31 May 2014

Pre-sale information and auction prices for Australian Indigenous artworks*

Lisa Farrell and Tim R.L. Fry

School of Economics, Finance and Marketing
RMIT University, Australia

Abstract: In art markets, where every item sold is unique, price uncertainty naturally exists and information relating to the degree of risk is obviously important to potential buyers. In this context we investigate the role that pre-sale price information plays in determining auction outcomes for Australian Indigenous artworks, using sales data from 1987-2011. Importantly, we control for the degree of market concentration as many art markets are heavily concentrated and this might influence buyer's perceptions of fairness. The Indigenous art market is a newly emergent and rapidly growing contemporary art market, thus providing a perfect setting in which to investigate aspects of price uncertainty. Looking across three classes of artworks (objects, paintings and works on paper) we find the information contained within the pre-sale estimates has a differential impact on hammer prices depending on the type of art under consideration and the point in the realised price distribution under examination. We also find that, consistent with economic theory, the degree of market concentration can be a significant factor in the determination of price.

Keywords: Pre-sales information, auction prices, Indigenous artwork, risk and uncertainty, market concentration.

JEL Classification: Z11

Corresponding Author: Prof. Tim R.L. Fry, School of Economics, Finance & Marketing, RMIT University, GPO Box 2476, Melbourne, Victoria 3001, Australia.
Email: tim.fry@rmit.edu.au

* This work is part of a research project on "Indigenous art at auction" which has been supported by RMIT University funding. We are grateful to Jane Fry for her comments on an earlier version of this paper. We are also grateful to Jenny Hawkins for discussant comments. The usual disclaimer applies.

1. Background

This paper examines the role of pre-sale price information and market concentration in explaining the hammer price for artworks sold at auction. The role of pre-sale price estimates in art markets, set by intermediaries between buyers and sellers (i.e. auction house experts), is of obvious economic importance. Understanding how buyers respond to the information provided by auction houses helps inform our understanding of the mechanisms that drive price generation in art markets and the role of experts in these markets. In a marketplace where each item sold is unique uncertainly plays a key role and so *a priori* information is of high value to potential buyers.

Ashenfelter (1989) has argued from an auction theory perspective that the auction houses best policy when setting pre-sale estimates is to give unbiased estimates. Under this scenario we would expect price estimates to be accurate predictors of hammer prices- yet the empirical evidence to date appears to be mixed. There is evidence of pre-sale price estimates being good predictors of realised prices (for example, Czujack and Martins, 2004; McAndrew et al, 2012). But we also see pre-sale price estimates being poor predictors because of systematic under- or over-estimation (for example, Beggs and Graddy, 1997; Ekelund et al., 1998; Bauwens and Ginsburg, 2000). We explore the hypothesis that the reason for this lack of consensus is due to the existing literature failing to adequately capture all the information contained within pre-sale price estimates. In a market with price uncertainty buyers are interested in knowing the pre-sale latent price distribution for any item offered for sale, in order to assess the risk associated with purchase. We argue that pre-sale price estimates contain a lot of information regarding this distribution and that this information can be captured by a set of price estimate summary measures (defined in Section 2).

Further, we argue that while price uncertainty will be item specific, it will also be market specific: affected by the degree of market concentration. The greater the competition the less opportunity for collusion between auction houses and so buyers are more likely to perceive pre-sale price estimates as fair. The English houses

Christies and Sotheby's have historically been highly influential auction houses in art markets and have been the subject of a class action in 2001 accusing them of price fixing. The case led to convictions and compensation payments to buyers (see Stewart 2001 for details). It is therefore reasonable to assume that when buyers extract price information from pre-sale estimates they are mindful of the degree of concentration within the market. Interestingly, while Christies and Sotheby's dominate the art auction landscape there are numerous regional and small auction houses that also exist and often specialise in emerging and niche markets.

Our strategy to explore the importance of the information contained within the pre-sale price estimates and market concentration for auction outcomes is twofold. Firstly, we will include in our modeling a range of 'higher order' price estimate summary measures generated from the pre-sale published auction house price estimates. Secondly, we will account for the degree of market concentration by consideration of the number of auction houses in the market and their associated market shares, through the inclusion of an art market Herfindahl index.

The context of our study is artworks created by Australian Indigenous artists. This is an especially appropriate art market within which to test our hypothesis because it is a newly emerging (relatively speaking) and rapidly growing art market. Contemporary Indigenous Australian art is produced by Aboriginal Australians and comes in many forms. Early Indigenous artists painted traditional watercolour landscape painting (such as those produced by the Hermannsburg School in the mid 1930's onwards). Arguably the most famous of these painters is Albert Namatjira. The most well known form of Indigenous art is Dot paintings where the subject matter is the cultural 'Dreamtime'. But it was not until the early 70's that an art teacher Geoffrey Bardon facilitated the transfer of the Dreaming's of the Papunya people (known as the Tula artists) onto canvas. Until this point Indigenous artists had created their paintings in the sand and other none permanent mediums. Interestingly, the dots were first used to cover scared, secret and ritual aspects of the paintings. Famous artists include Clifford Possum Tjapaltjarri[1] and Johnny Warangkula. Indigenous art comes in many forms from paints on canvas and bark to carvings, sculpture and photography. Sales have

[1] In 2007 Clifford Possum Tjapaltjarri's Warlugung sold for $(AU) 2.4 million.

grown steadily over the last 50 years but have been affected by the Global Financial crisis. At its peak in 2007 the market was estimated to be worth $(AU) 26 million[2]

2. Theoretical Framework

Studies of art auction data typically contain many types and styles of artwork, making the data inherently heterogeneous. We reduce this variability by analysing only Indigenous artworks and by separating these into three categories/groups, namely objects, paintings and works on paper. Hence we create more homogenous art markets in which to test our hypothesis. Our primary attention is upon information contained within the auction house price estimates (contained in the auction catalogues) but our empirical modeling also controls for the prior information concerning the concentration of the auction market for Indigenous artworks as a whole.

The catalogue for an art auction contains information for potential buyers prior to the auction taking place. As well as the experts price estimate the catalogue also contains information regarding the hedonic properties of the art work (such as the artist, size of the work, medium etc.). It is reasonable to think that in estimating the hammer price for an artwork these might be important variables to consider. It is also reasonable to think that experts will have already taken these characteristics into consideration in establishing their price estimates and as such all publically available information will have been utilized. Abowd and Ashenfelter (1989) and Sproule and Valsan (2006) have shown that hedonic pricing models have no better predictive power than auction house price estimates. They conclude that pre-sale price estimates correctly incorporate the pre-sale publically available information. Following this evidence we focus on two key pieces of information in the auction catalogues namely, the lower (L) and upper (U) estimate of the likely hammer price for the artwork.

In prior research the lower and upper estimates have usually been combined into a single value to give a pre-sale price point estimate. Typically the pre-sale estimate is

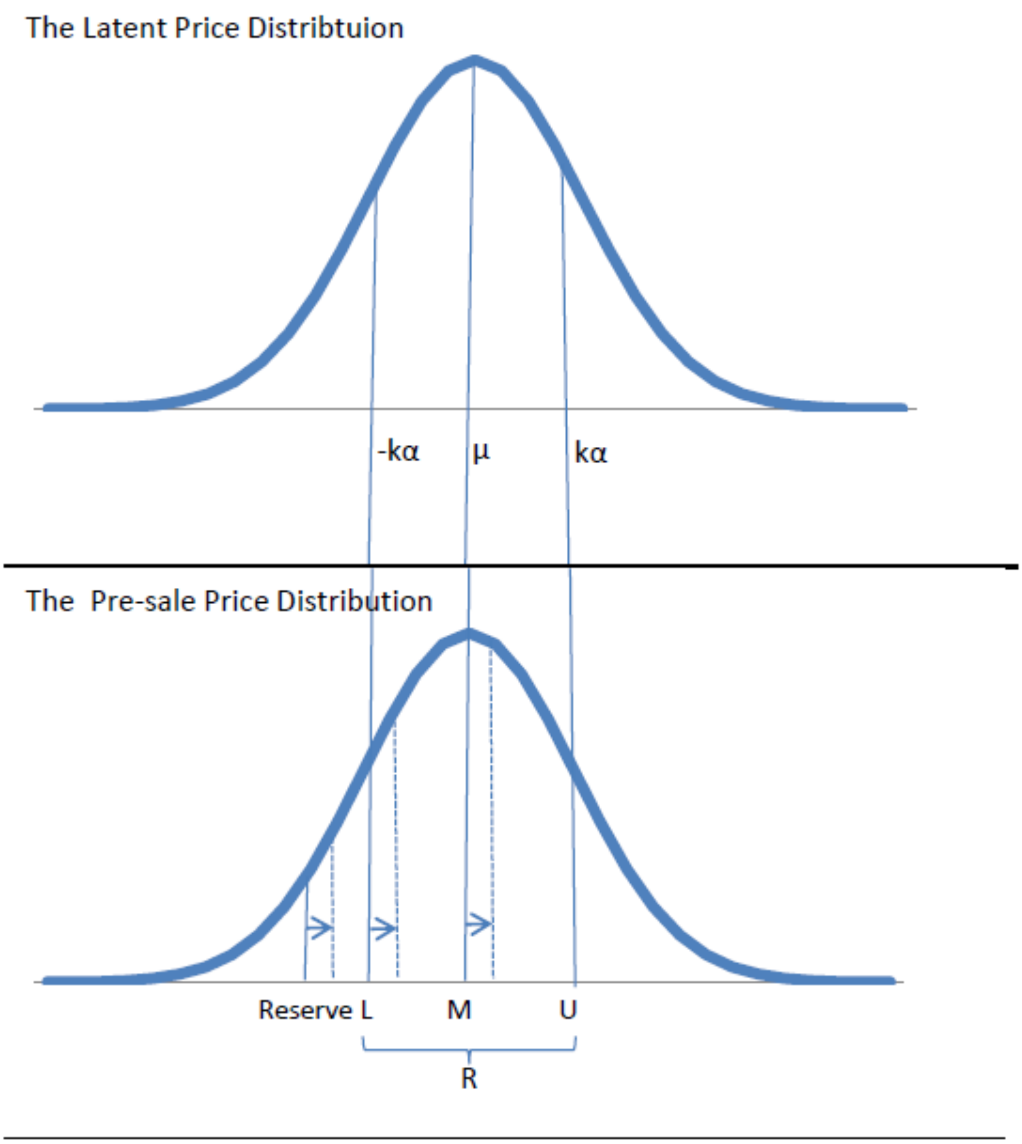
[2] Source: The Australian 9/8/13 http://www.theaustralian.com.au/arts/plunging-sales-crisis-for-indigenous-art/story-e6frg8n6-1226693853034

taken as the midpoint between the lower and upper estimates[3] ($M = (L+U)/2$). Ashenfelter and Graddy (2006) have shown that if we view L and U as lower and upper bounds on the true price μ ($L = \mu - k\sigma$ and $U = \mu + k\sigma$, $k > 0$, where σ is the standard deviation (uncertainty) in the latent price distribution, μ is the centre of that distribution and k is a constant parameter) then M provides a reliable estimate of the sale price. Moreover, in this framework the range $R = U - L$ is an estimate of the degree of uncertainty ($2k\sigma$) in the auction house pre-sale estimate. Thus L and U convey information about both the expected hammer price and the degree of (un)certainty surrounding that estimate.

Ashenfelter, Graddy and Stevens (2002) argue that the ratio of the two pre-sale estimates (the upper and lower bound) may also convey information. In particular, in art auctions the convention is that the seller's reserve price is set to be a proportion – usually 0.8 – of the lower estimate (L) in the catalogue. In situations when the seller requires a higher reserve than this implies, Ashenfelter, Graddy and Stevens (2002) suggest that the value for L will be inflated whilst the value of U will remain unchanged. In such a case the ratio ($S = (U/L)$), termed spread, will be compressed. Thus, the ratio of the two pre-sales estimates may itself convey information to potential buyers concerning the seller's reserve if the ratio on one item is very different to the ratios for other similar items offered for auction. In our modeling we are interested to know what role, if any, the midpoint (M), the range (R) and the spread (S) play in explaining the actual hammer price (P) at auction. These three statistics represent the set of pre-sale price estimate summary measures and the empirical investigation of their importance in determining realized prices is a key innovation here. Figure 1 represents the points of interest on the latent and pre-sale price distributions assuming that M is an accurate predictor of μ. We can see that as the reserve gets closer to L then L must be inflated and the range contracts. Importantly, in the context of prior studies, if this is the case then M also moves rightwards and may no longer be an unbiased predictor of the realized price, μ.

[3] An exception is Bauwens and Ginsburgh (2000) who use L and U separately.

Figure 1: The Latent and Pre-Sale Price Distributions under the assumption that M=μ



A further piece of information that may play a role concerns the degree of concentration of the auction market for Indigenous art prior to the sale. To capture this information we use the Herfindahl index (H) for the market in the previous year as a measure of how competitive the market has been. Buyer's willingness to pay prices above M and especially in the right hand tail of the per-sale latent price distribution (i.e. above U) may be influenced by the degree of competition in the market. In an uncompetitive market buyers may suspect auction house collusion could be pushing up price estimates and they may therefore be more cautious about bidding above M. The Herfindahl is calculated using the sale value of Indigenous works offered for sale by auction house. If the degree of competition in the market is found to influence buyers beliefs about the 'truth' of the pre-sale estimates and hence picks up uncertainty regarding auction house behaviour then the our findings for this variable will be informative in terms of competition policy for art markets.

3. Methodology

Empirical (regression) modeling is used to understand what, if any, role pre-sale information and market concentration play in explaining the hammer price for artworks sold at auction. In our analysis we regress the hammer price (P) of an artwork on pre-sale information from the auction catalogue – midpoint (M), range (R) and spread (S) – and on the Indigenous auction market concentration in the previous year (H) and its squared value (Hsq) included to capture possible nonlinearities.

The traditional ordinary least squares (OLS) regression model is a model for the conditional mean of price (P). Alternative specifications exist that model the conditional quantiles (or percentiles) as depending upon the set of explanatory variables. One example is a median regression that yields least absolute deviation estimates. These alternative specifications can be also used to investigate robustness to the conditional mean parameterization or as an alternative way to investigate the dependence of the conditional distribution on explanatory variables. Thus we estimate the model using both OLS and (simultaneous) quantile regression estimation.[4] We report robust standard errors (for OLS) and bootstrapped standard errors for the quantile regressions.

The model specification for the price of artwork $i = 1, \ldots, n$ is given by[5]:

$$P_i = \beta_0 + \beta_1 M_i + \beta_2 R_i + \beta_3 S_i + \beta_4 H_i + \beta_5 Hsq_i + \beta_6 T_i + u_i \qquad (1)$$

In this framework we can use hypothesis tests on the individual coefficients to determine whether the midpoint, range, spread or Herfindahl (and its squared values) are significant in explaining realised prices. Given that the Indigenous art market is an

[4] Estimation was carried out in Stata 13 using the sqreg command and standard errors were computed using 200 bootstrap replications.
[5] The regression model is estimated separately for each category of artwork.

emergent market it is important to control for the growth of the market over time. We would expect the pre-sale latent price distribution to be platykurtic in small, emerging markets and to be leptokurtic in large, establish markets. Obviously, in a leptokurtic distribution, M will be a better predictor of hammer prices due to the smaller variance. As the market expends there is better knowledge of value and less price uncertainty. It is therefore important to control for market growth in any empirical analysis of a nascent market. For robustness we estimate two specifications of the above equation: one with a linear trend term and another with a log trend term.

The intercept β_0 may be interpreted as the fixed amount by which the hammer price is over or under estimated. If the midpoint (M) is a good estimate of the price then $\beta_1 = 1$. It is possible that M could under or overestimate the true price. Increased uncertainty as measured through larger values for the range variable (R) may also reflect higher risk. The idea of "high risk, high return" would then suggest that the coefficient on R is positive. Alternatively, the auction house and the buyer(s) may have differing levels of knowledge of risk or different risk preference, in which case the sign on R is unknown. Reductions in spread (S) could reflect an increase in seller reserve. As spread falls, the hammer price may increase through the effects of an increased seller's reserve price. Thus we might expect the coefficient on S to be negative. Increased competitiveness in the market for Indigenous art is reflected in a lower value of H and is likely to lower the hammer price, so β_4 would be positive. Hsq is included to pick up possible nonlinearities and so β_5 may be positive or negative. Given the substantial growth in the market over the period being considered we would expect the time trend coefficient β_6 to be positive. If no "higher order" information or market information matters then the coefficients on R, S, H and Hsq are all zero. In this first order information world, a zero intercept and unit slope suggests that the midpoint is the best estimate of the true sale price.

An empirical point to discuss is the degree of exogeneity of the Herfindahl index in the model. It's potential endogeneity has been questioned in the industrial organisation literature where firm performance (defined as the value of sales) is regressed on a number of variables including H, but H is itself determined by firm performance (in value shares). For highly concentrated markets this can be a problem.

In the context of Indigenous art markets we will show that there are a number of auction houses participating in the market and the market is quite competitive over the time period considered in our modelling. However, in order to be mindful of the potential endogeneity issues, we choose to use lag values of H. Specifically, we use H based on the previous year's sales data[6].

4. Data and Descriptive Analysis

Our raw data covers 29,812 artworks by Australian Indigenous artists offered for sale at auction from 1969 to 2011 as recorded by Australian Art Sales Digest (AASD). We are concerned with understanding the role of pre-sale information on the hammer price and thus restrict attention on those artworks that were sold at auction[7]. We begin our descriptive analysis by considering the market concentration in terms of the number of auction houses with sales of Indigenous art. Figure 2 below shows the number of Auction Houses operating in the Indigenous art market during our window of observation. We can see quite clearly that during the early period there were very few auction houses operating in the market (in fact sales were predominantly handled by just two auction houses. It is not until 1987 that we see more that 5 auction houses operating in the market. The number of houses then grows steadily and in the penultimate year of our data there are 26 auction houses offering Indigenous art for sale. Many studies consider sales from the two leading Auction Houses, i.e. Christies and Sotheby's, whilst this may be appropriate in some art markets it is clearly not the case for Indigenous art markets. The market has seen steady expansion since 1987.

[6] It is possible that outliers in terms of very high value works of art might also cause endogeneity when we use a Herfindahl constructed from sales data. Therefore as a robust check the results presented in Tables 5-8 have also been estimated using the Herfindahl index defined over the volume of sales and the results are qualitatively the same.

[7] Ninety eight per cent of all artworks have pre-sale price estimates. The sale rates are 69.3% for objects, 57.8% for paintings and 78.1% for works on paper. It would be interesting to see the power of price uncertainty in determining a no sale for an artwork but with such a low number of unsold items in our data set this research question is not addressed here.

Figure 2: Number of auction houses with sales of Indigenous Art

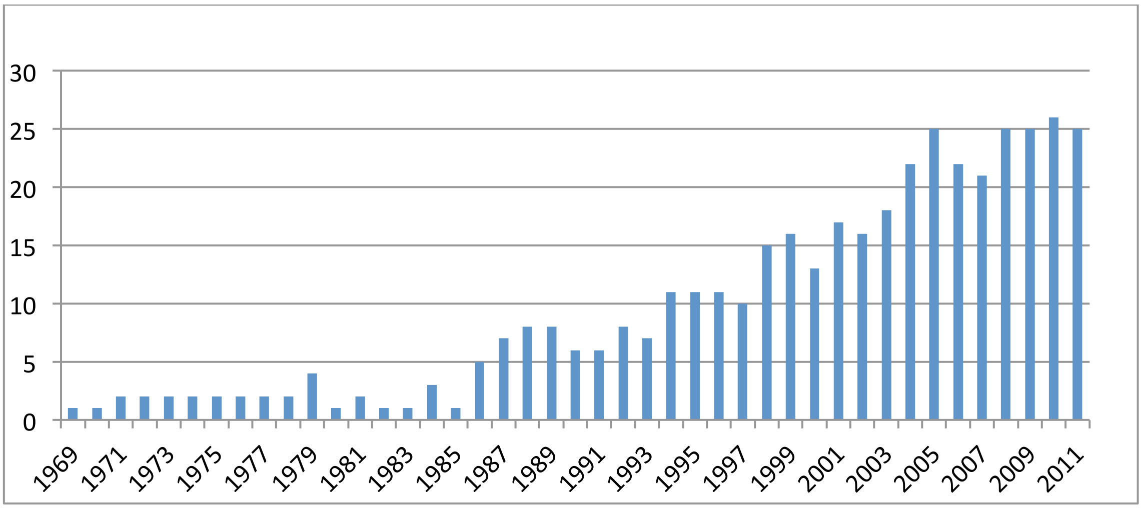
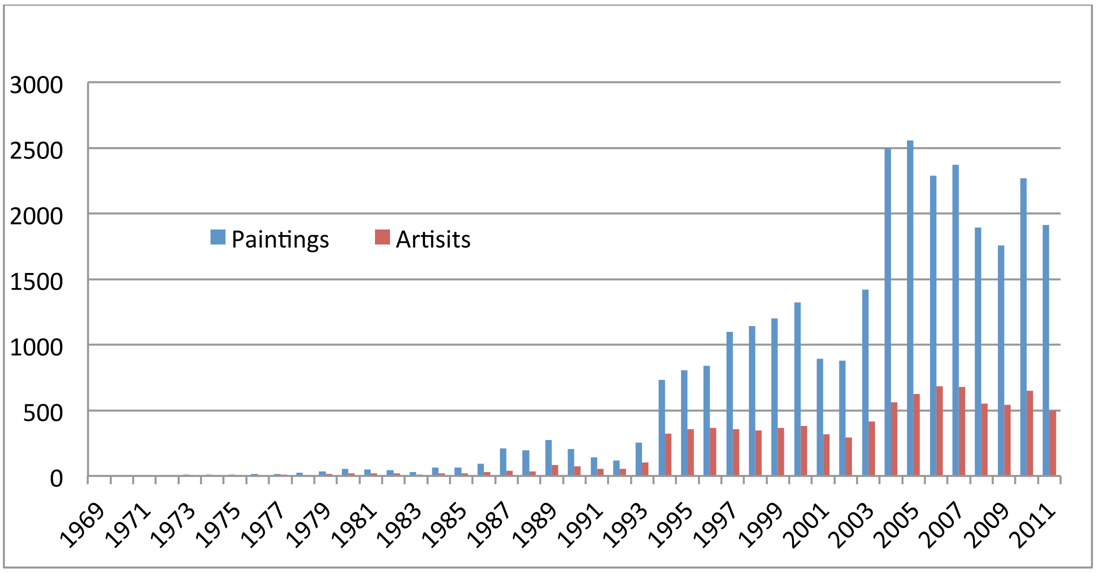


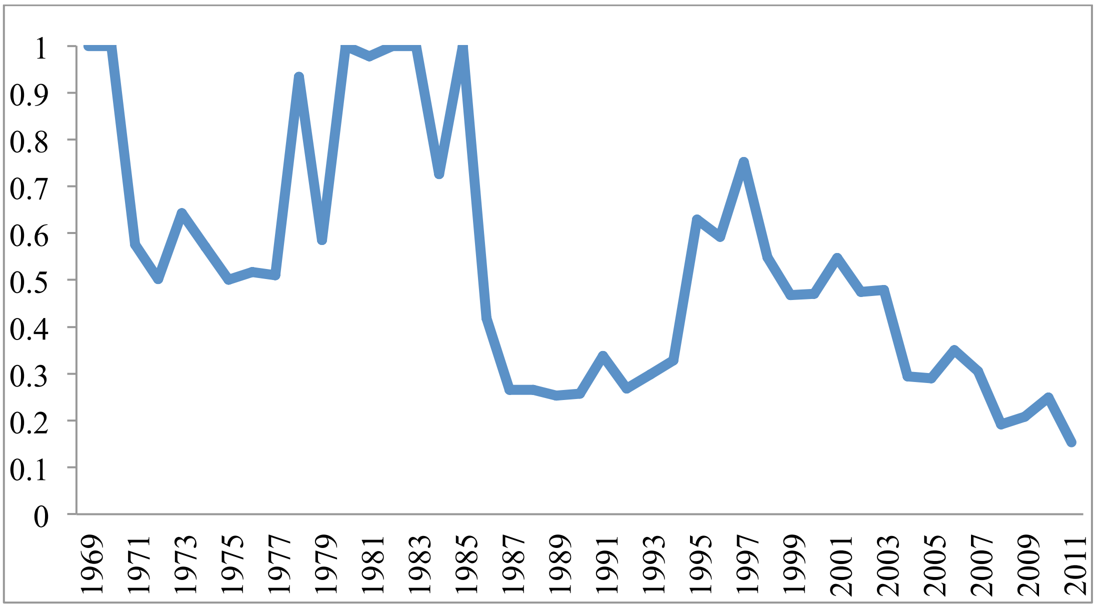
Figure 3 shows the growth in the volume of art sold and number of artists that generated the work. The growth is here is similar to the pattern in Figure 2. It is from 1987 onwards that we see a ratchet upwards in the degree of activity in terms of the volume of paintings offered for sale and the number of artists with works offered for sale via auction.

Figure 3: Number of Indigenous Paintings sold at Auction and number of Artists with work sold



Using the AASD data we derive a sales value Herfindahl index for the market for Indigenous artworks. The index is derived using the value of art sold at auction by each auction house each year. Figure 4 shows the value of the index over time.

Figure 4: Sale value based Herfindahl Index over time



The Herfindahl index shows that since 1987 the market for Indigenous artwork has become much more competitive (we can see there is a structural break in the time series at this point). This is due to a rapid expansion form 1987 onwards in the number of auction houses offering Indigenous artwork for auction. For this reason our estimation samples consider the data from 1987- 2011 only. The number of sales and auction houses in the market prior to 1987 are too few to provide reliable statistical findings. We construct H based on the Indigenous art market as a whole rather than disaggregated by the type of Indigenous art as we want to pick up buyer perceptions of fairness in the market which are most likely to be detected at the aggregate market level. Moreover, small numbers of sales at the naissance of the Indigenous art market means that disaggregation is not sensible in practice with these data, even when we consider only the period 1987 forward. However in order to control for heterogeneity within the class of Indigenous Art we study the market at the aggregate level and disaggregated into three main classes of Indigenous artwork – objects, paintings and works on paper[8]. Collectively these three categories represent 97% of the Indigenous art sold[9].

Table 1: Descriptive Statistics for all artwork, 1987-2011

	Price	Midpoint	Price - Midpoint	Range	Ratio
Mean	7561.61	7916.46	-354.85	2634.39	1.51
Median	2000	2500	-183	100	1.5
Standard deviation	27451.08	27647.86	9031.79	9246.07	0.35
Minimum	15	25	-245000	10	1.04
Maximum	2000000	2150000	385000	700000	15
Skewness	29.12	32.22	9.19	31.60	19.25
Kurtosis	1706.64	2120.04	465.12	1953.81	708.59

Sample size 17675.

Table 2: Descriptive Statistics for objects, 1987-2011

	Price	Midpoint	Price - Midpoint	Range	Ratio
Mean	4831.21	4446.98	384.23	1654.17	1.51
Median	2300	2500	-200	1000	1.5
Standard deviation	10132.21	8625.79	3761.84	2912.45	0.23
Minimum	30	40	-15000	20	1.09
Maximum	190000	175000	40000	50000	3
Skewness	10.15	11.69	4.05	8.74	1.78
Kurtosis	160.22	210.11	32.63	120.02	10.20

Sample size 757.

Table 3: Descriptive Statistics for paintings, 1987-2011

	Price	Midpoint	Price – Midpoint	Range	Ratio
Mean	9791.46	10380.58	-589.12	3450.43	1.50
Median	3000	3500	-450	1500	1.5
Standard deviation	33047.93	33287.09	10931.62	11122.58	0.37
Minimum	20	25	-245000	10	1.04
Maximum	2000000	2150000	385000	700000	15
Skewness	25.07	27.73	7.91	27.25	23.71
Kurtosis	1226.16	1522.92	329.43	1407.59	838.40

Sample size 11,614.

[8] The "text fields" in our database reveal that almost all Works on Paper are actually (watercolour) paintings.

[9] The remaining works are categorised as photographs, and prints and graphics. These groups have insufficient volume of works sold at auction to offer any statistically robust estimation results.

Table 4: Descriptive Statistics for works on paper, 1987-2011

	Price	Midpoint	Price – Midpoint	Range	Ratio
Mean	2784.01	2676.43	107.58	863.93	1.55
Median	475	500	-50	200	1.5
Standard deviation	6510.68	5870.703	2234.72	1944.40	0.31
Minimum	15	30	-15625	10	1.05
Maximum	120000	70000	50000	30000	4
Skewness	5.02	4.06	6.38	5.36	2.01
Kurtosis	46.41	25.85	101.58	48.02	9.69

Sample size 4,503.

For each type of artwork, all variables in the data are highly variable, positively skewed and heavy tailed. We also see that on average the hammer price and midpoint are different, with the hammer price exceeding midpoint for objects and works on paper but midpoint exceeding the hammer price for all artworks and paintings. One variable that is remarkably similar across all classes is the spread (or ratio) variable. The average in all classes is close to 1.5 suggesting that the upper bound (U) is, on average, some 50% higher than the lower bound (L). However, there is a wide range of values for the ratio suggesting that there is some movement away from the 50% mark up in practice.

If the midpoint is a good estimate of the hammer price then the difference between them should appear random and centred around zero. Histograms for the all artworks and the three classes of art show that the distribution of the price difference is unimodal but positively skewed, which results from a few works — particularly in the category of paintings — having hammer prices much larger than their midpoint (Figures 5 – 8).

Figure 5

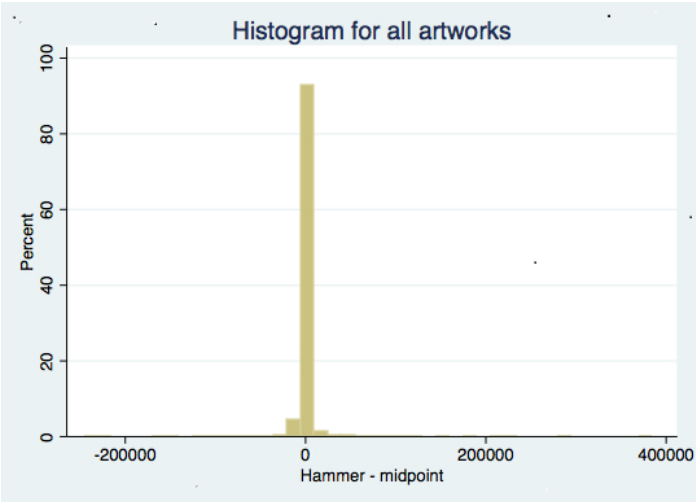


Figure 6

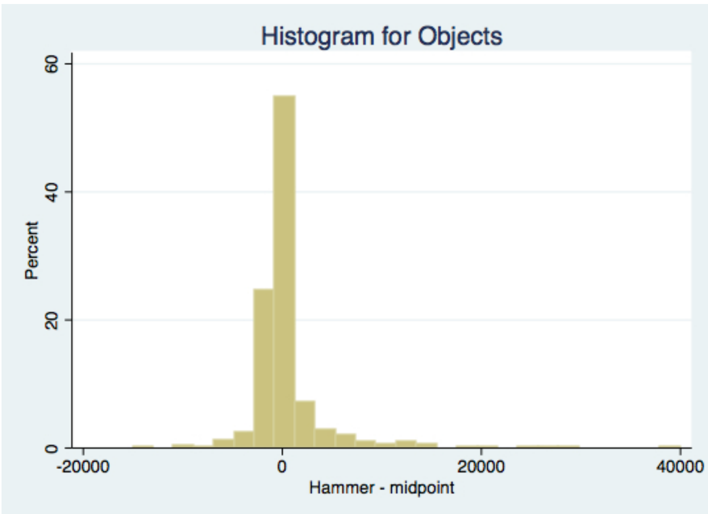


Figure 7

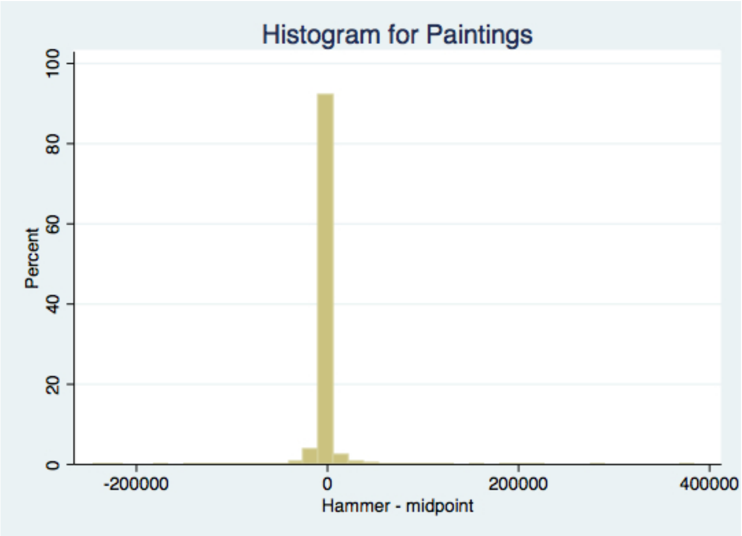
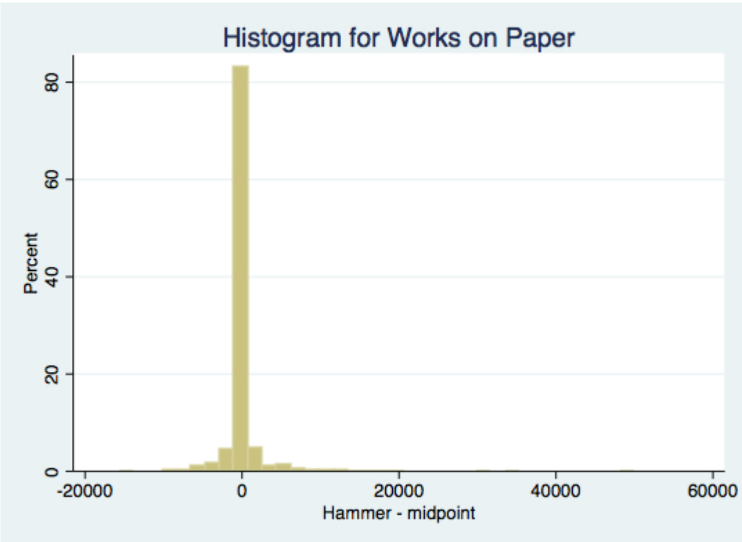


Figure 8



Finally, in order to explore our assumption that the Herfindahl Index is not endogenous in our modelling Table 3 below shows the correlation coefficients for the data in our estimation samples between the dependant variables and the Herfindahl. We see clearly that according to these statistics the hypothesis that the lagged Herfindahl is not endogenous to hammer prices is supported.

Table 3: Bivariate correlation matrix for the Herfindahl index.

	Hammer Price			
	All	Objects	Paintings	Works on paper
Herfindahl	-0.02	0.02	-0.02	-0.03
Herfindahl squared	-0.02	0.06	-0.02	-0.03

5. Results and Discussion

We begin by considering the results for Indigenous art at the market level (Table 5) to highlight the difference between OLS regression and simultaneous percentile regression. The OLS results with a linear trend term suggest that the midpoint is a significant and fair predictor of realised prices (the constants are zero and the hypothesis that the coefficient on the midpoint is one is supported). However when we switch to a log trend term the hypothesis is no longer supported. In both specifications the R^2 term is 0.9 so model fit will not help us in determining a preferred specification. Therefore our OLS results are mixed and not robust to the functional form chosen for the time trend. The conditional percentile regressions reveal a different story: the hypothesis of fair pre-sale estimates is never supported. Although the midpoint is a significant predictor of hammer prices and in most cases is not significantly different from 1 the constant term is significant and non-zero in the log trend specification and the range, spread and Herfindahl have significance at various points in the distribution. We see evidence that the range and spread are important determinants of realised prices at differing points in the market but they are never significant in the bottom 10% and 25%. Market concentration shows a pattern of importance in the lower half of the distribution but not in the upper half. Market concentration and its square are significant in the 10th and 25th percentiles for the log trend specification only. Finally, we see improved model fit as we move up the percentiles. The comparison of the modelling strategies highlights that different information has importance in determining outcomes at different points in the price realised distribution. This is perhaps not surprising as risk variers across the price spectrum.

We now turn to the results of our regression modelling for the separate categories of art (Tables 6 – 8). Turning first to the OLS results, across all three classes of artworks we see strong evidence that the midpoint matters. In all three cases (i.e. objects, paintings and works on paper) the coefficient on the midpoint is significant and the hypothesis that it equals one is accepted. In all OLS models the range and spread are never statistically significant. This suggests that only the midpoint (M) obtained from the catalogue upper and lower price estimates explains the hammer price and that it is a good estimator of the price. We also see that the Herfindahl index and its square, reflecting the competitiveness of the market, is significant (increasing at a decreasing rate) for objects only. Thus, an increase in competition, in the Indigenous art auction market, lowers the hammer price for objects: as would be predicted by economic theory. Interestingly objects are the category of Indigenous art which comes to the market less frequently (as evidenced by the relative sample sizes). Objects also tend to be more heterogeneous in nature than paintings and works on paper, which combined with their infrequency of sale, implies higher levels of uncertainty.

Table 5: Regression Results for Indigenous Art: Herfindahl defined over values of sales, 1987-2011

Indigenous Art	OLS		Spec 1: Percentile*					Spec 2: Percentile				
	Spec 1	Spec 2	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
Constant	2332.78	**5085.70**	190.68	100.15	59.09	**240.22**	280.07	**756.25**	**559.30**	**350.98**	**569.17**	**660.16**
t-stat	1.87	3.22	1.18	1.62	1.41	3.27	1.48	2.84	5.02	5.14	5.07	1.99
Midpoint	**0.89**	**0.89**	**0.67**	**0.75**	**0.89**	**0.84**	**1.05**	**0.67**	**0.75**	**0.89**	**0.84**	**1.05**
t-stat	10.76	10.76	17.26	30.64	33.47	24.01	10.36	20.04	34.28	37.34	24.07	10.03
Range	0.17	0.17	-0.07	-0.03	**-0.18**	**0.63**	**1.11**	-0.74	-0.02	**-0.18**	**0.63**	**1.09**
t-stat	0.67	0.67	-0.60	-0.36	-2.40	5.10	3.87	-0.68	-0.39	-2.50	5.27	3.69
Spread	-998.39	-997.71	-103.70	-63.47	3.72	**-114.26**	**-129.07**	-104.57	-62.85	2.91	**-114.95**	-122.47
t-stat	-1.64	-1.64	-1.06	-1.78	0.19	-4.46	-2.02	-1.14	-1.83	0.17	-4.80	-1.89
Herfindahl	900.82	1318.32	**505.77**	**547.56**	159.22	353.54	95.27	**590.38**	**624.43**	181.28	412.14	441.07
t-stat	0.36	0.53	2.65	4.59	1.46	1.53	0.14	3.19	4.52	1.44	1.58	0.12
Herfindahl Squared	1936.98	1622.78	-3.47.87	**-400.72**	-52.91	-1574.18	499.18	**-413.91**	**-467.61**	-72.36	-216.49	441.07
t-stat	0.71	0.60	-1.81	-3.41	-0.44	-0.58	0.53	-2.22	-3.32	-0.51	-0.68	0.28
Trend	**-39.66**		**-7.99**	**-6.28**	**-3.53**	**-4.08**	**-3.69**					
t-stat	-4.13		-4.01	-5.79	-5.92	-6.09	-2.34					
Ln Trend		**-1200.24**						**-244.06**	**-197.31**	**-118.61**	**-136.33**	**-149.71**
t-stat		**-4.14**						3.95	-6.37	-6.14	-6.36	-2.66
R^2	0.90	0.90	0.55	0.64	0.71	0.76	0.81	0.55	0.64	0.71	0.76	0.81

Sample size 17403

Table 6: Regression Results for Objects: Herfindahl defined over values of sales, 1987-2011

OBJECTS	OLS		Spec 1: Percentile					Spec 2: Percentile				
	Spec 1	Spec 2	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
Constant	-1509.23	-2162.93	-643.51	-188.39	-125.29	-806.73	-2344.27	-910.69	-45.68	-247.89	-1743.64	-4880.82
t-stat	-0.83	-0.66	-1.25	-0.39	-0.27	-1.18	-1.38	-0.78	-0.06	-0.42	-1.28	-1.45
Midpoint	**0.87**	**0.87**	**0.79**	**0.84**	**0.98**	**0.89**	**1.03**	**0.79**	**0.84**	**0. 98**	**0.89**	**1.03**
t-stat	3.99	3.99	11.44	8.81	5.26	4.16	2.81	11.17	9.47	5.20	4.36	2.79
Range	0.69	0.69	**-0.34**	-0.23	-0.39	1.04	1.67	**-0.34**	-0.23	-0.39	1.04	1.67
t-stat	0.96	0.96	-2.20	-0.97	-0.90	1.60	1.43	-1.97	-0.97	-0.84	1.68	1.45
Spread	-692.75	-691.05	43.35	12.99	-4.96	-142.01	-387.56	40.79	13.18	-5.56	-143.80	-411.64
t-stat	-1.02	-1.02	0.29	0.06	-0.02	-0.53	-0.87	0.21	0.06	-0.02	-0.45	-0.89
Herfindahl	**9431.24**	**9387.36**	1005.60	342.23	**-33.02**	2504.80	9277.75	983.69	358.45	-36.94	2475.162	8799.79
t-stat	2.35	2.39	0.88	0.34	-4.96	1.05	1.64	0.94	0.36	-0.03	0.95	1.60
Herfindahl Squared	**-8965.58**	**-8921.50**	-414.40	-48.85	640.55	-2376.71	-9394.68	-398.10	-62.30	642.70	-2358.85	-9038.981
t-stat	-2.12	-2.14	-0.33	-0.04	0.45	-0.85	-1.34	-0.34	-0.06	0.42	-0.76	-1.31
Trend	7.44		3.34	-1.82	1.65	13.37	37.54					
t-stat	0.35		0.37	-0.33	0.36	1.52	1.79					
Ln Trend		259.83						111.40	-59.45	51.34	397.74	1135.153
t-stat		0.39						0.37	-0.32	0.36	1.23	1.49
R^2	0.87	0.87	0.48	0.54	0.57	0.63	0.70	0.48	0.54	0.57	0.63	0.70

Sample size 757

Table 7: Regression Results for Paintings: Herfindahl defined over values of sales, 1987-2011

PAINTINGS	OLS		Spec 1: Percentile					Spec 2: Percentile				
	Spec 1	Spec 2	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
Constant	2922.301	**6456.92**	**696.91**	**580.27**	66.96	170.75	344.87	**1653.49**	**1241.18**	456.50	454.97	612.40
t-stat	1.80	2.79	2.55	3.57	0.03	0.28	1.13	3.64	5.82	1.41	0.02	0.07
Midpoint	**0.88**	**0.88**	**0.65**	**0.72**	**0.87**	**0.84**	**0.97**	**0.64**	**0.72**	**0.87**	**0.84**	**0.97**
t-stat	10.35	10.35	13.98	29.28	9.54	24.21	7.68	14.91	31.66	37.49	25.01	3.67
Range	0.18	0.18	0.01	0.07	-0.04	**0.56**	**1.19**	0.02	0.07	-0.14	**0.56**	1.19
t-stat	0.70	0.70	0.07	0.97	-0.50	4.19	3.62	0.13	1.06	-1.94	4.24	1.77
Spread	-1248.56	-1248.45	**-309.54**	**-330.05**	-3.51	-104.37	-157.96	**-317.35**	**-333.59**	-3.45	-102.49	-154.42
t-stat	-1.57	-1.57	-2.00	-3.39	-0.01	-0.70	-1.29	-2.14	-4.02	-0.03	-0.50	-0.60
Herfindahl	443.45	972.81	110.81	154.40	80.54	-48.79	-1056.21	238.61	227.68	134.01	-56.51	-1113.43
t-stat	0.12	0.28	0.27	0.75	0.01	-0.02	-0.79	0.56	1.09	0.10	-0.09	-0.10
Herfindahl Squared	3520.36	3119.21	209.01	225.06	205.52	789.03	2700.13	118.31	172.80	**160.92**	790.79	2764.35
t-stat	0.90	0.80	0.48	1.05	0.02	0.33	1.58	0.27	0.81	-2.93	0.92	0.20
Trend	**-50.67**		**-14.48**	**-9.11**	-4.96	-2.81	-1.49					
t-stat	-3.04		-4.50	-4.92	-0.17	-0.29	-0.39					
Ln Trend		**-1537.46**						**-419.65**	**-280.46**	456.50	-108.05	-85.91
t-stat		-2.98						-4.02	-4.93	1.41	-0.21	-0.05
R^2	0.90	0.09	0.55	0.64	0.70	0.75	0.81	0.55	0.64	0.70	0.75	0.81

Sample size 11614

Table 8: Regression Results for Works on Paper: Herfindahl defined over values of sales, 1987-2011

Works on Paper	OLS		Spec 1: Percentile					Spec 2: Percentile				
	Spec 1	Spec 2	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
Constant	586.09	1433.68	-112.85	-34.34	-17.55	-33.61	-79.76	15.64	111.14	120.54	66.05	143.77
t-stat	1.36	1.75	-1.90	-.089	-0.35	-0.40	-0.56	0.17	1.96	1.48	0.54	0.56
Midpoint	**1.01**	**1.01**	**0.76**	**0.90**	**0.99**	**1.12**	**1.31**	**0.76**	**0.89**	**0.99**	**1.12**	**1.03**
t-stat	12.36	12.33	26.78	36.60	24.04	14.40	10.92	26.01	36.21	24.25	13.02	10.83
Range	0.12	0.12	-0.13	**-0.29**	-027	0.27	**0.74**	-0.13	**-0.28**	-0.27	0.27	**0.74**
t-stat	0.43	0.43	-1.53	-4.78	-1.93	1.16	2.19	-1.53	-4.82	-1.96	1.06	2.08
Spread	-51.79	-51.82	18.55	20.87	31.55	-4.19	-38.80	17.18	19.46	31.17	-4.95	-38.43
t-stat	-0.39	-0.39	1.25	1.46	1.53	-0.13	-0.86	1.13	1.39	1.68	-0.13	-0.82
Herfindahl	-1119.51	-1001.19	292.53	166.10	116.93	**395.89**	**1169.20**	310.89	**189.9**	123.07	**412.01**	**1160.55**
t-stat	0.81	-0.73	1.61	1.68	0.98	2.09	3.62	1.88	1.98	1.05	2.01	3.84
Herfindahl Squared	1837.03	1748.38	-242.96	-163.86	-142.00	**-454.11**	**-1302.88**	-258.47	-184.17	-147.18	**-465.55**	**-1292.45**
t-stat	1.17	1.11	-1.30	-1.57	-1.11	-2.29	-3.82	-1.55	-1.78	-1.15	-2.11	-4.07
Trend	-11.74		**-1.72**	**-1.90**	**-1.56**	-1.32	-2.03					
t-stat	-1.92		-2.05	-3.79	-2.66	-1.55	-1.01					
Ln Trend		-364.29						**-53.80**	**-60.75**	**-54.81**	-42.12	-82.52
t-stat		-1.19						-2.02	-4.14	-2.19	-1.64	-1.35
R^2	0.88	0.88	0.56	0.64	0.71	0.79	0.85	0.56	0.64	0.71	0.79	0.85

Sample size 4503

Next we consider the results of the least quantile regression for each type of Indigenous art. Looking firstly at objects we see that the midpoint remains a significant predictor of hammer prices at all points across the conditional percentiles. Further, the constant term is never significant. There is evidence of the range having an influence at the bottom (10%) of the realised price distribution, consistent with the idea that uncertainty will play a bigger very bottom of the price distribution where artwork is typically characterised as low value- low return items. In terms of market concentration we see support only at the 50^{th} percentile in the linear trend specification and no statistical significance for the Hsq term. In summary, the results for objects sold at auction suggest that it is the midpoint that drives auction outcomes. But there is some evidence to suggest the range may be important at the lower tail of the realised price distribution. Finally, it is worth noting, the fit of the model improves as we move up the conditional percentiles.

Turning next to the results for paintings we see a very different story to that revealed by objects. Firstly, there is evidence of non-zero constants at the lower end of the market. Secondly, we see the same pattern of significance and importance of the midpoint in price determination. Thirdly, we see the range playing a role in price determination at the high end of the market (the 75% and 90%), suggesting that buyers consider information about the degree of price uncertainty when bidding for more expensive paintings. Interestingly, the coefficient is positive suggesting risk preferring buyers at this end of the realised price distribution. Fourthly, there is consistent evidence across the specifications of the spread having impact at the 10^{th} and 25^{th} percentile. The spread offers evidence of potential reserve inflation and reflects more considered buyer behaviour at the lower end of the price spectrum. The bottom of the market is characterised by low risk and low return, so any reserve price inflation may erode the profitability of the purchase. In terms of market concentration, we see that both the Herfindahl and the Herfindahl squared are never significant (except for the 50% in the log trend specification). Given the volume of paintings offered for sale we would not expect market concentration to be influential as there is less uncertainty in the market. Again the fit of the model improves as we move up the conditional percentiles.

The picture illustrated by looking at the results works on paper is similar to that of paintings but there are some important differences. Firstly, the midpoint is always significant but the test of the coefficient being equal to 1 is not always upheld. The range holds information for buyers at the 25%, 50% and 90% suggesting that there is price uncertainty in this market. Given the heterogeneous nature of this category of art the result is not surprising. The range also changes sign from negative to positive across the percentiles. One potential explanation for this may be that at the lower percentiles of the conditional distribution buyers are risk averse but at the higher conditional percentiles high risk is associated with high return (and price). We also see evidence of a role for market concentration in determining prices for this type of Indigenous art. Both the Herfindahl and its square are significant from the 75th percentile upwards. In terms of model fit we again see that the R-squared improves as we move up the conditional percentiles.

It is worth noting the overall patterns in the trend variables. Their significance seems to be specific to the type of art under consideration: insignificant in the case of objects, some significance for both trend and log trend in the case of paintings (at the low end of the price distribution and significant at all points in the price distribution in the case of works on paper (for both specifications)). Differential trend patterns reflect the trends in popularity of different types in Indigenous art. For example many collectors saw bark paintings (categorised here as objects) as tourist art but recently it has grown in popularity[10]. Further the significance of the trend terms and independent identification of the Herfindahl at various points in the market shows that the Herfindahl index is not simply picking up market growth. This point is further supported by examination of the correlation coefficient between the Herfindahl and linear trend in the aggregate raw data, which is -0.73 and -0.79 between in the Herfindahl and the log trend[11]. Importantly, the results show that with these data it is possible the separately identify the impact of market concentration and market growth: both at the aggregate and disaggregate levels of the market for Indigenous art.

[10] In 2013 the auction house Bonhams sold the Clive Evatt collection of 320 bark paintings with a 96% sold by lot success rate.

[11] The correlation coefficients, by category of art, range from -0.73 (for objects with a log trend) to -0.84 (for works on paper with a log trend).

As a final discussion point it is worth noting that the patterns across the classes of art in the disaggregated data set are different to those shown at the aggregate market level. This has important implications for policy. It is clear that not all art markets are the same. Even within a narrowly defined class of art such as Indigenous art we significant differences in the drivers of price determination when we examine different categories of art and different points in the realised price distribution. Different markets have different levels of price uncertainty associated with them and price uncertainty varies across the price distribution. These findings are perhaps not surprising when are consider different markets attract different buyers and not all buyers operate at all points in the price spectrum. Further auction houses differ in terms of the markets they operate in and their dominance in the market place changes across the price distribution also.

6. Conclusions

This paper has investigated the role that pre-sale information, and auction house market concentration, play in determining the hammer price for Indigenous art as a single market and as three classes of Indigenous artworks (objects, paintings and works on paper). The auction catalogue contains two important pieces of information – a lower and an upper estimate of the hammer price. These pieces of information can be combined to form a single price estimate (the midpoint, M), an estimate of uncertainty in the estimation of price (the range, R) and the spread of estimates (the ratio or spread, S). The results suggest that the midpoint is significant in explaining price. Further we find evidence that both the range and the spread offer information to buyers in the more uncertain segments of the market, typically at the lower or the upper end of the price distribution. We also investigate the potential role of market concentration of the Indigenous art auction market as a whole. While we find evidence that concentration matters in the aggregate market at the top end of the price distribution, the disaggregate market data tells us that it only matters in the case of works on paper at the high end of the price distribution. The median regression results show us that buyer behaviour is not the same at all points in the realised price distribution and OLS estimation can be misleading. Through disaggregation in terms of the category of art and across the price distribution, we find evidence that a wider set of measures derived from the auction house price estimates matter in determining realised prices than just the midpoint of the estimate range. Further, we find that market concentration also matters and the results are consistent with economic theory that more competition leads to lower prices.

References

Ashenfelter, O. (1989) "How auctions work for wine and art" *Journal of Economic Perspectives*, Volume 3, 13-25.

Abowd, J. and Ashenfelter, O. (1989). "Art Auctions: Price Indices and Sale Rates for Impressionist and Contemporary Pictures" Working paper, Mimeo, Princeton University November 1989

Ashenfelter, O., Graddy, K., (2006). "Art Auctions", in: Ginsburgh, V., Thorsby, D. (Eds.), *Handbook of the Economics of Art and Culture*, Vol 1. Elsevier B.V., Amsterdam, 909–945.

Ashenfelter, O., Graddy, K., Stevens, M. (2002). "A study of sale rates and prices in impressionist and contemporary art auctions". Unpublished manuscript.

Australian Art Sales Digest, http://www.aasd.com.au/

Bauwens, L., Ginsburgh, V., (2000). "Art Experts and Auctions: Are pre-sale estimates unbiased and fully informative?" *Recherches Economiques de Louvain*, Vol 66(2), 131–144.

Cockington, J. "The 'Picasso if Arnhem Land' defies expectations" The Age as accessed at http://www.theage.com.au/money/investing/the-picasso-of-arnhem-land-defies-expectations-20140522-zrihw.html on 29/5/14

Czujack, C. and Martins, M.F. (2004). "Do Art Specialists Form Unbiased Pre-sale Estimates? An Application for Picasso Paintings" Applied Economics Letters. Vol 11(4) P 245-49

Ekelund, R.B, Jr. Ressler, R.W. and Watson, J.K. (1998) "Estimates Bias and "No Sales" in Latin-American Art Auctions 1977-1996" Journal of Cultural Economics, Vol 22(1) p 33-42.

Sprole, R. and Valsan, C., (2006). "Hedonic Models and Pre-Auction Estimates: Abstract Art Revisited" *Economics Bulletin,* Vol. 26(5), 1-10.