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**TESTING FOR REFERENCE DEPENDENCE:  
AN APPLICATION TO THE ART MARKET**

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## Testing for Reference Dependence: An Application to the Art Market

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## Abstract

This paper tests for reference dependence, using data from Impressionist and Contemporary Art auctions. We distinguish reference dependence based on “rule of thumb” learning from reference dependence based on “rational” learning. Furthermore, we distinguish pure reference dependence from effects due to loss aversion. Thus, we use actual market data to test essential characteristics of Kahneman and Tversky’s Prospect Theory. The main methodological innovations of this paper are firstly, that reference dependence can be identified separately from loss aversion. Secondly, we introduce a consistent non-linear estimator to deal with measurement errors problems involved in testing for loss aversion. In this dataset, we find strong reference dependence but no loss aversion.

JEL: D81, D44, L82

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Paintings are unique items, and an individual painting is infrequently put up for sale. Some Impressionist and Contemporary paintings may never have exchanged ownership since the first sale or gift by the artist. Other paintings may have exchanged owners one or several times, either at auction or privately. Given the infrequency with which a specific item exchanges hands and the changes in the overall market between sales, it might seem somewhat surprising if the price at a previous sale had a large effect on an auctioneer's pre-sale valuation at the next appearance at auction, once an estimate is formed based on all hedonic characteristics of the paintings and the current state of the art market.

Reference dependence based on the previous sale price can result from 'rule of thumb' learning, often referred to as 'anchoring'. Suppose that an expert wishes to value a painting. He knows the price at which the current seller previously purchased the painting and makes an initial judgement about price. Psychologists would call this partial information processing. He then goes about making a new and detailed valuation by taking into account the observable painting characteristics and the current state of the art market. The expert then revises his new valuation based on a proportion of the difference between the last observable price that he has, i.e. his anchor, and his current estimate. We show that reference dependence based on 'rule of thumb' learning can be distinguished from reference dependence based on 'rational' learning.

We distinguish pure reference dependence from effects due to loss aversion. Loss aversion is characterised by a change in the appetite for risk, based on whether the owner of an object has a prospective loss or gain. In a series of influential papers, Kahneman and Tversky (1979) suggest that the outcome of risky prospects are

evaluated by a value function with three essential characteristics. The first is reference dependence, the second is loss aversion, and the third is diminishing sensitivity. Loss aversion implies that reference dependence has a greater impact on losses than on gains, and diminishing sensitivity implies that the marginal effect of losses or gains decreases with the loss or gain. In a sample of repeat sales of Impressionist and Contemporary art that occurred over approximately a 12 year period we find strong evidence indicating reference point effects, but we find no evidence of loss aversion.

Prospect Theory has been highly influential in recent years. Most of the evidence, and indeed Kahneman and Tversky's original motivation for developing it, comes from experimental data. There are relatively few studies using actual market data. Barberis et al (2001) test some of its implications for asset pricing. Jullien and Salanie (2000) look at data on race-track betting. Our study is most closely related to that of Genesove and Mayer (2001).

Our paper has two main methodological innovations over the earlier literature. Firstly, we show that reference dependence can be identified separately from loss aversion, which had been thought problematic. Secondly, we introduce a consistent non-linear estimator to deal with the measurement errors problems involved in testing for loss aversion. These contributions should have application beyond our particular study.

We examine the influence of past prices on pre-sale estimates. This allows us to test for reference dependence in the behaviour of the auctioneer or in the behaviour of the seller. Before the auction, a pre-sale catalogue is published that includes the auctioneer's low and high estimate. Generally, the pre-sale estimates are set in negotiation between the auctioneer and the seller, and by convention, the low estimate

must be set at or above the seller's secret reserve price. As the auctioneer does not own the painting, it is unlikely that the auctioneer could be 'loss averse.' Loss aversion must be attributed to the seller, and the interaction of the seller's reserve price and the pre-sale estimate, whereas reference point effects can be attributed to either the seller or the auctioneer.

Buyers could also be subject to reference point effects, but not of course subject to loss aversion. We test for reference point effects on the part of the buyers by looking at reference point effects on the hammer prices, and on the probability of sale.

The paper proceeds as follows. In section 2 we describe reference dependence and art auctions. In section 3, we construct our empirical model along with describing the intuition behind the empirical model. In section 4 we present our regression estimates focusing on the pre-sale estimates. In section 5 we present our regression estimates with hammer price as the dependent variable and probit estimates of sales probability. We conclude our analysis in section 6.

## **2. Reference Dependence and Art Auctions: Theory and Motivation**

Prospect Theory, as developed by Kahneman and Tversky (1979), has a number of elements. Firstly, it argues that agents evaluate decisions in terms of gains and losses relative to some reference point. Secondly, it argues that agents care more about a loss than a gain of the same absolute size – a feature termed 'loss aversion'. Thirdly, it argues that sensitivity to gains and losses diminishes with distance from the reference point. Fourthly, it argues that agents weight probabilities non-linearly. This last feature we cannot address in the current study, as we do not have access to data on probabilities, but we are able to evaluate the first three hypotheses.

We look at estimates of the selling prices of paintings. Since the reserve price on a painting cannot be above the lowest estimate, this provides a measure of agents' willingness to trade. We do not find evidence of loss aversion or declining sensitivity. We do, however, find evidence of reference point effects. A high selling price in the past is, *ceteris paribus*, likely to result in a higher estimate being set when the painting is next put on the market. A symmetric effect exists for losses.

There are several possible interpretations for the existence of reference dependence. One is that the influence of past prices on estimates reflects purely rational learning. If quality of a painting is not perfectly observable, then auctioneers (and buyers) may use past prices to estimate it. We show in Section 3, however, that we can identify the effect of this kind of rational learning on prices. Although there is some evidence for it, we find that much of the influence of past prices on estimates cannot be explained by this effect.

The interpretation we prefer is that reference dependence results from 'anchoring' or 'rule of thumb' learning on the part of the expert, as described in the Introduction. Another interpretation might be that experts are fully rational but buyers judge the value of a painting using such a heuristic. In this case experts will need to take this in their valuations.

Whatever the interpretation, reference point effects appear to exist on our data. Our study therefore provides support for an important element of Prospect Theory. It does not, however, find evidence for other elements, such as loss aversion.

### **3. An Empirical Model of Reference Point Effects**

We first provide some intuition, and then the model.

### 3.1 Some Intuition

Suppose the econometrician wishes to test whether the expert actually uses the reference point to revise his current valuation. He might first try to replicate the original valuation process by constructing a hedonic model based on all of his observable characteristics, including time dummies to control for the state of the market. Based on this model, the econometrician comes up with his prediction. As does the expert, the econometrician then revises his estimate based on a proportion of the difference between the last observable price that he has and his current estimate. He then might test to see whether this revision based on the reference point enters significantly in a regression of the expert's valuation on the econometrician's price prediction and the revision.

If the econometrician is able to observe all of the characteristics that the expert observes, then this is a reasonable test. However, it is likely that the econometrician cannot observe all of the variables. In this case, the difference between the last price and the current predicted price is simply picking up the variables that the expert observes but not the econometrician. The effect of the reference point is likely to be overestimated.

One way the econometrician can control for his poor predictions is to take the residual from his hedonic prediction and the actual price, and include it in his regression. This will take into account any characteristics that the market can observe, but not the econometrician. In effect, the econometrician is error-correcting his prediction. As we show below, if there are no asymmetric effects between losses and gains, then simply including the residual will provide consistent OLS estimates. However, in the presence of asymmetric effects on losses and gains, OLS is biased and non-linear estimation techniques are necessary.



### 3.2 The Empirical Model

Our empirical strategy extends that of Genesove and Mayer (2001). In particular we take into account both losses and gains. We construct a predicted price for each painting of the form

$$\pi_t = X\beta + \delta_t$$

$X$  represents hedonic characteristics of the painting and  $\delta_t$  time specific effects.

We then estimate an equation of the following form

$$Est = \mu\pi + \lambda(P_{-1} - \pi) + \nu(P_{-1} - \pi)^+ + \xi(P_{-1} - \pi_{-1}) \quad (1)$$

where  $()^+$  denotes the positive part.  $(P_{-1} - \pi)^+$  therefore denotes the predicted loss made on the painting in comparison to its previous selling price. We work in logs, which amounts to the assumption that gains and losses are felt in relative rather than absolute terms.  $Est$  denotes the estimate and for convenience time subscripts have been dropped. The subscript  $-1$  denotes value at the previous sale.

To understand this, note that the equation is equivalent to

$$Est = \mu\pi + \nu_1(P_{-1} - \pi)^+ - \nu_2(P_{-1} - \pi)^- + \xi(P_{-1} - \pi_{-1}) \quad (2)$$

where  $()^-$  denotes the absolute value of the negative part.  $(P_{-1} - \pi)^-$  therefore denotes the predicted gain. This is equivalent to the previous equation if one sets  $\lambda = \nu_2$  and  $\nu = \nu_1 - \nu_2$  since  $P_{-1} - \pi = (P_{-1} - \pi)^+ - (P_{-1} - \pi)^-$ .

Gains and losses have identical effects on estimates if  $\nu_1 = \nu_2$ , which is equivalent to  $\nu = 0$ . Even if this is the case, if  $\lambda$  is non-zero, there are still reference point effects in the formation of estimates: the auctioneer adjusts his estimate in the direction of the previous price.

If  $\nu$  is positive, then in addition, estimates are raised when selling at the unadjusted estimate would result in a loss for the seller. Since, as we noted in the introduction, reserve prices are by convention bounded above by the estimate, this can be taken to reflect adjustment in the reserve price on account of loss aversion.

Genesove and Mayer suggest that a procedure such as the above where, in effect, both gain and loss are included in the equation is not possible. Their argument is that since  $P_{-1} - \pi = (P_{-1} - \pi)^+ - (P_{-1} - \pi)^-$  the regressors are collinear. This is not correct, however, since we include  $P_{-1} - \pi_{-1}$  in (2), not  $P_{-1} - \pi$ . (2), or equivalently (1), are in fact identified. Of course if  $\pi$  and  $\pi_{-1}$  are very similar then the regressors will be very close to collinear and so the coefficients will be poorly identified. In our dataset this does not appear to be a problem.

We do, however, need to consider possible biases in our estimation procedure. In particular, past price may influence the estimate because there may be components to quality which are not captured by the hedonic characteristics but which are either observed by the auctioneer or which he uses past prices to learn about. We show below, however, that the term in  $P_{-1} - \pi_{-1}$  should capture these effects.

Suppose that the auctioneer believes that the true model for the price of the painting is

$$P_t = \pi_t + u_i + \varepsilon_t$$

where  $u_i$  and  $\varepsilon_t$  are independent and Normally distributed with mean zero,  $\varepsilon_t$  being independently and identically distributed across periods.  $u_i$  would represent unobserved quality and  $\varepsilon_t$  shocks particular to that period.

Suppose the auctioneer observes  $\pi_{-1}$  and a signal  $w_i$  which jointly is Normally distributed with  $u_i$ .  $w_i$  represents the knowledge of the auctioneer. In the case of perfect information,  $w_i$  equals  $u_i$ . In order to estimate, the price of the painting next period one would expect the auctioneer to set

$$Est_t = \pi_t + v_i$$

where

$$v_i = E(u_i | \pi_{-1}, P_{-1}, w_i)$$

The econometrician does not observe  $v_i$ , the auctioneer's estimate of quality.

However, note that the auctioneer's estimate of quality depends on the painting's past price and price estimate. Using the properties of conditional expectations one has

$$E(v_i | \pi_{-1}, P_{-1}) = E(u_i | \pi_{-1}, P_{-1})$$

Moreover, under joint Normality one has from the above equations

$$E(u_i | \pi_{-1}, P_{-1}) = \phi(P_{-1} - \pi_{-1})$$

where  $\phi$  is a constant. If the variances of  $\varepsilon_t$  and  $u_i$  are  $\sigma_\varepsilon^2$  and  $\sigma_u^2$  respectively,

then  $\phi$  equals  $\sigma_u^2 / (\sigma_u^2 + \sigma_\varepsilon^2)$ . The closer  $\phi$  is to 1, the larger the uncertainty in

unobserved quality in comparison to that in idiosyncratic shocks.

One can therefore write

$$Est_t = \pi_t + \phi(P_{-1} - \pi_{-1}) + \eta_t$$

where  $\eta_t$  is orthogonal to the remaining terms in the equation.

It follows that learning or superior information on the part of the auctioneer will indeed lead to  $P_{-1}$  appearing in the equation. Its appearance is, however, only consistent with this story if it appears in the form  $P_{-1} - \pi_{-1}$ .

A similar story applies if the auctioneer uses anchoring. Suppose for example that the auctioneer forms estimates according to

$$Est_t = \pi_t + \alpha(P_{-1} - \pi_{-1} - v_i) + v_i$$

In order to estimate this equation, the econometrician takes expectations of the above, conditional on observable variables. Thus, the estimation equation can be written as

$$Est_t = \pi_t + \alpha(P_{-1} - \pi_{-1}) + \mu(P_{-1} - \pi_{-1}) + \eta_t^* \quad (3)$$

where  $\eta_t^* = (1 - \alpha)(v_i - E(v_i | \pi_{-1}, P_{-1}))$  has mean zero and is orthogonal to the regressors and  $\mu$  equals  $\phi(1 - \alpha)$ . This equation can be consistently estimated by least squares and the coefficients of interest are identified.

A similar argument applies for any linear variation of the equations above. The coefficient on  $P_{-1}$  is identified by the condition that the unobserved components yield a term of the form  $P_{-1} - \pi_{-1}$ . Any further terms in  $P_{-1}$  do not arise from unobserved quality or rational learning about it.

Note that losses and gains are measured in nominal terms, as is common in the literature. It is straightforward to adjust  $P_{-1}$ , or equivalently  $\pi$ , to allow for real effects such as inflation. This formulation is also tried in Section 4. One cannot,

however, allow for real effects relative to the general art index. This would be equivalent to replacing  $(P_{-1} - \pi)$  by  $(P_{-1} - \pi_{-1})$  and so one could no longer separate reference point effects and unobserved quality.

The formal argument above uses the assumption of joint Normality. All that is really required is that the linear projection of  $v_i$  on the observable regressors have the form  $\beta(P_{-1} - \pi_{-1})$ , for some  $\beta$ , which will hold under weak assumptions. If this is so, then the argument above goes through, replacing conditional expectations by the best linear predictor, since one can regard least squares as calculating the best linear predictor.

Matters are more complicated when non-linear terms, such as losses, enter. The ideal equation we would like to estimate is

$$Est = \pi_t + v_i + \lambda(P_{-1} - v_i - \pi_t) + \nu(P_{-1} - v_i - \pi_t)^+$$

Unfortunately, we do not observe  $v_i$  and, unlike in the linear case, this term cannot simply be pulled out of the loss term. It is not enough therefore to simply add a term in  $(P_{-1} - \pi_{-1})$  to the regression to cope with the unobserved error term.

Genesove and Mayer (2001) proxy the loss term by  $(P_{-1} - \pi_t)^+$ . We also present estimates using this formulation. Such an estimator is, however, as they note in general inconsistent. They present simulations which suggest that the measured coefficient on loss aversion is a lower bound on the effect of loss aversion. Analytically, though the effect is ambiguous.

The problem of measurement error in nonlinear models is well known to be a difficult one. Newey (2001) presents some semi-parametric estimators but their

asymptotic properties are not completely characterised. Schennach (2004) presents an estimator which relies on repeated observations, which we do not possess. Hausman, Ichimura, Newey and Powell (1991) study estimators for polynomial models, but our model does not fall into this class.

It is possible to make progress if one is prepared to make some distributional assumptions. Suppose that as above the errors follow a normal distribution. To simplify matters assume that the auctioneer observes quality perfectly, so that  $v_i$  equals  $u_i$ . We then have

$$(P_{-1} - \pi_t - v_i)^+ = (\pi_{-1} - \pi_t + \varepsilon_{-1})^+$$

Now under the assumptions above we have that, conditional on  $P_{-1}$  and  $\pi_{-1}$ ,  $\varepsilon_{-1}$  is Normal with mean  $(1 - \phi)(P_{-1} - \pi_{-1})$ . The expectation of  $(P_{-1} - \pi_t - v_i)^+$  conditional on  $P_{-1}$ ,  $\pi_{-1}$  and  $\pi_t$  is therefore equal to that of  $U^+$  where  $U$  has a Normal distribution with mean

$$\pi_{-1} - \pi_t + (1 - \phi)(P_{-1} - \pi_{-1})$$

and some variance,  $\tau^2$  say. Under the assumptions above  $\tau^2 = \sigma_\varepsilon^2 \phi$ . Denote this expectation by  $z(\phi, \tau)$ . The estimating equation can be rewritten as

$$Est = \pi_t + \lambda(P_{-1} - \pi_t) + \nu z(\phi, \tau) + \mu(P_{-1} - \pi_{-1}) + \eta^{**} \quad (4)$$

where  $\eta^{**}$  is orthogonal to the regressors and has zero (conditional) expectation. This equation can then be estimated by nonlinear least squares. Consistency and asymptotic normality of this estimator follow from results of Hsiao (1989) (see his footnote 1 to see that the current model is covered by his results).  $\phi$  and  $\tau$  are not identified if  $\nu$  equals zero. The implications of this are discussed in Section 4. It is straightforward to check that the parameters are identified except in this case.

This method clearly makes some strong assumptions on the distribution of errors. On the other hand it has the virtue that if they are true, consistent estimates are produced.

## **4 Data and Estimation**

### **4.1 The Data**

In this paper, we use two datasets for all of our analyses. The first dataset, on Impressionist and Modern Art auctions, was constructed by Orley Ashenfelter and Andrew Richardson. This dataset is restricted to 58 selected Impressionist and Modern Artists and includes only paintings, not sculptures. These artists were chosen primarily because their work is well represented at auction. The period covered is 1980 to 1990, and the dataset includes over 16000 items in 150 auctions that were held in London and New York at both Christie's and Sotheby's. The auction prices were collected from public price lists, and the estimated prices and observable painting characteristics were collected from the pre-sale catalogues. This dataset does not include all items sold in each auction, only a sample of the 58 selected artists. Furthermore, we only have prices for items that were sold at auction. This dataset has been used in Richardson (1992), Abowd and Ashenfelter (1989), Beggs and Graddy (1997), and Ashenfelter and Graddy (2003).

The second dataset is a dataset on Contemporary Art that was constructed by Kathryn Graddy and includes all sales of Contemporary Art at Christie's auction house on King Street in London between 1982 and 1994. The data were gathered from the archives of Christie's auction house, and for each item, the observable characteristics were hand-copied from the pre-sale catalogues. The information on whether or not a lot is sold and the final bid from 1988 onwards was taken primarily from Christie's internal property system. Before 1988, many of the lots were missing

from the internal system. It appeared that, after a certain period of time, some of the lots were deleted from the system, for no predictable reason. From December 1982 through December 1987, access to the auctioneer's books was obtained and used to track the missing items. The Contemporary Art dataset includes 35 auctions and approximately 4500 items for sale. This dataset has been used in Beggs and Graddy (1997), and Ashenfelter and Graddy (2003).

Although the above datasets are large in themselves, there are in actuality a relatively small number of sales that can be positively identified as repeat sales.<sup>1</sup> This is a problem specific to working with sales of art. While there are some datasets, such as the dataset put together by Mei and Moses (2002), that deal with large numbers of repeat sales over huge expanses of time in varied locations, the large time intervals in their dataset between sales make it likely that the first purchaser of the painting is not the same as the seller of the painting. Furthermore, reference point dependence is much more likely to be identified in a dataset where the average holding period is 3.2 years, rather than in a dataset where the average holding period is 28 years.

We make use of these datasets in two ways. First, we use all observations in the datasets in which we have information on all hedonic characteristics and selling price in order to estimate the expected selling price. Due to currency differences, (and not wishing to convert British pound sales into dollar sales because we are looking for reference points), we estimate separate hedonic equations for Impressionist Art in London, for Impressionist Art in New York, and for Contemporary Art. As shown in detail in Tables 1 and 2 below, this consists of 3447 paintings of Contemporary Art, 3864 Impressionist paintings sold in London, and 4783 sold in New York.

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<sup>1</sup> By positively identify, we mean we have looked up the paintings and compared pictures in the pre-sale catalogues to ensure the paintings were identical. Many paintings can have the same artist, title, and dimensions and yet be different paintings.



Secondly, we use observations in which we have positively identified a first sale and a second listing in order to determine the relevance of pre-sale low estimates to a reference point. In total, this consists of 47 paintings of Contemporary Art and 94 paintings of Impressionist Art. For Impressionist and Modern Art, we only use paintings that appeared in the same location (either NY or London) the second time as the location they were purchased in during their first appearance. This restriction is in order to mitigate substantial exchange rate effects on the reference point for the paintings.

The summary statistics in Table 1 are notable for several reasons. First, the sale price in London for all paintings is substantially less than the sale price in New York for all paintings. Looking closely at the sample, during this period, London has sold proportionately less paintings by the top artists such as Degas and Monet, than has New York. Secondly, the selected sample of repeat sales for Impressionist and Modern art has substantially higher prices than the entire sample. It appears that more expensive paintings are likely to reappear at market. This is evidence for survival bias that has been noted in repeat sales indices (Goetzmann 1996). As shown in Table 2, this does not appear to be the case for Contemporary Art. Finally, note that the estimated selling price using hedonics in the first sale appears to be overestimated for Impressionist Art and underestimated for Contemporary Art. This is most likely due to the relatively small samples of repeated sales. Please see Appendix A for more information on the hedonic regression estimates.

Table 1  
Sample Means for Impressionist and Modern Art  
(Standard Deviations in Parentheses)

Variables	Sold items with observations on all hedonic characteristics		Observations with a Prior Sale in the Same Location	
	London	NY	LO	NY
Number of Observations	3864	4783	39	55
Low Estimate	\$169,447 (\$437,855)	\$293,982 (\$1,178,267)	\$422,423 (\$951,340)	\$353,436 (\$1,259,791)
High Estimate	\$219,602 (\$583,071)	\$390,948 (\$1,550,918)	\$525,333 (\$1,165,601)	\$459,400 (\$1,667,088)
Sale Price	\$221,801 (\$712,396)	\$383,649 (\$1,713,584)	\$352,129 (\$677,911)	\$351,341 (\$1,284,566)
Proportion with sale price > expected selling price	0.493	51%	44%	44%
Months since last sale			45 (24)	35 (19)

Table 2  
Sample Means for Contemporary Art  
(Standard Deviations in Parentheses)

Variables	Sold items with observations on all hedonic characteristics		Observations with a Prior Sale in the Same Location	
Number of Observations	3447		47	
Low Estimate	£21,836 (£60,052)		£20,724 (£20,928)	
High Estimate	£29,173 (£82,669)		£27,886 (£28,843)	
Sale Price	£24,159 (£59,525)		£20,587 (£19,797)	
Proportion with sale price > predicted selling price	52%		66%	
Months since last sale			36.86 (22)	

We have only reported summary statistics for the sample actually used. The entire sample for both Contemporary and Impressionist art includes both sold and

unsold items. Approximately 71% of paintings were sold in the Impressionist Art sample and 78% in the Contemporary Art sample.

#### **4.2 Regression Estimates**

Table 3 reports the regression results on the relationship between the estimates and prospective losses and gains relative to the reference point. In columns 1 and 4, we present our estimates of equation (3) above. In addition to the variables described in equation 3, we also control for the months since the previous sale in the regression. We use levels, rather than logs for this variable, as the fit is better. This equation restricts losses and gains to be symmetric, but allows for reference point effects. If the restriction of symmetry is correct, then ordinary least squares is consistent. The estimates for Impressionist Art in column 1 indicate there are strong reference point effects. The interpretation of the coefficient is that after an auctioneer comes up with a price estimate, a 10% increase in the difference between his estimate and the previous price leads him to adjust his estimate by 7.4%. The estimates for Contemporary Art in column 4 are also statistically significant, but not as large. The estimates indicate that an auctioneer adjusts his estimate by 2.8% after a 10% increase in the difference between his estimate and the previous price.

Table 3  
Reference Points and Estimates  
Dependent Variable: Ln(Low Estimate)

	Impressionist Art			Contemporary Art		
	OLS	OLS	Non-linear	OLS	OLS	Non-linear
	1	2	3	4	5	6
Reference Point Effect	0.737 (0.101)	0.724 (0.109)	0.722 (0.124) (0.120)	0.285 (0.105)	0.237 (0.179)	0.425 (0.246) (0.200)
Loss Effect		0.098 (0.145)	0.357 (1.283) (0.651)		0.079 (0.234)	-0.280 (0.354) (0.353)
Predicted Price at Current Auction	0.980 (0.036)	0.979 (0.036)	0.977 (0.040) (0.040)	0.972 (0.041)	0.969 (0.043)	0.981 (0.006) (0.056)
Residual from last sale price	0.208 (0.100)	0.201 (0.101)	0.202 (0.124) (0.122)	0.397 (0.167)	0.393 (0.170)	0.341 (0.214) (0.144)
Months since last sale	0.012 (0.004)	0.012 (0.004)	0.012 (0.003) (0.003)	0.007 (0.005)	0.007 (0.005)	0.008 (0.004) (0.004)
constant	0.199 (0.415)	0.188 (0.422)	0.206 (0.493) (0.435)	-0.133 (0.356)	-0.124 (0.364)	-0.169 (0.502) (0.501)
1-φ			0.439 (0.998)			0.423 (0.856)
τ			-9.394 (22368.78)			-9.132 (21417.63)
R-squared	0.904	0.904	0.904	0.905	0.905	0.906
No. of observations	94	94	94	47	47	47

Note: In columns 3 and 6, the standard errors reported immediately below the estimates are analytical, asymptotic errors calculated from the full sum of square. The standard errors reported below these errors are calculated by treating tau and 1-phi as fixed at the estimated values.

In columns 2 and 5 we allow for asymmetric loss effects by proxying the loss term by  $(P_{-1} - \pi_t)^+$  as in Genesove and Mayer (2001). The addition of the loss term has very little effect on the Impressionist Art data as indicated in column 2. The addition of the loss term has more of an effect on the Contemporary Art dataset, in that the reference term effect on its own is no longer statistically significant, though

the coefficients on the reference term effect in columns 4 and 5 are not statistically significantly different from one another. The loss term is far from significant. Jointly, the reference term and the loss term remain statistically significant, indicating that reference point effects remain both for Impressionist and Contemporary Art. Again, these OLS estimates are not consistent.

In columns 3 and 6, we present nonlinear estimates of equation 4. The nonlinear estimates are quite similar to the OLS estimates and are consistent. The equation is estimated by non-linear least squares. This is greatly simplified by the fact that, if there are no restrictions on the parameters, the equation is linear for fixed values of  $\phi$  and  $\tau$ . For any given values of  $\phi$  and  $\tau$  one can determine the values of the remaining parameters which yield the smallest sum of squares,  $SS(\phi, \tau)$ , by OLS. In order to find the overall minimum of the sum of squares one can then simply search for the values of  $\phi$  and  $\tau$  which minimize  $SS(\phi, \tau)$ . For more information on the nonlinear estimates, please see Appendix B.<sup>2</sup>

We wish to test the hypothesis that the coefficient of  $z(\phi, \tau)$  is zero. This is not entirely straightforward as under the null that it is zero,  $\phi$  and  $\tau$  are not identified since  $z$  does not enter the regression. Standard asymptotic theory therefore does not apply. This problem has been considered extensively by Davies (1977,1987,2002) in the statistics literature and by Andrews and Ploberger (1994) and Hansen (1996), amongst others, in the econometrics literature. The procedure suggested by Davies is to pick the values of the nuisance parameters  $\phi$  and  $\tau$  which make the test statistic for the null hypothesis largest. Unfortunately, it is not possible to calculate the exact limiting distribution of the resulting statistic. Davies provides some bounds. Hansen

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<sup>2</sup> Note that the standard errors on  $\ln \tau$  are very large. As discussed in Appendix B, the sum of squares is quite flat around the reported value of  $\ln \tau$ . The precise value of  $\ln \tau$  does not affect our results.

suggests a data dependent method for simulating critical values. It is also possible to use the bootstrap, see for example Hansen (1999).

Fortunately matters are somewhat simpler here. In order to test that the hypothesis that the coefficient of  $z$  is zero for fixed values of  $\phi$  and  $\tau$ , one would simply compute the t-statistic in the corresponding regression. Following Davies's procedure means picking  $\phi$  and  $\tau$  to make this as large as possible. This is, however, equivalent to picking them to make the sum of squares as small as possible. The relevant t-statistic is therefore that given in the tables. The t-values implied by Davies's procedure will be more conservative than the standard ones. It follows that if the coefficient of  $z$  is insignificant according to the standard critical values, it will be so if one uses the true critical values.

Column 3 and 6 in Table 3 report the standard errors on the coefficient of  $z$  with  $\phi$  and  $\tau$  held at their estimated values and treated as known. The t-values for  $z$  are clearly insignificant at the conventional levels and so by the argument of the previous paragraph will be so if one uses the true critical values.<sup>3</sup>

The residuals on our data show some evidence of heteroscedasticity when we test for it. Robust standard errors, however, are very similar and our conclusions are unaffected if we use them. The apparent heteroscedasticity seems to be generated by a few paintings which have been off the market for a long time. Dropping the observation which has been off the market longest in each sample gives almost identical estimates and removes all evidence of heteroscedasticity. Heteroscedasticity

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<sup>3</sup> This is clearly confirmed if one uses the bootstrap. Equation 4 was estimated under the null that the coefficient of  $z$  is zero. New values for Est were generated by setting them equal to the predicted value from this regression plus an error term derived from resampling from the residuals. The residuals were modified for leverage as suggested by Davison and Hinkley (1997) chapter 6. The maximum value of the t-statistic for  $z$  in the full regression on this artificial data was calculated when  $\phi$  and  $\ln \tau$  were allowed to vary between 0 and 1 and -10 and 2 on a grid with values separated by 0.05. Note that we did not exclude  $1 - \phi = 0$ . This procedure was repeated 1000 times. The estimated P-values for Contemporary and Impressionist Data were 0.82 and 0.72 respectively.

does not therefore appear to be an important issue in our data and so we simply present the OLS standard errors.<sup>4</sup>

As we use all of our observations to estimate the predicted price, but only a very small number of observations in the above regressions, OLS errors are consistent even though the predicted price is estimated.

The coefficient on predicted value is not significantly different from one in any of the regressions. The regressions also indicate that the hedonic model, as expected, does not pick up all fixed effects. The coefficients on lagged residual are significant in all of the regressions. Finally, for Impressionist Art, the estimates tend to increase the longer the time between sales. This coefficient is positive but not statistically significant for Contemporary Art.

We have also included squared terms for the loss effect in order to test whether sensitivity to gains and losses diminishes with distance from the reference point. These terms were far from significant and have very little effect on the coefficients of the other variables. Diminishing sensitivity does therefore not seem important in our dataset.

#### 4.3 Robustness checks

For a robustness check, we have separated out the fixed effects from the time effects in the prediction variable, but find that the coefficients on each are not significantly different from one another. We also interacted the number of months between auctions with the reference point effect. This term was insignificant, which probably reflects the relatively short time-span of the samples.

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<sup>4</sup> We calculated robust standard errors using Stata's HC1 method for the OLS regressions. The robust errors were similar to the OLS errors, and most importantly, would not change any of our conclusions.

The reference points for the regression estimates reported in Table 3 are based on the hammer price, as we believe the expert's valuation is attempting to determine the hammer price rather than the hammer price including commissions. We also constructed loss and gain functions when buyers' commissions were added to original purchase price. The regression estimates with these buyers' commissions added in were very close to being identical to the regression estimates without buyers' commissions. Buyers commissions were 10% for the entire period for Impressionist Art, and were 10% on Contemporary Art before the auctions in 1993, and afterwards, 10% on paintings that were more than £30000, and 15% on paintings less than £30000. We have little information on sellers' commissions. During the period in question, Christie's and Sotheby's would vary the sellers' commissions or waive the sellers' commissions completely as they were competing with one another for paintings. The period of our data is largely before any price fixing on commissions took place at the auction houses.

As another robustness check, we inflated the price used for the reference point by the difference in CPI between the first sale and the second sale to test whether individuals were considering real prices or nominal prices as reference points. Most of the theoretical literature suggests that individuals look at nominal rather than real prices. When using real prices, our results were almost identical to using nominal prices. The similarity in results most likely occurs because changes in art prices swamped any changes in CPI.<sup>5</sup> A more interesting check would be to deflate prices by the art index. However, as noted above, it is precisely changes in the art index that identifies the reference point effect from the error correction term.

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<sup>5</sup> We tried both UK CPI and US CPI for both Contemporary and Impressionist Art. Results were nearly identical.



As another check, we also looked at the effect of reference points on the high estimates. Again, the results are very similar to our results when using low estimates.

## **5. Anchoring and Bidders**

An obvious question is the extent to which the auction hammer price is influenced by reference dependence. This can occur in two ways. Firstly, bidders can exhibit reference point behaviour in the same ways as the auctioneers. In this case, auctioneers' estimates are simply reflecting market behaviour. Secondly, even if bidders do not exhibit reference point behaviour, sample selection can result because we only observe hammer prices that are above the reserve price.

With sample selection, if the reserve price is increased with prospective losses and decreased with prospective gains, there will be observed reference point effects on the hammer price due to pure sample selection, even if the bidders do not exhibit any reference dependence. However, these reference point effects should be less than the reference point effects on the estimates as they will only be driven by cases where the reserve price is binding in the cases of losses, and in cases where the bid falls between what would have been the reserve price in the absence of anchoring and the lower reserve price under anchoring with gains.

Furthermore, if the bidders do not exhibit any reference point behaviour, then the probability of sale should be higher with prospective gains and lower with prospective losses. If bidders do take reference points into account to the same extent as the auctioneer, then we should observe similar reference point effects on hammer prices, but we should not observe any effects on the probability of sale. We test these propositions below.

Firstly, in Table 4, we present results in which our dependent variable is the hammer price. Note that the number of observations is less than in our previous sample, as we only observe hammer prices for sold items.

Table 4  
Reference Points and Hammer Prices  
Dependent Variable: Ln(Hammer Price)

	Impressionist Art		Contemporary Art		
	OLS	OLS	OLS	OLS	Non-linear
	1	2	3	4	5
Reference Point Effect	0.708 (0.131)	0.700 (0.139)	0.051 (0.115)	0.016 (0.223)	0.158 (0.264) (0.237)
Loss Effect		0.049 (0.242)		0.059 (0.324)	-0.215 (0.423) (0.417)
Predicted Price at Current Auction	0.949 (0.049)	0.948 (0.050)	0.995 (0.069)	0.992 (0.072)	1.000 (0.073) (0.070)
Residual from last sale price	0.256 (0.133)	0.254 (0.135)	0.442 (0.161)	0.440 (0.164)	0.398 (0.255) (0.183)
Months since last sale	0.012 (0.003)	0.012 (0.003)	0.003 (0.004)	0.003 (0.004)	0.004 (0.005) (0.005)
constant	0.683 (0.533)	0.681 (0.537)	-0.043 (0.641)	-0.029 (0.656)	-0.062 (0.656) (0.650)
1- $\phi$					0.423 (1.506)
$\tau$					-9.764 (615033.40)
R-squared	0.890	0.890	0.892	0.892	0.893
No. of observations	76	76	34	34	34

Note: In column 5, the standard errors reported immediately below the estimates are analytical, asymptotic errors calculated from the full sum of square. The standard errors reported below these errors are calculated by treating tau and 1-phi as fixed at the estimated values.

We present non-linear estimates only for the case of Contemporary Data. Figures for both sets of data are presented in Appendix C. In the case of Impressionist Data the sum of squares is essentially flat, for sensible values of  $\tau$ , except in the

neighbourhood of  $1 - \phi = 0$ . This case we rule out for economic reasons as in the previous section (see Appendix B). Outside this region the estimates are indistinguishable from the OLS estimator (which corresponds to the case  $\phi = 0$  and  $\tau = 0$ ). As in the previous Section, even if one allows the case  $\phi = 1$ , our conclusions would not be affected if  $\tau$  takes on any reasonable value.

The results for Impressionist Art, when the natural log of price is used as the dependent variable, are almost identical to the results when the low estimate is used as the dependent variable. For Contemporary Art, we no longer find reference point effects for the hammer price, but these results are not significantly different from our previous results. We interpret our regression estimates to indicate that the estimate is in line with the sale price.

When we performed a probit of whether or not an item is sold on the entire range of independent variables (variables in columns 2 and 5), using the Wald test, we could not reject that the coefficients on all the variables were simultaneously zero.<sup>6</sup> We interpret this result to imply that reference points have no effect on the probability of sale. Thus, while the auctioneers' behaviour exhibits reference point effects, it does so in a way consistent with buyers' behaviour.

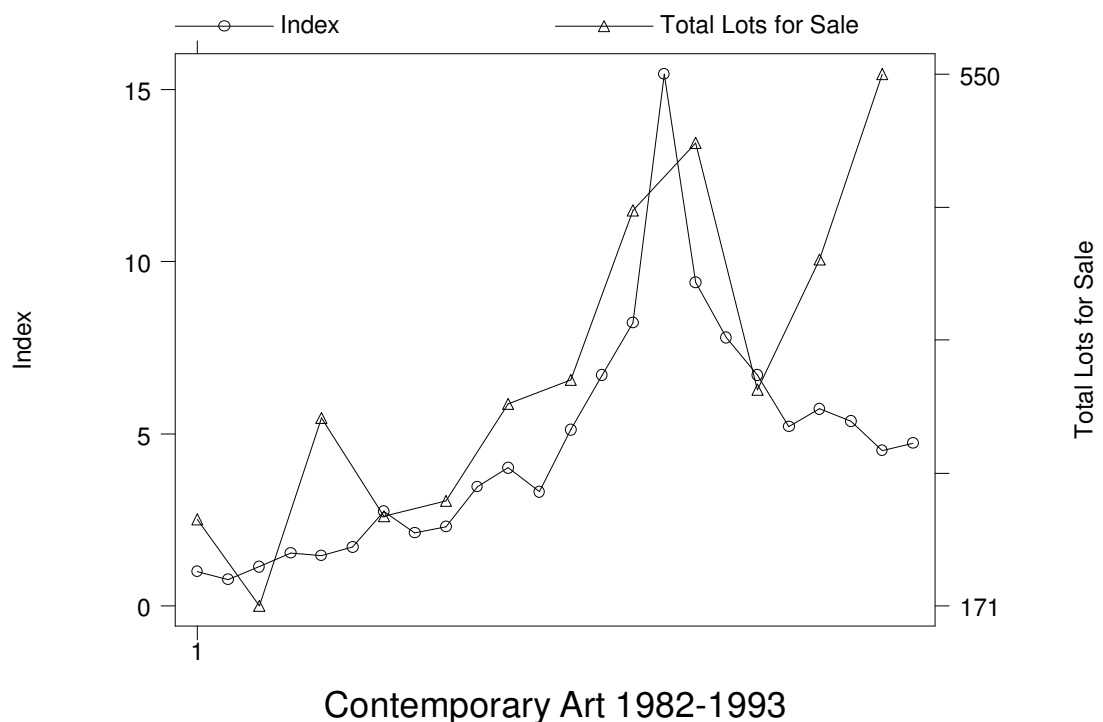
## 6. Interpretation

In this paper, we have found strong support for reference dependence, both in the context of expert's pre-sale estimates for both Impressionist and Contemporary Art, and in final prices for Impressionist Art. We have distinguished reference dependence from loss aversion as there are symmetric effects for both gains and losses. There does not appear to be diminishing sensitivity to the reference point.

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<sup>6</sup> For impressionist Art, the Chi-squared (5) is 6.91 resulting in a p-value of .2275, and for Contemporary Art, the Chi-squared(5) is 6.43 resulting in a p-value of .2670.

Although we do not find loss aversion with respect to pre-sale estimates, this does not necessarily mean that sellers are as keen to sell in down markets as in up markets. Indeed, as in both stocks and in real estate, there is some evidence that volume decreases when prices are slumping. Figure 1 below plots total yearly sales of Contemporary Art at Christie's King Street London against the Contemporary Art price index constructed above. Except for the outlier in 1993 (1994 was dropped as it was a partial year), volume appears to track the index. This could be interpreted as loss aversion, and in real estate and stocks, one explanation given for this phenomenon is loss aversion. However, there can also be other explanations for this pattern, such as sellers believing rationally in mean reversion of prices.



Reference dependence often results in a bias. A classical example of is given in Tversky and Kahneman (1982) when subjects are asked to estimate a number (for example the percentage of African countries in the United Nations.) The experiment begins by the subjects being given a number between 1 and 100 that is determined by

a spin of the wheel. The subjects then show a bias in their final estimates towards the number that they are originally given.

In this study, we do not find that the pre-sale estimates are biased relative to the final price. The bias is shown relative to a statistical prediction of the price that should occur given current market conditions and observable characteristics of the painting. Nonetheless, our finding of strong reference-point effects provides support for one important element of prospect theory.

## References

- Abowd, John and Orley Ashenfelter. 1988. "Art Auctions: Prices Indices and Sale Rates for Impressionist and Contemporary Pictures." Mimeo, Department of Economics, Princeton University.
- Andrews, Donald and Werner Ploberger. 1994. "Optimal Tests when a Nuisance Parameter is Present only under the Alternative." *Econometrica* 62, pp.1383-1414.
- Ashenfelter, Orley, and Kathryn Graddy. 2003. "Auctions and the Price of Art." *Journal of Economic Literature* 41, pp. 763-787.
- Barberis, Nicholas, Ming Huang, and Tano Santos. 2001. "Prospect Theory and Asset Prices." *Quarterly Journal of Economics* 116, pp. 1-53.
- Beggs, Alan and Kathryn Graddy. 1997. "Declining Values and the Afternoon Effect: Evidence from Art Auctions." *Rand Journal of Economics* 28, pp. 544-65.
- Davies, Robert. 1977. "Hypothesis Testing when a Nuisance Parameter is Present only under the Alternative." *Biometrika* 64, pp.247-254
- Davies, Robert. 1987. "Hypothesis Testing when a Nuisance Parameter is Present only under the Alternative." *Biometrika* 74, pp. 33-43.
- Davies, Robert. 2002. "Hypothesis Testing when a Nuisance Parameter is Present only under the Alternative: Linear Model case." *Biometrika* 89, pp.484-489.
- Davison, Anthony and David Hinkley. 1997. *Bootstrap Methods and their Application*. Cambridge University Press, Cambridge UK.

Genesove, David & Christopher Mayer. 2001. "Loss Aversion And Seller Behavior: Evidence From The Housing Market," *The Quarterly Journal of Economics* 116 pp. 1233-1260.

Goetzmann, William N. 1996. "How Costly is the Fall from Fashion? Survivorship Bias in the Painting Market," *Economics of the Arts: Selected Essays*. Victor Ginsburgh and Pierre-Michel Menger, eds. Amsterdam: Elsevier, pp. 71-83.

Hansen, Bruce. 1996. "Inference When a Nuisance Parameter is not Identified under the Null Hypothesis." *Econometrica* 64, pp. 413-420

Hansen, Bruce. 1999. "Testing for Linearity." *Journal of Economic Surveys* 13, pp.551-576

Hausman, James, Newey, Whitney, Ichimura, Hidehiko and James Powell. 1991. "Identification and Estimation of Polynomial Errors-in-Variables Models." *Journal of Econometrics* 50, pp.273-295.

Hsiao, Chiang. 1989. "Consistent Estimation for Some Non-linear Errors-in-Variables Models." *Journal of Econometrics* 41, pp. 159-185.

Jullien, Bruno and Bernard Salanie. 2000. "Estimating Preferences Under Risk: The Case of Racetrack Bettors." *Journal of Political Economy*, 108, pp. 503-530.

Kahneman, Daniel and Amos Tversky. 1979. "Prospect theory: An analysis of decisions under risk. *Econometrica* 47, pp. 263-291.

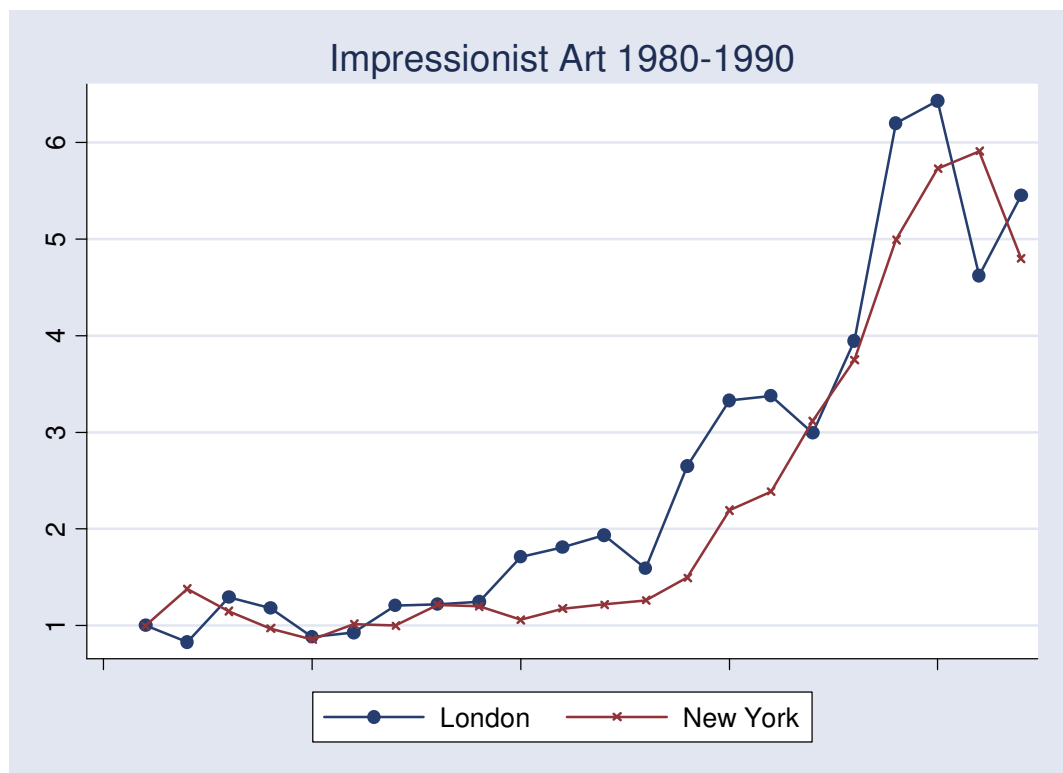
Mei, Jianping and Michael Moses. 2002. "Art as an Investment and the Underperformance of Masterpieces." *American Economic Review*, 92, 1656-1668.

- Newey, Whitney K. 2001. "Flexible Simulated Moment Estimation of Nonlinear Errors-in-Variables Models." *Review of Economics and Statistics* 83, pp. 616-627.
- Richardson, Andrew. 1992. "An Econometric Analysis of the Auction Market for Impressionist and Modern Pictures, 1980-1991." Senior thesis, Department of Economics, Princeton University.
- Schennack, Susanne, M. 2004. "Estimation of Nonlinear Models with Measurement Error." *Econometrica* 72, pp. 33-75.
- Tversky, Amos and Daniel Kahneman. 1982. "Judgements of and by Representativeness." *Judgement under Uncertainty: Heuristics and Biases*. D. Kahneman, P. Slovic and A. Tversky, eds. Cambridge University Press: 84-98.



## APPENDIX A

For the hedonic estimates of price, the log of the sale price is regressed on the hedonic painting characteristics in addition to half-year time dummies for each period. The hedonic characteristics used for Impressionist and Modern Art are painting date, length, width, signed, monogrammed, stamped, medium in which it was painted, and artist. We estimate separate equations for paintings sold in London and paintings sold in New York. Below, in Appendix Figure 1, we plot the price index. This is constructed as the exponential of the coefficients on the half-year date dummy variables.

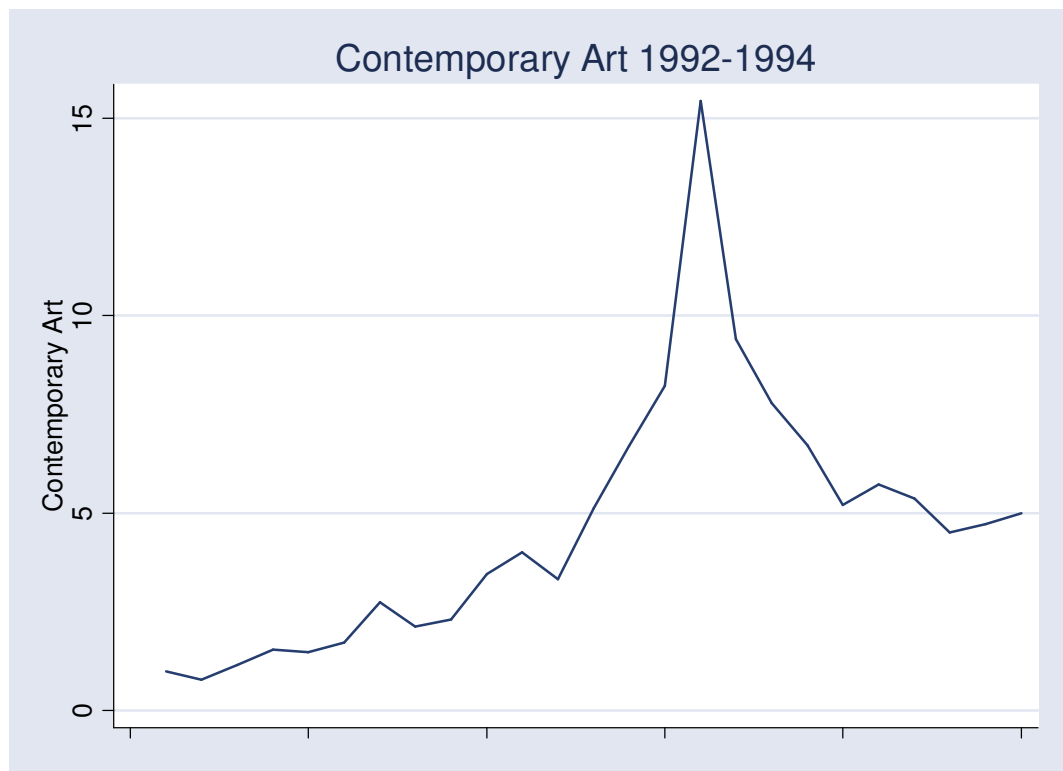


There are a couple of things to note about Appendix Figure 1. First, there is a very large rise in price from about 1985 to 1990, and then a drop-off at the end. In the

regression estimates in Table 3, in the regressions in which the residual is included, we are primarily relying on the times when there is a general market gain or loss to estimate the reference point effects. In the Impressionist dataset, there are 84 gains, but only 13 losses. There are sufficient losses in the early period to identify the loss effects. Secondly, as we have included a half-year rather than a full year index, the index appears more volatile than indices in which a full-year is included. This is because certain times of the year generally contain the “big” sales, so the coefficients on time are actually capturing some unobserved quality effects. The R-squareds of the two regressions are .7461 for London and .7908 for New York.

For the hedonic estimates of price, the log of the sale price is regressed on the hedonic painting characteristics in addition to half-year time dummies for each period. The following hedonic characteristics are used for Contemporary Art: painting date, length, width, medium, artist, and whether or not a painting is subject to VAT.

Appendix Figure 2 below plots the index for Contemporary Art.



A couple of things to note about the Contemporary Art regressions. First, there is a huge spike coincident with the sale on November 30, 1989. The average price for this sale was approximately twice the average price for the preceding sale. This was immediately before the crash in 1990. For Contemporary Art, very often the half-year time dummies encompass only one sale. Again, because some sales are more “important” than other sales, the time dummies are also picking up unobserved quality effects. The R-squared for Contemporary Art is .7746. In the Contemporary Art dataset, there are 27 gains and 20 losses.

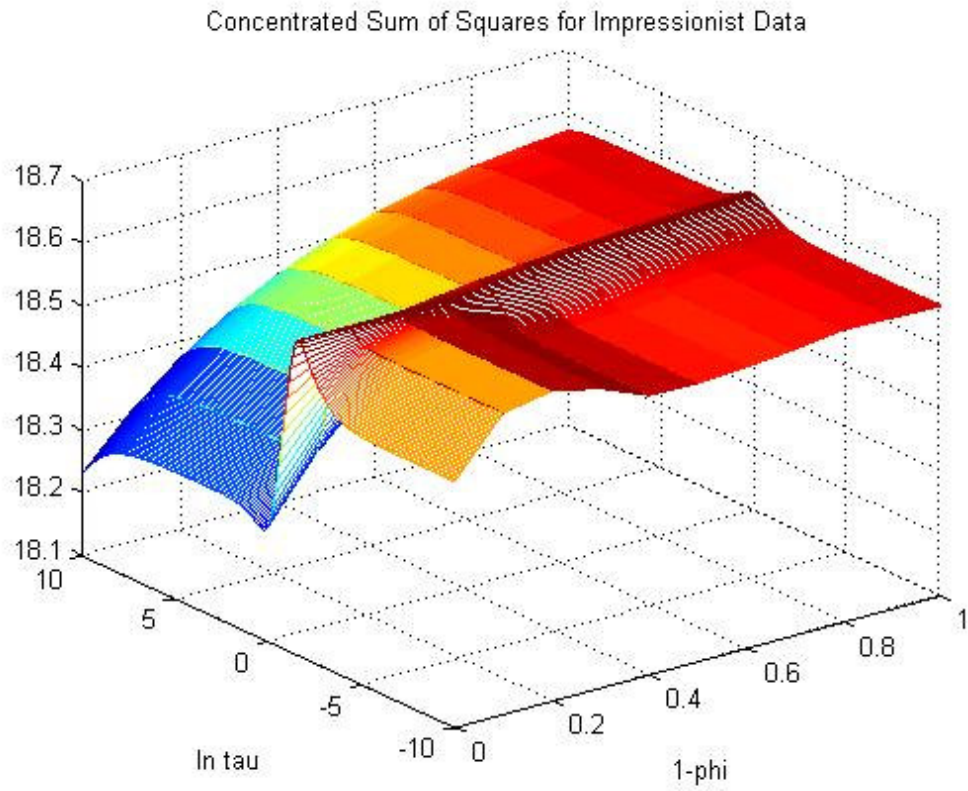
To construct the estimated value and the index, we used hammer prices, and not prices including buyers’ commissions. The reason is that we are trying to formulate an expected price, on which to base the low estimate.

## APPENDIX B

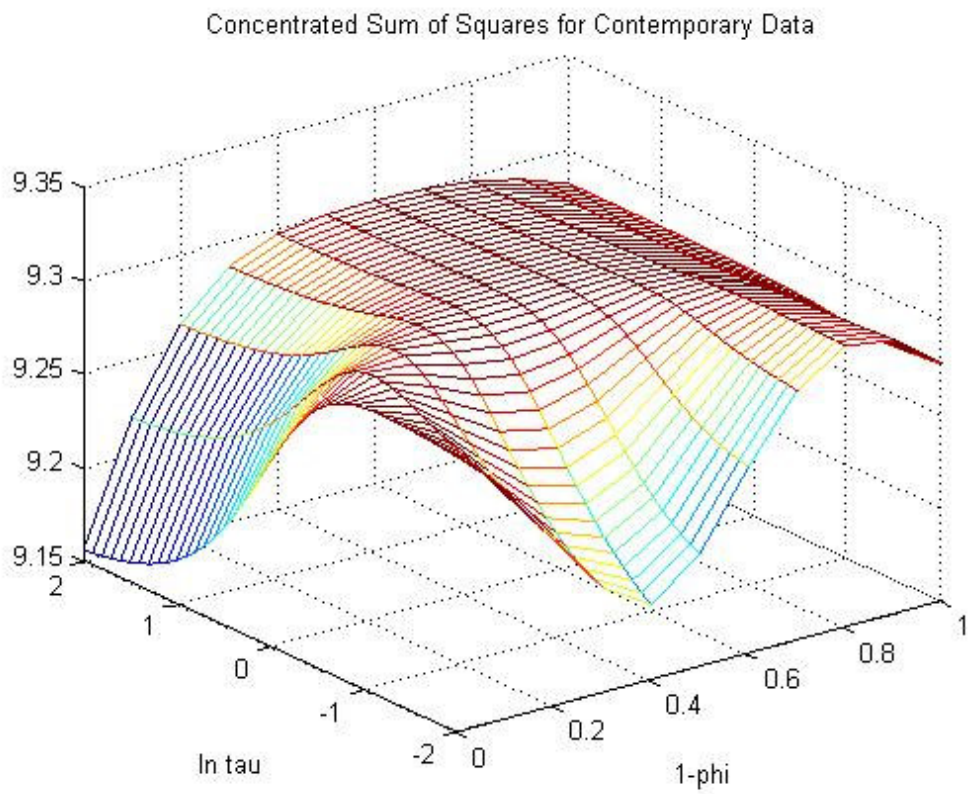
The theory implies two restrictions on the coefficients: that  $\phi$  lie between 0 and 1 and that the coefficient of  $(P_{-1} - \pi_{-1})$  should equal  $\phi(1 - \alpha)$ . The first we impose but the second we do not directly as it greatly complicates the estimation. It can be checked however that the estimates we present are approximately consistent with it.

The concentrated sums of squares are graphed as functions of  $1 - \phi$  and  $\ln \tau$  in Appendix Figures 3 and 4. As can be seen surfaces are fairly flat, especially in the case of Impressionist Art. If the coefficient of  $z$  is indeed zero this is not surprising as  $\phi$  and  $\tau$  then do not enter the regression. As can be seen, more clearly in the case of Contemporary data, there are minima at the values we report. There are also minima

around  $1 - \phi = 0$ . In the case of Contemporary Art these correspond to absurdly large values of  $\tau$  and estimates which are grossly inconsistent with the restriction that the coefficient of  $(P_{-1} - \pi_{-1})$  should equal  $\phi(1 - \alpha)$ . We therefore do not report this case. In the case of Impressionist data the estimates are less absurd. The case of  $1 - \phi = 0$  is, however, still implausible in this case as well. It implies (see Section 3) that idiosyncratic shocks are unimportant in the determination of prices. This in turn implies (again see Section 3) that  $\tau$  should be very small, as there is little uncertainty about the value of idiosyncratic shocks (for example, particular tastes of the buyers present at the auction). Values of  $\tau$  which are small in comparison to the variation in observed prices, so  $\ln \tau$  is negative, generate in the Impressionist Data values of the non-linear loss term which are essentially zero for all but two values. Again this does not seem sensible and we do not report this case. However, even in these cases, the values of the test statistics obtained are in any event similar to the case we report. We would therefore reach the same conclusions even if we retained the case  $1 - \phi = 0$ .



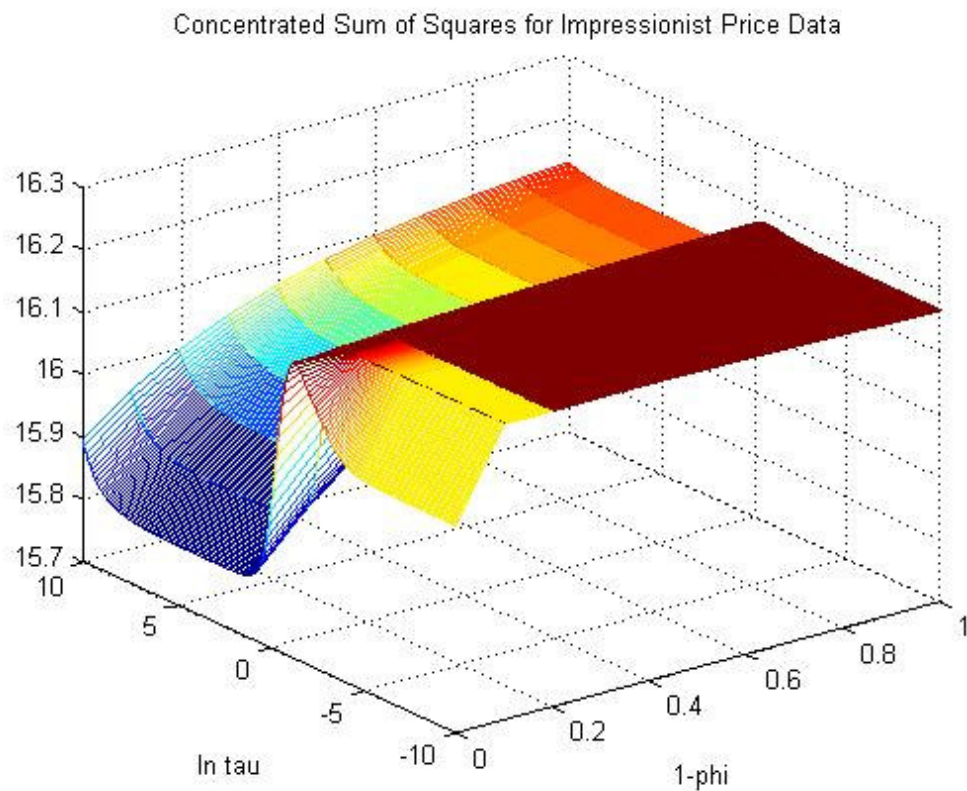
Appendix Figure 3



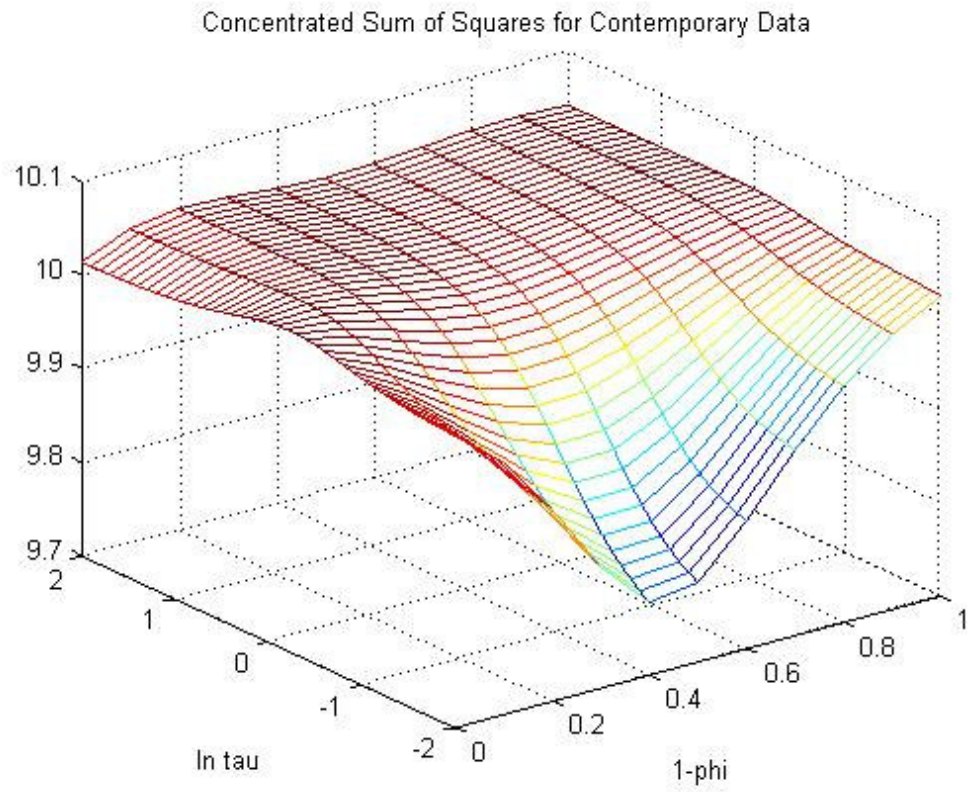
Appendix Figure 4

For comparison with the linear estimates, note that in the linear case one is effectively choosing  $\phi = 0$  and  $\tau = 0$ .  $\tau$  is driven towards zero – note that we report  $\ln \tau$ . This is not entirely consistent with the theory as it implies that, conditional on the observables, there is no uncertainty about the idiosyncratic component of the painting's price last period. The sum of squares is, however, not very sensitive to  $\tau$  when it is small, at the given values of  $\phi$ , and is therefore not very precisely determined, so the conflict is perhaps not too great. This is reflected in the very large standard error reported for  $\ln \tau$ . The standard errors are analytical, asymptotic ones calculated from the full sum of squares. Note that the standard errors only make sense under the alternative, when the loss term actually enters. Fixing  $\tau$  at a small but reasonable value would not alter our conclusions.

## APPENDIX C



Appendix Figure 5



Appendix Figure 6