Art experts and auctions Are pre-sale estimates unbiased and fully informative ? *

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1 Introduction

Sales catalogues prepared by Christies' and Sotheby's include pre-sale price estimates established by experts. This makes it possible to analyze whether salerooms provide their customers (consignors as well as buyers) with unbiased predictions of realized prices.

Intuition leads to conjecture that such estimates should be unbiased. Though a seller may obviously like high pre-sale estimates, these may discourage buyers from showing up at the sale : the estimate is not independent from the seller's reserve price, which prospective buyers may then believe to be too high. On the other hand, a seller is unlikely to accept low pre-sale estimates, since this depresses his/her reserve price, which, as a rule, should be lower than the lower bound of the estimate[1]. Therefore, one may think that pre-sale prices should be unbiased estimates of actual sale prices. This argument is made formal in Milgrom and Weber (1982) who show that in most auction models–first-price, second-price and English auctions–

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1 This is at least announced as a rule by Christie's : "It is Christie's general policy that the reserve for any lot shall not exceed its low pre-sale estimate." (Christie's sale catalogues, Information for Prospective Buyers).

, "honesty is the best policy" for the seller in the absence of reserve prices. When these are introduced, the number of buyers may depend on the details of the information which is released : if the information is favourable (resp. unfavourable), more (resp. less) bidders will participate. However, it is also shown that the seller can adjust the reserve price so that the "honesty result" will continue to hold.

One should also expect that all the information available to the experts is reflected in the pre-auction prices.

The two assumptions are tested using a sample of some 1,600 lots of English silver sold between 1976 and 1991 by Christie's and Sotheby's. Section 2 briefly describes the dataset. Section 3 discusses the econometric model used to test for unbiasedness of pre-sale estimates and presents the empirical results, which show that pre-sale prices are biased, though the bias is quite small and can therefore be neglected in practice. In Section 4, we analyze whether experts use all the information that is available to them when they make their estimates and show that this is not the case : their pre-sale estimates could therefore be improved.

2 The data

Our estimates are based on a data set, collected by Dorchy (1992), consisting of 1,621 English silver coffee- and teapots, auctioned by Christie's and Sotheby's London between 1976 and 1990[2]. The number of pieces sold varies between 242 in 1980 and 39 in 1976; pieces were chosen in sales catalogues that were at hand; in principle, there should therefore be no selection bias. For each piece, we collected a certain number of characteristics, described in the sales catalogues (see Table 2), as well as pre-sale estimates and hammer prices.

Since prices will play an important role in what follows, a brief description of the data is in order. Salerooms publish a range for the pre-sale price estimate. Table 1 gives over- and underestimations (p is the saleprice, $\hat{p}_{min}$ and $\hat{p}_{max}$ are respectively the minimum and the maximum of the pre-sale price range). The proportion of hammer prices that fall within the range varies between 49% (in 1982 and 1989) and 37% (in 1988 and 1990). Under- and overestimations vary more from year to year, but there seems to be no "error correction mechanism" at work. We also checked whether there were differences between "cheap" and "expensive" pieces[3], and, though the proportions vary across time, there seems to be no obvious pattern. Details can be found in Table 1. Note that the proportion of collectibles below the

[2] London is the main market for silverware, and New York sales are not included in the database. It would of course be interesting to check whether auctioneers in London and New York behave similarly or not.

[3] The cutting point between "cheap" and "expensive" is the median price in each year.

Table 1 : *Observed under- and overestimations* (in %)

	$p < \hat{p}_{min}$	$\hat{p}_{min} \leqslant p \leqslant \hat{p}_{max}$	$p > \hat{p}_{max}$	Nb of obs.
Christie's all	12.3	42.7	45.0	1,053
Sotheby's all	13.0	38.7	48.3	568
"Cheap" pieces	14.8	42.6	42.6	825
"Expensive" pieces	10.2	40.0	49.8	796
All together	12.6	41.3	46.1	1,621

minimum estimate ($p \leqslant \hat{p}_{min}$) is low, since it includes only those lots which have reached the reserve price set by the seller. Unsold lots are not included.

Table 2 presents aggregate information on the sample, in particular, average hammer prices by saleroom and the number of observations according to each categorical variable (for instance, number of Queen Ann style objects, etc.). These variables are defined in the next section, after equation (3.4).

3 Testing for unbiasedness

In this section, we test whether pre-sale estimates are unbiased predictions of realized prices. Let $\hat{p}_i$ be the pre-sale estimate of the price of lot i. Unbiasedness requires that the best estimate be $\hat{p}_i = E(p_i|\Omega)$, where Ω is the information set available to the expert. The actual price p_i will then be equal to

$$p_i = \hat{p}_i + u_i; \tag{3.1}$$

u_i is a random disturbance with zero mean and $E(u_i|\Omega)$ should be equal to zero, implying that the random disturbance is orthogonal to every variable contained in the information set Ω, or that the estimate $\hat{p}_i$ takes into account all the information contained in Ω.

It is straightforward to test whether $\hat{p}_i$ is an unbiased prediction of p_i. Indeed, one could run a regression of realizations p_i on estimates $\hat{p}_i$

$$p_i = \alpha + \beta\hat{p}_i + \nu_{1i} \tag{3.2}$$

and test the hypothesis $H_0 : \{\alpha = 0, \beta = 1\}$. If H_0 is accepted, predictions are unbiased[4].

[4] Note that, as is shown in Gouriéroux and Pradel (1986), this procedure can be used on cross section data; for time series, this test may be invalid, if the disturbance ν_{1i} is correlated with future predictions $\hat{p}_{t+k}$, $k > 0$.

Table 2 : *Main characteristics of the data*
(No. of items and average prices in £)

	No. of items or sample means	Average prices		
		Sotheby's	Christie's	Both
All items	1621	1480	1524	1509
Weight (in oz.)	27.5			
Teapots	910	1216	1070	1126
Coffeepots	711	1799	2111	1998
Provenance				
Without	1558	1343	1436	1403
With	63	5900	3462	4120
Goldsmiths				
Unknown	819	1004	836	894
Moderately known	710	1834	1937	1899
Well-known	92	3295	4198	3962
Style				
Queen Ann (1688-1713)	39	5118	5731	4939
George I (1714-1726)	86	6799	7730	7416
George II (1727-1759)	391	2088	2256	2195
George III (1760-1782)	258	1293	1118	1180
Regency (1783-1819)	389	658	557	596
George IV (1820-1829)	136	479	435	449
William IV (1830-1849)	159	571	508	532
Victorian (1850-1880)	72	610	453	499
Modern (post 1880)	91	467	316	353
Other characteristics				
Arms	551	2231	2196	2208
No arms	1070	1100	1175	1148
Monogram	126	1063	1352	1242
No monogram	1495	1518	1538	1531
Stand	27	693	712	705
No stand	1594	1494	1538	1522
Other	201	1551	1449	1478
No other	1420	1472	1536	1513

We also assume that houses may behave differently in setting the pre-sale estimate, but that this is not the case for the reserve price which is suggested by the seller and not by the saleroom[5]. Equation (3.2) is therefore extended to

$$p_i = \alpha_c \delta_{ci} - \alpha_s \delta_{si} + \beta_c \delta_{ci} \hat{p}_{ci} + \beta_s \delta_{si} \hat{p}_{si} + \nu_{1i} \tag{3.3}$$

where $\delta_{ci} = 1$ (resp. $\delta_{si} = 1$) if lot i is sold by Christie's (resp. Sotheby's), with $\delta_{ci} + \delta_{si} = 1$[6]; the parameters are respectively (α_c, β_c) and (α_s, β_s) for Christie's and Sotheby's, while $\hat{p}_{ic}$ and $\hat{p}_{is}$ are their pre-sale estimates. This specification makes it possible to take into account possible differences in the behaviour of experts of both salerooms.

In our case however, the price p_i is observed only if the lot is sold, that is, if there are bids that reach the (unobserved) reserve price r_i. Therefore, instead of the simple model (3.3), we are led to consider the truncated regression model[7] consisting of equation (3.3), where the price p_i is observed only if $p_i \geqslant r_i$, as well as an equation which explains the reserve price r_i. The reserve price is a stochastic variable that is latent, but we observe the variables that determine it; these are precisely the variables z_k in the information set Ω. The equation for the reserve price is therefore

$$r_i = \sum_k \gamma_k z_{ki} + \nu_{2i} \tag{3.4}$$

where the γ_k's are parameters to be estimated; ν_{1i} and ν_{2i} are both random disturbances. If errors are normal and homoskedastic, the maximum likelihood method can be used to estimate model (3.3)-(3.4)[8].

The variables appearing in equation (3.4) are the following: (a) one dummy to distinguish between teapots and coffeepots; (b) weight (in ounces); (c) a dummy that takes the value one if the lot has a "good" provenance, i.e. if, in the past, it was owned by a well-known collector or by some historical figure; (d) two dummies to distinguish unknown, moderately known or well-known silversmiths[9]; (e) eight dummies for styles (Queen

5 In reality, the reservation price is probably influenced by experts and may depend on the price estimate.

6 This parametrization is chosen, since it simplifes the presentation in what follows.

7 If our dataset contained observations on lots that were bought-in, we could maximize the likelihood function of the censored version of the model. Both the censored and the truncated model lead to consistent and asymptotically normal estimators of the parameters under usual regularity conditions. For small samples, there is (limited) evidence that the ML estimates are not very different in the two cases. See Wales and Woodland (1980).

8 See Maddala (1983), pp.174-178. If errors are not normal, estimates are inconsistent. Therefore, it would be appropriate to estimate the parameters using a semi parametric technique that does not rely on normality. No such technique is available yet. On the other hand, testing for normality cannot be done using the observed skewness-kurtosis of the residuals, since the errors are truncated.

9 Silversmiths were classified by Mr. Brand Inglis, an English silver expert and collector. Instead of classifying silversmiths into three categories, we could have used artist (silversmith) dummies, as is usually done in hedonic regressions with paintings. However, in our case, the number of lots per artist was often fairly small, and the estimated coefficients would have been very imprecise.

Ann to Modern); (f) four dummies for other possible characteristics, such as the presence of arms, of a monogram, etc.). We also include a general price index for silverware, which is constructed on the basis of an OLS regression of the prices of the 1,621 lots of the sample on time dummies representing the year of sale[10], as well as characteristics[11]. This two-step procedure is used to avoid estimating 15 additional coefficients (15 annual dummies) in equation (3.4). When estimating (3.4), the coefficient of the price index is constrained to be equal to unity.

Finally, there remains the question of which value to choose for $\hat{p}$, the value of the pre-sale estimate. Intuition suggests the midpoint of the range $(\hat{p}_{max}; \hat{p}_{min})$ published in the sales catalogues, but this might be a simplification since it assumes the distribution of pre-sale estimates to be unimodal and symmetric. Note that this is the assumption used by Ashenfelter (1989). We decided to let the data determine the pre-sale estimate by specifying it as

$$(3.5) \qquad \hat{p}_k = \theta_k \hat{p}_{k,min} + (1 - \theta_k)\hat{p}_{k,max}, 0 \leqslant \theta_k \leqslant 1, k = c, s.$$

This includes two additional parameters θ_c and θ_s (one for each saleroom) into equation (3.3). The midpoint of the range corresponds of course to $\theta = 0.50$, and it is possible to test whether houses are different $(H_0 : \theta_c = \theta_s)$ and whether the θ are significantly different from 0.50 $(H_0 : \theta_c = \theta_s = 0.50)$.

Since we suspected errors in (3.3)-(3.4) to be heteroskedastic, we first ran a White-test on the residuals of (3.3) estimated by OLS. The test detects the presence of very strong heteroskedasticity, which is avoided if all variables are weighted. We chose as weights the midpoint of the pre-sale estimate range $(\hat{p}_{max}; \hat{p}_{min})$[12].

Estimation results are displayed in Tables 3 and 4. Table 3 provides the results of equation (3.3) estimated both by OLS and ML, when $\theta_c = \theta_s = 0.50$ and when the θ are left unrestricted[13]. As can be checked, the results with $\theta = 0.50$ (midpoint of the range) or with θ free are very close. In both the OLS and the ML cases, all the tests show that the hypotheses $H_0 : \theta_c = \theta_s$ and $H_0 : \theta_c = \theta_s = 0.50$ cannot be rejected at the 5% probability level. The intuitive view that the best value of the pre-sale estimate is the midpoint of the range seems thus acceptable.

Therefore, in order to simplify the presentation, we concentrate our discussion on the case in which we impose the restriction $\theta_c = \theta_s = 0.50$.

10 An alternative would be to use auction dummy variables. These were not available in our dataset.

11 See Chanel et al. (1992) for further details of the method, which, in essence, takes the form of a "hedonic regression."

12 We could also have chosen $\hat{p} = \theta\hat{p}_{min} + (1 - \theta)\hat{p}_{max}$, where θ is the unknown coefficient. This would have made the model highly nonlinear, and we chose to simplify estimation somewhat. Actually, what matters here is to remove heteroskedasticity, and this weighting does so.

13 Estimated coefficients for (3.4) are not shown in the ML results of Table 3. They are given in Table 4 for the case $\theta_c = \theta_s = 0.50$. The corresponding results for θ unrestricted are almost the same.

Table 3 : *Estimation results for model (3.3)-(3.4)*
Testing for the value of θ in $\hat{p} = \theta\hat{p}_{min} + (1 - \theta)\hat{p}_{max}$

	(1a) OLS $\theta = 0.50$		(1b) NLS[a] θ unrestricted		(2a) ML $\theta = 0.50$		(2b) ML θ unrestricted	
	Coeff.	St.dev.	Coeff.	St.dev.	Coeff.	St.dev.	Coeff.	St.dev.
α_c	18.87	(4.99)	18.65	(5.06)	15.06	(7.56)	14.89	(7.58)
α_s	13.79	(11.61)	14.88	(11.62)	−71.42	(23.95)	−68.84	(23.89)
β_c	1.17	(0.02)	1.16	(0.05)	1.05	(0.03)	1.03	(0.07)
β_s	1.20	(0.03)	1.09	(0.07)	1.14	(0.04)	1.05	(0.10)
θ_c	0.50	–	0.47	(0.14)	0.50	–	0.44	(0.21)
θ_s	0.50	–	0.15	(0.21)	0.50	–	0.17	(0.31)
Likelihood function	−966.33		−964.43		−851.69		−850.96	
$H_0 : \theta_c = \theta_s$								
Wald test			$\chi^2(1) = 1.61$				$\chi^2(1) = 0.52$	
LR test			$\chi^2(1) = 1.68$				$\chi^2(1) = 0.92$	
$H_0 : \theta_c = \theta_s = 0.50$								
Wald test			$\chi^2(2) = 2.80$				$\chi^2(2) = 1.23$	
LR test			$\chi^2(2) = 3.80$				$\chi^2(2) = 1.46$	

[a] This is the result of an estimation using non-linear least squares.

Complete results are given in Table 4 and include : (1) the OLS estimation of equation (3.3) (OLS); (2) the maximum likelihood estimation of the truncated model (3.3)-(3.4) (ML1); (3) the results for the same model, in which we assume that Christie's and Sotheby's behave identically (ML2); (4) the results for the same model, with the restriction that houses behave identically and that estimates are "unbiased" (ML3). Results can be summarized as follows :

(i) OLS results reject unbiasedness : the F-statistic for the hypothesis H_0 : $\{\alpha_c = \alpha_s = 0; \beta_c = \beta_s = 1\}$ is equal to 111.4, while the tabulated value with 4 and 1,617 d.f. is equal to 3.30 at the 1% probability level.

(ii) The coefficients for the reserve price equation (3.4) are roughly the same in equations (2), (3) and (4) of Table 4, and lead to reasonable results : Weight has a positive and significant influence. Good provenance does not seem to matter. The reason is probably due to the fact that the variable is very imprecise : Good provenance may go unobserved if the seller wishes to remain anonymous[14]. The reserve price for well-known silversmiths is higher than for moderately known and unknown artists,

[14] The dummy variable (well-known collector or not) is constructed on the basis of the information provided by the pre-sale catalogue.

Table 4 : *Estimation results for model (3.3)-(3.4)*
Testing for the unbiasedness of pre-sale estimates ($\theta_c = \theta_s = 0.50$)

	(1) OLS		(2) ML1		(3) ML2 Houses identical		(4) ML3 Houses identical and unbiased	
	Coeff.	St.dev.	Coeff.	St.dev.	Coeff.	St.dev.	Coeff.	St.dev.
α_c	18.87	(4.99)	15.06	(7.56)	17.03	(6.31)	0.00	–
α_s	13.79	(11.61)	−71.42	(23.95)	17.03	(6.31)	0.00	–
β_c	1.17	(0.02)	1.05	(0.03)	1.06	(0.02)	1.00	–
β_s	1.20	(0.03)	1.14	(0.04)	1.06	(0.02)	1.00	–
Teapots			.00	–	.00	–	.00	–
Coffee pots			101.15	(27.07)	147.98	(30.92)	107.76	(23.62)
Weight (in oz.)			5.29	(0.70)	5.87	(0.76)	5.83	(0.71)
No provenance			.00	–	.00	–	.00	–
Provenance			−1.95	(28.64)	16.28	(30.03)	0.70	(27.81)
Unknown			.00	–	.00	–	.00	–
Moderately known			27.28	(15.53)	26.25	(19.83)	24.22	(16.16)
Well-known			75.39	(70.45)	100.30	(71.34)	93.43	(70.00)
Queen Ann (1688-1713)			.00	–	.00	–	.00	–
George I (1714-1726)			214.30	(137.00)	233.43	(135.15)	233.78	(142.59)
George II (1727-1759)			50.63	(104.44)	35.34	(106.31)	56.43	(109.62)
George III (1760-1782)			53.60	(102.32)	50.88	(103.30)	55.13	(107.81)
Regency (1783-1819)			−25.93	(100.91)	−31.60	(100.71)	−36.35	(106.70)
George IV (1820-1829)			−54.51	(104.40)	−135.23	(134.67)	−60.07	(109.50)
William IV (1830-1849)			−64.63	(104.08)	−105.78	(107.44)	−66.00	(109.19)
Victorian (1850-1880)			−47.20	(106.73)	−101.32	(109.50)	−48.86	(110.42)
Modern (post 1880)			−102.22	(104.83)	−148.25	(105.71)	−119.45	(109.55)
No special charact.			.00	–	.00	–	.00	–
Arms			−11.52	(18.48)	−4.25	(23.65)	−5.69	(19.05)
Monogram			49.73	(22.15)	69.82	25.76	(54.09)	(23.04)
Stand			−778.06	(337.64)	−768.22	(350.68)	−766.40	(337.34)
Other			79.63	(24.86)	120.23	(30.95)	89.57	(23.19)
Intercept			−83.75	(101.43)	−121.33	(100.64)	−80.82	(106.73)
St. dev. of resid. of eq. (3.3)			0.50	(0.01)	0.49	(0.01)	0.52	(0.01)
St. dev. of resid. of eq. (3.4)			0.29	(0.02)	0.28	(0.03)	0.32	(0.02)
Likelihood function	−966.33		−851.69		−861.22		−872.07	

Table 5 : *Testing of hypotheses*
$(\theta_c = \theta_s = 0.50)$

H_0	Wald-test	LR-test	χ^2 – critical value (1%)	Result
Style coefficients				
(all 8 coefficients are zero)	40.8	29.1	20.1	rejected
Both houses "identical"				
$(\alpha_c = \alpha_s; \beta_s = \beta_s)$	16.2	19.1	9.2	rejected
Unbiasedness Christie's				
$(\alpha_c = 0; \beta_c = 1)$	18.6	13.3	9.2	rejected
Unbiasedness Sotheby's				
$(\alpha_s = 0; \beta_s = 1)$	12.4	12.8	9.2	rejected
Both houses "identical" and unbiased				
$(\alpha_c = \alpha_s = 0; \beta_c = \beta_s = 1)$	44.5	40.8	13.3	rejected

though not significantly so. Most of the style coefficients in equations (2), (3) and (4) are not significantly different from zero, though Wald and likelihood ratio tests strongly reject the hypothesis that style coefficients have no effect (i.e. are equal to zero) (see Table 5) : They point to the fact that reserve prices are generally lower for more recent pieces. Some special characteristics, such as a monogram, increase the reserve price significantly. On the contrary, the presence of a stand has a strong negative effect on the reserve price; though this may be due to the items included in our sample, it is consistent with the data presented in Table 2, which shows that an object with a stand is some £700 to £800 cheaper than the average object[15].

(iii) The hypothesis that Christie's and Sotheby's behave identically is strongly rejected and so is the hypothesis that either house is unbiased. Obviously the hypothesis that both houses provide unbiased estimates and behave identically is also rejected. The Wald and the likelihood ratio tests for these hypotheses are given in Table 5.

We therefore consider equation (2) of Table 4 to be our basic result. Unbiasedness of price estimates is strongly rejected for both houses, though, as can be seen from Table 4, the bias is not very large: equation (3.3) is

$$p = 15.06 + 1.05\hat{p} \qquad \text{for Christie's}$$

and

$$p = -71.42 + 1.14\hat{p} \qquad \text{for Sotheby's.}$$

[15] Estimations which were run without these items are very close to those which include them. The "stand" dummy seems thus to capture the effect well enough.

Table 6 : *Testing of hypotheses*
(θ_c, θ_s unrestricted)

H_0	Wald-test	LR-test	χ^2 – critical value (1%)	Result
Style coefficients				
(all 8 coefficients are zero)	40.6	28.9	20.1	rejected
Both houses "identical"				
($\alpha_c = \alpha_s; \beta_s = \beta_s$)	15.2	20.3	9.2	rejected
Unbiasedness Christie's				
($\alpha_c = 0; \beta_c = 1$)	4.4	3.9	9.2	accepted
Unbiasedness Sotheby's				
($\alpha_s = 0; \beta_s = 1$)	8.7	9.9	9.2	rejected
Both houses "identical" and unbiased				
($\alpha_c = \alpha_s = 0; \beta_c = \beta_s = 1$)	18.6	16.7	13.3	rejected

Christie's has a tendency to underestimate systematically, while Sotheby's overvalues inexpensive (worth less than £510) pieces and undervalues expensive ones (worth more than £510). This finding is consistent with the observation that globally, in both houses, 46% of the objects are sold at values above the maximum estimate (see Table 1).

The results which appear in the last column of Table 3 could lead to the impression that when θ is left unrestricted for each saleroom, there is no bias. If we do not impose this restriction, the outcomes of the tests of Table 5 are unchanged, except in one case : Christie's pre-sale estimates are found to be unbiased (the LR statistic is 3.9 instead of 13.3) with $p = 14.89 + 1.03\hat{p}$, which is not very different from above. The complete set of tests when θ is left unrestricted is given in Table 6. It shows that the evidence against unbiasedness, while still present, is less strong than in Table 5.

4 Orthogonality of the information set and the estimates

We can obviously not exclude that the equation for the unobserved reserve price is misspecified : Indeed, experts have a chance to look at the lot, can judge its quality and its "beauty", which is hardly described by the rather limited set of characteristics that we use in equation (3.4).

Nevertheless, one may wonder whether the characteristics which are described in the sales catalogues are fully taken into account by experts in their pre-sale assessments. This assumption can be examined by testing whether characteristics are orthogonal to errors made in estimating prices; this implies running a regression of forecasting errors $p_i - \hat{p}_i$ on characteristics z_{ki}

$$(4.1) \qquad p_i - \hat{p}_i = \sum_k \phi_k z_{ki} + \varepsilon_i$$

and testing $H_0 : \phi_k = 0$, all k. However, as before, $p_i - \hat{p}_i$ is observed only if $p_i \geqslant r_i$, and OLS estimates of (4.1) would be inconsistent (since ε has an expectation which depends on the z_k's and on $\hat{p}$, given the truncation condition). To correct for this inconsistency, we estimate (4.2) instead of (4.1)[16]:

$$(4.2) \qquad p_i - \hat{p}_i = \sum_k \psi_k z_{ki} + \lambda w_i + \varepsilon_i$$

where λw_i is the conditional expectation of ε given that $p_i \geqslant r_i$ and w_i is the inverse Mills ratio:

(4.3)
$$w_i = \frac{\phi[(\alpha_c\delta_{ci} + \alpha_s\delta_{si} + \beta_c\delta_{ci}\hat{p}_{ci} + \beta_s\delta_{si}\hat{p}_{si} - \sum_k \gamma_k z_{ki})/(\sigma_1^2 + \sigma_2^2)^{\frac{1}{2}}]}{\Phi[(\alpha_c\delta_{ci} + \alpha_s\delta_{si} + \beta_c\delta_{ci}\hat{p}_{ci} + \beta_s\delta_{si}\hat{p}_{si} - \sum_k \gamma_k z_{ki})/(\sigma_1^2 + \sigma_2^2)^{\frac{1}{2}}]}$$

In (4.3), $\phi(.)$ and $\Phi(.)$ are the normal density and the cumulative normal respectively, and the parameters α_c, α_s, β_c, β_s, γ_k, as well as the variances of the residuals σ_1^2 and σ_2^2 of the two equations are set at the values estimated in eq. (2) of Table 4, since these are consistent estimates (under normality). To correct for heteroskedasticity, all the variables in (4.2) are, as before weighted by the midpoint value of the pre-sale estimate range.

The result of this regression is given in the first two columns of Table 7. Orthogonality now simply consists in testing $H_0 : \psi_k = 0$, all k, using an F-test, thus comparing the residual variance of (4.2) with that of model

$$(4.4) \qquad p_i - \hat{p}_i = \lambda w_i + \zeta_i$$

The value of the F-test is 4.74 (with 17 degrees and 1,602 of freedom)[17] and shows that the z_k characteristics are not orthogonal to the prediction errors: Experts do not take into account all the information contained in the characteristics.

However, in this test, we assume that experts can correctly predict the time trend also, which is probably too demanding. Therefore, we ran the

16 See Bloom and Killingsworth (1985).

17 A White test was run and in both cases, and heteroskedasticity is strongly rejected.

Table 7 : *Orthogonality between forecasting errors and characteristics* ($\theta_c = \theta_s = 0.50$)

	Without time correction		With time correction	
	Coeff.	St. dev	Coeff	St. dev.
Teapots	0.00	–	0.00	–
Coffee pots	3.91	(10.41)	4.36	(10.22)
Weight (in oz.)	1.56	(0.36)	1.82	(0.35)
No provenance	0.00	–	0.00	–
Provenance	−15.62	(16.04)	−7.00	(15.84)
Unknown	0.00	–	0.00	–
Moderately known	15.20	(7.76)	19.31	(7.63)
Well-known	45.84	(40.78)	34.92	(39.81)
Queen-Ann	0.00	–	0.00	–
George I	148.74	(98.88)	176.69	(96.75)
George II	−52.13	(70.40)	−21.56	(69.02)
George III	−59.49	(69.58)	−2.22	(68.45)
Regency	−86.16	(68.85)	−43.84	(67.66)
George IV	−86.99	(69.16)	−46.73	(67.95)
William IV	−85.39	(69.25)	−56.97	(67.98)
Victorian	−72.41	(69.63)	−34.88	(68.36)
Modern	−100.89	(69.01)	−58.49	(67.85)
No special charact.	0.00	–	0.00	–
Arms	16.16	(7.97)	11.09	(7.87)
Monogram	13.48	(13.79)	9.92	(13.66)
Stand	104.69	(35.35)	73.18	(34.71)
Other	27.74	(12.20)	43.11	(12.16)
Inv. Mills ratio	21.57	(7.62)	−27.15	(9.64)
Time dummies	–	–	yes	
Intercept	85.35	(69.03)	22.10	(68.55)
Residual sum of squares				
Full model	316.6		297.4	
Model with $\psi_k = 0$	332.5		315.7	
F-test (17 and n d.f.)*	4.74		5.76	
n	1,602		1,587	

* The critical value at the 1% probability level is 2.0.

same test, introducing time dummies among the variables, so that model (4.2) now reads

$$\hat{p}_i = \sum_t \delta_t y_{ti} + \sum_k \psi_k z_{ki}; \hat{p}_i) + \lambda w_i + \zeta_i \tag{4.5}$$

where y_{ti} is a dummy equal to unity if the sale i took place in year t, and is equal to zero otherwise, and δ_t is the corresponding regression coefficient. This formulation makes it possible to take into account the fact that experts may have mispredicted the actual time trend. Again, orthogonality consists in testing $H_0 : \psi_k = 0$, all k. The resulting F-statistic is equal to 5.76 (with 17 and 1,587 d.f.) with the same result as before : Even if experts are "forgiven" for possible errors they make in estimating the trend, they can be seen as not using all the information they have access to[18].

5 Conclusions

Estimates of pre-sale prices made by experts are significantly biased (especially if the pre-sale estimate is taken as the midpoint of the high and low estimates), though the bias is rather small. Sotheby's overestimates low prices (less than £510) and underestimates high prices. One possible explanation is that Sotheby's wishes to shun buyers of cheap collectibles by predicting higher prices, and attract others by predicting lower prices. Christie's has a tendency to undervalue more systematically. For both houses, the undervaluation is larger the more expensive the collectible, and this is consistent with a behaviour by which salerooms try to make more attractive the objects they sell[19]. This conclusion is somewhat less optimistic than Ashenfelter's (1989) who considers that "auctioneers do seem to provide genuine expertise in predicting prices," and is at odds with the theoretical prediction of Milgrom and Weber (1982). This bias is smaller if the pre-sale estimate is not taken as the midpoint of the high-low range. But this can also be considered as odd, since the midpoint is an intuitive choice, and one can hardly explain why experts would not center their range on their best price prediction.

An even more surprising fact is that experts do not seem to take fully into account the information that is contained in the sales catalogues which they set up before the sale[20]. The results of Section 4 show that their prediction error could be reduced by making better use of this information. This is somewhat at variance (but not in contradiction) with Ashenfelter's remark that "the auctioneer's price estimates are far better predictors of

[18] Alternatively, the information provided in the catalogues may be irrelevant in the estimation process, but then one may wonder why it is collected and published.

[19] In a rational world, this should be well-known by buyers !

[20] See Beggs and Graddy (1997) for a similar result.

the prices fetched than any hedonic price function." Our result seems to imply that auctioneers could provide better pre-sale estimates by adding to their information the one that is given by hedonic functions (e.g. large differences between the hedonic prediction and the pre-sale estimate could at least trigger experts to wonder why this happens).

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