2019

New Technology, Old Ways? The Gender Price Discount in Online Contemporary Art Auctions

Madeleine Peterson

NEW TECHNOLOGY, OLD WAYS?
THE GENDER PRICE DISCOUNT IN ONLINE CONTEMPORARY ART AUCTIONS

by

MADELEINE PETERSON

SUBMITTED TO SCRIPPS COLLEGE IN PARTIAL FULFILLMENT
OF THE DEGREE OF BACHELOR OF ARTS

PROFESSOR VAN HORN
PROFESSOR PEDACE

DECEMBER 14, 2018

Abstract

There is evidence there is a global gender price gap in traditional global art auctions. Taking into account recent technological advances in the secondary art market, this study examines if there is a gender gap for the sale prices of female artists' work in the contemporary, online art auction market. The analysis uses a unique data set of art works sold in Christie's Online-Only Auctions for the year of 2018. We regress measures of price on gender and controls for various characteristics of the art work and artist. We find that while there is discount in prices of 17% for artwork created by female artists, further analysis indicates the difference is not necessarily the result of bidder's biased prices, but rather rooted in the pre-sale estimates given by the auction houses.

Acknowledgements

I would like to thank Professors Van Horn and Pedace for helping me through this journey that is senior thesis, for allowing me to indulge in my combined love for art and economics. I appreciate their patience and understanding as I worked with a topic that was new to us all. Working with a topic that does not have easily accessible data sets required us to come up with some creative solutions for simply gathering and entering the data, and without their insight I would have never been able to even collect it at all, let alone analyze it.

I would also like to thank my parents, and my siblings, for encouraging me, for believing in me and for all of their support through this process. Thank you for talking through my paper with me all those times, Mom!

Lastly, I want to acknowledge all of the women artists who inspire me in my creative pursuits. My hope is that there is continued research on this topic, but just as importantly, we can continue to simply create great art.

Table of Contents

I. Introduction

Why are there no great women artists? In 1971, Linda Nochlin argued in her famous essay "Why Have There Been No Great Women Artists?" that institutions could be the cause of this. She argues that this difference is due to the systematic way in which women have been excluded from being nurtured as artists throughout the ages, which is rooted "in our institutions and our education" (Nochlin,1971).

Perhaps then, one of these institutions is art auctions. There is economic evidence that women are paid proportionately less than men in the form of wages (Goldin et al., 2017) all over the world, but most notably in the United States and in the UK (Dias et al., 2018). Are women compensated less for their artistic work as well? In global art auctions, there seems to be evidence of this phenomenon. This, dubbed here as the "auction gap", is the notion that art made by women is sold for lower auction prices than art made by men. Recently, this idea was supported by a study conducted in 2017 that found there is as high as a 47.6% gender discount in auction prices for paintings created by women artists born from 1850 to the present time (Adams et al., 2017).

Given then, that there is evidence of an auction gap existing for art created and sold across a wide time period, I want to examine the possible existence of this auction gap from a more specific time period, particularly for contemporary art created by women artists, sold as recently as possible. I will seek to answer the question, can auction prices for contemporary artists' art be explained by the gender of an artist? I will go about answering this question through gathering auction price points from the last year, and using three ordinary least square (OLS) regression models to analyze the effect of gender on these prices.

For contemporary art sold at auction today, recent headlines make it seem as though the auction gap may not be as prominent for contemporary art created by women artists. Although there is virtually no formal statistical analysis of this evidence, there is anecdotal evidence that work generated by prominent contemporary women artists are fetching higher prices at auction. In recent years, auction prices specifically for contemporary art by women artists seems to be on the rise, as women artists break their own records and defy auction price predictions. For example, *Suddenly Last Summer* (1999) by Cecily Brown, went for $6.8 million, more than double her prior record, at a Sotheby's auction in New York in May 2016. Likewise, Louis Bourgeois' Sculpture *Spider* (1996) piece jumped three slots ahead of predicted auction sales at a Christie's Post-War sale in the fall of 2015, selling for $28.2 million. Additionally, Cady Noland, another contemporary artist, had her work *Bluewald* (1989) sell for $9.7 million, exceeding the high estimate of $8 million as a Christies New York Auction in 2015, which also surpassed the artist's prior record which was *Oozewald* (1989), which drew in $6.5 million in 2011 (Shultz, 2018). Of course, anecdotal evidence of trends does not guarantee statistical proof of anything. However, through analyzing a subset of contemporary artworks and artists, we do have a better chance of finding if auction prices actually can be explained by a contemporary artist's gender, and by how much.

Women being compensated less than their male counter parts, even in secondary markets, is an economic problem because it perpetuates gender inequality in the field of visual arts. Auctions are secondary markets, which means the paintings have already been traded in the primary market, (through galleries, perhaps even from the artist directly). When a work of art goes up for sale on the secondary market, this signals that the artist is producing work that is valued and in demand for resale (Bocart et al., 2017). Once an artist's work enters the secondary market, the auction results are more visible to the public than those of the primary market. Consultants, gallery owners, appraisers and art collectors use this readily available information when they value artists current and potential worth. This means that while auction prices do not directly compensate the artist, they do influence gallery prices, and can have a significant effect on an artist's career and incentives for making art (Galeson, 2000). The implications of this, if there is a gender price discount, are serious, as it means that women may have less of an incentive to continue to create art or even enter artistic careers at all, perpetuating gender inequality in the field of visual arts even further.

Using OLS, we regress auction prices against certain variables characterizing the artists and the work of art sold on online, contemporary art markets. Section II delves into past literature on gender biases in valuing women's art and the gender price gap in art auctions. Section III outlines the data used in our empirical study. Section IV explains the models and theory behind it, and Section V describes the results of the study. Finally, Section VI discusses the importance of these results, their limitations, and their implications for future research.

II. Literature Review

While multiple studies have examined certain biases within both secondary and primary art markets, few studies have examined solely gender biases in the art market. In addition, the field of art market economics has historically focused largely on evaluating patterns related to the rate of return in art as an investment, rather than linked with determinants of prices. However, in the past year, there have been multiple paramount studies using both empirical and experimental techniques to determine the role gender plays in the auction prices artworks gather.

In the art market, there are two points where prices are determined: The primary and secondary markets. The primary market is when the painting is sold for the first time, which can include galleries, art fairs and studios (Zorloni, 2005). The secondary market (which is the focus of this paper) examines the point when existing artworks exchange, generally in auctions. The nature of the secondary market has been found to be considerably more predictable than primary markets, because of information available on the art and the artist (Zorloni, 2005). Although our research focuses on data drawn from the secondary market, it is useful to examine both types of markets to gain a general understanding of how cultural gender biases can play a role in determining art prices. Across the literature, conclusions regarding the presence of a gender bias against women are mixed.

In a study of Australian contemporary art controlling for artist specific characteristics, such death day or projected life span, age and fame, researchers found that non-indigenous female artists sold their paintings for more than men in galleries (Coate and Fry, 2012). However, in a study of Dutch contemporary art, Rengers and Velthuis (2002) find that in the male-dominated Dutch primary art market, female artists receive lower prices for their work. They explain that because they determine that age contributes positively to explaining art prices, the difference in age between genders in the data set can be blamed in part for the discount, as female artists tend to be younger than their male colleagues.

Additionally, there have been three empirical studies released in the past year examining art exclusively in the secondary art market, using considerably large data sets (millions of recent auction prices) of artworks which span across styles and centuries. Findings regarding a gender gap in this type of study are inconclusive as well. The two most comprehensive studies, in terms of sheer amount of data points used, have found female artists' work to be associated with significant price discounts in auction markets (Bocart et al., and Adams, 2017). The third study however, (Cameron et al., 2017) which samples Yale MFA artists' work, concludes that auction prices aren't negatively biased against female artists' work, going so far as to refute the previous literature by concluding that women's work commands a premium. This last study is interesting, as its sample focuses only on artists who graduated from one of the most prestigious art school in the country. This characteristic of the study could account for this study's diverging findings, as institutional barriers on the art market may require female artists pass through more rigorous quality filters as compared to male artists (Cameron et al., 2017). In other words, there is sample selection bias: it makes sense that the female artists in this study- those who graduate from Yale (a rigorous institution acting as a quality filter) would demand a premium, as they likely had to have been making art of a higher quality than their male counterparts in order to even get into the school.

Although results on that front are mixed, consistent across a majority of the literature is the theory that the art auction market follows a "winner take all" model (Bocart et al., 2017). This model stipulates that an extremely small amount of sales, usually no larger than a single percentage point or two, represents a large portion of the total dollar volume gathered by sales in the market. As Bocart et al. observe, (2017) the distribution of rewards market is highly skewed with the largest profits concentrated on top. Because of this skewness, and the nature of information in secondary art markets, there seems to be a subsequent ‘superstar’ effect suggesting that it is only a select few artists at the top who rake in a majority of these sales.

The Adams et al study, which uses a sample of roughly 1.5 million transactions from 1970 to 2013, found a 47.6% gender discount in auction prices for paintings created by women artists born from 1850 to the present time. When accounting for mega-transactions, (the superstar effect) the discount drops from 43.6% in the 1970s to an average of 25% after 2000 (2017). Similarly, because the data was highly skewed by a small number of women located at the top of the market that they were discovering, the Bocart study similarly accounted for the number of artworks sold per artist and found a discount of 10% for female artists’ work (2017).

Experimental studies have also concluded that there may be a cultural bias to deem women’s artwork as less valuable than men’s. Adams et al. (2017) conducted a study in which they had participants take a survey and value art on a scale based on how much they liked it. Names of female and male artists were displayed under the artwork, even though in reality the artwork was generated with a computer algorithm. Researchers found that more affluent individuals (people who indicated they visit an art gallery or exhibition at least a few times a year) were shown to be associated with a 6% gender discount in valuing art they were told was created by women artists, which is economically significant (Adams et al., 2017). This is particularly striking, as this population represents the subset of people most similar to the population likely to be bidding at art auctions. In an additional experiment, the same researchers asked participants of a study to say if they thought an artwork was made by a male or female artist, and then rate their appreciation for it. Results showed that participants could not correctly guess the gender of an artist by looking at a painting, suggesting that structural differences that might exist between genders are not readily observable.

Some research suggests that the gender disparity in auction prices has decreased in recent years, supporting the hypothesis that as cultural gender inequality decreases over time, this decrease influences the discount (Adams et al., 2017). Is this true of only certain kinds of art created in a specific period or is the auction gap also closing for contemporary artists' work as well? There seems to be a bias in the data gathered and observed in the studies as it includes work spanning styles and centuries instead of focusing on a single genre. The auction years span widely, including both artists that are dead and alive, but certainly weighing toward artists who are deceased. This means that the data used in these studies could be largely influenced by the historical repression of women artists, barring historical women's art from entering the art market and changing the standards by which they were valued (Adams et al., 2017).

There also seems to be a gap for the type of auctions observed. The existing literature focuses on auction markets that take place almost exclusively in physical salerooms. In recent years, however, there has been a trend toward art auctions moving online, with the two largest traditional auction houses, Christie's and Sotheby's, offering year-round online-only auctions.

By focusing my research supremely on the contemporary, Avant Garde online art market, my study would seek to fill in the gap that exists in studying 1) contemporary art markets, 2) the responsiveness of the market for living and recently deceased artists, and 3) the advent of online auctions. It would also serve to capture the Feminist art movement within this time frame, which beginning in the 1960's, greatly increased women's participation in visual arts institutions such as galleries, museums and auctions (Shultz, 2018). The data from this market differs considerably from that of the aforementioned studies because this market is international, highly speculative, and unpredictable.

III. Data

The auction data was obtained from Christie's database of online auction results. Christie's is ranked the first auction house in the world when it comes to online auction sales, based on a conglomerate of rankings determined by visitors' and buyers' experiences with the house (Hiscox, 2018).

In order to understand this section more completely, some background on art auctions must first be given. Online art Auctions are conducted through online platforms. They are timed, usually over a period of a few days or weeks. Bids can be submitted anytime during the course of an online auction, and a next bid is submitted, using predetermined bidding increments. The person with the highest bid is selected and this final price is known as the hammer price (or as in my data, the price realized). When bids are placed, they do not include transaction fees. Transaction fees include a buyer's premium, which is an additional fee the buyer pays to the auction house based on the hammer price, and indirect taxes (a VAT or sales tax as applicable) appropriately applied on the buyer's premium (Christie's, 2018).

In the data set, there are a total of 815 transactions. We restrict our analysis to online auctions held in 2018. This is the most recent data available, as Christie's only started publishing online auction results in May of 2017. Transactions were drawn from a total of 9 auctions held throughout the year. Only auctions characterized as dealing with pieces identified by Christie's as "Contemporary and Post-war" in style/time-period were considered.

Within this these style constraints, transactions cover a wide range of work, including paintings, drawings, sculptures, pottery, photography, works on paper, and prints and multiples. Transaction information provided by the auction house that we gathered included the piece title, the auction it was sold in and its date, artist, pre-sale price estimations (a range of values expected for the initial sale of a particular artwork given by the auction house based upon prices recently paid at auction for comparable property, taking into account condition, rarity, quality, provenance, and other specific factors), hammer price (the final bid price, not transaction costs), material/medium, dimensions (size), if there is the artist's signature, and year the work was created. The artist's birth year, and death year if applicable, was also provided. Sales totals for each auction were also provided. These sales totals include buyer's premiums, but are net of additional taxes and fees. Three out of the 9 auction used were conducted in GPB and not USD. These values were converted using conversion rates from the average conversion rate of the day of the auction opening. The data was scraped from Christie's website for each auction, and compiled, using the free web scraping program ParseHub.

To find our variable of interest, the artist's gender, we initially went through the artists and determined the gender of those with obvious male or female names. If the name provided was unisex or ambiguous, the artist was then manually researched. If the artist's gender could not be determined, their data was excluded. Works and projects created by multiple artists were also removed from the data.

Additionally, lots with multiple works were excluded from the data. If there was no "overall" size given for a work, meaning that the lot was likely selling more than one work (i.e. a set of prints) that data point was also removed. Finally, if a piece was cylindrical, or oddly shaped enough that it had no distinguishable height and width, then this observation was also removed.

In Table 1, we define the variables we use in our analysis. As can be seen in the table, we use a mix of variables that describe artist characteristics (Female, Age, Created, Deceased), artwork characteristics (Size, Signature, Highestimate), and even auction characteristics (Auctionsaletot).

A. Summary Statistics

In total, the data amounted to 815 transactions for 576 different artists. About 23.7% of transactions were female artists' work. In total, the transactions amounted to $11,770,332.9 with women's work earning 14.76% of total sales. As the literature suggests, the data seemed to reflect the winner-take all model, as the price distribution was quite skewed.

Referring to Table 2, differences are observed between the means of our variables. The mean transaction price for male artists was about $16,157, while for female artists is about $8,952, resulting in a mean transaction difference of -7204.53 USD, which is significant at the 1% level. Relative to the mean price of art gathered by male artists, the mean price for female artists shows a discount of 44.5%. This gap in price means for male and female artists hints that there may be a gender price discount in our coefficients as we continue into the regression analysis.

Also, to note is that the variables Highestimate, Log(price) and Log(estrange) all measured differences in means for male and female artists that were negative and statistically significant. This negative number is as would be expected, given that we observe the large difference in mean transactions given gender.

IV. Theory and Empirical Models

Traditionally, the world of art auctions has been one the most exclusive markets in the world, drawing in only the most affluent and powerful bidders into transactions, the machinations and specifics of which are not always transparent or widely available. But the advent of the internet and online auctions is largely disrupting this market in multiple ways. Now, online auctions mean that there is considerably less of the exclusivity that is seen in traditional auctions. Barriers to entry are eliminated in online markets, such as bidders having to have the resources available- time and money- to travel to physical Auction Houses. Now, anyone with a credit card can bid on art put up for auction on online sales. For Christies, the auction house used to collect data in this paper, this removal of barriers to entry has resulted in their online auctions being their largest entry point for new buyers. Additionally, the ratio of buyers and bidders to lots offered for online sales is now double that of traditional offline auctions.

Because of this, it is important to consider that online auction prices may be less affected by gender than in traditional auction houses. With more bidders per lot, the market becomes more competitive, leaving less room for bidding below the estimated prices that auction houses make available, and therefore not allowing room for such a large systematic discount on willingness to pay for female artists' work. Also, because online auctions are the largest entry point for new buyers, this may mean new bidders who tend not to know much about art markets don't want to overpay for the art and tend to stay within the estimates given by the auction house, which, assuming those are reasonably unbiased, would mean that the online sale price is not as affected by the artist's gender either.

To estimate the possible gender price discount in online contemporary Art auctions, we estimate three ordinary least squares (OLS) regression models. Each model uses a different dependent variable. We will start by estimating the following regression:

$$Log(Priceph) = \alpha + \beta_1 Female + \beta_2 \text{Age} + \beta_3 \text{Created} + \beta_4 \text{Deceased } \beta_5 \text{Size} + \beta_6 \text{Signature} + \beta_7 \text{Auctotsale} + \beta_8 \text{Drawdum} + \beta_9 \text{Paintdum} + u$$

Where variables are defined as follows:

- Log(Priceph) is the natural log of the final sale price as a percentage of the high estimate given by the auction house. We use the natural log here because auction prices tend to be skewed, and also because we are using price in this function, which lends itself to gaining more precise estimates when natural log is used.
- Female is a dummy for if the artist is female. Even though we consider the possibility that online auction prices may be less affected by gender than in live salerooms because of the differences in market structure and bidder identity, we still hypothesize that there will be a gender discount for this variable.
- Age represents the age of the artist, despite if the artist is still alive. We would expect this to be higher for artists' who are older and the coefficient to be positive, as their supply is now seen as more limited by the consumer, and therefore probably more valuable. Art auction houses like Christie's post the dates that an artist was born, and if it applies, the year they died, right next to the name, making it one of the first defining variables that a bidder will see when browsing the lot.

- Deceased is a dummy variable for whether the artist is dead. As implied, this coefficient likely to be positive meaning if they are dead, their work goes for more.
- Created is the year in which the artist executed the work. The general trend in art markets seems to be that art increases in value as time passes (people see buying art as an investment). Older art will be valued higher by bidders, meaning we expect this coefficient to be negative.
- Size is the "face" surface of the piece (Height x Width) in total squared cm. We expect this coefficient to be positive, as the bigger the work, the more materials and time put into the work, demanding a higher price.
- Signature is a dummy for if the piece is signed by the artist. We believe that bidders are especially concerned about the authenticity of an artwork in online auctions. This is also one of the few characteristics specified about each work and verified by Christie's online. Therefore, we hypothesize that signed work will be more valuable to bidders, resulting in a positive coefficient.
- Auctiontotsale is a way to control for the auction the piece was sold in. We assume that online auctions with a higher total sale value would mean pieces that were a part of it were worth more, driving a positive coefficient for this variable.
- Paintdum is a dummy for if the artwork is a painting, as identified on Christie's Website as "painted". We hypothesize that this coefficient would be positive. Paintings are the most traditional type of art, easily displayed and collected. For the most part, with a painting it is easy to see exactly what you are bidding on from the display pictures online. We assume that because of this people will be willing to pay more for this straightforward kind of art. (For other types of contemporary art, like statues or sculptures or more conceptual pieces, we hypothesize that bidders cannot gather enough information about the piece from the information about it online to drive them to bid higher.)

- Drawdum is a dummy variable that indicates if the piece is a drawing. We hypothesize that the coefficient will be negative, as drawings tend to be less valuable than paintings in general, as they are not only smaller, but usually made with materials that are less valuable.

The logic behind this is that by taking price as a percentage of high estimate, we can get capture the willingness to pay of bidders proportional to the estimated value of the piece.

Moving on to a second model, we simply use the natural log of the price as the dependent variable, instead of the price as a percentage of the high estimate. Using this model, we can test more generally how well our variables estimate raw auction prices:

$$Log(Price) = \alpha + \beta_1 Female + \beta_2 \text{Age} + \beta_3 \text{Created} + \beta_4 \text{Deceased}\ \beta_5 \text{Size} + \beta_6 \text{Signature} + \beta_7 \text{Auctotsale} + \beta_8 \text{Drawdum} + \beta_9 \text{Paintdum} + u$$

For this regression, we hypothesize the same signs for the coefficients as in the previous model.

In our third regression, instead of looking at price at all, we use the high-end estimates to further examine if there is a price discount present in the estimates that could be influencing the bidder's behavior. The general model can be shown by:

$$Log(Highestimate) = \alpha + \beta_1 Female + \beta_2 \text{Age} + \beta_3 \text{Created} + \beta_4 \text{Deceased}\ \beta_5 \text{Size} + \beta_6 \text{Signature} + \beta_7 \text{Auctotsale} + \beta_8 \text{Drawdum} + \beta_9 \text{Paintdum} + u$$

V. Results

A. Model 1: Natural Logarithm of Price Percentage as the Dependent Variable

In table 3, we observe the regression which uses the price as a percentage of the high estimate as the dependent variable. In column 1, we observe immediately that the simple regression using only the female dummy and the dependent variable does not demonstrate a statistically significant relationship at 1%. 5%, or 10% percent levels. The results for the entire regression using all of our variables, as shown in column 2, do not yield any statistically significant relationships either. As we add variables to each regression, the only combinations that yield statistically significant results for the regression represented in column 2, where only the variables that are associated with the artist's characteristics are controlled for (including the dummy for if the artist is dead, the age of the artist, and the female dummy variables), is the age coefficient, yielding a positive relationship of 0.0052784, being significant at the 1% level. The sign of this coefficient is as we anticipated, showing a positive relationship between the percentage of price over the high estimate, and the artist's age, even if it is quite small. In column 3, which is the regression which includes all of our variables, the only statistically significant result was the created coefficient, which yielded a negative relationship of -0.0047*, significant at the 10% level. The sign of this coefficient is negative, as we hypothesized.

Observing column 3, it is curious that only one of our other variables is statistically significant. In order to check if multicollinearity could be a problem between our variables, a Variance Inflation Factor test was performed. This resulted in a value of 1.78, signifying that multicollinearity is not an issue.

From the R-squared value from our regression in column 3, we can determine that only a small fraction, about 2.5%, of the changes in the dependent variable can be explained by our independent variables. This suggests that this using price percentage variable is perhaps not the best dependent variable to use in a model with these independent variables.

B. Model 2: Natural Logarithm of Price as the Dependent Variable

The motivation behind this regression was to examine the relationship between auctions price and all of our variables more generally. Even though this model is likely weaker in that it does not directly take the auction estimates into account and allows for potentially more unexplained variability in our model, it is definitely worth examining.

As we can see from column 3 of Table 4, using Log(Price) as the dependent variable rather than Log(Priceph) shows an increase in explanatory power, as we now observe an R-squared value of 0.1722, indicating a this model better fits our data.

In column 1, when log(price) is regressed solely against the female dummy, a coefficient of -0.4020 is given, statistically significant at the 1% level, showing already that there is a gender discount of 40.2%, when not controlling for any of the other variables. We add our variables into our model, first controlling for artist-specific identifiers in column 2, and then moving onto include both artist-specific variables and variables that characterize the artwork. In column 3, all but two of the coefficients yielded are significant at least at the 10% level.

Looking at column 3, we can see that the model estimates a coefficient of -.1707 for our female dummy variable for log(price). This means the price is 17.07 % lower for female artists work than for work by male artists. This negative sign on the coefficient is as we predicted, as we anticipated that the online art market would ultimately show a price discount for female artists work. Continuing to observe column 3, it is interesting to note that the out of the five statistically significant coefficients, the female dummy was far from the most impactful. Interestingly enough, the dummy variable for painting shows the largest coefficient, revealing a 51% percent increase in price works that exhibit this characteristic. The sign on this variable is as we hypothesized as well. The last observation worth noting is that the coefficient of the signature dummy is not only the third most impactful in the regression, but also negative. It shows that signed pieces actually sell for at a price discount of 19.95%. This unexpected outcome may be a result of the artists choices, as perhaps as artists become more well-known and their art more valued, they stop signing their now easily recognizable pieces.

The gender discount of 17% is striking, but it should be taken with a grain of salt. Considering our model, there are certainly significant limitations. Other factors that are not observed could certainly go into determining this difference. Of particular concern are the pre-sale estimates.

C. Model 3: Log(Highestimate) as the Dependent Variable and Comparison in Female Dummy Coefficients

In order to see if the pre-sale estimates themselves were biased, this last model was created and the subsequent regressions run. Immediately, just regressing our dependent variable on the dummy coefficient, we notice that there is a price discount for female artists pieces of 40.2%. In our complete regression in column 3, we observe that similar to our Log(Price) model, as the movement from male artists to females artists produced a -19.71% difference in auction price. This similar gender price discount to the Log(price) model drives us to directly compare their difference with a statistical test for significance. If the coefficients for the two models are similar, then we can conclude that this difference in prices is likely coming from the pre-sale estimates, and specifically the high estimates.

Drawing from research on comparing regression coefficients between models conducted by Clogg et al., (1995), we identify and use the following equation:

$$Z = \frac{\beta_1 - \beta_2}{\sqrt{(SE\beta_1)^2 + (SE\beta_2)^2}}$$

where SE$\beta$is the standard error of β

By plugging our coefficients into the formula, we can check if the difference in coefficients is statistically significant. This test results in a p-value of 0.421. This high p-value means we fail to reject the null that the difference between the coefficients is statistically significant.

This finding further supports the conclusion that virtually all of the price difference as manifested in the female dummy coefficient in the Log(price) model is coming from the auction house through the pre-sale high estimates they set, and not directly from the bidders.

VI. Conclusion

The finding that the price difference is rooted in the pre-sale auction estimates, and likely not a result of bidders, of course begs the question: Why is the price difference coming from the estimates? This could be due to simply gender bias, but another likely answer is that there are characteristics about the art pieces or artists that are known to the appraisers, but unknown to us and unaccounted for our model. This limitation lends itself to ample room for additional research. In continuing research, it may be enlightening to include variables capturing more of the expert knowledge that the appraisers are considering when valuing an art piece. Examples of these variables would be if the artist has had their work displayed in certain galleries, museums or shows that suggest the artist is trending in the art world, or some type of measure for quality of work.

Additionally, drawing upon our analysis and the fact that the artist-specific variables (female, age, deceased) tend to be significant in our last two models, it would likely also be beneficial to measure the effect of more variables that describe artists' characteristics, such as ethnicity or country of origin, and some type of measure for fame. Taking these variables into account would likely lend a model of better fit for the dependent variable of price that we want to describe.

Through investigating the price discount for women's art in online auctions, and also the fact that an overwhelming majority of male artists in this sample (about 75%) reflects the art world's long history of gender inequality, we bring to light issues of gender inequality in art as it intersects with not only economics, but with technology as well. The finding that the estimates are what is driving the female price discount in our second model has important implications as it relates to online markets. Although certain aspects of online auctions and the incorporation of technology into the way the market works (as we discussed in the Theory section) could potentially deter bidders from exhibiting gender biases, if the pre-sale estimates are biased, then these could still be reflected in bidder's prices. This is because bidders won't want to feel like they are overpaying, so sale price likely acts a function of the estimated price.

Although this study has its limitations, it has broad implications for the continued study of the economic outcomes of women artists with regards to the biases not only in buyers, but in the auction houses valuing their work before bidding even begins.

VII. Appendix

Table 1: Variable Descriptions

Variable	Definition
Price	Final sale price for the work in 2018 US$. In regression frameworks, we use the natural logarithm of this variable, written as Log(Price)
Female	Dummy Variable equal to one if the artist is female, and zero if male.
Age	Age of the artists at the time of auction (2018) in years. Variable is calculated regardless of if the artist is dead or alive at the actual auction time.
Created	The year in which the artist executed the work.
Deceased	Dummy variable equal to one if the artist is deceased at the time of the auction.
Size	The "face" surface of the piece (Height x Width) in total squared cm.
Signature	Dummy variable equal to one if the work is signed with the artist's name, initials, or stamp.
Auctiontotsale	The sale total the auction accrued in 2018 US$.
Highestimate	The high-end estimate given by the house for the work in 2018 US$. In regression frameworks, we use the natural logarithm of this variable, written as Log(Priceph)
Priceph	Price as percentage of the high-end estimate given for the work, in 2018 US$. In regression frameworks, we use the natural logarithm of this variable, written as Log(Priceph)
Log(Estrange)	The natural log of the range between the high and low-end estimates given by the house

Table 2: Variable Summary Statistics

Variable	Total Sample	Female Artists	Male Artists	Difference	Gender Gap (%)
N. Transactions	815	194	621		
Price	14442.13 (802. 57)	8952.55 (670.794)	16157.07 (200.522)	-7204.53*** (1223.16)	-44.5%
Female	.2380368 (0.014927)	-	-	-	-
Age	64.92761 (0.768377)	56.96392 (1.218072)	67.41546 (0.911630)	-10.45154*** (740.9747)	
Created	1995.745 (0.599572)	2002.335 (0.8415589)	1993.686 (0.722372)	8.649*** (1.109073)	
Deceased	.2110429 (0.01430)	0.0670103 (0.017998)	0.2560386 (0.0175279)	- 0.1890283*** (.0251231)	
Size	10683.91 (582.354305)	11624.59 (1220.940977)	10390.04 (662.419143)	1234.55 (1389.063)	
Signature	0.802454 (0.013955)	0.7835052 (0.029646)	0.8083736 (0.0158065)	-0.0248684 (.0335966)	
Auctiontotsale	2124028 (35879.24374)	1895590 (69083.40583)	2195392 (41466.8669)	-299802*** (80573.07)	
Paintdum	0.2331288 (0.014819)	0.2216495 (0.029898)	0.236715 (0.0170710)	-0.0150655 (.0344284)	
Drawdum	0.0576687 (0.0081707)	0.0463918 (0.015140)	0.0611916 (0.0096258)	-0.0147998 (.0179409)	
Highestimate	10323.07 (486.149657)	6635.052 (408.722594)	11475.2 (618.052944)	-4840.148*** (740.9747)	
Log(Price)	8.852222 (0.31008)	8.545907 (0.0836593)	8.947914 (0.0503173)	-0.402007*** (.0976254)	
Log(Priceph)	0.159099 (0.005573)	0.1197612 (0.0580846)	0.1713881 (0.0309867)	-0.0516269 (.0658331)	
Log(estrange)	7.568298 (0.036526)	7.309785 (0.067181)	7.649057 (0.0426107)	-0.339272*** (.0795553)	

Notes: *** Signifies significance at the p<0.01 level (1%) level, determined by a two-sample t-test.
Table 3: Regression Analysis using Price as Dependent Variable

	(1)	(2)	(3)
	Log(Price)	**Log(Price)**	**Log(Price)**
Variables			
Female	-0.4020*** (0.10)	-0.1894*** (0.09)	-0.1708* (.0963)
Age		0.0127 *** (2.91)	0.0117*** (0.004)
Deceased		0.4248 *** (0.84)	0.3661997** (0.154)
Created			-0.006258 (0.004)
Size			2.14E-06 (0)
Signature			-0.1995** (0.102)
Auctiontotsale			9.98E-08** (4.12E-08)
Drawdum			-0.0837 (0.177)
Paintdum			0.5176*** (0.097)
Constant	8.9478* (0.0495)	7.985 *** (2.26)	10.99 (8.53)
Observations	815	815	815
R-Squared	0.0189	0.1300	0.1722

Notes: Table shows the results for the OLS estimation of a model, showing the coefficients associated with each variable and robust standard errors in parenthesis. The asterisks ***, **, * indicate significance at the 1%, 5% and 10% levels respectively.

Table 4: Regression Analysis Using Price as Percentage of High Estimate as Dependent Variable

	(1)	(2)	(3)
	Log(Priceph)	**Log(Priceph)**	**Log(Priceph)**
Variables			
Female	-.0516269 (.06)	.0144779 (.06)	0.0263 (0.07)
Age		.0052784*** (.00)	0.0030 (0.002)
Deceased		.0578615 (.10)	0.0038 (0.10)
Created			-0.0047* (0.003)
Size			1.33-07 (1.63E-06)
Signature			-0.0230 (0.07)
Auctiontotsale			2.82E-08 (2.79E-08)
Drawing			-0.1970 (0.12)
Paint			0.0549 (0.07)
Constant	.1713881 (.03)	-.1992721 (.11)	9.3014 (5.77)
Observations	815		815
R-Squared	0.1300	0.0292	0.0282

Notes: Table shows the results for the OLS estimation of a model, showing the coefficients associated with each variable and robust standard errors in parenthesis. The asterisks ***, **, * indicate significance at the 1%, 5% and 10% levels respectively.

Table 5: Regression Analysis for Using High-End Estimates as Dependent Variable

	(1)	(2)	(3)
	Log(Highestimate)	**Log(Highestimate)**	**Log(Highestimate)**
Variables			
Female	-.3503807*** (.09)	-.2038857** (.08)	-.1970595*** (.08)
Age		.0073793*** (.002	.0087643*** (.003
Deceased		.3669808*** (.13)	.3246421** (.13)
Size			-1.59e-06 (2.12e-06)
Created			.0031594 (.003)
Signature			-.1765126** (.09
Auctiontotsale			-.1765126** (3.62e-08)
Drawdum			.1133147 (.16)
Paintdum			.4626918*** (.09)
Constant	8.776526*** (.0424138)	8.185085*** (.1506771)	1.68937 (7.5)
Observations	815	815	815
R-Squared	0.0196	0.0912	0.1313

Notes: Table shows the results for the OLS estimation of a model, showing the coefficients associated with each variable and robust standard errors in parenthesis. The asterisks ***, **, * indicate significance at the 1%, 5% and 10% levels respectively.

VIII. References

Adams, Renee B. and Kräussl, Roman and Navone, Marco A. and Verwijmeren, Patrick. (2017). Is Gender in the Eye of the Beholder? Identifying Cultural Attitudes with Art Auction Prices. Social Science Resource Network Electronic Journal.

Allen, Greg. (2005). "The X Factor: Is the Art Market Rational or Biased?" *The New York Times*, May 1. Available at: http://www.nytimes.com/2005/05/01/arts/design/the-x-factor-is-the-art-market- rational-or-biased.html?_r=0.

Bocart, Fabian & Gertsberg, Marina & Pownall, Rachel. (2017). Glass Ceilings in the Art Market. Social Science Resource Network Electronic Journal. 10.2139/ssrn.3079017.

Cameron, Laurie and Goetzmann, William N. and Nozari, Milad. (2017). Art and Gender: Market Bias or Selection Bias? Social Science Resource Network Electronic Journal.

Chrsities. (2018). Auction Results. [Online]. https://www.christies.com/results/
Clogg, C. C., Petkova, E., & Haritou, A. (1995). Statistical methods for comparing regression coefficients between models. *American Journal of Sociology, 100*(5), 1261-1293.

Coate, Bronwyn S. and Fry, Tim L. R. (2012). Better off dead? Prices realised for Australian paintings sold at auction, *in ACEI 2010 : Proceedings of the 16th International Conference on Cultural Economics 2010*, Association for Cultural Economics International, Copenhagen, Demark, pp. 1-27.

Galenson, D. W. and Weinberg, B. A. (2000). Age and the quality of work: The case of modern american painters. Journal of Political Economy, 108(4):761–777.

Goldin C, Kerr SP, Olivetti C, Barth E. (2017). The Expanding Gender Earnings Gap: Evidence from the LEHD-2000 Census. American Economic Review: Papers and Proceedings. 2017;107 (5) :110-114.

Hiscox. (2018). *Hiscox Online Art Trade Report 2018*. [PDF]. Available at https://www.hiscox.co.uk/online-art-trade-report

Nochlin, L. (1971) From 1971: Why Have There been No Great Women Artists? Reprinted in Artnews 05/30/15. [online] Available at: http://www.artnews.com/2015/05/30/why-have-there-been-no-great-women-artists/
Rengers, Merijn, and Olav Velthuis. "Determinants of prices for contemporary art in Dutch galleries, 1992–1998." *Journal of cultural economics* 26.1 (2002): 1-28.

Shultz, A. (2018). Female Artists' Works on the Rise. [Online] Barron's. Available at https://www.barrons.com/articles/female-artists-works-on-the-rise-1529467305

Zorloni, Alessia. (2005). "Structure of the Contemporary Art Market and the Profile of Italian Artists." *International Journal of Arts Management* 8, no. 1: 61-71.