

# **Are Investors Credulous?**

## **Some Preliminary Evidence from Art Auctions**

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This paper constructs a new data set from art auctions that include auctioneer presale price estimates to examine the credulity of art investors. While auction houses typically made no price estimates before 1973, they start providing high- and low- price estimates for all artworks thereafter. Thus, we have a natural experiment to observe changes in price behavior under the influence of auctioneer estimates. We find that the price estimates tend to have an upward bias for expensive paintings and high estimates at the time of purchase are associated with adverse future abnormal returns. These results are consistent with the view that investors are credulous. They do not discount fully the strategic incentives of auctioneers. However, we have some preliminary evidence that investors may have made some adjustment recently for the systematic bias in provided information.

(JEL G12, G14, Z10)

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### **Abstract**

This paper constructs a new data set from art auctions that include auctioneer presale price estimates to examine the credulity of art investors. While auction houses typically made no price estimates before 1973, they start providing high- and low- price estimates for all artworks thereafter. Thus, we have a natural experiment to observe changes in price behavior under the influence of auctioneer estimates. We find that the price estimates tend to have an upward bias for expensive paintings and high estimates at the time of purchase are associated with adverse future abnormal returns. These results are consistent with the view that investors are credulous. They do not discount fully the strategic incentives of auctioneers. However, we have some preliminary evidence that investors may have made some adjustment recently for the systematic biases in provided information.

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Rationality has long been a key assumption of modern economics. If rational economic agents process information efficiently and there are complete capital markets and well defined property rights, then economic theory directly supports a laissez faire policy. The role of government is limited to enforcing contracts and protecting property rights. Given the importance of this key assumption, numerous studies recently have examined its empirical validity and have discovered some evidence of limited rationality or limited information efficiency.

For example, in behavioral finance, several studies have provided evidence suggesting that investors on average do not discount sufficiently the incentives of interested parties, such as firms, brokers, and analysts, to manipulate the information they provide.<sup>1</sup> Womack (1996) finds that securities analysts are biased in their forecasts and recommendations. Stock recommendations favor buys over sells. John Capstaff, Krishna Paudyal, William P. Rees, (1998) and Lawrence D. Brown, (2001) also discover that earnings forecasts are generally optimistic, especially at long time horizons. These biases may result from agency problems. Information is manipulated in order to drum up investment banking business,<sup>2</sup> to maintain access to information, or to stimulate trading by investors. (See for example, Rachel M. Hayes, (1998), Terence Lim (2001), and Roni Michaely and Kent L. Womack (1999))

While it is not surprising that agency problems could result in analyst biases, an important question is whether investors are gullible. Siew Hong Teoh, Ivo Welch, T.J. Wong (1998a, b) and Srinivasan Rangan (1998) discover that investors can be influenced by analyst forecasts and do not adequately discount for earnings manipulation at time of IPOs or seasoned equity issues. They show that greater earnings management at the time of these equity issues is associated with more adverse subsequent long-run abnormal stock returns. In a separate study, Christopher Avery and Judith Chevalier (1999) also find that prices in football markets are influenced by investors' mistaken belief in 'hot hands' and they tend to overweigh meaningless 'expert opinions'. These researchers note that cognitive limitations make it hard for economic agents to make the appropriate adjustments for the biases systematically. Critics, however, point

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<sup>1</sup> For an extensive literature survey of behavioral finance, see Daniel, Kent, David Hirshleifer, and Siew Hong Teoh (2002).

<sup>2</sup> Numerous telecom analysts were alleged or found to have inflated earnings forecasts for companies such as Global Crossing, Quest, Worldcom and Winstar. Despite mounting loss and falling revenues, many continued their buy recommendation for investors until their bankruptcy.

out that survivorship issues may create statistical problems for some of the above studies involving long-horizon returns (see S.P. Kothari (1999)). Moreover, the results of Michael P. Keane and David E. Runkle (1998) even cast doubt on the existence of bias in analysts' forecasts.

This paper will join the investigation by employing a new data set from a different field (art auctions) to examine the credulity of art investors. While auction houses typically made no price estimates before 1973, they start providing high- and low- price estimates for all artworks thereafter. Thus, we have a natural experiment to observe changes in price behavior under the influence of art auctioneer presale price estimates. By using data with over 5,500 pairs of transactions and covering a long time period, between 1875-2002, we can control price fluctuations due to art market movements and isolate the price impact from auctioneer estimates. This unique data set permits us to test three hypotheses in behavioral economics. First, whether auctioneer estimates impact art prices. Second, whether high estimates at the time of purchase are associated with negative future abnormal returns. This will help us find whether investors make appropriate adjustments for these auction biases. Third, we employ the capital asset pricing model to control for difference in risks of artworks when measuring abnormal returns. As a result, our study complements the existing empirical literature that has focused on analyst earnings estimates and stock prices.

Our study builds on a small literature on the study on art prices and auctions. Orley Ashenfelter (1989) was first to examine whether auctioneer estimates impact art prices. He also pointed out the potential agency problem of auction houses in providing price estimates. James E. Pesando (1993) and Jianping Mei and Michael Moses (2000) presented strong evidence of masterpiece underperformance. Their evidence could be consistent with the view that investors overpay for masterpieces under the influence of auctioneer estimates. This paper goes a step further by directly examining whether the "masterpiece effect" is directly related to auctioneer estimates. Our study will employ a repeated sales regression approach to controls for heterogeneity in artworks. In addition, we will measure the return volatility of masterpieces by decomposing art risk into systematic and painting specific risks.

The remainder of the paper is organized as follows. Section I describes the art auction data set and provides a discussion of sampling biases. Section II reviews the repeated sales regression procedure. Section III provides an empirical examination of investor credulity based

on measuring the influence of auctioneer estimates. We then offer several alternative explanations to our empirical results. Section IV examines investor learning and demonstrate that the sample selection bias common in auction data does not affect our credulity results. Section V will conclude the paper.

## **I. Auction Data and Potential Biases**

Since individual works of art have yet to be securitized, studying the value of works of art from financial sources is not possible. Gallery or direct-from-artists prices tend not to be reliable or easily obtainable. Auction prices however are reliable and publicly available. Since 1973, the two major auction houses in New York, Sotheby's and Christie's, have also provided presale price estimates for all objects up for sale in catalogues. As a result, the prices and their estimates can be used as the basis for a data base for determining the change in value of art objects over various holding periods as well as the influence of auctioneer presale estimates.

We created such a database for the American market, principally New York based on repeated sales. We searched the catalogues for all American, 19<sup>th</sup> Century and Old Master, Impressionist and Modern paintings sold at the main sales rooms of Sotheby's and Christie's (and their predecessor firms) from 1950 to 2002.<sup>3</sup> If a painting had listed in its provenance a prior consummated public sale, at any auction house anywhere, we went back to that auction catalogue and recorded the sale price. In addition to price and date information we also recorded auctioneer price estimates when they become available after 1973.<sup>4</sup> The New York Public Library as well as the Watson Library at the Metropolitan Museum of Art were our major sources for this auction data history. Some paintings had multiple resales over many years resulting in a subset of observations that had three public sales with one of the pairs straddling 1973, the year of the introduction of auctioneer presale price estimates. Each resale pair was considered a unique point in our database that now totals over fifty five hundred entries.

As well as analyzing our data as a totality we have also separated it into three popular collecting categories. The first is American Paintings (American) principally created between

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<sup>3</sup> Our data does not include "bought-in" paintings that did not sell due to the fact that the bid was below reservation price. Our data for the year 2002 only includes sales before July.

<sup>4</sup> A small fraction of our data has the presale estimates missing due to missing auction catalogues. We will exclude these data in the regression if the relevant variables are missing.

1700 and 1950. The second is Impressionist and Modern Paintings (Impressionists) principally created between the third quarters of the 19<sup>th</sup> and 20<sup>th</sup> century. The third is Old Master and 19<sup>th</sup> century paintings (Old Masters) principally created after the 12<sup>th</sup> century and before the third quarter of the 19<sup>th</sup> century. For convenience, we will call the first price from each price pair “purchase price” and the second price “sale price” from the perspective of the collector for the time period between the two transactions. Most artworks bought are held for long time periods (on average 28 years).

Before 1979 auction houses made their money by charging a fee to the seller, for consummated sales, of ten percent. This fee was negotiable, like real estate commissions, based on the importance or forecasted value of the work or collection being offered for sale. Items not reaching their reserve price were also charged a small fee. After 1979 an additional fee was imposed on the successful bidder, the one offering the highest price in the English style outcry auction used by most of the world’s major auction houses. This fee was initially set at 10% of the winning bid (hammer price) and was not negotiable. Since 1979 this latter fee has been changed 3 times and is now 19.5% of first \$100,000 and 10% of every thing above \$100,000 at both of New York major auction houses. Thus it is clear that auction houses are interested in results that yield high prices and high percent of lots sold.

The percent of lots sold is dependent on market demand and reservation price. Reservation prices are generally set based on sellers’ expectation of market demand and their own funding needs. The exact number of works offered with a reserve has grown substantially over the last 50 years to a point today where probably over 95 percent of the lots are so offered. The typical reserve price is often 50-70% of the low estimate but its actual level is negotiable but legally cannot be above the low estimates at New York auctions. Auction houses often compete to get the seller’s business by providing high price estimates. But they are constrained by the fact that the painting may fail to sell if reservation prices are set too high due to high price estimates. Moreover, auction houses also have a reputation to protect. Their long-term business viability depends on their reputation as experts in the art field who understand market conditions.

The selection bias in the data set is an important issue that could bear on the interpretation of our empirical study. The selection procedures based on multiple sales from major US auction houses tend to truncate both sides of the return distribution. Our sample may

suffer from a “backward filled” data bias since our transactions data before 1950 are collected only from those paintings that were sold in Christie’s and Sotheby’s after 1950.<sup>5</sup> Mei and Moses (2002), however, argue that this bias tend to be moderated by several offsetting factors, such as masterpieces collected by museums through donations.<sup>6</sup> Orley Ashenfelter, Kathryn Graddy, and Margaret Stevens (2001) pointed out that another source of selection bias is that not all items that are put up for sale at auctions are sold because some final bids may not reach the reservation prices. In section IV, we will demonstrate that, under certain conditions, our results are unaffected by this sample selection bias.

## II. Methodology For Repeat-Sales Regression

This paper will use the repeat-sales regression (RSR) methodology to measure the impact of auctioneer estimates after controlling for overall art market movements. The RSR uses the purchase and sale prices of individual properties to estimate the fluctuations in value of an average or representative asset over a particular time period. William N. Goetzmann (1993), Pesando (1993), and Mei and Moses (2002) apply it to the art market. The benefit of using the RSR is that the resulting index is based upon price relatives of the same painting that controls for the differing quality of the assets. Thus, it does not suffer from arbitrary specifications of a hedonic model.<sup>7</sup>

We begin by assuming that the continuously compounded return for a certain art asset  $i$  in period  $t$ ,  $r_{i,t}$ , may be represented by  $\mu_t$ , the continuously compounded return of a price index of art, and an error term:

$$(1) \quad r_{i,t} = \mu_t + \varepsilon_{i,t}$$

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<sup>5</sup> This bias is similar to the “back-filled” data bias for emerging market stocks where historical data on their returns is “back-filled” conditional upon the survival of emerging markets. Thus, data for those emerging markets that submerged as result of revolution or economic turmoil were not included, which tend to create a downward bias. We like to note, however, unlike Russian bonds and Cuban stocks, paintings from established artists sold in auctions seldom disappear from the market completely. Thus, one can still observe a large number of art pieces sold at estate auctions at a fraction of their purchase price.

<sup>6</sup> Goetzmann (1993) also argues that the decision by an owner to sell a work of art (and consequently the occurrence of a repeat sale in the sample) could be conditional upon whether or not the value has increased.

<sup>7</sup> The drawback is that the index is constructed from multiple sales, which are a subset of the available transactions. Olivier Chanel, Louis-Andre Gerard-Varet, and Victor Ginsburgh (1996) provided a detailed discussion on the weakness of the RSR model.

where  $\mu_t$ , may be thought of as the average return in period  $t$  of paintings in the portfolio and the painting specific return,  $\varepsilon_{i,t}$ , is assumed to be uncorrelated over time and across paintings. We will use sales data about individual paintings to estimate the index  $\mu$  over some interval  $t = 1 \dots T$ . Here,  $\mu$  is a  $T$ -dimensional vector whose individual elements are  $\mu_t$ . The observed data consist of purchase and sales price pairs,  $P_{i,b}$ , and  $P_{i,s}$ , of the individual paintings comprising the index, as well as the dates of purchase and sale, which we will designate with  $b_i$ , and  $s_i$ . Thus, the logged price relative for asset  $i$ , held between its purchase date  $b_i$  and its sales date,  $s_i$ , may be expressed as

$$(2) \quad r_i = \ln \left( \frac{P_{i,s}}{P_{i,b}} \right) = \sum_{t=b_i+1}^{s_i} r_{i,t}$$

$$= \sum_{t=b_i+1}^{s_i} \mu_t + \sum_{t=b_i+1}^{s_i} \varepsilon_{i,t}$$

In order to measure the impact of auctioneer presale price estimates on returns, we may run a regression like the following,  $r_i = \sum_{t=b_i+1}^{s_i} \mu_t + \theta x_i + \sum_{t=b_i+1}^{s_i} \varepsilon_{it}$ , where  $x_i$  is a painting  $i$  specific variable such as price estimates at purchase. Thus,  $\theta$  measures directly the impact of  $x_i$  on art returns adjusted for overall market movements.

To estimate equation (2), let  $\mathbf{r}$  represent the  $N$ -dimensional vector of logged price relatives for  $N$  repeated sales observations. Goetzmann (1992) shows that a generalized least-squares regression of the form,

$$(3) \quad \hat{\mu} = \left( X' \Omega^{-1} X \right)^{-1} X' \Omega^{-1} r,$$

provides the maximum-likelihood estimate of  $\mu$ , where  $X$  is a matrix, which has a row of dummy variables for each asset in the sample and a column for each holding interval. In addition, it also includes a column of  $x_i$ .  $\Omega$  is a weighting matrix, whose weights could be based on error estimates from a three-stage-least-square estimation procedure used by Karl E. Case and Robert J. Shiller (1987).



### III. An Empirical Examination of Investor Credulity

#### A. Art prices tend to be affected by expert opinion.

Following Ashenfelter (1989), we begin by examining whether auctioneer presale price estimates impact art prices. Figure 1 provides a graphic plot of log prices paid by art collectors against average auctioneer estimates over the 1973-2002 period. The regression is estimated with 6114 observations with a  $R^2$  of 0.90, using all transactions with price estimates. Our results confirm that auctioneer estimates are highly correlated with the actual prices paid, implying that auctioneers do have the ability to predict or influence prices. Moreover, given the slope coefficient is 0.969 with a standard deviation of 0.004, there generally seem to be a slight upward bias for high price paintings, indicating the actual price paid is often less than the average of high- and low- estimates. Given the fact that the regression is based on paintings actually sold and the highest bid for unsold pictures is generally below the lower estimate, our results suggest that there is an upward bias for high price paintings. This result is consistent with the view of Kent, Hirshleifer, and Teoh, (2002) who point out that the problem of credulity is likely to be greater for firms with high valuations or firms that are able to weave hard-to-refute stories to tell investors about future prospects. They note that the empirical findings of inferior performance of stocks with high market/book ratios (Chan et al., 2001) are consistent with credulity.

To find the persistency of this result, we also run the above regression annually from 1973-2002. We allow the intercept and the slope coefficients to vary over time.<sup>8</sup> The results on the slope coefficient and goodness-of-fit ( $R^2$ ) is presented in a graphic plot in Figure 2. We can see that the persistence of upward bias for high priced paintings, since the slope estimates are below one for most years. The mean of the slope coefficient is 0.966 with a standard deviation of 0.006. Thus, the slope coefficient is quite close to but different from one. The slight tilt downward in the slope of the regression allows the price estimates to be somewhat biased upwards for the high price paintings. This result is consistent with the view that auction house performs a delicate balance between their long-term reputation and short-term interest. As a

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<sup>8</sup> By allowing for time-varying intercept, we have also removed a common factor which may cause cross-sectional correlation among the residuals. Keane and Runkle (1998) pointed out that the t-statistics for the slope coefficient in Figure 1 may bias upward if no adjustment is made for the cross-sectional correlation.

result, they will try to maintain an overall unbiasedness in their estimates, but tilted their estimates upward for expensive paintings, since they can benefit the most from such bias if investors are credulous.

An alternative way of measuring the influence or forecast ability of auctioneer presale price estimates is to run the following regression (4):

$$(4) \quad r_i = \sum_{t=b_i+1}^{s_i} \mu_t + \alpha D_{1,i} \ln\left(\frac{\bar{P}_{i,s}}{P_{i,b}}\right) + \beta D_{1,i} \ln\left(\frac{(P_{i,s}^H - P_{i,s}^L)}{\bar{P}_{i,s}}\right) + \sum_{t=b_i+1}^{s_i} \varepsilon_{it},$$

where  $\bar{P}_{i,s}$  is the average of the high- and low estimates.  $D_{1,i}$  is a dummy variable indicating that the sale of the painting happened after 1973 and information on  $\bar{P}_{i,s}$  is not missing. Here we adjust the price estimate by the original purchase price so that  $\frac{\bar{P}_{i,s}}{P_{i,b}}$  stands for expected holding period returns. In order to measure the impact the spread of the sale estimates, i.e., the difference between high- and low- estimates, we also include the difference  $(P_{i,s}^H - P_{i,s}^L)$  in regression (4). We then scale it by the average estimate for that object at the time of the sale ( $\bar{P}_{i,s}$ ). Our hypothesis is, if investors are credulous and they are given two paintings with same average estimates, they maybe inclined to pay more for the painting with a higher  $P_{i,s}^H$ . We will estimate equation (4) using all artworks as well as for the three collecting subcategories. Thus, if auctioneer estimates simply forecast market returns and have no impact on prices of individual artworks, then we would expect  $\alpha$  and  $\beta$  to be close to zero.

The regression results are reported in Table 1. Our results are uniform across all collecting categories. Average estimates of sale price significantly affect returns, implying the investors at the sale are influenced by the price estimates when they decide how much to pay for the paintings. Our  $\alpha$  estimate for American artworks indicates that a 1% increase in sale price estimates on average tend to increase price (excess returns) by 0.66%. Moreover, our  $\beta$  estimate for American artworks suggests that a 1% increase in estimate spread on average tend to increase excess returns by 0.049%. Thus, our study seems to suggest that art investors are likely influenced by price estimates. They tend to pay more for paintings with high estimate and they tend to pay even more when the estimate spread is larger.

An interesting result from Table 1 is that the impact of auctioneer presale price estimates seems to be highest for Old Masters.<sup>9</sup> Given the fact that Old Master paintings, on average were created much earlier than American and Impressionist paintings, investors will tend to have less information about them. There is a wider difference of opinion as to authenticity, quality and condition for many of the works of art created 200-400 years ago than there would be about works created 50-125 years ago. Most major Old Master pictures are in museums so more of the work available is by lesser known artists. However the supply of Impressionist and Modern work by the well known masters is still abundant. Thus the buying public has less need for expert advice on whom is important. As a result, it might be easier for auctioneers to use their “expertise” to sway potential investors in the Old Master market. Thus, our results are consistent with the view that investors are more credulous when they have less information.

### *B. Underperformance due to the Influence of Auctioneer Estimates*

The above study has shown that investors are influenced by auctioneer estimates. But this does not necessarily imply that investors are credulous. If auctioneers do have information on the value or future performance of paintings, then investors could be simply taking advantages of the information and buying according to their suggestions. In order to prove credulity, we at least need to show that investors have been influenced by information that is adverse to their future returns. Our first test involves a simple study in which we compare the return performance of two groups of paintings with triple sales. Our first group (A) of paintings consists of those whose 1<sup>st</sup> sale occurred before 1973 with no price estimates, and 2<sup>nd</sup> and 3<sup>rd</sup> sale happened after 1973, when auctioneer presale price estimates were made available. As a result, the 1<sup>st</sup> sale price is not influenced by auctioneer estimates while the 2<sup>nd</sup> and 3<sup>rd</sup> prices are. Our second group (B) of paintings consists of those whose 1<sup>st</sup> and 2<sup>nd</sup> sales occurred before 1973 and 3<sup>rd</sup> sale happened after 1973. If price estimates have an upward pressure on prices, we would expect that the first holding period return for A will be higher than that of B. This is because the 2<sup>nd</sup> sale price of A is under the influence of estimates while that of B is not. On the other hand, if the auctioneer presale estimates have lead to high purchase prices and then lower return for the future, we would expect that the second holding period return for A will be lower than that of B.

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<sup>9</sup> A simple t-test indicate that both  $\alpha$  and  $\beta$  for Old Masters is higher then those of Impressionist at 1% significance

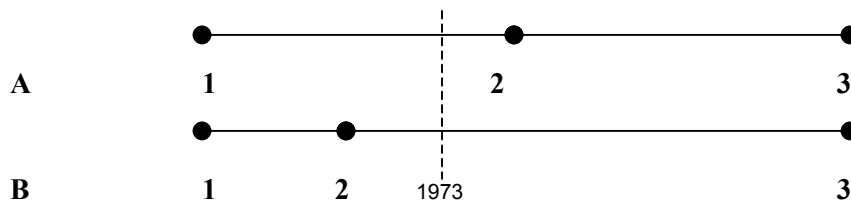


Table 2 presents our empirical findings. We discover that, while the overall holding period returns (1<sup>st</sup> to 3<sup>rd</sup>) is only slightly different (1.2%), the first holding period return for A is 3.97% higher than that of B with a statistical significance of 1%. Moreover, the second holding period return for A is 3.79% lower than that of B. Both findings are consistent with the view that investors are influenced by auctioneer estimate information which then turns out to be adverse to their future returns.

Critics may argue, however, that while the above results are suggestive of investor credulity, its estimation procedure did not adjust for differences in time periods and market movements. To address this concern, we will evaluate the impact of auctioneer estimate on future returns by explicitly control for market movements in the following regression:

$$(5) \quad r_i = \sum_{t=b_i+1}^{s_i} \mu_t + \gamma D_{2,i} \ln(\bar{P}_{i,b}) + \sum_{t=b_i+1}^{s_i} \varepsilon_{it}$$

where  $D_{2,i}$  is a dummy variable indicating that the *purchase* of the painting happened after 1973 and  $\bar{P}_{i,b}$  is the average of the high- and low-estimates at the purchase.<sup>10</sup> The results are reported in Table 3 while Figure 3 provide a simple plot of art returns and price estimates for Old Master paintings. Our results are uniform across all categories: the higher the purchase price estimates, the more the future under-performance of the artworks with respect to art market indices. Moreover, our results are robust to whether nominal prices or real prices are used in the regressions. To understand the economic significance of our results, an average Old Master Painting has an average price estimate of \$19,200 during the period of 1981-1985. A one

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level.

<sup>10</sup> In the second exercise, we use prices deflated by the US CPI index, since the nominal value of art may change due to inflation.

standard deviation increase in price estimate of \$19,400 would increase  $\ln(\bar{P}_{i,b})$  by 9.8, which would on average imply a drop of future return by 29%!

While the results in Table 3 suggest investors tend to receive negative future abnormal returns if they pay the high price estimates, they could receive even less if they pay above the high price estimates in a bidding war. To assess the impact of over payment, i.e. the difference between actual price paid and the price estimate at purchase, we add the overpayment term to the regression (5) and obtain:

$$(6) \quad r_i = \sum_{t=b_i+1}^{s_i} \mu_t + \gamma D_{2,i} \ln(\bar{P}_{i,b}) + \phi D_{2,i} \ln\left(\frac{P_{i,b}}{\bar{P}_{i,b}}\right) + \sum_{t=b_i+1}^{s_i} \varepsilon_{it},$$

where  $P_{i,b}$  is the actual purchase price and  $\bar{P}_{i,b}$  is the average of the high- and low-estimates at the purchase. The results are reported in Table 4. Our results are uniform across all categories: the higher the purchase price estimates, the more the future under-performance of the artworks. Moreover, the higher the over payment, the lower the future abnormal return. To understand the economic significance of our results, a 1% over payment on Old Master Painting tends to reduce future return by 0.24%!

One of the difficult tasks of this study is to show that our results are because credulous investors believe analyst forecast and not because smart analysts simply reflect the beliefs (or exuberance) of the investors.<sup>11</sup> While our results here are not conclusive, it nonetheless suggests that the latter is unlikely. Unless the decision to provide price estimates coincides with a permanent upward shift in investor sentiment, it is hard to explain why the year 1973 has had such an important impact on art returns. It is worth noting that, until very recently when internet has made art price information widely available, auction catalogue was probably the most important source of price information for art objects on sale. Moreover, heterogeneity and infrequent trading makes it hard to evaluate works of art even for a knowledgeable person. As a result, the price estimates were an important part of the information set based on which investors form their price expectations. As a result, auction houses are in a good position to affect and not just reflect investor expectation.

Our case is further strengthened by a common advice given to their clients by art dealers, which is to buy the best (i.e. most expensive) artworks they can afford. This advice presumes that masterpieces of well-known artists will outperform the market. In other words, masterpieces might have a higher expected return than middle-level and lower-level works of art. Casting doubt on this popular advice, Pesando (1993) was first to show that masterpieces (defined by their high prices) actually tend to under perform the market.<sup>12</sup>

Why would auction houses recommend expensive paintings to their clients while there is no (or even opposing) evidence of masterpiece over-performance? We suspect that it could be due to their self-interest. As we know, auction house commissions (both seller commission and buyer premium) are based on the prices of art fetches at auction. The higher the price, the higher the commission. So to the extent auctioneer estimates could influence prices, auction houses would naturally inflate their price estimates and recommend investors to buy “masterpieces”. This paper establishes a statistical relationship between price estimates and future returns. We extend the results of earlier studies by showing that the underperformance could be due to investor credulity by paying dearly for paintings with high price estimates.

Our results here are consistent with those in behavioral finance. Firms tend to “manage” their earnings when they are selling equity. Teoh et al. (1998a, b) and Rangan (1998) discovered that accruals tend to be abnormally high at the time of new IPO and seasoned equity issues, suggesting firm earnings are reported higher than cash flow. Teoh and Wong (2001) also found that greater earnings management is associated with more optimistic errors in analyst earnings forecasts both in new and seasoned equity issues. They found that greater earnings management at the time of a new issue is associated with more adverse future abnormal stock returns. This suggests “...investors, possibly under the influence of analysts, do not adequately discount for earnings manipulation.”<sup>13</sup>

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<sup>11</sup> See Raghuram Rajan and Henri Servaes (1997) for a detailed discussion on the difficulty of separating the two in the IPO literature.

<sup>12</sup> Pesando’s (1993) discovery was based on repeated sales of modern prints from 1977-1992. Since his data only cover prints that tend to have much lower value when compared to American, Old Masters and Impressionists paintings, one may wonder if this underperformance exists for truly expensive artworks. Moreover, Goetzmann (1996) found no evidence of underperformance of masterpieces. Using repeated sales data covering American, Old Master, Impressionist and Modern paintings, Mei and Moses (2002) further examined the performance of masterpieces. They found strong evidence on the underperformance of masterpieces.

<sup>13</sup> See Daniel, Hirshleifer, and Teoh (2002 ) for further discussion.

### *C. Do Auctioneer Estimates Reduce Risk?*

An alternative explanation to our results is that auctioneer estimates provide valuable information to investors by reducing the risk in art investment.<sup>14</sup> The auctioneer presale estimates are particularly valuable for expensive paintings because market participants believe that they tend to be the most risky. Thus, investors are willing to pay a premium for masterpieces when price estimates are available. To examine the validity of this explanation, we need to systematically estimate the return risk of art works. This is not a trivial task, since artworks do not trade very often and they have different holding periods and thus are under the influence of different overall market movements. We will approach this problem by using the classic capital asset pricing model (CAPM) to decompose the return risk into systematic and painting specific risks. As a result, we have two possible explanations related to risk.

The first explanation would be masterpieces have smaller systematic risk. As a result, investors would be willing to pay a premium for them relative to other works of art due to smaller market risk exposure. To test this hypothesis, we partition our data into two groups for each year based on purchase prices (or price estimates) and define those whose prices are in the top one third to be masterpieces. Because it is not possible to estimate stock market betas for each artwork, we assume that all masterpieces (non-masterpieces) have the same betas. Here, we allow betas to vary over the two groups and over two time periods, before and after 1973, to take into account a possible change in betas due to the availability of price estimates or other changing market conditions. For simplicity, we will use the classic CAPM model to estimate the systematic risks of artworks and we will employ the S&P 500 as the market index. Using equation (2) and the CAPM, we have:

$$\begin{aligned}
 (7) \quad r_i &= \sum_{t=b_i+1}^{s_i} r_{i,t} = \sum_{t=b_i+1}^{s_i} (r_{ft} + \beta_{it} R_{mt} + \varepsilon_{it}) \\
 &= \sum_{t=b_i+1}^{s_i} r_{ft} + \sum_{t=b_i+1}^{1972} \beta_{1,k} R_{mt} + \sum_{1973}^{s_i} \beta_{2,k} R_{mt} + \sum_{t=b_i+1}^{s_i} \varepsilon_{it}, \text{ k=M and NM}
 \end{aligned}$$

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<sup>14</sup> The expert's job is meant to basically reduce the range and weight in the tails of the density function of prices for a work of art. The data in Table 2 tends to bear this out. The standard deviation of the objects sold during the era of no estimates (B 1 T0 2) 27.02 is much higher than the standard deviation of returns during the era of estimates (A 2 T0 3) 14.41.

where M (NM) stands for masterpieces, (non-masterpieces). Note that we may not have either the first term if the purchase happened after 1973 or the second term if the sale happened before 1972. Re-arranging terms and adding a constant to measure the Jensen's  $\alpha$  (risk adjusted excess return), we have the following regression:

$$(8) \quad r_i - \sum_{t=b_i+1}^{s_i} r_{ft} = a_k + \beta_{1k} \sum_{t=b_i+1}^{1972} R_{mt} + \beta_{2k} \sum_{1973}^{s_i} R_{mt} + \sum_{t=b_i+1}^{s_i} \varepsilon_{it} .$$

Here we will use return to the United States Treasury Bills Total Return Index as the risk free rate. The sources of this data are from Federal Reserve Board and Global Financial Data (5th edition). We employ the same Case and Shiller (1987) estimation procedure to estimate (8) separately for the masterpieces and non-masterpieces. The results are reported in Table 5.

There are several interesting results. First, with the exception of Impressionist in the post-1973 period, masterpieces tend to have *lower* systematic risk than non-masterpieces. Thus, market participants were wrong if they believed that masterpieces tend to be risky. Second, there is a substantial drop in systematic risk after 1972. This could be a confluence of many factors. While the availability of prices estimates may have contributed to the drop, Japanese influence in the 1980s and art market correction in the 1990s may have also reduced correlation with the US equity market. It is interesting to note that there is little difference in systematic risks between the American masterpieces and non-masterpieces after 1973. While impressionist masterpieces do have higher betas, the opposite was true for Old Masters. Lastly, after adjusting for systematic risk, masterpieces tend to have a more negative excess return (Jensen's  $\alpha$ ) than non-masterpieces. For example, while artworks generally tend to have a negative excess return after adjusting for risk, a typical American masterpiece would have a -21% excess return (0.75% annually on a 28 year holding period)) comparing to -7% return for non-masterpiece. The result is statistically significant at 1% level for Old Masters and All collecting category. Thus, systematic risk cannot explain the "masterpiece effect".

The second explanation related to risk would be masterpieces have smaller idiosyncratic risk. Idiosyncratic risk matters because art investment is lumpy. As a result, investors could be paying a premium for masterpiece relative to other works of art due to smaller painting specific



risk. To obtain the annual idiosyncratic volatility  $\sigma_{\varepsilon}^2$  estimate, we take the squared residuals from (8) and scale it by  $(s_i - b_i)$ . We next sum them up for all paintings sold before 1973 (or purchased after 1973) and divided it by the total number of paintings sold during the period.

That is:  $\sigma_{1,\varepsilon}^2 = \sum_{s_i < 1972} \left( \frac{\eta_i^2}{s_i - b_i} \right) / N_1$ , where  $N_1$  is the total number of paintings sold before 1973,

and  $\eta_i^2$  is the squared residuals in equation (8).<sup>15</sup> We discard the sample of paintings bought before 1973 and sold after 1973 to get a clean estimate of idiosyncratic volatility before and after 1973. We then compute two F-statistics, which is the ratio of idiosyncratic volatility of non-masterpiece over masterpieces.<sup>16</sup> Under the assumption of annual homoscedasticity across the two time periods, we can show that the F-statistic has a distribution with the degrees of freedom equal to the numbers of paintings used in the computation of the volatility minus one.

The results are reported in Table 6. Our results are uniform across all categories that idiosyncratic volatility of masterpieces is smaller than those of non-masterpieces. Our  $\sigma_{\varepsilon}^2$  estimate on the American masterpieces indicates that annual volatility is 0.063 compared to 0.075 for non-masterpieces after 1973. Moreover, volatility has generally declined after price estimates were made available after 1973. Thus, price estimates tend to help reduce future return volatility. Thus, idiosyncratic risk may help explain why investors would pay a premium for masterpieces. However, since paintings are usually bought by wealthy individuals and large institutions, it is a puzzle why investors would pay more because painting specific volatility can be easily diversified.

To further test the robustness of our results in Table 5, we also employ a three-factor model of Eugene Fama and Kenneth French (1996) to control for systematic risks. Following equation (8), we allow the factor loadings to vary over the two groups and over two time periods, before and after 1973, to take into account a possible change in factor loadings due to the availability of price estimates or other changing market conditions. Replacing the CAPM model equation (7) by the Fama and French (1996) three-factor model, we obtain:

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<sup>15</sup> By the same token,  $\sigma_{2,\varepsilon}^2 = \sum_{b_i > 1972} \left( \frac{\eta_i^2}{s_i - b_i} \right) / N_2$ , where  $N_2$  is the total number of paintings bought after 1973.

$$(9) \quad r_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha_k + \beta_{1k} \sum_{t=b_i+1}^{1972} R_{mt} + \beta_{2k} \sum_{1973}^{s_i} R_{mt} + \gamma_{1k} \sum_{t=b_i+1}^{1972} S_{mt} + \gamma_{2k} \sum_{1973}^{s_i} S_{mt} + \theta_{1k} \sum_{t=b_i+1}^{1972} H_{mt} + \theta_{2k} \sum_{1973}^{s_i} H_{mt} + \sum_{t=b_i+1}^{s_i} \varepsilon_{it}$$

where  $S_m$  is for the “small minus big” size factor and  $H_m$  stands for the “high minus low” book-to-market factor. For simplicity, we here only report the abnormal returns in Table 7. Our results are quite similar to those reported in Table 5. After adjusting for systematic risk, masterpieces tend to have a more negative excess return than non-masterpieces. Again, risk cannot explain the “masterpiece effect”. Moreover, the so-called winner’s curse, the tendency for buyers to overbid at auctions, would have a hard time explain the effect either, since the impact of overbidding at the purchase may be cancelled out at the sale if the new buyer also has a tendency to overbid.<sup>17</sup>

There is however a totally different explanation to our results that has little to do with art as investment. Rather art becomes consumption good. In this case, collectors buy paintings for their aesthetic value or other pleasures associated with owning works of art. When auctioneers put up a high estimate for a painting, it could indicate high fashion of the time or other consumption values. It is conceivable that collectors may pay more for these paintings despite their negative abnormal future returns, because the high consumption values could compensate for the lower returns.

#### IV. Sale Rates and Selection Bias

##### A. Why do Sale Rates Change Over Time?

An effective strategy against auctioneer bias is refusing to pay the high prices suggested by their estimates. Given the upward bias of price estimates and the high reservation price set based on the estimates, the painting may fail to sell at the auction (i.e. “be bought-in”) if we have shrewd investors. If more and more investors learn over time that there is an inherent bias in

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<sup>16</sup>  $F_1 = \sigma_{1,NM}^2 / \sigma_{1,M}^2$  and  $F_2 = \sigma_{2,NM}^2 / \sigma_{2,M}^2$ .

<sup>17</sup> The impact of overbidding would exactly offset each other if the overbidding is proportional to prices.

auctioneer estimates, then more and more paintings will fail to sell at auctions if auctioneer do not significantly alter their behavior. Here we have some preliminary evidence that this may be the case. Figure 4 presents a graphic plot of sale rates for various collecting categories for one of the world's major auction house, Sotheby New York. We can clearly see that there is a downward trend for all collecting categories, implying a higher percentage of paintings have been unsold in recent auctions.

This evidence on declining sale rates could be quite interesting, because it may suggest that art buyers do care about future returns. They have refused to offer high bids for a larger percentage of paintings recently. This cast some doubt on the fashion or consumption explanation. If high price estimates simply proxy for high consumption level or "hot" styles, then one may wonder why collectors have stopped chasing them and why auctioneers (or sellers) have consistently priced an increasingly large percentage of their products out of the market.

There may be several reasons why auctioneers have not significantly adjusted their price estimates to counter the declining sale rates. First, self-interest may lead them to believe that the declining sale rates could be temporary. Second and more importantly, competition among auction houses could lead to a bidding war on price estimates, because the sellers may be tempted by the prospects of fetching higher prices if they believe investors are credulous. This is especially the case when auction houses sometime provide financing or minimum sale price guarantees based on the lower price estimates. The interaction among sellers, auctioneers and buyers is an interesting topic. Unfortunately, data on reservation prices are hard to obtain.

### *B. Does Sample Selection Bias Affect Our Results?*

A main statistical feature of our study is that it is based on artworks sold at the auction. Thus, we do not observe the prices of those paintings that are unsold at the auctions. While we argue in Section IIIA that the upward bias of price estimates with respect to masterpieces should not be affected by the selection bias, it makes us wonder whether the same can be said about our credulity results derived from regression (5). In this subsection, we will demonstrate that, under certain conditions, our results are unaffected by the sample selection bias. We begin by assuming that the errors in regression (5) follow a normal distribution:

$$(10) \quad r_i = \ln P_{is} - \ln P_{i,b} = \sum_{t=b_i+1}^{s_i} \mu_t + \gamma D_{2i} \ln(\bar{P}_{i,b}) + \sum_{t=b_i+1}^{s_i} \varepsilon_{it}, \quad \sum_{t=b_i+1}^{s_i} \varepsilon_{it} \sim N(0, (s_i - b_i)\sigma^2)$$

For simplicity, we will re-write (10) as:

$$(11) \quad \ln P_{is} = \ln P_{i,b} + \sum_{t=b_i+1}^{s_i} \mu_t + \gamma D_{3,i} \ln(\bar{P}_{i,b}) + \sum_{t=b_i+1}^{s_i} \varepsilon_{it},$$

or simply as:

$$(12) \quad y_i = \ln P_{is} = aX_1 + \gamma X_2 + \sum_{t=b_i+1}^{s_i} \varepsilon_{it},$$

where  $X_1$  would include the exogenous variables in the first two terms of equation (12), and  $X_2$  would be  $D_{3,i} \ln(\bar{P}_{i,b})$ . According to William Greene (2000, pages 899-902),

$$(13) \quad E[y_i | y_i > \phi \ln(\bar{P}_{i,s})] = aX_1 + \gamma X_2 + (s_i - b_i)\sigma\lambda(\alpha_i),$$

where  $\alpha_i = (\phi \ln(\bar{P}_{i,s}) - aX_1 - \gamma X_2) / (s_i - b_i)\sigma$ . Here, we assume that a painting will be sold if  $y_i > \phi \ln(\bar{P}_{i,s})$  and  $\lambda(\alpha)$  is the inverse Mills Ratio.<sup>18</sup> It is then easy to show that:

$$(14) \quad \begin{aligned} \frac{\partial E[y_i | y_i > \phi \ln(\bar{P}_{i,s})]}{\partial X_2} &= \gamma + (s_i - b_i)\sigma \frac{d\lambda(\alpha_i)}{d\alpha_i} \frac{\partial \alpha_i}{\partial X_2} \\ &= \gamma + (s_i - b_i)\sigma\lambda(\alpha_i) \left[ \lambda(\alpha_i) - \alpha_i \right] \left( \frac{-\gamma}{(s_i - b_i)\sigma} \right) \\ &= \gamma [1 - \delta(\alpha_i)] = \hat{\gamma}, \end{aligned}$$

It is well known that:

$$(15) \quad \delta(\alpha_i) = \lambda(\alpha_i)(\lambda(\alpha_i) - \alpha_i), 0 < \delta(\alpha_i) < 1.$$

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<sup>18</sup> More generally, our results also hold if the condition of sale is  $y_i > f(P_{i,s}^H, P_{i,s}^L)$ .

Equation (14) shows that  $\hat{\gamma}$  is the marginal effect of price estimates at purchase, which is estimated using regression (5) *conditional* on sold artworks. From equation (14) and (15), we can see that the true  $\gamma$  has the same sign as  $\hat{\gamma}$ . Moreover, the estimated negative impact  $\hat{\gamma}$  is smaller in absolute value than the actual  $\gamma$ . As a result, our conclusion of the *negative* relationship between price estimates and future abnormal returns is not affected by the sample selection bias.

## VI. Conclusions

This paper constructs a new data set from art auctions that include auctioneer estimates when they are available to examine the credulity of art investors. It complements existing empirical literature on behavioral economics, which focus on analyst earnings estimates and stock prices. We find that auctioneer estimates are highly and significantly related to prices paid by investors for artworks. High estimates at the time of purchase are associated with adverse subsequent abnormal returns. These results are consistent with the view that investors are credulous. They do not discount fully the strategic incentives of auctioneers. However, we have some preliminary evidence that investors have made some adjustment recently for systematic biases in provided information. So our results seems to be consistent with the view that “You can fool some of people some of the time, but not all the people all the time.”

In addition to examining the credulity hypothesis, our study has also studied the validity of two alternative explanations to our empirical findings—risk and fashion. While we find it inconceivable that our results are driven exclusively by risk considerations, we cannot reject the hypothesis that art is consumption good and thus its investment returns are of secondary concerns to investors. While it is possible that the lower returns we documented for paintings with high estimates are offset by psychological rewards associated with market fashion of the time, the evidence on declining sale rates documented in Section IV seem to suggest that investors do care about future returns. They have refused to offer high bids for a larger percentage of paintings recently. This cast some doubt on the fashion explanation. But we cannot rule it out.

If investors are indeed credulous as indicated by our preliminary evidence, then they are subject to manipulation by interested parties, such as auction houses and other providers of

information to the market. Recent conflict of interest scandals on Wall Street suggest that exploitation of investor credulity could be quite pervasive in the market place.<sup>19</sup> In that case, there might be some interesting policy implications for government regulation. To protect the unwary, government could provide better education to investors or mandate a warning label on auction catalogs that warns investors against the agency problem. Much like warnings on cigarette package for smokers, it could warn that the price estimates could be upward biased. While this may have a dampening effect on the alleged art market euphoria such as the Impressionist bubble of the 1980s, we are doubtful that more government intervention could prevent the Japanese investors from paying tens of millions for Van Gogh paintings.

Experience in the art market may also shed light on the effectiveness of two policy tools for government to curb speculation: transaction tax and trading halt, such as the circuit breaker on the stock exchange. Since transaction cost in art market is certainly among the highest in all asset transactions, the existence of the Impressionist bubble cast doubt on the effectiveness of Tobin's tax to curb market speculation. Moreover, since the art auction market is as illiquid as you can get—it trades only once every six month at major seasonal auctions, it implies that a mere trading halt probably could not do much to cool the speculative craze of frenzied investors.

Our research has left many interesting issues. While the paper has studied the impact of auctioneer estimates on investors, we have not examined how investor behavior influence auction price estimates. It might be interesting to study the impact of auction house competition on price estimates. Another interesting question is whether sellers are credulous as well by offering their paintings to auction houses that offer them the highest price estimates. In addition, we have also not studied the optimal bidding strategies for rational investors when price estimates are upward biased and most investors are credulous. We will leave these for future research.

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<sup>19</sup> Recent the New York State attorney general has made numerous investigation into leading Wall Street firms for issuing inflated investment ratings and offering “hot” IPOs in turn for investment banking business from telcom companies.

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TABLE 1--TESTS OF INFLUENCE OF AUCTIONEER ESTIMATES

	American	Impressionist	Old Master	All
Sample Period	1941-2000	1941-2000	1900-2000	1875-2000
$\alpha$	0.662	0.580	0.687	0.665
t-stat	[17.81]	[22.12]	[20.60]	[35.91]
$\beta$	0.061	0.040	0.290	0.076
t-stat	[1.757]	[2.332]	[6.651]	[5.034]
$R^2$	0.773	0.800	0.651	0.676
OBS	968	1927	2345	5606

Note: Three-stage-generalized-least square RSR estimation of Case and Shiller (1989) are used to estimate:  $r_i = \sum_{t=b_i+1}^{s_i} \mu_t + \alpha \ln\left(\frac{\bar{P}_{i,s}}{P_{i,b}}\right) \cdot D_{1,i} + \beta \ln\left(\frac{(P_{i,s}^H - P_{i,s}^L)}{\bar{P}_{i,s}}\right) \cdot D_{1,i} + \sum_{t=b_i+1}^{s_i} \varepsilon_{it}$ , where  $D_{1,i}$  is a dummy variable indicating that the sale of the painting happened after 1973 and information on  $\bar{P}_{i,s}$  is not missing.  $(P_{i,s}^H - P_{i,s}^L)$  is the difference between high- and low- estimates at the sale.

TABLE 2-- SUMMARY STATISTICS OF AVERAGE RETURNS

		OBS		1 <sup>st</sup> To 2 <sup>nd</sup> (%)	2 <sup>nd</sup> To 3 <sup>rd</sup> (%)	1 <sup>st</sup> To 3 <sup>rd</sup> (%)
A	1 <sup>st</sup> Sale	227	Mean	10.73	6.28	9.52
	Prior 1973		STD	6.40	14.41	4.17
B	1 <sup>st</sup> & 2 <sup>nd</sup> Sale	256	Mean	6.76	10.07	8.32
	Prior 1973		STD	27.02	5.20	3.96
Difference				3.97**	-3.79**	1.20**

\*\* indicates significance level at 1%.

TABLE 3--TESTS OF FUTURE UNDERPERFORMANCE

	American	Impressionist	Old Master	All
Sample Period	1941-2000	1941-2000	1900-2000	1875-2000
Panel A: Test using Nominal Value for $\bar{P}_{i,b}$				
$\gamma$	-0.011	-0.005	-0.030	-0.010
t-stat	[-2.062]	[-1.375]	[-5.984]	[-4.476]
$R^2$	0.758	0.791	0.636	0.666
Panel B: Test using Real Value for $\bar{P}_{i,b}$				
$\gamma$	-0.020	-0.007	-0.060	-0.019
t-stat	[-2.190]	[-1.275]	[-6.176]	[-4.728]
$R^2$	0.758	0.791	0.636	0.666
OBS	814	1699	2078	4957

Note: Three-stage-generalized-least square RSR estimation of Case and Shiller (1989) are used to estimate:  $r_i = \sum_{t=b_i+1}^{s_i} \mu_t + \gamma D_{2,i} \ln(\bar{P}_{i,b}) + \sum_{t=b_i+1}^{s_i} \varepsilon_{it}$ . Here  $D_{2,i}$  is a dummy variable indicating that the *purchase* of the painting happened after 1973,  $P_{i,b}$  is the actual purchase price and  $\bar{P}_{i,b}$  is the average of the high- and low-estimates at the purchase.

TABLE 4--TESTS OF FUTURE UNDERPERFORMANCE WITH OVERPAYMENT

	American	Impressionist	Old Master	All
Sample Period	1941-2000	1941-2000	1900-2000	1875-2000
Panel A: Test using Nominal Value for $\bar{P}_{i,b}$				
$\gamma$	-0.008	-0.003	-0.025	-0.007
t-stat	[-1.607]	[-1.065]	[-4.895]	[-3.216]
$\phi$	-0.099	-0.211	-0.237	-0.205
t-stat	[-1.655]	[-3.746]	[-4.206]	[-6.627]
$R^2$	0.759	0.783	0.636	0.666
OBS	814	1699	2078	4957

Note: Three-stage-generalized-least square RSR estimation of Case and Shiller (1989) are used

to estimate:  $r_i = \sum_{t=b_i+1}^{s_i} \mu_t + \gamma D_{2,i} \ln(\bar{P}_{i,b}) + \phi D_{2,i} \ln\left(\frac{P_{i,b}}{\bar{P}_{i,b}}\right) + \sum_{t=b_i+1}^{s_i} \varepsilon_{it}$ . Here  $D_{2,i}$  is a dummy variable

indicating that the *purchase* of the painting happened after 1973 and  $\bar{P}_{i,b}$  is the average of the high- and low-estimates at the purchase.

TABLE 5—ESTIMATES OF ABNORMAL RETURN

	American	Impressionist	Old Master	All
Sample Period	1941-2000	1941-2000	1900-2000	1875-2000
<b>A: Estimates for Masterpieces</b>				
$\alpha_M$	-0.217	-0.380	-0.414 <sup>a)</sup>	-0.233 <sup>a)</sup>
t-stat	[-2.782]	[-5.504]	[-6.491]	[-7.178]
$\beta_{1,M}$	0.687	0.815	0.172 <sup>a)</sup>	0.320 <sup>a)</sup>
t-stat	[10.92]	[18.25]	[5.647]	[11.74]
$\beta_{2,M}$	0.102	0.192 <sup>a)</sup>	0.157 <sup>a)</sup>	0.076
t-stat	[2.240]	[5.026]	[4.159]	[3.119]
$R^2$	0.368	0.438	0.023	0.031
OBS	300	579	710	1589
<b>B: Estimates for Non-Masterpieces</b>				
$\alpha_{NM}$	-0.079	-0.236	-0.140	-0.123
t-stat	[-1.208]	[-4.343]	[-2.946]	[-4.358]
$\beta_{1,NM}$	0.824	0.898	0.443	0.582
t-stat	[17.68]	[25.65]	[21.21]	[32.97]
$\beta_{2,NM}$	0.109	0.101	0.274	0.129
t-stat	[2.966]	[3.426]	[9.700]	[7.235]
$R^2$	0.403	0.417	0.198	0.254
OBS	654	1237	1511	3402

Note: Three-stage-generalized-least square RSR estimation of Case and Shiller (1989) are used

to estimate  $r_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha_k + \beta_{1k} \sum_{t=b_i+1}^{1972} R_{mt} + \beta_{2k} \sum_{1973}^{s_i} R_{mt} + \sum_{t=b_i+1}^{s_i} \varepsilon_{it}$ , k=M, NM.

<sup>a)</sup> indicates a difference of same coefficients between masterpieces and non-masterpieces that is significant at 1% level.

TABLE 6—ESTIMATES OF IDIOSYNCRATIC RISK

	American	Impressionist	Old Master	All
Sample Period	1941-2000	1941-2000	1900-2000	1875-2000
<b>A: Estimates for Masterpieces</b>				
A: Annual Variance Before 1973				
$\sigma_{1\varepsilon}^2$	0.031	0.039	0.143	0.118
B: Annual Variance After 1973				
$\sigma_{2\varepsilon}^2$	0.063	0.092	0.071	0.078
<b>B: Estimates for Non-Masterpieces</b>				
A: Annual Variance Before 1973				
$\sigma_{1\varepsilon}^2$	0.154	0.192	0.165	0.179
B: Annual Variance After 1973				
$\sigma_{2\varepsilon}^2$	0.075	0.102	0.118	0.099
P-value (F <sub>1</sub> )	0.003	0.000	0.249	0.005
P-Value (F <sub>2</sub> )	0.084	0.157	0.000	0.000

Note: Three-stage-generalized-least square RSR estimation of Case and Shiller (1989) are used

to estimate  $r_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha_k + \beta_{1k} \sum_{t=b_i+1}^{1972} R_{mt} + \beta_{2k} \sum_{1973}^{s_i} R_{mt} + \sum_{t=b_i+1}^{s_i} \varepsilon_{it}$ , k=M, NM.  $\sigma_{\varepsilon}^2$  is the

annual volatility.  $\sigma_{1\varepsilon}^2 = \sum_{s_i < 1972} \left( \frac{\eta_i^2}{s_i - b_i} \right) / N_1$ , where  $N_1$  is the total number of paintings *sold*

before 1973 and  $\eta_i^2$  is the squared residuals in equation (2).  $\sigma_{2,\varepsilon}^2 = \sum_{b_i > 1972} \left( \frac{\eta_i^2}{s_i - b_i} \right) / N_2$ , where

$N_2$  is the total number of paintings *bought* after 1973.  $F_1 = \sigma_{1,NM}^2 / \sigma_{1,M}^2$  and  $F_2 = \sigma_{2,NM}^2 / \sigma_{2,M}^2$ .

TABLE 7—ESTIMATES OF ABNORMAL RETURN USING FF FACTORS

	American	Impressionist	Old Master	All
Sample Period	1941-2000	1941-2000	1900-2000	1875-2000
<b>A: Estimates for Masterpieces</b>				
$\alpha_M$	-0.161	-0.324 <sup>a)</sup>	-0.417 <sup>a)</sup>	-0.241 <sup>a)</sup>
t-stat	[-2.006]	[-5.289]	[-7.590]	[-7.534]
$R^2$	0.397	0.503	0.162	0.227
<b>B: Estimates for Non-Masterpieces</b>				
$\alpha_{NM}$	0.003	-0.151	-0.113	-0.094
t-stat	[0.051]	[-3.027]	[-2.345]	[-3.118]
$R^2$	0.417	0.476	0.397	0.421

Note: Three-stage-generalized-least square RSR estimation of Case and Shiller (1989) are used to estimate the following regression:

$$r_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha_k + \beta_{1k} \sum_{t=b_i+1}^{1972} R_{mt} + \beta_{2k} \sum_{1973}^{s_i} R_{mt} + \gamma_{1k} \sum_{t=b_i+1}^{1972} S_{mt} + \gamma_{2k} \sum_{1973}^{s_i} S_{mt} + \theta_{1k} \sum_{t=b_i+1}^{1972} H_{mt} + \theta_{2k} \sum_{1973}^{s_i} H_{mt} + \sum_{t=b_i+1}^{s_i} \varepsilon_{it} ,$$

k=M, NM.

<sup>a)</sup> indicates a difference of same coefficients between masterpieces and non-masterpieces that is significant at 1% level.

FIGURE 1: REGRESSION OF PRICES ON AUCTIONEER ESTIMATES

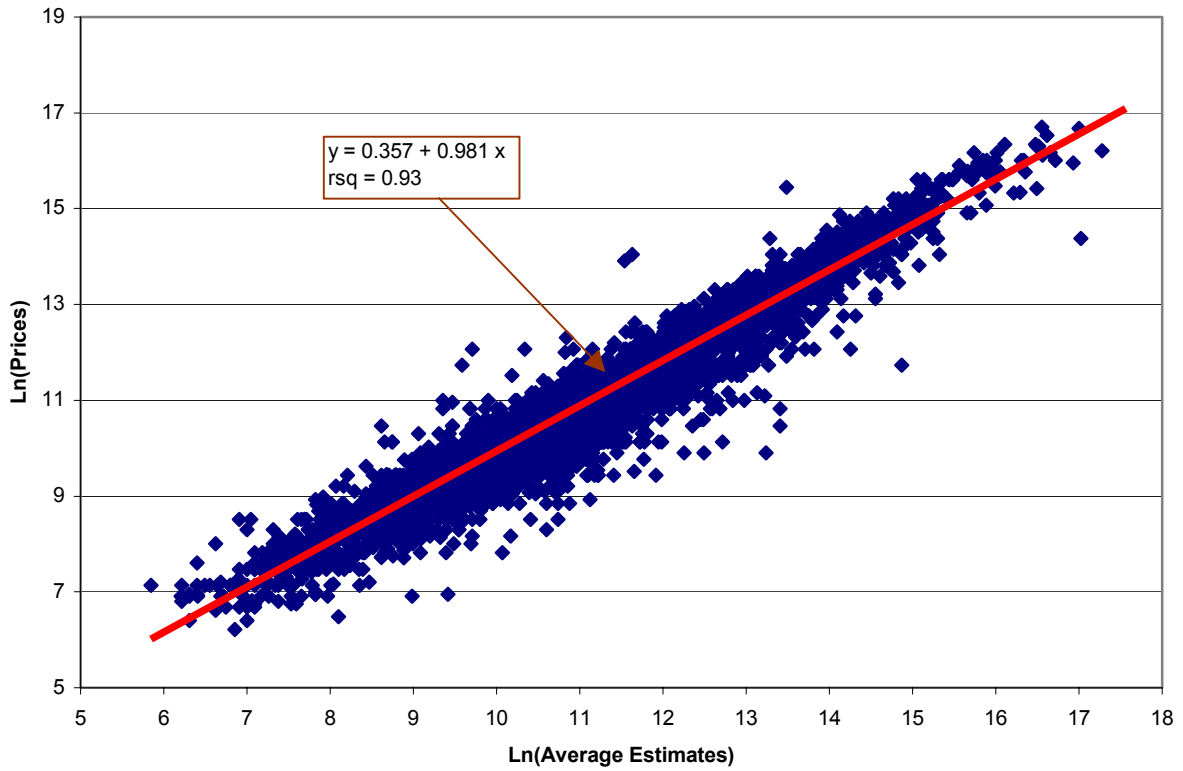
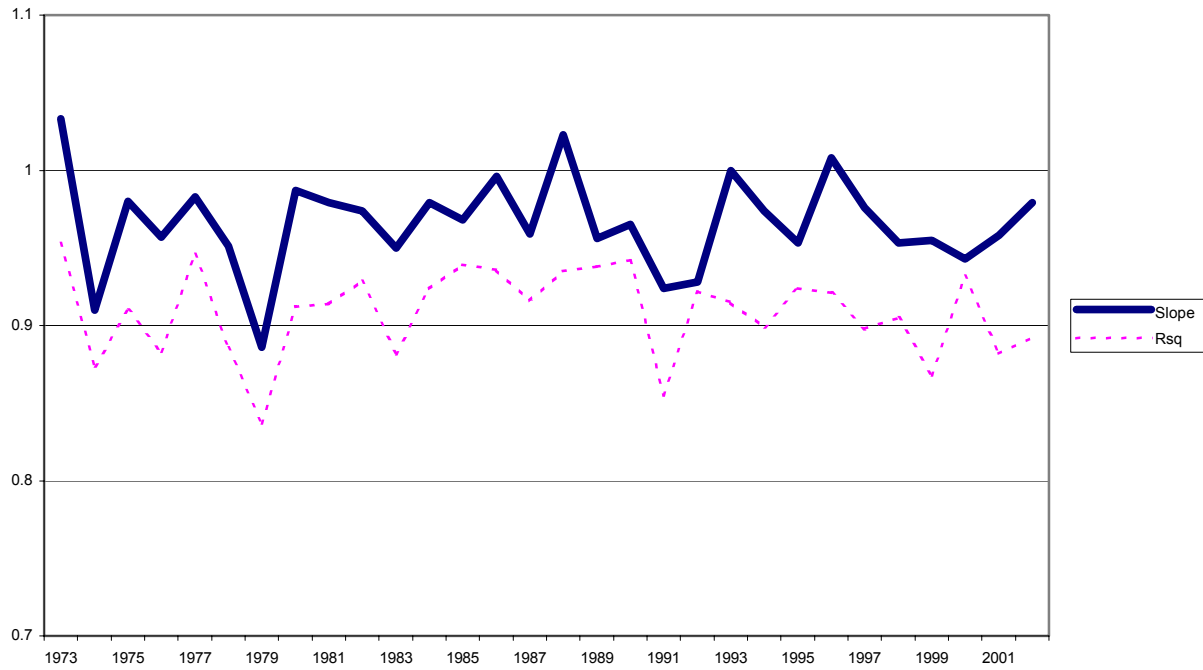


FIGURE 2: THE SLOPE COEFFICIENTS AND R-SQUARES



Note: Slope coefficients ( $d_s$ ) and R-squares for the following cross-sectional regressions over the time periods between 1973 and 2002.  $\ln P_{i,s} = c_s + d_s \ln \bar{P}_{i,s} + v_{i,s}, s = 1973, \dots, 2002$ .



FIGURE 3: OLD MASTER PAINTINGS RESALE RETURNS

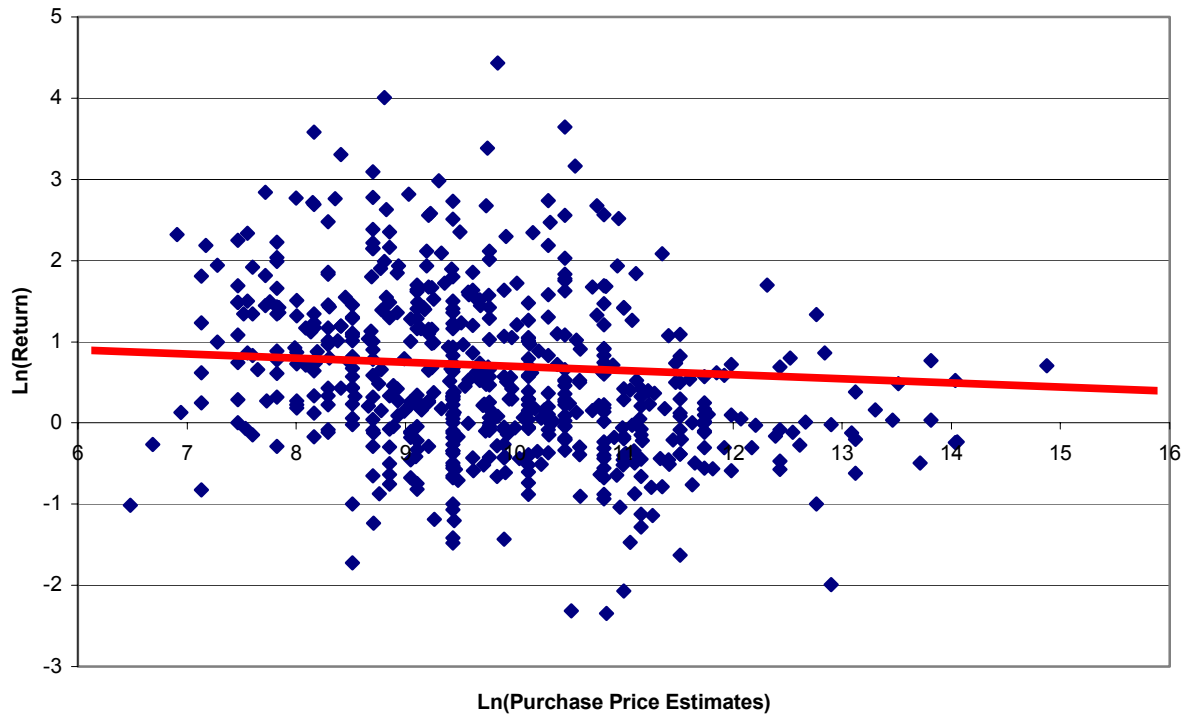


FIGURE 4: SALE RATE DECLINING OVER TIME

