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Failure to meet the reserve price: the impact on returns to art

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Abstract This article 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, it will sell for less in the future. We have constructed a new dataset specifically for the purpose of testing this proposition. To preview our results, we find that paintings which 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 Classification D44 · L82

Keywords Reserve prices · Burning · Bought-in · Art · Auctions

In the art trade, it is often claimed that when an advertised item goes unsold at auction, it will sell for less in the future. Such items are said to have been "burned." Using data on art auctions, we empirically test whether failure to meet the reserve price helps to predict an item's final selling price.

So far there has been little work in this area, 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 the characteristics. Ideally, one would like to observe two sales of the same

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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 sales return about 30% *less* than other paintings, contrary to the 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 help to predict an item's final selling price. Common values, when buyers take into account the opinion of others while valuing an item, can easily generate burning effects. This explanation would be causal. In addition, changes in the seller's reserve price—perhaps because of a previous failure—can cause final observed prices to be either higher or lower after an item fails to sell, in which case observed price changes are not caused directly by failure, but result from sample selection. Finally, burning effects can be observed without common values due to downward price trends because of an artist falling out of fashion or other idiosyncratic reasons. In this case failure to meet the reserve price would not directly cause a lower final price but would help to predict it if correlated with these trends. We cannot empirically distinguish between these effects, though we can shed light on the plausibility of the different explanations with the help of our regression results.

Empirical validation of lower returns for failed items and estimation of the magnitude in art auctions are 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."[1] Yet, there have been no studies attempting to measure whether failure to sell is even correlated with a lower final selling price. 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 article proceeds as follows. In Sect. 2, we describe bidding in art auctions. In Sect. 3, we discuss why failure to sell may impact on the final price. In Sect. 4, we describe the dataset. In Sect. 5, we describe our estimation technique and present the regression results. In Sect. 6, we interpret the results, and in Sect. 7, we conclude our analysis.

1 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."

[1] The plaintiff alleged that Christie's did not use sufficient care in marketing and auctioning eight 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.

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 article, 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 maximize 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.

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 the individual 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 that revealed by others' bids or risk over-paying for the painting and falling prey to the so-called "winner's curse".

2 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. First, 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.

Second, reserve prices can both increase and decrease the final observed price. For example, in real estate, Genesove and Mayer (1997) argue that individuals with higher loan to value ratios are also likely to have higher reserve prices. Levitt and Syverson (forthcoming) 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. In an art auction, it is also possible that failure may indicate that the owner has a high reserve price, not because of asymmetric information but perhaps because of individual preferences, 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 final observed selling price. 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.[2]

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 as reserve prices may not be adjusted upwards in line with the trend.[3]

We now move onto estimating whether failure to sell helps predict an item's final selling price; we then discuss the plausibility of the various explanations.

3 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 the 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

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

[3] Goetzmann and Spiegel (1995) argue that if a painting is put back on the market shortly after its initial sale it is likely to decline in price even in a private value models since the bidder who valued it most has dropped out and few new bidders are likely to have appeared. That is the number of bidders is trending downwards. This is unlikely to be important in our data as holding times are not short.

contains over 16,000 observations on paintings by 58 selected artists in 150 auctions at Sotheby's and Christie's in New York and London between 1980 and 1990. These artists were chosen primarily because their work is well represented at auction. The auction prices were collected from public price lists, and the estimated prices and observable painting characteristics were collected from the pre-sale catalogues.

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 to present that are included in a dataset constructed by Mei and Moses (2002, 2005) and used in the MeiMoses™ art index. 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 and 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 to 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

[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.

their prices. We have removed the commissions; the prices used in both datasets are hammer prices.

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 the painting fails at auction between the two sales observations, and (2) sales pairs in which we do not observe the painting coming up for sale at auction 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 2 (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.

There are at least two sources of bias that can result from the way in which our dataset is constructed. First, if failure causes a price decline (and the price decline does not result from trend effects or sample selection), then paintings which are "fail, sold, sold" could possibly bias our results towards finding a larger failing effect in that there may be a larger return between the two observed sales for these paintings, as the first sale may be biased downward. This only causes a bias if there is, in fact, a fail effect, so any bias would be about its magnitude rather than its existence. Whether or not there is a bias depends upon how long the effects of a failure last. Second, the Mei and Moses dataset was constructed very differently from our dataset. As it comprises mostly very well-known paintings, if a "Masterpiece Effect" exists—where highly valued paintings have a higher return—this could be increasing the returns to paintings in this dataset and again biasing our returns. However, there is very little evidence in any of the literature for a "Masterpiece Effect" and no theoretical justification. Ashenfelter and Graddy (2003, 2006) provide a thorough discussion. Furthermore, in all likelihood, there were some paintings (though probably only few due to the way it is constructed using the provenance) in the Mei and Moses dataset that came to auction and failed between the two successful sales observations. These unobserved failures could tend to bias any results on observed failures downward, as the return for these paintings would be less than for paintings that did not come to auction and fail. In light of the discussion above, we believe that the size of the potential biases, in both directions, is relatively small and it is valid to use the Mei and Moses dataset as a control.

In Table 1 below, we summarize the number of data points. We additionally categorize the data as having come back to auction 2 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 1,405 observations. Forty-three observations consist of sales pairs that have come to auction and failed between sales. Of these paintings, about half came back to market within 2 years of

[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 2 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	40
Number of "sold, sold" observations from Mei and Moses dataset	1,104
Total observations	1,405

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 40 observations on paintings that sold three times at auction (sold, sold, sold). We included 1,104 observations on sold pairs from the Mei and Moses dataset, for a total of 1,405 observations.[7]

Table 2 presents summary statistics for the combined dataset, with prices expressed in US dollars, with the year 2000 as the base year. 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 and the average price ratio, defined as the difference (or ratio) 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") and as discussed above, numerous empirical studies have shown that a Masterpiece Effect does not exist. Some studies have even found evidence of a negative "Masterpiece Effect" (Mei and Moses 2002).

We also looked at the price to low estimate ratio for both the purchase and the sale for the two groups. It appears that the price to estimate ratio is slightly lower for the group that failed between auctions, but the differences are not statistically significant.

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. The likely reason for the difference is that the Mei and Moses dataset was constructed by looking at the provenance of the paintings. Not all previous sales are

[7] The main time period used in this study to select failed paintings, 1980–1990, was a period of mostly increasing prices. During the late 1980s, the art market was booming, and not until 1989 did a turnaround occur. Hence, this period may have had an unusually low level of failed items for paintings that had previously sold at auction. The failures are not grouped around a particular date, but are approximately evenly spread throughout the 1980–1990 time period.

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)
Price ratio	1.64 (1.32)	1.89 (1.33)	2.08 (4.45)
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)
Purchase price/low estimate	1.18 (0.45)	1.25 (0.55)	1.27 (0.49)
Sale price/low estimate	1.20 (0.46)	1.22 (0.49)	1.28 (0.54)
Years between sales	7.65 (4.13)	5.22 (3.89)	11.72 (6.37)
Observations	43	258	1,104

Prices are expressed in US dollars and adjusted for inflation, with a base year of 2000

Standard deviations are in parentheses

* As paintings before 1973 do not have estimates, the number of observations with estimates are 39, 244, and 876, respectively, for the above three columns

included in a painting's provenance, especially if the painting was sold and then resold in short succession. Our dummy variables in the regressions that follow partly 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, with some exceptions. For example, Picasso has a very high number of paintings that sold twice, but Picasso appears only once in the "sold, fail, sold" subsample. As discussed above, downward trends in the value of an item such as the artist falling out of fashion may cause an artist to appear multiple times in the "sold-fail-sold" subsample.

4 Estimation and results

4.1 Estimation

The model that we estimate is

$$\ln p_{i,s} - \ln p_{i,b} = \sum_{j=1}^{J} \phi_j x_j + \beta fail_i + v_{i,sb}, \tag{1}$$

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, $v_{i,sb}$ 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

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
Guillaumin	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

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. We chose to use half-year periods in order to control as much as possible for systematic changes in painting prices while still allowing us to identify the effect of failure at auction. Thus, the coefficient on fail tells us the percentage difference in returns between paintings that have failed between two sales and other paintings that have not failed at auction but 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).

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.[8]

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 as b_i and s_i. Thus, the logged price relative for painting i held between its purchase date b_i and its sales date, s_i may be expressed as

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

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,

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

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 et al. (1987). The weights are required because the size of the error increases with the length of the holding period.

[8] This methodology was developed by Baily et al. (1963) and used by Case et al. (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.

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

4.1.1 Prices

The results from estimating Eq. 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, as described above. 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 28% less than other paintings ($1-\exp(-0.328) = 0.28$). 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 3.3% less per year, taking into account the effect of compounding ($1.28^{(1/7.65)} = 1.0328$)).

These results are robust to outliers for (sold, fail, sold) observations. We ran the above regression on a subsample of data in which we excluded the (sold, fail, sold) observations with the ratio of saleprice to purchase price in the top 10% and with the ratio in the bottom 10%. The coefficient on fail in the GLS regression was −0.388 with a standard error of 0.083. This result is not significantly different than the coefficient using the full sample.

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

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 (0.089)**	**−0.328 (0.083)**
Time dummies	39	39
F-statistic	290.54	325.69
Constant	Yes	Yes
R-squared	0.636	0.610
Observations	1,405	1,405

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

Coefficients that are significant at the 5% level are indicated in bold

Table 5 Effects of failing at auction on price sample with estimates (1973–2000)

	$\ln(p_{i,s}/p_{i,b})$		$\ln(\text{estimate}_{i,s}/\text{estimate}_{i,b})$	
	OLS	Case–Shiller 3-stage LS	OLS	Case–Shiller 3-stage LS
Fail	**−0.256 (0.088)**	**−0.236 (0.080)**	**−0.234 (0.110)**	−0.190 (0.106)
Time dummies	30	30	30	30
F-statistic	371.59	398.51	95.11	176.37
Constant	Yes	Yes	Yes	Yes
R-squared	0.616	0.596	0.577	0.562
Observations	1,159	1,159	1,159	1,159

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

Coefficients that are significant at the 5% level are indicated in bold

doubt that paintings that fail to meet their reserve price end up returning less than other paintings.[9]

4.1.2 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 is the convention that the low estimate must be greater than or equal to the reserve.[10] 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 Ginburgh (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, 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 1,159 observations out of 1,405 in the entire sample. Thirty-nine of these paintings have failed at auction between sales, as compared to 43 in the full sample.

[9] Note that we also estimated a hedonic model. 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.

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

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 statistically significantly different from one another. Furthermore, the coefficient on *fail* with the low estimates used as the dependent variable is not significantly different from the coefficient on *fail* with prices used as the dependent variable.

These results are consistent with the view that auctioneers or sellers recognize the effect that failure has on the predicted return of a painting. If failure is due to, say, an idiosyncratic downward trend in the valuation of the painting then it may be they observe this and adjust the estimate in light of this rather than directly as a result of failure. In any event, it appears that auctioneers and sellers are correctly interpreting market events.

4.1.3 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. For those 40 paintings that have sold three times, we separate observations into those that have a second price that is less than the first price ($soldless_i$), which is the case for seven paintings, and those paintings which have a second price greater than the first price ($soldgreater_i$) and thus have a positive signal between two auctions. Thus, we estimate a variation of Eq. 1 above that includes two dummy variables, $soldless_i$ and $soldgreater_i$ for paintings that appear three times in our constructed dataset and sold each time at auction.

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

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.

As shown in Table 6, in this regression, β is not significantly different from the coefficient on *fail* in Eq. 1. However, it is significantly different from θ, the coefficient on those items that have sold three times, but in which the second sale price was less than the first sale price. These paintings have had a negative signal also – and exhibit a downward trend in prices between the first two sales. Yet, the return for these paintings is not significantly different from the return for paintings that have sold twice at auction and not appeared at auction in between. Therefore, one can argue that paintings that fail at auction are different from paintings that are just exhibiting a downward trend in price, but do not actually fail. Though, of course, paintings that have actually failed may simply be exhibiting a larger downward trend than paintings that have a lower price and therefore negative signal but have not failed.

Table 6 Positive signals

	Full sample		Sample with estimates			
	$\ln(p_{i,s}/p_{i,b})$		$\ln(p_{i,s}/p_{i,b})$		$\ln(\text{estimate}_{i,s}/\text{estimate}_{i,b})$	
	OLS	Case–Shiller 3-stage LS	OLS	Case–Shiller 3-stage LS	OLS	Case–Shiller 3-stage LS
Fail	**−0.367 (0.089)**	**−0.331 (0.082)**	**−0.264 (0.087)**	**−0.239 (0.077)**	**−0.246 (0.110)**	−0.194 (0.106)
Sold sold sold (2nd sale ≥ 1st sale)	**0.802 (0.109)**	**0.765 (0.094)**	**0.730 (0.113)**	**0.706 (0.091)**	**0.703 (0.125)**	**0.668 (0.105)**
Sold sold sold (2nd sale < 1st sale)	0.061 (0.169)	0.091 (0.165)	0.214 (0.149)	0.222 (0.149)	0.271 (0.212)	0.276 (0.226)
Time dummies	30	30	30	30	30	30
F-statistic	59.47	61.92	58.84	59.65	68.68	69.03
Constant	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.644	0.624	0.632	0.620	0.588	0.580
Observations	1,365	1,365	1,120	1,120	1,120	1,120

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

Coefficients that are significant at the 5% level are indicated in bold

Table 7 Repeat sale estimates effects of failing at auction on price sample with estimates (1973–2000)

	$\ln(p_{i,s}/p_{i,b})$		$\ln(\text{estimate}_{i,s}/\text{estimate}_{i,b})$		$\ln(p_{i,s}/p_{i,b}) - \ln(\text{estimate}_{i,s}/\text{estimate}_{i,b})$	
	OLS	Case–Shiller 3-stage LS	OLS	Case–Shiller 3-stage LS	OLS	Case–Shiller 3-stage LS
Fail1	**−0.543 (0.129)**	**−0.463 (0.117)**	**−0.692 (0.168)**	**−0.554 (0.177)**	0.149 (0.132)	0.151 (0.132)
Fail2	**−0.338 (0.156)**	−0.272 (0.156)	**−0.581 (0.163)**	**−0.513 (0.175)**	0.243 (0.173)	0.240 (0.173)
Different house	**0.331 (0.161)**	0.254 (0.154)	**0.877 (0.152)**	**0.795 (0.157)**	**−0.547 (0.126)**	**−0.545 (0.126)**
Different location	0.154 (0.156)	0.110 (0.142)	0.163 (0.167)	0.075 (0.173)	−0.010 (0.136)	−0.010 (0.136)
Time dummies	30	30	30	30	30	30
F-statistic	371.14	75.68	162.06	49.15	35.47	69.6
Constant	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.618	0.598	0.585	0.570	0.087	0.087
Observations	1,159	1,159	1,159	1,159	1,159	1,159

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

Coefficients that are significant at the 5% level are indicated in bold

Interestingly, the coefficient on *soldgreater* is very positive and significant both on the price regressions and on the estimate regressions. This could be the result of common values, common trend effects or reserve price effects, as described above. Alternatively, the large positive coefficient on *soldgreater* could indicate sample selection, paintings that have gone up in value tend to be brought to auction more often.

4.1.4 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.

First, it is very possible that in the art market information decays over time, especially amongst casual buyers, and 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 2 years after it failed, and another dummy variable, *fail2*, if an item is brought back to auction more than 2 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.

Second, 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 7.

As shown in columns 1 and 2, the point estimates indicate that the failing effect may be less if a painting returns to auction more than 2 years after it originally appeared, but the difference is not statistically significant.[11]

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.

[11] This is true whether 1 year, 1 ½ years, or 2 ½ years is used as the time period.

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 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 28%, but the decrease in returns varies enormously. Paintings that were brought back to the same auction house within 2 years of failing return about 37%[12] 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.

Our results are clearly consistent with the view that failure at an auction directly damages the prospects of a painting, perhaps, because of common value effects. We cannot of course rule out that changes in reserve prices are the reason for apparent burning effects or that failure is correlated with an unobserved downward trend in demand for the painting.

The fact that prices are no lower when paintings change auction houses provides some evidence against the importance of trend effects—changing auction house would not render the painting immune to trend effects. It may though allow a fresh presentation, less associated with past failure, and perhaps help to alleviate common value effects. A new house might have access to a different clientele but given that art catalogues are widely available this seems unlikely. Some further evidence against the view that failure simply signals a downward trend in prices or that the paintings which fail are those which had unusually good fortune in the first auction is that the price to estimate ratios at the initial sale are if anything lower for the paintings which fail (see Table 2).

Since reserve prices are not directly observed, it is hard to determine whether they have an influence. By convention in some localities and by law in others, the reserve price is at or below the low estimate. As we have seen estimates do fall after a failure, and so therefore presumably do reserve prices, but this would also happen if there are common value effects. If clients set reserve prices then there is no immediate reason why changing house should affect them (and so realized prices). On the other hand, auction houses may feel repeated failures are bad for their reputation and so insist on lower prices if clients stay. Also the clients who are prepared to go through the trouble of changing houses may those who are patient enough to keep reserve prices high.

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

[12] See column 2 of Table 7: $1-\exp(-0.463) = 0.37$.

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. First, 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. Second, 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 (forthcoming) found that homes owned by real estate agents sell for about 3.7% more and stay on the market 9.5 days longer. Genesove and Mayer (1997) found that a condominium with a loan to value ratio of 100% sells for 4% 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.

6 Conclusion

This research has identified and estimated lower returns for items that fail at auction. These lower returns may occur because of common value effects, changes in the seller's reserve price or idiosyncratic downward trends in taste.

The results of this study rely on 43 paintings that failed at auction between two successful sales. While this is a small sample of identifying paintings, at nearly 30%, the effect of failing at auction on a painting's predicted return is large and economically significant. This article has not definitively determined the cause of the failing effect, but if the effect is due to common values and is therefore causal, a fear of failing could have a profound effect on pre-sale estimates and reserve prices. While this research has added to an understanding of what happens when an item fails to meet its reserve price, more research is needed into the importance of the various explanations of why failed paintings return so much less than other paintings.

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