RESERVE PRICE EFFICIENCY: EVIDENCE FROM THE FINE ART MARKET

by

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Abstract

Many fine-art paintings are sold at auctions where the seller has nominated a minimum reserve price. If the reserve price was set too low, the seller risks selling the painting too cheaply. But a too-high reserve risks the painting being passed-in, which still incurs some transaction costs and typically requires the would-be seller (consignor) to return to market at a later date. Accordingly, choosing the reserve involves a delicate trade-off. Testing the efficiency with which reserve prices have been set would be straightforward if these prices were publicly available, however they are known only to the seller and the auction house. We overcome this problem by applying an innovative augmented repeat sales regression (RSR) to an art market dataset that incorporates the high bids from passed in auctions, ultimately finding that art market participants are setting their reserves too high. The methodology developed in this paper helps to fill a gap in the literature: while much theoretical work has been done on auction reserve prices, little has been studied empirically.

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1. Introduction

Key to this paper is the notion of Reserve Price Efficiency. We identify the efficiency of a passed-in auction's reserve price with reference to the highest bid in a later, successful auction: if the passed-in auction's reserve price was efficient then the consignor will have prevented their artwork from selling too cheaply, and will thus be able to sell (at a subsequent auction) their artwork for *more than they were offered at the passed-in auction*.

Figure 1 illustrates this concept visually for three artworks that sell over a sequence of three auctions. All three are purchased on a first auction, pass-in at a second, and finally sell successfully on a third. Where the three artworks differ is on the price realised on the third auction. Panel A depicts an artwork that not only had an efficient reserve price but also realised a profit over the course of the three auctions: thanks to the reserve price preventing the consignor from selling the painting for too little on the passed-in auction, they were able to sell the painting for a profit (relative to the initial purchase price) on the third and final auction. Panel B most clearly illustrates the distinction between an efficient reserve price and a profitable transaction: here, the consignor still loses money over the three auction cycle (that is, their overall holding of the artwork, from initial purchase to final sale, is unprofitable), as the artwork ultimately sells for less than they purchased it for – however, the reserve price on the passed in auction was still efficient, as it prevented the consignor from selling the artwork for less than they were able to sell it for on the third and final auction. Panel C illustrates an inefficient reserve price, in that not only does the consignor ultimately end up selling the artwork for less than they purchased it for, but they also end up selling it *for less than they would've received on the passed-in auction, had they sold it at that auction* (i.e. had their reserve price been lower on the second auction).

Ultimately, a reserve price is inefficient if the consignor ends up selling the artwork for *the same or less than they would have received on the passed-in auction, had they sold their artwork for the passed-in auction's highest bid*. Crucially, the consignor does not *necessarily* have to realise a profit relative to their initial purchase price; as long as they sell for more than the reserve price on the passed-in auction, their reserve price was efficient.

Note, also, that this paper assumes that the highest bid at a passed-in auction represents a reasonable proxy for market valuation. This assumption might initially seem counterintuitive: clearly the consignor placed a higher value on the artwork than the highest bidder, and this higher valuation (the consignor's) is *not* the valuation that is incorporated into the dataset. However, it is worth remembering that a similar thing (almost) holds true for the highest bids in successful auctions: the highest bid does not represent the valuation of the highest bidder, but rather the valuation of the *second highest bidder*, plus the one-bid increment necessary to for the highest bidder to beat the second-highest bidder's valuation.[2] Therefore, in both passed-in and successful auctions, the highest bid (approximately) reflects the *second* highest valuation among art market participants. This symmetry helps to justify the use of high bids from passed-in auctions as an indicator of market valuation.

2. Literature Review

The study of the informational content of "passed-in" auctions in the fine art market has been the subject of a small but notable literature. Beggs and Graddy (2008) study the so-called art market burn effect – the tendency of artworks that pass in at a second auction to sell for less than purchased for at a third – via an augmented RSR. Their dataset includes 43 observations on artworks that appeared in three successive auctions in a "purchased, passed-in, sold" cycle (that is, the painting was purchased in the first auction, then passed-in at the following auction, then sold on the third auction), with such triplets indicated by a dummy variable in an RSR regression that is otherwise comprised of the usual RSR "sale, sale" pairs. They find that the dummy variable corresponding to these auction "triples" implied a 30% loss over the three-auction cycle (that is, the painting sold for 30% less than it was purchased, with market movements controlled for by the RSR index).

Passed-in art auctions have also been studied in the broader context of aggregate movements in the art market. Zanola (2007) employ a Heckman correction model on data of Picasso prints sold over the period 1988 to 1995 to construct an RSR index that is adjusted for non-random sample selection. In this index, the selection equation dependent variable is unity for prints that were sold at least twice over the period (and were therefore included in the RSR) and zero for prints that were only included once; this selection equation used standard hedonic data

[2] Bidding increments are typically a small percentage of the final sale price, particularly in the high end of the market. For instance, the highest price ever fetched for an artwork at auction was USD 160m (hammer price); the second highest bid was 159.5m, meaning the final increment was only 0.31% of the final hammer price.

relating to static variables for the artwork. Surprisingly, the selection corrected index yielded both higher returns and lower volatility than the uncorrected index.

Marinelli and Palomba (2011) also adopt a Heckit approach to correct for sample selection bias. They develop a Heckit-hedonic model of Italian contemporary artists, where once again the selection equation dependent variable is the success/passed-in state of the auction. The response equation is a fairly standard art market hedonic model (artist, medium etc.). While these authors appear to be the first to apply a Heckit approach to a hedonic model of the art market, they does not compare the resulting index with an uncorrected (non-Heckit) hedonic index, so it is difficult to know the impact of the sample selection correction on the final index.

Collins et al. (2009) apply a similar hedonic-Heckit model to a database of symbolist paintings, with a dataset comprising of 1,174 realised sales and 741 buy-ins (passed-in auctions). However, in this paper the authors contrast the Heckit-hedonic index with the equivalent OLS-based index. Somewhat surprisingly (in view of the general belief that sample selection in art market research typically results in an upward bias), the Heckit model actually gives a slightly higher implied return than the basic/uncorrected hedonic model, although the differences are small. It is of some interest that both Zenola (2007) (in an RSR context) and Collins et al. (2009) (in a hedonic context) both find that the Heckit correction increases the returns implied by the extracted index, relative to the uncorrected least squares indexes.

Interestingly, findings from the real estate market seem to indicate a narrative that is completely at odds with that of the art market. Whereas in the art market passed-in auctions are typically associated with lower eventual realised prices, in the real estate market the opposite occurs, with properties that spend longer on the market realising a higher final price. Genesove and Mayer (2001) and Levitt and Syverson (2008) both observe this positive correlation between the time a property spends on the market and the price that property eventually sells for. In the real estate market, it seems that the consignor (existing owner) appears to be trading off liquidity/immediacy for the sake of a higher final price.

3. Data & Notation

The data was assembled by Kathryn Graddy and is available for download from her website at http://people.brandeis.edu/~kgraddy/datasets/contemporary_art.csv. The dataset uses a combination of hand-copied information from Christie's pre-sale catalogues coupled with information on auction results (including, importantly, the high bids on passed-in auctions) from the Christie's internal property system. The recorded auctions occurred at Christie's auctions houses in London and New York between 1982 and 1994. Although this dataset is somewhat dated, Ashenfeldter and Graddy (2011) incorporate this dataset into a larger one that includes sales of impressionist art from 1985 to 2007 and find that sale rates are largely stationary over the period. This imparts some confidence in the relevance of the findings from this older dataset to the art market as it currently stands. The key "unique selling point" of this dataset is its provision of values for the highest bids in failed auctions; while there are other datasets that provide "NA" values for failed sales, they typically do not include information on the highest bid in these auctions. The Graddy dataset is thus unique, and uniquely valuable.

It is worth considering some patterns in the return of art markets over the period covered by the dataset. Bocart et al. (2011) point out the art market was in a significant bubble during this period due to the influx of money from cashed-up Japanese investors, although they also note that this money mostly flowed into post-impressionist arena. Nonetheless, other research has indicated the existence of significant bubble in the overall market during this period (e.g. Mei and Moses, 2002, and Renneboog and Spaenjers, 2013). The existence of a bubble in the fine art market should be kept in mind when interpreting the implied returns of the repeat sales index: the period was somewhat more volatile than is generally the case in the art market. This volatility may indeed be seen as an asset in the present context, as it allows for a consideration of the impact of passed-in auctions on art market indexes in periods of both market growth and market contraction.

The Graddy dataset is comprised of observations on 4,456 auctions. However, due to the need of a repeat sales regression to match at least two sales of an identical work for every single observation, the RSR dataset is necessarily a substantially smaller subset of the complete Graddy database.[3] Moreover, the RSR dataset in this paper is complicated by the mixing (in a single auction pair) of high bids from successful auctions with high bids from auctions that passed-in. That is, as RSR dependent variable element pairs involve two auctions (in the typical RSR, this involves a Period 1 auction in which the artwork is purchased, and a Period 2 auction in which the artwork is sold) and as this database contains two different auction complete states for each auction (namely, successful or passed-in), there are thus four different types of auction pairs:

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[3] Importantly, a hedonic regression of the full 4,456 observation dataset yielded a broadly similar index to the subset used for the augmented RSR detailed in the results section.

Pair Type	Period 1 Auction Completion State	Period 2 Auction Completion State (s'')	Obs. Count
P1	Successful	Successful	84
P2	Passed-in	Passed-in	Omitted
P3	Passed-in	Successful	94
P4	Successful	Passed-in	18

Note the substantial difference in observation counts between pairs that go from passed-in to successful (Pair Type P3) vs successful to passed-in (Pair Type P4): the ladder has 94 observations whereas the former only adds only 18 observations. One potential explanation might be that sellers are motivated by liquidity needs, and the consignor of a passed-in auction will hurry back to market in a year or two to try their luck again. However, after successfully purchasing an artwork, a buyer is more likely to hold on to it and enjoy it.[4] Given the sample window of 1982 to 1994, this tendency for longer holding periods following successful purchase makes sense.

Figure 2 depicts the annualised observation count for the RSRs. One issue surrounding RSRs is the unavoidable "thinness" that occurs at the start and end of the regression sample period: at the start of the period, only transactions with a *future* match (the partner in the transaction pair) can be included in the sample. Similarly, at the end of the sample period, only transactions with a *previous* observation can be included. Whereas in the middle both kinds of transactions can be included. This tendency is clearly visible in Table 1, with the first and last years having 9 and 8 transactions respectively, whereas the middle five years of the sample have an average of 17 observations per period.

4. The Model

As the models in this paper rely on a mix of data from successful and passed-in auctions, the notation used in equations (particularly the left-hand side of equations) differs from that used in most art market research. Rather than deal in log prices, we deal in log high bids, from auctions that may or not have been successful. If they were successful, then the high bid clearly

[4] It is also worth considering the sophisticated art market investors who profit from flipping strategies. Such investors are more informed about the art market and are less likely to set reservation prices too high, or to make purchases that have limited resale potential in the future – that is, experienced "flippers" might be characterised by short holding periods, but also a lower likelihood of experiencing a passed-in auction.

also represents a price, however due to the possibility for passed-in auctions a price may never be realised. Starting first with the left-hand side of the equation:

$$\log \mathrm{B}_{\mathrm{is}'\mathrm{t}'}$$

B = high bid at auction

t′ = year of auction, with t′ for first

i = artwork at auction, including time-invariant hedonic information (dimension, medium etc.)

s′ = binary indicator for auction completion state, with s′ = 1 for a successful auction or s′ = 0 for a passed-in auction

That is, $\mathrm{B}_{\mathrm{ist}'}$ is the high bid of an auction of artwork i at time t′ with auction completion state s′, where s′ is a binary indicator that identifies whether the auction was successful or passed-in. If the auction was successful, then the s′ binary indicator is equal to unity and B is equal to the realised sale price. If this auction passed-in, then the s′ binary indicator is equal to zero and B is equal to the highest bid in the passed-in auction.

To illustrate the use of the s′ and s″ subscripts in RSR auction pairs, consider the two following examples:

- If s′ = 0 and s″ = 1, then we are looking at an auction pair where the consignor tried to sell the artwork at time t′ but failed (that is, the auction passed-in), and then returned to market at time t″ for a successful sale.
- If s′ = 1 and s″ = 0, then we are looking at a transaction pair where a purchaser bought the artwork (at a successful auction) in time t′ but then tried unsuccessfully to "flip" the painting back to the market at time t″ (that is, the time t″ auction passed-in).

Having outlined the notation, we may now move on to outline the basic model for this section, which uses an augmented RSR comprised of auction pairs that go from "successful auction to successful auction," "successful auction to passed-in auction," and "passed-in auction to successful auction." The usual RSR index is augmented by a pair of dummy variables that identify the returns associated with the latter two pair types, while controlling for market movements with the main RSR index.

As such, there is one dummy for auction pairs that go from a successful auction to a passed-in auction, and another dummy for passed-in to successful. This leads to the following model:

$$\underbrace{\log B_{is''t''} - \log B_{is't'}}_{\substack{Change\ in\ High\ Bid \\ for\ Artwork\ i}} = \underbrace{\sum_{t=2}^{T} \alpha_t \left[1_{\{t=t''\}} - 1_{\{t=t'\}}\right]}_{Index} + \underbrace{\gamma 1_{\{s'=1\}} 1_{\{s''=0\}}}_{\substack{Dummy\ for \\ Successful \\ to\ Passed-In}} + \underbrace{\lambda 1_{\{s'=0\}} 1_{\{s''=1\}}}_{\substack{Dummy\ for \\ Passed-In\ to \\ Successful}} + \varepsilon_{it't''}$$

Testing for reserve price efficiency – that is, seeing if the reserve price on a passed-in auction prevented the consignor from selling too low and thereby missing out on a higher price for their piece at a future auction – is conducted by a simple test of the λ coefficient. If the λ is significantly positive, then consignors are setting their reserve prices efficiently. If it is insignificant or negative, they are setting them inefficiently.[5]

Finally, note that in this model, the market index controls for movements in the art market as a whole. In this sense, the RSR index functions almost like the $\beta(r_m - r_f)$ component of the CAPM: it factors out movements in the market to identify the actual efficiency with which consignors are setting their reserve prices, and the extent to which their artworks are being "burned."

5. <u>Results</u>

The "Model 1" column group of Table 1 tabulates the results from the basic augmented RSR. The λ coefficient is positive, but insignificantly so, and even if we take the numerical value as precise (and consider that the holding period for passed-in to successful auctions is about two years) it is still so small that it implies per annum returns that are less than the US 3 Month T-Bill rate over any period in the sample. Therefore, even without considering transaction costs, it is fair to say that the consignor in the average passed-in auction set their reserve price to high: at the very least, they would've been better letting go of the piece for the high bid offered at the

[5] Intuitively, the case of the insignificant lambda coefficient might seem neutral with respect to reserve price efficiency. However, the art market's hefty transaction costs means that a pair of auctions that are neutral in terms of high bid change are still ultimately going to be costly to the seller.

earlier passed-in auction and investing in the risk-free rate. This is a potentially important finding, with practical consequences for art market participants. By lowering reserve prices, not only will sellers improve the financial performance of their investments, but auction houses will avoid the stigma of hosting a passed-in auction.[6]

Robustness: Alternative Model Specifications

Implicit in the previous section's model is the assumption that there is no interaction between holding period and the valuation changes implied by a passed-in auction. For instance, the model assumes that a "burned" painting will not recover a higher proportion of its value if the consignor waits longer to return to market following a passed-in auction. The model also assumes that an artwork will not experience a greater decline in value when a greater period of time elapses between purchase and passed-in sale.

Models 2 and 3 from Table 2 investigate these assumptions. Model 2 interacts the dummy variables of Model 1 with numerical values for the holding periods between the two auction pair types. This tests for trend effects in the valuation changes associated with passed-in auctions, and finds that the valuation change when going from a successful auction to a passed-in auction does indeed interact with time (that is, the φ coefficient is significant), with the valuation decreasing further over longer holding periods. One possible explanation for this might be that the consignor of the passed-in auction failed to update their own valuation of their item in the face of a declining market valuation. However, Model 3 regresses the trend effects of Model 2 alongside the static dummies of Model 1, which results in the static dummies dominating the trend effects. This domination in turn leads us back to the findings of Model 1, as identified in the previous section.

7. Conclusion

This paper has examined the (in)efficiency with which consignors are setting their reserve prices. It appears that the consignors of passed-in auctions had typically overestimated the value of the pieces they were consigning, a mistake which caused them to choose a reserve price that was inappropriately high relative to the market's eventual valuation of their artwork.

[6] Although, taking a more cynical view of the market, the auction houses do still take fees from passed-in auctions, so there may well still be some incentive for auction houses to have a proportion of auctions pass-in.

For the auction after their failed auction, they set their reserve price in line with the high bid received on the passed-in auction; that is, they update their expectations to reflect the valuation implied by the previous (passed-in) auction. In conclusion, the typical art market seller should be setting a lower reserve price when they consign their artwork for auction. This finding has significant implications for market participants in the 60 billion p.a. fine art industry. Moreover, and perhaps even more usefully, the methodology developed in this paper could be profitably employed to analyse auction behaviour in the somewhat-larger global real estate industry.

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TABLE 1 of 2

RESERVE PRICE EFFICIENCY AUGMENTED RSR

$$\overbrace{\log B_{is''t''} - \log B_{is't'}}^{\substack{Change\ in\ High\ Bid \\ for\ Artwork\ i}} = \overbrace{\sum_{t=2}^{T} \alpha_t \left[1_{\{t=t''\}} - 1_{\{t=t'\}}\right]}^{Index}$$

$$+ \underbrace{\gamma 1_{\{s'=1\}} 1_{\{s''=0\}}}_{\substack{Dummy\ for \\ Successful \\ to\ Passed-In}} + \underbrace{\lambda 1_{\{s'=0\}} 1_{\{s''=1\}}}_{\substack{Dummy\ for \\ Passed-In\ to \\ Successful}} + \varepsilon_{it't''}$$

	Coefficient		Index: Value	Index: Implied Return	Dummy Count: -1	Dummy Count: +1	Dummy Count: Total
	Panel A. Dummies for RSR Observations with Passed-In Auctions						
Successful to Passed-in	-0.56	(0.12)			0	94	94
Passed-in to Successful	0.04	(0.05)			0	18	18
	Panel B. RSR Index						
1982	0.00	-	1.00	-	0	21	21
1983	0.32	(0.13)	1.37	0.37	6	15	21
1984	0.58	(0.13)	1.78	0.30	13	13	26
1985	0.90	(0.15)	2.45	0.38	9	23	32
1986	0.85	(0.16)	2.34	-0.04	11	15	26
1987	1.41	(0.15)	4.11	0.75	17	30	47
1988	1.72	(0.17)	5.59	0.36	16	16	32
1989	2.00	(0.16)	7.41	0.32	18	23	41
1990	2.00	(0.16)	7.41	0.00	35	19	54
1991	1.68	(0.18)	5.36	-0.28	19	8	27
1992	1.59	(0.20)	4.89	-0.09	13	6	19
1993	1.37	(0.20)	3.94	-0.19	17	4	21
1994	1.00	(0.21)	2.73	-0.31	19	0	19
Total (Sum)				1.58			
Average:				0.13			
Observations	193						
Weighted r^2 (%)	64						
Unweighted r^2 (%)	61						

Notes: Standard errors in parenthesis. RSR estimated via GLS as per Graddy et al. (2012). B_{ist} is the high bid for an artwork i in an auction at time t. The s subscript indicates whether or not the auction for artwork i at time t was successful or unsuccessful, with s = 1 indicating success and 0 indicating failure.

TABLE 2 of 2

RESERVE PRICE EFFICIENCY ALTERNATE MODELS

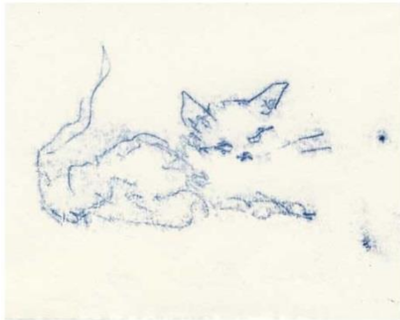
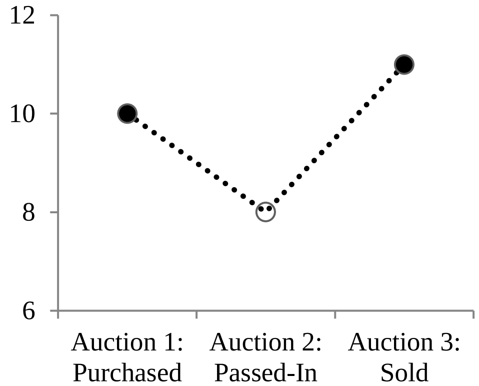
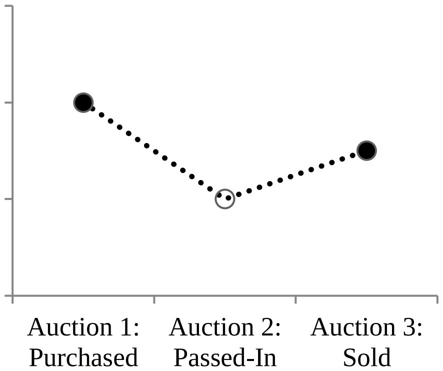
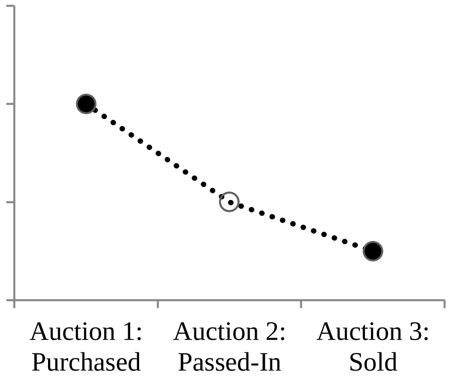
$$\underbrace{\log B_{is''t''} - \log B_{is't'}}_{\substack{\text{Change in High Bid} \\ \text{for Artwork } i}} = \underbrace{\sum_{t=2}^{T} \alpha_t \left[1_{\{t=t''\}} - 1_{\{t=t'\}}\right]}_{\text{Index}} + \underbrace{\gamma 1_{\{s'=1\}} 1_{\{s''=0\}}}_{\substack{\text{Dummy for} \\ \text{Successful} \\ \text{to Passed-In}}} + \underbrace{\lambda 1_{\{s'=0\}} 1_{\{s''=1\}}}_{\substack{\text{Dummy for} \\ \text{Passed-In to} \\ \text{Successful}}} + \underbrace{\varphi 1_{\{s'=1\}} 1_{\{s''=0\}} (t'' - t')}_{\substack{(\text{Dummy for Succesful to} \\ \text{Passed-In}) \times (\text{Holding Period})}} + \underbrace{\psi 1_{\{s'=0\}} 1_{\{s''=1\}} (t'' - t')}_{\substack{(\text{Dummy for Passed-In to} \\ \text{Succesful}) \times (\text{Holding Period})}} + \varepsilon_{it't''}$$

	Base Model: Auction State Only (Model 1, repeating Table 2)				Auction State × Holding Period (Model 2)				Auction State + (Auction State × Holding Period) (Model 3)			
			Index				Index				Index	
	Coefficient		Value	Imp. Ret.	Coefficient		Value	Imp. Ret.	Coefficient		Value	Imp. Ret.
γ	-0.56	(0.12)			-				-0.49	(0.22)		
λ	0.04	(0.05)			-				0.03	(0.04)		
φ	-				-0.17	(0.05)			-0.03	(0.08)		
ψ	-				0.02	(0.03)			0.03	(0.04)		
1982	0.00	-	1.00	-	0.00	-	1.00	-	0.00	-	1.00	-
1983	0.32	(0.13)	1.37	0.37	0.30	(0.13)	1.35	0.35	0.31	(0.13)	1.36	0.36
1984	0.58	(0.13)	1.78	0.30	0.57	(0.14)	1.77	0.31	0.57	(0.14)	1.77	0.30
1985	0.90	(0.15)	2.45	0.38	0.89	(0.16)	2.43	0.37	0.88	(0.15)	2.41	0.36
1986	0.85	(0.16)	2.34	-0.04	0.84	(0.17)	2.32	-0.05	0.83	(0.17)	2.30	-0.05
1987	1.41	(0.15)	4.11	0.75	1.36	(0.17)	3.91	0.69	1.38	(0.17)	3.98	0.73
1988	1.72	(0.17)	5.59	0.36	1.70	(0.18)	5.45	0.39	1.70	(0.18)	5.45	0.37
1989	2.00	(0.16)	7.41	0.32	1.96	(0.18)	7.12	0.31	1.97	(0.18)	7.16	0.31
1990	2.00	(0.16)	7.41	0.00	1.97	(0.18)	7.20	0.01	1.97	(0.18)	7.18	0.00
1991	1.68	(0.18)	5.36	-0.28	1.65	(0.20)	5.23	-0.27	1.65	(0.20)	5.21	-0.27
1992	1.59	(0.20)	4.89	-0.09	1.57	(0.22)	4.82	-0.08	1.56	(0.22)	4.76	-0.09
1993	1.37	(0.20)	3.94	-0.19	1.32	(0.22)	3.73	-0.22	1.33	(0.22)	3.79	-0.20
1994	1.00	(0.21)	2.73	-0.31	0.94	(0.24)	2.56	-0.31	0.96	(0.24)	2.60	-0.31
Average:				0.13				0.12				0.13
Regression Statistics:												
Weighted R^2 (%)	63.58				63.29				64.12			
Unweighted R^2 (%)	60.53				59.97				60.60			

Notes: Standard errors in parenthesis. RSRs estimated via the Graddy et al. (2012) GLS approach. B_{ist} is the high bid for an artwork i in an auction at time t. The s subscript indicates whether or not the auction for artwork i at time t was successful or unsuccessful, with s = 1 indicating success and 0 indicating failure. All regressions N=193.

FIGURE 1 of 2

THREE EXAMPLES OF RESERVE PRICE EFFICIENCY

	Panel A. Painting	Panel B. Screen Print	Panel C. Etching
Type of Work			
Sale History (Highest Bid, $’000)			
Realised Loss?	No	Yes	Yes
Reserve Price Efficient?	Yes	Yes	No

Note: In the figures, the successful auctions are indicated by filled-in circles and the passed-in auctions are indicated by hollow circles.

FIGURE 2 of 2

BREAKDOWN OF RSR AUCTION PAIRS FOR INDEX I2