Dynamic Price Forecasting In Simultaneous Online Art Auctions

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Abstract

The global art market has undergone a huge transition in the last decade leading to the creation of new art hedge funds, art mutual funds, and art online auction sites. The increasing interest in the overall art market has also helped popularize emerging art markets such as Indian contemporary art. In this paper we focus on simultaneous online auctions (SOA) for Indian contemporary art. SOAs sell high-value items in auctions that take place simultaneously and are different from popular individual auctions (e.g. eBay) in multiple ways and in particular in that they induce high levels of competition both within and between auctions. The SOA art marketplace has the promise of extremely high profits but also the risk of high losses if not monitored carefully. Forecasting price during an ongoing SOA is therefore important to auction house managers, who can make real-time decisions and intervene while an auction is in progress. We present a novel dynamic forecasting approach for predicting price in ongoing simultaneous online art auctions. Our model forecasts the price from the time of prediction until auction close and updates its prediction in real-time as the auction progresses based on newly arriving information and price dynamics. We find high predictive accuracy of the dynamic model for a data set of contemporary Indian art SOAs and compare its performance to more traditional approaches. We then investigate the source of the predictive power of price dynamics and find that dynamics capture bidder competition within and across auctions. The importance of this finding is both conceptual and practical: price dynamics are simple to compute at high accuracy, as they require information only from the focal auction and are therefore a parsimonious representation of different forms of within-auction and between-auction competition.

Keywords: *Dynamic Price Forecasting, Functional Data Analysis, Simultaneous Online Art Auctions; Within-auction bidder competition; Between-auction bidder competition*

Introduction

With the growing popularity of online auctions and the increasing number of items sold through them, price prediction has become a vital research topic in recent years. In contrast to earlier studies (Ghani and Simmons 2004; Gneezy 2005) who rely solely on "static" characteristics that are known at the start of the auction (e.g., the opening price, product characteristics, and seller reputation), more recent approaches (Bajari and Hortacsu 2003; Jap and Naik 2008; Wang et al. 2008) attempt to capture the dynamic aspects of the auction process along with the more traditional static components. To that end, Wang et al. (2008) consider the price velocity (or rate of change in price), and Jap and Naik (2008) and Bajari and Hortascu (2003) incorporate the underlying bid distribution into the forecasting process. A common aspect across all of these studies is that they focus on *individual auctions* where auctions for a particular item are held independently of each other and bidders typically bid only on one auction at a time.

Recently, there has been increasing interest in an alternative auction format, commonly known as *Simultaneous Online Auctions (SOA)*, which has become very popular for selling high-priced complementary items such as fine art and collectables. These auctions are held by specialized online auction houses dedicated to selling only one type of item (e.g., SaffronArt.com sells only Indian contemporary art, Attinghouse.com sells only Chinese art and Southeast Asian art) and with a price tag ranging from a few thousands to a few millions of dollars. With such high stakes, forecasting prices in SOAs is crucial to both auction house managers and bidders. A method that can provide information on the *expected* price can help auction house managers make real-time decisions on promotions and invitations during the ongoing auction. It can also help bidders make more informed real-time decisions on items with high expected surplus as the auction is progressing. In this paper, we present a dynamic forecasting model based on Functional Data Analysis (FDA) to predict price of an ongoing auction. Prior studies (Wang et al. 2008) have provided some evidence that dynamics in online auctions matter, and that capturing dynamics leads to improved real-time forecasting. Our first question addresses the role of price dynamics in forecasting SOA prices and how it differs from the individual-auction case. The second question is one that no previous study has addressed: What are the *sources* of price dynamics? In this study, we investigate why incorporation of dynamics results in superior prediction, and in particular, we examine the role of bidder competition and its relation to price dynamics. This is done in the context of simultaneous online fine art auctions, where two types of bidder competition are salient: competition within one auction and competition across different auctions.

SOAs are different from the auctions held on popular auction sites such as eBay, both in terms of the auction design and the types of items that they sell. SOAs sell multiple objects simultaneously in a first-price ascending auction format. This means that auctions start and end at the same time for all items. Since many items are highly complementary, bidders are typically interested in purchasing more than one item at a time. As a result, bidders frequently compete against each other, not only within the same auction (i.e., for the same item), but also across other auctions that sell complementary items, which leads to unique bidding dynamics (Rothkopf 1977). In contrast, items on eBay are sold in a variant of the second-price sealed-bid auction (Krishna 2002) and are held independently of each other. On eBay bidders are rarely observed to consciously compete against each other across different auctions that take place simultaneously, as it is unlikely that bidders will have similar product demand and even if they do, it is highly implausible that they will compete for the same item, as products in eBay typically have multiple listings. Moreover, eBay now masks bidder identities thereby eliminating the ability of bidders to identify competitors across auctions. Another difference between eBay auctions and SOAs is the type of closing rule. While eBay has mostly fixed hard-closing times, SOAs tend to have soft-closing times where the time automatically extends after a late bid. A soft-close auction format not only encourages bidders to bid early (Roth and Ockenfels 2002), but also discourages *sniping*[1] in the last moments. Finally, SOAs are organized by only one seller, i.e. the auction house, whereas eBay provides an auction platform for many different sellers.

Real-time price forecasting in SOAs such as online art auctions is beneficial to both the auction house and the bidders for several reasons. For the auction house managers, accurate and real-time forecasts allow often necessary adjustments during the ongoing auction such as inviting additional bidders or running promotions to attract more bidding activity. Typically, online art auctions are held for three days and, as a consequence, auction house managers have an opportunity to actively intervene in the auction process by running promotions or by calling additional bidders who may have an interest in the art and who are likely to influence the auction process based on their behavior in previous auctions (Dass et al. 2007). Individual bidders also benefit from real-time price forecasts. For example, auctioned items can be dynamically ranked based on their forecasted price, from lowest to highest surplus for the bidder (Ghani and Simmons 2004; Wang et al. 2008). Such rankings can help bidders to focus on items that are within their budget and/or maximize their expected surplus.

Price forecasting in online auctions and particularly in SOAs is challenging due to their dynamic environment. One aspect of this environment is the changing bid density, where the number of bids per unit time changes dramatically throughout the auction (Roth and Ockenfels 2002; Russo et al. 2008). The resulting unequally-spaced time-series of bids deem traditional

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

forecasting models (which assume evenly spaced measurements) inadequate. Furthermore, price dynamics across different auctions follow different price paths. In other words, the speed at which the price travels during the auction and the rate at which this speed changes varies across auctions. Therefore, traditional forecasting models, which do not account for such instantaneous change, fail to accurately predict auction prices. To incorporate the dynamic nature into a forecasting model, we take a functional data modeling approach.

Functional Data Analysis (FDA) is an emerging statistical methodology that operates on functional observations such as the price curves in online auctions. While FDA has received a lot of enthusiasm within the statistics literature, it is only slowly entering the marketing literature. Only recently, Sood, James and Tellis (Sood et al. 2007) have proposed an FDA-based model as an alternative to the Bass model for predicting market penetration of new products. Foutz and Jank (Foutz and Jank 2007) use an FDA-based method to early and dynamically forecast box-office success by analyzing the trading shapes from online virtual stock markets. In online auctions, FDA has been shown to be useful as a graphic tool for advanced data visualization of electronic commerce data (Jank et al. 2008) and as a mechanism to capture price dynamics in online auctions (Bapna et al. 2008; Jank and Shmueli 2006). In this paper, we employ FDA to capture the dynamic components of an SOA and to build a real-time forecasting model for price. We follow the approach in Wang et al. (2008) and incorporate price dynamics in addition to other available information into the forecasting model. The underlying idea is to represent the price path during an auction as a continuous curve that describes the price formation process. Then, following functional principles, we "recover" (i.e., estimate) the price curves of individual auctions using smoothing techniques (Ramsay and Silverman 2005). From the price curves, we then obtain estimates of the *price dynamics* via first and second derivatives. The price curves and price dynamics are subsequently incorporated into the forecasting model to produce the real-time price forecast.

In this study, we develop several Dynamic Forecasting Models, DFM-I and DFM-II, to predict price in an SOA. The first model (DFM-I), incorporates both the price path until the time of prediction and the price velocity information until the time of prediction, whereas the second model (DFM-II) considers only the price path until the time of prediction. Both models also include static pre-auction information, but neither directly incorporates bidder competition information. We later supplement these two models with direct measures of bidder competition to create DFM-III and DFM-IV in order to study the relationship between price dynamics and competition. We investigate the predictive performance of all models to uncover the source of price dynamics. We compare the dynamic models with two additional models: one that predicts the final price based only on static pre-auction information (STATIC) and another that is a simple dynamic model (DFM-0) as it includes only price at the time of prediction in addition to static information. Comparing the mean absolute percentage error (MAPE) of all models on a holdout set, we find that DFM-I outperforms all competing models in terms of predictive accuracy. Thus, our first conclusion is that, like in individual-auction forecasting, price dynamics, and in particular the price velocity, has a major impact on forecasting price in SOAs. We also conclude that the dynamic forecasting model DFM-I is flexible and powerful to capture very different types of price dynamics, and that it can be used in a wide range of auction formats.

Our second goal is to investigate the origin of the predictive power of price dynamics. Prior studies (Ariely and Simonson 2003; Heyman et al. 2004; Ku et al. 2005) suggest that bidder emotions play a significant role in the formation of auction dynamics. Such emotions result from rivalry (or competition) among bidders to acquire the item (Ariely and Simonson

2003) and thus affect auction dynamics. Therefore, we expand our study to analyze the relationship between bidder competition and auction dynamics. In SOAs, bidders compete both within an auction as well as across multiple simultaneous auctions. This results in two types of bidder-competition, namely, within-auction competition and between-auction competition. We derive new metrics for measuring within- and between-auction bidder competition and examine the performance of the resulting forecasters (DFM-III and DFM-IV) in the presence of directly observed bidder competition information. Compared to the advantage of DFM-I over DFM-II, we find that the difference in predictive performance between DFM-III and DFM-IV vanishes, suggesting that dynamics essentially proxy for competition. That is, both DFM-III and DFM-IV predict price equally well compared to DFM-I, which implies that a forecaster with *direct* bidder competition information is equivalent to its counterpart using only a *proxy* based on price dynamics. The practical implication of this finding is that price dynamics can provide a simple and parsimonious measure for the competitive nature of online marketplaces. It is simple because it only requires the information from within the focal auction; it is parsimonious because it summarizes many different forms of competition between auction participants in one single measure.

The importance for the marketer is that a single, simple measure captures many different, important pieces of information. This is very similar to other forecasting situations where a simple but powerful measure significantly enhances the predictive capability of a model. A recent example is Bell’s, Koren’s and Volinsky’s (Bell, Koren and Volinsky, 2008) use of a parsimonious latent factor structure to predict the choice of *Netflix* customers – and in doing so outbeating several hundred competitor models.

We further examine this phenomenon using another formulation, where we condition the forecasting model on the level of competition. This is done by splitting auctions into 4 segments based on different levels of within-auction and between-auction competition. Once again, we find that the effect of dynamics vanishes after controlling for bidder competition, suggesting that dynamics effectively capture bidder competition in SOAs.

This paper discusses several important practical issues for the marketer. First, we present an innovative and powerful approach for generating real-time forecasts in dynamic environments. Second, we propose a simple and parsimonious measure vis-à-vis dynamics that effectively captures different forms of customer competition. We study the "connected customer" in the virtual world, and in particular how connectivity results in competition within and across auctions. These issues have been identified as top MSI research priorities[2].

The rest of the paper is organized as follows. First, we describe the mechanism of simultaneous online art auctions and in particular that on SaffronArt.com. We also describe and explore our available data. Second, we derive and estimate the dynamic forecasting models and discuss the results. Third, we define and incorporate bidder competition information into the forecasting models and study their relationship with price dynamics. We conclude with answers to our two research questions as well as managerial implications and future directions.

Simultaneous Online Art Auctions

During the last decade, the world art market has gone through a tremendous amount of transition. Reports of better return on investment on art items (Mei and Moses 2002) as compared to stock markets have encouraged the establishment of many new art hedge funds and mutual funds. They have also encouraged new bidders and art enthusiasts to attend auctions with

[2] http://www.msi.org/research/index.cfm?id=43

an intention to buy art items that they can enjoy and that can generate profit over time. According to Artprice.com, art prices have seen a growth of 80% during the last decade (1997-2007). The increasing interest in the overall art market has also helped popularize emerging art markets such as Indian contemporary art, Chinese art, and Russian art to new collectors and investors.

Another prominent change in the art marketplace is the emergence of online auction houses like SaffronArt.com and Attinghouse.com, which specialize in selling only one particular genre of art. These auction houses sell high quality, genuine art work comparable with the ones sold by the traditional auction houses such as Christie's and Sotheby's. These online art auctions use a simultaneous auction format, which is popular when selling a wide range of high-priced items. Examples are FCC radio spectrum auctions (Milgrom 1998), U.S. treasury bills auctions (Rothkopf et al. 1998), and timber and car auctions (Kwasnica and Sherstyuk 2007).

For this study, we collected the bid histories of auctions held on SaffronArt.com in December 2005. The auctions lasted three days and 196 art items were sold. All auctions started at the same date and time, but their closing times were sequential in the following way: Auctions were divided into 8 groups, with each group consisting of 20-30 auctions. After the third day, all auctions belonging to the same group closed simultaneously, but each group closed sequentially, typically within 30 minutes from the previous group. This gives bidders an opportunity to counter any late bids if they are competing in multiple groups of auctions. Bidders interested in participating in SaffronArt.com auctions are required to go through an elaborate registration process. Unlike on eBay, where bidders merely need a valid email address and credit card, bidders on SaffronArt.com go through a lengthy credit check and they are required to provide names of references. Such a lengthy enrollment process increases participation of serious bidders.

Like Christie's or Sotheby's, SaffronArt.com examines items that are offered to them by individual owners and then sells the items on the owners' behalf. Since the complete auction is held online, the auction house arranges live viewing events prior to the auction date where bidders are invited to attend and inspect the paintings in person. This increases the legitimacy of and trust in the auction process.

SaffronArt.com exclusively sells Indian contemporary art. In the following, we briefly discuss the importance of Indian contemporary art to the entire art market.

Indian Contemporary Art

Indian contemporary art, with over $100 million in auction sales in 2006, is one of the leading emerging art markets in the world. Although traditional auctions for contemporary Indian art have existed since 1995, it is only since 2000[3] that the market has exploded, with prices growing at a brisk 68.7% annually. In 2006, online auction sales of contemporary Indian art from SaffronArt.com ($36.76 million) had more sales (of contemporary Indian art) than the traditional auction houses like Sotheby's ($35.29 million) and Christie's ($33.08 million). Further, SaffronArt.com sold more art items (537) than Sotheby's (484) and Christie's (329) in that year. This trend has been consistent over the years. For example, in 2005, online auction sales of contemporary Indian art by SaffronArt.com were $18.06 million, more than that of Sotheby's ($10.49 million) and Christie's ($14.89 million). SaffronArt.com also sold more art items (390) compared to Sotheby's (276) and Christie's (248) in 2005. The top ten Indian artists sold 31% of the overall lots and contributed to 57% of the total value realized at the auction site since 1995 (Reddy and Dass 2006). Two of these artists are now ranked in the top 100 artists in the world based on their auction sales in 2005. A new set of emerging artists (the new trendsetters,

[3] Coincidentally, this is the year when SaffronArt.com, the source of our data, started its online auctions of Indian contemporary art.

typically born after 1955) have contributed 2% in value and 3% in items and are becoming increasingly popular, commanding ever higher prices.

Data Used in This Study

Like other online auction houses, SaffronArt.com posts detailed bid histories of items for sale on their website during periods when auction is in progress. A snapshot of a bid history is shown in Figure 1. The bid history includes information on each submitted bid, its time, amount and the bidder's ID. Apart from the bidding activity information, each bid history also includes information about the item: name of the artist, physical characteristics of the item (size and media), pre-auction estimates, the item's expected value based on analysis by auction house art experts, and provenance of the item. The auction house also provides information about auction results of previously sold comparable items by the same artist. A snapshot of the item listing is provided in Figure 2. Since the items are of high value, the auction house tries to provide as much information about the items as possible in order to help bidders make rational bidding decisions. Additional information about the auction format, general bidding rules, and the closing schedules is also provided by the auction house.

Insert Figure 1 and Figure 2 about here

SaffronArt.com organizes anywhere from three to five auction events per year. In each of these events, they typically sell 100 to 200 contemporary Indian paintings and sculptures. Although the bid history is posted online *during* the auction, it is promptly removed as soon as the auction closes and there is no way of revisiting it afterwards (unlike eBay where information is stored for 15 days after an auction closes). This policy complicates the data collection task. To overcome this obstacle, we developed a java-based web agent that visits the bid history during the very last moments of the auction and that captures the entire information automatically. Since the auction is extended after a late bid, our web agent is able to capture all of the bid history without losing any information.

For this study, we collected data from auctions held in December 2005. In these auctions, 196 art items (lots) from 70 different artists were sold. 256 bidders participated, posting 3042 bids. The average number of bids per lot is 15 and the average number of bidders participating in an auction is 6. The average value realized for all 196 items is $56,233, ranging between $3,135 and $1,486,100. Other descriptive statistics of the data are shown in Table 1.

Insert Table 1 about here

Bidder Competition in Simultaneous Online Auctions

Bidder competition in art SOAs is different from eBay auctions as bidders compete against each other not only within an auction, but also across auctions. Therefore, bidder competition in simultaneous online auctions can be defined in two ways. The first type of competition is the rivalry-intensity level between two specific bidders for the same item, and thus is termed *within-auction competition.* The second type of bidder competition is the level of the rivalry between bidders across different auctions, and is thus termed *between-auction competition* (Dass et al. 2007).

Operationally, we compute within-auction competition between two bidders as the maximum number of sequential pairs of bids between two bidders. For every auction, we first determine the unique pairs of bidders j, k participating in the auction. Then for each of these bidder pairs, we count the number of times the two bidders bid sequentially n_{jk} (e.g., A→B→A). The maximum number of sequential bid pairs denotes the within-auction competition. Therefore, within-auction competition *(wa)* for auction *i* is given by

$$wa_i = \max\left(n_{jk}\right) \text{ for } j = 1\cdots B_i - 1, \text{ and } k = j + 1\cdots B_i \tag{1.1}$$

where B_i denotes the number of bidders in auction *i*, n_{jk} the number of sequential bids between bidder *j* and bidder *k*.

Consider the example shown in Figure 1: There are five bidders participating in the auction. Therefore, we have $\binom{5}{2}$=10 unique bidder pairs. For each of the 10 pairs, we compute the number of times two bidders bid sequentially and compute the maximum value of all pairs. In the case of Figure 1, the within-auction competition equals 3. We use the maximum value as our measure because heated rivalry between a specific pair of bidders can induce higher bidder dynamics in the entire auction (Ariely and Simonson 2003; Heyman et al. 2004)[4].

In contrast to within-auction competition, between-auction competition measures the competitive reach of a bidder pair across several auctions. Like for the previous measure, we first determine the number of unique bidder pairs. Then, for all bidder pairs, we count the number of auctions in which the pair is competing simultaneously. The between-auction competition for a certain auction is the average of this number across all pairs. Therefore, between-auction competition *(ba)* for auction *i* is given by

$$ba_i = \sum_{j=1}^{B_i - 1} \sum_{k=j+1}^{B_i} cl_{jk} \Big/ N_i \tag{1.2}$$

where B_i denotes the number of bidders in auction *i*, cl_{jk} the number of common auctions bid by bidders *j* and *k*, N_i the number of bidder pairs in auction *i*.

[4] We also analyzed within-auction competition as the average value across all the bidder pairs. Results from that analysis are similar to those obtained using the maximum value.

For example, consider auction #36 in Figure 3. There are 4 bidders participating in the auction leading to $\binom{4}{2}$=6 unique pairs of bidders. Considering only the three auctions displayed in that Figure (#36, #39 and #43), we find that the total number of auctions bid simultaneously by the bidder pairs Anonymous118-Anonymous3, Anonymous11-Poker, Anonymous118-Kyozaan, Poker-Kyozaan, Poker-Anonymous3 and Kyozaan-Anonymous3 are 1,1,1,2,1, and 1 respectively. Therefore, the between-auction competition for auction #36 is 1.167 (=7/6).

Insert Figure 3 about here

Earlier studies on online auction competition have considered bidder rivalry as a component influencing bidding dynamics during the auction (Ariely and Simonson 2003; Heyman et al. 2004). They showed that such rivalry increases bidders' quasi-endowment feeling and escalates their commitment towards the item, thereby leading to a phenomenon called "auction fever.[5]" Since these studies focus on eBay and eBay-like individual online auctions, they do not consider between-auction rivalry. Our paper extends this literature by considering bidder competition which goes beyond the rivalry within a single individual auction and looks in addition at competition across simultaneous auctions.

In the next section we describe a general dynamic forecasting model that incorporates price dynamics in addition to other auction-related information. The model, whose principles are outlined in Wang et al. (2008), does not incorporate bidder competition directly. After applying its ideas to the SOA context, we use it to study the relationship between bidder competition and price dynamics. We will show that introducing bidder competition into the model directly makes price dynamics redundant. This, in turn, supports the relationship between within-auction rivalry

[5] Auction fever is an emotional phenomenon where bidders become irrational in their bidding decision and bid higher than what they would normally pay for the item.

and bidding dynamics found by Ariely and Simonson (2003) and Heyman et. al (2004). Moreover, it also extends their results to between-auction rivalry.

Dynamic Price Forecasting

Prior research on price forecasting in online auctions is limited and has mostly focused on predicting the final price of items using *static* or *pre-auction* information. For example, Ghani and Simmons (2004) use data-mining techniques to predict the final price in eBay auctions using only information available at the outset of the auction such as the opening price, product characteristics, and seller reputation. Their model therefore does not account for new information arriving during the ongoing auction. Bajari and Hortascu (2003) recover the bid distribution using a structural modeling technique, but they too only predict the final price. And finally, Gneezy (2005) uses step-level models of reasoning to predict the auction outcome, but like others, does not account for the dynamics during the auction. Only two recent studies dynamically forecast price in online auctions. Jap and Naik (2008) develop a method to estimate dynamic bidding models in online corporate procurement reverse auctions. Wang et al. (2008) (referred to as WJS from hereon) build a dynamic forecasting model using FDA. In both studies, the models are designed for individual auctions such as those on eBay. Our forecasting model builds upon the WJS approach and adapts it to the SOA setting.

Model Formulation

Following WSJ, our model consists of an initial step of recovering (or estimating) the underlying price curves and their dynamics from the observed bid histories. Since bids arrive at unevenly spaced time intervals, we need the flexible FDA approach to approximate a continuous underlying price curve and its first order derivative (i.e. the rate of change in price, or *price-velocity*). This is done by using monotone smoothing splines (Ramsay and Silverman 2005;

Simonoff 1996) in order to guarantee price curves that are continuous and monotonically non-decreasing. See Appendix A for further details on the curve recovery step. The smoothed price curves and their first derivatives (i.e., price velocity) for our 196 auctions are shown in Figure 4. The average price and price velocity plots show that the price formation is fast at the beginning and near the end of the auction. Also note that the average price velocity (i.e., the rate of change in price) nearly doubles towards the end of the auction compared to the beginning of the auction.

Insert Figure 4 about here

After creating smooth price curves and their dynamics, we use these components as the basis for our dynamic forecasting model. Our model contains 3 conceptually different pieces of information: static pre-auction and time-varying information, price path, and price dynamics information. We later supplement it with a fourth piece, which is bidder competition. The dynamic forecasting model of price at time t $(y(t))$ is given by Wang et al. (2008) as:

$$y(t) = \alpha + \sum_{i=1}^{Q} \beta_i x_i(t) + \sum_{j=1}^{J} \gamma_j D^{(j)} y(t) + \sum_{l=1}^{L} \eta_l y(t-l) + \varepsilon(t) \qquad (1.3)$$

where $x_1(t),...,x_Q(t)$ is a set of static (pre-auction) and time-varying predictors, $D^{(j)}y(t)$ denotes the j^{th} derivative of price at time t, and $y(t-l)$ is the l^{th} price lag. The static predictors, which do not change over the course of the auction, include the opening bid, item characteristics (size of the item and type of art work), and artist characteristics (artist type, average price per sq. inch of the artist's sold items in the previous year's auction); see also category 1a in Table 2. Time-varying predictors, which do change as the auction progresses, include the number of bids (see category 1b in Table 2). Note that although WSJ did not directly include bidder competition information in their model, the model in (1.3) is flexible enough to incorporate any type of static, time-varying, or dynamic component. A brief description of all model-components is given in Table 2. We perform two sets of analysis with the above predictors. In the first set, our model follows WJS closely and does not use the competition covariates; in the second set, we introduce the two competition variables into the DFM-I, DFM-II models to create DFM-III and DFM-IV.

Insert Table 2 about here

Using equation (1.3), the resulting *h-step ahead* forecast, given information until time T, is given by

$$\tilde{y}(T+h\,|\,T)=\hat{\alpha}+\sum_{i=i}^{Q}\hat{\beta}_i x_i(T+h\,|\,T)+\sum_{j=1}^{J}\hat{\gamma}_j\bar{D}^{(j)}y(T+h\,|\,T)+\sum_{l=1}^{L}\hat{\eta}_l\tilde{y}(T+h-1\,|\,T) \quad (1.4)$$

As explained in WSJ, equation (1.3) faces two challenges that need to be addressed. First, the price dynamic components $D^{(j)}y(t)$ are coincident indicators, and therefore must be forecasted prior to their use in equation (1.4). The solution in WSJ is to forecast price dynamics using a polynomial-trended linear regression model with static and time-varying predictors and autoregressive (AR) residuals. It is of the form:

$$D^{(j)}y(t)=\sum_{k=0}^{K}a_k t^k+\sum_{i=1}^{P}b_i x_i(t)+u(t) \quad (1.5)$$

where $t=1,2,...T$ and *u(t)* follows an AR model of order R.

Once this model is estimated from a training set, it can be used to forecast price dynamics of a new ongoing auction. See Appendix B for further details.

The second challenge with the forecasting model in equation (1.3) is that the static predictors do not change during the auction, i.e. they are independent of time *t*, and therefore their estimated coefficients are confounded with the price function. The solution in WSJ is to transform the static variables into time varying predictors by considering each static variable's impact on the price evolution. This is done by fitting a functional regression model of price on each of the static predictors and then using their resulting time-varying estimated coefficient as a time-varying predictor in equation (1.3). See Wang et al. (2008) for further details.

Two Dynamic Forecasting Models (DFM-I and DFM-II)

With the above general approach, we build two Dynamic Forecasting Models (DFMs). DFM-I consists of the static, time-varying, current price and dynamic components 1-3 in Table 2 and is therefore equivalent to eq. (1.4). The two price components that we include are the price curve and its first derivative (i.e. price velocity). For the purpose of investigating the specific role of price dynamics, we also consider DFM-II, which uses the same information as above, except for the price velocity (i.e. only components 1 & 2 from Table 2). Comparing DFM-I and DFM-II allows us to assess the importance of price dynamics in the SOA price prediction process.

. ***Benchmark Models***

In order to benchmark the performance of our dynamic models DFM-I and DFM-II, we consider a competing static model (STATIC) that includes only pre-auction information (i.e. only component 1a from Table 2) via a linear regression model on price (e.g. Lucking-Reiley 1999), and a simple dynamic model (DFM-0) that includes the price at the time of prediction in addition to the static information (i.e. components 1a & 2 from Table 2).

Model Estimation and Evaluation

In order to test and compare the performance of the different models, we randomly partition our data into a training set (70% or 137 auctions) and a holdout set (30% or 59 auctions), where the training set is used to estimate the model, and the holdout set is used to measure predictive accuracy. For the DFM-I and DFM-II models, the training set is used for fitting price curves, for estimating the dynamics prediction model (equation 1.5), and for estimating the final forecasting model. The STATIC and DFM-0 models are estimated using the same training set. Note that the training set consists of auctions that are fully observed between the start and end; in contrast, auctions in the validation set are only partially observed, i.e. information is only available until time T, the time at which a forecast is desired. T is flexible and can be set by the user.

Since our art auctions are 3-day long, our intention is to forecast the price of an ongoing auction early enough so that the auction house managers can take action and potentially intervene, and that bidders can decide which items to concentrate on in each auction. Therefore, we forecast the price during the last T=18 hours prior to the closing of the auction. We also assess the robustness of our model to the different choices of T. We discuss the results in the next section.

Results

Estimated Models

The estimated coefficients for the STATIC and the DFM-0 models are given in Table 3. As the primary goal of this paper is predictive, our main emphasis is on the forecasting performance of the different models, rather than on inference. From Table 3, we see that three static predictors are significant both in the STATIC and DFM-0 models (at the 1% level): opening bid, previous auction history of the artist, and size of the art item. The effect of these static predictors on the final price has already been shown in prior research. In particular, the positive effect of the opening bid reflects the direct relation between an item’s value and the choice of the starting price. This is in accordance with findings from prior studies (Bajari and Hortacsu 2003; Czujack et al. 1996). The negative effect of an artist’s previous year’s values on this year’s price could imply that bidders are looking for “bargains” (i.e. artists that had low values in the previous year) and are willing to bid rather aggressively for them. Finally, the negative effect of the size of the art works on price is in accordance with the findings of Czujack et al. (1996). We also find the current price to have a positive and significant impact in the DFM-0 model.

In the dynamic models we have time-varying coefficients and static variables that were transformed into time varying predictors via functional regression weighting. This impact of each of the predictors can now be assessed at different times of the auction. Figure 5 displays the time-varying *coefficient-curves* (together with associated confidence bands). The results show that size has a significant negative effect only at the end of the auction. This indicates that smaller art objects are more expensive than the bigger ones in accordance with the findings of Czujack et al. (1996) and that bidders take this into consideration more consciously towards the auction-end. We also find the current number bidders to have an initial significant positive effect, suggesting that high initial bidder participation is a strong signal for price. Previous auction history is found to have an initial negative effect, but becomes positive as the auction progresses. This indicates that while bidders may be shopping for "bargains" early on, as the auction comes to a close they trust more artists that have previously done well. Finally, we find that opening bid has an initial positive effect that later switches to a negative effect at the auction end. This finding is similar to that of Reddy and Dass (2006) and suggests that bidders initially draw information from the opening bid, but then gradually discount this information as more signals come in from competing bidders.

In what follows, we discuss the impact of the other variables in the dynamic forecasting model. Recall that the model for *price velocity* is a linear regression model with quadratic trend (K=2) and three static predictors. Figure 6 illustrates the accuracy of the price velocity prediction for four randomly selected auctions (#12, #26, #39 and #54). For each of these auctions we see that the true and forecasted price curves are close for all but auction #39, where the velocity is under-predicted.

Insert Table 3, Figure 5a, Figure 5b and 6 about here

Forecasting Performance

Since our main goal for modeling is generating accurate price forecasts, we evaluate and compare the different models in terms of their predictive accuracy. To that end we use the mean absolute percentage error (MAPE) computed on the holdout set. MAPE is computed here as the difference between the forecasted curve and the true curve. The MAPE values for all four models (DFM-0, DFM-I, DFM-II, STATIC) are shown in Figure 7. Recall that we observe the first 75% (or 54 hours) of the 3-day auction, and forecast the last 25% (or 18 hours). We see that DFM-I and DFM-II outperform DFM-0 and STATIC, but that DFM-I (which includes price velocity) is by far the best of all four forecaster. Figure 8 shows price forecasts for the same four auctions as in Figure 6, using only DFM-I. We see that while the velocity (Figure 6) is forecasted very accurately for auction #12, its price is not. More importantly, we can see that DFM-I accomplishes dynamic and real-time forecasts, and "customizes" its forecast for each individual auction, depending on that auction's dynamic environment.

Insert Figure 7 and Figure 8 about here

Bidder Competition and Price Forecasting

The previous results show that dynamics matter and that they result in a superior forecaster. An important yet unanswered question is *why* dynamics lead to better predictive performance. To study this question and in particular the relationship between price dynamics and bidder competition, we incorporate direct measures of bidder competition into the dynamic models DFM-I and DFM-II. This results in two new models DFM-III and DFM-IV, respectively[6]. Under the hypothesis that bidder competition is one of the main forces behind price dynamics, we expect that the inclusion of direct bidder competition information will mitigate the effect of price dynamics. In other words, DFM-III will lose its advantage over DFM-IV. We incorporate bidder competition into the forecasting model in two different ways: One approach is to incorporate the within- and between-auction competition measures directly into the models as additional time-varying predictors. The second approach is to segment the auctions by competition levels and then estimate models separately within each segment. The results from both approaches are consistent, indicating that price dynamics proxy for bidder competition. We describe the results for each of these approaches next.

Bidder Competition as Time-varying Predictors

We repeat the estimation process described earlier and now include the two bidder competition measures (category 4 in Table 2) in the dynamic models DFM-I and DFM-II to create DFM-III and DFM-IV. Qualitatively, the resulting estimated coefficients are all very similar except for one important difference: comparing DFM-I and DFM-III in Figure 5b (top left panel), we see that dynamics, which are highly significant in DFM-I, become less significant in the presence of the direct competition predictors (DFM-III). In other words, price dynamics appear to carry the same information about price as bidder competition, i.e. they act as a proxy. Moreover, examining the estimated coefficients of bidder competition (bottom panels of Figure 5b), we find that the inclusion of dynamics (DFM-III) reduces the size of the competition-effect

[6] Correlation (Within-auction, Between-auction) = 0.1909, Correlation (Within-auction, Price Dynamics) = -0.1081 and Correlation (Between-auction, Price Dynamics) = -0.0380.

by a factor of almost 10, which is another indicator that both components carry similar information.

Figure 9 (similar to Figure 7) compares the predictive accuracy for all models (now including DFM-III and DFM-IV). We see that the initial advantage of DFM-I over DFM-II due to price dynamics (Figure 7) vanishes when including direct measures for competition (i.e. DFM-III vs. DFM-IV). In other words, the inclusion of competition mitigates the impact of price dynamics. Further, we find that both DFM-I, DFM-III and DFM-IV perform equally well. However, note that DFM-I is conceptually simpler and more parsimonious compared DFM-III and DFM-IV: it is conceptually simpler because it only requires information on the focal auction (i.e., an estimate of the price dynamics); in contrast, the other two models require information on the focal auction (i.e. within-auction bidder competition) as well as on all other simultaneous auctions (i.e. between-auction bidder competition). While conceptually simpler, it is also operationally easier to compute measures only from within the focal auction, compared to monitoring and measuring all other, simultaneous auctions. Another advantage of the use of dynamics is parsimony. In order to capture price dynamics, we only need one additional predictor. In contrast, bidder competition requires two predictors, and might even require further predictors in other types of auctions, such as eBay, which sells a much wider variety of items, over a much longer period of time.

Insert Figure 9 about here

Bidder Competition as a Conditioning Variable

To evaluate the relation between bidder competition and price dynamics from another angle, we extend our investigation by splitting the 196 auctions into 4 competitive segments based on their level of within-auction and between-auction competition. To that end, we split our dataset into four parts based on low-high[7] values of the within-auction (wa) and between-auction (ba) competition and then estimate the forecasting models separately within each segment. Summary statistics for each of the segments are given in Figure 10. The average price-path and price-dynamics (Figure 10) support prior empirical findings (Dass et al. 2007)[8] that suggest that high between-auction competition has a negative effect on the auction outcome as they result in a slower price growth than other types of auctions. In contrast, the average price curve for low between-auction competition steadily increases throughout the auction with a dramatic increase near auction-end.

Insert Figure 10 about here

In each of the four segments we randomly partition the auctions into a training set (70%) and a validation set (30%) and estimate the models DFM-0, DFM-I, DFM-II and STATIC as described earlier. The predictive accuracy for each of the four segments (Figure 11) shows that, as in the combined dataset (Figure 7), DFM-I and II outperform DFM-0 and STATIC. But unlike the results for the combined dataset, for each segment the advantage of DFM-I over DFM-II vanishes. This further supports our above conclusion that, when explicitly controlling for competition, the predictive power of price dynamics are mitigated.

In summary, we control for competition in two different ways: by including competition predictors directly into the forecasting model and by segmenting auctions based on their competitive landscape. In both cases, we observe that the power of price dynamics is mitigated

[7] To classify each item as low-high level of bidder competition, we first create the scatter plot of the two types of competition and took the natural separation line for the measures. The separation value for within-auction competition is 2.94 and for between-auction competition is 6.

[8] Dass et. al attributed this phenomenon to tacit collusion among bidders.

in the presence competition. We therefore conclude that price dynamics effectively proxy for competition in art SOAs.

Insert Figure 11 about here

Robustness of the Dynamic Forecasting Models

As pointed out earlier, we forecast the last T=18 hours for our art auctions. In practice, to the desired forecast period can be shorter (T > 18 hours) or longer (T < 18 hours). Intuitively, the forecast accuracy should decrease the further into the future we forecast. In the following, we investigate how our forecasting models are affected by varying the forecasting time T.

In particular, we compare the following scenarios: forecasting only the last 7 hours prior to the end of the auction (10% time remaining), the last 11 hours (15%), 14 hours (20%), 22 hours (30%) and 29 hours (40%). For each of these time periods, we proceed exactly as in Figure 7 or 9. The results are shown in Figures 12 and 13. We find that the predictive accuracy is nearly unaffected by T, and in particular, that the dynamic models always outperform the static model. Moreover, DFM-I is predominantly better than DFM-II, which speaks to the importance of dynamics throughout the entire auction.

Insert Figure 12 and Figure 13 about here

Conclusion and Future Direction

During the last two decades, the art market has become one of the most dynamic markets in the world, posting 25.4% growth annually (ArtPrice 2006). In 2006, global public auctions (which constitute only 20% of the overall art market) fetched $6.4B. The remaining 80% of the market is dominated by private dealing and sales through art exhibitions which are expected to result in a total market capacity of $50B. Indian contemporary art, the context of our study, is one of the most dynamic segments of the art market with a growth of 480% during the last 10 years. As a dynamic art movement, it is now in fourth position, just behind English Pop Art (ArtPrice 2007). Indian artists have also enjoyed the sharpest inflation during the last 10 years. For example, a $100 investment in the works of the prominent Indian artist Francis Newton Souza would have fetched an average of $7,227 in 2007. Such dynamics in the market place create a burning need for art investors, collectors, and auction houses for better price prediction tools.

Using functional data analysis, we propose an innovative forecasting model for ongoing simultaneous auctions and use it to predict auction prices in real-time. We also compare our dynamic model with competing approaches and show that dynamics matter and result in superior predictive capabilities. We also investigate the source for the predictive power of dynamics and find that dynamics essentially proxy for bidder competition. One practical implication of this finding is that dynamics which are conceptually simpler to obtain than direct measures of competition, result in a more parsimonious model for competitive marketplaces.

Considering the higher stakes associated with online art auctions, our forecasting model gives added power to both auction house managers and bidders. For auction house managers, knowing the expected final price early enough gives them sufficient time to run promotions or call specific bidders to participate. It also provides them valuable insights regarding what combinations of items generate higher dynamics in simultaneous art auctions. For bidders with budget constraints, our models provide vital information regarding the items which are within their budget or provide them with the largest surplus. In these art auctions, most bidders participate with a desire to purchase more than one art object. Therefore, our forecasting model provides a tool for selecting complementary art items that are more affordable. Finally, our model can be used to build a dynamic price estimation system. Auction houses provide pre-auction estimates for their auctioned items. These values are computed by experts, curators, etc. Using our model, they can supplement the expert estimates with data-driven estimates, thereby providing richer pre-auction information. Moreover, using our dynamic forecaster, the initial estimates can be dynamically updated during the auction, thereby providing bidders with more up-to-date information. This can make the auction process more transparent.

Although our initial model is based on the approach developed by Wang, Jank and Shmueli (2008), we improve upon their work in two important ways. First, we apply their dynamic forecasting framework to the simultaneous online auction context where high-end art items are sold, ranging from a few thousands to a few millions of dollars. Finding that the dynamic forecasting framework is useful beyond individual-auction eBay-type auctions is important, as it shows the strength and flexibility of this dynamic forecaster. Second, we show that price dynamics that are represented by functional objects in fact capture bidder competition. This provides an explanation to why dynamics matter and how to interpret them in an online auction context.

Online auctions are becoming a popular marketplace for high-priced products such as fine art and collectables. Still, not enough work has been done to understand how price is formed and how that can be related back to bidder behavior. To the best of our knowledge, our paper is the first to investigate and predict price dynamically in such high end auctions. We hope that this research will encourage further investigation on bidder competition and price dynamics in the online auction setting.

Appendix A: _Estimating Price Curves from Observed Bid Histories_

Data Pre-Processing: The first step is to recover a smooth price curve from the observed bid history. This recovery stage often needs to be preceded by data preprocessing. Let $y_i^{(j)}$ denote the bid placed at time t_{ij}. To better capture bidding activity at the beginning and near the end of the auction, we transform the bids into their log score. Next, we linearly interpolate the raw data and sample it at a common set of time points $t_i, 0 \le t_i \le 3,$ where $i = 1, \ldots n$ in order to account for the irregular spacing of the bid arrival. Thus, each auction can be represented by a vector of equal length

$$y^{(j)} = (y_1^{(j)}, \ldots, y_n^{(j)}) \tag{1.6}$$

which forms the basis for the smooth price curves.

Recovering the Underlying Price Function: To recover the underlying price curves, we use penalized monotone curves (Ramsay and Silverman 2005; Simonoff 1996), which provide both small local variation and overall smoothness. They also readily yield higher-ordered derivatives of the target price curve as desired in our case. We first start with selecting an appropriate basis function for the price dynamics. We decided on using b-spline basis function as it is commonly used in cases when the data is not periodic. Next, for every auction, we express a price function *w(t)* as a linear combination of a basis function $\phi_k(t)$. Therefore,

$$w(t) = \sum_{k=1}^{K} c_k \phi_k(t) \tag{1.7}$$

where c_k is a constant and k ranges from 1 to K basis functions. Then, we fit the data by minimizing the error sum of squares by

$$SSE = \sum_{j=1}^{n} [y_j - f^{(j)}(t_j)]^2 \tag{1.8}$$

where y_j is the price of item *j* observed in time t_j. *j* is 1…100 in our case and *f(t)* is the price function that fits the observed values. A roughness penalty function is imposed to measure the degree of departure from the straight line

$$PEN_m = \int \left[D^m f(t) \right]^2 dt \tag{1.9}$$

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

$$PENSS_{\lambda,m}^{(j)} = \sum^{n} \left(y_i^{(j)} - f^{(j)}(t_i) \right)^2 + \lambda \times PEN_m^{(j)} \tag{1.10}$$

where the smoothing parameter λ provides the trade-off between fit $[(y_i^{(j)} - f^{(j)}(t_i))^2]$ and variability of the function (roughness) as measured by PEN_m.[9] We use the monospline module developed by (Ramsay 2003) for minimizing $PENSS_{\lambda,m}^{(j)}$.

Appendix B: *<u>Forecasting Price Dynamics</u>*

Since the forecasting model (equation 1.6) uses the price dynamics component of the same time-period, we must predict this component before forecasting price. To do so, we model $D^{(j)}y(t)$ as a polynomial in *t* with autoregressive (AR) residuals along with other covariates x_i as they also play a significant role in affecting the price dynamics (Figure 4). This leads to the following model for predicting price dynamics

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

$$D^{(j)}y(t)=\sum_{k=0}^{K}a_k t^k+\sum_{i=1}^{P}b_i x_i(t)+u(t) \tag{1.11}$$

where $t=1,2,...T$ and $u(t)$ follows an AR model of order R

$$u(t)=\sum_{i=1}^{R}\phi_i u(t-i)+\varepsilon(t),\ \text{where } \varepsilon(t) \sim \text{iid N}(0,\sigma^2) \tag{1.12}$$

This results in a two-step forecasting procedure as we first estimate the parameters

$a_0, a_1,..., a_K, b_1,..., b_p$ and the residuals $\hat{u}(t)$. Then, using the residuals, we estimate $\phi_1,...,\phi_R$.

Therefore with the information until time T, we first forecast the next residual by

$$\tilde{u}(T+1|T)=\sum_{i=1}^{R}\tilde{\phi}_i u(T-i+1) \tag{1.13}$$

and then use it to predict the corresponding price derivative

$$D^{(j)}\tilde{y}(T+1|T)=\sum_{k=0}^{K}\hat{a}_k(T+1)^k+\sum_{i=1}^{P}\hat{b}_i x_i(T+1|T)+\tilde{u}(T+1|T) \tag{1.14}$$

We can rewrite equation 1.10 to predict $D^{(j)}y(t)$ with *h* steps ahead by

$$D^{(j)}\tilde{y}(T+h|T)=\sum_{k=0}^{K}\hat{a}_k(T+h)^k+\sum_{i=1}^{P}\hat{b}_i x_i(T+h|T)+\tilde{u}(T+h|T) \tag{1.15}$$

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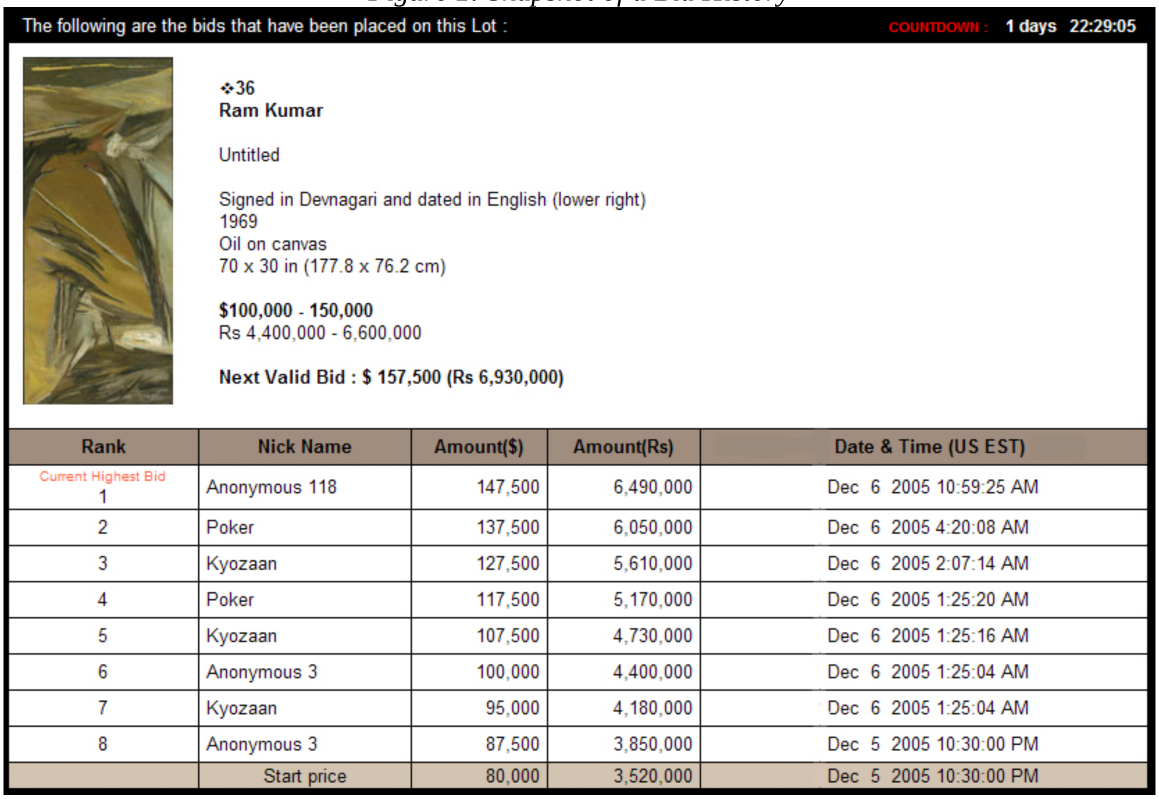
Figure 1: Snapshot of a Bid History



The following are the bids that have been placed on this Lot : COUNTDOWN : 1 days 22:29:05

36
Ram Kumar

Untitled

Signed in Devnagari and dated in English (lower right)
1969
Oil on canvas
70 x 30 in (177.8 x 76.2 cm)

$100,000 - 150,000
Rs 4,400,000 - 6,600,000

Next Valid Bid : $ 157,500 (Rs 6,930,000)

Rank	Nick Name	Amount($)	Amount(Rs)	Date & Time (US EST)
Current Highest Bid 1	Anonymous 118	147,500	6,490,000	Dec 6 2005 10:59:25 AM
2	Poker	137,500	6,050,000	Dec 6 2005 4:20:08 AM
3	Kyozaan	127,500	5,610,000	Dec 6 2005 2:07:14 AM
4	Poker	117,500	5,170,000	Dec 6 2005 1:25:20 AM
5	Kyozaan	107,500	4,730,000	Dec 6 2005 1:25:16 AM
6	Anonymous 3	100,000	4,400,000	Dec 6 2005 1:25:04 AM
7	Kyozaan	95,000	4,180,000	Dec 6 2005 1:25:04 AM
8	Anonymous 3	87,500	3,850,000	Dec 5 2005 10:30:00 PM
	Start price	80,000	3,520,000	Dec 5 2005 10:30:00 PM

Figure 2: Snapshot of Item Information

Painting	Description	Bidding
View Bigger Image add to my auction gallery Send to a friend	3 M.F. Husain (b.1915) Untitled Signed in English (lower left) Circa 1980's Oil on canvas 53.5 x 81 in (135.9 x 205.7 cm) **$232,600 - 290,700** Rs 10,000,000 - 12,500,000 Click here to read more	Comparables

http://www.saffronart.com - Painting Description - Mozilla Firefox

Shortly following the formation of the Progressive Artists' Group, its founding members M.F. Husain, and F.N. Souza visited an exhibition in New Delhi in 1948, which was to have a profound effect on their work; allowing them to imbibe India's Classical aesthetic tradition. The show was to affect the manner in which Husain presented the human form and its movement within the confines of two-dimensional pictorial space. This trip was a "turning point" in his career. "It was at this juncture that he conceived the essential form that is pivotal to his work.

He states, 'One reason why I went back to the Gupta period of sculpture was to study the human form – when the British ruled we were taught to draw a figure with the proportions from Greek and Roman sculpture...That was what I thought was wrong...In the east the human form is an entirely different structure... the way a woman walks in the village there are three breaks...from the feet, the hips, the shoulder...they move in rhythm...the walk of a European is erect and archaic.' " (Yashodhara Dalmia, The Making of Modern Indian Art: The Progressives, OUP, 2001, p. 102)

[Close]

Figure 3: Between-Auction Competition

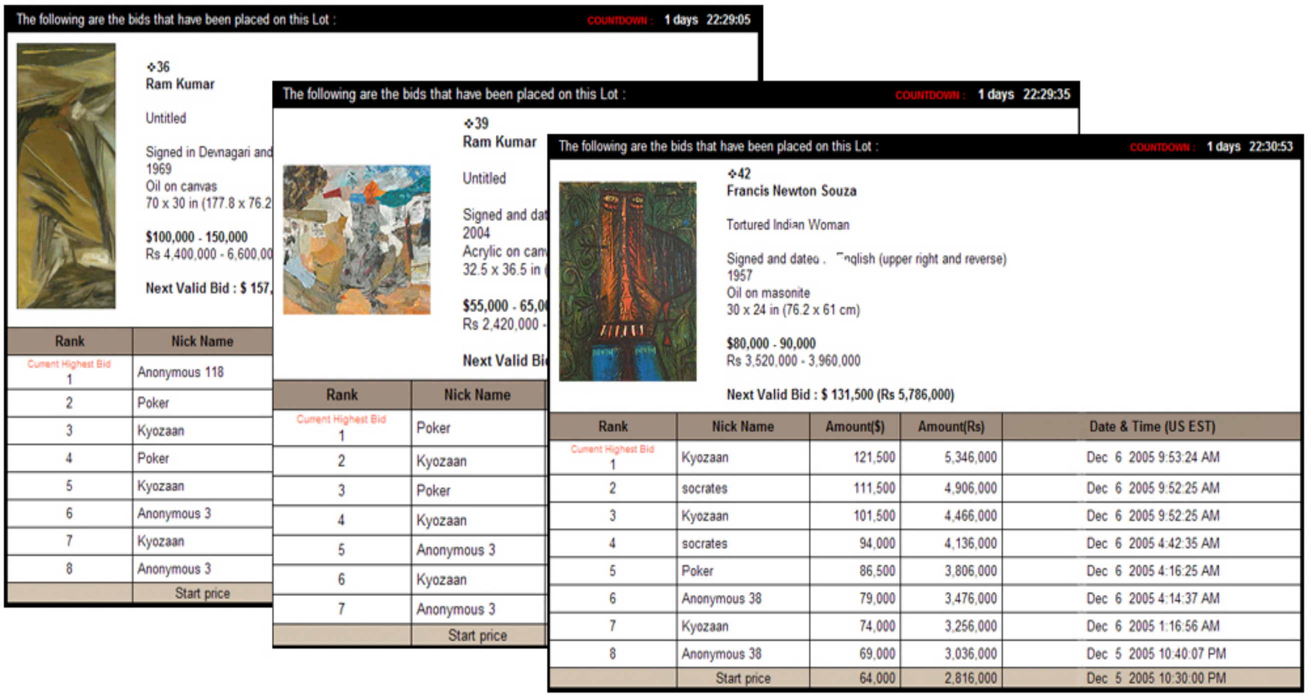


Figure 4: Price Dynamics for 196 Lots Sold in the Online Art Auction

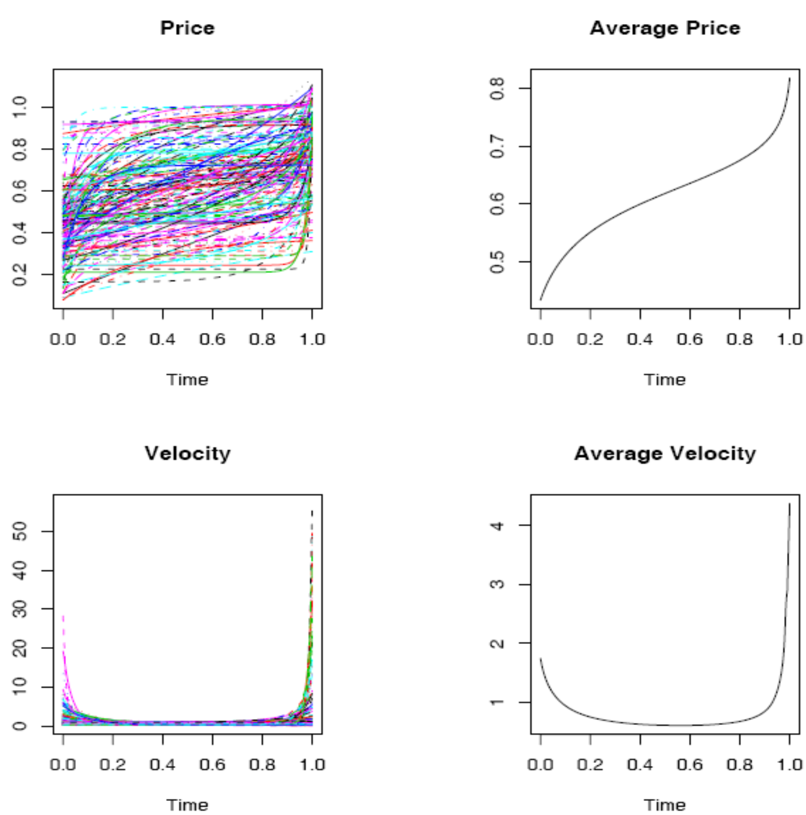


Figure 5a: Parameter Estimates of Time-varying Covariates in the Model with Training Set

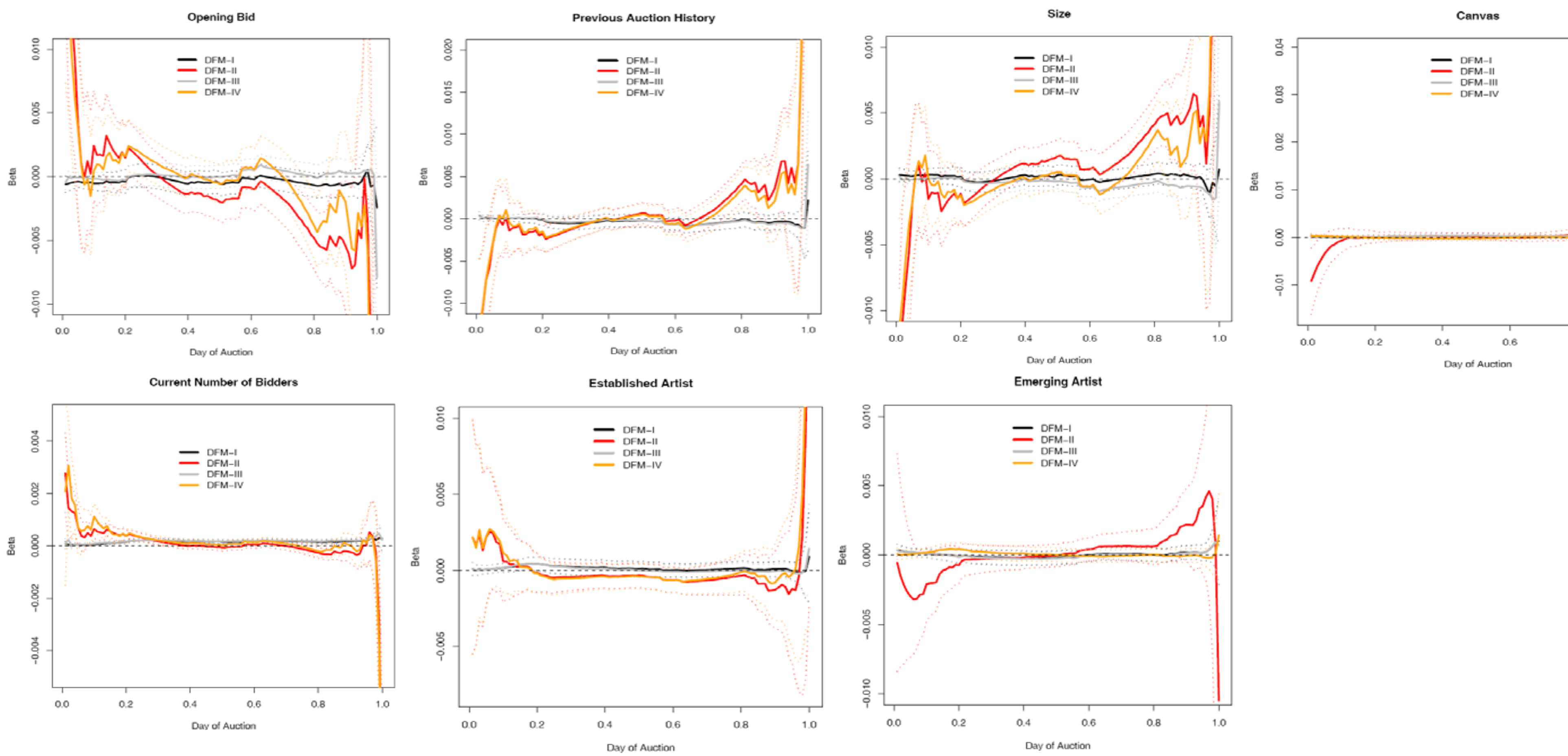


Figure 5b: Parameter Estimates of Time-varying Covariates in the Model with Training Set

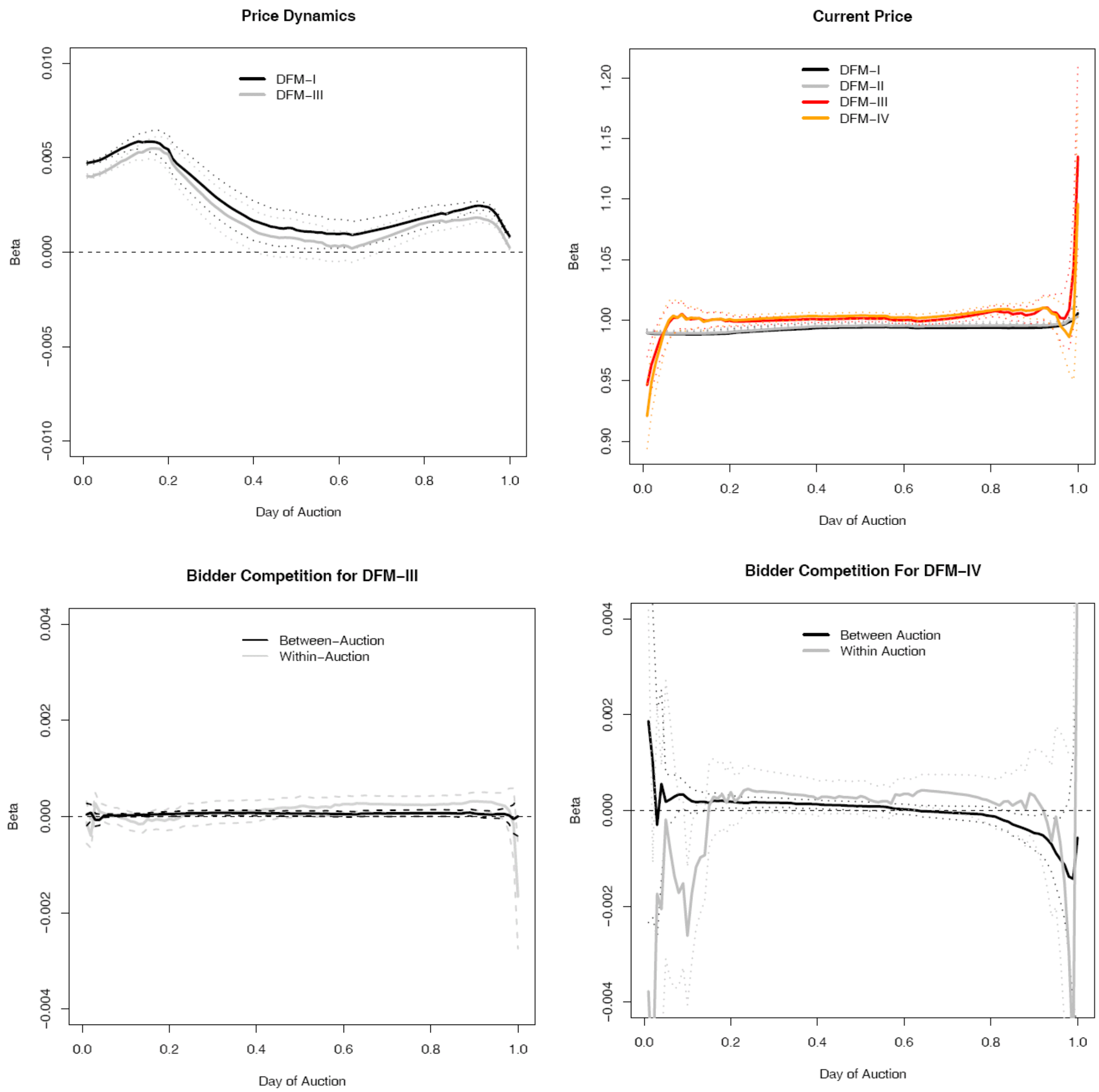


Figure 6: Performance of Forecasting Price Dynamics of the Last 18 Hours for Four Sample Lots using DFM-I

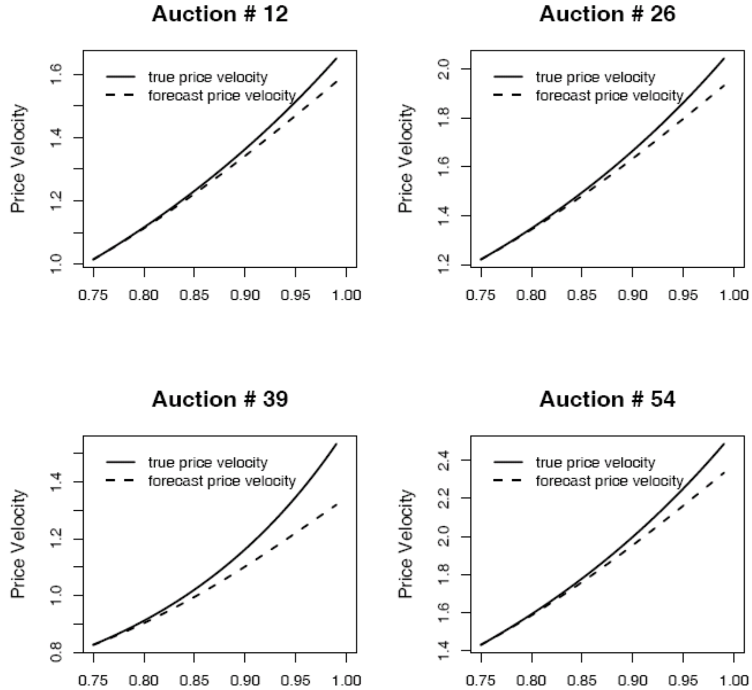


Figure 7: Mean Absolute Percentage Errors (MAPE) of Models without Bidder Competition

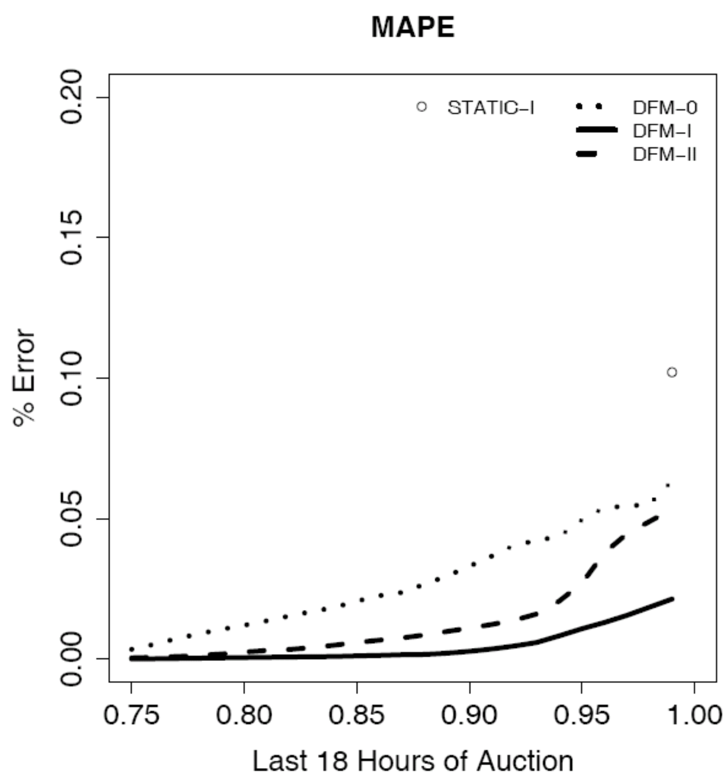


Figure 8: Dynamic Forecasting of the Last 18 Hours for Four Sample Auctions using DFM-I

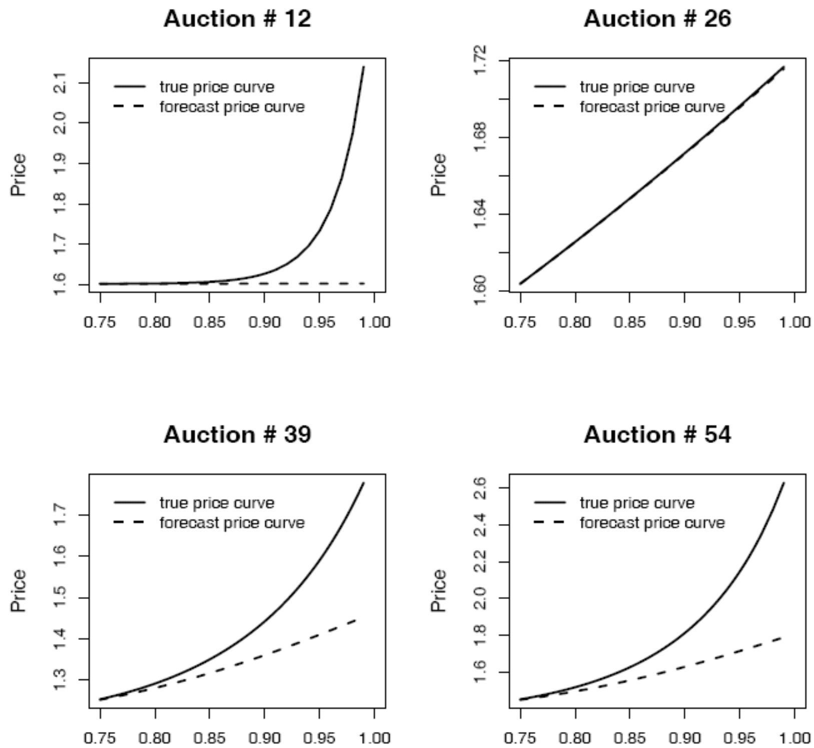


Figure 9: Mean Absolute Percentage Errors (MAPE) of Models with (DFM-III, DFM-IV) and without (DFM-I, DFM-II) Bidder Competition Component for Model Comparison

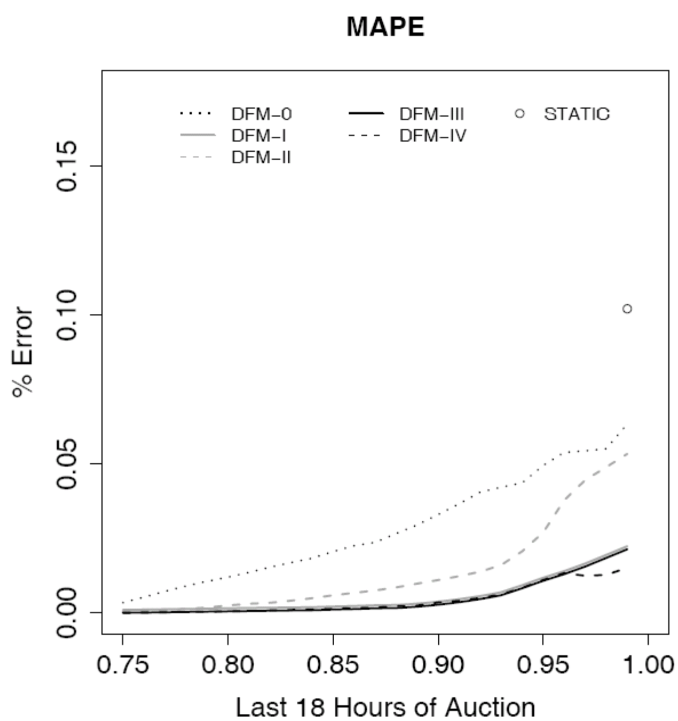


Figure 10: Average Price and Velocity Curves by Bidder Competition

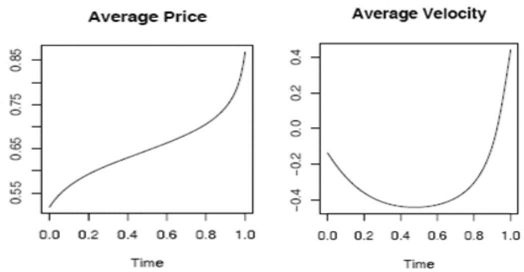
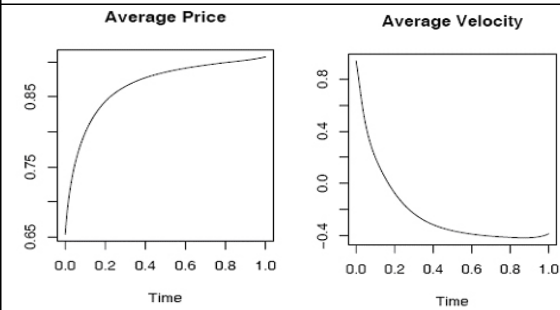
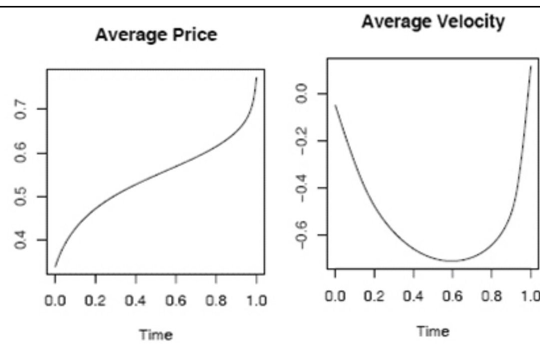
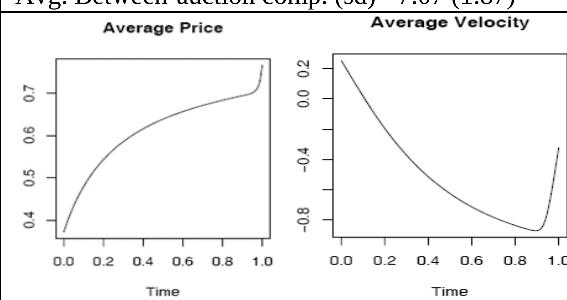
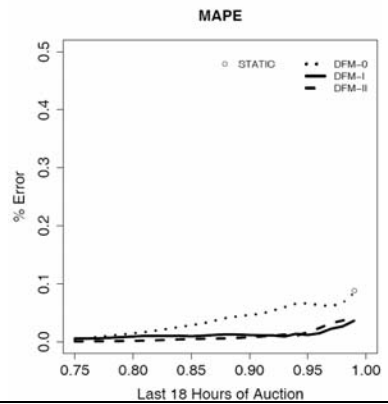
Within-auction dyadic bidder competition mean (sd) = 2.96 (1.44**)**	**Between-auction dyadic bidder competition** mean (sd) = 3.18 (2.63)	
	Low	**High**
Low	 Sample Size = 62 Avg. Within-auction comp. (sd) = 1.76(0.43) Avg. Between-auction comp. (sd) = 2.07(0.93)	 Sample Size = 25 Avg. Within-auction comp. (sd)= 1.69 (0.48) Avg. Between-auction comp. (sd)= 7.07 (1.87)
High	 Sample Size = 67 Avg. Within-auction comp. (sd)= 3.94 (1.2) Avg. Between-auction comp. (sd)= 2.27 (0.9)	 Sample Size = 42 Avg. Within-auction comp.(sd)= 3.86 (1.29) Avg. Between-auction comp.(sd)= 8.25 (3.46)

Figure 11: Mean Absolute Percentage Errors of Competing Models by Bidder Competition

<table>
<tr><th rowspan="2">Within-auction Dyadic bidder competition</th><th colspan="2">Between-auction Dyadic bidder competition</th></tr>
<tr><th>Low</th><th>High</th></tr>
<tr><td>Low</td><td>


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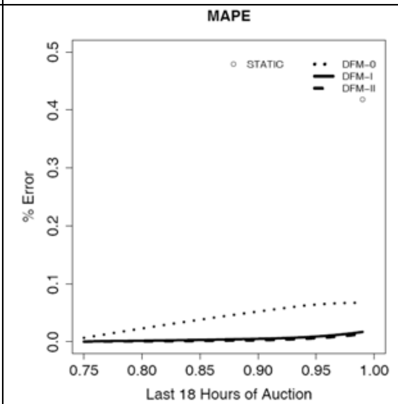
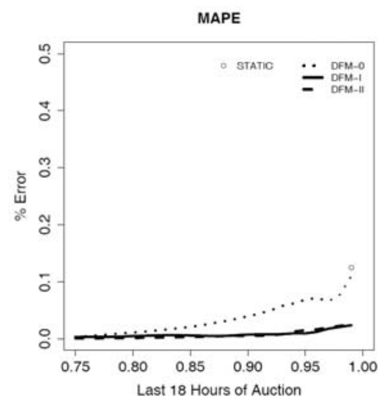
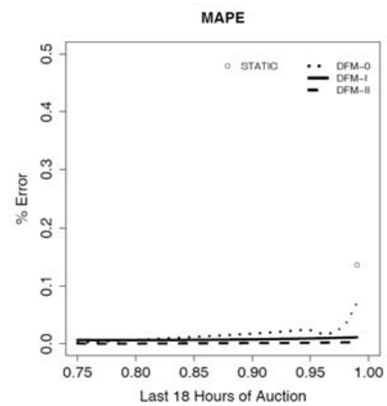


</td></tr>
<tr><td>High</td><td>


</td><td>


</td></tr>
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Figure 12: Comparison of Final Price Forecasting Models at different Forecasting Time

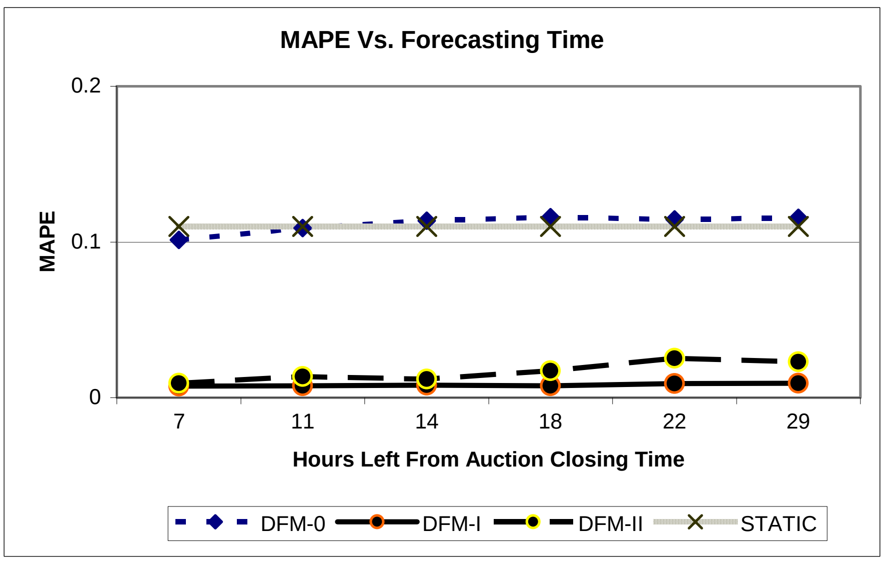

Figure 13: Comparison of Final Price Forecasting Models with Bidder Competition at different Forecasting Time

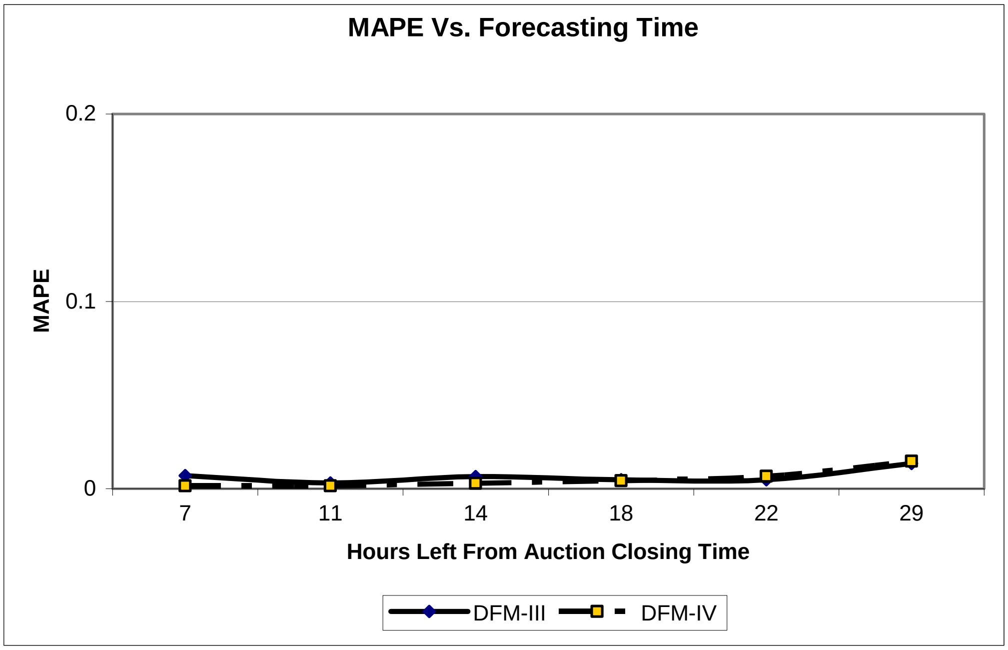

Table 1: *Summary Data Description*

	Mean (SD)	Median	Min.	Max.
No. of Unique Bidders/ Lot	6.38 (2.47)	6	2	14
No. of Unique Lots Bid / Bidder	4.89 (7.76)	3	1	63
No. of Bids/lot	15.52 (7.49)	15	2	48
Opening Bid in $	$19,145 ($36,830)	$6,400	$650	$300,000
Pre-Auction Low Estimates of the Lots	$23,880 (45,954)	$8,000	$795	$375,000
Pre-Auction High Estimates of the Lots	$30,816 (60,676)	$10,230	$1,025	$475,000
Realized Value of the Lots in USD($)	$61,845 (134,109)	$21,400	$3,135	$1,486,100
Realized Sq. Inch Price of the Lots in USD($)/ Sq. Inch	$109.39 (227.13)	$45.06	$1.40	$1,865.42

Table 2: *Predictors Used in the Model*

Category	Covariates	Description
Static Predictors		
1a	Opening Bid	Opening bid is the first bid in the auction.
	Size of the Item	It is the dimension of the artwork in square area.
	Type of Artwork	Artworks can be categorized into works on paper and works in canvas. We used an indicator variable in our model to indicate whether the item is a canvas work or not.
	Artist Reputation	The artists are categorized into established artists and emerging artists.
	Previous Auction History	The price/sq. inch of the artworks of the artists in the previous years
Time-varying Predictors		
1b	Current number of Bids	This is a time-varying predictor indicating the current number of bids placed in the auction.
Current Price		
2	Current and previous price (price path)	Price lags at time t, t-1…
Price Dynamics		
3	Price Velocity	First derivative of price at time t
Competition		
4	Within-auction competition	This indicates the current level of within-auction competition in the auction.
	Between-auction competition	This indicates the current level of between-auction competition in the auction.

Table 3: Parameter Estimates of the Models in the Training Set

Covariates	STATIC (Std. Error)	DFM-0 (Std. Error)
Opening Bid	0.1894** (0.0230)	0.0810** (0.0249)
Previous Auction History of the artist	-0.2127** (0.0248)	-0.1239** (0.0258)
Size	-0.2018** (0.0254)	-0.1199** (0.0259)
Current Price		0.4836** (0.0693)

** Significant at 0.01 level
* Significant at 0.05 level