td>
</tr>
</tbody>
</table>

(Continued)
6.5 BIDDER DYNAMICS

Analyzing competitive bidding is vital to understand bidder dynamics in online auctions. Fortunately, the available bid history provides sufficiently detailed information on these activities to facilitate our study. Competitive bidding, i.e., repeated...
outbidding between two specific bidders, is common in most auctions (Gupta 2002). At a fundamental level, such consecutive bids on common items among bidders can be conceptualized into a dyadic relationship between them. This exposes not only the bidding patterns of the bidders but also private information such as their purchase intention, depth of pocket, and private value of the lots they are bidding on. In this section, we focus on this phenomenon and determine how such dyadic bidder relations are formed during the auction. We also identify the bidder subgroups in the auctions based on such interdependence. To facilitate our goal, we introduce a new approach of forming a bidder network based on these dyadic bidder activities and analyze it with social network analysis (SNA). A bidder network, like any other network, is defined as a set of bidders with connections or relationships between them. Therefore, in our case, the nodes of the network represent the bidders, and the strength of the link between them corresponds to the intensity of competitive bidding between them. We use SNA (Wasserman and Faust 1994) to perform our investigation.

6.5.1 Method

The concepts of social network (Wasserman and Faust 1994) and network analysis have found a wide variety of applications in sociology, marketing, and statistics. This powerful tool has been used in the investigation of interorganizational communications (Hutt et al. 1988; Gloor et al. 2004), buying centers (Bagozzi 1978; Johnston and Bonoma 1981), channels (Dwyer et al. 1987; Stern and Scheer 1991), brand-switching behavior in the auto industry (Jacobucci et al. 1996), the World Wide Web (Katona and Sarvary 2005), and relationships among family members (Corfman and Lehmann 1987; Qualls 1987). More recently, researchers have focused on the dynamic aspect of network evolution, with Barabasi and his colleagues (2002) leading the research stream. The popularity of this concept has even crept into modern culture. A game called "Six Degrees of Kevin Bacon," where the challenge is to connect any given actor or actress directly or indirectly to Kevin Bacon, a renowned actor, has become very popular. This game considers a link between two social entities (actor or actress) if they have worked together in the same movie. Another social network application is the work of a motivated photographer, Andy Gotts, who developed a photographic collection of movie actors and actresses called "Degrees," where each entry is a result of another entry's referral (Gotts 2005). SNA has also recently been used as a powerful tool in national security applications. For example, Krebs (2001) used such analysis to map terrorists' participation in the 9-11 attack and determined the central player in the event. Further, SNA is widely used by the U.S. security agencies to scan telephone databases for possible threats to national security (Dryer 2006).

SNA focuses on relationships among social entities and on the patterns and implications of these relationships (Wasserman and Faust 1994). In particular, it investigates how the interactions among social entities constitute a framework to

7 For more information, visit http://oracleofbacon.org/
understand various roles played by them in the network. We capture competitive bidding as dyadic interactions between a pair of bidders. We define the bidder network as a set of \( g \) bidders whose relationship strength is based on the number of times 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 \( X_m \) as a bidding relation of type \( m \). \( X_m \) is a set of ordered pairs recording the extent of a relationship of type \( m \) between pairs of bidders. In this case, we define the extent of a relationship as the number of times \( p \) that bidder \( i \) and bidder \( j \) bid sequentially on the lots in the auction. \( X_m \) is represented as a \( g \times g \) matrix (Figure 6.4), where \((X_m)_{ij} = p; p = \{0, 1, 2, \ldots, P\}\), where \( P \) is the maximum number of consecutive bids placed in the auction. We create this nondirectional, symmetric matrix \( X_m \) for \( g = G \) bidders in the online auction which forms the basis for the network analysis.

Let us illustrate the process of the network formation with an example (Figure 6.5). Consider the two bid histories shown in Figures 6.5a and 6.5b. In the first bid history (Figure 6.5a), Anonymous 3 and Kyozaan are found to bid sequentially three times. Therefore, we consider two nodes in the network, one representing Anonymous 3 and
the other Kyozaan, and link them with an arc having the value of 3 (Figure 6.5c). In the same bid history, we find that another bidder, Poker, has also bid against Kyozaan three times. Therefore, we include another node in our network to represent this bidder and link it to Kyozaan with an arc of value 3 (Figure 6.5d). Now, let’s consider the second bid history (Figure 6.5b). Here we find that Socrates and Anonymous 38 have bid against Poker and Kyozaan. We add two more nodes in our network to represent these bidders and link them to related bidders with appropriate values (Figure 6.5e). In this manner, we consider the complete bid history of the 199 items sold in the auction, consider each of the sequential bids between the bidders, and develop the network. If two bidders appear sequentially in more than one item, we add all their appearances to compute the strength between them. Further, to explore the evolution of the bidder network and the presence of bidder subgroups, we measure the network centrality indices Degrees and Bonacich’s Power of the individual bidders and the overall bidder network. Both of these measures not only specify the extent of connectivity among bidders, but also indicate the role they play during the auction.

**Degree** refers to the number of links an actor has with other actors in a network (Freeman 1979). In our case, it is the number of interdependence relationships each bidder has with other bidders. The greater the number of bidder links, the more centrally located the bidder will be in the network. A central bidder, with the advantage of his or her location in the network, is more capable of playing an influential role in the auction than others. Bidders having minimum degree reside on the periphery of the network and have few interdependence relationships. The degrees are normalized and computed as (Freeman 1979)

\[ C_D(n_i) = \frac{d(n_i)}{(g - 1)} \]

where \( C_D = \text{degree of a bidder } i \), \( d(n_i) \) is the total number of bidders linked to bidder \( n_i \), and \( g \) is the total number of members in the network. We also compute average degree indices of the overall network at various time periods in the auction as

\[ C_D = \frac{\sum_{i=1}^{g} [C_D(n^*) - C_D(n_i)]}{((g - 1)(g - 2))} \]

where \( C_D(n_i) \) is the degree of bidder \( i \), \( C_D(n^*) \) is the largest observed degree in the network, and \( g \) is the total number of bidders in the network. This provides the normalized degree measure and compares networks formed at different auction times.

**Bonacich’s Power** measures the total influence power of particular bidders over other bidders based on the possibility of influencing other bidders during auctions. Consider a hypothetical scenario where bidder A is connected to bidder B. Further, bidder A is connected to three more bidders (X, Y, and Z) and bidder B is connected to only one more bidder, say H. In this case, bidder A’s influence over bidder B will be greater than that of bidder B over bidder A. This is because connectivity of bidder B is shared only between bidders A and H, but that of bidder A is shared between bidders B, X, Y, and Z. This is the fundamental notion of Bonacich’s Power.
6.5 BIDDER DYNAMICS

Bonacich further argues that although a bidder's connection to other bidders makes that bidder central, this does not necessarily make him or her powerful. Therefore, a bidder connected to other minimally connected bidders is powerful, whereas a bidder connected to a well-connected bidder is not.8

Bidders with similar product choices and sometimes with similar bidder behavior typically engage in competitive bidding and thus tend to form dyadic relations. Given the heterogeneous nature of the products we are studying, maximally complete (well-connected) bidder subgroups will indicate the number of bidder clusters defined by bidders' bidding characteristics and the linkages in the bidder network. We used Bron and Kerbosch's (1973) algorithm to compute such subgroups in our bidder networks and a popular social network analysis program called Ucinet (Borgatti and Freeman 2002) to perform our analysis. We reconfirmed our analysis using the "sna" library in R (Butts 2006). We also divided the auction time into 10 equal periods and then analyzed the bidder interdependence network at each of them to investigate its evolution.

6.5.2 Results

6.5.2.1 Overall Bidder Network. The evolution of the bidder network in time periods 1, 5, and 10 shows a very interesting changing competitive bidding pattern (Figure 6.6).9 Our initial observation indicates that as the auction progresses, more bidders arrive and create a densely connected network. By the first time period in the auction, there are 309 bidder relations in the network. This number increases to 1463 at the end of the auction. Although graphically our bidder network looks

![Figure 6.6 Evolution of a bidder network over the duration of the auction.](image)

8 See Bonacich (1987) for details on how Bonacich's Power of individual actors in a network is estimated.

9 This is a Fruchterman Reingold's three-dimensional plot obtained from the SNA software called Pajek.
Figure 6.7 Degree of distribution of the interdependence bidder network.

well connected, we find that in reality, it is sparse \[2L/g(g - 1) = 0.04482\] and the average degree centrality of the bidders is only 2.914, which is small compared to the number of possible degrees: \(g - 1 = 255\). This indicates that our observed bidder network is neither regular (where all bidders are equally connected) nor random (where most of the bidders' degrees are concentrated around the mean degree). We further find that degree distribution (Figure 6.7) is left skewed, indicating that most bidders have fewer bidder linkages than a handful of active bidders. Decline in network centrality (degree) with progression in the auction indicates that the network becomes fragmented over time. This network fragmentation with the increase in the number of bidders implies that the central role played by the average bidders is reduced.

One of the central theses of bidder interdependence is that it results in bidder familiarity during auctions. Such familiarity is formed due to the transparency and repeated meetings among the bidders. If the bidder network characteristics support faster information flow from one peripheral end node to another, bidders may rapidly become familiar with other bidders. In network theory, networks exhibiting small-world properties are ideal for faster information dissemination. A network is said to have small-world properties when it is highly clustered, like a regular graph.

\[\text{The sparse network test is illustrated by Braha and Bar-Yam (2004) with } L \text{ as the number of bidder relationships and } g \text{ as the number of nodes/bidders.}\]
6.5 BIDDER DYNAMICS

(C_{real} \gg C_{random}) but possesses a small path length, like a random graph \((l_{\text{real}} \approx l_{\text{random}})\) (Watts and Strogatz 1998; Watts 1999). Our bidder network has a high clustering coefficient \((C_{\text{bidder}} = 0.881)\) compared to a random network with the same number of bidders \((256)\) and bidder relationships \((1463)\) \((C_{\text{random}} = 0.022)\), but a similar path length like a random network \((l_{\text{bidder}} = 3.097 \approx l_{\text{random}} = 3.391)\), thus showing that it is possible that bidder information was disseminated rapidly in the network.

Average Bonacich’s Power of the network also increased as the auction progressed (from 3.06 in the first time period to 11.33 at the end). This interesting finding suggests that as the auction progresses, power is not uniformly distributed and some key bidders are more powerful than others. Such bidder characteristics indicate that network characteristics of bidders are useful in defining their bidding behavior and thus may be a way to classify them.

6.5.2.2 Bidder Subgroup Analysis. Cohesive subgroups in a network are groups of actors who are more strongly connected to members belonging to the same subgroup than to members belonging to other subgroups (Wasserman and Faust 1994). The strength of a subgroup is determined by the level of interconnectivity among its members. In our case, bidder subgroups represent bidders who bid on similar lots frequently and compete against each other. Investigation of such bidder groups is vital in determining various types of bidders and, more importantly, various types of bidding activities. We used the algorithm developed by Bron and Kerbosch (1973) to compute the subgroups in the bidder interdependence network.

We find seven bidder subgroups in our bidder network, each represented by a unique set of bidders. The strongest subgroup contains 30 bidders, mostly the active bidders of the network. These bidders participated in the auction of the largest number of lots \((190)\), illustrating participatory behavior (Bapna et al. 2004) (active bidding throughout the auction, without a significantly low winning percentage). To compare the characteristics of the strongest subgroup with those of a weaker subgroup, we analyzed the bidders in these groups and their bidding activity (Figure 6.8). Unlike bidders associated with the strongest group, bidders in the weaker groups tend to be opportunists who join the auction late, bid on a small number of lots, and bid less frequently. Such bidder behavior is quite similar to the sniping behavior of bidders in eBay auctions, although such activity is discouraged by the flexible closing time of these auctions. Moreover, these bidders have a higher winning percentage than those in the strongest group.

In summary, our bidder dynamics model illustrates some important issues regarding the bidder behavior in online auctions:

1. With more bidders joining the auction, the bidder network becomes more fragmented, thus reducing the average degree of centrality (bidder connectivity) in the network.

\(^{11}\)Opportunism is also another bidding style found by Bapna and his colleagues (2004).
2. The average power in the network increases, with few bidders having more power than others.
3. There are seven bidder subgroups in the auction based on their bidding behavior.
4. Bidders in the strongest subgroup exhibit participatory bidding behavior, whereas those in the weaker subgroup show opportunist bidding behavior.

6.6 MARKET STRUCTURE

Finally, in this section, we illustrate an important use of bid history information to derive insights into the market structure. At a fundamental level, bid history represents the preference information of the bidders who participated in the auction. Specifically, using the available data, we can now identify the lots a bidder is interested in or not. Considering such preference information about all the participating bidders, in this section we investigate the market structure of modern Indian art using the second dataset discussed in Section 6.3.

As with any heterogeneous market, the structure of the art market is difficult to analyze. Contemporary Indian art especially is represented by a variety of artists with a diverse set of techniques and styles. Further, these artists have had different types of training, and most of them have fashioned their own forms of creation.

12From the time of its introduction as an emerging art market (1995), works of more than 750 artists have been sold in various auctions.
Therefore, any traditional method of determining the underlying market structure is not appropriate in this market. Our approach of observing bidder preferences to determine the market structure is both innovative and insightful. We assume that the number of common bidders on two lots indicates the degree of similarity between the artworks. In other words, we are segmenting the market based on the popularity of the artworks. For example, consider the bid history illustrated in Figure 6.1. It looks like A1 is interested in purchasing lot 25. If she also bids on lots 3 and 6, then in her preference space, lots 3, 6, and 25 are close to each other but far from other lots listed in the auction. Now if other bidders also show an inclination to acquire lots 3, 6, and 25, then these lots are considered closer to each other. If we consider the preferences of all the participating bidders, we will be able to create a perceptual map of lot similarity and dissimilarity. In our analysis, the number of dimensions and the location of the art objects on these dimensions on the perceptual map are derived solely from the preference/choice data of bidders; thus, ours is a kind of internal analysis of the market structure as defined by Elrod and DeSabro and their colleagues (DeSabro and Rao 1986; Elrod 1991; DeSabro et al. 1993).

6.6.1 Method

Using the second dataset from an online auction held in March 2005, we construct a sociomatrix of the artists (instead of the bidders, as in the bidder network). Therefore, in other words, we create an artist network where nodes are two artists and the strength of the link indicates the pairwise demand for these two artists. There are few ways to determine the artist network for the market structure analysis. One of them is to create links between artists whenever a bidder has shown interest in purchasing their works. Considering the purchase intent of all the bidders in the auction, we will be able to form an artist network. This approach is feasible, but it fails to capture the ranges of similarity and dissimilarity among artists in the auction. Another reasonable approach is to assume a dyadic relationship between artists when a bidder posts a bid on their artworks sequentially. Although this approach captures the level of similarity/dissimilarity among the lots, we can further refine the measure by considering the bid time difference of the bidder on these lots. For example, if a bidder bids on the works of two artists within a short period, it is more likely that these two artists are closer in the bidder’s preference space than far apart.

We construct an asymmetric $9 \times 9$ matrix\textsuperscript{13} (Figure 6.9), with each element computed to facilitate the above concept of lot similarity. Taking a conservative measure, we calculate each element $y_{ij}$ in the sociomatrix as the total number of common bidders $y$ bidding on lot $i$ and lot $j$. We perform nonmetric multidimensional scaling (Kruskal 1964) to determine the underlying perceptual map. We further verify the market structure obtained from the previous stage by clustering the lots with the hierarchical clustering technique (Johnson 1967). Once again, we use the popular SNA program Ucinet (Borgatti and Freeman 2002) to perform our analysis.

\textsuperscript{13}Forty-four works of nine artists were auctioned, and 66 bidders participated in the auction.
6.6.2 Results

The resulting perceptual map obtained from the nonmetric multidimensional scaling of the artist sociomatrix (Figure 6.10) shows some interesting patterns of consumer preference for modern Indian art. The map shows that bidders who are interested in purchasing works of J. Swaminathan are not interested in purchasing works of other artists. Works of J. Swaminathan are very different from those of other artists. They are typically low-priced (average price = $19,575) compared to those of other artists (average price = $46,818) and of low value ($27.05/square inch compared to $52.49/square inch) for other artists. We also find that the artist pairs Ram Kumar–M.F. Husain and F.N. Souza–A. Padamsee are plotted close to each other. One reason for such close links is the similar content of these artists. For example, works of Ram Kumar and M.F. Husain are both abstract. Works of
6.7 CONCLUSION AND FUTURE DIRECTIONS

F.N. Souza and A. Padamsee are mostly head shots. We also find S.H. Raza and J. Sabavala to be plotted opposite to each other. Raza's works are mostly painted with bright primary colors, whereas Sabavala's paintings contain light mixed colors. Considering all the works of these artists, we suggest that the dimension of the y-axis is "abstract," where it varies from "figures" (top) to "abstract" (bottom). The x-axis tends to be the realized price of the artworks, with low-priced paintings located on the right and high-priced paintings on the left.

To verify the concluding perceptual map from the nonmetric multidimensional scaling, we cluster the given artist network with a hierarchical clustering technique. The resulting dendrogram (Figure 6.11) not only validated our earlier results, but also provided insights into lot similarity.

6.7 CONCLUSION AND FUTURE DIRECTIONS

This chapter has investigated three vital issues in online auctions. Using the available bid history, we study price dynamics, bidder dynamics, and market structure. We also applied three innovative approaches—FDA, SNA, and multidimensional scaling—to auction data to achieve our goals. Our approach of representing bidding data in the form of a network provides a new paradigm for looking at auction data. From the auction managers' perspective, our analysis addresses some of the concerns they face when organizing a new auction event. These issues can be broadly categorized into three questions: what to sell, how to sell, and to whom to sell.

Before designing new auction events, auction managers need to come up with the item lineup, i.e., what items to sell and how to organize them. Most of the time they have a mixed set of art inventory, which they must use to make their selection. In our price dynamics analyses, we find that a preauction estimate has a positive effect on the price formation process. Since these estimates provide information about item quality, they are highly regarded as value signals by the bidders. The positive effect of this variable suggests that managers may consider auctioning
only high-end items. Unfortunately, they do not have enough control over the available inventory. Most of the time, they also have art items from emerging/less popular artists in their auction lineup. Therefore, the issue of item organization becomes vital in such a situation. We found that the price dynamics of works by established and emerging artists are opposite to each other. This suggests that managers should present works of emerging artists right after those of established artists. This may result in a spillover effect of the high price dynamics of the established artist to the emerging artist, thus increasing the overall auction revenue. Our market structure analyses also provide some practical suggestions for managers. This approach illustrates which artists are similar and which are different based on the bidders' intent to purchase. For example, we find that the artist groups Ram Kumar–M.F. Husain and F.N. Souza–A. Padamsee are similar, thus forming substitutes for each other. The perceptual map (Figure 6.9) will also be beneficial if the managers desire to create theme-based auctions in the future.  

Finally, our study helps managers decide whom to invite to the auction. Before the auction starts, auction houses send a printed catalog and an invitation to all the bidders on their client list. Still, auction managers desire to concentrate on a smaller group of bidders who ultimately play a crucial role in the auction process. Using the results from the analysis of the bidder subgroups, managers can identify the most active bidders, their tastes, and their bidding strategies. This information may also be used to classify different bidders in the auctions.

From the research perspectives, our use of FDA to analyze price dynamics may be extended to develop models to predict final prices in online auctions. Although Wang and her colleagues (2006) have used similar techniques to predict the results of eBay auctions, extending them to include auctions of hedonic items like works of art will be useful. Further, using our approach of determining the dynamics of competitive bidding with a bidder network, future studies can now investigate their effect on price dynamics. One of the important contributions of our chapter is this new approach of examining bidder dynamics. Although we stop short of exploring the effects of these dynamics on price dynamics, future studies should investigate this subject in detail.

We used Bonacich’s Power to determine the aggregate influence level of the bidders. Further investigation may be performed to determine the exact amount of influence of a bidder over another bidder in the auction. Using social network models developed by Hoff (2005) for our bidder framework, we will be able to get such information about bidders, similar to the recent works of Dass and his colleagues (2007b). The concept of value affiliation among bidders (Milgrom and Weber 1982) in auctions of hedonic products like works of has existed art for  

14Although theme-based auctions are not very common in traditional auction houses, recently newly established auction houses such as Osians and SaffronArt have been organizing auctions with specific themes. For example, SaffronArt’s March 2005 auction focused only on nine established artists producing contemporary Indian art. Osians’ November 2006 auction was themed as “Historical Series.”

15Meaning that a high value of a bidder’s estimate makes high values for other bidders’ estimates more likely.
two decades, but there has been no empirical investigation of how such affiliation takes place or how the bidders process the value information during the auction. With our network approach, we can now examine the evolution of a bidder’s valuation. Finally, our use of a traditional multivariate technique to determine the underlying market structure is unique, and more advanced models such as latent structure modeling (Hoff et al. 2002) can be used to obtain more detailed market information.

The studies presented in this chapter provide an alternate way of analyzing bidding data on online auctions. We hope that these studies will motivate other researchers to further our advance understanding of online auctions.

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REFERENCES


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