Auctions and Estimates: Evidence from Indian Art Market

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Abstract: We examine whether presale estimates of paintings by Indian artists are unbiased predictors of the hammer price. Our analysis includes both sold and unsold artworks. Unbiasedness of estimates is tested by performing a two-stage Heckit model on 5,077 artworks auctioned between 2000 and 2018. The results of our study show that presale estimates are upward biased for expensive artworks and downward biased for others. In addition, we also find that in the market for Indian paintings, characteristics of auction, artist, and artwork determine the biasedness of estimates.

1 INTRODUCTION

On May 5, 2004, Picasso's "Boy with a Pipe" created the history by fetching US$ 104 million at Sotheby's auction in New Yok. Charles Moffet, then co-director of Impressionist and modern art at Sotheby's, described the painting as a masterpiece ("Picasso painting sells for $104m," 2004). On the other hand, famed art critic Robert Hughes called "huge sums paid to immature Rose Period Picasso a cultural obscenity"(Kennedy, 2004). Such divergent views about artworks and artists are not a recent phenomenon. Back in 1863, the Paris Salon jury rejected *The Luncheon on the Grass,* which is now one of the well-known works of Edouard Manet (Spolsky, 1996). The differences in opinions are caused due to subjectivities involved in valuing a product for which the criteria of valuation are not well defined (Beckert & Rossel, 2013; Velthuis, 2003). The complexities in valuation accentuate since the quality of artworks is defined not only by monetary value but also by cultural, aesthetic, and social values (Klamer, 2004; Throsby & Zednik, 2014). The problems involved in determining the quality of artworks have inspired a large body of research from multiple disciplines, such as art history, sociology, and economics. The economics of the art market has witnessed a growing interest in the last two decades. The interest is fuelled primarily due to the availability of auction data and, to some extent, due to the rapid growth in the art market and the appeal of art as an alternative investment.

The extant research on the economics of art has generally focused on three issues- determinants of price (Galenson & Weinberg, 2000; Garay, 2020; Renneboog & Spaenjers, 2013); returns on investment in art (Baumol, 1986; Buelens & Ginsburgh, 1993; Mei & Moses, 2002); and the relationship between the auction price and presale estimates (Ashenfelter & Graddy, 2003; Beggs & Graddy, 1997; Ekelund, Jackson, & Tollison, 2013; Mei & Moses, 2005). The focal point of this paper is the last of the three issues, specifically whether presale estimates are unbiased predictors of auction price. While the literature on the first two issues has found some uniform patterns, the debate on presale estimates is far from settled. Milgrom & Weber (1982) and Ashenfelter (1989) suggest that it is best for auction houses to be honest and provide truthful information to customers; therefore, presale estimates are unbiased and reflect the true price of an artwork. However, the later studies by Beggs and Graddy (1997), Ekelund, Ressler, and Watson (1998), Bauwens and Ginsburgh (2000), Mei and Moses (2002), and Ashenfelter and Graddy (2003) provide evidence for systematic under or overvaluation of artworks by auction houses.

Rejecting the claims of biased estimates, McAndrew, Smith, & Thompson (2012) argue that since the previous studies do not take into account the artworks that were unsold at auctions, the sample used is not a random sample. Using both sold and unsold artworks, they conclude that the estimation bias observed in the previous studies can be attributed to the sample selection bias. To verify the claims of McAndrew, Smith, & Thompson (2012), Ekelund, Jackson, & Tollison (2013) perform a two-stage Heckit regression (Heckman, 1979) on artworks by

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American artists. They find that the presale estimates are downward biased even after adjusting for the sample selection, i.e., presale estimates systematically underestimate the realized price.

In this study, we first test the biasedness of presale estimates in the Indian art market by employing the model specification suggested by Ekelund, Jackson, & Tollison (2013). Next, we extend the model by incorporating information about artists, artworks, and auctions. Our research contributes to the literature in the following ways- first, revisiting Ekelund, Jackson, & Tollison (2013), we examine the findings of the study, and second, by investigating the behaviour of presale estimates in the Indian market, we provide a much-needed perspective from a developing art market.

The rest of the paper is organized as follows. In section 2, we provide a summary of prices in the auction market. The data and methodology employed by us are discussed in Section 3. In Section 4, we present the results of this study. Finally, we discuss our findings and conclude in Section 5.

2 AUCTION BACKGROUND

There are multiple prices in the auction market for artworks – reserve price, hammer price, and purchase price. The reserve price is the lowest price the owner of artwork is willing to sell it for. The hammer price is the final price fetched by the artwork at auction, and the purchase price is the price a buyer finally pays to the auction house. The purchase price includes the hammer price plus taxes and commission paid by the buyer. Before an auction, auction houses publish a catalogue containing information about the artwork and artist as well as presale low and high estimates. These estimates provide a band around which the auction house experts believe an artwork will be sold for. However, these estimates are neither ceiling nor floor price. It is possible that the realized price (hammer price) is higher or lower than presale estimates.

3 DATA AND METHODOLOGY

3.1 The Data

Our estimates are based on 5,077 paintings by 307 Indian artists for the period January 2000 and June 2018. The data is collected from Blouin Artinfo (Blouin Artinfo), an online database of auction records for fine art, design, decorative objects, etc.

The dataset contains the following information:

- Artist related characteristics: artist name.
- Artwork related characteristics: medium of painting; dimensions of artworks; painting title.
- Auction related characteristics: name of the auction house; year of auction; whether an artwork was sold or not; the hammer price if sold; presale estimates (low and high) of artworks.

In addition to the information provided in the dataset, we have added the gender of artists, size of artwork (height*width), living status at the time of the auction (dead or alive), the reputation of an artist (computed as per methodology suggested by Kraeussl & van Elsland, 2008). In order to estimate the influence of movement affiliation on price and estimates, we have created a categorical variable "movement affiliation", which is equal to 1 (yes) if an artist has been a part of a well-known artistic movement; otherwise, 0 (no). The prominent art movements in India and artist association are selected from art history literature (Brown, 2009; Kapur, 2000; Mitter, 2001). All prices in the dataset- the hammer price, low estimate, high estimate- are in USD and adjusted using US CPI 2018.

Out of 5,077 paintings, 3,139 were sold at auctions, while 1,938 were "bought in", i.e., they were not sold.

3.2 Methodology

Let P_i denote the hammer price of i^{th} painting and (P_{Li}, P_{Ui}) be its low and high presale estimates. The presale estimates are unbiased if the expected value of P_i is equal to the mean of estimates (P_{AV})

$$E[P_i] = P_{AV} \tag{1}$$

where,

$$P_{AV} = \frac{P_{Li} + P_{Ui}}{2} \tag{2}$$

However, the hammer price can be available for the artworks that are sold; for those that are not sold, we cannot witness the hammer price. By excluding the artworks that were not sold from the analysis, we may commit sample selection bias due to incidental truncation (Wooldridge, 2013). Therefore, to account for artworks that came to auctions but were not sold, we use a two-stage Heckit model (Heckman, 1979).

In the first stage (selection equation), we fit a probit model on the entire data, with sales status (sold/unsold) as a dependent variable and average estimates (P_{AV}), painting title, gender of artists, natural log of reputation score, natural log of artwork area, medium of artwork, auction house name, movement affiliation, living status, and year of the auction as independent variables. The categorical variables in the model have the following categories as reference: unsold for sales status, female for gender, yes for painting title, oil on canvas for medium, no for movement affiliation, Saffronart for auction house name, and 2000 for the year of auction.

We use the Inverse Mills Ratio (IMR)- computed from the first stage, in the second stage of the Heckit model (output equation). The second stage is a hedonistic OLS regression with natural log of hammer price as a dependent variable and IMR as one of the independent variables. However, in the second stage, we use only those observations for which the sales status is sold, i.e., only those artworks that were sold at auction. For Heckit model to perform, the independent variables used in the second stage must be a subset of those in the first stage (except for IMR).

In the second stage, we specify two models. In the first model, we use the average of estimates (P_{AV}) and IMR as independent variables. This model corresponds to the model specified by Ekelund, Jackson, & Tollison (2013). We think the hammer price depends not only on the average price but also on other characteristics variables. Therefore, in the second model, we use all the characteristics variables from stage 1, and IMR and P_{AV}. The specifications of the two models are as follows:

Model 1:

$$ln[P_i] = \beta_0 + \beta_1 ln(P_{AV,i}) + \beta_2(IMR_i) + \varepsilon_i \quad (3)$$

where, $\beta_0, \beta_1, and\ \beta_2$ are intercept, coefficient of the natural log of P_{AV}, coefficient of IMR respectively, and ε_i is the error term. Eq. 3 can also be written as

$$P_i = \exp(\beta_0) * (P_{AV,i})^{\beta_1} * \exp(\beta_2 * (IMR_i) + \varepsilon_i) \quad (4)$$

Eq. 4 implies that P_{AV} is an unbiased estimator of the hammer price when $\beta_0 = 0$ and $\beta_1 = 1$. Furthermore, when both β_0 and β_1 are greater than 1, P_{AV} underestimate the hammer price. The joint test of unbiasedness ($\beta_0 = 0$ and $\beta_1 = 1$) is measured by the F-statistic. Ekelund, Jackson, & Tollison (2013) calls the effect of β_0 a "multiplicative bias", while β_1 is designated as "proportional bias".

Model 2:

$$ln[P_i] = \beta_0 + \beta_1 ln(P_{AV,i}) + \beta_2(IMR_i) + \sum \beta_{i,j} X_{,ij} + \gamma_i \quad (5)$$

where, $\beta_0, \beta_1, and\ \beta_2$ are similar to model 1. $X_{i,j}$ is the j[th] characteristic of painting i and $\beta_{i,j}$ is the coefficient of $X_{i,j}$; γ_i is the error term.

4 EMPIRICAL RESULTS

In this section, we present the findings of our study. First, we present the result of the selection equation (Table 1), and subsequently, we present findings of model 1 and model 2 (Table 2 & 3). Since time effect is found to be insignificant in Table 2, we have not included in the table to keep tables concise. The diagnostic plots for model 1 and 2 are shown in Figure 1 and 2. From plots it follows that models satisfy assumptions of ordinary least square regression.

Table 1 indicates that the chances of artworks getting sold at an auction increase by nearly 36% when artists are affiliated with recognized art movements. The chances of sell also increase with an increase in the artist's reputation as well as with an increase in the area of artworks. On the other hand, an increase in the average value of presale estimates and artworks with certain mediums (Acrylic on Canvas and Watercolour) decreases the probability of artworks being sold. Other characteristics such as auction house name, painting title, gender and living status of artist do not have any impact on sales status.

Table 2 shows the result of model 1, i.e., replication of the model by Ekelund, Jackson, & Tollison (2013). Consistent with the authors, we also find that the joint test of unbiasedness ($\beta_0 = 0$ and $\beta_1 = 1$) can be rejected (F-statistic = 1.013e+04). The coefficient of intercept is 0.87, which implies that auction houses systematically underestimate by a multiplicative effect of 138% ($e^{0.87} - 1$). In agreement with Ekelund et al. (2013), we also observe that the multiplicative bias is greater than 1. However, our results indicate that the proportional bias is less than 1 (0.95), while Ekelund et al. (2013) found it to be greater than unity. It should be noted that the inverse mill's ratio (IMR) is statistically significant at 0.001 level (Table 2). A significant IMR suggests that errors in the selection and outcome models are correlated. In other words, fitting a regression model with only sold works will cause sample selection bias. The results of model 2 are shown in Table 3. This model includes variables from model 1, along with additional control variables. Similar to model 1, we can reject rejected (F-statistic = 513 on 57 and 3081 DF) the joint test of unbiasedness ($\beta_0 = 0$ and $\beta_1 = 1$). An important difference between model 1 and model 2 is that the Inverse Mills Ratio (IMR) is insignificant in model 2. This finding suggests that when full information is used, the errors are not correlated, and therefore, model 2 can very well be estimated by OLS without correcting for sample selection bias. The multiplicative and proportional biases show similar behaviour as in model 1. In addition, we observe that the characteristics of artists, artworks, auctions, and time effect also influence the predictive power of estimates. For artist related characteristics, the hammer price is generally greater than the average estimates when the reputation score is high. In other words, the artworks by highly reputed artists on an average command a higher price than the mean of estimates. We also witness gender differences. Compared to female artists, the works of male artists are underestimated. It suggests that buyers generally pay higher than average estimates when the artist is a male. Further, Artworks of artists who have not been part of an art movement are overestimated. For artwork related characteristics, our results show that the prices are underestimated for paintings with a large area, and for paintings that have titles. The medium of artwork also determines the biasedness. In general, compared to oil on canvas, acrylic leads to overestimation, but tempera on card underestimates. While analyzing auction related variables, we find that in comparison to Saffronart, all other auction houses except Pundole's overestimate. Underestimation or overestimation is also a function of time. Paintings sold during 2004-2008 and 2010-2012 are underestimated compared to paintings sold in the year 2000.

Table 1: Stage 1 of the Heckit model: Sample Selection Equation.

Variable	estimates	std error	p-value
(Intercept)	9.193	991.468	0.993
Painting Title: Yes	0.026	0.102	0.798
Gender: Male	0.077	0.153	0.615
Living Status: Alive	-0.063	0.090	0.480
Movement Affiliation: No	-0.438	0.102	0***
log(Artwork Area)	0.154	0.050	0.002**
log(Reputation)	0.416	0.073	0***
log(Average Estimate)	-0.378	0.051	0***
<u>Auction House</u>			
Artcurial	-5.529	1721.708	0.997
Bonhams	-4.952	1721.708	0.998
Christie's	-4.912	1721.708	0.998
Osian's	-3.713	200.468	0.985
Other	-3.448	1721.708	0.998
Pundole's	4.211	0.218	0***
Sotheby's	-4.047	1721.708	0.998
<u>Artwork Medium</u>			
Acrylic on Board	-0.222	0.587	0.705
Acrylic on Canvas	-0.374	0.120	0.001**
Acrylic on Paper	-0.438	0.323	0.174
Acrylic on Tarpaulin	-4.866	1138.869	0.997
Mixed Media on Board	-0.414	0.677	0.541
Mixed Media on Canvas	-0.269	0.255	0.291
Oil and Acrylic on Canvas	-0.137	0.451	0.761
Oil on Board	0.267	0.186	0.151
Oil on Linen	-0.006	0.913	0.995
Oil on Masonite	0.256	0.468	0.585
Oil on Masonite Board	-0.277	0.930	0.766
Oil on Panel	-0.197	0.443	0.657
Oil on Paper	-0.575	0.546	0.292
Tempera on Board	-4.917	166.213	0.976
Tempera on Canvas	0.812	0.467	0.082
Tempera on Card	0.230	0.332	0.490
Tempera on Paper	0.084	0.391	0.829
Watercolor	-1.291	0.600	0.031*
Other-Acrylic	-0.971	0.215	0***
Other-Gouache	-0.508	0.552	0.357
Other-Mixed	0.260	0.350	0.457
Other-Oil	-0.216	0.187	0.246
Other-Tempera	0.529	0.336	0.116
All other	-0.581	0.219	0.007**
Null deviance	6751.4		
Residual deviance	1294.9		
AIC	1420.9		

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

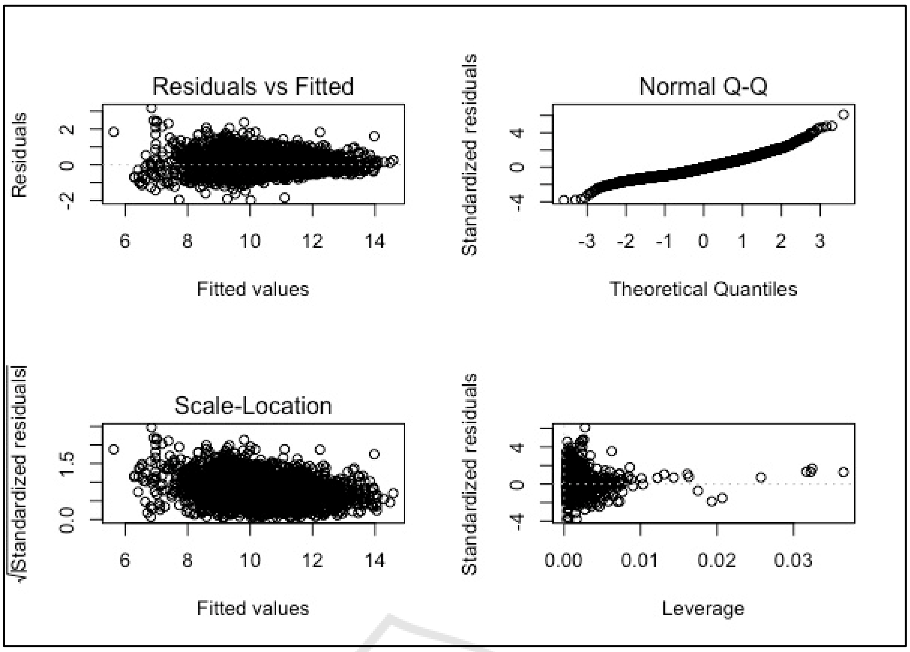

Figure 1: Regression diagnostic plots for model 1.

Table 2: Stage 2 of the Heckit model for model 1 (Eq. 3).

Variable	estimates	std error	p-value
(Intercept)	0.870	0.068	2E-14***
log(Average Estimate)	0.947	0.006	2E-14***
Inverse Mills Ratio (IMR)	-0.349	0.030	2E-14***
Adjusted R-squared	0.865		
F-statistic	1.013e+04		

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

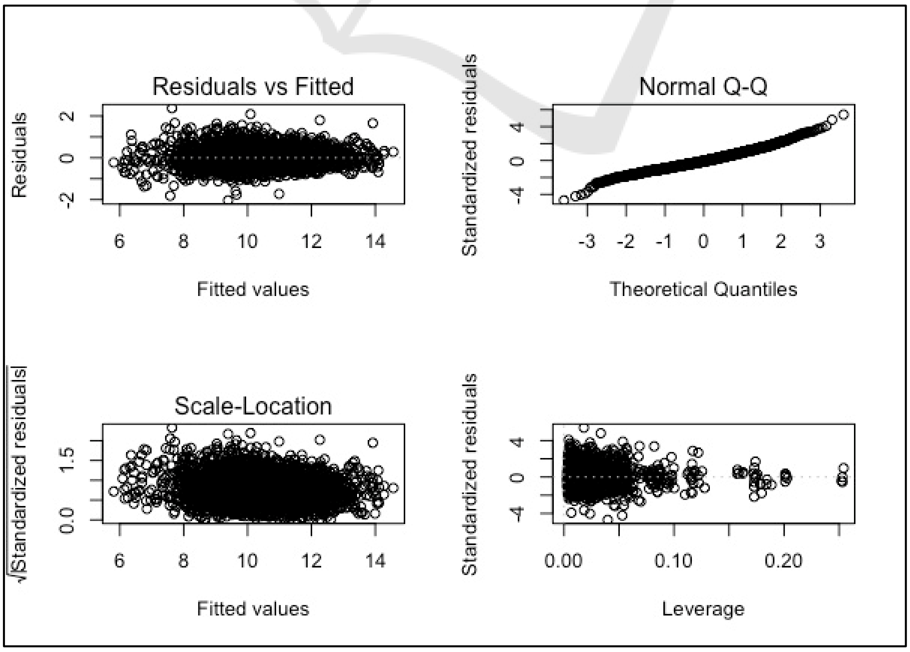

Figure 2: Regression diagnostic plots for model 2.

Table 3: Stage 2 of the Heckit model for model 2 (Eq. 5).

Variable	estimates	std error	p-value
(Intercept)	1.161	0.103	0***
log(Average Estimate)	0.740	0.011	0***
IMR	-0.071	0.062	0.249
Painting Title: Yes	0.055	0.019	0.003**
Gender Male	0.092	0.030	0.002**
Living Status: Alive	-0.028	0.019	0.147
Movement Affiliation: No	-0.325	0.022	0***
log(Artwork Area)	0.114	0.010	0***
log(Reputation)	0.296	0.015	0***
Auction House			
Artcurial	-0.214	0.066	0.001**
Bonhams	-0.187	0.038	0***
Christie's	-0.115	0.027	0***
Osian's	-0.394	0.033	0***
Pundole's	0.629	0.094	0***
Sotheby's	-0.186	0.025	0***
Other	-0.067	0.043	0.115
Artwork Medium			
Acrylic on Board	-0.293	0.094	0.001**
Acrylic on Canvas	-0.110	0.025	0***
Acrylic on Paper	-0.314	0.061	0***
Acrylic on Tarpaulin	-0.013	0.199	0.946
Mixed Media on Board	-0.179	0.129	0.166
Mixed Media on Canvas	0.020	0.072	0.784
Oil and Acrylic on Canvas	-0.098	0.088	0.266
Oil on Board	0.125	0.032	0.***
Oil on Linen	-0.196	0.222	0.376
Oil on Masonite	0.078	0.077	0.313
Oil on Masonite Board	0.107	0.183	0.560
Oil on Panel	-0.104	0.120	0.389
Oil on Paper	-0.175	0.083	0.035*
All other	-0.125	0.052	0.015*
Other-Acrylic	-0.200	0.052	0**
Other-Gouache	-0.170	0.135	0.211
Other-Mixed	-0.067	0.102	0.509
Other-Oil	-0.023	0.040	0.558
Other-Tempera	-0.095	0.081	0.242
Watercolor	0.022	0.148	0.881
Tempera on Board	-0.133	0.182	0.466
Tempera on Canvas	0.084	0.070	0.233
Tempera on Card	0.224	0.064	0***
Tempera on Paper	0.124	0.069	0.074
Year of Auction			
2001	0.144	0.094	0.126
2002	0.080	0.079	0.314
2003	0.044	0.068	0.514
2004	0.444	0.058	0***
2005	0.826	0.057	0***
2006	0.949	0.059	0***
2007	0.810	0.062	0***
2008	0.391	0.164	0.017*
2009	0.346	0.229	0.130
2010	0.449	0.130	0***
2011	0.763	0.184	0***
2012	0.671	0.127	0***
2013	0.067	0.115	0.560
2014	0.130	0.109	0.233
2015	0.146	0.107	0.172
2016	-0.035	0.114	0.761
2017	0.069	0.116	0.554
2018	0.178	0.140	0.204
Adjusted R-squared	0.903		
F-statistic	513		

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

5 CONCLUSIONS

This study investigates whether presale estimates are a good predictor of hammer price in the Indian art market. We use the methodology employed by Ekelund, Jackson, & Tollison (2013). In their study, Ekelund, Jackson, & Tollison (2013) argue that presale estimates consistently underestimate the hammer price due to both multiplicative and proportional bias. However, at least in the Indian market, while multiplicative bias underestimates, the proportional bias seem to overestimate very expensive paintings. The joint effect of both the bias shows that the underestimation happens till the hammer price is below or equal to US$ 14,357,640; beyond US$ 14,357,640, the price is overestimated. This finding is consistent with results of Mei & Moses (2005), who showed that auction houses overestimates expensive artworks.

We also find that the characteristics of artwork, artist, and auction determine the biasedness of estimates. In agreement with Ashenfelter & Graddy (2003), our findings also suggest that paintings with a large area are underestimated. One of the significant findings of our research is that auction houses do not follow the same strategy for estimation. Two auction houses in our study – Saffronart and Pundole's seem to be more inclined to overestimate, but the rest often underestimate. In their study, Bauwens & Ginsburgh (2000) have also noted that the Christie's and Sotheby's follow different approaches to under/overestimate.

A systematic underestimation for artists with higher reputation indicates that buyers are willing to pay higher than estimates for famous and well-established artists; however, it is surprising to note that buyers are more willing to pay higher than estimates for male artists but not for female artists. We are curious to know whether the gender-based differentiation is peculiar to India or prevalent universally. We have not answered many other questions in this research, e.g., the biasedness of estimates in physical vs. online auctions. We hope future researchers will address these questions.

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