ISSN 1471-0498

DEPARTMENT OF ECONOMICS

DISCUSSION PAPER SERIES

FAILURE TO MEET THE RESERVE PRICE: THE IMPACT ON RETURNS TO ART

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Number 272

July 2006

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Failure to Meet the Reserve Price:
The Impact on Returns to Art

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The authors would like to thank Thomas Cochrane, Robyn Evans and Ben McClean for excellent research assistance. We thank Orley Ashenfelter and Andrew Richardson for the use of their Impressionist and Modern Art dataset, and we are also very grateful to Jiangping Mei and Mike Moses for the use of their repeat sales dataset. We would also like to thank seminar participants at the University of Florida, Oxford, the Tinbergen Institute, and Tilburg University for very useful comments.

This paper presents an empirical study of paintings that have failed to meet their reserve price at auction. In the art trade it is often claimed that when an advertised item goes unsold at auction, its future value will be affected. We have constructed a new dataset specifically for the purpose of testing this proposition. To preview our results, we find that paintings that come to auction and failed return significantly less when they are eventually sold than those paintings that have not been advertised at auction between sales. These lower returns may occur because of common value effects, idiosyncratic downward trends in tastes, or changes in the seller's reserve price.

JEL Clasification Numbers: D44, L82

Keywords: Reserve prices, Burning, Bought-in, Art, Auctions

In most markets sellers have reserve prices, and items remain unsold until a buyer is willing to pay the seller's reserve. The finding that an item has been advertised for sale but has not sold for a period of time can have an impact on the final selling price. The results of at least two recent studies have shown that, for some groups of sellers, houses that remain on the market for a longer period of time tend to achieve a final higher selling price because these sellers post higher list prices and therefore have higher reserves.[1] This is contrary to the perceived wisdom in the art market. In the art trade, it is often claimed that when an advertised item goes unsold at auction, its future price will be negatively affected. Such items are said to have been "burned."

We empirically test for "burning" effects using data on art auctions. There has so far been little work testing whether paintings are "burned", primarily because existing art datasets mostly contain information on sold items, and it is difficult to put together new datasets involving unsold items. As paintings are unique, it can be difficult to control for characteristics. Ideally, one would like to observe two sales of the same painting. We have constructed a new dataset of repeat sales specifically for the purpose of testing this proposition. Our results indicate that, controlling for holding period, paintings that have failed between

[1] Genesove and Mayer (1997) and Levitt and Syverson (2005)

sales return about 1/3 *less* than other paintings, contrary to findings in the real estate market.

We begin our study by first describing how bidding actually works in art auctions and then exploring the underlying theory -- reasons why failure to meet a reserve price may impact on an item's final selling price. Common values -- when buyers take into account the opinion of others when valuing an item -- can easily generate burning effects. In addition, changes in the seller's reserve price can cause final observed prices to be either higher or lower after an item fails to sell. Finally, burning effects can be observed without common values due to downward price trends due to an artist falling out of fashion or other idiosyncratic reasons.

Empirical validation of any "burning" effects and estimation of its magnitude in art auctions is important in itself. This belief is widely held amongst both academics and practitioners. Furthermore, a perceived loss in value after a failed auction has acted as part of the basis for legal proceedings such as "Cristallina, S.A.."[2] Yet, there have been no studies attempting to measure this effect. A related question is the extent to which auctioneers or sellers recognize burning effects, or strategically alter their estimates after an item has failed. We use data on estimates to study this question.

This paper proceeds as follows. In section 2, we describe bidding in art auctions. In section 3, we discuss why failure to sell may impact on the final price. In section 4 we describe the dataset. In section 5 we describe our estimation

[2] The plaintiff alleged that Christie's did not use sufficient care in marketing and auctioning 8 impressionist paintings consigned to them in 1981. Seven out of the eight paintings failed to meet their reserve price. The suit was eventually settled out of court.

technique and present the regression results. In section 6 we interpret the results and conclude our analysis.

2. Bidding in Art Auctions

Historically, the major auctioneers of art have been the English houses of Sotheby's and Christie's. Almost all art is auctioned in the "English" or "ascending price" format. Bidding starts low, and the auctioneer subsequently calls out higher and higher prices. When the bidding stops, the item is said to be "knocked down" or "hammered down", and the final price is the "hammer price."

Not all items that have been put up for sale and "knocked down" have been sold. Sellers of individual items will set a secret reserve price, and if the bidding does not reach this level, the items will go unsold. Auctioneers say that an unsold item has been "bought-in." It may be put up for sale at a later auction, sold elsewhere, or taken off the market. In this paper, we are interested in the price path of these unsold items that are put up for sale at a later auction.

Prior to an auction, it is common for a pre-sale catalogue to be published with information on the individual items coming up for sale. Included in the pre-sale catalogue is information on the title of a painting, the artist, the size of the painting, and the medium. The auction houses also publish a low and a high pre-sale price estimate for the work. The auction house does not publish, and indeed is very secretive about, the seller's reserve price for the work of art. By convention, the secret reserve price is at or below the low estimate.

A reserve price can play many roles. The seller may set a reserve because of an intrinsic worth of the object to himself, or he may believe that eventually someone will pay a certain price and he is willing to hold out for this price. In the auction literature (see for example Klemperer (2004)) the reserve price is often assumed to be set to maximise expected revenue in a given period, under the assumption that the auctioneer can commit himself not to put the object up for sale again. This is clearly inappropriate in our context. Reserve prices may also reflect a number of additional factors, for example, urgency (or non-urgency!) to sell. Below, we discuss different assumptions about sellers' behaviour when setting reserve prices and show that these different assumptions can and do have different effects on the final observed price.

Common values also play a role in the final price achieved both in the art market and in the real estate market. The assumption of common values reflects the idea that buyers may care about the opinion of others when valuing the item. In real estate, an individual will eventually want to sell the house or condominium that he purchases and will care how others value the property. In art auctions, individuals may wish to take into account others' views on its authenticity or value. In bidding in art auctions or in making offers on real estate, individuals therefore need to take into account information revealed by others' bids or risk over-paying for the painting, and falling prey to the so-called "winner's curse".

3. The Underlying Theory

The intuition behind our study is as follows. There are three primary ways in which failure to sell can affect the final price. Firstly, if buyers are attempting to learn about the true value of an item, which is common to all buyers, then past failure can lead to lower prices. Intuitively, failure to sale is bad news about the value of an item.

Secondly, reserve prices can both increase and decrease the final observed price. For example, in real estate, Genesove and Meyer (1997) argue that individuals with higher loan to value ratios are also like to have higher reserve prices. Levitt and Syverson (2005) argue that real estate agents are likely to have higher reserve prices, and set higher asking prices, because of better information. These higher reserve prices lead to longer times on the market and a higher sale price. This effect could also occur in art auctions. Failure may indicate that the new owner has a high reserve price and so is likely to achieve a high price when the painting sells.

It is, however, perfectly feasible that after an item fails to sell at an art auction, the seller may lower his reserve price because of an urgency to sell. This could lead to a lower observed price and thus observed "burning" effects. There are a number of other ways in which reserve prices can increase or decrease the final price. For example, if sellers exhibit reference dependence after "overpaying" for a painting, they may keep a high reserve price when they first attempt to sell the painting, which results in the painting going unsold. When they then bring the painting back to market, they may then lower the reserve price to a "reasonable" amount. Hence mean reversion in prices combined with reference dependence in reserve prices could create a "burning" effect. [3]

Finally, downward trends in the value of an item can also lead to lower prices in the final observed sale simply because failure to sell is correlated with a downward trend in price. In the regression analysis, it is possible to control for market trends but not for idiosyncratic trends in taste – for example, a certain artist falling out of fashion. Note that upward trends will not have a symmetric effect as it is less likely that an item will fail to meet its reserve with an upward trend in price. If buyers largely consider art as an investment then they will attempt to predict future tastes and so prices of individual paintings will follow a random walk

[3] Please see Mei and Moses (2002) for a discussion of mean reversion in prices and Beggs and Graddy (2005) for a discussion of reference dependence.

and trend effects will not occur. Nonetheless, trend effects may be a possibility as individuals also enjoy owning and observing art.

The intuition described above is confirmed by a specific model of bidding in Appendix A.

4. The Dataset

In order to test for and measure burning effects we construct a dataset of repeat sales of the same painting. For some paintings, in addition to at least two sales, the painting has also come to auction and failed. For other paintings, the painting has not appeared at auction between sales.

One of the major difficulties in testing for burning effects is construction of the appropriate dataset. Most repeat sales datasets have been constructed using sold items. Mei and Moses (2002) started out by looking at paintings *sold* at the major sales rooms of Sotheby's and Christie's, and then looked through the provenance as listed in the sales catalogues to find previous sales. Goetzmann (1993), Baumol (1986) and Anderson (1974) use data on auction *sales* as listed in Reitlinger (1961, 1963, and 1971). Goetzmann supplements this data with auction *sales* data found in Mayer (1971-1987). Pesando (1993) again uses data on *sales* of prints, as listed in Gordon's Print Price Annual (1978-1993).

This study takes a different approach. We start with a dataset on Impressionist and Modern Art (constructed by Orley Ashenfelter and Andrew Richardson) that contains over 16000 observations on paintings by 58 selected artists that appeared at auction at Sotheby's and Christie's between 1980 and 1990. We take the items that failed at least once and were sold at least once (either previously or subsequently to the failed appearance). We also included, as part of our control group, paintings that appeared twice as sold during the period but did not appear as coming to auction and failing. We then proceeded to look up previous and future sales of all of these items using Art Index (www.artindex.com) on the internet. If, after this search on Art Index, we were able to find at least two sold appearances (so that we have at least two final prices for each painting), we then included the painting in a potential dataset.

Once we finished this procedure, we then went back to the catalogues and photocopied each image to confirm that the paintings were indeed the same.[4] Through this procedure, we were able to construct a dataset that contains at least two sales observations (and thus at least two prices) on each painting in the dataset. In addition, for many paintings, we observe that the painting has failed at auction. The data that we have for each observation is as follows: artist, painting title, auction house, auction location, lot number, auction date, sale price in currency of auction location (either New York or London), painting ID that uniquely identifies paintings, and for most paintings, low and high price estimates in currency of auction location.[5] We do not know seller reserve prices or the identity of the sellers. Auction houses are very secretive about this information. To ensure that we have sufficient data to consistently control for time effects, we supplement our data with repeat sales data from 1965-present that are included in the dataset constructed by Jianping Mei and Mike Moses (Mei and Moses, 2002 and 2005) and used in the MeiMoses™ art index. The Impressionist and Modern Art dataset and the Mei and Moses dataset are described in more detail in Appendix B.

Consistent with our estimation technique, we consider an observation to be a sales pair that consists of a purchase and a sale of the same painting. For our purposes, we can classify the observations into two types: 1) sales pairs in which

[4] Note that we identified many painting that had identical titles, artists and even dimensions, but were in actuality, different paintings.

[5] Paintings that appear before 1973 do not have price estimates.

the painting appears as unsold between the two sales observations, and 2) sales pairs in which the painting does not appear as unsold between sales observations.[6] For clarity consider a 3-period framework. For all observations, we observe sales in periods 1 and 3. For some observations we observe a negative signal that the painting has appeared at auction and failed in period two (sold, fail, sold). For other observations, there is no signal in period 2 as the painting does not appear at auction (sold, sold). Note that for each painting, we can have more than one observation, indicating that they have sold at auction more than twice. In Table 1 below, we summarize the number of data points. We additionally categorize the data as having come back to auction two years or less after having failed. If the painting failed between two sales, we also categorize the data by whether or not it came back to auction at a different house or a different location than the place where it had previously failed.

As presented in Table 1, our combined dataset consists of 1405 observations. 43 observations consist of sales pairs that have come to auction and failed between sales. Of these paintings, about half came back to market within two years of failing. Fifteen paintings were sold at a different house after failing, and 15 paintings were sold in a different location. We have 258 observations that have not failed between sales. We have 60 observations on paintings that sold three times at auction (sold, sold, sold). We included 1104 observations on sold pairs from the Mei and Moses dataset, for a total of 1405 observations.

[6] This can include observations in which the painting appears unsold after two sales, as unsold before the two sales or in which the painting never appears as unsold in the dataset during the time period.

Table 1

Data summary

Number of "sold, fail, sold" observations from constructed dataset		43
Number which came back to market less than two years after failing	22	
Number which were sold at a different house after failing	15	
Number which were sold at a different location after failing	15	
Number of "sold, sold" observations from constructed dataset		258
Number of "sold, sold, sold" observations from constructed dataset	60	
Number of "sold, sold" observations from Mei and Moses dataset		1104
Total observations		1405

Table 2 presents summary statistics for the combined dataset, with prices expressed in 2000 U.S. dollars. A primary purpose of this table is to demonstrate how the "sold, fail, sold" observations compare with the "sold, sold" observations. The first point to note is that the average price difference, defined as the difference between the sale price and the purchase price, is lower for the group that failed at auction than for the "sold, sold" group, indicating that the "sold, fail, sold" group has appreciated less than the "sold, sold" group. The second noticeable difference is in purchase price between the two groups. Paintings that eventually failed at auction were cheaper than paintings that did not fail. While this could potentially be a concern when trying to disentangle the fail effect, in that perhaps cheaper paintings simply return less than more expensive paintings (known as "The Masterpiece Effect"), numerous empirical studies have shown that a Masterpiece Effect does not exist (see Ashenfelter and Graddy (2003)), and some studies have found evidence of a negative Masterpiece Effect (Mei and Moses 2002). Furthermore, there is no theoretical justification for a Masterpiece Effect. Finally, the difference in the duration of holding appears to exist because of the way the various datasets were constructed, as the duration in our constructed "sold, sold" dataset is less than the duration of holding in the "sold, fail, sold" dataset, but the duration in the Mei and Moses dataset is greater than in our "sold, fail, sold" sample. Our dummy variables in the regressions that follow explicitly control for differences in return due to different periods of holding.

Table 3 presents a list of the occurrences of specific artists in each of the groups. The most prevalent artists in the "sold, fail, sold" subsample are similar to the most prevalent artists in the "sold, sold" subsample.

Table 2
Summary Statistics

	"sold, fail, sold"	"sold, sold"	
		Constructed dataset	Mei and Moses dataset
price difference	$58,815 ($231,343)	$146,728 ($835,046)	$168,095 ($1,445,342)
purchase price	$238,540 ($453,252)	$309,775 ($1,162,514)	$493,074 ($1,566,382)
sale price	$297,355 ($451,873)	$456,503 ($1,526,215)	$661,169 ($1,915,374)
years between sales	7.65 (4.13)	5.22 (3.89)	11.72 (6.37)
observations	43	258	1104

Prices are expressed in 2000 U.S. dollars

Table 3
Comparison of Artists

"sold, fail, sold" constructed dataset		"sold, sold" constructed dataset	
valtat	6	pissarro	18
utrillo	5	renoir	18
loiseau	3	valtat	15
monet	3	leger	14
bonnard	2	miro	13
chagall	2	dongen	12
kisling	2	picasso	11
klee	2	matisse	10
leger	2	monet	10
pissarro	2	utrillo	10
renoir	2	degas	9
cezanne	1	dufyr	9
degas	1	laurencin	9
dongen	1	vlaminck	9
dufyr	1	foujita	8
ernst	1	vuillard	8
gogh	1	bonnard	7
guillaumi	1	loiseau	7
miro	1	signac	7
picasso	1	modigliani	6
signac	1	chagall	5
sisley	1	kisling	5
vuillard	1	magritte	5
		dufyj	4
		manet	4
		derain	3
		gogh	3
		klee	3
		rysselberghe	3
		delvaux	2
		forain	2
		mane katz	2
		toulouse-lautrec	2
		cezanne	1
		dali	1
		ernst	1
		gris	1
		sisley	1
Total	43	Total	258

Table 3 (continued)
Comparison of Artists

"sold, sold"
Mei and Moses dataset

picasso	78	marini	9	bouguereau	2
renoir	63	braque	8	brianchon	2
monet	55	dali	8	camoin	2
pissarro	40	gleizes	8	courbet	2
degas	31	kisling	8	cross	2
bonnard	30	moret	8	delaunay	2
boudin	30	redon	8	delvaux	2
dufyr	27	marquet	7	denis	2
vlaminck	27	picabia	7	dupre	2
dongen	26	soutine	7	feininger	2
chagall	25	d'espagnat	6	forain	2
rodin	23	montezin	6	gall	2
utrillo	22	pascin	6	kadar	2
sisley	21	chirico	5	laurens	2
valtat	21	dubuffet	5	lempicka	2
luce	20	dufyj	5	popova	2
lebasque	19	rouault	5	puigaudeau	2
sidaner	19	serusier	5	schwitters	2
vuillard	18	caillebotte	4	segonzac	2
signac	17	corot	4	stael	2
fantin-latour	16	daumier	4	tanguy	2
laurencin	16	manet	4	ziem	2
loiseau	16	maufra	4	rysselberghe	1
matisse	16	mondrian	4		
modigliani	16	andre	3	Total	1104
moore	15	bombois	3		
guillaumin	14	buffet	3		
leger	14	ernst	3		
martin	14	foujita	3		
derain	13	herbin	3		
magritte	13	lhote	3		
klee	12	lipchitz	3		
miro	12	morisot	3		
cezanne	11	nicholson	3		
gauguin	11	nolde	3		
gogh	10	valadon	3		
toulouse-lautrec	10	adrion	2		
gris	9	archipenko	2		
maillol	9	arp	2		

5. Estimation and Results

5.1 Estimation

The model that we estimate is

$$\ln p_{i,s} - \ln p_{i,b} = \sum_{j=1}^{J} \phi_j x_j + \beta fail_i + \nu_{i,sb} \quad (1)$$

where x_j is a time dummy variable for each half-year equal to one during the period between the initial and final sale and zero otherwise. $fail_i$ is a dummy variable equal to 1 if the painting has failed between auctions and zero otherwise, and $\nu_{i,sb}$ is an error term. $p_{i,b}$ and $p_{i,s}$ are the intial and final prices at which the paintings sold at auction. Our comparison is between paintings which have come to auction three times and have failed in the middle auction (sold, fail, sold) and those which have only come to auction twice and for which there is no signal between sales (sold, sold). We believe this is the natural comparison to make in the context of art auctions as failing at auction is a focus for both buyers and sellers. We discuss this in more detail below.

As x_j is a time dummy correcting for market trends in each half-year period, x_j also controls for holding period. It allows us to make predictions about returns if a painting had been held in a different period. Thus, the coefficient on fail tells us the percentage difference in returns for paintings that have failed than for other paintings that have been held for a comparable time period. Note that x_j corrects for market trends but does not correct for idiosyncratic trends in taste (e.g. artists falling out of fashion).

This model is very similar to a standard repeat sales model used to estimate art indices. The exact relationship to a repeat sales model is detailed in Appendix C.

5.2 Results

5.2.1 Prices

The results from estimating equation 1 above are presented in columns 1 and 2 of Table 4. Column 1 presents the OLS estimates, and column 2 presents the weighted estimates, based on the Case and Shiller weights (described in Appendix C). Both columns present robust error estimates. As is evident from the coefficients, failing significantly decreases the return. The coefficient on *fail* in the weighted regressions indicates that, controlling for holding period, items which fail to meet their reserve price between sales end up yielding a total return about 1/3 less than other paintings. Failure affects the level of the value of the painting not its rate of growth in our model. In our sample, however, the average holding period for failed is 7.65 years, so the loss is equivalent to a typical painting returning about 4.3% less per year.

The magnitude of the failing effect is surprisingly large and economically significant. While it is unclear as to whether the failing effect is occurring because of common value (causal) effects, reserve price effects or trend effects, there is little doubt that paintings that fail to meet their reserve price end up returning less than other paintings.

5.2.2 Pre-Sale Estimates

It is interesting to do the same exercise above with the pre-sale estimates. However, it is unclear what the estimates actually represent. The estimates could be interpreted as the auctioneer's expert opinion on the second highest bidder's valuation, or it could be the auctioneer's expert opinion on the second highest bidder's valuation, conditioning on the valuation being higher than the reserve, as it

Table 4
Effects of Failing at Auction on Price
Sample Period (1965-2000)
Dependent Variable: $\ln(p_{i,s}/p_{i,b})$

	OLS	Case-Shiller 3-stage LS
fail	-0.360	-0.328
	(0.089)	(0.083)
time dummies	39	39
F-statistic	290.54	325.69
constant	yes	yes
R-squared	0.636	0.610
observations	1405	1405

Estimated standard errors are calculated
using Stata's robust variance (hc1) method

is the convention that the low estimate must be greater than or equal to the reserve[7] Alternatively, the auctioneers could have other motivations when choosing the low and high estimates. While Ashenfelter's (1989) results generally show that auction houses are truthful and Abowd and Ashenfelter (1988) find that auctioneers' price estimates are far better predictors of prices fetched than hedonic price functions, other authors have shown systematic under or over valuation (see Chanel et. al. (1996), Beggs and Graddy (1997), Bauwens and Ginsburgh (2000) and Mei and Moses (2005)). Our question is quite specific. Do auctioneers systematically over or under value paintings that have failed at auction?

In Table 5 below we present results using the difference in the estimates as the dependent variable. As the sample with estimates is smaller than the entire sample, we first present the estimates on the subsample with prices used as the dependent variable, for comparison. Our subsample consists of 1161 observations out of 1405 in the entire sample. 39 of these paintings have failed at auction between sales, as compared to 43 in the full sample.

While a slightly smaller failing effect is indicated for the subsample, the full sample and subsample estimates with price as the dependent variable are not significantly different from one another. Furthermore, the coefficient on *fail* with the low estimates used as the dependent variable is almost identical to the coefficient on *fail* with prices used as the dependent variable.

[7] Ashenfelter (2000) defines expert opinion as efficient if it incorporates all of the publicly available information that is useful in making predictions.

Table 5
Effects of Failing at Auction on Price
Sample with Estimates (1973-2000)

	$\ln(p_{i,s}/p_{i,b})$		$\ln(estimate_{i,s}/estimate_{i,b})$	
	OLS	Case-Shiller 3-stage LS	OLS	Case-Shiller 3-stage LS
fail	-0.260	-0.239	-0.262	-0.182
	(0.088)	(0.080)	(0.118)	(0.108)
time dummies	30	30	30	30
F-statistic	371.27	75.97	46.46	177.62
constant	yes	yes	yes	yes
R-squared	0.615	0.596	0.552	0.536
observations	1161	1161	1161	1161

Estimated standard errors are calculated using Stata's robust variance (hc1) method

5.2.3 Positive Signals

As a primary focus of buyers and sellers alike at auction is whether or not a painting has previously failed, we first compared failed paintings (sold, fail, sold) with those that did not fail in between two sales (sold, sold). However, another comparison that can be made is to compare those paintings with a negative signal between auctions (sold, fail, sold) with paintings that have come to auction and sold three times, and thus have a positive signal between two auctions (sold, sold, sold). Thus, we estimate a variation of equation (1) above that includes a dummy variable "*sold*" for paintings that appeared three times in our constructed dataset and sold each time at auction.

$$\ln p_{i,s} - \ln p_{i,b} = \sum_{j=1}^{J} \phi_j x_j + \theta sold_i + \beta fail_i + v_{i,sb} . \quad (2)$$

The control group consists of paintings in our constructed dataset that have appeared only twice at auction (sold, sold) and paintings in the Mei and Moses dataset. In this regression, β is very similar to the coefficient on *fail* in equation (1). Interestingly, the coefficient on *sold* is very positive and significant. [8] This could be the result of common values, common trend effects, or reserve price effects, as described above. Alternatively, the large positive coefficient on *sold* could indicate sample selection – paintings that have gone up in value tend to be brought to auction more often.

[8] The coefficient on *fail* in the OLS regression is -.416 with a standard error of .103, and in the Case-Shiller regression it is -.382 with a standard error of .097. The coefficient on *sold* in the OLS regression is .710 with a standard error of .098 and in the Case-Shiller regression it is .640 with a standard error of .088.

5.2.4 Other Effects

The above model addresses the simple question of whether the average return of paintings that fail to sell at auction is less than for other paintings, controlling for overall market movements and the period in which the paintings are held. However, other factors may also affect returns and may be correlated with failing to sell.

Firstly, it is very possible that in the art market information decays over time, especially amongst casual buyers, hence common value effects may decrease over time. Perhaps more importantly time between a failed auction and a successful one may either indicate patience on the part of the seller and hence less of a need to decrease the reserve, or it is even possible that the painting has changed ownership. (It is not possible to get information on the identity of the sellers). Thus, if an item is presented at auction and doesn't sell, there may be a difference in subsequent returns based on whether the item is brought back to auction immediately after the failed sale, or after a period of time. We therefore include a dummy variable, *fail1,* if an item has been brought back to auction less than two years after it failed, and another dummy variable, *fail2,* if an item is brought back to auction more than two years after it failed. As information may also decay if an item is brought back to sale in a different location, we control for this possibility by including a dummy variable, *different location*, if the painting was sold in a different location (London vs. New York) after it failed at auction and a dummy variable, *different house*, if the painting was sold at a different house after it failed at auction.

Secondly, whether or not a seller waits to sell or changes houses or locations may also indicate the urgency with which a seller needs to sell his painting. Less urgent sellers may have higher reserve prices, as may owners of paintings that have changed hands after the failed sale.

Both of these effects lead one to believe that prices may be different if paintings are brought back to auction later, sold at a different house, or sold at a different location. We test for these effects in Table 6 below.

Table 6
Repeat Sale Estimates
Effects of Failing at Auction on Price
Sample with Estimates (1973-2000)

	$\ln(p_{i,s}/p_{i,b})$		$\ln(estimate_{i,s}/estimate_{i,b})$		$\ln(p_{i,s}/p_{i,b})$- $\ln(estimate_{i,s}/estimate_{i,b})$	
	OLS	Case-Shiller 3-stage LS	OLS	Case-Shiller 3-stage LS	OLS	Case-Shiller 3-stage LS
fail1	-0.550	-0.468	-0.749	-0.507	0.199	0.180
	(0.129)	(0.118)	(0.186)	(0.184)	(0.147)	(0.142)
fail2	-0.341	-0.274	-0.627	-0.487	0.286	0.294
	(0.156)	(0.156)	(0.172)	(0.185)	(0.180)	(0.176)
different	0.333	0.255	0.902	0.765	-0.570	-0.574
house	(0.161)	(0.155)	(0.162)	(0.166)	(0.130)	(0.129)
different	0.156	0.112	0.201	0.044	-0.045	-0.034
location	(0.157)	(0.143)	(0.177)	(0.180)	(0.142)	(0.141)
time dummies	30	30	30	30	30	30
F-statistic	78.4	75.59	46.28	44.83	65.96	36.94
constant	yes	yes	yes	yes	yes	yes
R-squared	0.617	0.597	0.561	0.543	0.074	0.076
observations	1161	1161	1161	1161	1161	1161

Estimated standard errors are calculated using Stata's robust variance (hc1) method

As shown in columns one and two, the point estimates indicate that the failing effect may be less if a painting returns to auction more than two years after it originally appeared, but the difference is not statistically significant.

However, sellers who move houses achieve a significantly higher price after their painting fails than do buyers who resell at the same house. The price achieved after moving house is not significantly different from the price achieved for paintings that did not fail at auction: there is no apparent burning effect for paintings that have changed houses. We interpret this finding below.

As columns 3 and 4 indicate, the presale estimate for those paintings that have failed at auction and then moved house is on average nearly twice that of those paintings that failed and were then resold at the same auction house. Columns 5 and 6 present evidence that sellers at "new" houses do significantly worse relative to the low estimate, i.e. the estimate is biased upwards at "new" houses. Time after failing that a painting reappears does not affect the level of the estimate.

5.2.5 An Alternative Regression

We chose to focus our regressions on a repeat sales dataset because of the heterogeneity across paintings. However, another feasible way to estimate the amount by which failing at auction affects a painting's value is to control for painting characteristics, or fixed effects, along with time effects. The attraction of a characteristics model, also known as a hedonic model, is that much more data can be used in the estimation, including data on objects that are only offered for sale once in the sample period. The big disadvantage of these models is the strong assumption that a small set of observable variables captures much of the variability in the fixed components of price. This is especially important in our case, as paintings that fail are on average less expensive than other paintings -- as shown in Table 2. Thus, if we cannot completely control for the painting characteristics, we may be overestimating the coefficient on fail in a hedonic model. Indeed, because of this problem, we would expect the coefficient on fail in a hedonic model to be larger than the coefficient on fail in a repeat sales model.

Below, we estimate the hedonic model,

$$\ln p_{it} = \alpha z_i + \sum_{t=1}^{T} \delta \gamma_t + \beta \, fail_i + v_{it} \, . \qquad (3)$$

where p_{it} is the price of painting i at auction t, z_i are fixed effects, γ_t are dummy variables for each auction, and v_{it} is an error term.

We use the impressionist and modern art dataset described above, which has data on the 58 selected artists that appeared at auction at Sotheby's and Christie's between 1980 and 1990. After identifying paintings that were possibly identical and that had failed but had subsequently sold, we went back to the auction catalogues to ensure that these were identical paintings. In this dataset, we have 99 paintings that failed and were confirmed to be identical to paintings that were subsequently sold. In total we have 8,624 observations.[9]

The results of our estimation are reported in Table 7 below.

[9] We started with 16000 observations, but about 30% of these were not sold, and hence we do not have prices. Furthermore, we dropped observations on which we do not have information on all of the characteristics included in the regressions.

Table 7
Effects of Failing at Auction on Price
(Hedonic Regressions: 1980-1990)

	ln(price)	ln(estimate)
fail	-0.463	-0.424
	(0.070)	(0.071)
ln (painting date)	-0.636	-0.652
	(0.062)	(0.060)
ln (length)	0.702	0.703
	(0.032)	(0.031)
ln (width)	0.424	0.433
	(0.031)	(0.030)
signed	0.423	0.367
	(0.041)	(0.040)
monagrammed	0.087	0.054
	(0.029)	(0.028)
stamped	0.023	0.015
	(0.017)	(0.016)
medium dummies	12	12
F-static	289.88	274.62
artist dummies	56	56
F-statistic	139.06	136.48
auction dummies	147	147
F-statistic	149.07	50.56
constant	yes	yes
R-squared	0.8011	0.8083
observations	8624	8624

Estimated standard errors are calculated using Stata's robust variance (hc1) method

As expected, the coefficients on fail in the hedonic regressions above are significantly more negative than the coefficient on fail in the previous repeat sale regressions. This finding is consistent with a biased estimate resulting from unobservable (to the econometrician) characteristics.

6. Interpretation

The regressions above have shown that returns are less for paintings that fail at auction, which is consistent with the perceived wisdom. Using our repeat sale estimates, the average decrease in returns is about 33%, but the decrease in returns varies enormously. Paintings that were brought back to the same auction house within two years of failing return about 55% less than other paintings, whereas those paintings that were re-auctioned at a different auction house suffer no statistically different decrease in returns than those paintings that did not fail.

The differences in predicted returns using auctioneer's estimates are similar to actual returns, except that predicted returns appear to be greater for failed paintings that are taken to a different auction house. One possible reason for this difference is that auction houses could be competing for these paintings. One way to compete for selling a painting is for auction houses to convince the seller that they will be able to achieve a higher price by suggesting a high estimate or a high return. These higher predicted returns do result in higher real returns for paintings resold at a different house than the one where they failed, though not as high as the predictions.

This observed result could be due simply to sample selection: otherwise identical paintings brought to a different house have a higher low estimate and therefore a higher reserve. Sellers with greater patience and less of a need to sell may change auction houses, as may sellers of paintings that have changed hands. Hence, we observe higher prices for paintings that sell. Alternatively, the pre-sale estimates may be correlated with the price in two different ways. Firstly, the unobservable quality of paintings that are moved to a new house could be "better" than otherwise identical failed paintings that remain at the previous house and thus the higher estimates are simply reflecting a higher expected price. There may be some duty felt by the previous house to accept a failed painting for auction, whereas the new house has no such duty and only accepts qualitatively "better" paintings. Secondly, the higher pre-sale estimates may be influencing the buyers of the paintings.

The results in the art market differ substantially from what has been found in real estate. This may not be surprising. Levitt and Syverson (2005) found that homes owned by real estate agents sell for about 3.7 percent more and stay on the market 9.5 days longer. Genesove and Meyer (1997) found that a condominium with a loan to value ratio of 100% sells for 4 percent more than a condominium with a loan to value ratio of 80% and stays on the market 15% longer. In real estate, unless a house has been on the market for a very long time, it can be difficult for a buyer to observe that a particular house has had more difficulty selling than another house. Hence, common value effects may have less of an impact than in art auctions where it is very obvious when a painting has failed at auction. Furthermore, a seller of real estate has many opportunities to sell his house and in many cases – especially cases with a high loan to value ratio -- has a real disincentive not to lower his reserve price. With art auctions, the opportunity to sell a painting arises relatively rarely. After a painting has failed, many sellers may be unwilling to risk another failed sale.

This research has identified and estimated lower returns for items that fail at auction – the so-called "burning" effect. These lower returns may occur because of common value effects, changes in the seller's reserve price, or idiosyncratic downward trends in taste. At over 30%, the effect of failing at auction on a painting's return is surprisingly large and economically significant. This information adds to a general understanding of what happens when items fail to meet their reserve price in a variety of markets and a particular understanding of the "burning" effect at art auctions.

Appendix A : A Model and Equilibrium Bidding Strategies

As the main conclusions of the model are intuitive and it is intended to be illustrative, we have not sought to present a model with maximum generality.

The value $v_i(t)$ to a bidder may depend on three things: common (observable) tastes $A(t)$, private tastes or signals of value, $s_i(t)$, and the signals others receive, $s_k(t)$, $k \neq i$. A simple model with these features would put

$$v_i(t) = A(t) s_i(t)^{\alpha+\gamma} \prod_{j \neq i} s_j(t)^{\alpha} \prod_{k,m \neq t} s_k(m)^{\beta} \qquad \text{(A1)}$$

The weight bidders put on the signals of bidders in the current periods is given by α. The weight given to signals received by bidders in other periods is given by β. The case of pure private values corresponds to $\beta=0$ and $\alpha=0$. The case of common values between bidders within a period but not between periods corresponds to $\beta=0$. The case of pure common values within a period corresponds to $\gamma = 0$. Signals are assumed to be strictly positive.

This kind of model, when $\beta=0$, has been widely studied in the case of a single period, see for example Bulow and Klemperer (2002). Signals are assumed to be independent across bidders, and from other variables, and drawn from a common distribution function F. We make the further assumption that signals are independent across periods. The number of bidders is assumed independent and identically distributed across periods. Any differences in general tastes or fashion between periods are assumed captured by $A(t)$. This model is one of common values but independent signals. [10]

[10] The assumption of independent signals is not crucial. If values are common, bidders will take account of information revealed by the bids of others whether or not signals are correlated. If values are private, bidders will not take into account the information revealed by the bids of others even if signals are correlated.

The common value effect is assumed to reflect uncertainty about the `true' quality of the painting rather than concern for future resale value. Bids are assumed to be determined by the enjoyment of owning a painting rather than investment concerns.

Consider bidding in a given period. Assume that all bidders have the same information about signals received in other periods. Taking conditional expectations of these, (A1) becomes

$$w_i(t) = A(t)s_i(t)^{\alpha+\gamma}\prod_{j\neq i} s_j(t)^{\alpha}\,\overline{S}(t) \qquad \text{(A2)}$$

where $w_i(t)$ denotes the value of bidder i conditional on information about other periods and S denotes the conditional expectation of the final term in (A1).[11] Let $s^{(i)}(t)$ denote the i-th highest signal. In an ascending auction bidders drop out successively and in equilibrium the object goes to the bidder with the highest signal $s^{(1)}(t)$. Suppose that only he and the bidder with the second highest signal, $s^{(2)}(t)$, are left in the race. The signals of the bidders who have dropped out can be inferred from the prices at which they dropped out. The bidder with signal $s^{(2)}(t)$ will stay in until he is indifferent between winning and not winning the object if the remaining bidder were to drop out at the same time. He will therefore drop out at price

$$\widetilde{p}(t) = A(t)s^{(2)}(t)^{\alpha+\gamma}\, s^{(2)}(t)^{\alpha}\prod_{i\neq 1,2} s^{(i)}(t)^{\alpha}\,\overline{S}(t) \qquad \text{(A3)}$$

If this is greater than the reserve price, $R(t)$, then this will be the price at which the object sells. If it is not, then the bidder with highest value, $s^{(1)}(t)$, will pay $R(t)$ to win the object if this is less than his estimate of the object's value

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[11] In this formulation, the model is essentially identical to that in Bulow and Klemperer (2002) (their model is additive, this multiplicative, but that is unimportant).

$$A(t)s^{(1)}(t)^{\alpha+\gamma}\prod_{i\neq 1} s^{(i)}(t)^{\alpha}\overline{S}(t) \qquad \text{(A4)}$$

If it is not, then the object will not sell.[12]

If the object sells in period t the price is therefore given by

$$p(t) = \max\{\widetilde{p}(t), R(t)\} \qquad \text{(A5)}$$

Consider the case when there are no common value effects, that is α and β are zero.[13] From equation (A5), one can see that the price in any period only depends on common observable tastes in that period, the signals, the number of bidders and the reserve price in that period. The number of bidders matters as the expected value of $s^{(2)}$ is increasing in the number of bidders. If signals and the number of bidders are independent between periods, reserve prices are constant, and there are no trends in common observable tastes, therefore, failure to sell in one period, will not influence future prices if there are no common value effects.

It follows that, absent common values, there are two reasons why failure to sell at time 2 might be informative about the change in prices. Firstly, a lower price could be observed after the painting fails at auction simply because that failure is correlated with a downward trend in common tastes for a specific painting.[14] That is, A(t) is decreasing over time. Trend effects could also occur if the number of bidders is trending downwards. Secondly it may be that reserve prices are lowered, that is $R(3)<R(1)$ after an item has failed to sell.

The above discussion implicitly assumed that there are different bidders in different periods. If bidders are the same in different periods, then there may be

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[12] The equilibrium we describe is not necessarily unique but it is the natural one. See Bulow and Klemperer (2002) for further discussion.

[13] Strictly speaking the argument only requires that β be zero. It is natural though to think that if there are common value effects within a period there are also such effects between periods.

[14] If bidders care about future resale then they may try to predict future tastes and so systematic trends may not lead to changes in prices.

correlation in the signals between periods. Correlation between signals will not however generate price trends unless there is some asymmetry in their distribution, that is there are trends in tastes. If bidders bid myopically, therefore, the results will still hold.

Consider now the case with identical reserve prices in periods 1 and 3 and no trends in common tastes but the presence of common values (α and $\beta > 0$). If the painting fails to sell at time 2 then intuitively this is bad news about the signals received at time 2. This information was not available at time 1 and so this should lower bids in period 3. If the reserve price in period 3 is independent of events in period 2, then since bids are lower if the painting fails to sell in period 2 the sale probability in period 3 should also be lower. As bids are lower, the expected price if there is a sale will in general also be lower.[15]

This intuition is formalised below. The analysis is somewhat technical and may be omitted if desired. We assume that bidders in any period can observe tastes, A, and the number of bidders in any previous period and also whether or not the painting sold in that period and, if so, at what price it sold. We also assume that the reserve price in each period can be observed in future periods. We assume, however, that they cannot observe the signals received by bidders in previous periods.

We consider the case of three periods, 1, 2 and 3. The painting may be sold in other periods but since information about the painting does not change during these three periods, they can be ignored.

The same information about period 1 is available to bidders in periods 2 and 3. Call this I_1. Bidders in period 3 can in addition observe tastes in period 2 and

[15] In our empirical model we look at the log of price but the same argument applies to this.

the number of bidders then. Call this T_2 the analogous information in period 3 T_3. We show that conditional on I_1, T_2 and T_3 the distribution of bids in period 3 is lower in the sense of first-order stochastic dominance if the object does not sell in period 2 than if it does. This implies that it is also lower if one conditions solely on whether it sells in period 2.

Consider bidding in period 2. All bidders have the same information about other periods. From equation (A4) we know that the object will not sell in period 2 if

$$A(2)s^{(1)}(2)^{\alpha+\gamma}\prod_{i\neq 1}s^{(i)}(2)^{\alpha}\overline{S}(2)\leq R(2) \qquad \text{(A6)}$$

Since bidders in future periods can observe all elements in equation (A1), except the signals in period 2, this is equivalent to saying that it will not sell if

$$s^{(1)}(2)^{\alpha+\gamma}\prod_{i\neq 1}s^{(i)}(2)^{\alpha}\leq M(2) \qquad \text{(A7)}$$

where M(2) is some number. Now from (A1) bidders in future periods are not interested in the left-hand side of (A2) but the product of signals in period 2.

$$\prod_{i}s_i(2) \qquad \text{(A8)}$$

If $\gamma = 0$, pure common values, (A2) immediately implies that the expected value of (A3) is lower than if the painting does not sell than if it had sold.

If $\gamma > 0$ then the same will be true under some further conditions. (A2) is equivalent to

$$s_i(2)^{\alpha+\gamma}\prod_{j\neq i}s_j(2)^{\alpha}\leq M(2) \qquad \text{(A9)}$$

holding for all i. Note that

$$\left(\prod_{i}s_i(2)\right)^{\varepsilon}=\prod_{i}s_i^{\alpha+\gamma}(2)\prod_{j\neq i}s_j^{\alpha}(2) \qquad \text{(A10)}$$

where $\varepsilon = N(2)(\gamma + \alpha N(2))$, where N(2) denotes the number of bidders in period 2.

The right-hand side of (A10) is increasing in the random variables $y_i = s_i^{\alpha+\gamma}(2)\prod_{j\neq i} s_j^{\alpha}(2)$. It follows from Milgrom and Weber (1982) Theorem 5 that if these random variables are affiliated the expectation of (A8) is lower if the painting fails to sell. This will clearly be true in the case of independent values $(\alpha = 0)$. It is also straightforward to check that this will be so if the s_i are independent and log-normally distributed with identical means and variances.[16]

Under weak conditions, therefore, expected value of the product of signals in period 2 is lower if the painting sells in period 2 than if it does not. From equation (A1) this implies that, conditional also on I_1, T_2 and T_3, the distribution of each bidder's valuation in period 3 is lower in the sense of stochastic dominance. This will therefore lower the probability of sale, for a given reserve price in period 3.

Since the distribution of valuations is stochastically lower for each bidder in period 3, this will in general imply that the price if it sells is lower as well. If there is no reserve price in period 3 this is immediate since then the painting always sells and the winning price is an increasing function of the valuations in period 3. It will therefore also be true if the reserve price is low. It need not be true for arbitrary reserve prices since one needs to examine the price conditional on the event that the highest valuation is greater than the reserve price rather than the unconditional distribution. If the painting fails to sell in period 2, it is possible that the only way

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[16] These assumptions imply that $\ln y_i$ have a joint multivariate Normal distribution whose inverse covariance matrix has negative off-diagonal elements and so (see for instance Example 3.1 of Karlin and Rinott (1980)) are affiliated. Taking increasing transforms of a set of random variables preserves affiliation (see Milgrom and Weber (1982) Theorem 3).

the painting can meet the reserve price is for the signals in period 3 to be extraordinarily high and so if the painting sells at all it will sell at a very high price. This possibility is unlikely to be important in practice.

Appendix B: Data Appendix

Impressionist and Modern Art

The dataset on Impressionist and Modern Art auctions was constructed by Andrew Richardson, under the direction of Orley Ashenfelter. This dataset is restricted to 58 selected Impressionist and Modern Artists and includes only paintings, not sculptures. These artists were chosen primarily because their work is well represented at auction. The period covered is 1980 to 1990, and the dataset includes over 16000 items in 150 auctions that were held in London and New York at both Christie's and Sotheby's. The auction prices were collected from public price lists, and the estimated prices and observable painting characteristics were collected from the pre-sale catalogues. This dataset does not include all items sold in each auction, only a sample of the 58 selected artists. Furthermore, we only have prices for items that were sold at auction.

Mei and Moses dataset

The Mei and Moses dataset on Impressionist and modern art is a subset of a larger dataset that covers price pairs for all types of art between the period 1875-2003. The Mei and Moses dataset was constructed by searching all art catalogues for the second half of the twentieth century from the main sales rooms of Sotheby's and Christie's. If a painting has listed in its provenance a prior public sale at any auction house anywhere, they went back to the auction catalogue and recorded its price. The New York Public Library and the Watson Library at the Metropolitan

Museum of Art were the major sources for the auction price history. As the provenance only lists previous sales, unsold items are not included in this dataset. The subset of the dataset used in our study is from 1965-2003, includes only Impressionist and Modern Art, and in order to be comparable with the Impressionist and Modern art dataset above, includes only sales at Sotheby's and Christie's. Originally, the Mei and Moses dataset included buyers commissions in their prices. We have removed the commissions; the prices used in both datasets are hammer prices.

Appendix C: Estimation Method

Our regression equation is very similar to a standard repeat sales model used to estimate art indices where it is assumed the return for asset *i* in period *t* can be broken up into the return for a price index of art and an individual error term,

$$r_{i,t}=\omega_t+\pi_{i,t}$$

where $r_{i,t}$ is the continuously compounded return for a particular art asset i in period t, ω_t is the average return in period t of paintings in the portfolio, and $\pi_{i,t}$ is an error term.[17]

The observed data consist of purchase and sales of auction price pairs, $p_{i,b}$ and $p_{i,s}$ of the individual paintings that comprise the index, as well as the dates of purchase and sale, which are designated b_i and s_i. Thus, the logged price relative

[17] This methodology was developed by Bailey, et. al. (1963) and used by Case and Shiller (1987) and Hosios and Pesando (1991) for the real estate market, and subsequently used by Goetzmann (1993) Pesando (1993) and Mei and Moses (2002) for the art market. In these papers $\varepsilon_{i,t}$ is assumed to be uncorrelated over time and across paintings.

for painting i held between its purchase date b_i and its sales date, s_i may be expressed as

$$r_i = \ln(\frac{P_{i,s}}{P_{i,b}}) = \sum_{t=b_i+1}^{s_i} r_{i,t}$$
$$= \sum_{t=b_i+1}^{s_i} \omega_t + \sum_{t=b_i+1}^{s_i} \pi_{i,t}$$

Rather than assuming that $\pi_{i,t}$ is uncorrelated across time and paintings as is standard if estimating an index is the purpose of the study, we allow $\pi_{i,t}$ to vary by whether or not the painting has failed.

The repeat sales model in our context becomes,

$$r_i = \ln(\frac{P_{i,s}}{P_{i,b}}) = \sum_{t=b_i+1}^{s_i} \omega_t + \beta fail + \sum_{t=b_i+1}^{s_i} \upsilon_t$$

There is an increasingly large literature on measuring the returns to art and we borrow our estimation methodology from this literature. Theory suggests that the dummy variables for each pair should equal 1 at the time of sale, -1 at the time of purchase, and 0 in all other periods. Goetzmann (1992) shows it is more efficient to allow the dummy variables to equal 1 during the periods between purchase and sale, zero otherwise, and then do GLS using weights suggested by Case and Shiller (1987).

In the first stage of Case and Shiller's (1987) method, the log of the ratio of the sale price to purchase price is regressed on time dummy variables and the fail dummy variable. In the second stage, a regression of the squared residuals from the first stage is run on a constant term and the time between sales. The constant term can be interpreted as an estimate of twice the variance of the painting specific error term. The slope coefficient indicates the degree to which the error term increases with the length the painting is held, as indicated in equation (1). Case and Shiller interpret the slope coefficient as an estimate of the variance of the change in the Gaussian random walk term.

In the third stage, a generalized least squares (weighted) regressions is run that repeats the stage-one regression after dividing each observation by the square root of the fitted value in the second stage.

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