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.
Kngwarreye, Emily Kame (Gini = .607)

Namatjira, Albert (Gini = .384)

Thomas, Rover (Julama) (Gini = .663)
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 $E(G) = \mu, \text{Var}(G) = \mu(1 - \mu)/(1 + \phi)$.

• This regression model both bounds to the unit interval and allows for both the mean and variance to depend upon characteristics of the artist and their works.

• The model is a member of class of generalised linear models and the link functions used are $\ln[\mu_i/(1 - \mu_i)] = x_i^\intercal \beta$ and $\ln(\phi_i) = w_i^\intercal \delta$. 
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 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

<table>
<thead>
<tr>
<th></th>
<th>Marginal</th>
<th>s.e.</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Price</td>
<td>0.0456</td>
<td>0.0066</td>
<td>6.855</td>
</tr>
<tr>
<td># Sold</td>
<td>-0.0003</td>
<td>0.0001</td>
<td>-4.613</td>
</tr>
<tr>
<td>Female (=Y)</td>
<td>-0.0247</td>
<td>0.0124</td>
<td>-1.986</td>
</tr>
<tr>
<td>North</td>
<td>-0.0264</td>
<td>0.0222</td>
<td>-1.193</td>
</tr>
<tr>
<td>Kimberley</td>
<td>-0.0777</td>
<td>0.0217</td>
<td>-3.580</td>
</tr>
<tr>
<td>Desert</td>
<td>-0.0098</td>
<td>0.0237</td>
<td>-0.411</td>
</tr>
<tr>
<td># Houses</td>
<td>0.0164</td>
<td>0.0023</td>
<td>7.220</td>
</tr>
<tr>
<td># Categories</td>
<td>0.0114</td>
<td>0.0062</td>
<td>1.827</td>
</tr>
</tbody>
</table>
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, $\pi_g$, for the components.
  • The $\pi_g$ 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, \(\pi_g\), 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.

<table>
<thead>
<tr>
<th>Component</th>
<th>Number</th>
<th>Mean</th>
<th>Coefficient of Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Component One</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sale Price (in $10,000s)</td>
<td>5,050</td>
<td>0.934</td>
<td>1.143</td>
</tr>
<tr>
<td>Component Two</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sale Price (in $10,000s)</td>
<td>1.279</td>
<td>5.928</td>
<td>1.478</td>
</tr>
<tr>
<td>Component Three</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sale Price (in $10,000s)</td>
<td>2,424</td>
<td>0.259</td>
<td>1.749</td>
</tr>
</tbody>
</table>

- 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

Graphs by Classification of subjects based on most likely LC membership
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.