Price dynamics in sequential auctions. New evidence using art auction data*

by

Lucio Picci and Antonello E. Scorcu+

Università degli Studi di Bologna

Abstract.

We analyze the price structure of sequential auctions of modern and contemporary art that took place in Italy during the period 1983-96. Contrary to previous empirical studies, we do not find any "afternoon" effect - i.e., a decline of auction prices relative to their estimates. If anything, we find the opposite, or "morning", effect.

Our results are robust to different econometric specifications. Taking into consideration the possible dynamic nature of price determination, we propose an interpretation of the empirical results that encompasses previous contributions.

Keywords:
Sequential auctions, price decline puzzle, panel data.

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+ Dipartimento di Scienze Economiche, Strada Maggiore 45, I-40125 Bologna, Italy. Lucio Picci: picci@spbo.unibo.it ; Antonello Scorcu: scorcu@spbo.unibo.it;

1. Introduction

In recent years the interest in the functioning of the auctions has considerably risen. Economists are examining auctions both theoretically, often with the aim of designing efficient mechanisms, and empirically, in the hope of better understanding why their actual working. In this paper, we perform an empirical analysis of the price structure of sequential auctions. In particular, we investigate the relationships between the bid price, the estimated price and the order of sale of the goods auctioned. We use a dataset of modern and contemporary art auctions that took place in Italy during the period 1983-96. The available data comprise the sale order, the price, and the estimate (in most cases a “low” and a “high” estimate) of the auctioned goods values. Unlike in previous empirical analyses, we take into account the possible heterogeneity between individual auctions and the effects of a high and a low estimate for each object. Moreover, we investigate the existence of a price dynamics effect in the course of the auction.

Our main results can be summarized as follows. No evidence of an afternoon effect is found. On the other hand, a “morning effect”, i.e., an increase in price, once auction house price estimates are taken into account, is detected when sub-auctions that take place within the same day are aggregated. Even in these instances, however, the effect tends to disappear once a dynamic model is considered instead of a static one. Moreover, a positive and significant upward trend in the estimated values series, identifying the auction house selling strategy, characterizes both auctions and sub-auctions. Taking into consideration the observed differences between auctions and sub-auctions, the likely dynamic nature of the auction pricing mechanism, and the price structure of the single auction, we are able to propose an encompassing explanation of our empirical results.

In the next section we review the empirical results on price decline. Section 3 describe an empirical model of the auction pricing relationships. Section 4 presents the data used in the empirical analysis of Section 5. Conclusions are in Section 6.

2. A review of previous empirical results

The motivation for this work is the analysis of the “afternoon effect”, a small but significant price decline that has been often observed over the course of a sequential auction of identical objects (Ashenfelter, 1989).

At first, this result has been considered an anomaly, since in sequential English auctions of identical objects with risk neutral bidders having private independent valuations, the expected bid price series should follow a martingale (Weber, 1983). Moreover, if bidders have affiliated valuations, the bid price series should be increasing with the order of sale (Milgrom and Weber, 1982b).[1] A number of different (and partial) theoretical explanations for such an “anomaly” have been proposed, some based on the existence of risk averse bidders (Mc Afee and Vincent, 1993), others on the endogenization of the number of bidders in each sale and on the strength of competition, possibly due to bidders’ strategies (Gale and Hausch, 1994) or to the presence of participation costs (von der Fehr, 1994).

The evidence about afternoon effects in the case of sequential auctions of heterogeneous objects is mixed. It is supported in the case of apartments (Ashenfelter and Genesove, 1992) and paintings (Beggs and Graddy, 1997), while in a case where jewelry data are considered, price declines and increases roughly balance (Chanel *et al.*, 1996).

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1 The same result should hold in the case of different but “similar” objects.

This ambiguous evidence is not surprising, since these auctions are quite complex to analyze because of the heterogeneity among bidders and objects. It would seem that the complexities of bidders' and sellers' actual strategies would rule out the emergence of a typical pattern in the price series (Vincent, 1998). Some specific features of sequential auctions of heterogeneous objects are worth mentioning. Bidders are served in sequence but, at a given moment, not all unsatiated bidders submit bids for each remaining object of a given auction sequence, nor are all the bidders that have already secured an object necessarily satiated. Different bidders are likely to be interested in different objects. If this is the case, it is very difficult for a bidder to infer the whole set of valuations of the other bidders. Also, reservation prices are specific to each bidder and are kept secret because a bidder has an incentive not to reveal her true reservation price.

Therefore specific theoretical results emerge only in particular cases. In particular, Beggs and Graddy (1997), under some simplifying assumptions, develop a model where two bidders compete for two objects that are ordered by declining values, and an afternoon effect emerges[2]. In general, however, the order of objects by declining estimates and the decline in the bid to estimate series is only one of several possible outcomes of a sequential auction.

3. Auction price structure and auction house behavior

In this Section we model the sequential auction of heterogeneous objects. We are interested in describing the price structure of the auction and, in order to assess the presence of any afternoon effect, we control for the different monetary valuations of the objects. Moreover, we want to describe the strategy of the auction house, which chooses the order of the goods auctioned possibly according to their estimated value.

A systematic relation between the order of sale and the bid price, after controlling for the estimated value, might arise also in sequential auctions of heterogeneous objects. In this case, any afternoon effect has to be distinguished from the issue of the order of sale, which is decided by the auction house. This order can be imagined to be random, if no connection is expected between the value of an object and the order of sale within an auction. Quite often, however, the goods auctioned within a single auction are unambiguously placed according to their estimated value, on average, either in ascending or in descending order. In these cases, the ordering should be thought of as the result of an explicit decision by the auction house, and as a part of its profit maximizing strategy.

We thus have two distinct, but linked, phenomena to detect and to explain when we consider auctions of heterogeneous objects. On the one hand, the order of sale of a particular object within an auction may depend on its value. Moreover, given the ordering of the objects as decided by the auction house, possibly in anticipation of an afternoon effect, such an effect may or may not be present.

Dynamic panel models of the auction structure

To allow for the testing of the presence of a relationship between the order of sale and the bid price, we need a model that explicitly describes the price structure of an auction. To this end, we consider the general dynamic panel model:

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2 In their model, unless satiated by the purchase of just one object, each bidder always submits a bid for the other object. Bidders valuations differ by a known coefficient of proportionality. As a bidder observes the other bidder's behavior during the sale of the first object, he obtains information on the other bidder's reservation price for the second object in the sequence. In this case, the auction house finds it optimal to order the objects by declining estimated values. This equilibrium outcome does not extend to more general cases.

[2.1] $$P_{ij} = a_j DU_j + b_1 i + b_2 HE_{ij} + b_3 LE_{ij} + b_4 P_{i-1j} + b_5 HE_{i-1j} + b_6 LE_{i-1j} + u_{ij}$$

where $i=1,...,N_j$, represents the selling order within an auction and $j=1,...,J$ is the (sub-)auction identifier. DU_j denotes an auction-specific dummy variable that is equal to 1 when the auction is *j* and 0 otherwise. In the present panel context, it expresses the "fixed effects" of each of the cross-sectional units (here, the single auctions, or sub-auctions). P_{ij} denotes the (logarithm[3] of the) highest recorded bid for the *i-th* object in the *j-th* auction *j*; HE_{ij} and LE_{ij} denote the high and low estimated value of the *i-th* object in the *j-th* auction. HE and LE are included because the objects are different and in analyzing the existence of a relationship between the order of sale and the bid price, we have to control for the estimated value of the object. The presence of an afternoon (morning) effect would be reflected by an estimated negative (positive) coefficient b_1. The model is dynamic, since the price of the *i-th* good auctioned depends on the relevant price and estimates of the good previously auctioned. Equation [2.1] allows for just one lag of these variables, but a richer dynamic model could obviously be considered as a straightforward extension.

The size of the dynamic effect is given by the coefficient b_4. Affiliations effects might emerge within each auction as information flows. Moreover, the outcome of the past sale of an object is an important source of information and could explain the relevance of lagged prices in sequential English auction of distinct, but similar objects: an increase in a bidder's offer raises the other bidders' valuations and, consequently, their bids. In fact, affiliated valuations imply a higher value for the currently auctioned object, when the previous object has been sold at a high price, in case the two objects, while distinct in nature, have similar characteristics. Also, causal observation on the working of art auctions suggest that there are important "psychological" factors at work, where the selling price of a given object possibly depends on the whole history of the auction up to that point, maybe as summarized by lagged prices and estimates. We expect $0<b_4<1$, as the typical learning mechanism suggests that a high price (relative to estimate) is, on average, followed by a smooth return. In fact, a high price might be explained by means of a idiosyncratic effect, specific to a given painting, and a "market" effect, common to all paintings. If $b_4=0$, the static model is the correct one. However, if this is not the case, and the dynamic adjustment term is omitted, the estimate of b_1 is biased, a fact that will be relevant later on in the interpretation of the empirical results.

We also consider a more parsimonious specification of the general model. If the sum of the weights of the low and high estimate add to one (so that $b_3=1-b_2$) we can recast the problem in terms of bid to estimate ratios:

[2.2] $$P_{ij} = a_j DU_j + b_1 i + b_2 HE_{ij} + (1-b_2) LE_{ij} + b_4 P_{i-1j} - b_5 HE_{i-1j} - b_6 LE_{i-1j} + u_{ij}$$

Moreover, if the further restriction $b_4=b_5+b_6$ is not rejected, lagged prices also enter the relationship in terms of bid to estimate ratios.

An alternative specification of the pricing model assumes *a priori* that the relevant measure of the estimated price is E_{ij}, the (log of the) arithmetic average of the low and high estimates:

[2.3] $$P_{ij} = a_j DU_j + b_1 i + b_2 E_{ij} + b_3 S_{ij} + b_4 P_{i-1j} + b_5 E_{i-1j} + b_6 S_{ij-1} + u_{ij}$$

In this case, we also consider a "spread" term, S_{ij}, defined as the difference between the (logs of) HE_{ij} and LE_{ij}. The introduction of this variable implicitly allows for different weighting of HE_{ij} and LE_{ij}, and might also proxy for the presence of a risk component linked with the

[3] In the following, all variables, with the exclusion of the time trend, are expressed in logarithms.

estimates' variance. This specification also allows for a more direct comparison with other models proposed in the literature. If the restriction $b_2=1$ is not rejected, the analysis of the auction structure once more can be recast in terms of the bid to (restricted) estimate ratios, and if $b_4+b_5=0$ the same reasoning can be extended to lagged terms. Again, only when the estimated value of the coefficient b_4 is not significantly different from zero, is the relevant model the static one.

The role of the auction house

The optimal strategy of an auction house that faces an expected price (relative to estimate) decline over the course of the auction, that is, an afternoon effect, is to put the objects with the highest valuations at the beginning of the auction, when prices are high relative to their estimates. On the contrary, should there be a morning effect, an optimizing auction house would place the objects with the highest valuations later in the sequence.

In order to investigate the selling strategy of the auction house, we consider the regression[4]

[2.4] $$E_{ij}=c_jDU_j+d_1i+u_{ij}$$

where E_{ij} is the estimated value of object *i* in auction *j*, DU_j is the auction-specific dummy variable, *i* is the order of sale and u_{ij} is an idiosyncratic error. If an order of sale effect is present, under the maintained hypothesis of a rational profit-maximizing auctioneer, we expect the estimated coefficient d_1 to be significantly different from zero: negative in the case of an afternoon effect, positive otherwise. The converse, however, is not true: if such an effect is not present, then the true d_1 could still be different from zero, maybe because of habit, of institutional reasons, or of convenience not reflected in the measured prices. In this sense, [2.4] alone does not provide a suitable test for the hypothesis of the relevance of order of sale effect.

General comments

Before we illustrate our data set, and we move on to the empirical analysis, some comments are in order.

Regarding the inclusion of auction dummies, we note that fixed effects are potentially relevant because price estimates are predetermined when the auction takes place, so that market news would affect all of the estimates of a given auction in the same way. Moreover, fixed effects may arise from the fact that the attendance at a given auction is likely to depend on exogenous factors that are fixed with respect to that auction.

We note that the estimation of panel data where lagged values of the dependent variable appear as regressors is not amenable to the familiar OLS fixed effects estimation, that in this case provide biased estimates. Various instrumental variable techniques have been developed to solve this problem. However, while OLS fixed effect estimates are biased when the model is dynamic, the size of the bias tends to zero as N tends to infinity. In our case N, the number of objects sold in an auction, is generally fairly big and likely to imply a negligible bias.[5] Further problems arise when the assumption of homogeneity of coefficients across units is not correct. We will consider these issues explicitly later on.

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4 The relation could be defined with the low or high estimate as the dependent variable, instead of their mean. In the empirical analysis these possibilities will be explicitly considered.

5 See, e.g., Baltagi 1995.

Another problem concerns the correct measure of the estimated value of an object when two estimates, a high and a low values, are available. While the estimated range is assumed to comprise the "true" market value of the painting, the usual practice of considering the average value of the two estimates might be incorrect. In fact, Ekelund *et al.* (1998) suggest that the low estimate value is often related to the seller's reservation price, while the high estimate tracks more closely the actual valuation of the auction house. In such cases, bidders might attach different weights to these estimated values. For this reason, whenever possible we will consider the effects of the two point estimates on the bid price separately.

We assume that the estimated value of an object is an unbiased guess of its market evaluation: A painting is assumed to have an intrinsic artistic (market) value because of certain "fundamentals" firmly held by society and amenable to quantitative measurement (see, among others, Frey and Pommerehne, 1989), even if measurement errors in the market value of these fundamentals may occur. Also, the auction house might be tempted to increase some estimates above their "true" value: higher estimates, might induce higher bids - if the 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 bidders and the competition, as the expected highest bid price is non decreasing in the number of bidders. However, both these practices might be unprofitable: if the auction house reveals all the available information, bidders might become more aggressive and expected bids might increase (Milgrom and Weber, 1982a). More importantly, reputational considerations, that are crucial in this market, also support the case of no strategic tinkering by the auction house with the estimates. Therefore, we assume that if, in a given auction, some biases in the estimates emerge, they are random. A bias however might be specific to a particular auction, because of publicly available news unknown when the estimates were made. If this is the case, the auction fixed effect dummy will incorporate (and neutralize for) such a bias.

The assumption of unbiased "objective" estimates has two important consequences. First, estimated values are exogenous with respect to the auction ordering. A painting's estimated value is independent of the order of sale in the auction. In fact, the structure of the whole auction (the number and the identity of the objects, and the auctioning order) is not known at the time the objects are estimated. Second, the effects of the non-price characteristics of the painting (such as, the identity of the painter, the medium or the size of the painting) that explain its value are fully accounted for by the (unbiased) estimate. Therefore the analysis of the link between the order of sale and the bid does not require the introduction of exogenous variables in addition of the price variables, unless the estimates were systematically biased - a possibility that we have ruled out.

Also the occurrence of *buy-ins* require a careful treatment. As is well known, the bid price is not always the actual sale price, because some paintings are "bought in", i.e., retired from the auction, if the highest bid falls short of the seller's reservation price. If the estimates are unbiased, to a buy-in there corresponds a higher than average probability of a low final bid (relative to estimate). Therefore, buy-ins and order of sale effects are intertwined: if there is an afternoon (morning) effect, then buy-ins are more likely to occur at the end (beginning) of the auction.

If the afternoon effect is regarded to be the consequence of a greater proportion of buy-ins at the end of the auction, the problem would be the explanation of the clustering of buy-ins rather than the afternoon effect *per se*. On the other hand, if buy-ins are considered the consequence of an afternoon (morning) effect, ignoring them would remove this effect. This practice, however, would not be justified, because 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, and therefore possibly affect the bidders' strategies in subsequent lots. Moreover, if buy-ins were concentrated in a given moment of the auction, the sellers would compete to avoid the least profitable selling placements in the order of sale. Excluding buy-ins would produce a fictitious sale order and could lead to misleading results, especially when dynamic effects are significant. In our empirical analysis, therefore, we do not distinguish between sold objects and buy-ins.

4. The data set

Our data set collects the transactions of modern and contemporary paintings auctioned by “Casa d’aste Finarte” in Rome, Milan and Lugano in the spring and the fall seasons during the period 1983-1996. Finarte is the leading auction house in Italy for modern and contemporary art and it is estimated to have about 60% of the relevant market. The paintings auctioned vary widely in terms of estimated price, medium (oils, watercolors, drawings, prints, etc.) and dimension. Paintings by Braque, Chagall, De Chirico, Fontana, Mirò, Morandi, Picasso and several other highly reputed painters were commonly auctioned during the period under scrutiny. This data set is representative of the whole Italian market and exhibits a price dynamics analogous to the major international art markets.[6] In each season, from 3 to 7 auctions took place, for a total of 115 auctions and 27,078 transactions. On average, 235 objects were auctioned in each auction.

For each auction, we record all the auctioned objects. For each transaction we consider two types of price.[7] One is the bid price, i.e., the highest recorded price. The second price that we consider is the estimated price. Estimates are released by auction house experts’ well before the auction takes place and are published in an auction presale catalogue.

In many cases, in the same day a single auction is divided into an afternoon and an evening sub-auction. In a few cases, in a single day there are a morning, an afternoon and an evening sub-auction. On average, 143 objects were auctioned in each one of the 190 sub-auctions. *A priori*, it is not straightforward to decide whether in the empirical analysis sub-auctions that take place during the same day should be considered as separate events. On the one hand, bidders are likely to attend different sub-auctions in the same day, and this might suggest their grouping. On the other hand, the aggregation of two different pools of paintings might be misleading if there is a “right place to be” for each object, when auctions are characterized by an intrinsic dynamic effect. Even when there is a large attendance at an auction, the group of bidders that actually compete for a class of relatively homogeneous objects might be significantly smaller. In fact, in several cases the afternoon sub-auctions deal with drawings and prints, while in the evening oils usually prevail. This would suggest instead that the afternoon and evening sub-auctions are different in kind, and that their aggregation would is inappropriate. In such a case, sub-auctions might track more precisely the dynamic effects. In the following, we take an agnostic view, and analyze the auction structure under both hypotheses.

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6 See Candela and Scorcu, 1997.

7 For a very limited number of objects the estimated price is produced only upon request. These few cases have been excluded from the data set. These cases are always put at the very end of an auction and therefore are unlikely to affect our empirical analysis, particularly with respect to its dynamic dimension.

5. The empirical evidence[8]

The general dynamic model

We begin by estimating the general dynamic model [2.1]. In Table 1 we consider the empirical evidence from the 115 auctions. The estimated coefficients of the static regression are shown in column 1, while two dynamic models are considered in columns 2 and 3. The auctions fixed effect coefficients are not reported. The (heteroscedasticity consistent) *t-statistics* are shown in parenthesis and the corresponding *P-values* are reported in brackets.

In the static model there is a positive and significant relationship between the order of sale and the bid price (a "morning effect"), after controlling for the estimated values of the paintings. That is, our static analysis, instead of detecting an afternoon effect, as in previous empirical studies, finds quite the opposite.

Table 1 - Bid price-order regression, 115 auctions

$P_{ij}=\Sigma_j a_j DU_j+b_1 i+b_2 HE_{ij}+b_3 LE_{ij}+b_4 P_{i-1j}+b_5 HE_{i-1j}+b_6 LE_{i-1j}+b_7 P_{i-2j}+b_8 HE_{i-2j}+b_9 LE_{i-2j}+b_{10} P_{i-3j}+b_{11} HE_{i-3j}+b_{12} LE_{i-3}+u_{ij}$

Dependent Variable	bid price	bid price	bid price
	0 lag	1 lag	3 lags
Trend	0.00021 (3.4774) [0.0005]	0.00015 (2.4800) [0.0131]	0.00010 (1.6331) [0.1024]
HE	0.64161 (18.016) [0.0000]	0.63853 (18.230) [0.0000]	0.63833 (18.3400) [0.0000]
LE	0.3497 (9.8310) [0.0000]	0.34730 (9.9223) [0.0000]	0.34368 (9.8707) [0.0000]
P(-1)	-	0.06141 (6.7823) [0.0000]	0.05750 (6.9150) [0.0000]
HE(-1)	-	-0.03308 (-1.2827) [0.1996]	-0.02917 (-1.1802) [0.2379]
LE(-1)	-	-0.01526 (-0.5836) [0.5595]	-0.02003 (-0.7962) [0.4259]
P(-2)	-	-	0.03469 (4.5736) [0.0000]
HE(-2)	-	-	-0.02496 (-0.9047) [0.3656]
LE(-2)	-	-	-0.00272 (-0.0993) [0.9209]
P(-3)	-	-	0.02069 (2.8438) [0.0045]
HE(-3)	-	-	-0.02701 (-1.4294) [0.1529]
LE(-3)	-	-	0.01479 (0.7135) [0.4755]
R^2	0.9314	0.9314	0.9313
TSS	36,353.7928	36,057.1835	35,538.2420
RSS	2,494.5940	2,472.1567	2,442.2418
n. obs	27,078	26,963	26,733

Note: *t-statistics* in parenthesis, *P-values* in brackets.

The 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 around 5%.

Note that 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 $b_2=½$ and $b_3=½$ are equal to 3.976 and –4.226 for HE and LE, respectively, and are both rejected at the usual 5% significance level.

From columns 2 and 3 the importance of the dynamic effects emerges clearly. In particular, the lagged values of the bid prices have the expected (positive) sign and are quite precisely estimated, while the lagged values of HE and LE are much more imprecisely estimated, even if in general they exhibit the expected negative sign[9]. The addition of more

[8] Data and (Ox) routines are available upon request.

[9] Note that the lagged low and high estimates, while generally non-significant individually, are mostly significant when considered jointly. Formal F-tests yielded the following P-values. In the one-lag dynamic

lags and the exclusion of the insignificant variables does not affect appreciably the results[10]. Also, in the dynamic cases, the dependent variable of the relationship can be expressed in terms of bid to estimate ratio.

An important aspect of our results is the presence of a morning effect, as shown by the significant and positive estimate of b_1. Even if the dynamic lagged effect and the order of sale effect are not mutually exclusive, in practice the inclusion of the lagged dependent variable leads to a reduction in size and significance of b_1[11], while all other estimated coefficients remain remarkably stable in the various specifications[12]. If one uses a static model, when the true relationship is dynamic, it is easy to show that the sign of the bias in this coefficient depends on the sign of the correlation between the included variable (the time ordering) 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 smaller (bigger) than its true value[13]. Using a properly specified dynamic model should avoid the problem. We will return to this point later on.

Table 2 - Bid price-order regression, 115 auctions

$P_{ij}=\Sigma_j a_j DU_j+b_1 i+b_2E_{ij}+b_3S_{ij}+b_4P_{i-1j}+b_5E_{i-1j}+b_6S_{i-1j}+b_7P_{i-2j}+b_8E_{i-2j}+b_9S_{i-2j}+b_{10}P_{i-3j}+b_{11}E_{i-3j}+b_{12}S_{i-3}+u_{ij}$

Dependent Variable	Bid price	bid price	bid price
	0 lag	1 lag	3 lag
Trend	0.000207 (3.4891) [0.000486]	0.000151 (2.4955) [0.01258]	0.00010 (1.6452) [0.09994]
E	0.99174 (224.760) [0.0000]	0.98627 (261.610) [0.0000]	0.98248 (261.2100) [0.0000]
S	0.08099 (2.1693) [0.030068]	0.08016 (2.1800) [0.02927]	0.08150 (2.2162) [0.02668]
P(-1)	-	0.061618 (6.8021) [0.0000]	0.057762 (6.9398) [0.0000]
E(-1)	-	-0.048604 (-5.9481) [0.0000]	-0.04950 (-6.2980) [0.0000]
S(-1)	-	-0.003471 (-0.13482) [0.89275]	0.00038 (0.015575) [0.9876]
P(-2)	-	-	0.034268 (4.5675) [0.0000]
E(-2)	-	-	-0.02732 (-3.7063) [0.0002]
S(-2)	-	-	-0.006896 (-0.2527) [0.80049]
P(-3)	-	-	0.02084 (2.8576) [0.00427]
E(-3)	-	-	-0.01237 (-1.7371) [0.08238]
S(-3)	-	-	-0.018354 (-0.93312) [0.35077]
R^2	0.931305	0.93135	0.93119
TSS	36,353.785	36,057.183	35,538.242
RSS	2,497.3157	2,475.194	2,445.367
n. obs	27,078	26,963	26,733

Note: *t-statistics* in parenthesis, *P-values* in brackets.

In Table 2 we consider the restricted model [2.3] where the average estimate and the spread are considered. This allows for a (partial) comparison with other empirical models so far developed in the literature. The results are in line with the findings shown in Table 1: in particular, a morning effect is present, but its relevance and statistical significance decreases once lagged prices are included (columns 2 and 3). The spread coefficient is positive and

specification: : H_0:b_5=b_6=0, P-value= 0.000. In the three-lag dynamic specification: H_0:b_5=b_6=0, P-value= 0.000; H_0:b_8=b_9=0, P-value= 0.009; H_0:b_{11}=b_{12}=0, P-value= 0.0656.

10 Results are available on request from the authors.

11 Given the small magnitude of the estimated lagged price coefficients, the magnitude of the order effect for the dynamic models does not depart significantly from the estimates of b_1.

12 In the 3-lag model shown in column 3, the size of the order of sale coefficient is less than ½ of the corresponding coefficient of the static model of column 1, and it is imprecisely estimated.

13 Beggs and Graddy (1997) apply a static model to auctions data characterized by an (overall) negative correlation between estimates and time ordering. Estimates and prices are highly and positively correlated, so it is reasonable to assume that in their case prices and ordering are also negatively correlated. Their “afternoon effect” could then at least in part be the result of a dynamically misspecified model.

significant, thereby confirming the greater weight attached to the high, relative to the low, estimate[14].

In these restricted specifications, the static model also turns out to be misspecified. The main difference with respect to the unrestricted model is that in the present case the lagged estimates are usually significant. On the other hand, the lagged spread, when present, is not.

Table 3 and 4 show the same exercises for the 190 sub-auction case. The results mirror those ones of Tables 1 and 2. A few findings, however, deserve specific comments. The dynamic effects are still important, but the size of the coefficients of the lagged terms is now smaller: in Table 3 all of the estimated price elasticities are lower than the corresponding estimates of Table 1[15].

Table 3 - Bid price-order regression, 190 sub-auctions

$P_{ij}=\Sigma_j a_j DU_j+b_1 i+b_2 HE_{ij}+b_3 LE_{ij}+b_4 P_{i-1j}+b_5 HE_{i-1j}+b_6 LE_{i-1j}+b_7 P_{i-2j}+b_8 HE_{i-2j}+b_9 LE_{i-2j}+b_{10} P_{i-3j}+b_{11} HE_{i-3j}+b_{12} LE_{i-3}+u_{ij}$

Dependent Variable	Bid price	bid price	bid price
	0 lag	1 lag	3 lag
Trend	0.000104 (1.2468) [0.2125]	0.000072 (0.88179) [0.37779]	0.000041 (0.50738) [0.61189]
HE	0.65060 (18.612) [0.0000]	0.64467 (18.365) [0.0000]	0.64170 (18.178) [0.0000]
LE	0.33367 (9.5472) [0.0000]	0.33687 (9.5838) [0.0000]	0.33825 (9.5739) [0.0000]
P(-1)	-	0.048982 (5.4605) [0.0000]	0.047616 (5.4956) [0.0000]
HE(-1)	-	-0.01899 (-0.7722) [0.4400]	-0.01925 (-0.78269) [0.43382]
LE(-1)	-	-0.02118 (-0.85448) [0.39285]	-0.021773 (-0.87085) [0.38385]
P(-2)	-	-	0.02296 (3.1714) [0.0015]
HE(-2)	-	-	-0.00947 (-0.32974) [0.7416]
LE(-2)	-	-	-0.008817 (-0.31122) [0.75563]
P(-3)	-	-	0.011499 (1.6127) [0.10682]
HE(-3)	-	-	-0.015445 (-0.77715) [0.43708]
LE(-3)	-	-	0.01025 (0.49803) [0.61846]
R^2	0.90311	0.902809	0.902607
TSS	25,383.568	25,038.199	24,498.060
RSS	2,459.251	2,433.486	2,385.936
n. obs	27,078	26,888	26,508

Note: *t-statistics* in parenthesis, *P-values* in brackets.

The most important change concerns the drop in the coefficient of the order of sale: the point estimate of b_1 is always positive, but smaller and not significant, even in the static case. With respect to the presence of an order of sale effect, aggregating or not aggregating sub-auctions turns out to be an important issue.

The same conclusions apply to the results of Table 4, where the restricted model is applied to the sub-auction case. Here again we find no evidence of morning (or afternoon) effect regardless of the dynamic dimension of the estimated relationships.

Why do the results change when we consider sub-auctions instead of auctions? The lack of an agreed-upon theoretical model for sequential auctions will confine our attempts at an answer to this question to a few educated guesses. We are inclined to believe that different

14 If the spread were linked to the presence of risk aversion, $b_3<0$ should be expected. We discard this interpretation because the estimated coefficient is positive in all specifications. However, the exclusion of the spread variable has no appreciable effect on the other estimated coefficients.

15 For this case also, the lagged low and high estimates, while generally non-significant individually, are mostly significant when considered jointly. Formal F-tests yielded the following P-values. In the one-lag dynamic specification: : H_0:$b_5=b_6=0$, P-value= 0.000. In the three-lag dynamic specification: H_0:$b_5=b_6=0$, P-value= 0.000; H_0:$b_8=b_9=0$, P-value= 0.0396; H_0:$b_{11}=b_{12}=0$, P-value= 0.5862.

sub-auctions are characterized by varying degrees of competition. If competition among bidders is tougher in the evening than in the morning and afternoon sub-auctions, the morning effect that emerges from the analysis of the 115 auctions would simply be a result of the increased competition in their afternoon and evening sub-auctions. Separating sub-auctions would then eliminate the source of the morning effect, since the different level of competition would then be accounted for by the individual (sub-auction) fixed effects.

How could such a different degree of competition between different sub-auctions arise? Morning and afternoon sub-auctions mostly deal with low-price prints, while evening sub-auctions are concerned mostly with more expensive objects such as oil paintings. Later on, we will deal explicitly with the determination of the auctioning order by the auction house, to conclude that on average expensive objects are placed later in the auction sequence. Since different sub-auctions within the same day deal on average with different types of object and bidders, it can be imagined too that these sub-markets could be characterised by different levels of competition: lower for low-priced, and higher for high-priced objects.

High quality objects might command a higher number of active bidders than low quality objects, and because of the harder competition, for these objects the expected price (with respect to estimate) might raise. While we cannot provide any substantive proof of this, the 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”[16]. In this case only the (less important) order of sale within sub-auction is left unexplained.

Table 4 - Bid price-order regression, 190 sub-auctions

$P_{ij}=a_jDU_j+b_1i+b_2E_{ij}+b_3S_{ij}+b_4P_{i-1j}+b_5E_{i-1j}+b_6S_{i-1j}+b_7P_{i-2j}+b_8E_{i-2j}+b_9S_{i-2j}+b_{10}P_{i-3j}+b_{11}E_{i-3j}+b_{12}S_{i-3j}+u_{ij}$

Dependent Variable	Bid price	bid price	bid price
	0 lag	1 lag	3 lag
Trend	0.000104 (1.2478) [0.21212]	0.000072 (0.87893) [0.37945]	0.000041 (0.5063) [0.61593]
E	0.98480 (269.390) [0.0000]	0.98203 (284.1900) [0.0000]	0.98044 (280.4100) [0.0000]
S	0.092614 (2.4758) [0.013299]	0.08749 (2.3294) [0.019846]	0.084989 (2.2460) [0.024715]
P(-1)	-	0.049274 (5.4939) [0.0000]	0.047932 (5.5336) [0.0000]
E(-1)	-	-0.04046 (-4.7040) [0.0000]	-0.041336 (-4.8602) [0.0000]
S(-1)	-	0.0047782 (0.19623) [0.8444]	0.00047567 (0.19471) [0.84562]
P(-2)	-	-	0.022586 (3.1310) [0.00174]
E(-2)	-	-	-0.017948 (-2.5030) [0.012321]
S(-2)	-	-	0.0023895 (0.08434) [0.93279]
P(-3)	-	-	0.011723 (1.6405) [0.10091]
E(-3)	-	-	-0.0053735 (-0.76139) [0.44643]
S(-3)	-	-	-0.011653 (-0.58277) [0.56005]
R^2	0.90300	0.90268	0.90248
TSS	25,383.3299	25,038.199	24,498.060
RSS	2,462.154	2,436.653	2,389.107
n. obs	27,078	26,888	26,508

Note: *t-statistics* in parenthesis, *P-values* in brackets.

16 Cited in Pesando (1993), pg. 1083.

Heterogeneous parameters

We have shown that the correct model is the dynamic one. In such a case Pesaran and Smith (1995) argue that a pooled dynamic estimator provides consistent estimates of the mean effect of the variables only when the individual coefficients are indeed homogeneous across units. If this is not the case, the pooled estimates are biased; moreover, the bias does disappear as the sample size grows, and the problem is not amenable to instrumental variables techniques. In these instances, it is appropriate to estimate the average effect of the regressors by considering the average of the estimated coefficients of the equation estimated individually. 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].

In Table 5 we show the results of this exercise for the one-lag specification. The findings are not qualitatively different from the homogeneous case: the order effect is positive and significant when the sub-auctions that take place in the same day are considered together, and it is positive but not precisely estimated otherwise. The coefficients of HE and LE are similar to the homogeneous parameters case. The lagged dependent variable loses some of its importance even if the sign and the significance of the estimated coefficients are retained. The order of sale coefficient increases in size, but, again, it is significant only in the 115 auctions case. Overall, our previous empirical findings therefore turn out to be robust to the relaxation of the homogeneity hypothesis.

Table 5 – Average coefficients, heterogeneous parameters

	$P_{ij}=a_i+b_{1i}i+b_{2i}HE_{ij}+b_{3i}LE_{ij}+b_{4i}P_{i-1j}+b_{5i}HE_{i-1j}+b_{6i}LE_{i-1j}+u_{ij}$	
Dependent Variable	bid price	bid price
	115 auctions	190 sub-auctions
Constant	-2.8715 (-1.8842) [0.059544]	-3.3909 (-0.54210) [0.58775]
Trend	0.000224 (3.6373) [0.00027547]	0.0002696 (0.86380) [0.38770]
HE	0.59796 (28.492) [0.0000]	0.63638 (14.489) [0.0000]
LE	0.37799 (18.383) [0.0000]	0.32373 (7.5121) [0.0000]
P(-1)	0.035861 (6.2553) [0.0000]	0.024824 (2.1529) [0.031328]
HE(-1)	-0.034405 (-1.7574) [0.078849]	-0.030408 (-0.72185) [0.47039]
LE(-1)	0.0069731 (0.36629) [0.71415]	0.0087476 (0.19623) [0.84443]

Note: *t-statistics* in parenthesis, *P-values* in brackets.

The auction house strategy

We have already pointed out that, typically, more expensive objects are auctioned later in an auction. We now want to investigate in more detail the auction house's strategy in deciding where to place a given object. We do this by investigating whether there is a relationship between the order of sale and the estimated values, both between and within sub-auctions. This gives a measure of the *ex-ante* price structure of an auction, as anticipated by the auction house.

A departure from a random allocation of the objects might indicate the existence of a selling strategy of the auction house. If, for whatever reason, a morning (afternoon) effect is expected, it will be profitable for the auction house to place the most (least) expensive objects towards the end of the auction. Note that in principle departure from random allocation could

[17] An F test led to the rejection of the homogeneity hypothesis at conventional levels, both the auction and the sub-auction case. The reported *t-statistics* and *P-values* are computed from heteroscedasticity consistent standard errors.

be unrelated to the presence of morning or afternoon effects: for example, the auction house could place objects on a given order because of habit. From our results - a weak morning effect is present between sub-auctions but is absent within each sub-auction - we would expect a profit maximizing auction house to place more expensive objects in the sub-auctions that take place later in the day, while there is no strong expectation as to the placing order within sub-auctions.

We consider regression [2.4] where the estimates are regressed against their corresponding order in the sequential auction[18]. We run separate regression for average estimate, low estimate and high estimate and for auctions and sub-auctions. Results are shown in Table 6, where in columns 1-3 we consider the 115 auctions and in columns 4-6 the 190 sub-auctions.

The coefficient on the linear trend is positive and statistically significant in all cases. In the typical auction, the estimate of the *(i+1)*th object is 0.61% higher than the estimate of the *i*th object, for all the measures of the estimated values considered. Since the average length of the auction is 235, the estimated value of the last object is four times higher than the estimated value of the first object of the auction. The order of the estimation and the auction specific fixed effects explain more than 20% of total variability.

Table 6 - Order regression

	$E_{ij}=c_jDU_j+d_1i+u_{ij}$					
dependent variable	average estimate (1) 115 auctions	low estimate (2) 115 auctions	High estimate (3) 115 auctions	average estimate (4) 190 sub-auctions	low estimate (5) 190 sub-auctions	high estimate (6) 190 sub-auctions
Trend	0.0061	0.0061	0.0061	0.0034	0.0034	0.0034
	(14.2277)	(14.066)	(14.4490)	(8.6900)	(8.7319)	(8.6420)
	[0.000]	[0.0000]	[0.0000]	[0.000]	[0.000]	[0.0000]
R^2	0.2113	0.2090	0.2124	0.0398	0.0394	0.0400
RSS	26,755.8555	26,969.06	26,765.02	22,633.0948	22,751.996	22,708.81
TSS	33,925.6264	34,095.81	33,983.65	23,572.1476	23,684.051	23,655.41

Note: number of observations: 27,078; *t-statistics* in parenthesis, *P-values* in brackets.

When we consider sub-auctions instead (columns 4-6), we obtain qualitatively similar results. However, note that the estimated order coefficient, while still positive and significant, almost halves in size. Since the length of the typical sub-auction is 143, the difference between the estimates of the first and the of last object is about 160%. Therefore, while there is always an increasing order of the estimates, most of the difference seems to arise from the aggregation of sub-auctions. This result is consistent with our expectations. Moreover, while we also detect a positive and significant upward trend in objects' evaluations, the ordering, in this case, explains a mere 4% of total variability. The increasing trend that we obtain when we consider together the sub-auctions that take place within the same day (columns 1-3) is then mostly due to their different and increasing means.

Afternoon or morning effect?

Up until now we have assumed that the auction house strategy could follow from the presence of a morning or afternoon effect: objects could be ordered by increasing values in

18 The inclusion of a squared trend would allow for the presence of non-linear effects. The presence of both a linear and a quadratic trend would be compatible with several different auction house strategies, such as first increasing-then decreasing, etc. We experimented with a quadratic trend without finding it significant; all results are available upon request.

the former case, and decreasing in the latter. We now inquire into the possibility that the causal link, when a ordering effect is not due to a misspecified model, goes in the opposite direction: that is, a morning or an afternoon effect emerges from a given ordering strategy.

The presence of a morning, or afternoon, effect, could be the result of a causal link from auction ordering to bidders' behavior. We note that, if this is the case, we would expect to find a more pronounced morning (or afternoon) effect in those (sub-)auctions that are characterized by a stronger departure from the case of random placing of the objects. We investigate this point by regressing the *t-statistics* of the order of sale coefficients of the general unrestricted model with heterogeneous parameters, against the correlation between average estimated price and order, and a constant.[19] That is, the *t-statistics* on the general regression shown in Table 5, applied to each single sub-auctions, have been collected and used as the dependent variable in a regression where the regressors are a constant term and the correlation between the average estimate and the order of sale of the same auction. This has been done both for the sub-auction and the auction case. The results are shown in Table 7.

We see that, regardless of the case, the correlation coefficient between estimate and order of sale is significantly and positively related with the significance of the time trend: those (sub-)auctions having a stronger positive (negative) link between estimate and auctioning order, also present a stronger morning (afternoon) effect.

Table 7 – Significance of the estimate - order of sale relationships

	(1) 115 auctions	(2) 190 sub-auctions
Dep. Variable	Value of the t-stat. of the order coeff. in the 1 lag regression	Value of the t-stat. of the order coeff. in the 1 lag regression
Constant	-0.3233	0.0131
	(-1.1118)	(0.1001)
	[0.2686]	[0.9294]
Correlation between estimate and sale order	1.8353	0.9075
	(3.3053)	(2.1226)
	[0.0013]	[0.0351]
R^2	0.0882	0.0234

Note: 27,078; *t-statistics* in parenthesis, *P-values* in brackets.

The results for sub-auctions shown in column (2) and the non-significant estimate of the constant suggest a quite simple profit maximizing auction house strategy: if the objects were ordered randomly within each sub-auction, the correlation between the order of sale and the estimated value would be around zero, with no morning effect expected. However, if the auction house orders the objects within each sub-auction by increasing value, bidders' behavior become more predictable and a morning effect is more likely to emerge (in terms of size of the *t-statistics*). According to these results, the auction house is justified in preferring some relationship between the order of sale and the estimated value of the objects.

6. 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, the presence of a morning effect emerges from the data. This effect is less pronounced within sub-auctions and when a dynamic model is considered. Moreover, we find a positive and significant relationship between the auction ordering and the estimated values.

19 Experimentation with different lags of the general model did not change the results.

A distinctive feature of our pricing relationship is its dynamic dimension, that could be explained in terms of affiliation or psychological effects. Adopting a dynamic specification, both with homogeneous and with heterogeneous parameters, has allowed us to propose an encompassing explanation of previous empirical results: when the true relationship is dynamic, adopting a static model induces a spurious afternoon (morning) effect when the objects are placed according to their value in descending (ascending) order.

Apart and besides the spurious nature of a morning effect as detected using a static model, we consider a possible explanation for its emergence when a dynamic model is used on our auction data. This could be due to the existence of relatively stronger competition for the more valuable objects, and to the peculiar behavior of the auction house which prefers to put the high price sub-auctions in the evening.

Within sub-auctions, also, we find that those auctions with a higher correlation between ordering and value, are the ones characterized by a stronger morning effect, a result that might be explained by the behavior of the auction house.

Our analysis is consistent with much casual evidence according to which there is always a "good place to be" for a particular object in an auction[20], but this place depends upon several features and habits, sometimes idiosyncratic to the market and to the seller.

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