Gendered Prices*

Renée Adams**
University of Oxford, ABFER, ECGI, FIRN
renee.adams@sbs.ox.ac.uk

Roman Kräussl
University of Luxembourg and Hoover Institution, Stanford University
roman.kraussl@uni.lu

Marco Navone
University Technology Sydney, FIRN
marco.navone@uts.edu.au

Patrick Verwijmeren
Erasmus School of Economics and University of Melbourne
verwijmeren@ese.eur.nl

---

* This paper was previously circulated with the title: "Is Gender in the Eye of the Beholder? Identifying Cultural Attitudes with Art Auction Prices". First version: December 2017; This version: September 2020. We thank the editor, Stijn van Nieuwerburgh, and two anonymous referees for excellent comments. We also thank Sumit Aggarwal, Klaas Baks, Riccardo Calcagno, Tarun Chordia, Les Coleman, Joop Hartog, Michael Hertzel, Matti Keloharju, Peter Koudijs, Euphemia von Kaler zu Lanzenheim, Tibor Neugebauer, Leo Paas, Julien Penasse, Joshua Pollet, Raghu Rau, Joshua Rauh, Herbert Rijken, Zenu Sharma, Arjen Siegmann, Christophe Spaenjers, Aymeric Thuault, Mark Wahrenburg, Michael Weber, Amy Whitaker, and participants at SFS Cavalcade Asia-Pacific 2018 Conference, Financial Management Association 2018 Conference, Behavioral Finance and Capital Markets 2018 Conference, European Financial Association 2017 Conference, Hong Kong Baptist University's 2017 International Corporate Governance Conference, the Behavioural Economics: Foundations and Applied Research Conference, the Yale Art and Gender Symposium, and seminar participants at the University of Oxford, the University of Vienna, University of Technology Sydney, the University of Melbourne, Erasmus University Rotterdam, the University of Luxembourg, HEC Lausanne, London Business School and the Norwegian School of Economics for helpful comments. We thank Louise Blouin Media for giving us access to the Blouin Art Sales Index data (BASI) for research purposes. We thank Daniel Moevios, Ali NasserEddine, Matthias Thul, Constanze Weyland and Hugo Wolters for helpful research assistance.
** Corresponding author: renee.adams@sbs.ox.ac.uk. Saïd Business School, University of Oxford, Park End Street, Oxford, OX1 1HP, UK.

Gendered Prices

Abstract

We provide evidence that culture is a source of pricing bias. In a sample of 1.9 million auction transactions in 49 countries, paintings by female artists sell at an unconditional discount of 42.1%. The gender discount increases with measures of country-level gender inequality—even in artist fixed effects regressions. Our results are robust to accounting for potential gender differences in art characteristics and their liquidity. Evidence from two experiments supports the argument that women's art may sell for less because it is made by women. However, the gender discount reduces over time as gender equality increases.

Keywords: Law of One Price; Bias; Art; Gender; Auction; Culture; Inequality
JEL codes: Z11; J16; D44

> "[women] simply don't pass the market test, the value test… As always, the market is right." (Georg Baselitz quoted in Clark, 2013)

> "the [auction] market…is certainly one of the key components of our understanding of what is good and bad." Ashenfelter and Graddy (2003, p. 783)

I. Introduction

Although psychological biases may move prices away from fundamentals, the sources of these biases are still unclear. Many biases have biological roots, as the neurofinance literature shows. However, biases may also have social roots (Hinton, 2017). Social context may also moderate the extent to which biological phenomena manifest themselves (Cavalli-Sforza and Feldman, 1973). The role of social factors may be especially important in international contexts. Here we examine the role of one social factor, culture, as a potential source of pricing bias across countries.

We test whether country-level culture, specifically gender culture, affects prices using cross-country data on paintings from the secondary art market. We expect country-level culture to help explain variation in secondary art prices for two reasons. First, art purchases often have both consumption and investment motives. Second, art prices in the secondary market are determined by demand, not by supply (Mandel, 2009).

Research on consumption shows that the same product may be valued differently by different consumers (e.g., Thaler, 1985). One source of variance in price perceptions, and hence demand, may be culture (Akerman and Tellis, 2001; Mattila and Choi, 2006; Bolton, Keh and Alba, 2010). For many products, the shape of the supply curve will limit the extent to which culture will affect prices. But the demand-driven nature of the art market, combined with the notorious variability in private valuations of artworks, suggests that culture should play a role in the pricing of art.

We focus on one aspect of culture, gender culture, since it is well documented that gender can affect individuals' valuations of outputs such as work (see, for example, the survey by Blau and Kahn, 2017) and that culture modifies gender attitudes (e.g., Fernández, 2007). There is also accumulating evidence that gender can affect investors' preferences towards projects (e.g., Gafni, Marom, Robb and Sade, 2019; Ewens and Townsend, 2020). In the art world, gender bias has also been advanced as an explanation for women's lack of representation among top-ranked artists (Nochlin, 1971). As Allen (2005) writes:

> *Asking why women's art sells for less than men's elicits a long and complex answer, with endless caveats, entirely germane qualifiers and diverse, sometimes contradictory reasons. But there is also a short and simple, if unpopular, answer that none of those explanations can trump. Women's art sells for less because it is made by women.*

If culture is a source of pricing bias, we expect paintings by female artists to sell for less than paintings by male artists. Since, as we show, most artists' paintings are auctioned in their country of birth, we also expect the gender discount to be bigger in countries with higher gender inequality, controlling for fundamentals. Our evidence is consistent with our hypotheses.

Using a sample of 1.9 million auction transactions from 1970 to 2016 in 49 countries for 69,189 individual artists, we document that auction prices for paintings by female artists are significantly lower than prices for paintings by male artists.[1] In regressions in which we interact the female indicator with proxies for country-level gender inequality in the auction country and include country-year fixed effects, we find that the gender discount in auction prices is generally higher

---

[1] Cameron, Goetzmann and Nozari (2019) and Bocart, Gertsberg and Pownall (2018) document some gender premia. It is possible that the findings in Cameron et al. (2019) are different because they focus on a small sample of artists from the Yale School of Art, which is an elite art school. In our Online Appendix, we show that the reason the results in Bocart et al. (2018) sometimes differ from ours appears to be due to selection bias: their sample contains substantially fewer female artists and transactions for paintings by women than our sample does.

in countries with greater gender inequality. This suggests that the discount reflects an effect of culture on prices.

One drawback to using the art market to examine violations of the law of one price is that no two artworks are the same. To overcome this problem, Pesando (1993) focuses on sales of prints from the same series. He argues his evidence shows some violations of the law of one price. The identity of the auction house appears to matter, for example. He also finds that prints by the same artist may command different prices in different countries, although he does not explore the mechanism driving this result.

Mei and Moses (2002) argue that the law of one price is violated if there are systematic differences in returns for artworks sold at different auction houses and test this hypothesis using a sample of repeat sales of artworks. What is common to these approaches to testing violations of the law of one price is that the characteristic driving pricing differentials, country or auction house, is not specific to the art itself. Thus, to bolster the interpretation that our results reflect a pricing bias, we must rule out the idea that art by men and women is fundamentally different.

The art critic Jerry Saltz (2015) dismisses this idea: “No intelligent person thinks that art should be seen exclusively through a binary gender lens or bracketed in a category of "women’s art."” However, as Nochlin (1971) discusses, the proposition that men and women’s art differs has a long history. Since there are no formal refutations of the proposition, we must take it seriously.

Our main identification strategy builds on Pesando’s (1993) argument that the law of one price is violated if works by the same artist sell at different prices in different countries. If gender culture is a source of pricing bias, we expect a female artist to experience a higher average discount for her work in countries with higher gender inequality. That is exactly what we find. In artist fixed effect regressions, the coefficients on the culture interaction terms are positive for all measures of gender inequality. To ensure we are comparing prices for similar artworks, we further examine transactions which occur only after the artist died (so the training and productivity of the artist can no longer change), and also exploit painting fixed effects instead of artist fixed effects (so the intrinsic quality of the artwork is fixed), with similar results.

The artist and painting fixed effect specifications account for any time-invariant supply-side factor that could lead to a gender discount. They directly address an old hypothesis that biological factors would lead women to produce systematically worse art (see, for example, the discussions in Nochlin, 1971, and Cowen, 1996). They also address the possibility that the gender discount reflects a systematic quality difference that can be attributed to women's historical lack of access to art education and resources (see, for example, the discussions in Nochlin, 1971, and Davis, 2015) or to labor supply-side factors that influence their productivity, e.g., child-rearing.[2]

These specifications do not necessarily account for time-varying factors that may be correlated with culture, however. One possible explanation for our results is that the themes and styles in women's art are simply less appealing to "big-spending" collectors—the bulk of whom are male, according to Thornton (2008)—because they do not reflect their personal experiences, especially in countries with more gender inequality.[3] Evidence that the gender of the *investor* may matter is

---

[2] Selection arguments would suggest that the average quality of women's artworks entering the secondary market should be better, not worse, than the average quality of the men's artworks (see Cameron et al., 2019; Bocart et al., 2018). However, the importance of selection depends on the process through which art reaches the secondary market. Not all auctions emphasize "high art", so works by artists with differing degrees of training can enter the secondary market—in the extreme case through auctions of work by "naïve" painters. Variance in quality can also arise because "usually art is sold [at auction] because of "the three D's": death, divorce or debt, or because collectors' tastes have changed" (Thompson, 2017, p. 24).

[3] While buyer identity at auction events is generally unknown, according to an Art Basel and UBS survey (McAndrew, 2020) women represented only 37% of high net worth art collectors in 2019 in the 7 countries covered by the survey and Larry's List (2016) suggests that gender imbalance is even

suggested, for example by Ewens and Townsend's (2020) findings that male (female) investors express more interest in startups founded by male (female) entrepreneurs.

Nochlin (1971) dismisses the argument that the themes and styles in women's art may not appeal to men. She argues that there are no common qualities of "femininity" linking the styles of women artists and that the work of women artists is more closely related to the work of their contemporaries than they are to each other. However, she lacks quantitative evidence to support her arguments. To formally investigate topic differences in art painted by men and women, we use a naïve Bayesian classifier of words in a painting's title to estimate the probability it was painted by a woman.

Our title analysis shows that some topics have a greater gender imbalance. Cattle are less likely to be painted by women than roses. This is consistent with the idea that female artists may have a specific "style". But men paint more roses than women, so this is also consistent with the idea that female artists are influenced by their contemporaries in the period during which they work. Regardless of the explanation for the topic imbalance, on average paintings with female-prevalent topics are not less appealing to collectors—instead, they command a premium.

While our title analysis helps rule out the idea that our findings are driven by gender differences in "themes", we also conduct an experiment to provide more systematic evidence on the question whether one can identify the gender of the artist simply by looking at a painting. For a sample of paintings, half of which were by women, participants in the experiment guessed the artist was male 62.7% of the time. Overall, participants guessed the gender of the artist correctly 50.5% of the time, i.e., their guesses were statistically indistinguishable from random. Of

higher (~18%) at the top end of the market.

necessity, the sample of artists in our experiment is small. Nevertheless, our experimental evidence is consistent with Nochlin's (1971) and Saltz's (2015) arguments that there is no such thing as "women's art".

Another possible time-varying factor is liquidity. While the art market is generally illiquid, illiquidity may be an even greater concern for art by women in gender-unequal countries. If a prospective buyer perceives that the market demand for paintings by female artists is lower or art by female artists is more difficult to value, it could be rational to apply a discount to paintings by female artists. We use past transactions of female artists to construct various measures of liquidity and information sets, but do not find that their inclusion changes the interpretation of our results.

We believe our evidence is consistent with the idea that art by women sells for a lower price simply because it is made by women. Evidence from two experiments supports this interpretation. In Experiment #1, we asked participants how much they liked the painting on a scale of 0-10 after guessing the gender of the artist. This allows us to measure whether the perceived gender might affect a person's appreciation of the work. In a second experiment (Experiment #2), we randomly associated fake male and female artists' names with images of paintings and asked participants how much they liked the painting. To avoid associating fake artist names with real paintings, we "created" our own paintings following the neural network algorithm by Gatys, Ecker and Bethge (2015).

In the first experiment, we find that participants who are male, affluent and who visit art galleries have a lower appreciation of works they associate with female artists than other participants. In the second experiment, we find that affluent participants have a lower appreciation of works we associated with a female artist name, particularly when they visit art galleries. Since affluent males who visit art galleries are most similar to the typical bidder in an art auction, we believe the evidence is consistent with Allen's (2005) hypothesis that "Women's art sells for less because it is made by women".

Our paper adds culture to the set of sources of pricing bias (see, for example, Lamont and Thaler, 2003) and prices to the set of economic outcomes affected by culture (e.g., Guiso, Sapienza and Zingales, 2006; Fernández, 2008). Although we focus on country-level gender culture and the art market, the idea that culture shapes investors' preferences is applicable to other dimensions of culture, whether national or not, and markets for other assets with subjective valuations.

Although culture is slow-moving (e.g., Alesina, Giuliano and Nunn, 2013), it is not immutable. An important question is whether markets respond rationally to changes in culture. In a small sample of repeat sales, we find evidence that the returns to paintings by women are higher than the returns to paintings by men. This is consistent with the idea that the gender discount decreases as gender equality increases.

Our paper highlights the dangers of inferring quality from price. As the quotes at the beginning of the paper highlight, this is a common practice in the art market. In addition to affecting "the perceptions of an artist's oeuvre" (Thornton, 2008, p. 8), prices in the secondary market can affect prices in the primary market and alter incentives for creating art (e.g., Galenson and Weinberg, 2000). Thus, this practice may partly explain women's low representation in the art world. Even though the artist does not directly participate in the secondary market, outcomes in the secondary market can have a profound influence on an artist's career.

Many claim that there is a link between culture and women's low representation in the art world (see Nochlin, 1971; Guerrilla Girls, 1998; Reilly, 2015). Our work suggests that raising awareness about how culture can influence prices may help break this link, at least on the demand side.

II. Data

Our auction data comes from the Blouin Art Sales Index (BASI), an independent database on artworks sold at over 1,380 auction houses worldwide, including the two major players Christie's and Sotheby's. BASI sources its data from Hislop's Art Sales Index, the primary source of price information in the world of fine art, supplemented with catalogue data from auction houses (both electronic and hard copy). BASI is presently the largest known database of artworks, containing roughly 6.1 million art transactions (almost half of which are for paintings) by more than 500,000 individual artists since 1922.

The characterization of art is complex (see e.g. Bailey, 2020). Even changes in basic units of measurement can make comparisons of artworks across categories difficult (e.g. the size of a painting has a different relevance than the size of a sculpture). To help ensure our analysis is not biased due to measurement error in the fundamental characteristics of artworks, we restrict the BASI data to paintings. Our analysis focuses on transactions from 1970 to 2016 involving paintings created by artists born after 1850 for whom we can identify gender.[4] Transactions before 1970 are relatively sparse and impede a precise estimation of country- and year-level effects. Moreover, there are very few female artists born before 1850. Including these painters would skew our estimation of the effect of gender on prices, as we demonstrate in Online Appendix 2.

Our final sample contains 1,898,849 transactions conducted at more than 68,000 auctions in 49 countries from 69,189 individual artists. Our sample is the largest and most comprehensive data set on auction transactions for paintings to date. It is substantially larger than the repeat sales sample in Korteweg, Kräussl and Verwijmeren (2016), which consists of a subset of this data, and is roughly 74%

[4] The birthyear is missing for 8.16% of observations in the original sample. We exclude those observations.

larger than the sample in Renneboog and Spaenjers (2013), which consists of data on 1,088,709 art sales for 10,442 artists from 1957 to 2007.

Because of their focus on graduates from the Yale School of Art, the auction sample employed in Cameron et al. (2019) is substantially smaller. Of the 4,434 graduates from the Yale School of Art, Cameron et al. (2019) identify only 525 artists in the BASI data with a total of 10,906 sales. The sample in Bocart et al. (2018) is larger (2,677,190 transactions), because it includes other types of art such as photographs and sculptures in addition to paintings. But it has worse coverage of female painters. It contains only 33,064 transactions for female painters, as compared to 141,149 transactions in our sample. Even if we restrict our sample as in Bocart et al. (2018) to post-2000 transactions for European and North American artists born after the year 1250, our data contains substantially more transactions for female painters (83,761).

For each sold painting in our data set, we have detailed information about the artwork, the artist, and the auction it was sold at. We know the painting's title, artist, size, whether it was signed or stamped by the artist, and its medium (e.g., "oil on canvas"). The BASI database also categorizes each painting into one of six main styles as defined by the auction houses Christie's and Sotheby's: 19th Century European, American, Asian, Impressionist and Modern, Latin American, Post-war and Contemporary, and a residual "Other" style category. For each artist, we observe their name, nationality, year of birth, and year of death (where applicable). We also know the auction house and the date and location of the auction. Since BASI assigns a unique auction identifier to auctions, we can include fixed effects at the auction level in our regressions.

BASI includes an artist identifier, but no painting identifiers or information on the artist's gender. We build a painting identifier based on artist identifier and title of the painting. We acknowledge that this indicator is likely to be noisy given the fact that artists may use similar names for their paintings, e.g., "Untitled", and that auction houses may use different spellings for a given title. In spite of this limitation, we believe that this proxy is still informative. As we show in Figure 5B, the evolution of repeat sales indices based on unique artist and painting title identifiers follows the evolution of repeat sales indices in a small subsample of repeat sales from Korteweg et al. (2016). Nevertheless, to be conservative, we only use this painting identifier to confirm results obtained using identifying information provided by the data vendor.

To determine the artist's gender, we first correct for spelling mistakes in artists' first names and then match them to two lists of names and associated gender we compile from various sources. The first list comes from US Social Security Administration (SSA) data from 1880 to 2016 (available at https://www.ssa.gov/oact/babynames/limits.html). The second list comes from non-American and non-British directors of companies between 2000 and 2016 from Boardex. We use data from Boardex because it contains names and gender for individuals with 168 different nationalities.

We classify names as female/male in the SSA and Boardex data if there are at least 10 individuals with the same name and 95% of the individuals are female/male. If the classification of gender is inconsistent across data sets (e.g., female in SSA but male in Boardex) or we cannot classify gender at all using the two lists of names, we use a Google search to determine gender. If we cannot conclusively verify the gender of an artist, we set their gender to missing. Overall, we are able to classify gender for 89% of the starting BASI painting data set.

In Table OA1.1 of Online Appendix 1, we show that our finding of a discount for female paintings is not sensitive to a potential measurement error in the assignment of gender. Excluding gender identified through online searches (column 1), restricting our sample to the subsample of artists born in the US with unambiguous gender (100% of the name occurrences are female/male) according to Census data from 1880 to 2016 (column 3), and unambiguous gender according to the Census in the year the artist was born (column 4) does not change the interpretation of our results. Our results are also robust to examining transactions for artists from Western Europe or North America born after the year 1250 for whom gender might be easier to classify, as Bocart et al. (2018) argue (column 6).

The only subsamples in which we do not document a statistically significant gender discount is in the sample of artists whose gender could only be identified through online searches and a sample of 441 "visible" artists (89 of whom are women) whose gender was listed in "Oxford Art Online - Grove Art Online" or "The Getty Research Institute - Union List of Artist Names Online". The fact that we document a statistically insignificant, but positive premium in the latter sample is consistent with the idea that selection may play a role in particular subsamples of female artists as the results in Cameron et al. (2019) suggest. The fact that we do not document a statistically significant discount in a sample of artists whose gender we were only able to verify through online searches is consistent with our argument that gender matters: when it is difficult to infer the gender of the artists (because of gender ambiguity of their first name), there is no discount for paintings by female artists.

Art auctions are conducted as ascending bid (i.e., English-style) auctions, in which the auctioneer calls out increasingly higher prices. When a bid is solicited that no other bidder is prepared to exceed, the auctioneer strikes the hammer, and - provided it exceeds the seller's reserve price - the painting is sold at this highest bid price (called the "hammer price"). In our data, all hammer prices are converted to US dollars using the spot rate at the time of sale. For the sake of comparability, we convert prices into 2016 US dollars using the CPI, but we also show non-inflation adjusted results with auction fixed effects to account for the timing of the auction in Online Appendix 1.

We define the variables we use in our analysis in Table 1. Panel A describes the painting and artist variables we use in our regressions. Panel B describes our measures of gender culture in the auction country. Panel C describes the variables we use in our two experiments.

< Insert Table 1 about here >

For the countries in our sample, we obtain five different proxies for gender inequality. The first two, the *United Nation Gender Inequality Index* and the *World Economic Forum Gender Gap Index*, are composite indicators designed to provide a comprehensive view of the disparity between men and women within a country in terms of educational attainment, political empowerment, labor force participation, health, etc. Both variables have comprehensive geographic coverage but are available only from the year 2000 onwards. Thus, we use extrapolated versions of these measures that backfill the missing observations from the first available data points for each country.[5]

The remaining three measures are World Bank measures of the percentage of women in parliament, the tertiary education enrolment ratio, and the labor force participation ratio. These variables capture individual dimensions of gender equality (political empowerment, educational attainment, and economic participation) and have the advantage of being available in longer time series. Table 1 describes these variables in more detail.

All culture variables are increasing in gender equality (higher values represent less gender inequality), except for the Gender Inequality Index which is defined on a scale of 0 to 1 with zero representing equality. To make the interpretation consistent, we redefine this variable as one minus the original value of the index.

[5] Results are similar if we do not extrapolate.

Table 2 shows descriptive statistics for our auction data sample. Female artists account for 16.4% of the population of artists, but only for 7.4% of transactions. Consistent with our hypothesis that gender bias should lead to lower average prices for female artists' work, we observe that the mean transaction price for male artists is around US $50,480 but the mean price is only US $29,235 for female artists. Relative to the average price for paintings by men, the discount for paintings by women is 42.1%.

Not surprisingly, mean auction prices are heavily affected by a handful of transactions of "superstar artists" that are not representative of the general market. When we exclude transactions above 1 million dollars (which we label as mega-transactions), the discount drops to 19.4%. If we look at median prices, we obtain a similar discount (20.76%).

< Insert Table 2 about here >

In Panel A of Table 3, we show the evolution of the discount over time. While the gender discount for the entire sample is relatively stable over time, when we exclude mega-transactions, the discount drops from 33.1% in the 1970s to below 22% after 2000 (and to 8.4% after 2010). Since gender inequality has also gone down over time, this trend is consistent with the idea that gender inequality influences the discount.

< Insert Table 3 about here >

Panel B of Table 3 provides summary statistics on the geographic distribution of auction transactions in our sample. Most of our observations are from Continental Europe, North America and the United Kingdom. The fact that the price discount and the percentage of transactions by female artists varies across geographic areas suggests that factors related to the role of women in society may be important for explaining auction outcomes. The fact that there are positive gender price gaps for the relatively small samples of female artists in Asia and Africa is not necessarily inconsistent with this argument. Gender culture can vary considerably and can even favor women over men. In fact, five out of six matriarchal societies currently in existence are in Asia and Africa (Sawe, 2019).

Consistent with the idea that gender culture may vary within regions, we observe that the relative advantage of female artists occurs for local art styles (such as "Asian art"). For more general styles, such as Impressionist and Modern, Post-war and Contemporary art, we observe a 24.2% discount for the paintings of female artists in Asia (with a *t*-stat of 2.5) and a 51.2% discount in Africa (with a *t*-stat of 3.3).

III. "Women's art"

To examine whether our results could be driven by auction participants' preferences for themes in paintings by male artists, we use painting titles to classify the topics of paintings. We extend the approach in Renneboog and Spaenjers (2013) who use topic dummies based on the occurrence of highly used words in the title, such as "landscape" and "portrait", by using a naïve Bayesian classifier with a "bag of words" approach to estimate the probability that a painting was painted by a female artist given the words in the title of the painting. Appendix A provides the details of our approach.

< Insert Table 4 about here >

In Table 4, we show words that are least and most likely to be associated with paintings by women in a list of frequently occurring words. The table suggests that there is a gender imbalance in some topics. Female artists account for around 7.4% of transactions in our sample but they account for 15% of the uses of the words "FLOWERS" and "ROSES". At the same time, female artists account for only 2.5% of the uses of the word "PAYSAGE" (landscape in French). Thus, paintings by female artists are more likely to be still lifes and contain floral themes, while paintings by men are more likely to contain landscapes.

< Insert Figure 1 about here >

To examine the distribution of topics across genders more systematically, in Figure 1 we plot kernel densities for the estimated conditional probabilities that a painting was created by a woman for the subsamples of paintings by female and male artists. The fact that the densities do not fully overlap is consistent with the idea that there is a gender imbalance in some topics. Since there is a significant amount of overlap between the two distributions, however, the imbalance does not appear to be large. Moreover, no topic is exclusive to one gender—after all, male artists account for 85% of the uses of the words "ROSES".

< Insert Figure 2 about here >

We account for potential gender imbalances in topics by including the estimated probability that a painting has been created by a female artist given the words of the title, Pr(Female|Title), in our regressions. Table 2 shows summary statistics for the estimated conditional probability. Figure 2 shows the distribution of male and female artists within subsamples of our transactions by quintiles of the estimated conditional probability.

IV. Gender and auction prices

According to the World Economic Forum (2020), there is still an overall 31.4% average gender gap that remains to be closed globally. If culture is a source of pricing bias, we expect paintings by female artists to sell for less than paintings by male artists. We test this hypothesis by regressing auction prices on the artists' gender and other controls. In Section V, we test the corollary that the gender discount should vary with country-level gender culture after controlling for fundamentals.

To identify the effect of the artists' gender on the auction price, we control for Pr(Female|Title) and more standard artist and painting characteristics (see, e.g., Ashenfelter and Graddy, 2003), and include year and country or auction fixed effects in our regressions. The artist and painting characteristics are the natural logarithm of the surface area measured in squared millimeters, a dummy variable that is equal to one if the painting is signed or otherwise marked, the (natural logarithm of) the artist's age (at the time of the auction), a dummy variable that is equal to one if the artist was dead at the time of the auction, and style and medium fixed effects. The country fixed effects control for potential omitted variables related to the art market and women's participation in the art market. The auction fixed effects control for potential omitted variables specific to the auction the painting is sold at, such as the characteristics of the auctioneer, the auction house, the clientele, and the characteristics of the collection that is being sold, e.g., its size and theme.

While controlling for these factors may be important, we note that the inclusion of auction fixed effects may come at a cost. In our sample, 49.85% of the auctions (accounting for 18.43% of the transactions) have no transactions involving female artists, and only 33.43% of auctions (accounting for 68.3% of the transactions) sell more than one painting by a female artist. Since gender may partially explain the allocation of art to auctions, the auction fixed effects specifications may over-control and, thus, underestimate the size of the gender price gap.

We sharpen the fixed-effect identification by restricting our sample in various ways. As a first step towards controlling for potential differences in training or other personal characteristics (such as networking ability) that may influence the price, we restrict our sample to a subsample of data in which artists only appear if they have at least 20 transactions in our sample, which is roughly 22% of artists (who collectively account for 87% of transactions). We also restrict our sample to artists who were deceased at the time of the auction (74.9% of transactions) to help rule out any supply-side influence by the artist on prices at the time of the auction.

Table 5 shows regressions of auction prices on a dummy that is equal to one if the artist is female, the estimated probability of being a female artist given the words of the title, the (natural logarithm of) the artist's age (at the time of the auction), a dummy variable that is equal to one if the artist was dead at the time of the auction, the natural logarithm of the surface area measured in squared millimeters, a dummy variable that is equal to one if the painting is signed or otherwise marked, and the various fixed effects including style and medium fixed effects, country and year and auction fixed effects. While these fixed effects account for country, year and auction-specific correlation in the residuals, art price residuals may also be correlated within a country-year or a country-year gender group because current events influence the demand for art. As a result of the Black Lives Matter Movement, for example, the demand for art by Black artists increased (e.g. Pickford, 2020). Thus, we cluster the standard errors in our price regressions in Table 5 and the rest of the paper at the country-year-gender level. The interpretation of our results does not change if we cluster standard errors at the country-gender level or double cluster at the country and year level, following Petersen (2009).

Because auction prices are truncated and extremely skewed, our dependent variable is the natural logarithm of inflation-adjusted auction prices. In Online Appendix 1, we show that accounting for skewness in prices by restricting our sample to transactions of paintings that sold for less than $100,000 or using quantile regressions instead of OLS does not change the interpretation of our results. Since inflation may vary by country, we also show that our findings are robust to using non-inflation adjusted prices with auction fixed effects to account for time and location effects. In Online Appendix 2, we show that the interpretation of our results is robust to using different specifications as in Bocart et al. (2018) and highlight that selection seems to be the main reason why they find a gender premium in some specifications.

Column 1 of Table 5 shows the regression results of auction prices on the Female Painter dummy and year and country fixed effects. In column 2, we replace the Female Painter dummy with the estimated probability of a female painter given the title of the painting. In column 3, we consider both variables together. In column 4, we include additional control variables. In column 5, we replace country and year fixed effects with auction fixed effects. In columns 6 and 7, we re-estimate the model specifications in columns 4 and 5 after excluding mega transactions. At the bottom of Table 5 we report the coefficients on Female Painter and Pr(Female|Title) in the regressions restricted to the subsamples of artists with at least 20 transactions or deceased artists at the time of the auction.

< Insert Table 5 about here >

We note that our results are not consistent with the idea that the themes in "women's art" are not appealing to collectors. If anything, female-prevalent topics command a premium, not a discount. Across all specifications, the coefficients on

Pr(Female|Title) are positive and statistically significant at greater than the 1% level. But, regardless of topic, art by women is valued less. The gender price discount persists after addressing potential omitted variable biases, even in the restricted sample. In the unrestricted sample, the magnitude of the discount in log prices varies between 21.2% (with country fixed effects in column 4) and 9.9% (with potentially overcontrolling auction fixed effects in column 7). The discount decreases for more prolific artists in the restricted sample, but the magnitude of the discount is similar since the mean prices are higher in the restricted sample.

V. Culture and the gender discount

We expect the gender discount to be bigger in countries with higher gender inequality, controlling for fundamentals. Local attitudes can directly affect how much is bid in auctions. Local attitudes can also inform pre-sale estimates of art, and hence auction outcomes (see, e.g., Mei and Moses, 2005), because auction houses use information they solicit about clients' preferences through pre-show cocktail parties and social events in setting their estimates (as discussed in, e.g., Bruno, Garcia and Nocera, 2018).[6] Local attitudes may also influence how the auction is conducted, for instance through the employment of local auctioneers. As Lacatera, Larsen, Pope and Sydnor (2016) show, auctioneers can affect bidding outcomes. On the other hand, the increased prevalence of online bidding should make it more difficult for us to detect an effect of local culture.

To test the hypothesis that culture affects prices, we first augment our regressions with auction-country-level variables that proxy for cultural attitudes

[6] We do not focus on auction house price estimates in our analysis because our data set has poor coverage of estimates in earlier years. For the sample of paintings for which we have estimates, the correlation between the midpoint of the estimate and the hammer price is 0.93. Not surprisingly, our results are similar in the sub-sample of auction house estimates.

towards women and their interactions with the artist's gender and Pr(Female|Title). In the next subsection, we build on Pesando's (1993) argument that the law of one price is violated if works by the same artist sell at different prices in different countries by adding artist fixed effects or proxies for painting fixed effects to these regressions.

We estimate the following regression:

$$\begin{aligned} Log(Price) = {} & \alpha + \beta Female\ Painter + \delta Female\ prevalent\ Topic \\ & + \lambda Female \times Culture + \eta Female\ prevalent\ Topic \times Culture \\ & + Controls\ (including\ Log\ (GDP)\ interactions) \\ & + Country \times Year + Style + Medium + \varepsilon \end{aligned}$$

In this regression, we are primarily interested in the coefficient on the interaction coefficient λ. To identify λ, we include the interactions between the natural logarithm of per-capita GDP and the artists' gender and Pr(Female|Title) to ensure the interactions with culture do not simply reflect non-linear effects of economic development.[7] To capture other (possibly time-varying) country-level confounding factors, we include country-year fixed effects (as well as fixed effects for style and medium of the painting). This makes it impossible to estimate the coefficients on our measures of culture directly, however we can still estimate the coefficients on their interactions with the female dummy variable. Since we analyze the relative effect of country-year cultural variables on male and female artists, we continue to cluster the standard errors at the country-year-gender level as in Table 5.

[7] The results are similar without the GDP interactions and are available on request.

< Insert Table 6 about here >

Table 6 presents the results of the regressions for the five measures of culture. To aid comparisons of uninteracted gender effects across models, we also show *Female Painter* coefficients from models in which all interaction variables are normalized to be mean zero within sample at the end of the table.[8] Four of the estimated λ coefficients are significant at greater than the 1% level, and all of them are positive, which suggests that an increase in gender equality in the country of auction is associated with a lower auction price discount for paintings by female artists. Consistent with the idea that attitudes towards women explain part of the discount, we also find that the premium for Pr(Female|Title) is generally higher in more gender equal countries.

< Insert Figure 3 about here >

To illustrate the economic importance of these coefficients, we present in Figure 3 estimates of the gender price gap for values of the culture variables in a ± 1 standard deviation range around the mean. If we consider, for example, the percentage of women in parliament, we see that paintings of female artists sell at a 37.68% discount in countries/years where this percentage is "low" (12.70%, one standard deviation below the mean) but sell at a 6.97% discount when the percentage is "high" (31.38%, one standard deviation above the mean). In the same way, we estimate a gender price discount of 34.22% when gender inequality is "high" according to the UN Gender Inequality Index, but a discount of 6.81% only when inequality is "low".

[8] We thank the referee for this suggestion.

V.1 Artistic talent/style

To identify culture as a source of pricing bias, we follow Pesando (1993) in examining whether works by the same artist sell at different prices in different countries. We also follow Baumol (1986) and Mei and Moses (2002) by examining whether the same painting sells at different prices in different countries to identify violations of the law of one price. To examine the relationship between culture and prices while holding the identity of the artist or painting fixed, in Table 7 we add artist fixed effects (columns 1-5) and our proxies for painting fixed effects (columns 6-10) to the specifications in Table 6.

To be able to identify the coefficients on the interaction $Female\ Painter \times Culture$, the work of an artist must be sold in different years and different countries that vary in their gender culture. Cameron et al. (2019) document that the works of 525 graduates from the Yale School of Art were auctioned in 36 different countries. In our sample, 83.25% of transactions belong to artists whose paintings are sold in more than one country. This percentage increases to 89.15% in the subsample of artists for whom we have at least 20 transactions on record.

While including artist fixed effects cannot help us rule out the possibility that the skill or style of an artist may evolve over time, it allows us to rule out the idea that systematic skill or style differences drive the difference between prices of male and female artists. With the inclusion of artist fixed effects, we are no longer able to estimate the average gender price discount. However, we can still estimate the coefficient on the interaction between the Female Painter dummy and our gender culture proxy variables.

< Insert Table 7 about here >

After adding artist fixed effects (together with country-year and medium fixed effects), we observe that the coefficients on the interactions of Female Painter with culture are positive for all the culture indices in Table 7.[9] The coefficients on the interactions between Pr(Female|Title) and culture are consistent with the interactions between Female Painter and culture. The coefficients are all positive and highly significant. For a given painter, collectors appear to place a higher value on paintings of female-prevalent topics in more gender equal countries.

We note that the R^2 of the regressions increases significantly from 25% – 27% in Table 6 to 75% – 78% in columns 1-5 of Table 7. This is consistent with the idea that individual artist effects are extremely important for understanding auction outcomes. It is outside the scope of this paper to discuss whether the individual effects reflect objective differences in talent or style. Our goal here is simply to show that even after accounting for fixed individual effects, the difference between the average auction prices of paintings by female vs. male artists is related to variables that measure the inequality between women and men in society.

The results of the model specifications that include our proxies for painting fixed effects in columns 6-10 of Table 7 support the idea that gender inequality matters for auction outcomes. To the extent that artists do not use the same painting title throughout their lives, our proxies for painting fixed effects control for cultural characteristics specific to the period during which the painting was painted and the quality of the art itself—not just the talent of the artist. Since it is relatively rare for a painting with the same title by a given artist to be sold in multiple countries, the samples in columns 6-10 are smaller than in columns 1-5. Nevertheless, the coefficients on the interactions of Female Painter with culture remain positive and highly significant in some specifications.

[9] In this specification we drop style fixed effects since in our dataset artists are allocated to a single style.

V.2 Liquidity and uncertainty about quality

The artist and painting fixed effect specifications do not necessarily account for time-varying factors that may be correlated with gender culture. One possible time-varying factor is liquidity: if a prospective buyer perceives that the market demand for paintings by female artists is lower, it could be rational to apply a discount to paintings by female artists. If collectors base their assessment of the quality of a woman's work on other work by women, it could also be rational to apply a discount to paintings by female artists. In this case, the set of reference works for female artists will be smaller so valuation uncertainty will increase.

This reasoning does not question the existence of a gender-motivated price gap but proposes (subjective) risk assessments and liquidity concerns as the channel through which culture operates.

If subjective risk assessments or liquidity concerns drive the relationship between gender culture and prices, it must be the case that subjective risk or liquidity varies by country and is linked to gender inequality. If buyers were to use a worldwide sample of past transactions to assess the quality or liquidity of female artworks, then these estimates would not vary per country and could not generate a country-specific gender price gap. Culture-related valuation uncertainty and liquidity should thus be primarily driven by country/market information.

We exploit the history of sales by female artists in a country to construct our primary measure of liquidity, which is the natural log of one plus the number of auction sales of paintings by female artists in that country over the past ten years. As this measure increases, the market for paintings by female artists in a country and year should appear more liquid and more information will be available to estimate subjective risk. We also consider a number of variations on this measure that allow for a longer "memory" (using all transactions since 1970), a shorter memory (using only the past 5 years of transactions), a more restricted information set in the style dimension (10 years of transactions in the same style), and a more restricted information set in the auction dimension (10 years of transactions from the same auction house).

In untabulated analyses, we find that these "liquidity" measures are positively correlated with economic development (as measured by per-capita GDP). Their correlations with our cultural variables are less uniform but are also positive in most cases, which suggests that more artworks by female artists are sold in more gender-equal countries.

In a similar way, we exploit the prevalence of female artists to proxy for the information a prospective buyer may use to assess the quality of a female artist's work. We count the number of female artists born in the country of a given transaction in the fifty years prior to the year of the transaction. We also consider the percentage of artists born in a country in the last fifty years who are female.

To examine whether liquidity concerns or uncertainty about quality drive our results, we augment our models in Table 7 with interactions between the artist's gender and our measures of liquidity or the prevalence of female artists, as well as with Prob(Female|Title) and GDP, as in our prior analysis, as follows:

$$
\begin{aligned}
Log(Price) = {} & \alpha + \delta Prob(Female|Title) + \lambda Female \times Culture \\
& + \eta Prob(Female|Title) \times Culture \\
& + \beta Female \times Liquidity\ or\ Female\ prevalence \\
& + \gamma Prob(Female|Title) \times Liquidity\ or\ Female\ prevalence \\
& + Controls\ (including\ Log\ (GDP)\ interactions) + Country \times Year \\
& + Style + Medium + Artist + \varepsilon
\end{aligned}
$$

In Table 8 we report the estimated coefficients, focusing on liquidity variables in Panel A and the prevalence of female artists in Panel B.[10] In several of our specifications, the liquidity and female prevalence measures correlate with the relative pricing of paintings by female artists vs. paintings by male artists. However, since the interactions between gender and culture remain statistically and economically significant after accounting for the additional variables (similar to the results in Models 1-5 in Table 7), liquidity or uncertainty about quality do not seem to be the main channel driving the relationship between gender culture and prices.

< Insert Table 8 about here >

V.3 Limits to the law of one price and the returns to investing in women's artworks

In the absence of transaction costs, collectors should exploit culture-induced pricing biases by selling paintings by female artists in more gender-equal countries. The fact that the correlations between our sales-based liquidity measures and gender culture are generally positive suggests that some arbitrage may be occurring. However, in the absence of complete gender parity, the gender discount may persist. Moreover, it is well known that, similar to the real estate market, transaction costs in the art market are high. Despite the absence of systematic data on these costs, our sample allows us to shed some light on the forces that may either maintain or reduce cultural pricing biases.

Cultural pricing biases could persist if most art is sold locally. They could also persist if there is little variation in cross-country culture that might motivate across-market sales. In the context of gender culture, pricing biases could persist if

[10] Including both liquidity and female prevalence variables in the same regressions does not change our conclusions.

markets are more segmented for female artists. But the significant variation in gender culture across countries should spur cross-country arbitrage.

We consider an artist's market to be more segmented when more of their work is sold in their birth country. Besides transaction costs, such as transportation and insurance costs, name recognition could also be a reason to auction locally. If we measure the "fame" of an artist by the number of lifetime sales in our sample, we observe that a higher proportion of the work by unknown artists is sold in their country of birth (73.6% for artists in the first quintile vs. 63.2% for artists in the fifth quintile of lifetime sales). If we use the life-long average sale price as an alternative proxy for the artist's fame, this proportion becomes higher. In general, only 21.8% of transactions in the lowest price quintile are executed outside the artist's country of birth vs. 43.7% of transactions in the highest quintile.

Since art prices are on average lower for women, it is plausible that art markets are more segmented for women than men. Consistent with this argument, we find the percentage of sales executed outside an artist's home country is 28.8% over our entire sample, but higher for men (29.1%) than women (24.5%). Using a simple logit model in which gender is interacted with time indicators, we can estimate time trends in the probability artworks by male and female artists are sold abroad. Figure 4 shows that the likelihood artworks by women are sold abroad has been persistently lower than for men since the 1980s.

< Insert Figure 4 about here >

We can examine the potential role of arbitrage in reducing cultural biases by modelling the likelihood an artist's work is sold abroad as a function of birth country culture. We estimate a regression of the probability an artist's work is sold outside their country of birth as a function of a gender dummy, a country/year-level proxy for gender culture in the country of birth, and their interaction. We control for the year of the transaction, style and medium of the painting and other controls as indicated in Table 9. While we control for the (log of) per capita GDP in the birth country of the artist (and its interaction with the gender indicator) as a proxy for the development of the local art market, we can no longer include (birth) country fixed effects in this analysis. While an artist can sell in multiple countries (the transaction country as in the rest of our paper), she or he has a unique birth country.

In Table 9 we observe that the interaction between the female indicator and birth-country gender equality is negative and statistically significant for three out of five of our culture measures. Paintings by female artists are more likely to be sold abroad, relative to paintings by male artists, if their countries of birth exhibit greater gender inequality in terms of tertiary education enrolment, labor participation, and the WEF Gender GAP Index.

< Insert Table 9 about here >

The magnitude of this effect is economically large. If we consider labor force participation as our measure of gender equality, we observe that in countries with higher levels of gender equality (mean plus one standard deviation), the probability of a foreign sale of a painting by a female artist is 4.43% lower than for a painting of a male artist. In countries with lower levels of gender equality (mean minus one standard deviation), the probability is 5.06% higher. Considering that the unconditional likelihood of a painting being sold outside the birth country of the artist is only 28.8%, these differences can be considered economically meaningful.

The results in Table 9 suggest that cultural differences may spur arbitrage: collectors appear to respond rationally to different valuations of artworks across countries. We should also expect collectors to respond to changes in culture, in this case, increasing gender equality, over time. If so, prices for artworks by women should grow at a faster rate, and exhibit higher returns, than prices for artworks by men. Although the time trend in the discount we document in Table 3 is consistent with a higher growth rate in prices for artworks by women, we can examine this possibility more systematically by using the subsample of repeat sales of paintings identified in Korteweg et al. (2016) and our identifiers for unique artists and painting title combinations.

The Korteweg et al. (2016) sample consists of 63,622 transactions of 30,655 unique paintings by 8,449 artists, 541 of whom are women. Following Bailey, Muth and Nourse (1963), we construct monthly repeat-sale price indices with base year 1970 for the subsample of paintings by women and the subsample of paintings by men and plot them in Figure 5A.

< Insert Figure 5 about here >

Although the sample of repeat sales is small, the trends in the indices are consistent with our evidence that the discount is decreasing as gender equality increases: the returns to paintings by women are higher than the returns to paintings by men. In Figure 5B, we show the result of constructing monthly repeat sales price indices using repeat sales we identify based on our proxy for unique paintings (unique painting title for a given artist). The trends in the indices are similar to those in Figure 5A.

VI. Is gender in the eye of the beholder? Experimental evidence

For policy purposes, an important question is what the channel is through which culture influences art prices. Our hypothesis is that a buyer's valuation is influenced by their cultural attitudes. However, it is also possible that the conduct of the auction is a source of bias. While our auction fixed effect results already suggest that auction mechanics cannot fully explain our results, experiments can help us strengthen the interpretation of our results.

To examine the potential relationship between an artist's gender and the perceived value of their art we conduct two experiments using surveys.[11] For our experiments it is crucial that the participants do not recognize real paintings we use in the experiments. It is also crucial that the participants can be "fooled" by fake paintings. These requirements make actual art collectors less desirable as participants, although we also note that in other contexts, such as blind wine tastings, experts have been known to perform poorly (e.g., Hodgson, 2009).

Since in principle anyone can bid at auction,[12] we use SurveyMonkey® Audience services to identify samples of participants that are representative of the U.S. population in terms of gender, age, income and geographical distribution.[13] If the participants in our experiments were more influenced by gender culture than the typical art collector, the results of our experiments would not readily generalize. However, we believe it would be difficult to make this argument given the male dominance of the art world at all levels and our evidence that the art market appears segmented. For each participant, SurveyMonkey provides data on gender, age and income range. In the surveys, we ask for additional information related to educational attainment, frequency of visits to art galleries or exhibitions, state or U.S. territory of residence and family background (country of birth of both parents).

We conducted Experiment #1 two weeks apart from Experiment #2. We surveyed 1,000 participants in the first experiment and 2,000 in the second. The

---

[11] Both experiments received Human Ethics approval.

[12] For instance, to bid in a Christie's auction, bidders create an account by supplying their contact details, along with a government issued photo ID and proof of address. For certain transactions, bidders may be asked for a financial reference and/or a deposit as a condition of allowing them to participate in the auction.

[13] The responders are drawn from a large pool of participants in the SurveyMonkey Contribute program. Enrollees in this program agree to participate in periodical surveys in exchange for donations made to their charity of choice.

numbers of participants were dictated by funding constraints. Since Experiment #1 involved more questions, it was more expensive to conduct than Experiment #2. Because of missing data on income in SurveyMonkey, we end up with responses for 880 (1,823) participants in Experiment #1 (#2). While SurveyMonkey assured us that the likelihood the same individual would take part in both experiments was "extremely low", to increase confidence that our participant pools are distinct, we merged the two samples on all common characteristics (age, gender, income, reported family background, and state) to determine a potential overlap between them. We calculate that the samples overlap by at most 90 individuals. The results of dropping these individuals from our analysis are similar to the results using the full sample and are available on request.

Table B1 in Appendix B provides summary statistics for the two experimental populations as well as Chi-squared tests for the null hypothesis that the two populations are equal. Online Appendix 3 shows the surveys we used in the experiments and summary statistics for the appreciation scores by guessed gender (Experiment #1) and associated gender (Experiment #2).

VI.1 Experiment #1: Can you guess?

In our first experiment we ask our test subjects to look at a sample of paintings and a) guess the gender of the artist, and b) rate how much they like the artwork on a scale from 0 to 10. This experiment allows us to address two separate, but related issues. First, we are interested in examining whether it is possible to guess the gender of the artist by looking at a painting. If paintings by female artists have visually distinctive characteristics, there could be a taste-based explanation for the gender price discount we document that has nothing to do with the gender of the artist per se. This experiment also allows us to measure the effect of perceived (as opposed to actual) gender of the artist on the artistic appreciation of the artwork. The presence of such an effect would reinforce our main argument that the gender price gap is at least partially culturally motivated.

To conduct the experiment, we use a sample of ten paintings. To keep our selection as neutral as possible, we choose the ten paintings from the first paintings in our sample auctioned at the beginning of 2013. We impose the following restrictions on the selection: a) five paintings from male and five from female artists; b) only one painting per artist; c) painting's hammer price below US $100,000 (to ensure the paintings are relatively unknown); and d) availability of an electronic image with sufficient resolution. Table B2 in Appendix B describes our sample of the 10 paintings.

Each subject in our experiment is shown a random selection of five out of these ten paintings. After looking at each painting the subject is asked to guess: a) the gender of the artist; b) the place of birth of the artist (among a selection of six broad geographical areas); and c) the approximate period in which the painting was created (among a selection of three possibilities). Each participant was also asked to rate the painting on a scale of 0 – 10 based on subjective artistic appreciation ("How much do you like this painting?"). While we do not have any prior about the participants' ability to guess the place of birth of the artist and the period of creation of the painting, we use these two additional questions to avoid making it too obvious that our primary interest is in the perceived gender of the artist.

Table 10 summarizes the participants' ability to correctly guess the gender of the artist by looking at a painting. The table shows the name of the artist, the title of the painting, the artist's gender, the estimated probability that the artist is female based on the words in the painting's title, and the percentage of participants who guessed the artists' gender was male or female. Overall, participants guessed the artist is "Male" 62.7% of the time in the entire sample.

The fact that the frequency of "Male" guesses is significantly above 50% indicates that the respondents expect a higher incidence of male vs. female painters. In part, this may reflect respondents' limited exposure to women as artists.

Historically, women have been underrepresented in art history books (Galenson, 2009). For instance, not a single female artist appeared in H.W. Janson's *History of Art*, a definitive art history book, until the year 1987. The percentage of art by women in museums, art fairs and galleries is also much lower than 50% (Reilly, 2015). As a result, female artists also receive less press coverage than men.

< Insert Table 10 about here >

Consistent with the idea that respondents who are likely to have more knowledge of art are more likely to guess "Male", we document in Table 11 that the probability of answering "Male" is higher for older, more affluent and better educated respondents. However, we also observe that the proportion of "Male" guesses does not differ significantly by the gender of the respondent or the frequency of visits to art galleries.

< Insert Table 11 about here >

The proportion of "Male" guesses was roughly the same (~63%) for the five paintings by male artists and the five paintings by female artists. Globally the frequency of correct guesses was 50.5%, which is statistically indistinguishable from a random guess. The only painting for which a significant majority of respondents guessed a female artist is a painting of a vase of flowers, *Vase de fleurs au pichet vert*, painted by Marie Lucie Nessi-Valtat. The fact that we also assign this painting a high estimated probability that the artist is female (71.19%), suggests that some topics are perceived as being more "feminine".

Just because a representative sample of individuals is unable to correctly guess the gender of an artist by looking at a painting is not per se proof that there are no structural differences between the artistic production of male and female artists. However, it is suggestive that any structural differences that might exist are not readily observable. In addition, the experiment provides us with a measure of "perceived gender" that is orthogonal to the actual gender of the artist. Using "perceived gender" allows us to measure the effect of gender perceptions on the artistic appreciation of a painting.

In Table 12 we report the results of OLS regressions of the appreciation score of each painting on the perceived gender of the artist, *Female Guess,* which is equal to one if the respondent guessed the artist is female, as well as Pr(Female|Title), and dummy variables that proxy for respondent characteristics. *Affluent* is equal to one if the respondent has a family income above $100,000; *Art Expert* is equal to one if the respondent visits a museum or art exhibition at least a few times a year; *Male* is equal to one for male respondents; *Mature* is equal to one for respondents in the 45-59 and 60+ age groups; *College Educated* is equal to one if the respondent has a college degree. In every model, we also control for respondents' guesses concerning the perceived period of the painting and the perceived geographic origin of the artist. We also control for participants' responses about their parents and state of residence. In column 10, we include painting fixed effects to control for the characteristics of the individual artworks as well as the actual gender of the artist. Standard errors are clustered at the respondent level.

< Insert Table 12 about here >

In column 1 of Table 12, we report the regressions of the appreciation score on *Female Guess* and controls. On average, it appears as if participants like paintings they think are painted by women more. However, as columns 2 and 3 suggest, this appears to be driven by the themes of the paintings. When we add Pr(Female|Title) to the regression, we see that the coefficient on *Female Guess* becomes insignificant and decreases in magnitude. In contrast, the coefficient on

Pr(Female|Title) is positive and significant at greater than the 1% level. This finding provides external validity for our previous result that female-prevalent topics appear to command a premium at art auctions.

In columns 4-10, we add interaction terms between *Female Guess* and respondent characteristics. The coefficients on all interaction terms except *Female Guess x Mature* and *Female Guess x College Educated* are negative and significant.[14] Respondent who are male, affluent respondents, and respondents who often visit art galleries appreciate paintings less when they perceive the artist to be female. For example, for male respondents the perceived femininity of the painter is associated with a 0.64 reduction in appreciation, which represents a roughly 12.9% "discount" from the average score.

The fact that the perceived gender of the artist is related to respondents' appreciation is consistent with our hypothesis that attitudes towards women can play a role in explaining the gender price discount we document in earlier. The fact that affluent males who visit art galleries appreciate paintings by artists they believe to be female less is particularly striking as these respondents are likely to be the most similar to participants in auction markets.

VI.2 Experiment #2: What's in a name?

While the results of this first experiment support our main hypothesis, they do not represent a direct test that gender attitudes are reflected in auction prices. To test this hypothesis more directly, we design a second experiment in which we again ask our participants to rate how much they like ten paintings on a 0 – 10 scale. The difference to Experiment #1 is that the participant sees a randomly drawn male or female artist's name beneath the painting before scoring it.

---

[14] Coefficients on the interaction terms are similar if we include participant fixed effects in addition to painting fixed effects.

To avoid ethical issues related to misattribution of real paintings we generate the ten images using the algorithm described in Gatys et al. (2015), which is available online at https://deepart.io/. The authors develop an artificial system based on a Deep Neural Network that creates artistic images of high perceptual quality. The system uses neural representations to combine content from an image (in our case pictures of everyday objects and scenery) with the artistic style of arbitrary images (in our case an existing painting). The result is an artistic representation, a "painting", with the subject of the first image and the artistic style of the second (see Table B3 in Appendix B for these 10 generated images).

We associate each image with one of two possible artist names. To create names that are immediately recognizable as male and female but that are neutral with respect to race or country of origin, we choose the ten most common last names in the U.S. from the 2000 census and combine them with the ten most popular given names for male and female babies born between 1980 and 1989 taken from the Social Security Administration.[15]

Similar to Experiment #1, we run OLS regressions of the artistic appreciation score on the name of the artist, *Female Name*, which is equal to one if the name is female, respondent characteristics, painting fixed effects and family background controls and state fixed effects. Table 13 presents our regression results. Standard errors are clustered at the respondent level.

< Insert Table 13 about here >

Panel A of Table 13 indicates that female artists' names are on average

[15] The last names come from http://www.census.gov/topics/population/genealogy/data/2000_surnames.html. We skip three names of Hispanic origin to keep the names as neutral as possible. The first names come from https://www.ssa.gov/oact/babynames/decades/names1980s.html.

unrelated to respondents' appreciation. In general, fewer respondent characteristics are significantly related to their appreciation and fewer interaction terms are significant. One reason may be that because we have fewer questions about the paintings, respondents pay less attention to the artworks. It is also possible that the artificially generated paintings lack artistic "depth". Finally, the gender of the artist may be less salient in this experiment than it is in Experiment #1 because we do not ask a question related to the artist. If participants focus only on rating the painting, they may overlook the artist's name.

Nevertheless, we still observe that female names are associated with lower scores for affluent individuals. This result is even stronger in Panel B where we restrict our analysis to individuals who indicate they visit an art gallery or exhibition at least a few times a year. The magnitude of the discount (a score reduction of 0.32) for affluent individuals in Panel B represents a 6% gender discount, which can be considered economically significant. As with Experiment #1, the results of Experiment #2 provide suggestive evidence that participants who are more likely to represent typical art auction participants may value art by women less.

VII. Conclusion

In her landmark 1971 article, Nochlin (1971) famously asks: "*Why Have There Been No Great Women Artists?*" She argues that the answer lies in the nature of social institutions, rather than in the nature of individual genius or the lack thereof. Our paper is the first to provide empirical evidence consistent with her argument by showing that gender culture may be a source of pricing bias. By focusing on the secondary art market, where artists themselves play no active role, especially once they have died, we isolate a role of social institutions that is distinct from the process of art production.

Consistent with gender culture being a source of pricing bias, we find that there is a substantial discount in art auction prices for paintings by female artists. This discount is not fully accounted for by the size, marking, style or medium of the paintings, the age of the painter or the topic. In fact, topics commonly associated with the production by female artists command a price premium, not a discount. The gender discount varies over time and across countries, and correlates with cultural factors related to gender inequality (such as the percentage of women in parliament in the country and year of the auction)—evidence that is difficult to reconcile with arguments about the nature of genius or "genetic" explanations.

While our evidence suggests that the gender discount may decrease over time as gender equality increases, the impact of historic social institutions on woman's participation in the art market are likely to be long-lasting. As Nochlin (1971) writes:

> *"And while great achievement is rare and difficult at best, it is still rarer and more difficult if, while you work, you must at the same time wrestle with inner demons of self-doubt and guilt and outer monsters of ridicule or patronizing encouragement, neither of which have any specific connection with the quality of the art work as such."*

While gender inequality is a serious policy concern, it is often challenging to prove that economic outcomes for women can be a product of culture and institutions. By applying one of the most fundamental laws of economics, the "law of one price" to the art market, we highlight the importance of culture as a source of pricing biases and the importance of both continuing to eliminate institutional impediments to gender equality and to improving market efficiency.

References

Akerman, D., and G. Tellis, 2001. Can culture affect prices? A cross-cultural study of shopping and retail prices. *Journal of Retailing* 77(1), 57-82.

Alesina, A., P. Giuliano, and N. Nunn, 2013. On the origins of gender roles: Women and the plough. *Quarterly Journal of Economics* 128(2), 469-530.

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

Ashenfelter, O., and K. Graddy, 2003. Auctions and the price of art. *Journal of Economic Literature* 41(3), 763-787.

Bailey, M., R. Muth, and H. Nourse, 1963. A regression method for real estate price index construction. *Journal of the American Statistical Association* 58(304), 933-942.

Bailey, J. (2020). Can Machine Learning Predict the Price of Art at Auction? Harvard Data Science Review. https://doi.org/10.1162/99608f92.7f90ce96

Baumol, W.,1986. Unnatural value: Or art investment as floating crap game," *American Economic Review (Papers and Proceedings)* 76(2), 10-14.

Blau, F., and L. Kahn, 2017. The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature* 55(3), 789-865.

Bocart, F., M. Gertsberg, R. Pownall, 2018. Glass ceilings in the art market. Available as SSRN WP #3079017.

Bolton, L., H. Keh, and J. Alba, 2010. How do price fairness perceptions differ across culture? *Journal of Marketing Research* 47(3), 564-576.

Bruno, B., A. Garcia, and G. Nocera, 2018. Experience and brokerage in asset markets: Evidence from art auctions. *Financial Management* 47(4), 833-864.

Cameron, L., W. Goetzmann, and M. Nozari, 2019. Art and gender: Market bias or selection bias? *Journal of Cultural Economics* 43(2), 279-307.

Cavalli-Sforza, L., and M. Feldman, 1973. Cultural versus biological inheritance: Phenotypic transmission from parent to children. *American Journal of Human Genetics* 25(6), 618-637.

Clark, N., 2013. What's the biggest problem with women artists? None of them can actually paint, says Georg Baselitz" *The Independent*, February 6. Available at: www.independent.co.uk/arts-entertainment/art/news/what-s-the-biggest-problem-with-women-artists-none-of-them-can-actually-paint-says-georg-baselitz-8484019.html.

Cowen, T., 1996. Why women succeed, and fail, in the arts", *Journal of Cultural Economics* 20(2), 93-113.

Davis, B., 2015. Why are there still so few successful female artists? ARTnews, June 23. Available at: news.artnet.com/market/female-artists-pay-gap-307951.

Ewens, M., and R. Townsend, 2020. Are early stage investors biased against women? *Journal of Financial Economics* 135(3), 653-677.

Fernández, R., 2007. Women, work, and culture. *Journal of the European Economic Association* 5(2-3), 305-332.

Fernández, R., 2008. *Culture and Economics*, in the *New Palgrave Dictionary of Economics*, 2nd edition, ed. by S. Durlauf and L. Blume, Palgrave Macmillan (Basingstoke and New York).

Gafni, H., D. Marom, A. Robb, and O. Sade, 2019. Gender dynamics in crowdfunding (Kickstarter): Evidence on entrepreneurs, investors, deals and taste-based discrimination. Available as SSRN WP #2442954.

Galenson, D., 2009. *Conceptual Revolutions in Twentieth-Century Art*. Cambridge University Press.

Galenson, D., and B. Weinberg, 2000. Age and the quality of work: The case of modern American painters. *Journal of Political Economy* 108(4), 761-77.

Gatys, L., A. Ecker, and M. Bethge, 2015. *A Neural Algorithm of Artistic Style*. arXiv preprint arXiv:1508.06576.

Guerilla Girls, 1998. *The Guerrilla Girls' Beside Companion to the History of Western Art*. Available at: www.guerrillagirls.com/store/book-bedside

Guiso, L., P. Sapienza, and L. Zingales, 2006. Does culture affect economic outcomes? *Journal of Economic Perspectives* 20(2), 23–48.

Hinton, P., 2017. Implicit stereotypes and the predictive brain: Cognition and culture in "biased" person perception. *Palgrave Communications* 3, Article #17086.

Hodgson, R. 2009. How Expert are "Expert" Wine Judges? Journal of Wine Economics, 4(2), 233-241. doi:10.1017/S1931436100000821

Korteweg, A., R. Kräussl, and P. Verwijmeren, 2016. Does it pay to invest in art? A selection-corrected returns perspective. *Review of Financial Studies* 29(4), 1007-1038.

Lacatera, N., B. Larsen, D. Pope, and J. Sydnor, 2015. Bid takers or market makers? The effect of auctioneers on auction outcomes," *American Economic Journal: Microeconomics* 8(4), 195-229.

Lamont, O., and R. Thaler, 2003. Anomalies: The law of one price in financial markets." *Journal of Economic Perspectives* 17(4), 191-202.

Larry's List Ltd., 2016. *Private Art Museum Report*. Ed. by Larry's List Ltd. and AMMA, Published by Modern Arts Publishing, Vienna Distributed by D.A.P.

Mandel, B., 2009. Art as an investment and conspicuous consumption good. *American Economic Review* 99(4), 1653-63.

Mattila, A., and S. Choi, 2006. A cross-cultural comparison of perceived fairness and satisfaction in the context of hotel room pricing. *International Journal of Hospitality Management* 25(1), 146-153.

McAndrew, C., 2020. *The Art Market 2020: An Art Basel & UBS Report*. Available at www.artbasel.com/signin?redirect=/theartmarket2020.

Mei, J., and M. Moses, 2002. Art as an investment and the underperformance of masterpieces. *American Economic Review* 92(5), 1656-1668.

Mei, J., and M. Moses, 2005. Vested interest and biased price estimates: Evidence from an auction market. *Journal of Finance* 60(5), 2409-2435.

Nochlin, L., 1971. From 1971: Why have there been no great women artists? Reprinted in ARTnews, May 30, 2015. Available at: www.artnews.com/2015/05/30/why-have-there-been-no-great-women-artists/.

Pesando, J., 1993. Art as an investment: The market for modern prints. *American Economic Review* 83(5), 1075-89.

Petersen, M., 2009, Estimating Standard Errors in Finance Panel Data Sets, *Review of Financial Studies* 22(1), pp 435-480.

Pickford, James. 2020. "Black artists matter: The winds of change are blowing through the art world," *Financial Times*, August 25, 2020.

Reilly, M., 2015. Taking the measure of sexism: Facts, figures, and fixes. ARTNews, May 26. Available at: www.artnews.com/2015/05/26/taking-the-measure-of-sexism-facts-figures-and-fixes/.

Renneboog, L., and C. Spaenjers, 2013. Buying beauty: On prices and returns in the art market. *Management Science* 59(1), 36-53.

Saltz, J., 2013. Jerry Saltz: My final word on MoMA's woman problem". Available at: www.vulture.com/2013/11/jerry-saltzs-final-word-on-momas-woman-problem.html.

Sawe, B., 2019. Matriarchal societies around the world. January 9. Available at: www.worldatlas.com/articles/matriarchal-societies-around-the-world.html

Sorvino, C., 2017. The world's 56 self-made women billionaires: The definitive ranking. *Forbes*, March 8. Available at: www.forbes.com/sites/chloesorvino/2017/03/08/the-worlds-56-self-made-women-billionaires-the-definitive-ranking/#daf7e9068a26

Sotheby's, 2017. *The Collection of Edward Albee*. Auction Catalogue, New York, September 26. Available at: www.sothebys.com/pdf/2017/N09678A/index.html.

Thaler, Richard. (1985). Mental Accounting and Consumer Choice. *Marketing Science*. 4. 199-214. 10.1287/mksc.4.3.199.

Thompson, D., 2017. *The Orange Balloon Dog*. Douglas and McIntyre Ltd., Madeira Park, BC, Canada.

Thornton, S.,2008. *Seven Days in the Art World*. W.W. Norton.

The World Economic Forum, 2020. *Global Gender Gap Report 2020*. Available at: www.weforum.org/reports/gender-gap-2020-report-100-years-pay-equality.

Appendix A
Estimating the probability that a painting was created by a woman

We use a naïve Bayesian classifier with a "bag of words" approach to estimate the probability that a painting was created by a female artist given the words in the title of the painting. We estimate the posterior probability

$$P(g_i|\mathbf{w}_i) = \frac{P(\mathbf{w}_i|g_i) \cdot P(g_i)}{P(\mathbf{w}_i)} \qquad with\ g = \{F, M\},$$

where:

- g_i is the gender of the artist of the painting i,
- $\mathbf{w}_i$is the vector of the words in the title of painting i,
- $P(g_i|\mathbf{w}_i)$ is the probability that the artist of the painting i belongs to the gender g given the words of the title of painting i,
- $P(g_i)$ is the prior (unconditional) probability that the artist of the painting i belongs to the gender g; Here we assume an unconditional probability of 50%, and
- $P(\mathbf{w}_i)$ is scaling factor and represents the probability of encountering this particular title and is simply calculated as:

$$P(\mathbf{w}_i) = P(\mathbf{w}_i|F_i) \cdot P(F_i) + P(\mathbf{w}_i|M_i) \cdot P(M_i).$$

An additional assumption of naïve Bayes classifiers is the conditional independence of features. Under this assumption the conditional probability of observing a given vector of words is simply the product of the conditional probabilities of the individual words

$$P(\mathbf{w}|g_i) = P(w_1|g_i) \cdot P(w_1|g_i) \cdot \ldots \cdot P(w_n|g_i) = \prod_{k=1}^{n} P(w_k|g_i).$$

The individual conditional probability of observing a specific word given the gender of the artist is estimated with the sample frequency by *Laplace Smoothing*:

$$P(w_k|g_i) = \frac{N_{w_k,g_i} + 1}{N_{g_i} + 2},$$

where:

- N_{w_k,g_i} is the number of times the word k appears in the titles of paintings of artists with gender i,
- N_{g_i} is the total number of words in titles of paintings of artists with gender i, and
- the +1 and +2 address the issue of estimating a non-zero conditional probability for a word that has never been used by a female artist.

When applied to text classification this model is usually implemented with a "bag of words" approach. This states that the words used for the classification should be

- Salient: The words are important and meaningful with respect to the problem domain.
- Discriminatory: The selected words bear enough information to distinguish well between the classes (gender).

Accordingly, we drop from our analysis punctuation, articles and prepositions (see below for the detailed steps). We also reduce all the numbers to a common “word” (“Landscape n. 35” and “Landscape n. 43” are considered equal). Finally, while in this model the sequence of words is not relevant, we address the issue that in this particular domain the sequences “Still Life” and “Self Portrait” (and their equivalent in different languages) have a very specific meaning. So, in our model we consider these expressions as a single word.

To increase the salience of our analysis we drop multiple occurrences of the same words in a given title and we only consider words that occur at least 1,000 times in our sample. The final result of our model is the estimated conditional probability that a given painting has been created by a female artist, given the words in the title.

In the estimation of our naïve Bayes classifier of topics we follow these steps:

1. Start from the text strings of the titles.
2. Capitalize the strings (Portrait = portrait).
3. Clean for leading spaces, trailing spaces and spaces between words.
4. Eliminate the following: **/ D’ L’ N. No.**
5. Drop punctuation.
6. Transform all the numbers in **0**. The idea is that n. 37 and n. 35 convey similar information.
7. Do the same with ordinal numbers (1^{st}, 2^{nd}, 3^{rd}, 4^{th}, etc. are all substituted with the string $\mathbf{0^{th}}$).
8. Transform “STILL LIFE” into a single word **STILLLIFE.** These words clearly violate the unconditional independence assumption since these two words together have a very domain-specific meaning. We do the same for the Italian, French and Spanish language equivalents (it is not necessary for the German language equivalents).
9. Drop the following list of articles and prepositions: **"THE IN OF WITH A AND DE ON LA AT LE BY AU ET LES AN DU EN TO SUR UN ST VON DER OFF FOR MIT CON FROM DANS AUX DES UNE SOUS UND DEL AUF VOR PAR DEM NEL SUL"**.
10. Drop all the words with length shorter than 3 characters.
11. Drop multiple instances of the same word in a single title.

Appendix B: Inputs into experiments

Table B1. Summary statistics for experimental populations

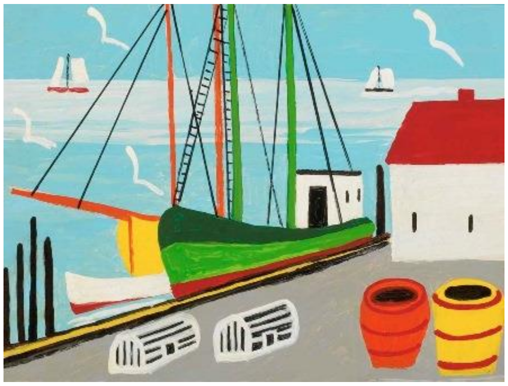
	Experiment #1 Can you guess?	Experiment #2 What's in a name?	Chi-2	*p*-value
No. of participants	880	1,823		
Gender				
Female	51.7%	51.0%		
Male	48.3%	49.0%	0.113	0.737
Age				
18 - 29	20.8%	20.2%		
30 - 44	26.9%	26.3%		
45 - 59	28.3%	28.3%		
60 +	24.0%	25.2%	0.516	0.915
Education				
Less than high school degree	0.8%	2.0%		
High school degree	9.4%	9.5%		
Some college but no degree	25.1%	22.9%		
Associate degree	10.5%	9.8%		
Bachelor degree	29.5%	31.9%		
Graduate degree	24.7%	23.9%	8.180	0.147
Income				
$0 to $9,999	6.8%	8.0%		
$10,000 to $24,999	11.4%	10.4%		
$25,000 to $49,999	19.8%	20.6%		
$50,000 to $74,999	18.4%	17.6%		
$75,000 to $99,999	14.5%	15.0%		
$100,000 to $124,999	11.6%	9.8%		
$125,000 to $149,999	6.3%	5.2%		
$150,000 to $174,999	3.3%	3.9%		
$175,000 to $199,999	2.0%	2.8%		
$200,000 and higher	5.9%	6.7%	7.639	0.571
Visits to museums				
Rarely or never	58.2%	56.4%		
A few times a year	38.1%	40.2%		
Once a month or more	3.8%	3.4%	1.173	0.556
Region				
East North Central	15.1%	16.0%		
East South Central	3.8%	4.7%		
Middle Atlantic	12.4%	13.2%		
Mountain	6.8%	8.0%		
New England	5.9%	6.5%		
Pacific	19.8%	18.6%		
South Atlantic	16.3%	15.6%		
West North Central	8.4%	7.1%		
West South Central	9.5%	8.8%	5.216	0.734

Notes: The table reports the demographic and socio-economic distribution of the participants with complete income data in our two experiments. Gender, age, region, and income are supplied by SurveyMonkey. Education, visits to museums, state, and family background are self-reported. We also provide a Chi-2 test against the null hypothesis that the two samples share the same distribution.

Table B2. Images for Experiment #1 "Can you guess?"

Painting 1
David Bierk, *After Gustave Courbet; The Love Valley*
(1/3/2013 - Heffel Fine Art)

Painting 2
Maud Lewis, *Harbour; Nova Scotia*
(1/3/2013 - Heffel Fine Art)



Painting 3
Benny Andrews, *The Pride of Flesh*
(1/8/2013 - Christie's)

Painting 4
Cheryl Laemmle, *Bullocks Oriole; from American Decoy Series*
(1/8/2013 - Christie's)

Painting 5
Nikolai Kozlenko, *Still Life with Fruit*
(1/9/2013 - Skinner Auctioneers)

Painting 6
Oliver Clare, *Still life of fruit*
(1/10/2013 - George Kidner Fine Art)

Painting 7
John Alexander, *Birds in Love*
(1/12/2013 - Brunk Auctions)

Painting 8
Joyce Wahl Treiman, *Ruins & Visions*
(1/12/2013 - Clark Cierlak Fine Arts)

Painting 9
Betty M Bowes, *Quiet Harbor*
(1/13/2013 - Kaminski Auctions)

Painting 10
Marie Lucie Nessi-Valtat, *Vase de fleurs au pichet vert*
(1/13/2013 - Eric Pillon Enchères)

Notes: This table shows the ten paintings used in our "Can you guess?" experiment. To keep our selection as neutral as possible, we choose the first paintings in our sample auctioned at the beginning of 2013. We impose the following restrictions on the selection: a) Five paintings from male and five from female painters; b) Only one painting per artist; c) Realized auction price is below US $100,000 (we want relatively unknown paintings); d) Availability of an electronic image with sufficient resolution.

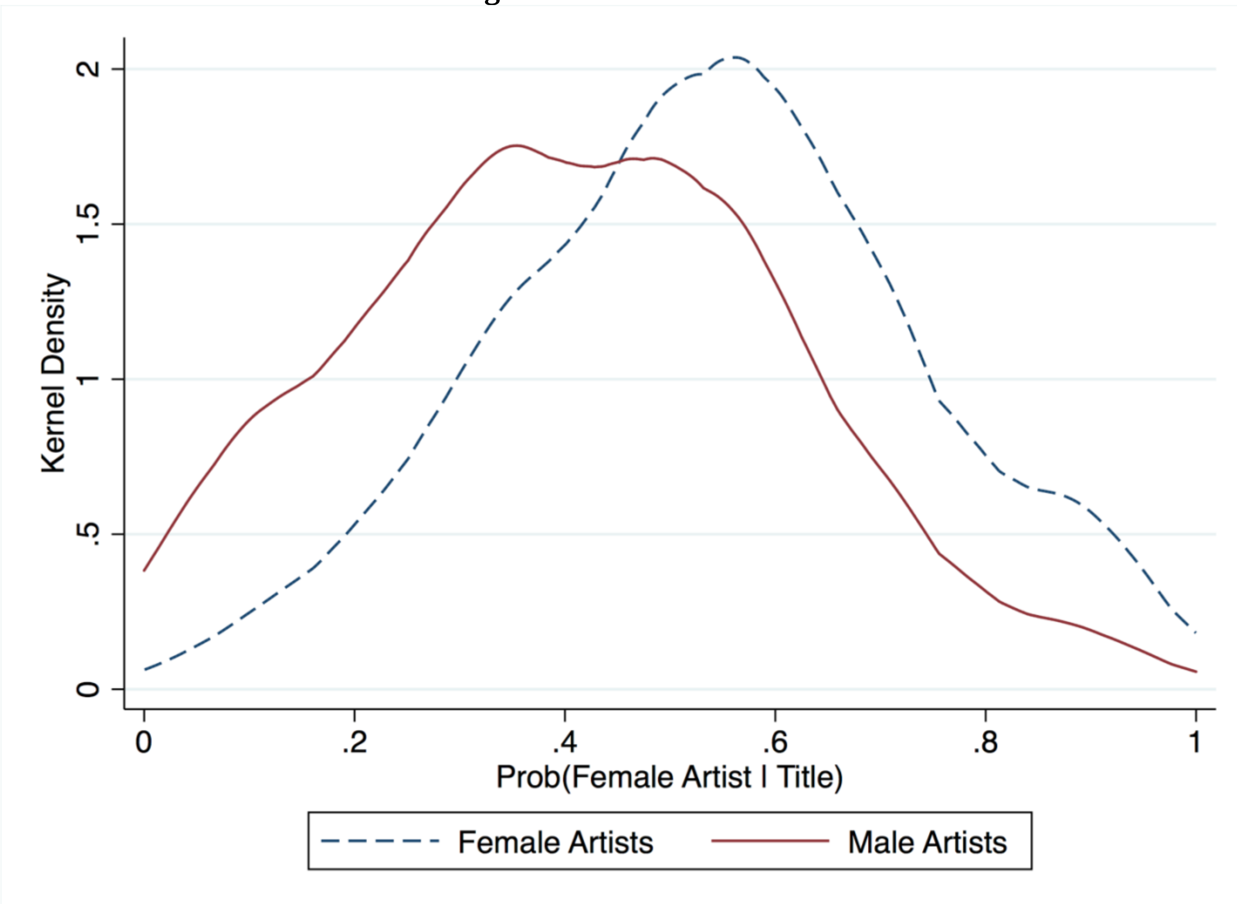
Table B3. Generated images for Experiment #2 “What’s in a name?”

Content	Style	Final
 [pixabay.com]	 *Impressionist Landscape, Lynne French*	 Jessica / Michael Smith
 [pixabay.com]	 *Cubo-futurist rendering of Trotsky, uncredited (probably Yuri Annenkov, 1922)*	 Jennifer / Christopher Johnson
 [pixabay.com]	 *Rousse, Henri de Toulouse-Lautrec*	 Amanda / Matthew Williams
 [pixabay.com]	 *Uncredited Picture*	 Ashley / Joshua Brown
 [pixabay.com]	 *Fabrizio Acciaro, Untitled*	 Sarah / David Jones

 [pixabay.com]	 *Patrick Gunderson, Composition #53*	 Stephanie / James Miller
 [pixabay.com]	 *Girl with mandolin, Pablo Picasso*	 Melissa / Daniel Davis
 [pixabay.com]	 *Geoff Hands, Cornish Coast*	 Nicole / Robert Wilson
 [pixabay.com]	 *Grass, Dheeraj Kattula*	 Elizabeth / John Anderson
 [pixabay.com]	 *Setting fire to the Sugar Cane, Timmy Mallett*	 Heather / Joseph Taylor

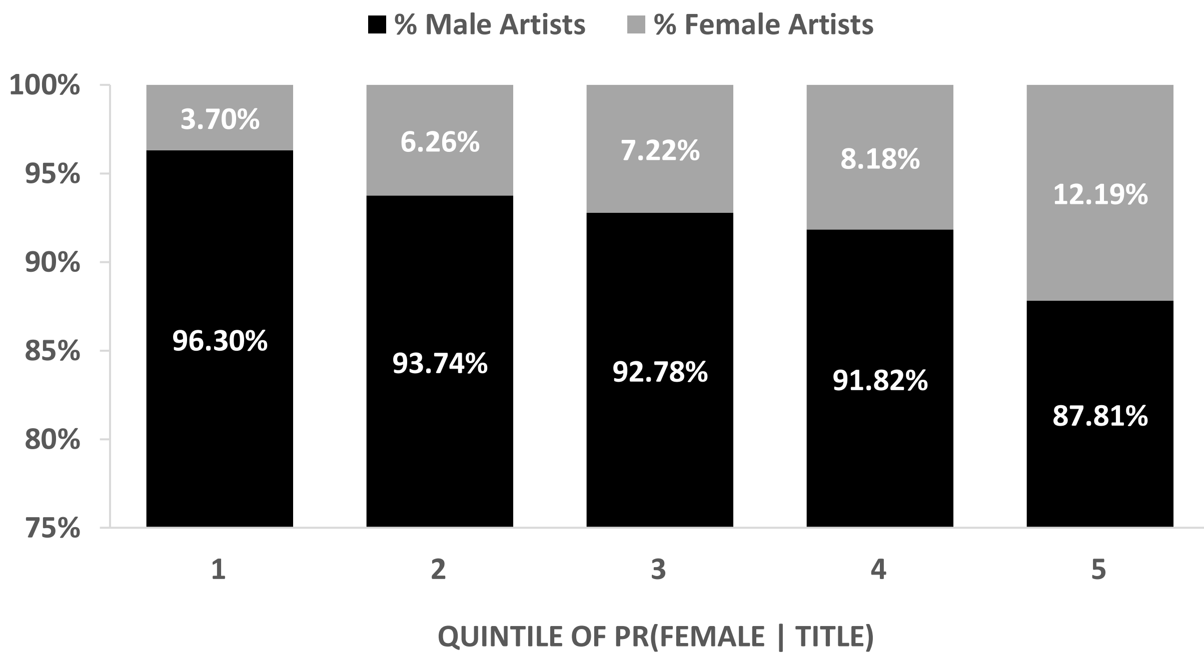
Notes: This table shows the artificially generated pictures used in our second experiment. The first column contains the picture used as the "subject" of our final image, while the second contains the picture that provided the "visual style". The third column shows the final image obtained through combining subject and visual style with the algorithm developed in Gatys et al. (2015). The last column contains the male/female names we paired with the image. We generated the names using the ten most common last names in the US from the 2000 census and the ten most popular given names for male and female babies born during 1980 – 1989 from the US Social Security Administration. Hyperlinks in the table redirect to the original images.

Figure 1. Kernel densities of estimated probability that a painting was created by a female artist given the words in the title



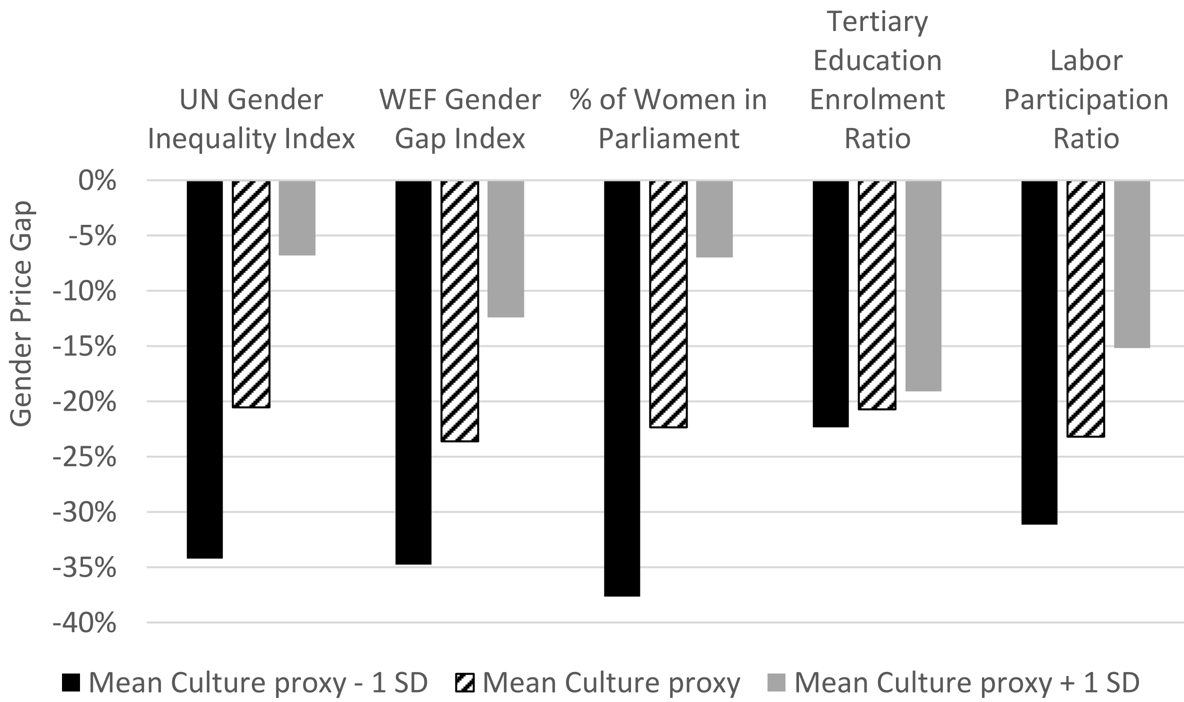
Notes: The graph shows the kernel density for the estimated conditional probability that a given painting has been created by a female artist given the words of the title for the subsamples of paintings by male and female artists. Details on the estimation of the conditional probability are given in Appendix A.

Figure 2. Distribution of artists by gender within subsamples built on the estimated probability of a painting being created by a female artist



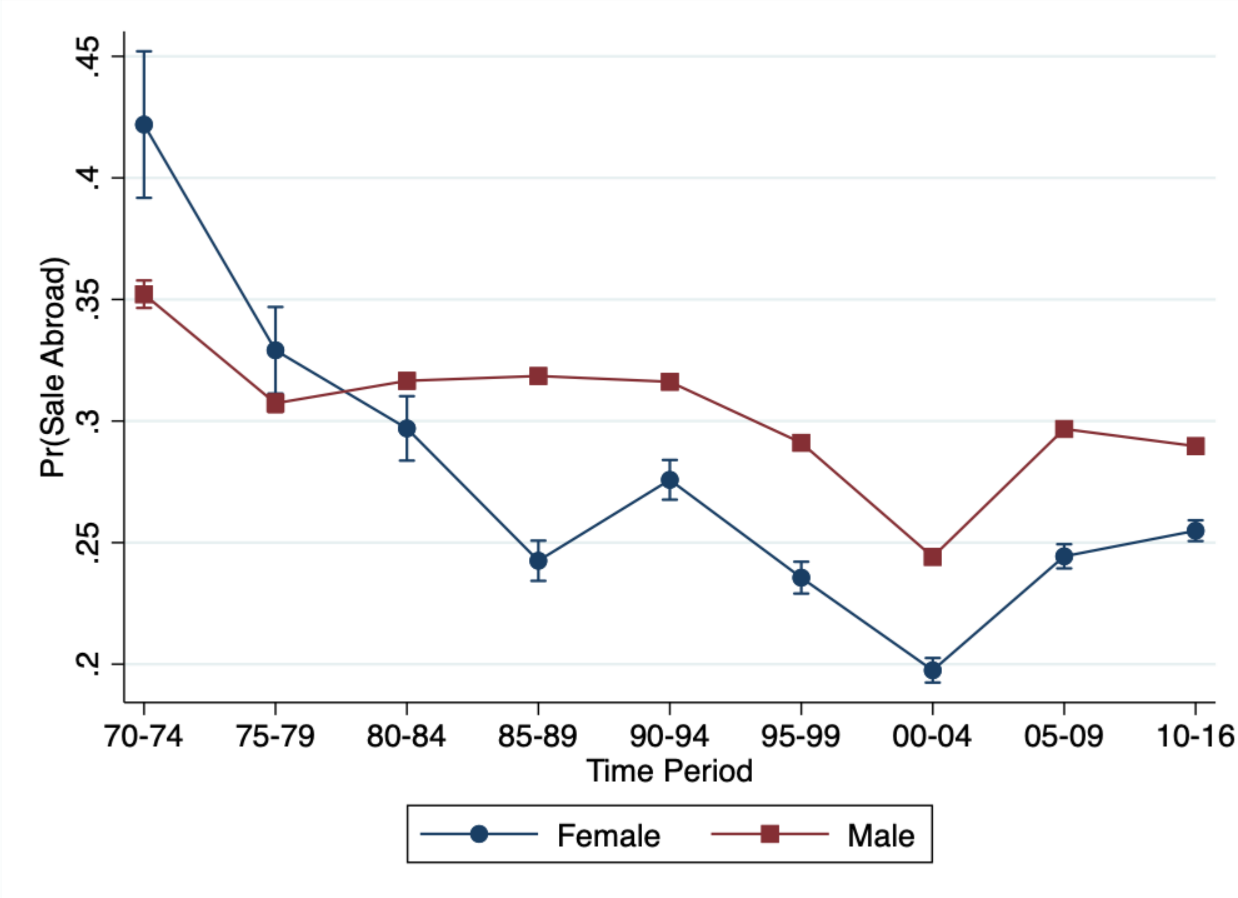
Notes: The graph shows the percentage of paintings created by male and female artists in five subsamples of our dataset based on the predicted probability that the painting has been created by a woman conditional on the words of the title, Pr (Female|Title). This probability is estimnated with a naïve Bayesian classifier with a "bag of words" approach. See Appendix A for the full methodology.

Figure 3. Estimated marginal effect of cultural proxy variables on the gender price gap



Notes: The graph shows the marginal effect of a ±1 standard deviation change in the level of of our culture proxy variables on the estimated level of the gender price gap according to the models in Table 6.

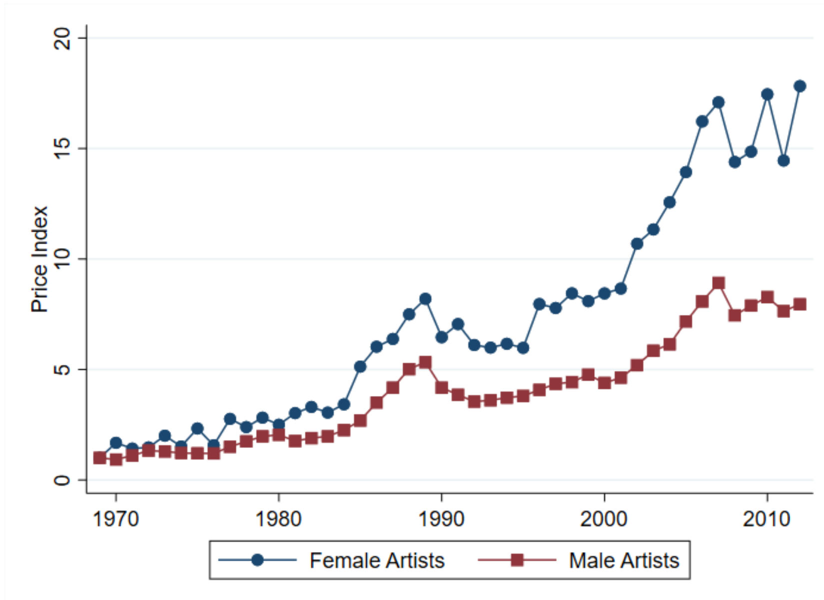
Figure 4. Estimated probability that female and male artists sell abroad



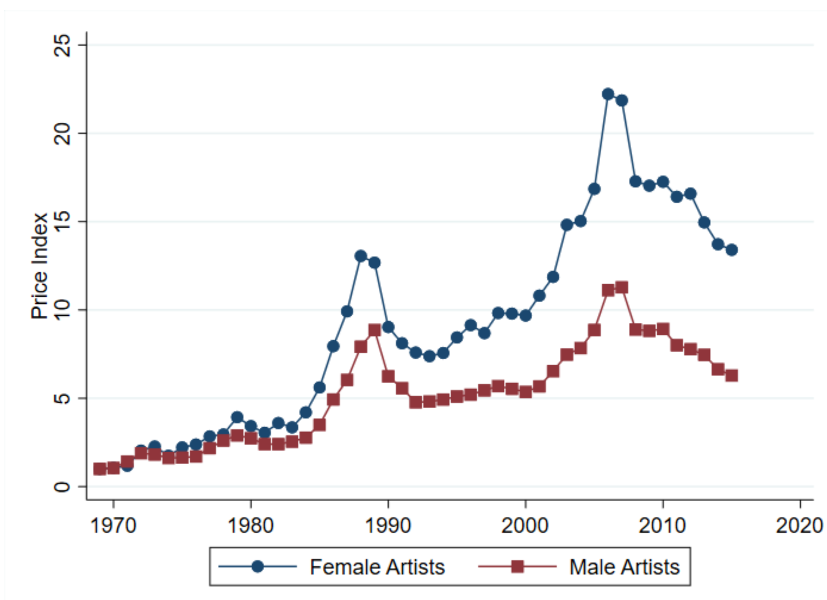
Notes: The graph shows the estimated probability that female and male artists sell their paintings outside their home country in different periods of time.

Figure 5. Repeated-sales price indices for paintings by female and male artists

Panel A – Sample from from Korteweg et al. (2016)



Panel B – Our Sample



Notes: The graph shows the monthly values of price indices for a subsample of paintings by male and female artists with repeat sales. Panel A uses data on repeat sales from Korteweg et al. (2016). The sample consists of 63,622 transactions involving 30,655 individual paintings from 8,449 artists (7,908 male and 541 female). Panel B uses data from our sample with individual paintings identified based on title and author. The sample consists of 576,227 transactions involving 179,660 paintings from 27,717 individual artists (25,022 male and 2,695 female). The construction of the index follows Bailey et al. (1963).

Table 1. Variable description

Panel A. Regression variables	
Deceased	Dummy variable equal to one when the artist is deceased at the time of the auction sale.
Female Painter	Dummy variable equal to one when the artist is female, and zero if male.
Gender Gap (%)	The discount for paintings by female artists relative to the average sales price of male artists.
Log(Age)	Natural logarithm of the age of the artist at the time of the auction sale in years. The variable is calculated regardless of whether the artist is dead or alive at the time of the auction sale.
Log(GDP)	Natural logarithm of per capita GDP in constant dollars from the World Bank (Code: NY.GDP.PCAP.KD).
Log(Surface)	Natural logarithm of the surface of the painting measured in squared millimetres.
Marked	Dummy variable that denotes whether the painting is signed or otherwise marked.
Medium	Synthetic classification of the medium of the painting. Paintings are classified as: Acrylic on Canvas, Oil on Board, Oil on Canvas, Oil on Panel, Oil on Paper, Mixed Media, and Tempera.
Pr (Female|Title)	The probability of the painting having been produced by a female artist (given the words in the title) estimated with a naïve Bayesian classifier with a "bag of words" approach. See Appendix A.
Price	Sale price of the painting in 2016 US$. In regression frameworks we consider the natural logarithm of this quantity labelled as Log (Price).
Style	Synthetic classification of the artistic style of the painter. Artists are classified as: 19th Century European, American, Asian, Impressionist and Modern, Latin American, Post-War and Contemporary, and Other.
Panel B. Proxies for gender culture	
% of Women in Parliament	From World Bank Data. Proportion of seats held by women in national parliaments (%) (Code: SG.GEN.PARL.ZS), defined as the percentage of parliamentary seats in a single or lower chamber held by women. Available for 1990 and with continuity from 1997. The indicator is decreasing in inequality.
Labor Force Participation Ratio	From World Bank Data. Calculated as the ratio between female (Code: SL.TLF.CACT.FE.ZS) and male (Code: SL.TLF.CACT.MA.ZS) labor force participation (population age 15+, modelled ILO estimates). Available from 1990. The indicator is decreasing in inequality.
Tertiary Education Enrolment Ratio	From World Bank Data. Formally known as the "Gross enrolment ratio, tertiary, gender parity index (GPI)" (Code: SE.ENR.TERT.FM.ZS). Ratio of female gross enrolment ratio for tertiary education to male gross enrolment ratio. It is calculated by dividing the female value for the indicator by the male value for the indicator. A value equal to 1 indicates parity between females and males. In general, a value less than 1 indicates disparity in favor of males and a value greater than 1 indicates disparity in favor of females. Available from 1971. The indicator is decreasing in inequality.
UN Gender Inequality Index	A composite measure reflecting inequality in achievements between women and men in three dimensions: reproductive health, empowerment, and the labour market. Available for the years 1995, 2000, 2005, 2010, and yearly from 2013. We use linear interpolation between the available years. The index is scaled between 0 and 1, and is increasing in inequality. For sake of comparability with other results we reformulate the index as one minus the original value in order to obtain an indicator decreasing in inequality.

WEF Gender Gap Index	This index is calculated yearly by the World Economic Forum and ranks countries according to how well they are leveraging their female talent pool, based on economic, educational, health-based and political indicators. The index is calculated yearly from 2006 for a large sample of countries. For a smaller subsample data is available from 2000. The index is decreasing in inequality.

Panel C. Variables in experiments

Affluent	Household income of US $100,000 or more.
Art Expert	Self-reports visiting a museum or art gallery at least a "few times a year".
College Educated	Self-reported attainment of an associate degree or higher.
Family Background	A series of five dummy variables set equal to one if at least one of the parents of the respondent was born in 1) Asia, 2) Africa (including the Middle East), 3) Latin America (including Central America and the Carribean), 4) Europe, and 5) Oceania.
Female Guess	Respondent guess about the gender of the artist (Experiment #2).
Female Name	Painting associated with a female artist name (Experiment #1).
Guessed Country	A series of six dummy variables set equal to one if the respondent in Experiment #1 guessed that the painter was born in 1) Asia, 2) Africa (including the Middle East) , 3) Latin America (including Central America and the Carribean), 4) North America, 5) Europe, and 6) Oceania.
Guessed Period	A series of three dummy variables set equal to one if the respondent in Experiment #1 guessed that the painging was created 1) Before 1850, 2) Between 1850 and 1945, 3) After 1945.
Male	Gender of the respondent.
Mature	Age of 45 years or more.
Score	Artistic appreciation of a painting expressed on a scale from 0 to 10.

Table 2. Descriptive statistics for auction data

Panel A: Auction Variables

	Total Sample	**Female Artists**	**Male Artists**	**Difference**	**Gender Gap (%)**
N. of Transactions	1,898,849	141,149	1,757,700		
% of Mega Transactions	0.62%	0.40%	0.64%		
Price	48,901	29,235	50,480	-21246***	-42.1%
	(719,946)	(293,789)	(743,627)	(1992)	
Price (excluding	22,467	18,382	22,796	-4414***	-19.4%
Mega Transactions)	(73,060)	(64,328)	(73,708)	(203)	
Log(Price)	8.546	8.323	8.564	-0.242***	
	(1.616)	(1.567)	(1.618)	(0.004)	
Surface (m^2)	0.502	0.534	0.499	0.035***	
	(0.612)	(0.680)	(0.606)	(0.002)	
Marked	0.75	0.71	0.75	-0.05***	
	(0.433)	(0.455)	(0.431)	(0.001)	
Age	103.659	98.459	104.077	-5.618***	
	(29.044)	(30.118)	(28.915)	(0.080)	
Deceased	0.749	0.655	0.756	-0.101***	
	(0.434)	(0.475)	(0.429)	(0.001)	
Prob (Female|Title)	0.463	0.530	0.457	0.073***	
	(0.172)	(0.168)	(0.171)	(0.000)	

Panel B: Gender Culture Variables

	Mean	**St. Dev.**	**Percentiles**		
			10	**50**	**90**
UN Gender Inequality Index	0.210	0.143	0.067	0.165	0.431
WEF Gender Gap Index	0.713	0.056	0.643	0.713	0.783
% of Women in Parliament	23.532	10.958	9.800	22.300	38.700
Tertiary Education Enrolment Ratio	1.130	0.529	0.696	1.101	1.435
Labor Participation Ratio	0.725	0.121	0.558	0.753	0.853

Notes: Our sample consists of Blouin Art Sales Index (BASI) auction sales data between 1970 to 2016 involving paintings created by all artists born after 1850 for whom we can identify the gender of the artist. Panel A reports mean values (and standard deviations in parentheses) for characteristics of the paintings in our data set. Statistics are calculated both for the total sample and for the subsamples of transactions involving male and female artists. The table also provides a *t*-test for the difference between the two subsamples (standard errors in parentheses). The gender gap in % is calculated relative to the mean painting price for men. Panel B reports descriptive statistics for our gender culture proxy variables. Table 1 provides the variable definitions. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

Table 3. Gender discount in time and space

Panel A: Gender Price Gap by Sub Period

	Full Sample				**Excluding Mega Transactions**		
Sub Period/Area	Number of Transactions	% of Trans. involving female artists	Gender Gap (2016 US$)	Gender Gap (%)	% of Mega Transactions	Gender Gap (2016 US$)	Gender Gap (%)
1970 - 1979	92,075	4.03%	-10,213***	-39.1%	0.14%	-7,895***	-33.1%
			(1,536)			(1,026)	
1980 - 1989	260,582	5.73%	-16,202***	-39.0%	0.45%	-4,470***	-17.3%
			(4,401)			(640)	
1990 - 1999	410,380	6.76%	-18,468***	-50.3%	0.41%	-6,500***	-31.6%
			(3,204)			(409)	
2000 - 2009	648,989	8.13%	-19,861***	-43.0%	0.60%	-4,782***	-21.9%
			(2,671)			(323)	
2010 - 2016	486,823	8.62%	-35,125***	-45.1%	1.00%	-2,027***	-8.4%
			(5,565)			(418)	
Panel B: Gender Price Gap by Geographic Area of Auction							
Africa	19,567	12.83%	24,333***	221.7%	0.09%	13,700***	127.5%
			(1,703)			(832)	
Asia	28,086	9.65%	7287*	12.8%	0.66%	1671	3.6%
			(3,949)			(2,020)	
Cont. Europe	1,004,575	5.71%	-3,324***	-19.3%	0.11%	-2,423***	-17.3%
			(909)			(200)	
North America	436,832	9.22%	-63,252***	-56.3%	1.41%	-10,005***	-28.8%
			(6,925)			(513)	
Oceania	83,900	14.02%	-8,305***	-44.6%	0.11%	-6,468***	-38.8%
			(748)			(480)	
South America	14,462	5.66%	-440	-4.2%	0.03%	-2,962***	-29.4%
			(1,381)			(912)	
United Kingdom	311,427	8.27%	-49,333***	-56.9%	1.34%	-12,433***	-34.0%
			(4,784)			(653)	

Notes: The table reports the number of transactions, the percentage of transactions involving female artists and the average gender discount (labelled Gap for brevity) for different sub-periods (Panel A) as well as the different geographical regions of auction (Panel B). The gender discount is calculated as the difference between the average sale price (in 2016 US$) of paintings of female and male artists. The gender discount in percent is the discount relative to the average sales price of male artists. The standard errors for the *t*-test for the hypothesis that the discount is 0 are given in parentheses. We conduct the analysis both including and excluding transactions with prices above one million (mega transactions) of 2016 US$. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

Table 4. Among frequent title words, percent least and most used by female artists

Low use by female artists		High use by female artists	
Word	**% of uses by female artists**	**Word**	**% of uses by female artists**
CATTLE	1.549%	ROSES	15.266%
DUTCH	1.626%	FLOWERS	14.667%
WOODED	1.869%	STILLIFE	12.919%
VUE	2.304%	VASE	12.352%
SAILING	2.360%	WHITE	11.417%
RIVER	2.392%	BLUE	10.811%
PEASANT	2.485%	GARDEN	10.484%
BORD	2.506%	UNTITLED	10.240%
HIS	2.522%	BOUQUET	10.220%
SHEEP	2.564%	RED	10.158%
PAYSAGE	2.654%	FRUIT	9.653%
COWS	2.743%	GIRL	9.387%
SEASCAPE	2.845%	TABLE	9.217%
FIGURES	3.042%	SPRING	8.299%
PORT	3.142%	COUNTRY	8.286%
SAINT	3.151%	NEW	8.188%
COAST	3.158%	JEUNE	8.109%
NEAR	3.214%	PARK	8.086%
STREAM	3.289%	HOUSE	8.010%
LANDSCAPE	3.462%	BLACK	8.007%
MAN	3.639%	CHILD	7.528%
VILLAGE	3.658%	SUMMER	7.512%
PARIS	3.777%	BEACH	7.452%
CANAL	3.810%	CHILDREN	7.429%
VIEW	3.863%	SEATED	7.377%

Notes: The table shows the 50 words in the 100 most frequently used words in painting titles with the highest and lowest uses by female artists. The left column reports the 25 words that are used least frequently by female artists. The right column reports the 25 words that are used most frequently by female artists. The percentages are the percentages of paintings with a given word in the title belonging to female artists.

Table 5. Art prices and artist's gender

	Full Sample					Excluding Mega Transactions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female Painter	-0.270***		-0.309***	-0.212***	-0.100***	-0.198***	-0.099***
	(-11.662)		(-13.338)	(-10.712)	(-17.823)	(-10.231)	(-17.662)
Pr(Female|Title)		0.553***	0.599***	0.414***	0.165***	0.404***	0.162***
		(23.398)	(26.813)	(23.454)	(21.177)	(22.623)	(20.461)
Log(Surface)				0.386***	0.256***	0.359***	0.251***
				(70.126)	(80.992)	(79.865)	(77.500)
Marked				-0.520***	-0.040***	-0.469***	-0.038***
				(-8.539)	(-4.989)	(-8.539)	(-4.756)
Log(Age)				1.037***	0.784***	0.974***	0.770***
				(49.561)	(47.661)	(43.911)	(45.773)
Deceased				0.248***	0.115***	0.231***	0.112***
				(15.653)	(18.059)	(14.595)	(17.558)
Year, Country FE	Y	Y	Y	Y	N	Y	N
Style, Medium FE	N	N	N	Y	Y	Y	Y
Auction FE	N	N	N	N	Y	N	Y
N	1,898,849	1,898,849	1,898,849	1,898,849	1,890,754	1,887,112	1,878,979
adj. R-sq	0.104	0.106	0.108	0.257	0.650	0.245	0.624
Only painters with at least 20 sales							
Female Painter	-0.135**		-0.181***	-0.117**	-0.039	-0.104*	-0.037
	(-2.129)		(-2.855)	(-2.123)	(-1.350)	(-1.953)	(-1.295)
Only deceased painters							
Female Painter	-0.229***		-0.277***	-0.211***	-0.084***	-0.197***	-0.084***
	(-8.843)		(-10.750)	(-9.742)	(-12.268)	(-9.146)	(-12.353)

Notes: The table reports results for the OLS estimation of a model where the (natural log of) inflation-adjusted sale price is regressed on a gender dummy and a series of control variables detailed in Table 1. In different specifications we introduce style, medium, year, country, and auction fixed effects. We repeat the analysis both including and excluding transactions with auction sales prices above one million 2016 US$ (mega transactions). The last two sections report the main coefficients of interest re-estimated on the subsample of artists for whom we have at least 20 transactions in our sample and on the subsample of artists who were deceased at the moment of the sale. All standard errors are clustered at the country-year-gender level. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Table 6. Gender culture and gender discount in art prices

	(1)	(2)	(3)	(4)	(5)
	UN Gender Inequality Index	WEF Gender Gap Index	% of Women in Parliament	Tertiary Education Enrolment Ratio	Labor Participation Ratio
Period Covered	1995 - 2016	2000 - 2016	1990 - 2016	1970 - 2016	1990 - 2016
Female Painter	1.997***	-0.135	1.066***	0.497**	1.545***
	(8.058)	(-0.438)	(4.824)	(2.202)	(7.520)
Pr(Female|Title)	-0.493	-2.355***	-0.113	-0.403	-0.017
	(-1.416)	(-3.801)	(-0.316)	(-1.092)	(-0.055)
Female x Culture Proxy	1.721***	2.734***	0.016***	0.068	1.061***
	(10.749)	(7.317)	(15.517)	(1.500)	(5.947)
Pr(Female|Title) x Culture Proxy	-0.911***	4.907***	0.001	0.213***	1.966***
	(-3.173)	(6.475)	(0.634)	(2.648)	(6.288)
Female x Log (GDP)	-0.343***	-0.196***	-0.157***	-0.075***	-0.245***
	(-12.344)	(-8.300)	(-7.607)	(-3.632)	(-10.676)
Pr(Female|Title) x Log (GDP)	0.155***	-0.074	0.045	0.056	-0.104***
	(3.462)	(-1.543)	(1.368)	(1.596)	(-2.786)
Log(Surface)	0.407***	0.425***	0.410***	0.378***	0.400***
	(71.062)	(65.610)	(70.848)	(57.465)	(73.838)
Marked	-0.601***	-0.697***	-0.615***	-0.333***	-0.564***
	(-8.170)	(-7.872)	(-8.175)	(-5.955)	(-8.109)
Log(Age)	1.090***	1.082***	1.093***	1.110***	1.082***
	(45.100)	(37.544)	(43.829)	(44.015)	(48.203)
Deceased	0.255***	0.266***	0.252***	0.248***	0.249***
	(13.770)	(11.256)	(13.053)	(13.556)	(14.834)
Country-Year, Style, Medium FE	Y	Y	Y	Y	Y
N	1,366,038	980,373	1,305,075	1,333,915	1,545,945
adj. R-sq	0.262	0.274	0.271	0.291	0.272
Only painters with at least 20 sales					
Female x Culture Proxy	1.225***	3.011***	0.017***	0.150***	1.499***
	(5.009)	(6.254)	(12.410)	(2.616)	(6.997)
Only deceased painters					
Female x Culture Proxy	1.853***	3.744***	0.018***	0.010	1.754***
	(10.313)	(9.163)	(15.042)	(0.194)	(8.637)
Gender Effect with Demeaned Interactions					
Female Artist	-0.177***	-0.213***	-0.210***	-0.210***	-0.217***
	(-13.036)	(-14.953)	(-19.182)	(-15.924)	(-19.148)

Notes: The table reports results for the OLS estimation of the (natural log of) inflation-adjusted sale price on a gender dummy, a country/year-level proxy for gender culture, and their interaction. We control for style and medium of the painting, and a series of control variables detailed in Table 1. We also control for country-year of the transaction. The next two sections report the main coefficient of interest re-estimated on the subsample of artists for whom we have at least 20 transactions in our sample and on the subsample of artists who were deceased at the moment of the sale. Finally, we report the value of the gender coefficient from an estimation of our models where all the interaction variables are demeaned within our sample, thus making the gender discount comparable in size across models. All standard errors are clustered at the country-year-gender level. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Table 7. Gender culture and gender discount with artist and painting fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	UN Gender Inequality Index	WEF Gender Gap Index	% of Women in Parliament	Tertiary Education Enrolment Ratio	Labor Participation Ratio	UN Gender Inequality Index	WEF Gender Gap Index	% of Women in Parliament	Tertiary Education Enrolment Ratio	Labor Participation Ratio
Period Covered	1995 - 2016	2000 - 2016	1990 - 2016	1970 - 2016	1990 - 2016	1995 - 2016	2000 - 2016	1990 - 2016	1970 - 2016	1990 - 2016
Pr(Female|Title)	-0.307	-0.937***	-0.396*	-1.483***	-0.618***					
	(-1.415)	(-2.695)	(-1.875)	(-5.997)	(-3.348)					
Female x Culture Proxy	0.269*	0.603***	0.005***	0.172***	0.449***	0.305	0.111	0.009***	0.200***	0.467
	(1.804)	(3.193)	(4.938)	(5.246)	(3.649)	(0.884)	(0.220)	(3.853)	(2.702)	(1.523)
Pr(Female|Title) x Culture Proxy	0.580***	1.585***	0.006***	0.325***	0.527***	1.617***	3.894***	0.010**	0.167	1.946***
	(3.597)	(4.353)	(4.735)	(7.704)	(3.121)	(3.231)	(3.835)	(2.157)	(1.618)	(3.328)
Female x Log (GDP)	0.028	0.023	0.043*	0.065**	0.031	0.056	0.047	0.068	0.077	0.083
	(0.972)	(0.991)	(1.906)	(2.502)	(1.237)	(0.988)	(1.069)	(1.499)	(1.208)	(1.579)
Pr(Female|Title) x Log (GDP)	-0.009	-0.014	0.031	0.116***	0.028	0.261**	0.255**	0.300***	0.255***	0.112
	(-0.335)	(-0.558)	(1.572)	(5.229)	(1.400)	(2.254)	(1.990)	(2.652)	(2.727)	(0.962)
Log(Surface)	0.514***	0.527***	0.516***	0.496***	0.511***					
	(170.078)	(166.313)	(171.256)	(148.646)	(173.585)					
Marked	-0.123***	-0.135***	-0.126***	-0.029	-0.114***					
	(-5.211)	(-5.402)	(-5.320)	(-1.566)	(-4.943)					
Log(Age)	3.341***	2.989***	2.724***	1.921***	2.411***	4.492***	3.174***	3.358***	2.333***	3.088***
	(25.506)	(15.517)	(10.679)	(15.712)	(15.111)	(13.699)	(7.418)	(7.269)	(10.942)	(9.743)
Deceased	0.139***	0.145***	0.121***	0.052***	0.105***	0.127***	0.139***	0.123***	0.060***	0.091***
	(15.050)	(11.770)	(9.200)	(5.626)	(10.614)	(7.889)	(6.262)	(6.984)	(4.578)	(6.172)
Country-Year, Medium, Artist FE	Y	Y	Y	Y	Y	N	N	N	N	N
Country-Year, Painting FE	N	N	N	N	N	Y	Y	Y	Y	Y
N	1,349,428	964,579	1,288,523	1,319,020	1,529,151	289,934	199,170	274,904	310,788	338,774
adj. R-sq	0.778	0.798	0.782	0.761	0.773	0.833	0.845	0.835	0.821	0.829
Only painters with at least 20 sales										
Female x Culture Proxy	0.509***	0.948***	0.007***	0.238***	0.823***	0.510	0.329	0.009***	0.201***	0.665**
	(3.102)	(4.596)	(6.598)	(6.708)	(5.736)	(1.334)	(0.625)	(3.917)	(2.614)	(2.038)
Only deceased painters										

Female x Culture Proxy	0.444***	1.114***	0.006***	0.180***	0.618***	0.375	0.892	0.008***	0.312***	0.247
	(2.670)	(5.525)	(4.784)	(4.935)	(3.948)	(1.023)	(1.573)	(3.188)	(3.397)	(0.608)

Notes: The table reports results for the OLS estimation of the (natural log of) inflation-adjusted sale price on a country/year-level proxy for gender culture and its interaction with a gender dummy. The model includes artist (columns 1-5) or painting (columns 6-10) fixed effects and thus a standalone gender dummy is not included. We only consider artists or paintings for which we observe transactions in multiple years and/or countries. We control for style and medium of the painting, and a series of control variables detailed in Table 1. We also control for country-year of the transaction. The last two sections report the main coefficient of interest re-estimated on the subsample of artists for whom we have at least 20 transactions in our sample and on the subsample of artists who were deceased at the moment of the sale. All standard errors are clustered at the country-year-gender level. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Table 8. Accounting for liquidity and uncertainty about the quality of art by female artists

Panel A – Accounting for Liquidity

	(1) UN Gender Inequality Index	(2) WEF Gender Gap Index	(3) % of Women in Parliament	(4) Tertiary Education Enrolment Ratio	(5) Labor Participation Ratio
10-Years Liquidity					
Female x Culture Proxy	0.207	0.746***	0.005***	0.134***	0.558***
	(1.383)	(3.749)	(4.806)	(3.652)	(3.980)
Female x Liquidity	-0.015*	-0.021**	-0.005	-0.003	-0.014
	(-1.789)	(-2.131)	(-0.597)	(-0.384)	(-1.606)
Female x Log (GDP)	0.058*	0.050*	0.051*	0.067**	0.043*
	(1.780)	(1.931)	(1.940)	(2.493)	(1.682)
5-Years Liquidity					
Female x Culture Proxy	0.196	0.680***	0.005***	0.159***	0.558***
	(1.300)	(3.579)	(4.782)	(4.487)	(4.200)
Female x Liquidity	-0.015*	-0.020**	-0.006	-0.005	-0.017**
	(-1.872)	(-2.134)	(-0.760)	(-0.707)	(-2.049)
Female x Log (GDP)	0.058*	0.048*	0.052**	0.070***	0.046*
	(1.791)	(1.888)	(2.044)	(2.670)	(1.786)
1970 Liquidity					
Female x Culture Proxy	0.233	0.773***	0.005***	0.150***	0.526***
	(1.567)	(3.748)	(4.785)	(4.341)	(3.581)
Female x Liquidity	-0.010	-0.018**	-0.003	0.008	-0.008
	(-1.392)	(-2.006)	(-0.342)	(1.356)	(-0.991)
Female x Log (GDP)	0.051	0.050*	0.047*	0.049*	0.039
	(1.563)	(1.908)	(1.750)	(1.796)	(1.507)
Style Liquidity					
Female x Culture Proxy	0.226	0.611***	0.005***	0.121***	0.472***
	(1.569)	(3.019)	(4.698)	(3.360)	(3.605)
Female x Liquidity	-0.007	0.004	0.002	0.004	-0.002
	(-0.872)	(0.397)	(0.281)	(0.552)	(-0.255)
Female x Log (GDP)	0.037	0.016	0.039	0.058**	0.029
	(1.222)	(0.686)	(1.569)	(2.100)	(1.138)
Auction House Liquidity					
Female x Culture Proxy	0.216	0.632***	0.005***	0.133***	0.467***
	(1.475)	(3.076)	(4.774)	(3.764)	(3.475)
Female x Liquidity	-0.007	-0.003	-0.005	0.003	-0.005
	(-0.901)	(-0.281)	(-0.611)	(0.499)	(-0.694)
Female x Log (GDP)	0.031	0.016	0.037	0.054**	0.025
	(1.074)	(0.682)	(1.644)	(2.042)	(1.010)

[Panel B and Table Description on next page]

[Panel A on previous page]

Panel B - Accounting for Uncertainty about Quality					
	(1)	(2)	(3)	(4)	(5)
	UN Gender Inequality Index	WEF Gender Gap Index	% of Women in Parliament	Tertiary Education Enrolment Ratio	Labor Participation Ratio
N. of Female Artists					
Female x Culture Proxy	0.202	0.545***	0.005***	0.174***	0.430***
	(1.140)	(2.815)	(4.654)	(5.260)	(3.478)
Female x N. of Female Artists (x000)	-0.032	-0.098	0.055	-0.134**	-0.090*
	(-0.477)	(-1.229)	(0.757)	(-2.510)	(-1.747)
Female x Log (GDP)	0.037	0.033	0.038*	0.060**	0.036
	(1.223)	(1.338)	(1.726)	(2.269)	(1.439)
% of Female Artists					
Female x Culture Proxy	0.221	0.516**	0.004***	0.136***	0.355***
	(1.451)	(2.489)	(4.260)	(4.047)	(2.690)
Female x % of Female Artists	0.323	0.132	0.284	0.455**	0.265
	(1.620)	(0.613)	(1.360)	(2.001)	(1.634)
Female x Log (GDP)	0.025	0.023	0.037	0.059**	0.035
	(0.863)	(1.014)	(1.578)	(2.247)	(1.386)

Notes: The table reports the key interaction coefficients for the OLS estimation of the models in columns 1-5 of Table 7 augmented by interactions between the gender dummy and different country-year proxies for the liquidity of artworks by female artists (in Panel A), and interactions between a gender dummy and different country-year proxies for the prevalence of female artists (in Panel B). All standard errors are clustered at the country-year-gender level. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are provided in parentheses.

Table 9. Birth country gender equality and the decision to sell abroad

	(1)	(2)	(3)	(4)	(5)
	UN Gender Inequality Index	WEF Gender Gap Index	% of Women in Parliament	Tertiary Education Enrolment Ratio	Labor Participation Ratio
Period Covered	1995 - 2016	2000 - 2016	1990 - 2016	1970 - 2016	1990 - 2016
Birth Country Culture	-0.786	-1.961*	-0.026***	-1.417***	1.494***
	(-1.188)	(-1.711)	(-7.184)	(-7.327)	(2.933)
Log(Birth Country GDP)	-0.995***	-0.919***	-0.958***	-1.402***	-1.210***
	(-8.343)	(-6.765)	(-9.414)	(-11.414)	(-11.668)
Female Artist	0.121	3.082*	0.170	-0.853	0.437
	(0.081)	(1.688)	(0.129)	(-0.492)	(0.332)
BC Culture x Female Artist	1.484*	-6.636***	-0.017***	0.084	-3.361***
	(1.700)	(-4.032)	(-2.949)	(0.341)	(-4.049)
Log(BC GDP) x Female Artist	-0.130	0.164	0.018	0.075	0.205
	(-0.767)	(0.990)	(0.142)	(0.458)	(1.357)
Log(Age)	0.203***	0.189***	0.235***	0.244***	0.159***
	(3.792)	(3.073)	(4.357)	(4.312)	(3.234)
Deceased	-0.156***	-0.137***	-0.130***	-0.151***	-0.149***
	(-5.353)	(-3.745)	(-4.400)	(-5.794)	(-5.522)
Log(N of Sales)	0.109***	0.094***	0.101***	0.139***	0.106***
	(11.057)	(7.567)	(10.320)	(14.370)	(11.154)
Log(Surface)	0.056***	0.063***	0.070***	0.075***	0.052***
	(4.365)	(4.079)	(5.357)	(7.171)	(4.880)
Marked	-0.311***	-0.415***	-0.320***	-0.249***	-0.282***
	(-4.166)	(-4.679)	(-4.124)	(-3.309)	(-4.007)
Pr(Female|Title)	0.286***	0.323***	0.338***	0.308***	0.282***
	(3.845)	(3.086)	(4.153)	(5.160)	(4.587)
Constant	8.623***	8.171***	7.564***	9.353***	9.451***
	(7.290)	(5.529)	(6.623)	(7.173)	(8.918)
Year, Style, Medium FE	Y	Y	Y	Y	Y
N	1,324,741	942,667	1,264,366	1,312,531	1,495,496
Pseudo R-sq	0.117	0.114	0.123	0.103	0.121
Excess Prob(Abroad) of female artists (vs. male) for levels of home-country culture proxy					
Mean Culture proxy - 1 SD	-2.33%	5.70%	2.50%	0.13%	5.06%
Mean Culture proxy	-0.08%	0.37%	-0.52%	0.43%	0.29%
Mean Culture proxy + 1 SD	2.16%	-4.07%	-2.80%	0.64%	-4.43%
Only painters with at least 20 sales					
HC Culture x Female Artist	0.562	-7.452***	-0.022***	0.002	-4.256***
	(0.547)	(-4.092)	(-3.670)	(0.006)	(-4.721)
Log(HC GDP) x Female Artist	0.022	0.149	0.037	0.075	0.299**
	(0.115)	(0.867)	(0.291)	(0.449)	(1.988)
Only deceased painters					
HC Culture x Female Artist	1.109	-4.394***	-0.012**	0.263	-3.470***
	(1.126)	(-2.689)	(-2.078)	(1.079)	(-4.640)
Log(HC GDP) x Female Artist	-0.095	0.042	-0.007	0.006	0.207
	(-0.518)	(0.236)	(-0.051)	(0.038)	(1.382)
Gender Effect with Demeaned Interactions					
Female Artist	-1.238*	4.796***	0.354**	-0.072	2.573***
	(-1.690)	(3.987)	(2.351)	(-0.245)	(4.007)

Notes: The table reports the estimation results for the logit estimation of the probability an artist's work is sold outside their birth country on a gender dummy, a country/year-level proxy for gender culture in the birth country, and their interaction. We control for the year of the transaction, style and medium of the painting and other artist and painting control variables. We report the marginal effect of a (±1 SD) change in the gender culture proxy on the probability of selling abroad for paintings by female artists (in excess over male artists). The next two sections report the main coefficients of interest re-estimated on the subsample of artists for whom we have at least 20 transactions in our sample, and on the subsample of artists who were deceased at the moment of the sale. Finally, we report the value of the gender coefficient from an estimation of our models where all the interaction variables are demeaned within our sample, thus making the gender discount comparable in size across models. All standard errors are clustered at the country-year-gender level. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Table 10. Ability to guess the gender of a painter by looking at his/her work

Artist Name	Artwork Title	Artist Gender	Prob (Fem|Title)	% of Male Guesses	% of Female Guesses	% of Correct Guesses	Z-Stat	*p*-value (Non-Random)
Individual Paintings								
Betty M Bowes	Quiet Harbor	Female	59.42%	75.83%	24.17%	24.17%	-10.972	0.000
Cheryl Laemmle	Bullocks Oriole, from American Decoy Series	Female	53.51%	61.84%	38.16%	38.16%	-5.058	0.000
Joyce Wahl Treiman	Ruins & Visions	Female	16.47%	71.02%	28.98%	28.98%	-8.937	0.000
Marie Lucie Nessi-Valtat	Vase de fleurs au pichet vert	Female	71.19%	34.04%	65.96%	65.96%	6.589	0.000
Maud Lewis	Harbour; Nova Scotia	Female	41.89%	69.12%	30.88%	30.88%	-7.847	0.000
Benny Andrews	The Pride of Flesh	Male	50.00%	48.99%	51.01%	48.99%	-0.426	0.670
David Bierk	The Love Valley in Thunderstorm (after Gustave Courbet)	Male	44.62%	79.49%	20.51%	79.49%	12.215	0.000
John Alexander	Birds in Love	Male	61.40%	80.19%	19.81%	80.19%	12.432	0.000
Nikolai Kozlenko	Still Life with Fruit	Male	81.78%	45.97%	54.03%	45.97%	-1.655	0.098
Oliver Clare	Still life of fruit	Male	81.78%	59.38%	40.62%	59.38%	3.994	0.000
Grouped by Gender								
Female Artists		Female		62.60%	37.40%	37.40%	-11.838	0.000
Male Artists		Male		62.67%	37.33%	62.67%	11.815	0.000
Entire Sample								
All Artists				62.63%	37.37%	49.94%	-0.076	0.940

Notes: The table reports the results of an experiment in which a sample of 1,000 individuals representative of the US population have been asked to guess the gender of the artists of the 10 listed paintings. The table reports the actual gender of the artist and the estimated probability the painting was created by a woman conditional on the words in the title. The table also shows the percentage of male/female guesses together with the percentage of correct guesses and the *p*-value of a test against the null hypothesis that this last quantity is different from what would result from a random guess.

Table 11. Frequency of “male” guesses and characteristics of the respondents

By Age of the Respondent	I	II	III	IV
	18-29	**30-44**	**45-59**	**60+**
% of Male Guesses	0.605	0.596	0.645	0.658
Difference		-0.009	0.041*	0.053**
		(-0.417)	(1.924)	(2.434)
By Income of the Respondent				
	<50 k$	**50k$ - 100k$**	**100k$ - 175k$**	**175k$+**
% of Male Guesses	0.599	0.640	0.635	0.667
Difference		0.041**	0.036*	0.069***
		(2.360)	(1.712)	(2.756)
By Education of the Respondent				
	No college degree	**Associate degree**	**Bachelor degree**	**Graduate degree**
% of Male Guesses	0.602	0.609	0.636	0.657
Difference		0.007	0.034*	0.055***
		(0.258)	(1.844)	(2.869)
By Art Experience of the Respondent (frequency of visits to museums)				
	Rarely or never	**At least few times a year**		
% of Male Guesses	0.619	0.637		
Difference		0.018		
		(1.237)		
By Gender of the Respondent				
	Female	**Male**		
% of Male Guesses	0.627	0.625		
Difference		-0.002		
		(-0.123)		

Notes: The table reports the frequency with which groups of respondents with different characteristics in terms of age, income, education, art experience, and gender have answered “Male” when asked to guess the gender of the artist who created one of the 10 paintings listed in Table 10. The table also reports Z-stats (in parentheses) on tests on the difference between the different sub-groups and the group in the first column (I). The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

Table 12. Perceived gender and artistic appreciation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female Guess	0.185**		0.029	0.160*	0.165*	0.335***	-0.091	0.037	0.387**	0.422***
	(2.334)		(0.372)	(1.800)	(1.754)	(2.993)	(-0.806)	(0.306)	(2.339)	(2.636)
Pr(Female|Title)		2.460***	2.447***	2.358***	2.790***	2.756***	2.258***	2.007***	2.523***	
		(13.171)	(12.926)	(10.387)	(11.690)	(10.537)	(7.866)	(6.138)	(5.539)	
Affluent	-0.178	-0.182	-0.181	-0.162	-0.180	-0.183	-0.181	-0.179	-0.173	-0.061
	(-1.526)	(-1.551)	(-1.547)	(-0.625)	(-1.537)	(-1.558)	(-1.545)	(-1.528)	(-0.667)	(-0.454)
Art Expert	0.401***	0.392***	0.392***	0.395***	0.986***	0.399***	0.391***	0.392***	1.110***	0.522***
	(3.771)	(3.672)	(3.675)	(3.698)	(3.990)	(3.736)	(3.658)	(3.669)	(4.511)	(4.237)
Male	0.065	0.066	0.066	0.065	0.070	0.697***	0.067	0.066	0.740***	0.341***
	(0.632)	(0.642)	(0.640)	(0.629)	(0.678)	(2.949)	(0.648)	(0.637)	(3.124)	(2.845)
Mature	-0.055	-0.061	-0.059	-0.058	-0.058	-0.058	-0.350	-0.060	-0.272	-0.168
	(-0.511)	(-0.558)	(-0.548)	(-0.538)	(-0.539)	(-0.539)	(-1.436)	(-0.553)	(-1.146)	(-1.362)
College Educated	-0.384***	-0.388***	-0.388***	-0.386***	-0.386***	-0.397***	-0.386***	-0.768***	-0.867***	-0.449***
	(-3.400)	(-3.427)	(-3.420)	(-3.405)	(-3.404)	(-3.497)	(-3.403)	(-2.939)	(-3.312)	(-3.533)
Female Guess x Affluent				-0.451**					-0.431**	-0.316*
				(-2.548)					(-2.371)	(-1.833)
Pr(Female|Title) x Affluent				0.253					0.264	
				(0.652)					(0.665)	
Female Guess x Art Expert					-0.335**				-0.306*	-0.299**
					(-2.075)				(-1.921)	(-1.967)
Pr(Female|Title) x Art Expert					-0.837**				-1.066***	
					(-2.264)				(-2.857)	
Female Guess x Male						-0.638***			-0.620***	-0.649***
						(-4.150)			(-4.068)	(-4.442)
Pr(Female|Title) x Male						-0.700*			-0.778**	
						(-1.942)			(-2.162)	
Female Guess x Mature							0.236		0.280*	0.331**
							(1.528)		(1.803)	(2.236)
Pr(Female|Title) x Mature							0.360		0.196	
							(0.992)		(0.547)	

Female Guess x College Educated								-0.015	0.070	0.185
								(-0.097)	(0.449)	(1.237)
Pr(Female|Title) x College Educated								0.690*	0.804**	
								(1.778)	(2.050)	
Family Background, Guessed Country and Period, State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Painting FE	N	N	N	N	N	N	N	N	N	Y
N	4,354	4,354	4,354	4,354	4,354	4,354	4,354	4,354	4,354	4,354
adj. R-sq	0.057	0.087	0.087	0.088	0.089	0.092	0.088	0.087	0.095	0.155

Notes: The table reports results for an OLS estimation of the effect of a female artist guess on artistic appreciation after controlling for respondent characteristics. In every model we also control for the guessed period of the painting and the guessed geographic origin of the artist. We also control for family background and state of residence of the respondent. We include painting fixed effects in column 10. All standard errors are clustered at the survey respondent level. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Table 13. Associated gender and artistic appreciation

Panel A: Entire sample							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female Name	0.037	0.075*	0.039	0.066	0.018	0.048	0.060
	(1.011)	(1.729)	(0.772)	(1.276)	(0.351)	(0.794)	(0.723)
Affluent	-0.133	-0.064	-0.133	-0.133	-0.133	-0.133	-0.057
	(-1.574)	(-0.684)	(-1.573)	(-1.572)	(-1.571)	(-1.574)	(-0.593)
Art Expert	0.576***	0.575***	0.579***	0.576***	0.576***	0.576***	0.572***
	(7.864)	(7.854)	(7.114)	(7.863)	(7.862)	(7.864)	(7.022)
Male	-0.137*	-0.137*	-0.137*	-0.107	-0.137*	-0.137*	-0.111
	(-1.858)	(-1.856)	(-1.858)	(-1.310)	(-1.857)	(-1.858)	(-1.354)
Mature	-0.201***	-0.202***	-0.201***	-0.201***	-0.218***	-0.201***	-0.232***
	(-2.682)	(-2.695)	(-2.681)	(-2.683)	(-2.627)	(-2.684)	(-2.768)
College Educated	-0.131	-0.131	-0.131	-0.131	-0.130	-0.122	-0.138
	(-1.553)	(-1.559)	(-1.553)	(-1.555)	(-1.550)	(-1.319)	(-1.491)
Female Name x Affluent		-0.136*					-0.149*
		(-1.716)					(-1.755)
Female Name x Art Expert			-0.005				0.005
			(-0.073)				(0.069)
Female Name x Male				-0.059			-0.051
				(-0.818)			(-0.705)
Female Name x Mature					0.034		0.059
					(0.469)		(0.789)
Female Name x College Educated						-0.018	0.015
						(-0.235)	(0.190)
Family Background	Y	Y	Y	Y	Y	Y	Y
State-FE	Y	Y	Y	Y	Y	Y	Y
Painting-FE	Y	Y	Y	Y	Y	Y	Y
Obs.	18,230	18,230	18,230	18,230	18,230	18,230	18,230
adj. R-sq.	0.083	0.083	0.083	0.083	0.083	0.083	0.083

[Panel B on next page]

Panel B: Only people who visit museums						
	(1)	(2)	(3)	(4)	(5)	(6)
Female Name	0.040	0.114*	-0.030	-0.061	-0.061	-0.197*
	(0.775)	(1.818)	(-0.436)	(-0.841)	(-0.682)	(-1.823)
Affluent	0.064	0.174	0.063	0.066	0.065	0.230*
	(0.572)	(1.455)	(0.561)	(0.588)	(0.581)	(1.888)
Male	0.012	0.013	-0.064	0.014	0.013	-0.066
	(0.126)	(0.136)	(-0.588)	(0.138)	(0.132)	(-0.601)
Mature	-0.226**	-0.228**	-0.225**	-0.321***	-0.226**	-0.355***
	(-2.206)	(-2.226)	(-2.194)	(-2.861)	(-2.203)	(-3.153)
College Educated	-0.238*	-0.239*	-0.237*	-0.238*	-0.306**	-0.330**
	(-1.953)	(-1.962)	(-1.946)	(-1.957)	(-2.322)	(-2.506)
Female Name x Affluent		-0.218**				-0.324***
		(-2.023)				(-2.829)
Female Name x Male			0.153			0.163
			(1.475)			(1.594)
Female Name x Mature				0.190*		0.257**
				(1.861)		(2.437)
Female Name x College Educated					0.134	0.181
					(1.235)	(1.624)
Family Background	Y	Y	Y	Y	Y	Y
State-FE	Y	Y	Y	Y	Y	Y
Painting-FE	Y	Y	Y	Y	Y	Y
Obs.	7,940	7,940	7,940	7,940	7,940	7,940
adj. R-sq.	0.063	0.064	0.064	0.064	0.064	0.065

Notes: The table reports results for an OLS estimation of the effect of association with a female artist name on artistic appreciation after controlling for respondent characteristics. Panel A analyzes the entire sample, while Panel B focuses on respondents who visit museums or art galleries at least a few times a year. We also control for family background and state of residence of the respondent. Finally, we include painting fixed effects to control for the characteristics of the individual works of art. All standard errors are clustered at the survey respondent level. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Online Appendix 1: Robustness checks

Table OA1.1. Robustness to classifications of gender

	(1)	(2)	(3)	(4)	(5)	(6)
	Excluding gender identified through online searches	Only artists with gender identified through online searches	Unambiguous gender in US artist sample (Every Year)	Unambiguous gender in US artist sample (Year of birth)	Restricted to Oxford - Getty Sample	Sample Restrictions of Bocart et al. (2018)
Female Painter	-0.216***	-0.200	-0.661***	-0.328*	0.092	-0.196***
	(-4.627)	(-1.459)	(-4.642)	(-1.797)	(0.506)	(-4.238)
Pr(Female|Title)	0.388***	0.653***	0.341	0.119	0.116	0.450***
	(6.953)	(5.732)	(1.086)	(0.623)	(0.795)	(10.205)
Log(Surface)	0.386***	0.394***	0.426***	0.356***	0.492***	0.417***
	(44.309)	(14.247)	(8.566)	(9.242)	(14.122)	(45.234)
Marked	-0.523***	-0.479***	-0.761***	-0.834***	-0.321***	-0.585***
	(-26.033)	(-13.991)	(-8.750)	(-10.577)	(-5.396)	(-26.675)
Log(Age)	1.012***	1.241***	1.287***	0.799**	1.122***	1.161***
	(12.232)	(5.637)	(2.826)	(2.156)	(2.994)	(14.574)
Deceased	0.245***	0.304***	0.234	0.513	0.170	0.245***
	(4.675)	(2.608)	(1.091)	(1.544)	(0.879)	(3.644)
Year, Country, Style, Medium FE	Y	Y	Y	Y	Y	Y
N	1,731,343	167,505	23,262	56,803	25,122	1,298,140
adj. R-sq	0.254	0.302	0.332	0.369	0.387	0.251

Notes: The table reports results for the OLS estimation of a model where the (natural log of) inflation-adjusted sale price is regressed on a gender dummy and a series of control variables detailed in Table 1. In Model 1 we exclude artists whose gender has been identified with ad-hoc online searches. In Model 2 we only consider artists whose gender has been identified with ad-hoc online searches. In Model 3 we only consider American artists whose name has a 100% gender specificity in the US Census Records from 1880 to 2016. In Model 4 we only consider American artists whose name has a 100% gender specificity in the US Census Records in the year of birth of the artist. In Model 5 we only consider artists whose names appear in the database "The Getty Research Institute - Union List of Artist Names Online" (Link: http://www.getty.edu/research/tools/vocabularies/ulan/?find=&role=&nation=&page=1) or the "Oxford Art Online - Grove Art Online". The sample contains 441 individual artists (352 males and 89 females). In Model 6 we impose the same restrictions as in Bocart et al. (2018): Artists born after the year 1250 in Western Europe or North America and with transaction years after 2000 (ending in 2016 in our sample). Our restricted sample contains 47,023 individual artists (39,887 males and 7,136 females). Female artists account for 82,644 transactions. In all models we include style, medium, time, and country fixed effects and exclude transactions with auction sales prices above one million (mega transactions) 2016 US$. All standard errors are clustered at the individual artist and auction level. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Table OA1.2. Controlling for skewness of the dependent variable

	(1)	(2)	(3)	(4)
	Inflation adjusted (non-Log-) Prices	Non-Inflaition Adjusted Log-Prices	Only Transactions lower than 100'000 US$	Quantile Regression
Female Painter	-22,772.582***	-0.100***	-0.165***	-0.220***
	(-3.534)	(-4.397)	(-4.963)	(-49.764)
Pr(Female|Title)	23,856.052**	0.165***	0.369***	0.423***
	(2.395)	(7.061)	(10.712)	(62.024)
Log(Surface)	38,675.795***	0.256***	0.285***	0.357***
	(7.016)	(55.746)	(39.557)	(283.802)
Marked	-69,826.739***	-0.040***	-0.336***	-0.430***
	(-6.557)	(-5.810)	(-24.699)	(-115.869)
Log(Age)	92,668.007***	0.784***	0.729***	0.868***
	(4.531)	(19.229)	(13.064)	(149.433)
Deceased	25,986.648*	0.115***	0.202***	0.234***
	(1.664)	(5.180)	(6.902)	(58.387)
Constant				0.216***
				(4.341)
Year, Country FE	Y	N	Y	Y
Style, Medium FE	Y	Y	Y	Y
Auction FE	N	Y	N	N
N	1,898,849	1,890,754	1,798,783	1,887,112
adj. R-sq	0.016	0.646	0.204	

Notes: This table reports the OLS estimates of a model where the sale price is regressed on a gender dummy and a series of control variables detailed in Table 1. In Model 1 the dependent variable is the inflation-adjusted sale price (without logarithmic adjustment). In Model 2 the dependent variable is the (natural log of) the non-inflation-adjusted sale price. In Model 3 the dependent variable is the (natural log of) inflation-adjusted sale price but we only consider transactions with price lower than 100,000 in 2016 US$. In Model 4 we use a quantile regression model where the dependent variable is the (natural log of) inflation-adjusted sale price. In all models we include style, medium, time, and country fixed effects and exclude transactions with auction sales prices above one million (mega transactions) 2016 US$. All standard errors are clustered at the individual artist and auction level (except for Model 4 where we present robust standard errors). The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Online Appendix 2: Comparison with Bocart et al. (2018)

In a contemporaneous paper, Bocart et al. (2018) document an overall premium for artworks created by women in a sample of 2,677,190 auction transactions for photography, prints and multiples, works on paper, paintings, design objects and sculptures from data provider Artnet AG. Although the focus of our paper is different than theirs, i.e., we are interested in identifying whether culture explains auction outcomes for female artists, while they are interested in superstar effects, it is, nevertheless, important to identify potential reasons why our results might differ.

A direct comparison of our papers is complicated by the fact that Bocart et al. (2018) include artworks other than paintings in most regressions. Unfortunately, we were unable to obtain data or code from the authors that would enable us to directly compare the underlying data sources and the analysis for paintings. Thus, we proceed by replicating the analysis as described in their paper as best we can. While this replication is not perfect, we believe it is still able to rule out coding errors as a source of the differences in results. As we show below, sample composition, and ensuing selection effects, seem to be the main reasons why our results differ.

Our first observation is, as we summarize in Table OA2.1, that Bocart et al. (2018) contains far fewer transactions for paintings by women and far fewer female artists than our sample does. The sample in Bocart et al. (2018) contains 1,165,467 transactions for paintings between 2000 and April 2017 by 81,847 artists born after the year 1250 in Europe or North America. While our sample ends in December 2016, if we impose the same sample restrictions as in Bocart et al., we end with more transactions (1,298,122). Of these transactions, 83,761 are for paintings by women, whereas Bocart et al. have only 33,064 transactions for women. If we relax the assumption that artists need to be born in Europe and North America and require artists to be born after 1850, i.e., we focus on our main sample, the number of transactions for female artists increases to 141,149 in our sample.

Table OA2.1. Sample Size Comparison

	Our Sample with artists born from 1250		Our Sample with artists born from 1850		Our Sample with restrictions of Bocart et al. (2018)		Bocart et al. (2018)	
	Painters	**Transactions**	**Painters**	**Transactions**	**Painters**	**Transactions**	**Painters**	**Transactions**
Female	12,467	158,854	11,369	141,149	8,556	83,761	3,663	33,064
Male	78,366	2,514,210	57,820	1,757,700	61,164	1,214,361	78,184	1,132,403
Total	90,833	2,673,064	69,189	1,898,849	69,720	1,298,122	81,847	1,165,467

Notes: The table reports size in terms of number of transactions and number of artists for (a) Our sample considering all artists born from 1250; (b) Our sample with artists born from 1850 (the main selection used in this paper); (c) Our sample after imposing the same sample restrictions as in Bocart et al. (2018): artists born from 1250 in Europe or North America and transaction years after 2000 (ending in 2016 in our sample); (d) The sample of Bocart et al. (2018), data extracted from Table 1 in their manuscript.

In their paper, Bocart et al. (2018) document a high sample concentration for female artists: the top 47 artists account for 25% of the total number of sales of artworks by female artists (in our sample this number is 17.42%). To mitigate the effect of this concentration they implement a weighted average least square estimation where the weigths are the inverse of the square root of the number of artworks sold by each individual artist. We note that in this estimation (Table 6) they obtain a gender discount of 8.3%, similar in size to what we observe in our sample.

In OLS regressions, Bocart et al. (2018) document a premium for all artworks (Table 4) and for paintings (Table A6, first column). When they divide their sample into style categories, they document a discount for Modern, but a premium for Contemporary, Post War and Old Masters. They also document that their premium for artworks by women seems to be primarily driven by artists who were born prior to the 1850s. The magnitude of the premium is much smaller for women born after 1950 and becomes a discount for some later generations of artists.

The regression results in Bocart et al. (2018) together with the observation that their sample contains a relatively small number of transactions for female artists suggests that the premium they document could be driven by an underrepresentation of female artists in their sample, especially among painters born in the 20th century. We provide suggestive evidence that this may be the case in Tables OA2.3 and OA2.4. But first we show that differences in results do not stem from differences in regression specifications across papers.

In column (1) of Table OA2.2, we replicate the regression of log price on the female dummy for paintings in Table A6 of Bocart et al. (2018) with the same sample restrictions as in Bocart et al. (2018), i.e., artists born after 1250, born in Europe or North America, transaction years after 2000. Consistent with our previous results, we find a statistically significant discount for paintings by female artists. The discount is also present in column (2), where we use the same specification as in column (1) in our primary sample (artists born after 1850).

Table OA2.2. Replication of the base model of Bocart et al. (2018)

	Sample restrictions of Bocart et al. (2018)	**Excluding artists born before 1850**
	(1)	(2)
Female Painter	-0.153***	-0.147***
	(-33.759)	(-30.791)
Log(Surface)	0.308***	0.314***
	(282.829)	(248.649)
Alive	-0.510***	-0.455***
	(-164.479)	(-143.287)
Eastern Europe	0.052***	-0.002
	(7.472)	(-0.232)
Northern Europe	-0.406***	-0.423***
	(-42.856)	(-36.591)
Southern Europe	0.099***	0.042***
	(15.384)	(5.647)
Western Europe	-0.158***	-0.203***
	(-33.353)	(-37.447)
Auction House FE	Y	Y
N	1,298,122	1,000,468
adj. R-sq	0.467	0.477

Notes: The table reports the OLS estimates of a model where the (natural log of) inflation-adjusted sale price is regressed on a gender dummy and a series of control variables used in Bocart et al. (2018). Alive is defined equal to one if the artist is alive at the moment of auction sale. The four regional dummies are defined based on the nationality of the artists with the base case equal to "North America". In Model (1) we impose the same sample restrictions as in Bocart et al. (2018): Artists born after 1250 in Europe or North America and transaction years after 2000 (ending in 2016 in our sample). In Model (2) we only consider artists born after 1850. In all models we include auction house fixed effects. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

In Table OA2.3, we use the same regression specification and sample restrictions as in column (1) of Table OA2.2, i.e., with the Bocart et al. (2018) sample restrictions, for different style subsamples. While we generally document a discount for female artists, we document a premium for women in a small sample of Latin American transactions. We also document a premium for paintings by female Old Masters, which is consistent with the findings in Bocart et al. (2018).

In Table OA2.4, we use the same regression specification and sample restrictions for different cohorts of artists. While we document a discount for each cohort of artists born after 1850, we find a premium for paintings by women for most cohorts of artists born prior to 1850. Our analysis suggests that the discount we document is widespread and can be considered to reflect the average outcome experienced by women's art in the secondary market since few female artists were born prior to 1850. However, art by selected samples of female artists may experience a premium relative to art by similar male artists. Thus, our sample seems more suited for analyzing the role of culture in the art market. The sample by Bocart et al. (2018) may be more suited for analyzing the presence of superstar effects.

Table OA2.3. Gender discount by style

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	19th Century European	American	Asian	Impressionist and Modern	Latin American	Old Masters	Other	Post-war and Contemporary
Female Painter	-0.034***	-0.145***	-0.665***	-0.128***	0.410***	0.089**	-0.061***	-0.230***
	(-3.321)	(-12.581)	(-2.842)	(-9.548)	(3.525)	(2.510)	(-8.884)	(-20.313)
Log(Surface)	0.303***	0.260***	0.640***	0.288***	0.338***	0.293***	0.259***	0.350***
	(164.616)	(74.342)	(20.714)	(84.959)	(9.062)	(69.778)	(117.235)	(141.717)
Alive	-0.753***	-0.518***	-0.567***	-0.565***	-0.037	-1.070***	-0.478***	-0.523***
	(-11.774)	(-46.685)	(-7.511)	(-44.218)	(-0.363)	(-2.596)	(-94.048)	(-91.414)
Eastern Europe	0.418***	0.948***	4.022***	0.195***	-0.266	0.164	0.578***	-0.599***
	(14.652)	(14.270)	(10.039)	(4.027)	(-1.094)	(1.309)	(39.130)	(-34.208)
Northern Europe	-0.248***	-1.087***	0.513	-0.521***		0.216*	0.062***	-0.597***
	(-8.633)	(-9.141)	(1.453)	(-9.100)		(1.873)	(2.752)	(-25.736)
Southern Europe	0.220***	-0.499***	1.025***	0.472***	-0.132	0.658***	0.272***	-0.396***
	(7.904)	(-2.945)	(2.601)	(9.555)	(-0.884)	(5.961)	(15.361)	(-30.904)
Western Europe	-0.139***	-0.143***	1.100***	0.055	0.360***	0.385***	0.189***	-0.438***
	(-5.199)	(-3.938)	(4.133)	(1.150)	(2.877)	(3.496)	(15.291)	(-40.446)
Auction House FE	Y	Y	Y	Y	Y	Y	Y	Y
N	348,368	139,839	1,887	209,223	1,208	72,447	290,600	233,972
adj. R-sq	0.399	0.400	0.526	0.524	0.557	0.400	0.446	0.568

Notes: The table reports results for the OLS estimation of a model where the (natural log of) inflation-adjusted sale price is regressed on a gender dummy and a series of control variables used in Bocart et al. (2018). Alive is defined equal to one if the artist is alive at the moment of sale. The four regional dummies are defined based on the nationality of the artists with the base case equal to "North America". The model is estimated separately for the eight styles represented in our sample. We impose the same sample restrictions as in Bocart et al. (2018): artists born after 1250 in Europe or North America, and transaction years after 2000 (ending in 2016 in our sample). In all models we include auction house fixed effects. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Table OA2.4. Gender discount by artist cohort

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	<1700	<1800	<1825	<1850	<1875	<1900	<1925	<1950	<1975	<2001
Female Painter	0.299***	-0.001	0.158***	0.053***	-0.100***	-0.120***	-0.068***	-0.193***	-0.274***	-0.306***
	(5.230)	(-0.033)	(5.573)	(2.864)	(-8.782)	(-12.984)	(-7.394)	(-16.615)	(-20.208)	(-6.688)
Log(Surface)	0.244***	0.358***	0.310***	0.319***	0.317***	0.314***	0.374***	0.331***	0.352***	0.320***
	(47.606)	(63.824)	(78.799)	(96.366)	(120.886)	(112.536)	(140.363)	(124.787)	(89.787)	(20.241)
Alive						-0.821***	-0.156***	-0.321***	-0.985***	-1.099***
						(-17.179)	(-22.004)	(-50.303)	(-42.091)	(-4.057)
Eastern Europe	0.877**	0.166**	0.832***	0.722***	0.496***	0.239***	-0.435***	-0.480***	-0.553***	-1.070***
	(2.131)	(2.222)	(22.954)	(31.386)	(30.631)	(17.468)	(-26.096)	(-23.126)	(-20.146)	(-11.108)
Northern Europe	0.799**	-0.082	-0.496***	-0.298***	-0.173***	-0.527***	-0.458***	-0.477***	-0.450***	-0.608***
	(1.960)	(-1.473)	(-15.615)	(-12.638)	(-8.945)	(-19.500)	(-18.545)	(-17.170)	(-9.711)	(-3.463)
Southern Europe	1.364***	0.418***	-0.092***	0.303***	0.278***	0.564***	-0.152***	-0.410***	-0.263***	-0.811***
	(3.374)	(10.236)	(-2.884)	(14.771)	(16.613)	(34.188)	(-10.254)	(-25.886)	(-12.399)	(-5.166)
Western Europe	1.252***	-0.248***	-0.395***	-0.021	-0.092***	0.022*	-0.292***	-0.480***	-0.247***	-0.336***
	(3.098)	(-7.159)	(-20.438)	(-1.548)	(-8.304)	(1.905)	(-25.758)	(-38.273)	(-15.128)	(-4.963)
Auction House FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	47,910	43,018	77,238	129,110	229,596	277,224	234,020	184,512	71,266	3,517
adj. R-sq	0.371	0.431	0.410	0.451	0.453	0.479	0.455	0.553	0.631	0.700

Notes: The table reports results for the OLS estimation of a model where the (natural log of) inflation-adjusted sale price is regressed on a gender dummy and a series of control variables used in Bocart et al. (2018). Alive is defined equal to one if the artist is alive at the moment of sale. The four regional dummies are defined based on the nationality of the artists with the base case equal to "North America". The model is estimated separately for artists grouped by year of birth. We impose the same sample restrictions as in Bocart et al. (2018): artists born after 1250 in Europe or North America, and transaction years after 2000 (ending in 2016 in our sample). In all models we include auction house fixed effects. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Online Appendix 3: The surveys

In this Appendix, we show screenshots of the surveys we used in the two experiments. Comments explaining the purpose of the screenshots are in italics. Table OA2.1 provides descriptive statistics for the appreciation scores by guessed gender (Experiment #1) and associated gender (Experiment #2). Appendix A describes the inputs into the experiments.

Experiment #1

Step 1 – Introduction

Each subject is shown an introductory page that explains the purpose of the experiment.

Can you guess?

Introduction

My name is [redacted] and I am an academic at [redacted].

The purpose of this academic survey is to measure the characteristics that make a painting "attractive".

Below you will be shown a series of *five paintings that have been sold in a major auction in 2013*. For each one of them you will have to guess the artist's gender and place of origin and, approximately, when the painting was created. We will also ask you to rate how much you like it on a scale from 1 to 10.

These are not famous paintings so you will be probably seeing them for the first time. Answer the questions purely based on your first impression of each work of art. Our goal is to establish whether the visual style of a painting can be used to infer information about the artist. **We only ask you to look at each painting for at least 30 seconds before answering.**

We will also ask you few questions about your background and general knowledge of art and art history.

You can change your mind at any time and stop completing the survey without consequences.

If you agree to be part of the research and to research data gathered from this survey to be published in a form that does not identify you, please continue with answering the survey questions.

If you have concerns about the research that you think I can help you with, please feel free to contact me on +[redacted] or [redacted]. You can also contact SurveyMonkey directly at http://help.surveymonkey.com/contact

If you would like to talk to someone who is not connected with the research, you may contact the [redacted] Research Ethics Officer on +[redacted] or [redacted] and quote this number ([redacted] HREC REF NO. ETH16-0847)

Next ▸

Step 2 – Biographical information
The survey provider supplies us with basic demographic information on each subject (gender, age range, and geographical provenance). Here we augment this set with five survey questions.

Can you guess?

Tell us something about you

How often do you visit an art gallery, museum or exhibition?

- Rarely or never
- A few times a year
- Once a month or more

What is the highest level of school you have completed or the highest degree you have received?

- Less than high school degree
- High school degree or equivalent (e.g., GED)
- Some college but no degree
- Associate degree
- Bachelor degree
- Graduate degree

In what state or U.S. territory do you live?

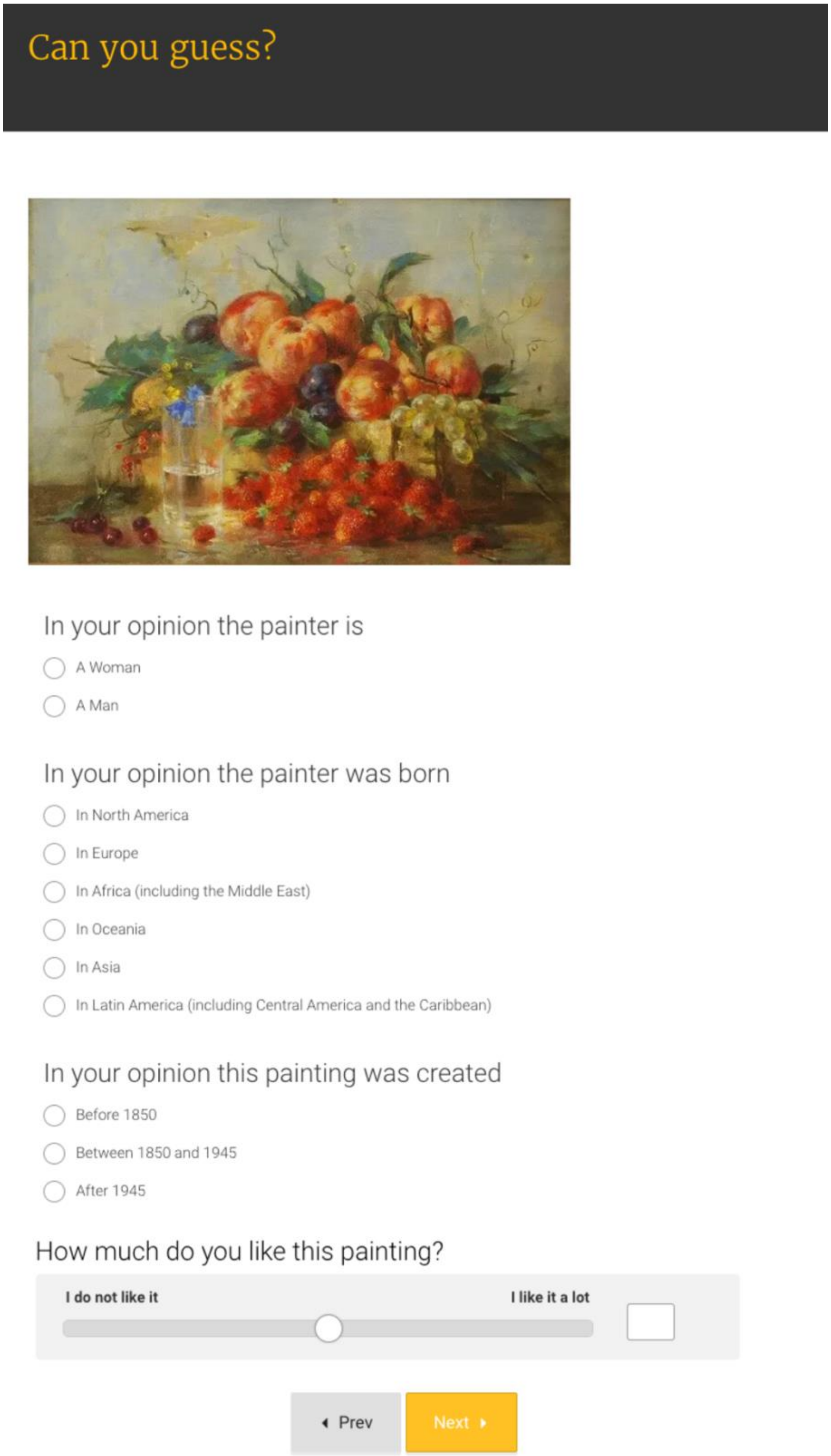
In what country was your father born?

In what country was your mother born?

Prev Next

Steps 3 to 7 – The experiment

Each subject is shown a random selection of five paintings. For each painting the subject must guess gender and place of origin of the painter and approximate creation period of the painting. After this, the subject is asked to rate the painting on a 1-10 scale.


Can you guess?

In your opinion the painter is

- A Woman
- A Man

In your opinion the painter was born

- In North America
- In Europe
- In Africa (including the Middle East)
- In Oceania
- In Asia
- In Latin America (including Central America and the Caribbean)

In your opinion this painting was created

- Before 1850
- Between 1850 and 1945
- After 1945

How much do you like this painting?

I do not like it … I like it a lot

Prev | Next

Step 8 – Conclusion

The survey concludes with a closing page where we thank the subject.

Can you guess?

Conclusion

Thank you very much for taking some time to answer our questions.

Your answer will help us to understand whether a) it is possible to infer gender and other characteristics of a painter only by looking at their works, and b) whether these perceived characteristics affect how much we instinctively like a painting.

Let me stress again that in terms of artistic appreciation there is no right or wrong answer, is a totally subjective issue. We just wanted to measure if what we think about the painter affects how much we value their work.

◂ Prev | Done ▸

Experiment #2

Step 1 – Introduction

Each subject is shown an introductory page that explains the purpose of the experiment.

What makes Art beautiful?

Introduction

My name is [redacted] and I am an academic at [redacted]

The purpose of this academic survey is to measure the characteristics that make a painting "attractive".

Below you will be shown a series of ten paintings. *For each one of them you will have to rate how much you like it on a scale from 1 to 10.*

These are not famous paintings so you will be probably seeing them for the first time. Answer the questions purely based on your first impression of each work of art. **We only ask you to look at each painting for at least 30 seconds before answering.**

We will also ask you few questions about your background and general knowledge of art and art history. Altogether we estimate that completing this survey will take less than 20 minutes.

You can change your mind at any time and stop completing the survey without consequences.

If you agree to be part of the research and to research data gathered from this survey to be published *in a form that does not identify you*, please continue with answering the survey questions.

If you have concerns about the research that you think I can help you with, please feel free to contact me on +[redacted] or [redacted] You can also contact SurveyMonkey directly at http://help.surveymonkey.com/contact

If you would like to talk to someone who is not connected with the research, you may contact the [redacted] Research Ethics Officer on +[redacted] or [redacted] and quote this number (ETH16-0568).

Next ▸

Step 2 – Biographical information
The survey provider supplies us with basic demographic information on each subject (gender, age range, and geographical provenance). Here we augment this set with five survey questions.

What makes Art beautiful?

Tell us something about you

How often do you visit an art gallery, museum or exhibition?

- Rarely or never
- A few times a year
- Once a month or more

What is the highest level of school you have completed or the highest degree you have received?

- Less than high school degree
- High school degree or equivalent (e.g., GED)
- Some college but no degree
- Associate degree
- Bachelor degree
- Graduate degree

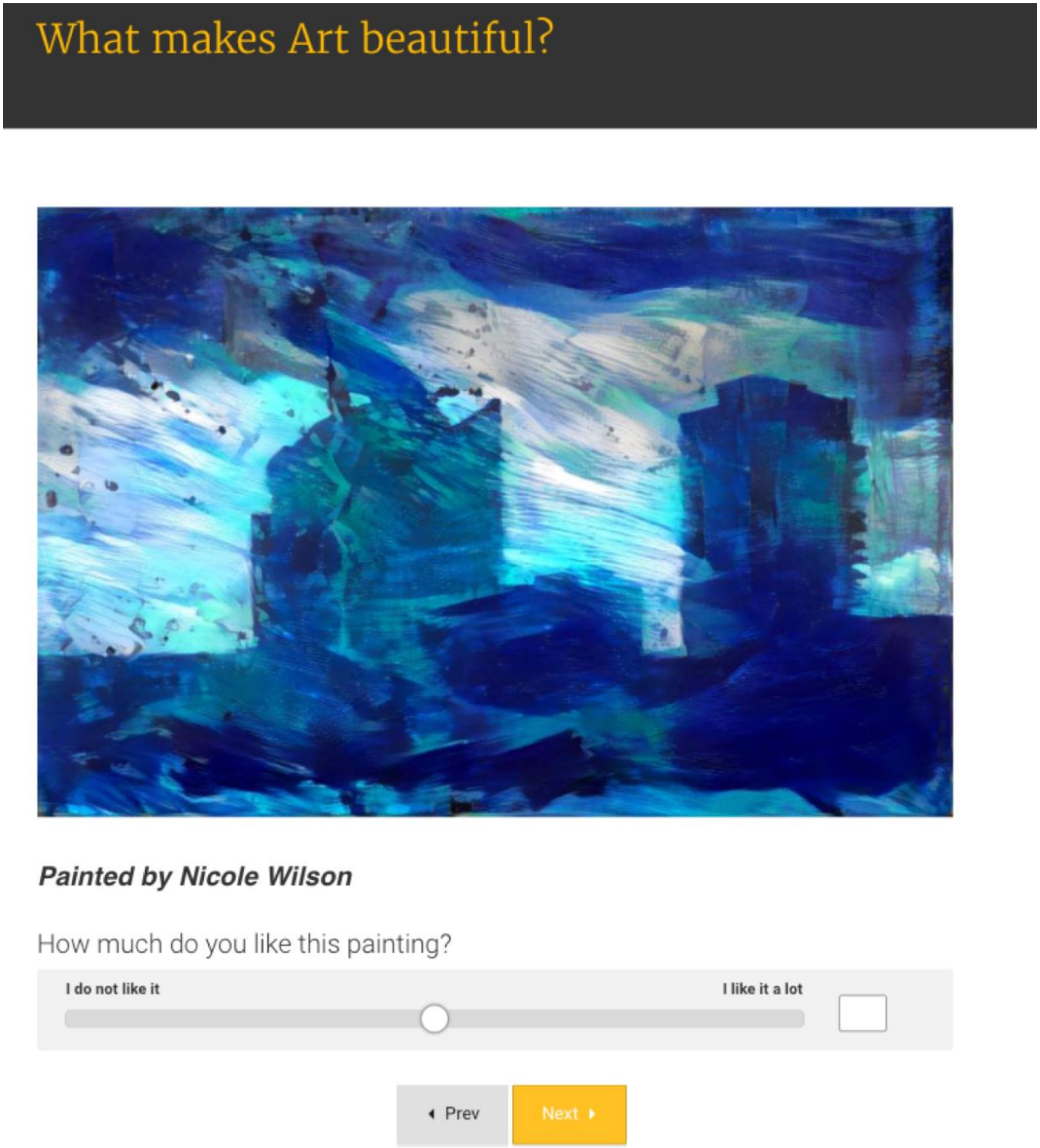
In what state or U.S. territory do you live?

In what country was your father born?

In what country was your mother born?

Prev Next

Steps 3 to 12 – The experiment
Each subject is shown the ten synthetic images in random order. Each image is randomly associated with a male or a female artist name. The subject is asked to rate the painting on a 0-10 scale.



Step 13 – Conclusion
The survey concludes with a closing page where we thank the subject.

What makes Art beautiful?

Conclusion

Thank you very much for taking some time to answer our questions.

Here is where we confess to a little deception...

The works of art presented have been created using a computer algorithm (a deep neural network) that combines an image (in our case pictures of everyday objects or scenes) with the visual style of an existing painting (the names associated with each painting are just random combinations of the most common names in the US).

Using this methodology we can control the subject and visual style of the painting and create a large number of distinctive images to better analyze which factors drive artistic appreciation.

◂ Prev | Done ▸

Table OA3.1 Summary statistics for experimental data

Panel A: Experiment #1				Panel B: Experiment #2		
Artist Name	**Gender**	**Female Guess**	**Male Guess**	**Painting**	**Female Name**	**Male Name**
John Alexander	Male	5.524 (84)	4.506*** (340)	1	5.403	5.203*
Benny Andrews	Male	3.456 (228)	2.89** (219)	2	5.273	5.209
David Bierk	Male	6.409 (88)	5.654*** (341)	3	5.583	5.556
Betty M Bowes	Female	5.596 (109)	5.497 (342)	4	6.269	6.417
Oliver Clare	Male	5.679 (184)	5.743 (269)	5	5.959	6.01
Nikolai Kozlenko	Male	5.921 (228)	6.005 (194)	6	4.805	4.633
Cheryl Laemmle	Female	4.649 (174)	4.638 (282)	7	4.338	4.274
Maud Lewis	Female	5.046 (130)	4.735 (291)	8	5.263	5.352
Marie Lucie Nessi-Valtat	Female	5.466 (281)	5.469 (145)	9	5.988	5.935
Joyce Wahl Treiman	Female	4.122 (131)	4.019 (321)	10	5.675	5.607

The table reports descriptive statistics for the appreciation scores for the images in our two experiments by guessed gender (Experiment #1) and associated gender (Experiment #2). For the first experiment we also report the number of female and male guesses each painting received. The table shows the results of *t*-tests for the difference between the average score each painting received by guessed or associated gender. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively.