Heterogeneity in auction price distributions for Australian Indigenous artists

Tim R.L. Fry

School of Economics, Finance & Marketing

RMIT University

Abstract: Studies of auction prices for artworks typically relate the conditional moments of a single realised price distribution with either characteristics of the artist, the artwork and the auction or with pre-sale information. Using data from the Australian Art Sales Digest for the one hundred top selling Australian Indigenous artists over the period 1987 to 2014 we look at two alternative ways to understand heterogeneity in auction prices. First, we model the determinants of an index of price heterogeneity at the artist level, and second, we use finite mixture models to model the hammer prices for artworks as a combination of realised price distributions. Our results complement the existing literature by identifying new ways in which factors used in the literature may be related to price heterogeneity.

Keywords: auction prices, heterogeneity, Gini index, Beta regression, finite mixture models.

JEL Classification: Z11

Address for correspondence: School of Economics, Finance & Marketing, RMIT University, GPO Box 2476, Melbourne, Victoria 3001, Australia.
Email: tim.fry@rmit.edu.au

This paper refers to deceased Indigenous artists by name. May their spirits find rest and peace as part of their lands, waters, spirits and all living things. I would like to thank the Australian Art Sales Digest for supplying the data used in this paper and note that responsibility for the information and views set out in this paper lies entirely with the author.

Studies of auction prices for artworks typically employ regression models that associate the hammer price with either characteristics of the artist, the artwork and the auction (Forster and Higgs, 2018; Fedderke and Li, 2019; Hawkins and Saini, 2016; Hodgson and Hellmanzik, 2019; Ursprung and Wiermann, 2011) or with pre-sale information (Bauwens and Ginsburg, 2000; Czujack and Martins, 2004; Ekelund, Jackson and Tollison, 2013; Farrell, Fry and Fry, 2018). Such an approach relates the conditional moments of a single realised price distribution to these other factors. Recent work has shown either that the relationship may vary over the conditional quantiles of this single price distribution (Farrell and Fry, 2017) or that the assumption of a single price distribution may not be valid and that a mixture of two or more price distributions is required (Prieto-Rodriguez and Vecco, 2018).

Heterogeneity across artists has received less attention but is consistent with the finding for Australian Indigenous artists (Farrell, Fry and Fry, 2018) that individual artists are significantly different. Thus, an alternative way to capture price heterogeneity is to consider the artist not the artworks as the level of observation (Castellani, Pattitoni and Scorcu, 2012). Such an approach takes a measure of price heterogeneity at the artist level and seeks to relate this to characteristics of the artist, their work and the market.

In this paper, we use data from the Australian Art Sales Digest for the one hundred top selling Australian Indigenous artists over the period 1987 to 2014 to look at two alternative ways to understand heterogeneity in auction prices. First, we model the determinants of price heterogeneity at the artist level, and second, we use finite mixture models to model the hammer prices for artworks as a combination of realised price distributions.

I MODELLING FRAMEWORK

Analysis of price heterogeneity at the artist level is rarely undertaken (Castellani, Pattitoni and Scorcu, 2012), yet understanding how artist characteristics and other factors influence variability in prices over artists is a valuable complement to the more traditional analysis conducted over artworks. Our analysis will take a summary measure of heterogeneity for the hammer prices of artworks by an artist, the Gini index, and relate the Gini index to the characteristics of the artist and their work. The Gini index is particularly useful as it ranges from zero for a homogenous price distribution to one as the degree of heterogeneity in the distribution increases. The Gini index, G, is bounded to the unit interval. Thus, any statistical model to relate the observed Gini index to explanatory factors needs to ensure this boundedness. We choose to use a regression model with the Beta distribution (Ferrari and Cribari-Neto, 2004; Smithson and Verjuilen, 2006). The Beta distribution is characterised by a location parameter μ and a scaling parameter ϕ. This gives $E(G) = \mu$ and $Var(G) = \mu(1-\mu)/(1+\phi)$. The resultant model is a member of the class of generalized linear models and can be estimated by maximum likelihood. In our application we use two link functions to allow the Beta distribution to both bound to the unit interval and to depend upon explanatory variables. In particular, a mean function $\ln\,[\mu_i/(1-\mu_i)] = \boldsymbol{x}_i'\boldsymbol{\beta}$ and a scale function $\ln(\phi_i) = \boldsymbol{w}_i'\boldsymbol{\delta}$.

Consistent with the model in Leifer and White (2004) for markets with differentiated products, artists share a common context of costs and buyer valuations that shapes both the way that their market will function and shape the inequality in their outcomes (price heterogeneity. Thus, the Gini index will be related to both demand factors (e.g. buyer preferences) and supply factors (e.g. quality differentiation). Such factors are typically unobservable (Castellani, Pattitoni and Scorcu, 2012). However, there are a number of observable factors that may act as proxies for the unobservable determinants and thus be related to the Gini index. The number of artworks sold by an artist and the number of auction houses selling an artist's work measure both supply and demand for the artist and the average price of works sold represents quality of the artworks. Specialisation or diversity in an artist's work is captured by the number of categories (paintings, works on paper, photographs, prints and graphics, and objects) that (s)he works in. A final artist characteristic of interest is the region to which the artist belongs (North, Kimberley, Desert). This is an important variable in the context of Australian Indigenous art as different regions are known for different types of art and those represent particular niches in the differentiated market that will have different levels of price heterogeneity.

Our second analysis looks at understanding variability in the hammer prices for the individual artworks themselves. Understanding price heterogeneity in this way is common in the literature. The typical approach taken is to model data for the hammer price using either hedonic regression models, relating the hammer price to observed characteristics of the artwork, the artists and the auction, or with regression models that relate the hammer price to pre-sale information. Occasionally such models use quantile techniques (Farrell and Fry, 2017) or correct for sample selectivity (Ekelund, Jackson and Tollison, 2013; Farrell, Fry and Fry, 2018), the latter as not all artworks offered for sale are sold. However, these approaches assume that variability in the sample of data for hammer prices (heterogeneity) can be explained using a single distribution (typically Normal or Log-Normal) and an associated regression model. Recent work using art auction data (Prieto-Rodriguez and Vecco, 2018) has suggested that this may not be appropriate. Thus, in our analysis of hammer prices we will use a finite mixture model (Deb and Trivedi, 1997; McLachlan and Peel, 2000; Prieto-Rodriguez and Vecco, 2018). In a finite mixture model (fmm) the observed data on hammer prices are assumed to come from *k* distinct components (or classes) and each individual component can be modelled with an appropriate distribution and associated regression model. The finite mixture model is a probabilistic model that combines the *k* distributions and also jointly models the probability that observations belong to a component.

In our application we use a mixture of three Log-Normal distributions for the hammer prices with the component probabilities modelled using a multinomial Logistic form. Our specification of the regression equations for the hammer price is guided by previous work with Australian Indigenous artworks (Farrell and Fry, 2017; Farrell, Fry and Fry. 2018) and relates the hammer price to pre-sale information on the artwork itself and the prior market for Indigenous artworks and a control for time effects. In particular, we use the pre-sale price estimate (= (Low Estimate + High Estimate)/2) typically used in the literature (Ashenfelter and Graddy, 2006), the value of the Herfindahl index for the market in the previous year and a time trend. We also model the component probabilities as a function of artist characteristics (gender, living status and region) and controls for auction house.

II DATA AND RESULTS

Our data is taken from the Australian Art Sales Digest (AASD) for the one hundred top selling Australian Indigenous artists over the period 1987 to 2014. This is transactions-based data containing data for all artworks by Australian Indigenous artists offered for sale by Australian auction houses. We choose to focus on the artworks sold by the top 100 artists (who constitute 84.4% of the total sales value in the period – see Table A1 in the Appendix for artist details) to concentrate on works of significance as defined by buyers in the market. Additionally, we focus sales from 1987 as prior to then the market for Australian Indigenous artworks was very thinly traded (Farrell and Fry, 2017).

We begin by looking at the data on our selected artists. The Gini index is computed from data on the hammer prices for works sold by each of our artists over the sample period. Table 1 contains the descriptive statistics for our one hundred artists.

Table 1: Descriptive statistics for artists

	Mean	Standard Deviation	Minimum	Maximum
Gini index	0.540	0.100	0.263	0.788
Average Price (in $10,000s)	1.528	1.417	0.064	7.284
Number Sold	89.490	105.371	4	762
Number of auction houses	1.990	2.294	1	18
Number of categories	2.430	1.066	1	5
Female (*Yes*)	0.260	0.441	0	1
Indigenous language region				
North	0.110	0.314	0	1
Kimberley	0.120	0.327	0	1
Desert	0.580	0.496	0	1
Other	0.190	0.394	0	1
Living status of the artist				
Living	0.320	0.466	0	1
Died before 1987	0.190	0.394	0	1
Died between 1987 and 2014	0.490	0.500	0	1

The distribution of the Gini index values across our artists ranges from 0.263 to 0.788. Twenty-six artists are female, thirty-two are living during our sample period and fifty-eight come from the Desert region. The table also shows that there is considerable variation in the average hammer price level, the number of artworks sold, the number of categories artists work in and the number of auction houses that an artist's work is sold in. Our Beta regression analysis is described in section 2 above and examines how the Gini index values are related to factors concerning the artist and their work. Table 2 presents the results of the estimation of the model.

Table 2: Beta regression estimates of artist Gini index model

	Coefficient	s.e.
Average Price	0.1874	0.02805
# Sold	-0.0014	0.00031
# Houses	0.0673	0.00947
# Categories	0.0468	0.02565
Female	-0.1015	0.05115
Region (Reference: Other)		
North	-0.1085	0.09107
Kimberley	-0.3173	0.08951
Desert	-0.0402	0.09787
Constant	-0.7411	0.13762
Scale function		
Average Price	-0.2087	0.09297
# Categories	0.2902	0.13471
Region (Reference: Other)		
North	1.4955	0.56468
Kimberley	1.0416	0.52262
Desert	0.4055	0.32271
Constant	3.0828	0.48099

The average sale price of an artist's work is a proxy for the quality of their work. Artists with higher average sale prices have more heterogenous price distribution (Gini index vales) but the variation in index values for such artists is lower (via the scale function). Product diversification, measured by the number of categories an artist works in and wider market coverage captured by the number of auction houses who sold an artist's work both increase price heterogeneity. Conversely an increase in the number of artworks sold by an artist in the period – a proxy for supply – reduces price heterogeneity. There are also strong effects of the region that an artist comes from. As factors in the Beta regression can influence both the level and scale (variance) of the distribution of the Gini index we also estimate the marginal effect of a change in a variable on the Gini index. These are found in Table 3.

Table 3: Estimated marginal effects from Beta regression model

	Marginal	s.e.
Average Price	0.0456	0.0066
# Sold	-0.0003	0.0001
# Houses	0.0164	0.0023
# Categories	0.0114	0.0062
Female	-0.0247	0.0124
North	-0.0264	0.0222
Kimberley	-0.0777	0.0217
Desert	-0.0098	0.0237

The strongest positive impact on price heterogeneity is that of average sale price (artwork quality). Diversification, either through increased categories of artworks produced or auction houses who sold the artist are also associated with increased price heterogeneity. Increased numbers of artworks sold reduces price heterogeneity and female artists have lower Gini index values. The region from which an artist comes from (broadly indicative of different styles of artwork and niches in the market) also has a strong impact on price heterogeneity.

Our second analysis concerns the data on the artworks sold by the artists in our dataset. This is the more common approach to price heterogeneity taken in the literature. However, in our analysis we will use a finite mixture model framework rather than a single regression model. Table 4 presents descriptive statistics for the 8,753 artworks produced and sold by the one hundred artists over our sample period.

Table 4: Descriptive statistics for artworks sold

	Mean	Standard Deviation	Minimum	Maximum
Sale Price (in $10,000s)	1.477	3.924	0.002	200
Pre-Sale Estimate	1.527	3.946	0.003	215
Herfindahl	0.363	0.148	0.163	0.747
Gender of artist				
Female	0.295	0.456	0	1
Status of artist				
Living	0.233	0.423	0	1
Died before 1987	0.262	0.439	0	1
Died between 1987 and 2014	0.505	0.500	0	1
Indigenous language region				
Other	0.132	0.338	0	1
North	0.077	0.267	0	1
Kimberley	0.091	0.287	0	1
Desert	0.700	0.458	0	1
Auction house				
Other	0.133	0.339	0	1
Sotheby's	0.298	0.457	0	1
Menzies Group	0.236	0.425	0	1
Deutscher-Hackett	0.060	0.238	0	1
Bonhams	0.075	0.264	0	1
Mossgreen	0.035	0.185	0	1
Christies	0.045	0.207	0	1
Shapiro	0.038	0.190	0	1
Leonard Joel	0.084	0.278	0	1

Hammer (sale) price varies considerably in the data as does the pre-sale estimate and the concentration of the market, measured by the Herfindahl index. Whilst the proportion of artworks sold by artist characteristic are similar to the proportion of artists (e.g. 26% of artists are female and 29.5% of artworks sold are by female artists), one exception is Desert where 70% of all artworks sold are by artists from the Desert region compared to 58% of artists from that region. The results of the finite mixture modelling described above and presented in Table

5 show three distinct price distributions with artist characteristics (gender, living status and region) and auction house effects strongly associated with group membership.

Table 5: Finite mixture model estimates

	Coefficient	s.e.
Component 1		
Pre-Sale Estimate	0.9354	0.0569
Herfindahl	0.2493	0.0768
Trend	0.0007	0.0024
Constant	-1.4681	0.0988
σ_1	0.3535	0.0159
Component 2		
Pre-Sale Estimate	0.0696	0.0260
Herfindahl	0.9695	0.2353
Trend	0.0519	0.0116
Constant	-0.5396	0.1578
σ_2	0.6474	0.0530
Component 3		
Pre-Sale Estimate	3.5422	0.1906
Herfindahl	0.2696	0.1079
Trend	0.0134	0.0024
Constant	-3.3486	0.0828
σ_3	0.5413	0.0168
Pr(Component 1)		
Female	0.3897	0.1008
Living Status (Reference: Living)		
Died before 1987	-0.2347	0.1321
Died between 1987 and 2014	0.3751	0.1076
Region (Reference: Other)		
North	0.2189	0.1681
Kimberley	1.3099	0.2100
Desert	0.6988	0.1175
Auction House (Reference: Other)		
Sotheby's	1.9147	0.1422
Menzies Group	0.9310	0.1253
Deutscher-Hackett	3.2359	0.3587
Bonhams	0.8845	0.1696
Mossgreen	1.4232	0.2298
Christies	2.4041	0.3158

Shapiro	1.4908	0.2264
Leonard Joel	-0.3253	0.1663
Constant	-1.3858	0.2021
Pr(Component 2)		
Female	0.5440	0.1149
Living Status (Reference: Living)		
Died before 1987	0.0277	0.1898
Died between 1987 and 2014	1.4763	0.1444
Region (Reference: Other)		
North	-1.3456	0.3016
Kimberley	0.7495	0.2590
Desert	0.8613	0.1443
Auction House (Reference: Other)		
Sotheby's	3.9835	0.2874
Menzies Group	2.9143	0.2815
Deutscher-Hackett	4.9973	0.4389
Bonhams	2.4478	0.3103
Mossgreen	2.8184	0.3619
Christies	3.9723	0.4420
Shapiro	1.9647	0.3903
Leonard Joel	-1.4023	0.6484
Constant	-4.9664	0.3891

The regression equation for each price component shows that pre-sale information on the hammer price and the market along with a control from time (using a time trend) are related to the observed hammer price for an artwork. The estimates of the impact of the pre-sale price estimate are distinct. In the first component the pre-sale estimate is a good predictor of the hammer price (its coefficient is not statistically different from one), in the second component it is an over-estimate of the observed hammer price (its coefficient is statistically lower than one) and in the third component it is an under-estimate (its coefficient is statistically higher than one). Market information is significant in all three components but has the highest impact in component two where the hammer price is over-estimated by the pre-sale estimate.

Group (component) membership is determined by the probability of group membership from the estimated finite mixture model that depends upon artist characteristics and the auction house conducting the auction. An artwork is assigned to the group for which its membership probability is the largest. It is also informative to look at the descriptive statistics for the hammer price in each component. These are contained in Table 6.

Table 6: Hammer price by finite mixture model component

	Number	Mean	Coefficient of Variation	Minimum	Maximum
Component One					
Sale Price (in $10,000s)	5,050	0.934	1.143	0.110	35
Component Two					
Sale Price (in $10,000s)	1.279	5.928	1.478	0.190	200
Component Three					
Sale Price (in $10,000s)	2,424	0.259	1.749	0.002	7.4

For artworks in component one the hammer price is correctly estimated by the pre-sale price estimate. These are artworks with an average hammer price of $9,340. In component two (over-estimation) the average price is $59,275 and in component three it is $2,585. Thus, it is in the middle of the overall price distribution where relative variation in hammer prices is lowest that the pre-sale estimate is correct. At the top of the overall distribution it is over-estimated and under-estimated at the bottom of the distribution which is also the one with the largest relative variation. Such a pattern of association between pre-sale price estimates and observed hammer prices may be consistent with the market for Australian Indigenous artworks being clearly differentiated. Experts "get it right" in the heavily traded (mid-price segment) where values are potentially easier to estimate. In the low-price segment, where buyer preferences and (private) valuations may be important, the experts under-estimate the hammer price. Finally, in the "high end" segment hammer prices are over estimated. Such over-estimation may be related to strategic behaviour by auction houses to draw a crowd of potential bidders.

III CONCLUSIONS

Studies of auction prices for artworks typically employ regression models that associate the hammer price with either characteristics of the artist, the artwork and the auction This approach relates the conditional moments of a single realised price distribution to these other factors. In this paper we use data from the Australian Art Sales Digest for the one hundred top selling Australian Indigenous artists over the period 1987 to 2014 to look at two alternative ways to understand heterogeneity in auction prices that complement the traditional approach. In particular, we look at variability at the artist level using an index of price heterogeneity (the Gini index) and at modelling hammer prices as a finite mixture of three distributions.

Price heterogeneity across artists is little studied. Our analysis of the Gini index finds two sets of factors associated with price distribution: artist characteristics and market conditions. Understanding how factors relating to the artist, such as gender and Indigenous region (associated with styles of artworks), and their work, such as how diverse their artworks are, provides new insights to our overall understanding of price heterogeneity in the secondary art auction market. Our finite mixture modelling is also an extension to the traditional approach that yields new insights. We identify three distinct price distributions with artist characteristics and auction house effects associated with group membership. The three price distributions represent segments in the secondary art auction market for Indigenous artworks where pre-sale information is associated with hammer prices in very different ways. Taken together our approach suggests new ways to understand price heterogeneity and the results complement the existing literature by identifying different ways in which factors used in the literature may be related to price heterogeneity.

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APPENDIX

Table A1: Top 100 Indigenous artists by sales value

Abdulla, Ian W.	Male	Pareroultja, Otto	Male
Andrew, Brook	Male	Petyarre, Gloria Tamerre	Female
Barak, William (King Billy)	Male	Petyarre, Kathleen	Female
Bedford, Paddy Nyunkuny	Male	Pwerle, Minnie	Female
Bennett, Gordon	Male	Ramsey, Rammey	Male
Billycan, Jan	Female	Roughsey, Dick (Goobalatheldin)	Male
Britten, Jack	Male	Thancoupie, Gloria Fletcher	Female
Cherel, Janangoo Butcher	Male	Thomas, Billy Joongarra	Male
Dowling, Julie	Female	Thomas, Rover (Julama)	Male
Downs, Jarinyanu David	Male	Timms, Freddie	Male
Gabori, Sally	Female	Tjakamarra, Anatjari	Male
Jaminji, Paddy (Jampin)	Male	Tjakamarra, John Kipara	Male
Jandany, Hector	Male	Tjakamarra, Long Jack Phillipus	Male
Kantilla, Kitty	Female	Tjakamarra, Michael Nelson	Male
Karruwara, Wattie	Male	Tjakamarra, Old Mick Wallankarri	Male
Kngwarreye, Emily Kame	Female	Tjampitjin, Boxer Milner	Male
Kubaku, Mick	Male	Tjampitjin, Sunfly	Male
Malangi, David	Male	Tjampitjinpa, Anatjari	Male
Marika, Mawalan	Male	Tjampitjinpa, Kaapa Mbitjana	Male
Marralwanga, Peter	Male	Tjampitjinpa, Old Walter	Male
Mawurndjul, John	Male	Tjampitjinpa, Ronnie	Male
McRae, Tommy	Male	Tjangala, Uta Uta	Male
Mingelmanganu, Alec	Male	Tjapaltjarri, Bill Whiskey	Male
Moffatt, Tracey	Female	Tjapaltjarri, Billy Stockman	Male
Munduwalawala, Ginger Riley	Male	Tjapaltjarri, Clifford Possum	Male
Mungatopi, Deaf Tommy	Male	Tjapaltjarri, Mick Namarari	Male
Munkara, Enraeld Djulabinyanna	Male	Tjapaltjarri, P(addy) Cookie Stewart	Male
Murrumurru, Dick Ngulei-Ngulei	Male	Tjapaltjarri, Tim Leura	Male
Nadjamerrek, Lofty Nabardayal	Male	Tjapaltjarri, Tommy Lowry	Male
Nakarra, Queenie McKenzie	Female	Tjapaltjarri, Warlimpirrnga	Male
Namatjira, Albert	Male	Tjapanangka, Long Tom	Male
Namatjira, Ewald	Male	Tjapanangka, Tjumpo	Male
Namok, Rosella	Female	Tjapangati, Timmy Payungka	Male
Nampitjin, Eubena	Female	Tjapangati, Wimmitji	Male
Napaljarri, Susie Bootja Bootja	Female	Tjungurrayi, Charlie Tawara	Male
Napanangka, Makinti	Female	Tjungurrayi, G. Ward	Male
Napanangka, Walangkura	Female	Tjungurrayi, George Hairbrush	Male
Napangardi, Dorothy Robinson	Female	Tjungurrayi, Patrick Oloodoodi	Male

Napangardi, Judy Watson	Female	Tjungurrayi, Shorty Lungkarda	Male
Napangardi, Lilly Kelly	Female	Tjungurrayi, Willie Ryder	Male
Napangardi, Maggie Watson	Female	Tjungurrayi, Yala Yala Gibbs	Male
Naparrula, Mitjili	Female	Tjupurrula, Johnny Warangkula	Male
Naparrula, Ningura Gibson	Female	Tjupurrula, Turkey Tolson	Male
Nganjmira, Bobby Barrdjaray	Male	Wainburranga, Paddy Fordham	Male
Nickolls, Trevor	Male	Walbidi, Daniel	Male
Numbulmoore, Charlie	Male	Wales, Prince Of	Male
Nungurrayi, Elizabeth Nyumi	Female	Watson, Tommy	Male
Nungurrayi, Gabriella Possum	Female	Weir, Barbara	Female
Nungurrayi, Naata	Female	Yirawala, David	Male
Onus, Lin	Male	Yunupingu, Munggarawuy	Male