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The collateral value of fine art

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Abstract

In this paper, we examine the effect of implicit seller reserves on the estimation of value-at-risk based on historical asset sales data. We direct our examination toward how and whether fine art might prove an appropriate form of loan collateral for banks and other financial institutions. Using a data set of French Impressionist paintings brought to auction from 1985 to 2001, we control for the effect of works that are bought in-house to construct a distribution of potential sale values that corrects for sample selection bias. It turns out that the downside risk surrounding deviations of auction prices from expert presale estimates depends critically on how buy-ins are incorporated. If downside risk is assessed solely on historical experience with successful auction sales, the data appear to support loan-to-value ratios between 50% and a 100% larger than loan-to-value ratios that countenance the existence of seller reserves. The auction process, however, is quantifiable and can reveal the necessary risk information required for loan consideration.

JEL classification: G12; G21; C16; Z10

Keywords: Downside risk; Credit; Collateral; Art; Buy-ins

0. Introduction

In this paper, we examine the effect of implicit seller reserves on the estimation of value at risk (VAR) based on historical asset sales data. If historical sale price data come from voluntary transactions, we argue that the left tail of the empirical sales distribution

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contains a positive bias relative to market demand, caused by the fact that sales are only recorded when buyers offer more than the seller's implicit reserve. Using a unique data set of auction prices for fine art, we attempt to correct for this bias and estimate the true downside risk of lending against fine art as collateral. We examine fine art, in part, to begin a dialogue concerning whether this asset class meets the criteria required of lending institutions for loan collateral. To qualify it must be possible for banks and financiers to quantify two essential elements of standalone credit risk: the default probability (PD) – the probability that borrowers will fail to service their loan obligations; and the loss given default (LGD) – the extent of the loss incurred in the event a borrower defaults (Soberhart and Keenan, 2003). These two credit issues underlie most of the models for estimating credit risk that have been developed over the past three decades.[1]

This paper considers the situation where a borrower uses a portfolio of fine art as collateral on a loan without the art providing any cash flow. In this context default occurs in a two stage process: first the borrower chooses or is forced to sell the assets to repay the loan, and then once brought to market, the sale of the assets does not raise sufficient funds to cover the loan balance. This latter result we call a collateral shortfall. The focus of the analysis is on the probability of a collateral shortfall and the expected collateral shortfall, conditional on the asset sale taking place. Separating these aspects of credit risk from aspects of the likelihood that the borrower will choose or be forced to liquidate assets mirrors the approach developed in real estate markets where the properties of collateral value are modeled separately from the income and default characteristics of the borrower.[2]

The assessment of downside risk from monetizing an asset is usually achieved through sales experience with similar assets. Loans are extended as a percentage of appraised or expected value and the downside risk is determined by estimating the lower tail of the empirical distribution of observed sale prices around appraised values. In the case of real estate loans, for example, a data base of appraised values and contemporaneous real estate sales could be used to establish the observed probability of and expected loss from sales that yielded less than, say, 80% of appraised value. However, there is a drawback from directly measuring downside risk through historical sales experience. Unless the data are based exclusively on liquidations, voluntary sales have an important selection bias: sellers reserve the right not to sell below their own internal assessment of value. Thus, the lower tail of the empirical distribution is upward biased relative to the sales experience that would have occurred had assets been liquidated at random. Fortunately, for established asset categories like real estate there is a history of actual bank foreclosures to draw

[1] The quantitative modeling of credit risk was inspired by an early paper by Beaver (1966) that examined the relationship between companies' financial ratios and their propensity to default . Altman (1968) formalized the model in a multivariate framework by using a classification system. Merton (1974) developed structural form models based around option pricing. Others such as Frye (2003) built models in which credit risk was driven externally by the state of the economy. For an overview of the theory and approaches of credit risk models see Kao (2000) and Crouhy et al. (2000).

[2] See, for example, Wheaton et al. (2002). One issue we do not address is the practical arrangements associated with using fine art as collateral. Similar to jewelry and cars, fine art can be moved and physical possession would have to be monitored and insured. But many art genres including the paintings we examine derive much of their value from their provenance. A stolen work or one sold without recognition of a legal lien is worth a fraction of its value with provenance in tact. Recent advances in monitoring technology have also reduced the monitoring problem.

upon. Resorting to voluntary sales data is necessary when considering new asset categories, before a long experience of forced liquidations exists.

In the current paper, we endeavor to quantify the nature of this upward bias through the examination of a unique data set on fine art auctions. Certainly, the size of the art market justifies such an investigation. In 2003, approximately 1.2 million transactions took place internationally, representing around $22 billion of fine and decorative art changing ownership. Approximately 92% of these art sales took place in the US and Europe with over 72% in the US and UK alone.[3] Consumers are the stereotypical high net-worth individuals who participate in organized financial markets around the world. As a result, there is natural interest in drawing the markets for fine art and those for financial instruments onto what common footing exists across them. In the context of considering fine art as an asset class, the schism seems larger than it needs to be. While it has been commonplace for banks to lend to wealthy clients using their homes or other tangible assets as collateral, financial institutions have generally avoided lending on artworks, which are often viewed as difficult to value or within too volatile a market place. The art sector is also virtually devoid of trade financing. We attribute the failure of financial intermediaries to participate in the sector to lack of data and analysis, presented in a language they use and understand. The market failure has led to a substantial lack of liquidity, with many art dealers unable to obtain inventory financing.

Recently there has been renewed interest in the idea of art as an asset class and collateralizing art, spurred by ever increasing record prices at auction and changing cash requirements of high net worth banking clients.[4] For example, recent articles in Business Week (February 15, 2005) and the Wall Street Journal (November 10, 2004) discuss the emergence of art mutual funds, which buy and hold art as their underlying asset. JPMorganChase, Citi and Bank of America are now purportedly offering financial services to high-net-worth clients interested in art, presumably in response to market demand. Our investigation and the analytics presented in this paper should prove useful to this emerging sector and will hopefully provide traction for further quantification of the risks involved in using fine art as a collateral asset.

Section 1 discusses the relevant art and auction price literature. Section 2 describes the French Impressionist data set used in the analysis. In Section 3, we discuss how to incorporate the seller's reserve when estimating the implicit frequency distribution of market demand around prior value estimates. Section 4 develops the banking applications that can be used to assess the risk of art portfolios as collateral and Section 5 concludes the paper.

1. Art as an asset class, art auctions, and the nature of buy-ins

Several papers have inquired into the return history of investment in art and other collectibles (such as wine, stamps, and coins). Most of these studies concern the development of price indices for use in examining risk-return relations between art investment, investment in other financial assets and the overall market.[5] While results vary, the general

[3] Unadjusted estimates from Kusin & Company (2004).

[4] See, for example, the article "Pawning Your Picasso" by Frank (2004).

[5] The two most commonly used methods for constructing art indices involve repeat-sales regressions and the hedonic method, each with its own merits and drawbacks. For repeat sales see Baumol (1986), Goetzmann (1993), and Mei and Moses (2002a,b). The hedonic technique is studied in Barre et al. (1996), Chanel (1995), Chanel et al. (1996), and Ginsburgh and Jeanfils (1995).

conclusion has been that art investing has low correlation with the broad markets and provides a lower, though positive, average risk-adjusted financial return. The lower return has been justified by the existence of an additional aesthetic yield on art ownership. Nevertheless, this stream of literature legitimizes art as an investable commodity.

More germane to our inquiry, a second branch of art research has investigated the relationship between market prices for artworks and their contemporaneous presale estimates of value. This branch of research is motivated by the fact that individual artworks are unique and trade in thinner markets than most financial assets. Periodic expert valuations serve to neutralize the time variation in price appreciation. The main focus of this second branch has been to examine the average relationship between presale estimates and subsequent auction sale prices. Our goal in the current paper is to take the next step of attempting to quantify the risk surrounding presale estimates with particular attention to downside risk. A mere examination of the frequency distribution of auction sales relative to presale estimates is insufficient for the task. This is because auction data contain a feature known as "buy-ins" where works brought to auction are offered for sale, do not attain the seller's reserve price and therefore are bought "in house" by the auctioneer. In our sample of French Impressionist paintings, for example, about 30% of the works offered for sale did not find buyers. As these works had maximum bids below reserve, the winning bid would have fallen in the lower portion of the frequency distribution relating prices to pre-sale estimates of value. We wish to estimate the parameters of this censored tail, interpreting it in terms of credit-risk analysis.

To clarify the details of art auctions and how the data are recorded, Ashenfelter (1989) describes the format of "English" or "ascending price" auctions in art auction houses such as Sotheby's, Christie's, and Phillips. Bidding starts low and rises as the auctioneer calls out higher and higher prices. When the bidding stops the item is either "hammered down" at the final "hammer price" or "bought-in" by the auction house because the final bid price did not exceed the seller's reserve.[6] Works bought-in are either sold at a later date, put up for sale elsewhere, or taken off the market. Ashenfelter (1989) estimates that about one-third of the Impressionist paintings he examined did not find buyers, consistent with what we find in our data.

In auction catalogues, houses publish a presale lower and upper value estimate for each work of art. The auction house does not publish or indicate the sellers' reserve prices. However, the market place experience reported by major auction houses indicates a tendency for reserve prices to be set in a range around 75% of the presale low estimate. The way in which these reserve prices are established and their relationship to presale valuation estimates has captured the interest of a number of scholars.[7] Christie's stated reserve policy is that reserves must be set at or below the presale low and advise that it is usually between 70% and 80% for paintings. The stipulation in Sotheby's "Conditions of Sale" is that no reserve should exceed the low estimate, and they report that it generally ranges between 50% and 100% of the low estimate depending on the value of the item, and sellers' preferences. Ashenfleter et al. (2003) estimate the reserve price using a random effects probit model and come up with an estimate near 75% of the presale low.

[6] Auctions without reserve are uncommon but are occasionally observed in liquidations of well-known dealer stock or auctions that benefit charity.

[7] See McAndrew and Thompson (2004), Ashenfleter et al. (2003), Ashenfelter and Graddy (2003), and Ekelund et al. (1998).

The critical element for downside risk assessment is the existence of significant percentages of works bought in-house. Our goal is to incorporate the buy-in option in establishing the relationship between presale valuation estimates and the distribution of potential sale prices for works brought to auction. Having accomplished this we can quantify the downside risk faced by financiers who might consider lending capital to art buyers.

2. Data description

The data set used in this analysis was compiled by Kusin & Company using art auction data from ArtNet and ArtFact.[8] The works sold are French Impressionist paintings, which, using the Kusin Classification Code, comprised the complete set of 14 artists.[9] The data consist of 4280 attempted auction sales from the 16-year period between January 1985 and December 2001 from a cohort of 130 international auction houses. Prior to an auction, a presale catalogue is published with information on artist, title, date of sale, auction house/location of sale, size, medium, lot number, year, and a presale lower and upper price estimate.

The 4173 complete transactions that are analyzed consist of all fully attributed paintings for which the following items of information are available: high and low presale estimates, the date and location of the auction, the artist's name and lot number.[10] If the work was actually sold, the hammer price and/or the premium price are listed.[11] Where only a premium price is recorded, we convert it to a hammer by using published buyers' premiums from Christie's, Sotheby's and an average of the other major auction houses. Changes in the buyers' premium over time are taken into account although possible variation by value of the works is not accounted for.

Table 1 shows summary information about the paintings. In total, 2925 works were sold, representing over $3 Billion in transactions. The two largest auction houses, Christie's and Sotheby's, offered, respectively, 40% and 45% of the offerings. To give an initial perspective on the intrinsic value of works not sold, we show two estimates of value for paintings that were bought-in. The first is the mean of the upper and lower presale estimates. While valuations based on the mean presale estimate clearly contain an upward bias for buy-ins, it helps put an upper bound on valuations. With this measure, Table 1

[8] Data from both of these sources occasionally have errors or are incomplete, for example, missing a price or presale estimates or values outside the realm of marketplace reality, for example, a Renoir with a $50 hammer price. Where possible, Kusin & Company cleaned and corrected the data with reference to the original auction catalogues or correspondence with the relevant auction house. Auction data without an attributable hammer price or without presale estimates were omitted from the study.

[9] Work by these 14 artists represents the accepted scholarly canon of French Impressionist painters: Frederic Bazille, Gustave Caillebotte, Mary Cassatt, Paul Cezanne, Edgar Degas, Eva Gonzales, Paul Gauguin, Armand Guillaumin, Edouard Manet, Claude Monet, Berthe Morisot, Camille Pissarro, Auguste Renoir, and Alfred Sisley.

[10] A fully attributed painting is one for which there exists no controversy over the artist who created it. All works with attributions that include statements such as "in the style of", "in the school or circle of", or "attributed to" are not included in the data.

[11] The Premium price is the hammer price plus the auction house fee or charge on the sale, which is called the buyer's premium, The buyer's premium is a percentage that the buyer pays in addition to the final bid price (or hammer price). Table 1 indicates that the average buyer's premium is 12.54% for our data. As with the seller's commission, the buyer's premium varies across auction houses and over time. In some cases it may vary with the hammer price as well.

Table 1
Auction statistics on French Impressionists for the period 1/1985–12/2001

Summary of the original data set			
Number of works with complete data			4174
Number of works with incomplete data			215
Summary of works with complete data		Values stated in $1000	
		Value 1[a]	Value 2[b]
Number of works sold	2925	$3,015,452	$3,015,452
Number of buy-ins	1249	$890, 154	$574,825
Number of works at auction	4174	$3,905,606	$3,590,277
Buy-ins as percentage of works sold	42%	29.5%	19.1%
Summary of works sold	Average	High	Low
Sale prices	$1031	$78,100	$1
Hammer ratios (H = price/geometric mean presale estimate)	1.13	13.26	0.017
Percent sold below presale low estimate	40%		
Average ratio of presale low to geometric mean presale estimate	0.864		
Average buyer's premium	12.54%		

[a] In Value 1: The geometric mean of the high and low presale estimates is used to estimate the value for "buy-ins" and the subsequent total for "works at auction". "Works sold" in both Value 1 and 2 is the sum of the hammer prices.

[b] In Value 2: The buy-in value (and subsequent total at auction) is estimated using 75% of the presale low estimate, an approximation for the seller's reserve price. Hammer ratio is the ratio of hammer price to geometric mean presale estimate of value.

indicates that the works bought-in had a pre-sale estimated value equal to about 30% of the works sold.

As a second measure of value for works bought-in, we show value based on 75% of the presale low, which brings the total value down to about 20% of the works sold.[12] The presale low itself would indicate that buy-ins are worth about 25% of works sold. The table shows other summary information about the works sold including the range of hammer prices, the range of ratios of hammer price to presale average value estimate and the average buyer's premium of 12.54%. The average ratio of presale low estimate to mean estimate of 0.864 figures importantly into the censoring analysis later.

3. Considerations in modeling the relationship between prices and estimates

The downside risk associated with the sale of a work of art at auction is captured by the lower tail of hammer price deviations from presale estimated value. Since experts provide

[12] An alternative, investigated by Beggs and Graddy (1997), is to use the final bid although this bid might be fictitious and merely announced by the auctioneer on a seller's behalf to get the bids started (a phenomenon called 'bidding off the chandelier'). Their paper analyzed sales from two auction houses only, but the 130 houses in our sample made obtaining final bid data impossible. Picci and Scorcu (2003) also use 'highest bid' data to ensure that buy-ins are included in their analysis of the order of sale effects at auction. Again, they only used data from one auction house, Casa d'Aste Finarte, in Italy and covered only 115 auctions. The auction houses we approached, with the exception of Sotheby's, were unwilling to release final bid information. From the data set, we selected a random sample of 25 works bought-in from auctions at Sotheby's London. From this sample, the final bid was on average around 50% of the presale low (ranging from 39% to 71% with a standard deviation of 8%).

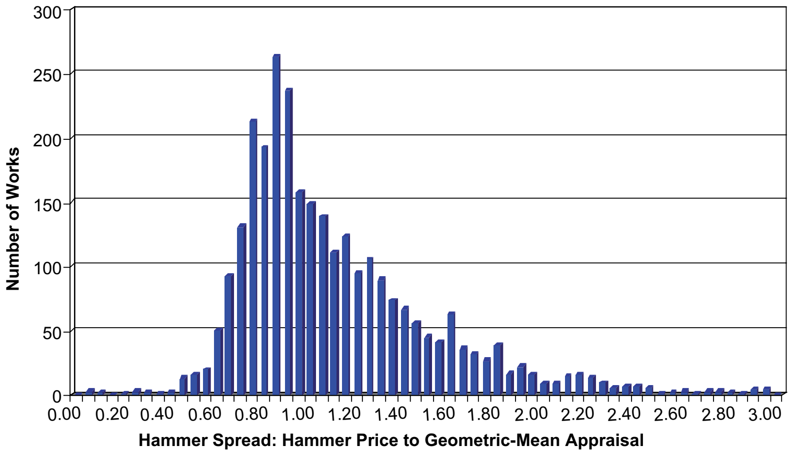

Fig. 1. Hammer spread frequency for 2924 French Impressionist paintings over the period 1/1985–12/2001.

an expected range in which they believe the price will fall- somewhere between an upper and lower estimate, the first step involves aggregating lower and upper estimates into an expectation of the future hammer price. As shown in Fig. 1, the error distribution of hammer prices around an average of the upper and lower estimates is not symmetric but highly skewed right; understandable since prices cannot be negative. Indeed, the distribution of the ratio of hammer prices to the average estimate appears similar to the lognormal, consistent with the distribution for stock values and other financial assets.

For a lognormal distribution, the arithmetic average of upper and lower estimates set with equal tail probabilities would underestimate the population arithmetic mean because of right skewness. But, if experts choose upper and lower estimates to equate the distance between their geometric mean and the *probability weighted* values in the right and left tails, then this *geometric* mean equals the mean of the lognormal.[13] For this reason, we model the presale estimation process as one where an (unbiased) expert first establishes the expected hammer price, and then selects a U and L pair whose geometric mean equals this value.[14] The spread between U and L could be used by an expert to communicate an assessment of price uncertainty independent of the signal that the geometric mean gives about the expected value of the distribution. In the data set, the average ratio of U to L is 1.34.[15]

The second consideration in the data is that deviations between hammer prices and mean estimates are very heteroscedastic. The correlation between the absolute value of hammer price minus geometric mean and the geometric mean itself exceeds 0.65 in our sample. To control for heteroscedasticity, we convert the data to ratios. The correlation

13 Proof is available from the authors.

14 Using an arithmetic average would not change any inferences except that the mean estimate would appear a bit higher; about 2% in our sample.

15 The correlation between U and L, and the absolute value of the future price deviation is 0.64 in our sample. This gives the false impression that experts have aptitude in prejudging price risk. The correlation between $(\ln U - \ln L)$ and the absolute value of $(\ln P - \ln M)$ is a negative -0.01. Thus, the correlation in levels is a manifestation of the fact that experts maintain a fairly consistent percentage spread across works.

between the absolute value of the ratio of hammer price divided by the geometric mean and the geometric mean is −0.04 and not statistically significant.

To formalize the way we report the data, let

$$P = \alpha M + \varepsilon, \tag{1}$$

where P is the hammer price; M is the geometric mean of the upper (U) and lower (L) pre-sale estimates, $=(U \cdot L)^{0.5}$; ε, an error term with variance proportional to M.

Dividing through by M, the hammer ratio becomes simply

$$H = \alpha\xi, \tag{2}$$

where H is the hammer ratio, $=P/M$; and ξ is a homoscedastic error term with mean equal to $\{\varepsilon/\alpha M\} + 1$.[16] For the purposes of risk estimation, it is not critical that experts provide unbiased pre-sale estimates (that $\alpha = 1$). The data reveal α and financiers can adjust their advance rates accordingly. The deviation of α from unity can be interpreted as the percentage bias in expert pre-sale valuations.

Standard practice in the analysis of value-at-risk (VAR) is to either examine the empirical frequency distribution of the left tail of the error distribution or approximate the left tail with a theoretical distribution that smoothes the empirical frequencies. Suppose we were to superimpose a lognormal distribution over the left tail of the error distribution in Fig. 1. Fig. 2 shows a lognormal distribution superimposed on the empirical hammer ratios in our sample. The parameters of the lognormal are chosen to maximize the fit between the empirical distribution and the lognormal, for hammer ratios below 1.00. The mean and variance of the lognormal are chosen to minimize the Kolmogorov–Smirnov D-statistic, which measures the maximum distance in cumulative frequencies between the empirical and theoretical distributions. Over the range from zero to a hammer ratio of unity, the D-statistic rejects lognormality at about the 10% level, with more mass near the mean in the empirical distribution and less near the point of inflection. Above this range, a large departure from the fitted distribution is indicated as can easily be seen in the figure.

Fitting the lognormal to observed hammer ratios overlooks the fact that the buy-in data have been censored from the sample. Fig. 3 shows a plot of the same data in conjunction with a lognormal fit to the right tail of hammer ratios, recognizing that censoring has taken place in the left tail. The fit is now maximized over just the hammer ratios wherein the hammer price exceeds the presale low. The frequency distribution of hammer ratios with prices below the presale low are potentially understated due to censoring of observations with maximum bids below seller reserves. In other words, while Table 1 shows that 40% of works sold had hammer prices below the presale low, the remaining 30% of works that were bought in also had high bids below their presale lows. Fig. 3 now reflects the full sample of 4194 works and the gap in the empirical distribution below the left tail of the fitted lognormal represents the expected frequency of hammer ratios that would have occurred if the bought-in works were sold without reserve.

Above 0.86, the average ratio of presale low to mean presale estimate, the empirical and lognormal distributions show a close correspondence. Notwithstanding a few spikes around unity and a slightly longer right tail in the empirical distribution, the Kolmogorov–Smirnov test for goodness of fit fails to reject at even the 30% level (z-statistic = 0.49). Thus, the

[16] $P = \alpha M + \varepsilon$ and $P = \alpha M\xi$. Thus $\alpha M + \varepsilon = \alpha M\xi$. Dividing through by αM implies $\xi = 1 + \{\varepsilon/\alpha M\}$.

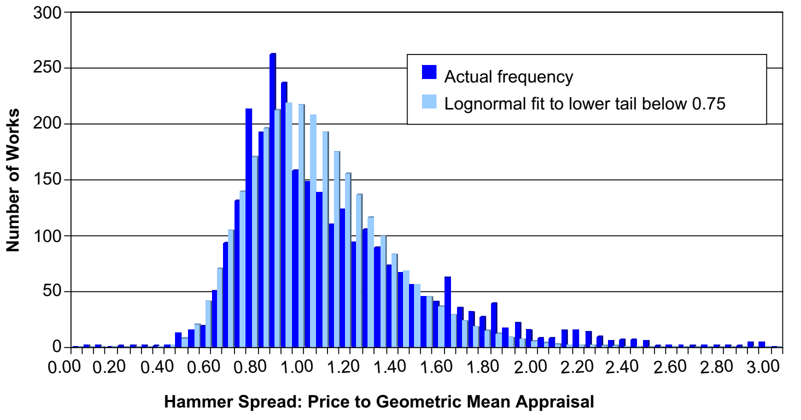

Fig. 2. Lognormal fit to the lower tail of hammer spreads for 2925 French Impressionist paintings over the period 1/1985–12/2001. Lognormal is fit to the lower portion of the distribution below 0.75.

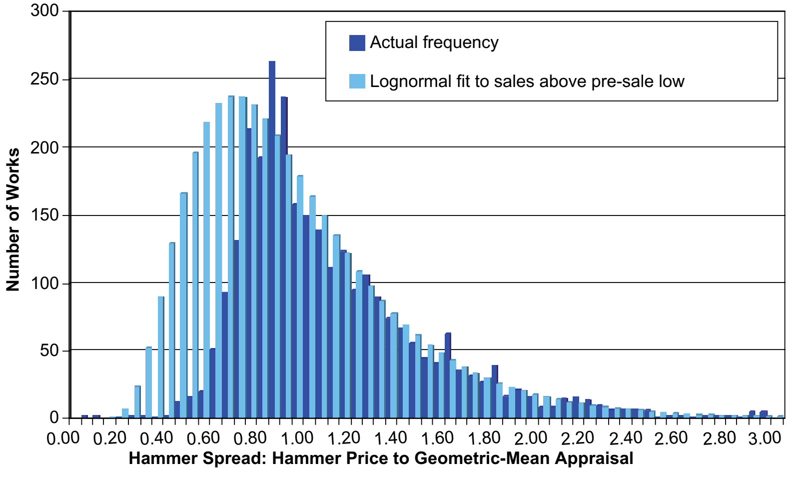

Fig. 3. Hammer spread and fitted lognormal recognizing buy-ins 4173 French Impressionist paintings over the period 1/1985–12/2001. Lognormal is fit to the upper tail of the distribution in recognition that 30% of the data have been censored from the bottom half of the distribution.

lognormal assumption is quite defensible for characterizing the distribution of hammer ratios were the data uncensored.

4. Assessing the downside risks of an art portfolio

Having established that the upper tail fits the lognormal assumption quite well, we adopt the approach of Cohen (1959) to recover maximum likelihood estimates of the mean and variance of the entire distribution. To correspond with the framework in Cohen, we take natural logs of the hammer ratios, which should then conform to a normal distribution above the point where buy-ins end. The model uses the observed hammer ratios for the data having ratios above 0.864 in the raw data or −0.146 in the logged data. The model only utilizes knowledge of the number of observations below the censoring point, which in our case is the number sold with hammer ratios below 0.864 plus the number of works bought-in.

In deriving estimates of the mean and variance of the full distribution, Cohen works with the relation between the mean and variance of the upper tail of the normal in relation to the mean and variance of the entire distribution. The intuition is that, if you know where the data are truncated, the mean and variance of the data in the upper tail bear a direct relation to the mean and variance of the full distribution. Cohen shows that the maximum likelihood estimates of the mean and variance of a normal distribution that has been left censored solve two simultaneous equations involving the sample mean and variance of the observed subsample of non-censored data (above 0.864 in our case). Specifically, the estimates solve

$$\hat{\mu} = \bar{x} - \hat{\lambda}(\bar{x} - t), \tag{3}$$

$$\hat{\sigma}^2 = s^2 + \hat{\lambda}(\bar{x} - t)^2, \tag{4}$$

where $\bar{x}$ is the sample mean of the observed (logged) hammer ratios above t; s^2 is the sample variance of observed (logged) hammer ratios above t; t is the truncation point, $=-0.146$ for the logged data,

$$\hat{\lambda} = \frac{\Gamma(\hat{\xi})}{\Gamma(\hat{\xi}) - \hat{\xi}},$$

$\hat{\xi}$ is the unique solution to

$$\frac{[1 - \Gamma(\Gamma - \hat{\xi})]}{(\Gamma - \hat{\xi})^2} = \frac{s^2}{(\bar{x} - t)^2},$$

and $\Gamma = \frac{n_1 f(\hat{\xi})}{n_2 F(\hat{\xi})}$. F and f represent the standard normal cumulative and density, respectively, while n_1 and n_2 are the number of observations above and below the point at which censoring begins. With our data, the system of equations in (3) and (4) converged easily with iterative methods, revealing a mean of −0.23 and 0.54 in the logged data.

The next step in quantifying downside risk is to determine the appropriate loan loss calculations using standard VAR analysis. Tables 2 and 3 contain results for the fitted distribution shown in Fig. 2 (fitting the distribution to the left tail) and the maximum likelihood estimates of the distributional parameters, which correct for censoring, from Eqs. (3) and (4).

To incorporate the effects of portfolio aggregation, we calculate portfolio risk by assuming that all works in a portfolio have the same expert valuation and individual variance. The general formula for portfolio variance is $w'\Sigma w$ where w is the vector of relative weights of the works and Σ is the covariance matrix of price deviations relative to presale estimates. With works all having the same weight and risk, this formula reduces to $\sigma_n^2 = \sigma^2 \cdot [1/n \cdot \{1 + (n-1) \cdot \rho\}]$ where n is the number of works, ρ is the common cross-correlation, σ is the standard deviation of each work and σ_n is the standard deviation of a portfolio consisting of n works.[17] Correlation in price deviations across works within a single portfolio is likely for two reasons. First, collectors often specialize in an artist or genre and second, even large

[17] The central limit theorem implies that portfolio aggregation changes the shape of the distribution toward the normal. But we retain the assumption of log normality in our measures to reflect the fact that the distribution of market values is always bounded from below.

Table 2
Shortfall risk for loans with fine arts as collateral

Assuming the uncertainly surrounding the value of works is uncorrelated

Panel A: Distribution parameters incorporating buy-ins

Mean hammer ratio (H)	0.920	Mean of $\log H$	−0.233
Sigma of H	0.543	Sigma of $\log H$	0.547

Number of works	Risk factor	Probability of shortfall with loan amount equal to 60%	Loan amount with less than 1% probability of shortfall	Expected loss % if loan defaults (1% shortfall risk)
1	1.00	30.6%	22.2%	15.4%
2	0.50	24.4%	31.2%	12.1%
5	0.20	14.2%	43.2%	8.2%
10	0.10	6.7%	51.5%	6.0%
20	0.05	1.7%	58.3%	4.3%

Risk factor is the portfolio's risk as a percentage of the risk of one work = $1/n$

Panel B: Distribution parameters ignoring buy-ins

Mean hammer ratio (H)	0.995	Mean of $\log H$	−0.04
Sigma of H	0.274	Sigma of $\log H$	0.271

Number of works	Risk factor	Probability of shortfall with loan amount equal to 60%	Loan amount with less than 1% probability of shortfall	Expected loss % if loan defaults (1% shortfall risk)
1	1.00	4.1%	51.1%	8.5%
2	0.50	0.8%	61.2%	6.2%
5	0.20	0.01%	72.1%	4.0%
10	0.10	0.00%	78.3%	2.9%
20	0.05	0.00%	83.1%	2.1%

Parameter estimates in Panel A are based on maximum likelihood incorporating the effects of censoring.
Parameter estimates in Panel B are based on a fit to the lower tail of the empirical distribution of observed transactions.
Hammer ratio, H, is the ratio of sale price to the geometric mean of the upper and lower presale estimates of value.

art indexes show deviations between aggregate prices and aggregate presale valuations, implying that pricing errors are cross-correlated (see Mei and Moses, 2002b).

Table 2 shows results for the case where individual artworks are assumed to have uncorrelated pricing errors relative to their presale estimates, while Table 3 assumes cross-correlation of $\rho = 0.5$. In each table, Panel A builds on the parameter estimates from the censored data model while Panel B works with the parameter estimates from a fit to the lower tail of the empirical distribution. In Panel A, the implied mean hammer ratio based on the censored data model is 0.92 with a standard deviation of 54.3%.[18] Panel B suggests much lower downside risk with mean and standard deviation of 0.995% and 27%, respectively. The corresponding mean and standard deviation of the logged data are also shown. The tables contain the downside risk characteristics of potential art portfolios consisting of from 1 to 20 works.

[18] A goodness of fit for the data above 0.864 could not reject lognormality based on the maximum likelihood parameter estimates for μ and σ.

Table 3
Shortfall risk for loans with fine arts as collateral

Cross correlation in uncertainly surrounding the value of works, $\rho = 0.5$

Panel A: Distribution parameters incorporating buy-ins

Mean hammer ratio (H)	0.920	Mean of $\log H$	−0.233
Sigma of H	0.543	Sigma of $\log H$	0.547

Number of works	Risk factor	Probability of shortfall with loan amount equal to 60%	Loan amount with less than 1% probability of shortfall	Expected loss % if loan defaults (1% shortfall risk)
1	1.00	30.6%	22.2%	15.4%
2	0.75	28.2%	25.8%	14.2%
5	0.60	26.2%	28.7%	13.0%
10	0.55	25.4%	29.9%	12.6%
20	0.53	24.9%	30.5%	12.4%

Risk factor is the portfolio's risk as a percentage of the risk of one work $= 1/n \times \{1 + (n-1) \times \rho\}$

Panel B: Distribution parameters ignoring buy-ins

Mean hammer ratio (H)	0.995	Mean of $\log H$	−0.04
Sigma of H	0.274	Sigma of $\log H$	0.271

Number of works	Risk factor	Probability of shortfall with loan amount equal to 60%	Loan amount with less than 1% probability of shortfall	Expected loss % if loan defaults (1% shortfall risk)
1	1.00	4.1%	51.1%	8.5%
2	0.75	2.3%	55.5%	7.5%
5	0.60	1.3%	58.7%	6.7%
10	0.55	1.0%	59.9%	6.5%
20	0.53	0.9%	60.6%	6.3%

Parameter estimates in Panel A are based on maximum likelihood incorporating the effects of censoring.
Parameter estimates in Panel B are based on a fit to the lower tail of the empirical distribution of observed transactions.
Hammer ratio, H, is the ratio of sale price to the geometric mean of the upper and lower presale estimates of value.

The three columns of calculations in each panel address the three central questions of shortfall risk exposure. If the portfolio is liquidated:

1. Column 1 shows the probability of a collateral shortfall for a fixed loan-to-value percentage (LTV) of 60%. Thus, it measures the probability that a loan of 60% of expert valuation would not be covered by an immediate sale of the loan portfolio. It solves the equation Prob $= \int_0^{0.6} g(v)\,\mathrm{d}v$ where $g(v)$ is the (lognormal) distribution of possible hammer ratios were the portfolio auctioned.
2. Column 2 shows the loan-to-value percentage that could be lent, while holding the probability of a shortfall at 1%.[19] It determines the lending policy consistent with a

[19] To motivate this cut point, Crosbie and Bohn (2003) state that the typical probability of default for a firm is around 2% per year, although this can range from 2 in 10,000 for a AAA rated firm to 4% for one that is CCC rated. The probability of a collateral shortfall is somewhat less than these figures since a default might trigger an asset sale that fully covers the loan.

1% shortfall risk and solves for the loan-to-value percentage, L, in the equation $0.01 = \int_0^L g(v)\,\mathrm{d}v$.

3. Column 3 shows the percentage of the loan amount expected to be lost if the portfolio is liquidated: the loss given default (LGD). One minus the LGD shows the loan percentage expected to be recovered if a shortfall occurs. LGD solves $\mathrm{LGD} = 1 - \frac{1}{L\cdot G(L)}\int_0^L vg(v)\,\mathrm{d}v$, where $G(L)$ is the probability of a shortfall given an LTV of L.[20] We solve the LGD equation through numerical integration.[21]

From Panels A and B in Table 2, for a portfolio of just one painting, the probability of a loss at a 60% LTV appears to be about 4% when buy-ins are ignored (Panel B) but is approximately 30% when buy-ins are considered through the censored data model (Panel A). A portfolio of five uncorrelated paintings has a shortfall probability exceeding 14% from the censored data model, while Panel B indicates almost no risk from a fit to the left tail of the empirical distribution, ignoring buy-ins. Switching to a consideration of column 2, a 1% shortfall probability allows an LTV ratio of 43.3% with 5 uncorrelated works based on the censored data model, but if buy-ins are ignored, it appears that the empirical distribution could justify an LTV ratio exceeding 70%. In column 3, the expected loss given default is about twice as large when the censored data model is used to estimate risk parameters rather than a fit to the lower tail.

Table 3 shows the case where works are assumed to have positively correlated pricing errors. This reflects the scenario of a common risk element in judging the evolving market demand for art of a particular school or genre. With 0.5 correlation in pricing errors across works, the effects of diversification are reduced considerably.[22] For a portfolio of five works and a 60% LTV, for example, the probability of loss increases to about 1% when buy-ins are ignored (Panel B) but to over 26% when buy-ins are accounted for (Panel A). The second column indicates that a portfolio of five works would not support an LTV beyond about 30% when the censored data model is used to estimate the risk parameters. Ignoring buy-ins in Panel B suggests LTVs approaching 60% would be consistent with a 1% shortfall risk.

4.1. Adding a time-series dimension

Tables 2 and 3 capture the downside risk relative to the pre-sale valuation just prior to the sale. Such a calculation is appropriate for short-term trade financing. Where a bank lends on an art portfolio for an appreciable period of time, however, the variation in values over time must also be included. There are two influences. On the one hand, there is the time-series variation in pre-sale expert valuations. On the other, there is the expected

[20] A corollary of LGD is the "recovery rate" (RR), which is just the second term: RR = 1 − LGD.

[21] We translate from the parameters of the normal to those of the lognormal through the standard formulas: $\mu_h = \exp(\mu_{\log(h)} + 0.5\sigma^2_{\log(h)})$, $\sigma^2_h = \mu^2_h \cdot \left[\exp(\sigma^2_{\log(h)}) - 1\right]$, where h is the hammer ratio.

[22] Our choice of 0.5 for the cross-correlation is roughly consistent with cross-correlations in individual annual stock returns. We show in Table 4, however, that the cross-correlation for artworks picked at random would be lower, more like 5–10%. This is based on the result that art index returns have only 5–10% of the annual return variance of individual works. We choose a higher correlation to reflect the likelihood that collectors will tend to concentrate in an artist or genre and thus have less diversification than implied by a portfolio of random works. Pinning down the correlation in an actual portfolio would be an interesting problem for lenders.

Table 4
Downside risk for one year loans with fine art as collateral

Panel A: Risk and return parameter estimates

Parameter	Parameter value in logs	Source
Annual σ_t of index price return	0.132	Campbell (2005, Table 2)
Time series correlation between index price and index presale value	0.95	Our data in time series. See also Mei and Moses (2002b, Fig. 1) for a similar value
R^2 for a fit of single work return to index of works	0.4	Typical for annual equity returns: Fama (1976, Chapter 4). See also Mei and Moses (2002b, Table 5) for similar art values
Correlation between pricing error and presale value	0	Unbiasedness of presale estimates (McAndrew and Thompson, 2004)
$\sigma\left(\ln\frac{M_1}{M_0}\right) = \sqrt{\left(\frac{\rho^2\cdot\sigma_t^2}{R_w^2}\right)}$	0.185	Using above values to determine annual risk of presale valuations for one work
Hammer ratio risk, σ_H	0.547	Table 3, Panel A
Annual risk: one work	$\sqrt{0.185^2 + 0.547^2} = 0.582$	**Implied sigma of hammer ratio = 0.634**
Mean log hammer ratio:	−0.233	Table 3, Panel A
Art index average annual return, r_t	0.062	Campbell (2005, Table 2)
Expected annual log hammer ratio	**−0.233 + 0.062 = −0.171**	**Implied expected hammer ratio = 0.998**

Panel B: Distribution parameters incorporating buy-ins

Mean hammer ratio (H)	0.998	Mean of $\log H$	−0.171
Sigma of H	0.634	Sigma of $\log H$	0.582

Number of works	Uncorrelated works		Correlation across works = 0.5	
	Risk factor	Loan amount with 1% probability of shortfall	Risk factor	Loan amount with 1% probability of shortfall
1	1.00	21.8%	1.00%	21.8%
2	0.50	31.1%	0.75%	25.5%
5	0.20	44.1%	0.60%	28.6%
10	0.10	53.1%	0.55%	29.8%
20	0.05	60.7%	0.53%	30.4%

Risk factor is the portfolio's risk as a percentage of the risk of one work = $1/n \times \{1 + (n-1) \times \rho\}$.
Hammer ratio, H, is the ratio of sale price to the geometric mean of the upper and lower presale value estimates.

price appreciation from holding art over time. Table 4, Panel A shows time-series risk and return parameters (sources are sited in the table) that illustrate how a time dimension can be added to the results in Tables 2 and 3. The parameter values are drawn from the most recent or well-cited sources we could find. Panel B shows the loan-to-value ratios with a 1% shortfall risk for one-year loans where the art portfolio is liquidated at maturity.

To encompass the time series risk-return parameters, define the hammer ratio from a one-year holding period as

$$H_1 = \frac{P_1}{M_0} = \frac{P_1}{M_1}\cdot\frac{M_1}{M_0}, \tag{5}$$

where the first term is the contemporaneous hammer ratio modeled above and the second term captures the time-series variation in expert valuations. In Eq. (5), we assume that expert valuations contain what is knowable about value at each point in time so variation in the second term is uncorrelated with variation in the first term. By assuming log normality of both terms, a reasonable approximation, we can take a log transformation of (5) and work with the standard algebra of risk and return to normal random variables. The risk and return of H_1 is then achieved through the usual translation described in footnote 21.

Various sources have estimates of the risk of log returns to art indexes. We cite Campbell (2005) rather than use a measure based on our own data because Campbell takes care to control for time variation in the quality of works brought to market. Our data show significant time series variation in artist and average size of works, things that Campbell's methodology is designed to neutralize.

To translate from the risk of index returns to log ratios of expert valuation for one work, we assume that prices have 0.95 correlation with expert valuation over a one-year horizon (consistent with our data and as reported in Mei and Moses, 2002b), and that a single work would have about 40% of its time series variation explained by the index. This figure is consistent with annual returns on stocks and with results reported by Mei and Moses (2002b). The annual time series standard deviation in expert valuation for one work would then be found through the formula shown in the table, which we show at 18.5% per year.

It is surprising how closely the shortfall risk in Table 4 compares to the shortfall risk in Tables 2 and 3. The loan-to-value ratios are predominantly lower but are actually slightly higher for the most diversified portfolios. Here, the time-series mean effect outweighs the risk effect. But in terms of general conclusions, the two forces of time almost offset one another for a one-year horizon.

4.2. Discussion

To put our tables in context, some of the larger auction houses occasionally offer loans using artworks as collateral. Probably the most famous case of a major art related loan default was that of Sotheby's in the late 1980's. The auction house lent Australian entrepreneur, Alan Bond, 50% of the $49 million purchase price for Van Gogh's *Irises* using the painting itself and others in his collection as collateral. Bond defaulted on the loan and *Irises* and other paintings were repossessed by Sotheby's and sold some time later to the Getty Museum for an undisclosed amount.[23]

Sotheby's still formally extends financial services to their consigners. Most items can be used by consigners as collateral for loans in advance of a sale of up to 40% of the low estimated auction value.[24] Sotheby's also previously allowed stand-alone borrowing against the value of collections of works of art, again, with advance rates up to 40% of the presale low. The minimum loan of this type was generally $1,000,000/£500,000. Although some of these loans remain outstanding, Sotheby's have ceased to offer any new loans of this nature.[25] Christies continues to extend lines of credit and financial guarantees using a similar lending percentage. Within our dataset, the low expert estimate of value averages about 86% of the mean estimate. Thus, a 40% loan to low-value estimate translates into about a 34% LTV based on the mean estimate. This figure implies a shortfall probability exceed-

[23] Lacey (1998).

[24] It is Sotheby's general policy, subject to exceptions, that the minimum loan for such an advance is $50,000 in the US and £25,000 in the UK. Also the auction of the work should be within 12 months (or preferably within 3–4 months) of making the agreement, meaning that the loan is essentially a short-term line of credit. Their rates vary but are generally 2–3% over prime.

[25] Sotheby's (2003) and correspondence with Sotheby's Financial Services (New York) May, 2004.

ing 1% based on Table 3. Indeed, reworking column 1 with an LTV of 0.34 implies a 2.6% shortfall probability in a portfolio of five correlated works.

Only one bank we know of, Citigroup Private Bank, consistently offers art services that include lending, through its "Art Advisory Service".[26] This service makes loans of up to 50% of the value of a collection or artwork. They conduct valuation in-house, basing value on their best estimate of market value, which they report as around the mid-point of the presale high and low.[27,28] Again, this LTV implies a rather high shortfall probability (about 15% for a portfolio of five correlated works). As a benchmark of comparison, delinquency rates on real estate loans in the first two quarters of 2005, as reported in the Federal Reserve Statistical Release, were about 1.35% while those on all loans and leases were about 1.58%. Standard and Poors (2000) reports an average default rate of about 1% per year for BB rated corporate bonds. A rating of BB corresponds to credit quality one rating below investment grade.

If a 1% shortfall risk is the baseline for comparison, the loan to value ratios in Table 3 or Table 4, column 2 seem low, or, equivalently, the shortfall risk seems high for art investing. Standard margin requirements for marketable securities allow loan amounts of 50% on single securities. Normal real estate loan percentages are 80% of the lesser of appraised value or transaction price at the time of purchase and 80% of appraised value at the time of refinancing.[29] Loan practice on oil and gas properties is in the neighborhood of 50–60% of proven reserves. Thus, art, as an asset class, reflects a more risky venture for lending institutions than the traditional assets with which these institutions have experience.

But before drawing this conclusion too strongly, we must reconsider that the probabilities underlying Table 2 through Table 4 reflect the loss characteristics *given* that the art portfolio is brought to market. As discussed earlier, the actual probability of a loss is the joint probability of a shortfall and the decision to liquidate the portfolio. Some types of assets and borrowing arrangements create a high correspondence between the probability of an asset sale and the probability of loss given that the loan collateral is liquidated. This is the case where the value of loan collateral is observable with high accuracy before the sale. In the case of art lending on the other hand, most of the loan risk is related to inaccuracy in the contemporaneous expert valuation. Thus, the probability of an asset sale is not as tightly linked to the probability of a collateral shortfall. Nevertheless, one would expect positive correlation for two reasons: (1) collectors might have inside information on the value of their collections, and (2) a general market downturn might cause collectors to

[26] According to Lacey (1998) a number of Japanese Banks such as Fuji Bank and Mitsubishi Bank, in the "bubble-culture" of the mid 1980's, lent large sums using art as collateral. These banks offered as much as 80–90% against prices paid for art at New York auction houses, drawing a lot of "uneducated money" in to the art market. It has been argued that this contributed to the sharp and inconsistent rise in prices that lead to the eventual art crises in 1989–1991. According to Shibaata (1999), nearly a decade later as many as 10,000 paintings valued at over $9.5 billion were still stored in bank vaults, the redeemed collateral against loans of failed corporations.

[27] Their rates on loans are 2–3 points above LIBOR, a very low lending rate, presumably due to the fact that the bank will only lend to its most creditworthy clients. Minimum loan amounts are $5 million with a minimum value per work of $100,000.

[28] Other banks such as Bank of America's Private Bank occasionally extend similar services to wealthy established clients but on an infrequent, ad hoc, and client initiated basis, and do not have a specific art department or advisory service. (Correspondence with Bank of America Private Bank, May 2004.)

[29] Rules of thumb used by banks according to Jokivuolle and Peura (2000).

abandon their portfolios when art prices are also depressed relative to stale appraisals. As long as the correlation is not perfect, however, the probability of a loss is correspondingly lower than the probabilities shown in column 1 of Tables 2–4.

5. Conclusions

This paper has examined how presale auction estimates can be used to help assess the risk of investment in works of art. Because of their virtual neglect in the literature on art investment and pricing until now, the phenomenon of buy-ins has been our particular focus. We would argue that truncation from the lower tail of voluntary transactions data is a generic problem in risk assessment. It should be possible to extend the basic approach adopted here to other asset categories where sales experience contains selection bias.[30]

Although our portfolio considerations are rudimentary, assuming equal valuations across artworks and no or 0.5 cross-correlation in pricing errors, it appears that advance rates for art should be more conservative than for other financial assets and much more conservative than implied by a naïve examination of the lower tail of the observed hammer price deviations from pre-sale value estimates. The conservatism suggested by the data seems consistent with anecdotal evidence from the art loan arrangements we could find. Few banks encourage art lending presumably because it is considered too risky. We hope that the approach and considerations introduced in this paper help clarify the risks and thus reduce the total level of perceived uncertainty.

A final caveat to quick extrapolation of the results in this paper is that the French Impressionist market is among the more well informed and liquid art markets.[31] There are probably fewer risks and distortions in this market place, and further research is needed to investigate how the dynamics of seller reserves play out in the numerous other art genres as well as within subsections of this specific market.

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[30] In a different context, prior work in bank credit management has also recognized the selection bias problem inherent in transaction histories. For example, Jacobson and Roszbach (2003) build a value-at-risk model that incorporates the prior screening by banks of credit applications. Their goal is to infer the downside risk of the applicant pool from knowledge of the criteria used to screen applicants and the credit history of those who were granted loans. Their approach does not need information about the upper tail of the value distribution as ours does, but requires knowledge of the screening model, which is not available for the buy-in reserve decision in art auctions.

[31] Lacey (1998) explains the importance of this genre in the small and short lived bank lending boom to the art market in the late 1980's "... Impressionists were good collateral. Compared with Old Masters, their precise, modern pedigrees made them acceptable security to banks ..." Lacey (1998, p. 256).

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