

Heterogeneity in auction price distributions for Australian Indigenous artists

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Introduction

- In this research we will be focussing on artworks by Australian Indigenous artists.
 - Indigenous art is of international relevance with collectors spread across the globe.
 - There is still considerable heterogeneity within works by Australian Indigenous artists.
 - In 2017 the value of art sold at auction by Australian artists was \$116.6 million of which artworks by Indigenous artists totalled \$10.9 million.



About the data

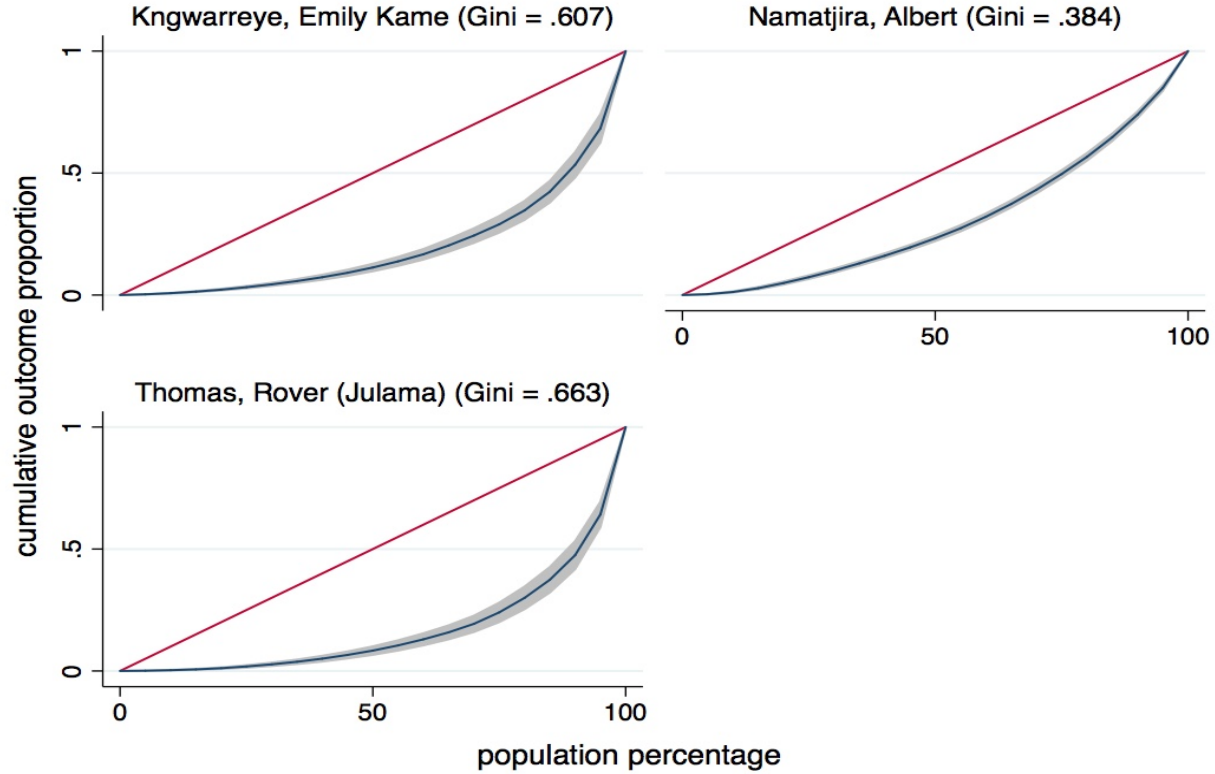
- Data source: Australian Art Sales Digest (AASD).
- Transactions based data for all art works by Australian Indigenous artists offered for sale from 1987 to 2014.
- We will focus on the works by the top 100 artists (by \$ value).
 - The top three artists are Emily Kame Kngwarreye, Rover (Julama) Thomas and Albert Namatjira.
- A total of 8,753 art works were sold at auction by these 100 artists over the period.

Traditional modelling approaches

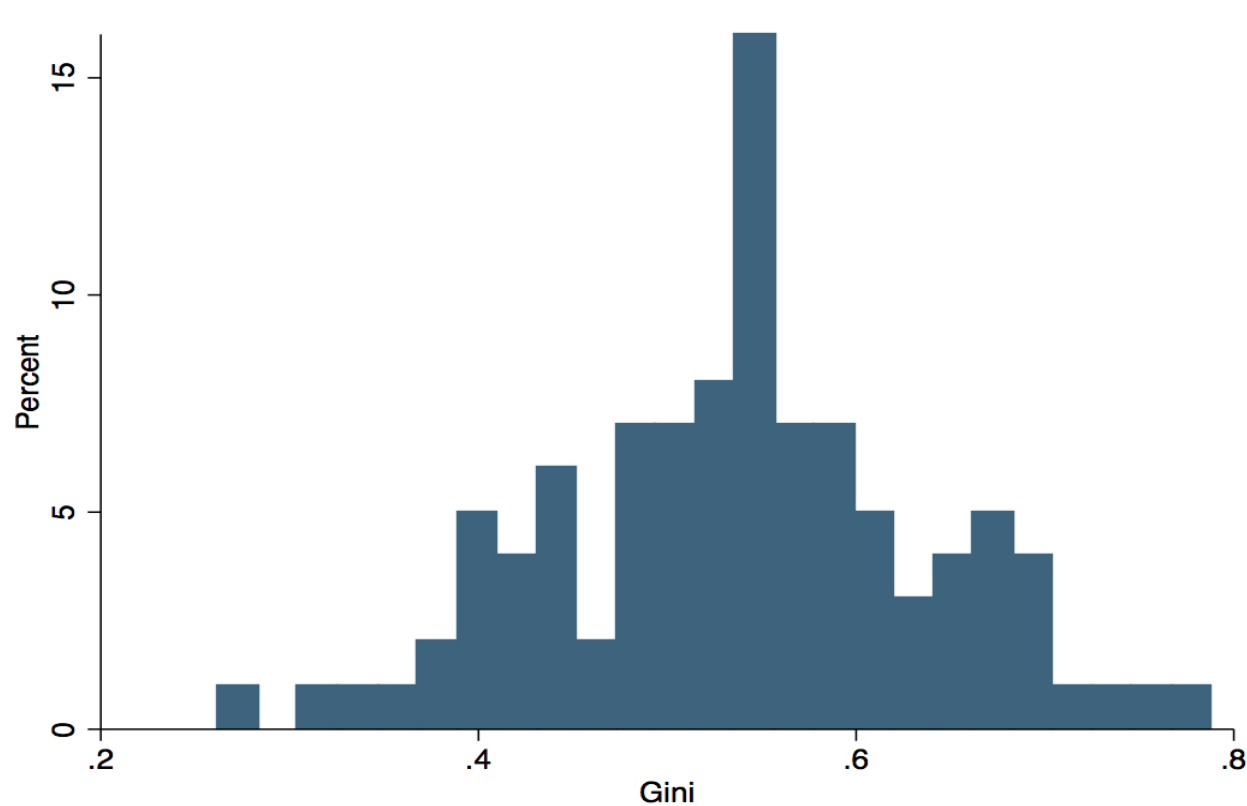
- It is common to model this data for the hammer price using either hedonic regression models or with regression models that relate the hammer price to pre-sale information.
 - Occasionally the modelling also corrects for any sample selectivity (not all art offered for sale is sold).
 - Occasionally a quantile regression is used.
- These approaches assume that variability in hammer prices (heterogeneity) can be explained using a single distribution (e.g. Log-Normal) for the pooled data.

Individual heterogeneity

- As a measure of price heterogeneity we will use the Gini coefficient.
- The Gini coefficient is a measure of the dispersion (heterogeneity) of prices *for an individual artist*.
- A value of zero would mean that all prices were the same, higher values denote more heterogeneity in the prices.
- The Gini coefficient is computed for each artist using the hammer price for all artworks sold by that artist over the time period.
- It is computed from a Lorenz Curve for prices of the artworks.

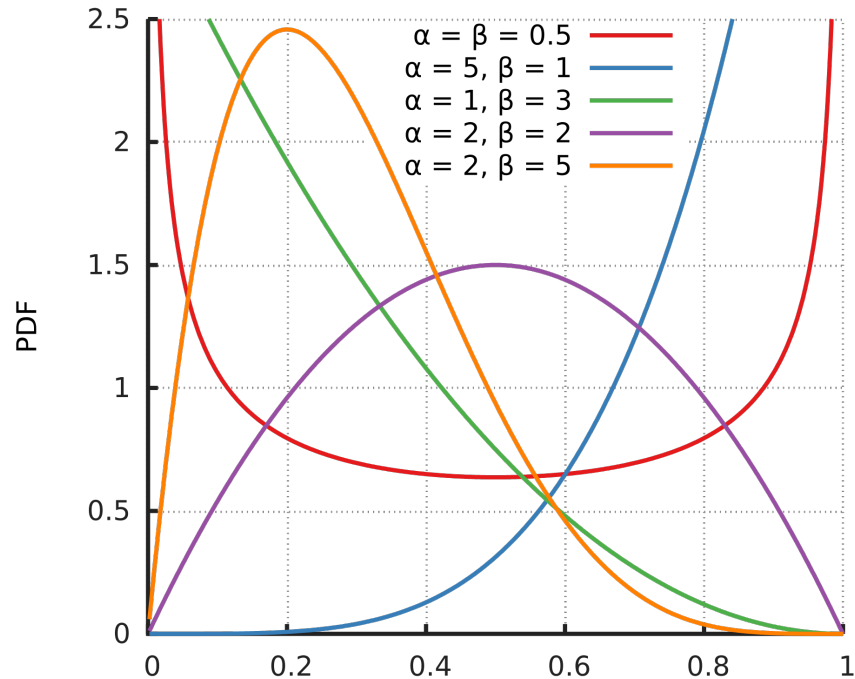


Distribution of Gini coefficients



Modelling heterogeneity

- We model the Gini coefficients using a Beta distribution, $B(\alpha, \beta)$



Modelling heterogeneity

- We model the Gini coefficients, G , using a Beta regression model, parameterised such that $E(G) = \mu, Var(G) = \mu(1 - \mu)/(1 + \phi)$.
- This regression model both bounds to the unit interval and allows for both the mean and variance to depend upon characteristics of the the artist and their works.
- The model is a member of of class of generalised linear models and the link functions used are $ln[\mu_i/(1 - \mu_i)] = \mathbf{x}_i'\boldsymbol{\beta}$ and $ln(\phi_i) = \mathbf{w}_i'\boldsymbol{\delta}$.

Modelling heterogeneity

- Price heterogeneity (the Gini index) in a market for differentiated goods will depend upon both supply and demand factors.
 - These are unobservable but can be proxied by characteristics of the the artist and their works.
- Mean function – Gender, Region (North, Kimberley, Desert and Other), average price of art works, # of works sold, # of auction houses selling their works, # categories they work in.
- Scale function – Region, average price of art works, # categories they work in.

Marginal effects from Beta regression

	Marginal	s.e.	t-value
Average Price	0.0456	0.0066	6.855
# Sold	-0.0003	0.0001	-4.613
Female (=Y)	-0.0247	0.0124	-1.986
North	-0.0264	0.0222	-1.193
Kimberley	-0.0777	0.0217	-3.580
Desert	-0.0098	0.0237	-0.411
# Houses	0.0164	0.0023	7.220
# Categories	0.0114	0.0062	1.827

Finite mixture (latent class) models

- In a finite mixture model the observed data (hammer prices) are assumed to come from g distinct components (classes).
 - Each individual component can be modelled with an appropriate regression model (distribution).
- Finite mixture models are probabilistic models that combine the g density functions and the probabilities, π_g , for the components.
 - The π_g can also be modelled.
- Estimation was conducted in Stata using likelihood based methods.

Model specification

- In our specification we use a mixture of three Log-Normal distributions for the hammer prices with component probabilities modelled using a multinomial Logistic form.
- The model relates hammer price to its pre-sale information (the price estimate ($M=(L+U)/2$) and the Herfindahl index for the market) and a time trend.
- The component probabilities, π_g , depend on artist characteristics (gender, region, living status) and auction house.

Estimation results

- The relationship with pre-sale information on both the artwork and the market is quite different for each component.
- The component probabilities are strongly associated with artist characteristics (gender, living status and region) and with auction house.
- Classifying observations using the most likely (maximum probability of) component membership the three components have 5,050 1,279 and 2,424 observations.

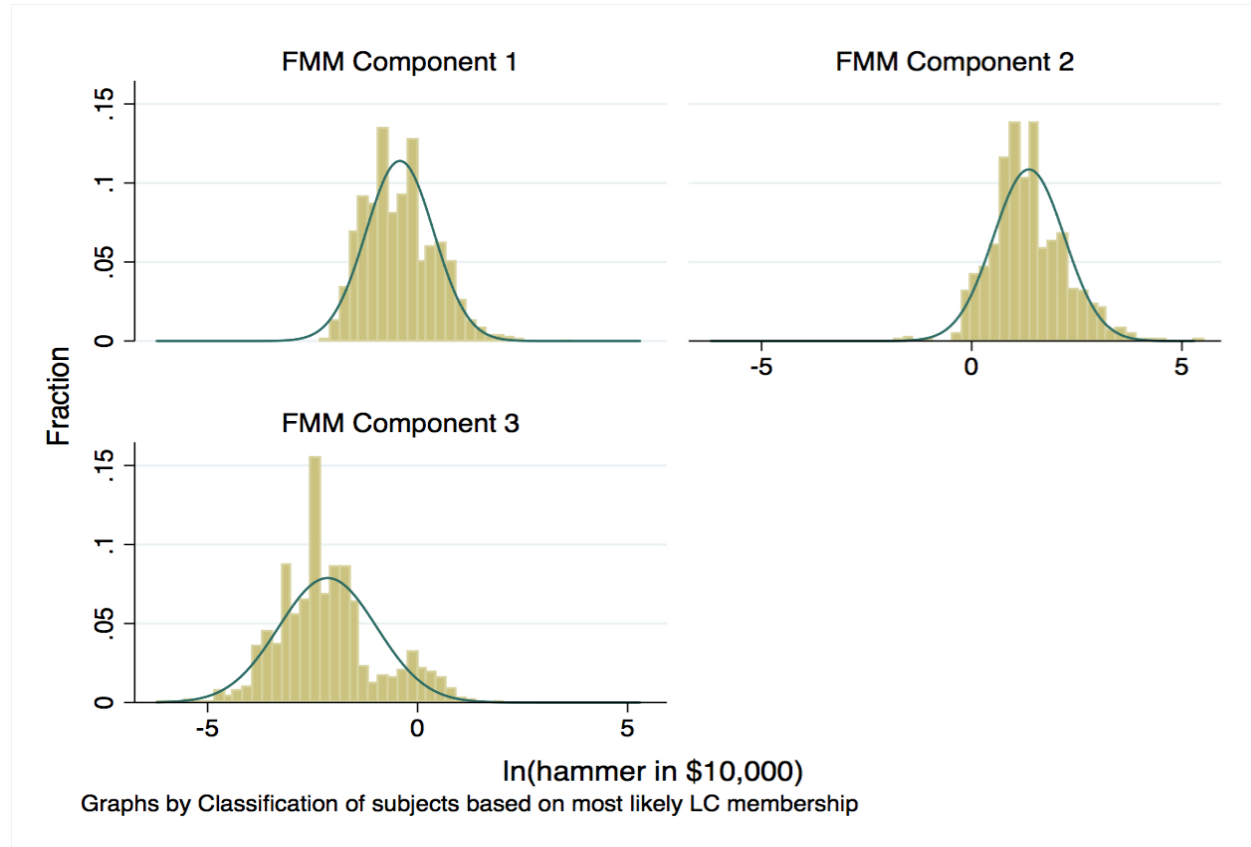
Estimation results

- The three components (market segments) are quite different.

	Number	Mean	Coefficient of Variation
Component One			
Sale Price (in \$10,000s)	5,050	0.934	1.143
Component Two			
Sale Price (in \$10,000s)	1,279	5.928	1.478
Component Three			
Sale Price (in \$10,000s)	2,424	0.259	1.749

- In component one the pre-sale price estimate, M , is a good estimate of the hammer price, in component two it is an over-estimate and in component three it is an under-estimate.

Distribution of log-price for each latent class



Conclusions

- Taken two little used, in this field, techniques – Beta regression modelling of Gini coefficients and finite mixture models for hammer prices – to investigate auction price heterogeneity.
- The Beta regression specifically focuses on heterogeneity across artists.
- The finite mixture model expands on the usual regression approach that relates hammer price to pre-sale information.
- The results are encouraging and identify new ways in which factors used in existing approaches may influence price heterogeneity.