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Bidders' and Sellers' Strategies in Sequential Auctions. New Evidence about the Afternoon Effect ⋆

LUCIO PICCI and ANTONELLO E. SCORCU⋆⋆
Università degli Studi di Bologna, Italy

Abstract. Using dynamic panel data econometric techniques, we analyze the price structure of sequential auctions of modern and contemporary art that took place in Italy during the period 1983–1996. Contrary to previous empirical studies, we do not find any "afternoon effect", or decline of auction prices relative to estimated values. Taking into consideration the structure of the auctions and the dynamic nature of price determination, we propose an interpretation of the empirical results that encompasses previous contributions.

Keywords: Panel data, dynamic specification, heterogeneity, sequential auctions, price decline puzzle

I. Introduction

In recent years the interest in auctions has considerably risen, in part following the increased use of auctions to distribute public scarce resources. A more accurate understanding of the stylized facts of auctions would then be welcome, both because it would allow for better theorizing, and also because, at least in principle, it would be conducive to more efficient allocation designs.

Empirical investigations on auctions have sometimes unveiled surprising results, such as the so called "afternoon effect" (a particular case of an "order of sale effect"), a small but significant price decline often observed over the course of a sequential English auction of identical objects, or of heterogeneous ones, once their estimated values are taken into account. In what follows, we take again on the empirical problem using data on auctions of modern and contemporary art objects held in Italy. Past empirical studies have analyzed static econometric models; here we use dynamic panel data techniques instead.

The results can be summarized as follows. When a static model is used, the auctions where objects are placed in a descending estimate value order are char-

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⋆⋆ *Author for correspondence*: Dipartimento di Scienze Economiche, Strada Maggiore 45, I-40125 Bologna, Italy; E-mails: picci@spbo.unibo.it; scorcu@spbo.unibo.it

acterized by the afternoon effect, that is, the bid price to estimate ratio tends to decrease as the auction goes on. When objects are placed in an ascending order, we find an opposite, or "morning", effect. Since, in our data, the majority of the auctions (and sub-auctions) fall in the latter case, overall the morning effect prevails. However, even within the static model, the evidence in favor of an order of sale effect is not robust, because it emerges significantly only if morning, afternoon and evening sub-auctions are aggregated into a single (daily) auction. If sub-auctions are considered, the evidence becomes much weaker.

Once we employ a dynamic model, allowing for affiliation, information, or other "psychological" effects, then morning or afternoon effects become statistically non significant. In a dynamic panel data model, the possibility that coefficients are not homogenous across units has to be taken into consideration since, as pointed out by Pesaran and Smith (1995), such heterogeneity leads to biased estimates. Such consideration does not change our results, but it is instructive from the methodological standpoint. Inquiring into the dynamic specification of the model, and considering the possibility of heterogeneous coefficients, form what we may define a tentative methodology for analyzing panel data characterized by a fairly long time dimension, as also pointed out, albeit in a different context, by Attanasio et al. (2000).

The paper is structured as follows. In the next section we present some of the characteristics of art auctions of heterogeneous objects. The possible emergence of an order of sale effect is briefly illustrated in Section III. Section IV describes an empirical model of the auction pricing relationships. The empirical analysis is in Section V, and the conclusions follow in Section VI.

II. Art Auctions

The first step of the typical art auction is the estimation of the objects' value. Let us consider the main reason why an unbiased estimation should be expected. A painting is assumed to have an intrinsic value because of certain "fundamentals" firmly held by society and amenable to quantitative measurement (see, among others, Frey and Pommerehne, 1989). The auction house might be tempted to increase some estimates above their "true" value, as higher estimates might induce higher bids when bidders are imperfectly informed about the true value of the object. A downward bias in the estimates might also emerge, if the auction house tries to increase the number of active bidders, as the expected highest bid price is non-decreasing in the number of bidders. However, in the long run both practices are unprofitable, and it can be shown that if the auction house truthfully reveals all the available information, bidders become more aggressive and the expected value of bids increases (Milgrom and Weber, 1982a). For these and related reputational reasons, a rational and forward looking auction house is unlikely to strategically manipulate the estimates. Therefore, in our empirical investigation we assume that errors in the estimated objects' values are random.

The assumption of unbiased estimates has two important consequences. First, estimates are independent of the order of sale in the auction. In fact, the structure of the auction (the number and the identity of the objects, and the order of sale) is not known at the time the objects are estimated. Secondly, the non-price characteristics of the painting (such as the medium, the identity of the painter, etc.) are fully accounted for by the estimates, and the analysis of the link between the order of sale and the bidders' behavior does not require any information in addition to the price variables.[1]

Another issue concerns the correct measure of the estimated value of an object when two such estimates, a high and a low values, are available. The usual practice in empirical work of averaging the two estimates might be incorrect. In fact, Ekelund et al. (1998) suggest that the low estimate is often related to the seller's reservation price, while the higher one tracks more closely the actual valuation of the auction house. In such cases, bidders might attach different weights to these estimated values;[2] hence, whenever possible, we will consider two different point estimates on the bid price. In our case, one of the advantages of the available data is that it contains information both on the minimum and on the maximum estimates.

After the objects' values have been estimated, the objects are grouped by auction. In many cases, the same daily auction is divided into morning, afternoon and/or evening sub-auctions. This division might be explained by several reasons, and it is not clear *a priori* whether sub-auctions taking place in the same day should be considered jointly or not. We will analyze both cases.[3]

Following the grouping of the objects by sub-auction, the order of sale for each object is determined, and the estimates, as well as other non price characteristics, are published in the auction presale catalogue. The order of sale strategy of the auction house could be determined in anticipation of the bidders' behavior, and could be influenced by the presence of an afternoon (morning) effect: if prices tend to decrease (increase) relative to the estimates in the course of an auction, the auction house would want to place more expensive items at the beginning (at the end) of the auction.

Last, after the auction has taken place, bid prices are collected and made public. As it is well known, if the highest bid falls short of the seller's reservation price, the painting remains unsold or, more precisely, "bought in" by the seller. If the estimates are unbiased, to a buy-in corresponds, on average, a low final bid (relative to estimate). Hence, buy-ins and order of sale effects are intertwined: if there is an afternoon effect, then buy-ins are more likely to occur at the end of the auction, and ignoring them would remove the order of sale effect. Discarding the buy-ins from the data would not be justified, since in most cases only the auctioneer knows whether or not an object has actually been sold. In fact, only in very few cases can buy-ins be immediately recognized as such by the bidders, and can therefore affect their strategies.[4] Hence, excluding buy-ins would produce a fictitious order of sale and could lead to misleading results. As buy-ins are included in our data set, in the empirical analysis we will consider all auctioned objects, regardless of whether they are actually sold or bought in.

III. Afternoon Effect and Price Dynamics in Sequential Auctions

The evidence on afternoon effects in sequential auctions of heterogeneous objects is mixed: it emerges in the empirical studies that have focused on apartments (Ashenfelter and Genesove, 1992) and paintings (Beggs and Graddy, 1997), while for jewelry (Chanel et al., 1996), price declines and increases roughly balance.

In sequential English auctions of identical objects with symmetric risk neutral bidders having private independent valuations and a unit demand, the expected bid price series should follow a martingale (Weber, 1983). On the other hand, if bidders have affiliated valuations, the bid price series should be increasing with the order of sale (Milgrom and Weber, 1982b). Hence the afternoon effect, where we observe bids *decreasing* with the order of sale, appears as an anomaly.

Theoretical rationalizations of such an anomaly are possible under specific assumptions. McAfee and Vincent (1993) obtain an afternoon effect in their theoretical model by assuming the existence of bidders with non-decreasing absolute risk aversion; Gale and Hausch (1994) resort to strength of competition considerations, possibly due to bidders' conservative strategies; von der Fehr (1994) considers the presence of participation costs, and Black and de Meza (1993) adopt what they call the "right to choose" option. Ginsburgh's (1998) solution relies on sub-optimal bidding strategies of absentee bidders, and Benoit and Krishna (2001) show how the presence of a budget constraint, in a common value and complete information setting, justifies the choice to sell the more valuable object first. Beggs and Graddy's (1997) results deserve more attention, given also their empirical findings on the afternoon effect. They propose a model for the heterogeneous objects case, where bidders with a unit demand compete for two different objects, and unsatiated bidders always bid for the remaining object. As it is assumed that bidders valuations for any object only differ by a constant coefficient of proportionality, full information about the reservation prices for the second object can be obtained simply by observing the behavior of the other bidders' during the sale of the first object. Within this set-up, an afternoon effect emerges, and the auction house finds it optimal to order the objects by declining estimated values.

However, the assumptions required to obtain an afternoon effect from the existing theoretical models tend to be quite peculiar. For example, regarding the Beggs and Graddy (1997) model, we note that in the real world different bidders are likely to be interested in different objects, and only a few unsatiated bidders submit bids for each remaining object, whereas some of the bidders who have already secured an object are not satiated; as a consequence the result of complete information about the bidders' reservation price is rather strong.

Another issue regards the possible dynamic nature of auctions. In this respect, following Milgrom and Weber (1982a), we note that typically there are two distinct types of bidders: collectors and merchants. "Pure" collectors hold private independent valuations, and "pure" merchants may hold a common valuation of a given object; the combination of the two causes affiliated values to emerge (Milgrom and Weber, 1982a). In this case, a bidder may usefully update his reservation price using the information provided by the current and the previous sales bids, and a dynamic effect emerges.

More generally, and also judging from casual observations by experts in the organization of auctions, as information accrues sequentially, "it may be advantageous to 'warm up the room' with some lower valued objects before bringing the auction to a climax with the more valuable masterpiece", even if more valuable objects should not be placed at the very end, because of the budget constraint effects (Benoit and Krishna, 1999). A profit maximizing auction house should take any effects of this type into account in deciding its selling strategy.

IV. Auction Price Structure and Auction House Behavior

Related to the investigation of any order of sale effect is the analysis of the profit maximizing strategy of the auction house, which decides the order of sale of the objects to be auctioned.[5]

The placing of the objects to be auctioned may depend on their values. In particular, the optimal strategy of an auction house expecting a decline (increase) in the price (relative to estimate) over the course of the auction is to put the objects with the highest valuations at the beginning (end) of the auction, when prices are high (low) relative to their estimates.

In order to investigate the selling strategy of the auction house, we consider the regression[6]

$$i = c_j \mathrm{DU}_j + d \cdot E_{ij} + u_{ij}, \tag{1}$$

where $i = 1, \ldots N_j$, represents the order of sale within (sub-)auction j and $j = 1, \ldots, J$ is the (sub-) auction identifier. E_{ij} denotes the (log[7] of the) arithmetic average of the low and high estimates of object i in auction j; DU_j denotes an auction-specific dummy variable that is equal to 1 when the auction is j and 0 otherwise. In the present context, and in panel-data models' parlance, DU expresses the "fixed effects" of each auction (or sub-auction).

In the case of the afternoon (morning) effect, the profit-maximizing order of sale should be influenced by the estimated value of the object, and we should expect the estimated coefficient d to be significantly negative (positive). However, d could be different from zero, maybe because of habit, institutional reasons, or convenience, independently from the strategic behavior of the auction house. In this sense, (1) alone does not provide a suitable test for the presence of an order of sale effect.

Turning to the price structure of an auction, we consider the following general dynamic panel data model:

$$P_{ij} = a_j \mathrm{DU}_j + bi + c_0 \mathrm{HE}_{ij} + d_0 \mathrm{LE}_{ij} + f_1 P_{i-1j} + c_1 \mathrm{HE}_{i-1j} + d_1 \mathrm{LE}_{i-1j} + u_{ij}, \tag{2}$$

P_{ij} denotes the (logarithm of the) highest recorded bid for the ith object in the jth auction j; HE_{ij} and LE_{ij} denote the high and low estimated value of the ith object in the jth auction. HE and LE are included because the objects are different and we have to control for their two estimated values.

Fixed effects could arise from the presence of (market) price adjustments specific to each auction, following from publicly available news unknown at the time when the estimates were made. Moreover, fixed effects might be due to the fact that attendance at a given auction is likely to depend on exogenous factors that are fixed with respect to that auction, like the location or the type of objects sold.

The presence of an afternoon (morning) effect would be reflected by a precisely estimated negative (positive) coefficient b. The model is dynamic, since the price of the ith good auctioned is allowed to depend on the relevant price and estimates of the object previously auctioned. Equation (2) allows for just one lag of these variables, but an extension to more lags is straightforward and will be considered below. The size of the dynamic effect is given by the coefficient f_1. If $f_1 = 0$, the static model is appropriate. However, if this is not the case, and if the dynamic adjustment term is omitted, the estimate of b will generally be biased, a fact that will be relevant later on in the interpretation of the results.

Interesting coefficient restrictions could be tested within this set-up. For example, if the sum of the weights of the low and high estimate add to one ($d_0 = 1 - c_0$) we can recast the problem in terms of current bid to estimate ratios. Moreover, if the restriction $f_1 = c_1 + d_1$ is not rejected, lagged prices also enter the relationship in terms of bid to estimate ratios.

The estimation of panel data where lagged values of the dependent variable appear as regressors is not amenable to the OLS fixed effects estimation, that in such cases provide biased estimates. Various instrumental variable techniques have been developed to solve this problem. However, the size of the bias tends to zero quickly as N tends to infinity (Nickell, 1981). In our case N, the total number of objects sold in an auction, is fairly big and is likely to imply a negligible bias.[8]

V. The Data Set and the Empirical Evidence

Our data set collects modern and contemporary paintings auctioned by "Casa d'aste Finarte"[9] in Rome, Milan and Lugano in the spring and the fall seasons during the period 1983–1996, for a total of 115 auctions, formed by 190 sub-auctions, and 27,078 transactions. On average, 235 objects were auctioned in each auction, and 143 objects were auctioned in each one of the 190 sub-auctions. For each auction, all the auctioned objects are recorded. For each transaction, we consider the order of sale, the bid price, i.e., the highest recorded price, and the estimated price (in most cases a "low" and a "high" estimate) of the auctioned goods values.[10]

Table I. The auction house strategy

	$i = c_j \mathrm{DU}_j + d \cdot E_{ij} + u_{ij}$					
Dep. Variable	Average estimate	Low estimate	High estimate	Average estimate	Low estimate	High estimate
	(1)	(2)	(3)	(4)	(5)	(6)
	115 Auctions	115 Auctions	115 Auctions	190 Sub-auctions	190 Sub-auctions	190 Sub-auctions
E	34.72	34.44	34.77	11.61	11.51	11.62
	(17.0)	(16.9)	(17.1)	(8.53)	(8.74)	(8.36)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R^2	0.2113	0.2090	0.2124	0.0398	0.0394	0.0400

Number of observations: 27.078; *t-statistics* in parentheses, *P-values* in brackets.

1. THE AUCTION HOUSE STRATEGY

We describe the auction house's strategy in deciding where to place a given object by regressing estimated values against the order of sale. We run separate regression for average estimate, low estimate and high estimate and for auctions and sub-auctions. Results are shown in Table I, where in columns 1–3 we consider the 115 auctions and in columns 4–6 the 190 sub-auctions. The (White heteroskedasticity consistent) *t-statistics* are shown in parenthesis and the corresponding *P-values* are reported in brackets.

The coefficient on the order of sale is positive and statistically significant in all cases. The estimated values and the auction specific fixed effects explain more than 20% of total variability. When we consider sub-auctions instead (columns 4–6), we obtain qualitatively similar results, even if in this case the regressions only explain about 4% of total variability. The coefficient d is still positive and highly significant, but smaller.

Such a departure from a random allocation of the objects might indicate that a morning effect is present, and is recognized as such by the auction house, that optimally reacts to it by placing the most expensive objects at the end of the auction, when they are sold at a premium. However, as noted, a departure from a random allocation of the objects could be unrelated to the presence of an order of sale effect, in the sense that it could simply arise out of habit. The contrast between the order of sale here detected, and the opposite one used by Sotheby's and Christie's (Beggs and Graddy, 1997) is compatible with such a possibility.

2. THE GENERAL DYNAMIC MODEL

We begin the analysis of the bid to estimate ratios in sequential auctions by estimating Equation (2). In Table II we consider the empirical evidence from the 115 auctions. The estimated coefficients of the static regression are shown in column 1, while the results for the dynamic models are in columns 2 and 3.[11] The fixed effect coefficients are not reported. The (White heteroskedasticity consistent) *t-statistics* are shown in parenthesis and the corresponding *P-values* are reported in brackets.

In the static model there is a positive relationship between the order of sale and the bid price, after controlling for the estimated values of the paintings. That is, our static analysis, instead of detecting an afternoon effect, finds a morning effect. The price effect of the increase of one object in the series is quantitatively negligible (0.02% of the bid price, controlling for the estimate), but unambiguously significant. The cumulated increase of the bids for the typical auction in which 235 objects are auctioned is about 5%.

Note that while the sum of the high and low estimates coefficients is very close to one, the estimated weights for the high estimates is about twice as big as for the low estimate. This result casts some doubt on the widespread use of the arithmetic mean of the two estimates. The *t-statistics* of the null hypothesis $c_0 = 1/2$ and $d_0 = 1/2$ are equal to 3.976 and -4.226 for HE and LE, respectively, and are both rejected at the usual significance levels.

The importance of the dynamic effects clearly emerges from the results of columns 2 and 3 of Table II: the lagged values of the bid prices have the expected (positive) sign and are precisely estimated, while the lagged HE and LE are much more imprecisely estimated, even if in general they exhibit the expected negative sign.[12] As for the adequacy of the specification chosen, a $\chi^2(3)$ test for the joint significance of the fourth lag coefficients c_4, d_4 and f_4 is equal to 16.79 with a P-value of 0.001, whereas the AR(1) and AR(2) test on the residuals are both below the usual 5% critical level. The relevant $N(0, 1)$ test statistics are, respectively -1.709 and -0.8698, with a P-value of 0.088 and 0.384. In fact, in the 5-lag specification the fifth lag coefficients are jointly significant ($\chi^2(3) = 15.14$, p-value $= 0.002$). However, the addition of more lags and/or the exclusion of the insignificant variables does not affect appreciably the results, which for the sake of brevity we do not show[13]

A significant and positive estimate of b in Equation (2) implies the presence of a positive order of sale effect in the static model. However, the inclusion of the dynamic effects lead to a reduction in size and significance of b. Hence, the emergence of the order of sale effect might be due to the misspecification of the model, implying a bias in b. We will return to this point later on.

Table III shows the same exercises for the 190 sub-auction case. The results mirror those of Table II with an important difference: the estimated b is always positive, but is now smaller and not significant, even in the static case. With respect to the order of sale effect, the aggregation of sub-auctions turns out to be important.[14] The 4-lag regression is adequate in terms of dynamic specification: a $\chi^2(3)$ test for the joint significance of the fourth lag coefficients is equal to 7.82, with a P-value of 0.050, whereas the fifth lag coefficients of the 5-lag specification are barely not significant, as the relevant $\chi^2(3)$ is equal to 6.067, with a P-value

Table II. Bid price-order regression, 115 auctions

$P_{ij} = \Sigma_j a_j \mathrm{DU}_j + bi + \Sigma_h c_h \mathrm{HE}_i - h_j + \Sigma_h d_h \mathrm{LE}_i - h_j + \Sigma_h f_h P_{i-hj} + u_{ij}$

Dep. variable	Bid price 0 lag	Bid price 1 lag	Bid price 4 lags
Trend	0.00021 (3.4774) [0.0005]	0.00015 (2.4800) [0.0131]	0.00008 (1.410) [0.158]
HE	0.64161 (18.016) [0.0000]	0.63853 (18.230) [0.0000]	0.64046 (18.400) [0.000]
LE	0.3497 (9.8310) [0.0000]	0.34730 (9.9223) [0.0000]	0.34043 (9.740) [0.000]
P(−1)	–	0.06141 (6.7823) [0.0000]	0.05623 (6.820) [0.000]
HE(−1)	–	−0.03308 (−1.2827) [0.1996]	−0.02863 (−1.170) [0.240]
LE(−1)	–	−0.01526 (−0.5836) [0.5595]	−0.02006 (−0.812) [0.417]
P(−2)	–	–	0.03351 (4.600) [0.000]
HE(−2)	–	–	−0.02521 (−0.920) [0.358]
LE(−2)	–	–	−0.00294 (−0.109) [0.913]
P(−3)	–	–	0.01919 (2.740) [0.006]
HE(−3)	–	–	−0.02499 (−1.350) [0.177]
LE(−3)	–	–	0.01265 (0.625) [0.532]
P(−4)	–	–	0.02749 (3.700) [0.000]
HE(−4)	–	–	−0.0175 (0.832) [0.406]
LE(−4)	–	–	−0.00286 (0.131) [0.896]
R^2	0.9314	0.9314	0.9312
TSS	36,353.7928	36,057.1835	35,339.6211
RSS	2,494.5940	2,472.1567	2,430.3668
No. obs	27,078	26,963	26,618

h = number of lags; *t-statistics* in parentheses, *P-values* in brackets.

of 0.108. The AR(1) and AR(2) tests on serial correlation of the residuals are both below the usual 5% critical level: the $N(0, 1)$ test statistics are, respectively -1.168 and -0.2814, with a P-value of 0.243 and 0.778.[15]

In interpreting the results, it might be the case that the bids on the current object auctioned are influenced by the past object "pricing error", defined as the ratio between the winning bid and the estimated prices (weighted using the appropriate estimated coefficients). For the one lag equation, we would write:

$$P_{ij} = a_j \mathrm{DU}_j + bi + c_0 \mathrm{HE}_{ij} + d_0 \mathrm{LE}_{ij} + F_1(-P_{i-1j} + c_0 \mathrm{HE}_{i-1j} + d_0 \mathrm{LE}_{i-1j}) + u_{ij}, \quad (3)$$

whose generalization to the case of more lags is straightforward. We have carried out the tests of the implied non-linear restrictions on the coefficients for our preferred 4 lags dynamic specification, both for the auction and the sub-auction case. However, in both cases the relevant null hypotheses of the type: $c_1 = f_1 c_0$ and $d_1 = f_1 d_0$ are rejected at the 1% significance level, thus indicating that whereas past bidders' behavior is relevant in determining the current price to estimate ratio,

Table III. Bid price-order regression, 190 sub-auctions

	$P_{ij} = \Sigma_j a_j \mathrm{DU}_j + bi + \Sigma_h c_h \mathrm{HE}_i - h_j + \Sigma_h d_h \mathrm{LE}_i - h_j + \Sigma_h f_h P_{i-hj} + u_{ij}$		
Dep. variable	Bid price 0 lag	Bid price 1 lag	Bid price 4 lags
Trend	0.000104 (1.2468) [0.2125]	0.000072 (0.88179) [0.3778]	0.00003 (0.327) [0.743]
HE	0.65060 (18.612) [0.0000]	0.64467 (18.365) [0.0000]	0.64163 (18.100) [0.000]
LE	0.33367 (9.5472) [0.0000]	0.33687 (9.5838) [0.0000]	0.33750 (9.490) [0.000]
P(−1)	–	0.048982 (5.4605) [0.0000]	0.04720 (5.440) [0.000]
HE(−1)	–	−0.01899 (−0.7722) [0.4400]	−0.01946 (−0.795) [0.427]
LE(−1)	–	−0.02118 (−0.85448) [0.3929]	−0.02163 (−0.871) [0.384]
P(−2)	–	–	0.02275 (3.190) [0.001]
HE(−2)	–	–	−0.01014 (-0.356) [0.722]
LE(−2)	–	–	−0.00925 (-0.329) [0.742]
P(−3)	–	–	0.01074 (1.530) [0.126]
HE(−3)	–	–	−0.01279 (−0.646) [0.518]
LE(−3)	–	–	0.00693 (0.339) [0.735]
P(−4)	–	–	0.01832 (2.48) [0.013]
HE(−4)	–	–	−0.00469 (0.245) [0.807]
LE(−4)	–	–	−0.00814 (0.406) [0.685]
R^2	0.90311	0.902809	0.90227
TSS	25,383.568	25,038.199	24,250.830
RSS	2,459.251	2,433.486	2,369.948
No. obs	27,078	26,888	26,318

h = number of lags; *t-statistics* in parentheses, *P-values* in brackets.

the dynamic adjustment cannot be restricted in terms of lagged pricing errors only. In the following we consider therefore the unrestricted Equation (2).

Two questions arise from the results just shown. First, why do the results change when we consider sub-auctions instead of auctions? Second, why do the results change when we consider a dynamic model rather than a static one?

Let us consider the two questions in turn. Different sub-auctions could be characterized by varying degrees of competition. Morning and/or afternoon sub-auctions mostly deal with low-price prints, while evening sub-auctions are concerned mostly with more expensive objects, such as oil paintings – a fact that helps the auction house in discriminating between classes of bidders. High quality objects might command more active bidders than low quality ones, and more intense competition may lead to relatively higher bid prices. While we cannot provide any substantive proof of this, such an interpretation is in line with a perceived habit of art collectors, as pointed out, for example, by the art dealer E. Merrin: “it’s always better to buy one \$10,000 object than ten \$1,000 objects or one \$100,000 object

– if that is what you can afford – than ten $10,000 ones" (cited in Pesando, 1993, p. 1083). If this is the case, the positive order of sale effect that emerges from the static regressions in Tables II and III would simply be a result of the increased competition for high-priced objects. Separating sub-auctions makes it clear that the order of sale effect seems to be mostly related to the differences between, rather than within, sub-auctions.

Let us now turn to the change of results that we observe once we use a dynamic model instead of a static one. If one uses a static model when the true relationship is dynamic, it is easy to show that the sign of the bias depends on the sign of the correlation between the included variable (the trend) and the omitted one (the lagged dependent variable). If this correlation is negative (positive), then the expected value of the estimated coefficients on the time ordering variable is lower (higher) than its true value.[16]

To have a closer look at this issue, we estimate the static model regressing separately those auctions (sub-auctions) characterized by positive and negative correlation between the order of sale and the estimated value. A positive (negative) bias is expected in the case of positive (negative) correlation. The results in Table IV support our prediction: the estimated b coefficient is positive for columns (1) and (3) and negative for columns (2) and (4). It can be shown that this order of sale effect is lost if lags are included. A positive and significant b coefficient is estimated in column (3), thereby suggesting that in a static model the order of sale effect arises also within sub-auctions. In conclusion, a morning or an afternoon effect, when a static model is used, is spuriously induced by the order of sale strategy of the auction house.

3. HETEROGENEOUS PARAMETERS

Pesaran and Smith (1995) argue that a pooled dynamic estimator provides consistent estimates of the mean effect of the independent variables on the regressand only when the individual coefficients are homogeneous across units – in our case, across auctions. If this is not the case, pooled estimates are biased, and the bias does not disappear as the sample size grows. Moreover, this problem is not amenable to instrumental variables techniques, and it is appropriate instead to assess the average effect of the regressors by considering the average of the estimated coefficients of the individually estimated equation. In our case, this amounts to estimating 115 equations (or 190 for the sub-auction case) and then computing the average of each of the estimated coefficients,[17] while appropriately computing the average coefficients' standard errors. In Table V we report the results of this exercise for the four-lag specification. The findings are not qualitatively different from the homogeneous case: the order effect is positive but not precisely estimated, and the coefficients of HE and LE are similar to the homogeneous parameters case. Note that lags 2–4 of the dependent variable are usually not significant, and the 4 lag specification has been retained mostly to facilitate comparison with the

Table IV. Bid price-order regression, by groups of auctions and sub-auctions

$$P_{ij} = \Sigma_j a_j \mathrm{DU}_j + bi + c_{im}\mathrm{HE}_{ij} + d_{im}\mathrm{LE}_{ij} + f_{im} P_{ij} + u_{ij}$$

Dep. variable	Auctions (1) Increasing order bid price	Auctions (2) Decreasing order bid price	Sub-auctions (3) Increasing order bid price	Sub-auctions (4) Decreasing order bid price
Trend	0.00024	−0.00027	0.00019	−0.00044
	(4.010)	(3.730)	(2.320)	(1.670)
	[0.000]	[0.000]	[0.021]	[0.094]
HE	0.64474	0.34977	0.68497	0.43608
	(17.900)	(1.100)	(19.400)	(4.850)
	[0.000]	[0.273]	[0.000]	[0.000]
LE	0.34413	0.66406	0.29617	0.55647
	(9.560)	(2.15)	(8.36)	(6.220)
	[0.000]	[0.032]	[0.000]	[0.000]
R^2	0.93071	0.94481	0.90325	0.89886
RSS	2,416.475	65.366	2,101.326	327.245
TSS	34,872.671	1,184.512	21,719.924	3,235.691
No. obs.	26,096	867	22,932	3,854

$m = 0, 1$; *t-statistics* in parentheses, *P-values* in brackets.

results shown so far. Overall, our previous empirical findings therefore turn out to be robust to the relaxation of the homogeneity hypothesis. This result is part of a growing body of evidence in favor of imposing the homogeneity restriction in dynamic models (cf. Baltagi and Griffin, 1997; Attanasio et al., 2000), even when this restriction is formally rejected.

VI. Conclusions

Our empirical investigation of the structure of sequential auctions of heterogeneous art objects does not indicate the presence of an afternoon effect. If anything, a morning effect seems to be present. Such an effect is less pronounced within sub-auctions, and non significant, although present in some specifications, when a dynamic model is considered.

The evidence unambiguously indicates that such an order of sale effect is spurious, and that it arises from misspecification of the static model. The results obtained using a dynamic model confirm the reliability of the sequential auctions as an efficient allocation mechanism: if the order of sale were relevant *per se*, the profit maximization strategy of the auction house would impose different treatments for different sellers (in terms of different expected price to estimate ratios), an outcome

Table V. Average coefficients, heterogeneous parameters

$$P_{ij} = a_j \mathrm{DU}_j + b_j i + \Sigma_h c_{hj} + \Sigma_h d_{hj} \mathrm{LE}_{i-hj} + \Sigma_h f_{hj} P_{i-hj} + u_{ij}$$

Dependent Variable	Bid price 115 auctions	Bid price 190 sub-auctions
Constant	−1.8468 (−0.643) [0.520]	−3.2210 (−0.279) [0.780]
Trend	0.00011 (0.971) [0.332]	0.00024 (0.365) [0.715]
HE	0.60059 (24.575) [0.000]	0.63336 (15.048) [0.000]
LE	0.37176 (15.451) [0.000]	0.32715 (7.380) [0.000]
P(−1)	0.03325 (5.441) [0.000]	0.02316 (2.4444) [0.015]
HE(−1)	−0.04364 (−1.728) [0.08403]	−0.03433 (−0.774) [0.439]
LE(−1)	0.01514 (0.634) [0.526]	0.01352 (0.322) [0.747]
P(−2)	−0.00737 (−1.172) [0.241]	−0.02214 (−1.851) [0.064]
HE(−2)	−0.2858 (−1.368) [0.171]	−0.00523 (−0.155) [0.877]
LE(−2)	0.04106 (2.113) [0.0346]	0.03111 (0.930) [0.352]
P(−3)	−0.00211 (−0.325) [0.745]	−0.01075 (−1.015) [0.310]
HE(−3)	0.02856 (1.348) [0.177]	0.01486 (0.433) [0.658]
LE(−3)	−0.02018 (-1.033) [0.301]	−0.00033 (−0.0103) [0.992]
P(−4)	−0.00402 (−0.674) [0.500]	−0.01161 (−0.946) [0.344]
HE(−4)	0.01498 (0.703) [0.481]	0.00817 (0.231) [0.818]
LE(−4)	−0.00506 (−0.232) [0.817]	0.00573 (0.164) [0.870]

h = number of lags; *t-statistics* in parentheses, *P-values* in brackets.

inconsistent with the reputation of a *super partes* auctioneer. More generally, the relevance of past sales in determining the current behavior within an auction is consistent with much casual evidence according to which in an auction there is always a "good place to be" for a given object.[18] However, this place depends upon several characteristics and habits, sometimes idiosyncratic to the market.

While this conclusions are interesting from the economic standpoint, and help clarify the working of real life auctions, they also have econometric methodological implications. The tradition of panel data analysis has indulged too often in using static models: when the time dimension allows for it, the dynamic specification is just as important for panel data as it is for single regressions. Also, when the model is dynamic, the possibility that the coefficients are heterogeneous has to be taken into consideration. In this respect, our results join a small but growing body of literature pointing out that while the coefficient heterogeneity issue is relevant in theory, in practice it seems not to matter much.

Notes

1. Obviously, systematic differences between the bidders' evaluation and the auction house estimate might arise when the former variable is a function of the entire auction.

2. This is also confirmed by Christies' officials, as reported by Ginsburgh (1998). Therefore, models based on average estimates, such as Bauwens and Ginsburgh's (2000) or Beggs and Graddy's (1997), might be misspecified.
3. In our data set, morning or afternoon sub-auctions often deal with drawings and prints, while in the evening oils prevail. Beggs and Graddy (1997) aggregate sub-auctions into a unique daily auction.
4. Again, if buy-ins are more likely in a given moment of the auction, then sellers would compete to avoid the least profitable selling placements in the order of sale.
5. For example, Christie's and Sotheby's place the paintings more or less according to the year of production, causing prices to be negatively correlated with the sale order. Cf. Beggs and Graddy (1997). As we will see, the opposite emerges from our data set.
6. The same relation could be defined with the high or low estimate instead of their average. We will explicitly consider such possibilities.
7. In the following, all variables, with the exclusion of the time trend, are expressed in logarithms.
8. In different terms, the loss of estimation precision that would follow the use of instruments would not be worth the riddance of a small bias. See Attanasio et al. (2000) for a similar point in a different application. Also note that our "N", the number of objects sold in a given (sub-) auction, is equivalent to the "T" in the panel-data econometric literature. On the other hand, the number of units of the panel, usually indicated as "N", is our "J".
9. Finarte is the leading auction house in Italy for modern and contemporary art, and it is estimated to have about 60% of the market. The paintings auctioned vary widely in terms of estimated price, medium (oils, watercolors, drawings, prints, etc.) and dimension. However, our data set does not include these non price variables. Several works of highly reputed painters were auctioned during the period under scrutiny. However, our data set does not include these non price variables.
10. For a very limited number of objects the estimated price is produced only upon request. These cases, excluded from the data set, are always put at the very end of the auction and therefore are unlikely to affect the results. For Christie's and Sotheby's, this is not true. In other studies, such as Beggs and Graddy (1997), there is no explicit treatment of the problem.
11. The data and the (Ox) routines used to compute all results are available upon request.
12. The lagged low and high estimates, while generally non-significant individually, are mostly significant when considered jointly. Formal $\chi^2(2)$ tests yielded the following P-values. In the one-lag dynamic specification: H_0: $c_1 = d_1 = 0$, P-val. 0.000. In the four-lag dynamic specification: H_0: $c_1 = d_1 = 0$, P-val. 0.0000; H_0: $c_2 = d_2 = 0$, P-val. 0.001; H_0: $c_3 = d_3 = 0$, P-val. 0.070, H_0: $c_4 = d_4 = 0$, P-val. 0.014, and the test for the joint significance of all lagged coefficients has a P-val. equal to 0.000.
13. All results mentioned in the text are available on request from the authors.
14. For this case also, the lagged low and high estimates, while generally non-significant individually, are mostly significant when considered jointly. In Table IV formal χ^2 tests yielded the following P-values. In the one-lag dynamic specification: H_0: $c_1 = d_1 = 0$, P-val. 0.000. In the four-lag dynamic specification: H_0: $c_1 = d_1 = 0$, P-val. 0.0000; H_0: $c_2 = d_2 = 0$, P-val. 0.028; H_0: $c_3 = d_3 = 0$, P-val. 0.597, H_0: $c_4 = d_4 = 0$, P-val. 0.203, and the test for the joint significance P-val. 0.000.
15. We also analyzed, both for the auction and the sub-auction case, a different specification where the average estimate and the difference between the (logs of) HE_{ij} and LE_{ij} are considered instead of HE_{ij} and LE_{ij}. The results are in line with the findings shown in Tables II and III: a positive order of sale effect is present, but its significance disappears once lagged prices are included.

16. Beggs and Graddy (1997) apply a static model to auctions data characterized by negative correlation between estimates and order of sale. Their "afternoon effect" could then be the consequence of a dynamically misspecified model.
17. An F test leads to the rejection of the homogeneity hypothesis at conventional levels, both for the auction and the sub-auction case. The reported *t-statistics* and *P-values* are computed from White heteroskedasticity consistent standard errors.
18. Cited in Beggs and Graddy (1997, p. 547).

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