Is Gender in the Eye of the Beholder? Identifying Cultural Attitudes with Art Auction Prices *

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Abstract

In the secondary art market, artists play no active role. This allows us to isolate cultural influences on the demand for female artists' work from supply-side factors. In a sample of 1.9 million auction transactions in 49 countries, the unconditional discount for paintings by female artists is 42.1%. In artist fixed effects regressions, the gender discount increases with country-level gender inequality. In experiments, participants are unable to guess the gender of an artist and they vary in their preferences for paintings associated with female artists. Women's art appears to sell for less because it is made by women.

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JEL codes: Z11; J16; D44

I. Introduction

A challenge in improving economic outcomes for women is to disentangle culture from biology. Culturally determined gender roles may explain why women have different labor market outcomes than men; biological gender differences (e.g., in strength) and differences in preferences can also explain why women have different labor market outcomes than men.[1] Presumably policy can only affect culture, not biology. To guide policy-making, it is thus important to identify settings in which culture, not biology, leads to worse outcomes for women. We argue that the secondary market for art is such a setting because artists have limited influence on it—especially when they are dead.

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. Although some have advanced the hypothesis that biological factors would lead women to produce systematically worse art (see, for example, the discussion in Cowen, 1996), there is no credible scientific evidence for this hypothesis. There is also no evidence that women produce art that is systematically less pleasing to art auction participants. In fact, we hypothesize and find that one cannot infer the gender of an artist by looking at a painting. This makes it difficult to attribute the price difference in paintings to biology. Since the gender discount in auction prices is higher in countries with greater gender inequality, we argue that the discount reflects an effect of culture on economic outcomes for female artists.

[1] A large literature has documented gender differences in psychological traits and measures of preferences (e.g., Bertrand, 2010; Niederle, 2014). While some of these differences may have biological origins (e.g., risk-taking preferences appear to be correlated with testosterone levels, which are on average higher in men), the role of biology in shaping preferences is not yet clear, see, e.g., Cobb-Clark (2017).

We use several empirical strategies and two experiments to identify potential explanations why culture matters. 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. In a landmark 1971 article, the American art historian Linda Nochlin dismisses this argument. 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. The art critic Jerry Saltz (2015) puts it more bluntly: “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, we are unaware of formal refutations of this theory.

To formally address the idea that art produced by women may be systematically different, 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, since men paint more roses than women, it 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, paintings with female-prevalent topics are not less appealing to collectors on average—instead, they command a premium.

Another possible explanation for our results is that the price difference reflects a quality difference that can be attributed to women’s historical lack of access to art education and resources (e.g., Nochlin, 1971; Davis, 2015). While selection might lead the average quality of women’s art entering the secondary market to be better, not worse, than the average quality of the men’s art (see also Cameron et al., 2017, and Bocart et al., 2018), 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.[2] 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).

To address a potential quality explanation, we exploit the fact that an artist' work is often sold in several countries and include artist fixed effects in our regressions of the auction price on country-level measures of gender inequality. While we are unable to estimate the average gender price discount in these regressions, we can still identify the coefficients on the interactions between a gender indicator and our proxies for country-level gender inequality. In artist fixed effect regressions, the coefficients on the culture interaction terms are positive for all measures of gender inequality. Under the assumption that talent or training is a fixed personal characteristic, a historic lack of access to training also does not appear to be the primary explanation for the price difference. This interpretation is supported by regressions that include proxies for painting fixed effects.

While our title analysis and artist fixed effect specifications help rule out the idea that our findings are driven by differences in "themes" or training, we also conduct an experiment (Experiment #1) 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,

[2] For instance, following Edward Albee's death, Sotheby's auctioned "The Collection of Edward Albee" on September 26, 2017. While Edward Albee's collection contained "a handful of stars", it also contained "unsung contemporary painters and sculptors" (Sotheby's, 2017, p.8).

i.e., their guesses were statistically indistinguishable from random. Of 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”.

A final cultural explanation is that the price difference simply reflects societal attitudes towards women. 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.*

Art is notoriously difficult to value (e.g., Ashenfelter and Graddy, 2003; Penasse and Renneboog, 2018) and it is widely recognized that factors such as taste play an important role in setting prices. Most directly, local attitudes towards women can affect the amount that is bid in the auction. But local attitudes can also inform pre-sale estimates of art, and hence the auction outcome (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 et al., 2018).[3]

Local attitudes may also influence how the auction itself is conducted. Lacatera et al. (2015) document that the auctioneers themselves can affect the bidding outcome. While there is little data on auctioneers, some observers characterize the auctioneer profession as male-dominated (e.g., Bellamy, 2005). To be able to solicit information about client’s preferences, it is also plausible that auction houses employ auctioneers from similar cultural backgrounds as the local

[3] The coverage of auction house price estimates in our data is poor 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, we also find a discount in the auction house estimates.

clientele. Of course, online bidding may work against the influence of local preferences on the auction outcome.

Our evidence that country-level measures of gender inequality are related to the gender discount in art prices after controlling for artist or auction fixed effects is consistent with the idea that art by women sells for a lower price simply because it is made by women. Variation in the fraction of transactions for paintings by women across countries and time trends in price indices for a small sample of repeat sales provide additional support for this argument. We use our experiments to examine the validity of an attitude explanation in more depth.

In Experiment #1, we asked participants how much they liked the painting on a scale of 1-10 after they guessed the gender of the artist. This allows us to measure whether 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 et al. (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 the idea that "Women's art sells for less because it is made by women" (Allen, 2005).

Since the 1985 founding of the Guerrilla Girls, the discussion about women's status in the art world gained increased momentum—in part because of the Guerrilla Girls' data gathering efforts ("weenie counts") that highlight women's low representation in the art world.[4] Our work provides direct evidence that supports the claims of many, including Nochlin (1971) and the Guerrilla Girls, that there is a link between women's low representation in the art world and cultural institutions.

In the economics literature, relatively little has been written on the role of women in the arts. Cowen (1996) examines the argument that women are unable to produce great art for genetic reasons. He argues that the fact that women's performance in the arts varies with circumstances and incentives is evidence against the genetics hypothesis. Using Finnish data from 1992, Heikkinen and Karhunen (1996) document that the income of female artists is lower than that of male artists. Throsby and Zednik (2010) document similar results in a 2009 survey of artists in Australia. They also find that time constraints are more binding for female artists than male artists.

More recently, Cameron et al. (2017) examine the career histories of graduates of the Yale School of Art. They document that female graduates had lower citations in art history books and their art was less likely to sell at auction, but when it did so it sold at a higher price. It is possible that their results are different from ours because of their focus on artists from an elite art school. Bocart et al. (2018) document premia and discounts for different samples of female artists in auction data from Artnet. In the Online Appendix, we compare our results to theirs and show that the reason their results sometimes differ from ours appears to be selection: their sample contains substantially fewer female artists and transactions for paintings by women than our sample does. This

[4] In 1985, seven female artists founded the Guerrilla Girls in response to the Museum of Modern Art's 1984 exhibition "An International Survey of Recent Painting and Sculpture" that included only 13 women out of 165 artists. Over 55 female artists have been members of the Guerrilla Girls.

suggests their estimates of the average gender difference in auction prices for paintings are biased.[5]

At a more general level, our paper contributes to the literature that relates country-level cultural characteristics to economic outcomes for women (for reviews of this literature, see e.g. Fernandez, 2007 and 2008 and Giuliano, 2017). Our paper differs from most of the papers in this literature in one key aspect: the outcomes we examine are not directly linked to decision-making by women. Once artists sell their work, what happens to their work is no longer under their control. This is especially true once the artist dies.[6] As a result, "supply side" factors commonly advanced to explain economic outcomes for women, such as preferences (e.g., Shurchkov and Eckel, 2017) and family considerations (e.g., Bailey and Lindo, 2017; Rossin-Slater, 2017) should not play a major role in our setting. The effects we document should be driven by demand-side considerations (for art). Thus, our setting allows us to isolate how cultural factors related to gender inequality affect the demand for an output produced by women.

Our results highlight the importance of culture in shaping economic outcomes for women. Even though the artist does not directly participate in the secondary market, outcomes in the secondary market can have a profound influence on artists' careers. Most directly, prices in the secondary market can affect prices in the primary market and alter incentives for creating art (e.g., Galenson and Weintraub, 2000). But, as Thornton (2008, p. 8) describes, auction prices can also affect "the perceptions of an artist's oeuvre". Similarly,

[5] In Online Appendix 1, we also show that the discount for female artists we document is robust to imposing similar sample restrictions as in Bocart et al. (2018). Since we cannot easily identify Yale graduates in our sample, to compare to Cameron et al. (2017) we restrict our sample to "visible artists" who appear in the "Oxford Art Online - Grove Art Online" or "The Getty Research Institute - Union List of Artist Names Online". We do not find any significant difference between prices for male and female artists in this subsample. Thus our results are consistent with the idea that on average female artists experience a discount, but women in selected subsamples may not.

[6] More than 75% of transactions in our sample are for dead artists.

Ashenfelter and Graddy (2003, p. 783) write: "the [auction] market…is certainly one of the key components of our understanding of what is good and bad." A good example of how market prices are used to judge quality is the recent statement by the German artist Georg Baselitz that: "[women] simply don't pass the market test, the value test… As always, the market is right." (Clark, 2013).

But, we know from Becker (1957) that just because a market is in equilibrium does not mean there is no discrimination. Our evidence suggests that policies to reduce gender inequality and negative attitudes towards women may improve outcomes for female artists and women who wish to be artists even if they do not directly target the art market. Until the time that gender inequality is eliminated, like auditions for orchestras (Goldin and Rouse, 2000), auction outcomes might be different if they were "blind".

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.

In this paper, we restrict our analysis to transactions from 1970 to 2016 involving paintings created by artists born after 1850 for whom we can identify gender.[7] Transactions before 1970 are relatively sparse and impede a precise

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

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 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-sale sample in Korteweg et al. (2016), which consists of a subset of this data, and is roughly 74% 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. (2017) is substantially smaller. Of the 4,434 graduates from the Yale School of Art, Cameron et al. (2017) 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. But, it has worse coverage of female painters. Their sample 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. to post-2000 transactions for European and North American artists born after 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 painting, the artist, and the auction it was sold at. We know the painting's title, artist, year of creation, size, whether it was signed or stamped by the artist, and its medium (e.g., "oil on canvas" or "oil on board"). 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 name lists, 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 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 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. (2017) 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. Panel C describes the variables we use in our 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 2000 onwards. Thus, we use extrapolated versions of these measures that backfill the missing observations from the first available data points for each country.[9]

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

[9] We acknowledge that this process will introduce some noise, but this may be mitigated by the low over-time variation (compared to cross-country variation) of these indicators. Results are similar if we do not extrapolate.

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.

Table 2 shows descriptive statistics for our auction data sample. Female artists account for 16.4% of the population of artists, but only 7.4% of transactions. The mean transaction price is around US \$50,480 for male artists and 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). Later we will show that this time trend persists in a multivariate setting and will use this evidence to support our hypothesis that the gender discount is influenced by cultural factors related to the role of women in society.

-Insert Table 3 about here-

Panel B of Table 3 provides statistics on the geographic distribution of auction transactions in our sample. The UK and the United States are the two largest art markets and together account for 36% of our sample. The gender price discount is large in both markets with and without mega-transactions. The fact that the price discount and the percentage of transactions by female artists varies across countries suggests country-level factors related to the role of women in society may be important for explaining auction outcomes.

III. “Women’s art”

To be able 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 6.9% of the paintings 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 painted 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. However, there is a significant amount of overlap between the two distributions, which suggests the imbalance is not strong. Moreover, no topic is exclusive to one gender—after all, male artists account for 85% of the uses of the words “ROSES”.

To facilitate comparisons to the gender dummy variable, we account for potential gender imbalances in topics by including a dummy variable “Female-prevalent Topic” in our regressions, which is equal to one if the estimated conditional probability that a painting was painted by a woman is greater than 50%. If we include the estimated probabilities directly, our results are similar.

Table 2 shows summary statistics for the estimated conditional probability and for the variable “Female-prevalent Topic”. In our sample, 96.09% of transactions belong to artists with both female-prevalent and female-non-prevalent topics. This percentage increases to 99.44% in the subsample of artists for whom we have at least 20 transactions on record. Figure 2 shows the distribution of male and female artists within subsamples of our transactions by quintiles of the estimated conditional probability and by female-prevalent topic.

-Insert Figure 2 about here-

IV. Gender and auction prices

In Table 5, we show regressions of auction prices on a dummy that is equal to one if the artist is female, Female-prevalent Topic, and various controls. 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 results 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 Bocart et al. (2018) find a gender premium in some specifications.

Column 1 of Table 5 shows the regression of auction prices on the Female Painter dummy and year and country fixed effects. In column 2, we replace Female Painter with Female-prevalent Topic. In column 3, we add Female-prevalent Topic to the specification in column 1. In column 4, we include standard artist and painting characteristics (see, e.g., the overview in Ashenfelter and Graddy, 2003). The artist characteristics we control for are the (natural logarithm of) the artist's age (at the time of the auction) and a dummy variable that is equal to one if the artist was dead at the time of the auction. The painting characteristics we control for 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, and style and medium fixed effects. In column 5, we replace country and year fixed effects with auction fixed effects that control for characteristics specific to the auction the painting is sold at, such as the characteristics of the auctioneer and the clientele and the auction itself, and the characteristics of the collection that is being sold, e.g., its size and theme.

-Insert Table 5 about here-

In columns 6-7, we reestimate the specifications in columns 4-5 after excluding mega transactions. As a first step towards addressing the fact that female artists historically had less access to training, 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 rerun all regressions in Table 5 in this subsample and report the coefficients on Female Painter and Female-Prevalent Topic at the bottom of the table.

Supply side factors commonly advanced as explanations for women's labor market outcomes, such as preferences and child-rearing considerations, are unlikely to affect the price of an artist's work once she is dead. To increase confidence that we are examining a demand-side effect for art, we restrict our sample to artists who were deceased at the time of the auction (74.9% of transactions) and report the results of rerunning the regressions in Table 5 at the bottom of the table. In all specifications, we cluster the standard errors at the artist and auction level.

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 Female-prevalent Topic 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 19.7% (with country fixed effects in column 4) and 9.4% (with 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 mean prices are higher in the restricted sample.

To examine whether the univariate time trends and geographical patterns in gender discounts persist in a multivariate context, we first add interaction terms between the gender variable and time period indicators to the regression in column 4 of Table 5. Figure 3 plots the point estimates for the interaction terms of gender with the period dummies for the full sample and the sample of artists with at least 20 transactions. Consistent with the univariate results, the discount is decreasing over time — especially for the sample of artists with at least 20 transactions. Since gender inequality has also gone down over time, the trend is consistent with the idea that gender inequality influences the discount.

-Insert Figure 3 about here-

Next, we add interaction terms between the gender variable and geographic indicators to the regressions underlying Figure 3. Figure 4 shows the point estimates for the interaction terms of gender with geographic dummies for countries with more than 60,000 transactions (all others are lumped into the "Other" category).

-Insert Figure 4 about here-

As Figure 4 suggests, there is significant heterogeneity in the discount across countries. While art by female artists sells at a discount in most countries, it sells at a premium in Sweden.

V. Culture and the gender discount

The significant variation of the gender price discount over time and across countries is consistent with the idea that the discount reflects attitudes towards women at the time and in the place of the auction. In this section, we test this idea more formally by augmenting our regressions with country-level variables that proxy for cultural attitudes towards women and their interactions with the artist's gender and Female-prevalent Topic. We also include the interactions between the natural logarithm of per-capita GDP and the artists' gender and Female-prevalent Topic to ensure the interactions with culture do not simply reflect non-linear effects of economic development. The results are similar without the GDP interactions and are available on request.

We start by estimating the following regression:

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

In this regression, we are primarily interested in the coefficient on the interaction coefficient λ. Because our culture variables are measured at the country/year level, they exhibit little variation over time. Thus, we do not include country or auction fixed effects in the regression. However, we cluster standard errors at the artist and auction level.

Table 6 presents the results of this estimation for the five measures of culture. Three of the estimated λ coefficients are significant at conventional levels 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 Female-prevalent Topic is higher in more gender equal countries. The estimated η coefficients are always positive and they are highly significant.[10]

-Insert Table 6 about here-

To gauge the economic importance of these coefficients we provide the estimate of the gender price gap for values of the culture variables in a ± 1 standard deviation range around the mean at the bottom of Table 6. If we consider, for example, the percentage of women in parliament, we see that paintings of female artists sell at a 31.26% discount in countries/years where this percentage is "low" (12.70%, one standard deviation below the mean) but sell at a 3.67% premium when the percentage is "high" (31.38%, one standard deviation above the mean). In the same way we estimate a gender price discount of 25.48% when gender inequality is "high" according to Gender Gap Index, but a discount of 7.95% when inequality is "low".

V.1 Artistic talent/style

To more formally address the idea that art produced by women may be

[10] One could argue that these results reflect the fact that there are more female buyers in more gender-equal countries. However, Thornton (2008) suggests most "big-spending" collectors are male. Moreover, it is not clear that there are more wealthy women in more gender-equal countries. For example, Sorvino (2017) describes that more than half of the world's 56 self-made female billionaires are from Asia, where gender equality measures are traditionally lower.

systematically different, 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. (2017) provide evidence that the art market is truly international. They document that the work of 525 graduates from the Yale School of Art was 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 Female Painter and our gender culture proxy variables. Since most artists in our sample paint both female-prevalent and female-non-prevalent topics, we can also still estimate the price difference for Female-prevalent Topic.

-Insert Table 7 about here-

After adding artist fixed effects, we observe that the coefficients on the interactions of Female Painter with culture remain positive and significant for all the culture indices in Table 7. From the calculated marginal effects at the bottom of the table we can see that the results are also economically significant. The coefficients on the interactions between Female-prevalent Topic and culture are consistent with the interactions between Female Painter and culture. The coefficients are all positive and statistically significant—even in the restricted sample. For a given painter, collectors appear to value paintings of female-prevalent topics more in more gender equal countries.

The R^2 of the regressions increases significantly from 19% – 22% to 74% – 77% between Tables 6 and 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 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 specifications that include our proxies for painting fixed effects in columns 6-10 of Table 7 support the idea that 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 significant in some specifications.

V.2 The supply of and the returns to investing in women's artworks

Before we turn to a more detailed examination of potential explanations for the findings in Tables 6 and 7, we provide two additional pieces of evidence that are consistent with the idea that culture affects the demand for artworks by women. If there is little demand for women's artworks in some countries, presumably auction houses and potential sellers would avoid selling collections with a large percentage of female artworks in those countries. It is difficult to examine this hypothesis in detail because, to the best of our knowledge, there is no systematic data on how items are bundled for auction and sellers' choice of auction house location. Moreover, it is not possible to get a long time series of data on all art up for auction (as opposed to all art sold at auction as in our data). Nevertheless, we provide some suggestive evidence consistent with this hypothesis in Table 8. We regress the percentage of auction transactions involving paintings by women in a country and year on our culture variables and Log (GDP) and year dummies and cluster our standard errors at the country level.

-Insert Table 8 about here-

Panel A of Table 8 reports the results for country/year observations with at least 100 transactions in the sample; Panel B reports the results for the subsample of country/year observations with at least 1,000 transactions in the sample. The evidence from Panel B in particular suggests that the supply of women's art may be relatively higher in countries with greater gender equality since the coefficients on the culture variables are positive and statistically significant for three out of five measures.

One could argue that less women's art is sold in countries with greater gender inequality because, for some reason, collectors in those countries are more pessimistic about the future growth in prices for paintings by women. If so, the price discount could also be explained by rational, but culturally-influenced, investment behavior. Although the time trend in the discount we document in Figure 3 already suggests that the growth in prices for women's art may be higher, not lower, we can examine this possibility more systematically by using the subsample of repeated sales of paintings identified in Korteweg et al. (2016)

and our identifiers for unique artists and painting title combinations.

The Korteweg et al. sample consists of 63,622 transactions of 30,655 unique paintings by 8,449 artists, 541 of whom are women. Following Bailey et al. (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-sale 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. Investing in women's art need not be a losing proposition.

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

Our artist fixed effect specifications help rule out the idea that our findings are driven by differences in "themes", intrinsic artistic ability or training. To conduct a more in-depth examination of our hypothesis that cultural attitudes towards women affect auction prices, we conduct two experiments using surveys.[11] Since in principle anyone can bid at an auction,[12] we use SurveyMonkey® Audience

[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

services to identify samples of participants that are representative of the US population in terms of gender, age, income and geographical distribution (according to SurveyMonkey).[13]

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 US 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 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 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

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bid.

[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.

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 1 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) 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 1 - 10 based on subjective artistic appreciation ("How much do you like this painting?"). While we do not have any prior about 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 9 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 9 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 10 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 10 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 painter. Using “perceived gender” allows us to measure the effect of gender perceptions on the artistic appreciation of a painting.

In Table 11 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 Female-prevalent Topic, 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 11 about here-

In column 1 of Table 11, 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 *Female-prevalent Topic* to the regression, we see that the coefficient on *Female Guess* becomes insignificant and decreases in magnitude. In contrast, the coefficient on *Female-prevalent Topic* 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

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

painter is associated with a 0.67 reduction in appreciation, which represents a roughly 13.5% "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 sections. The fact that affluent males who visit art galleries appreciate art 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 of culturally motivated gender attitudes 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 from Experiment #1 is that the participant can see a randomly drawn male or female artist's name beneath the painting before scoring it.

To avoid ethical issues related to misattribution of real paintings we generate the ten images using the algorithm 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 US 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 12 presents our regression results. Standard errors are clustered at the respondent level.

-Insert Table 12 about here-

Panel A of Table 12 indicates that female artists' names are on average 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 paintings. 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

[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.

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. We are the first to provide empirical evidence consistent with her argument. 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.

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 of 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 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 argue that economic outcomes for women are a product of culture and institutions, not biology. Using the market for art, we highlight the importance of continuing to eliminate institutional impediments to gender equality.

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Appendix A: Estimating the probability that an artwork was painted by a woman

We use a naïve Bayesian classifier with a "bag of words" approach to estimate the probability that an artwork was painted 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 painter 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 painter 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 painter 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 woman.

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 equivalents (it is not necessary for German 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 up	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)

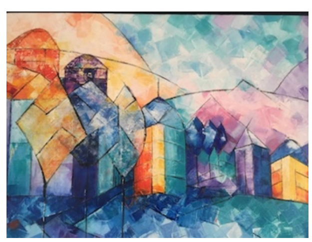
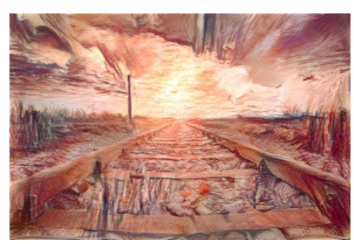
Painting 8
Joyce Wahl Treiman, *Ruins & Visions*
(1/12/2013 - Clark Cierlak Fine Arts)

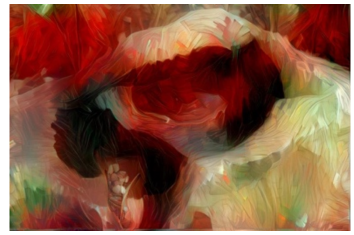
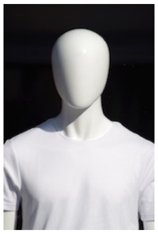
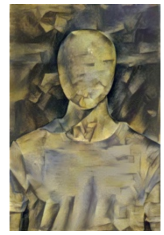
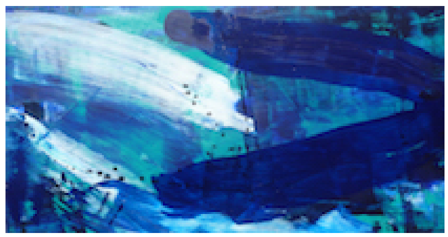
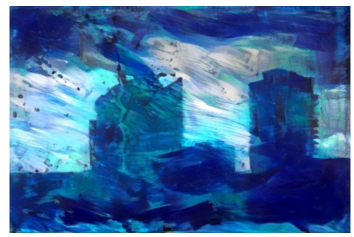
Painting 9
Betty M Bowes, *Quiet Harbor*
(1/13/2013 - Kaminski Auctions)

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) Auction price below US $100,000 (we want relatively unknown paintings); d) Availability of an electronic image with sufficient resolution.

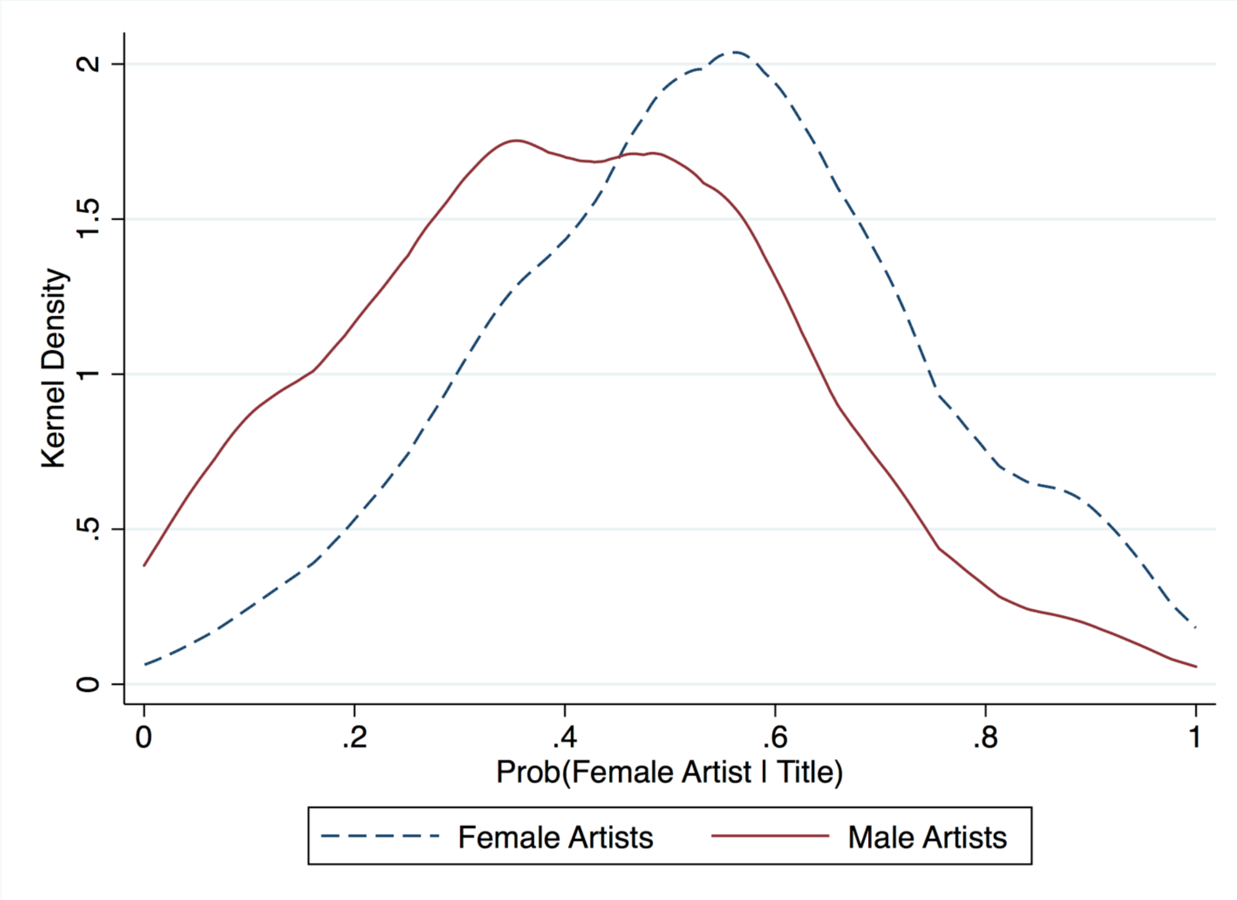
Table B3. Generated images for experiment #2 “What’s in a name?”

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 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 a painting being created by a woman given the words in the title



Notes: The graph shows the kernel density for the estimated conditional probability that a given painting has been produced 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 woman

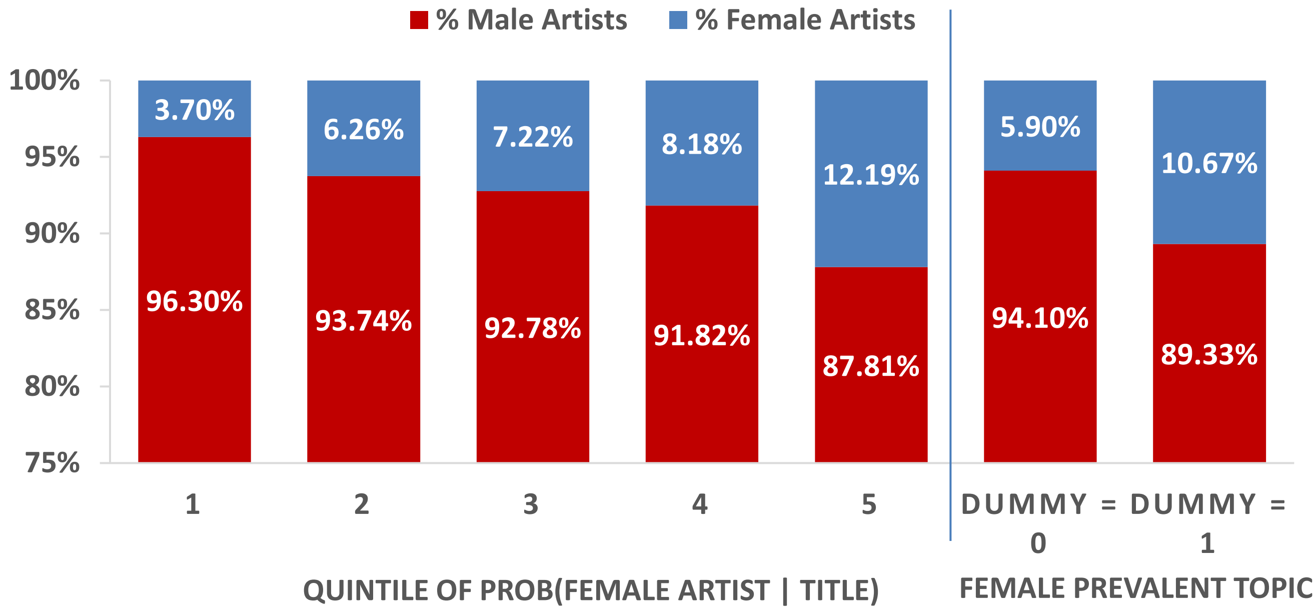
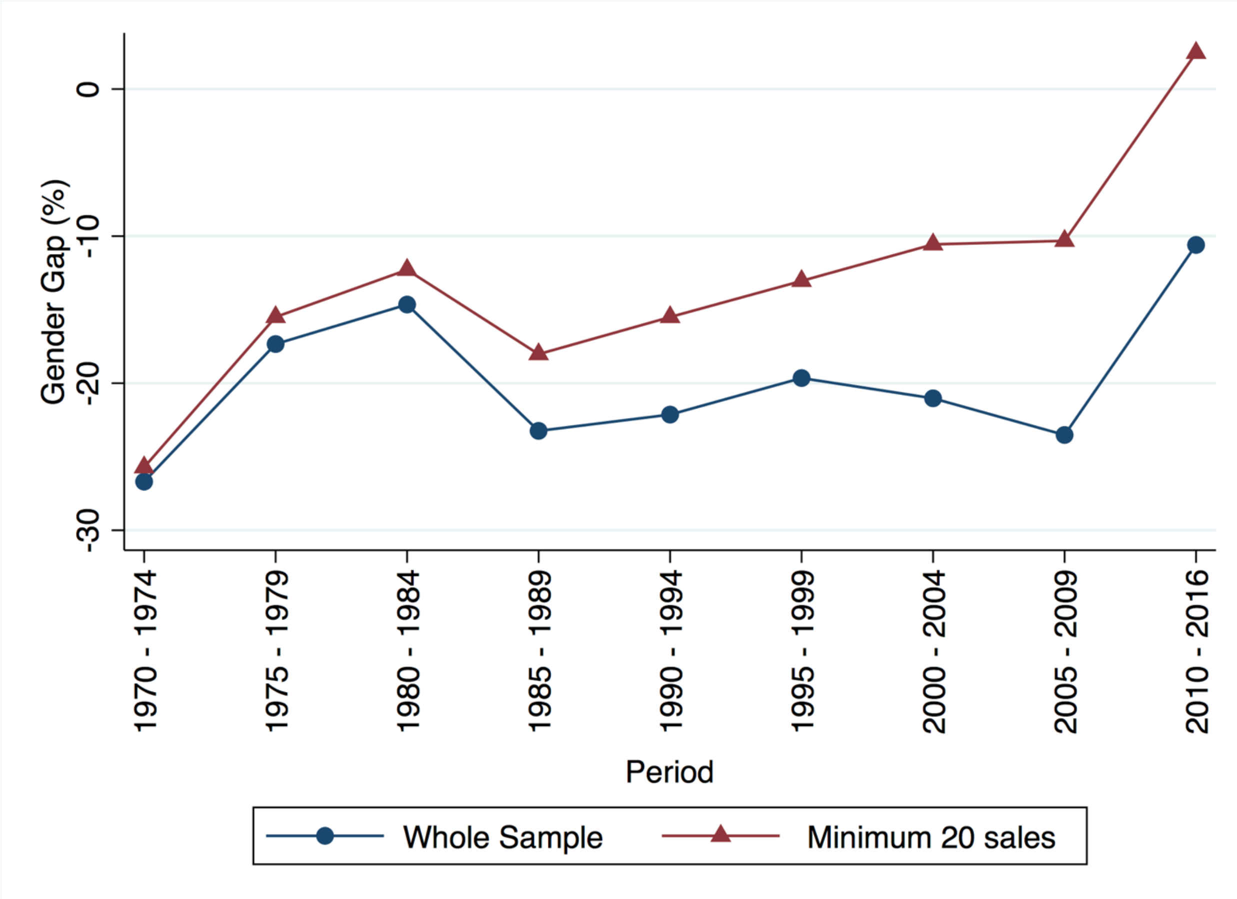
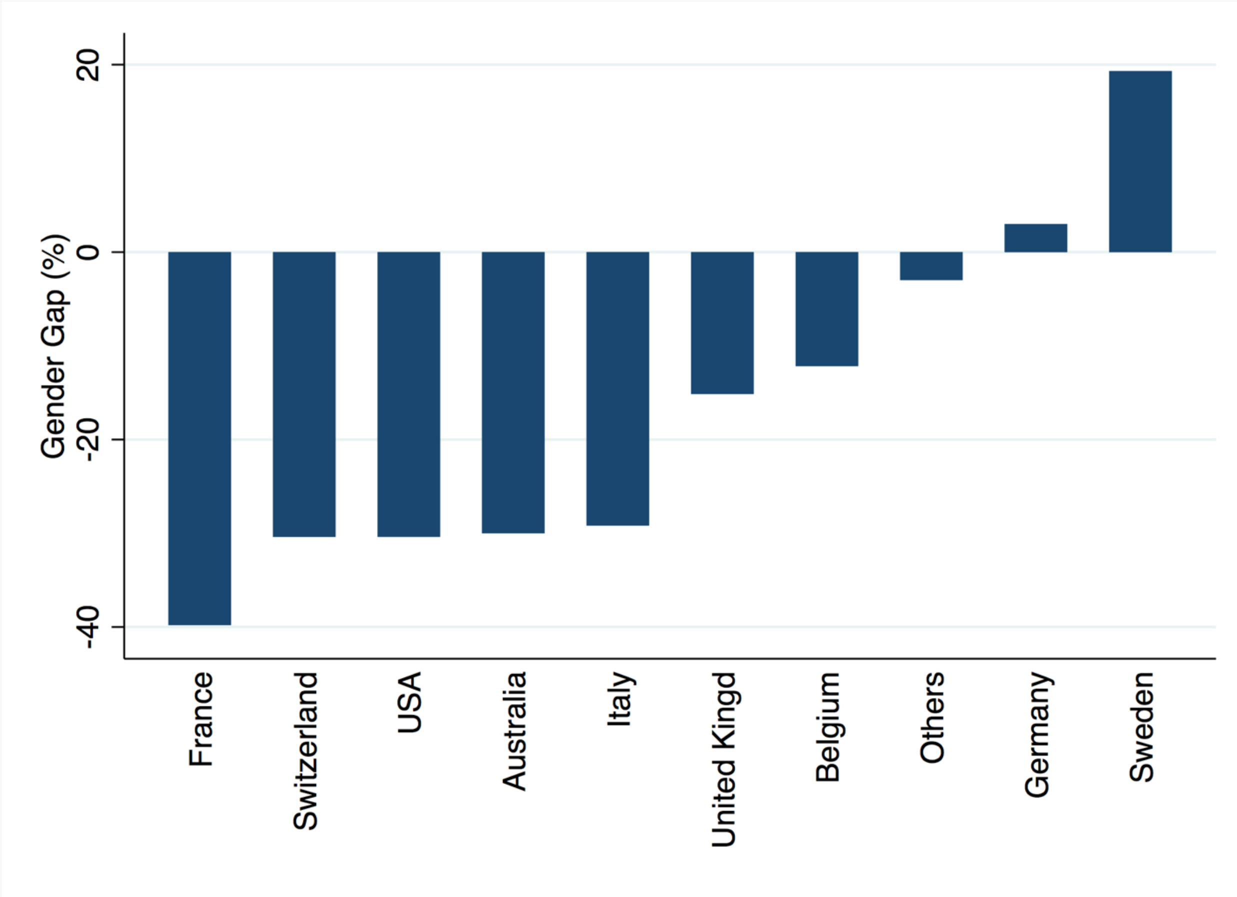


Figure 3. Marginal effect of time on gender price discount



Notes: The graph shows the predicted price gender discount (in %) for different time periods derived from the OLS estimation of the (natural log of) inflation-adjusted sales price on a gender dummy (female=1), its interaction with a time-period dummy variable, and a series of control variables detailed in Table 1. We also introduce style, year and country fixed effects. The model corresponds to adding interactions between period dummies and the gender indicator to the regression in column 4 of Table 5.

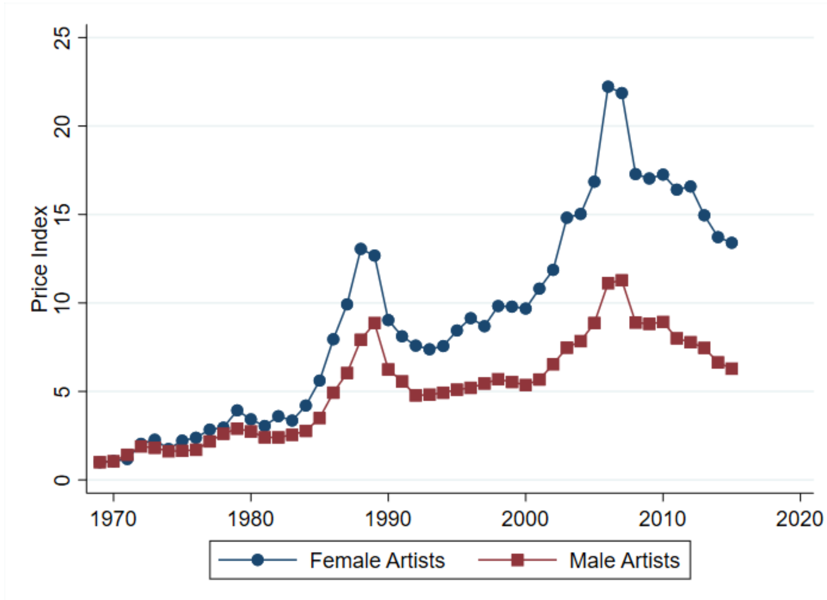
Figure 4. Marginal effect of country on gender price discount



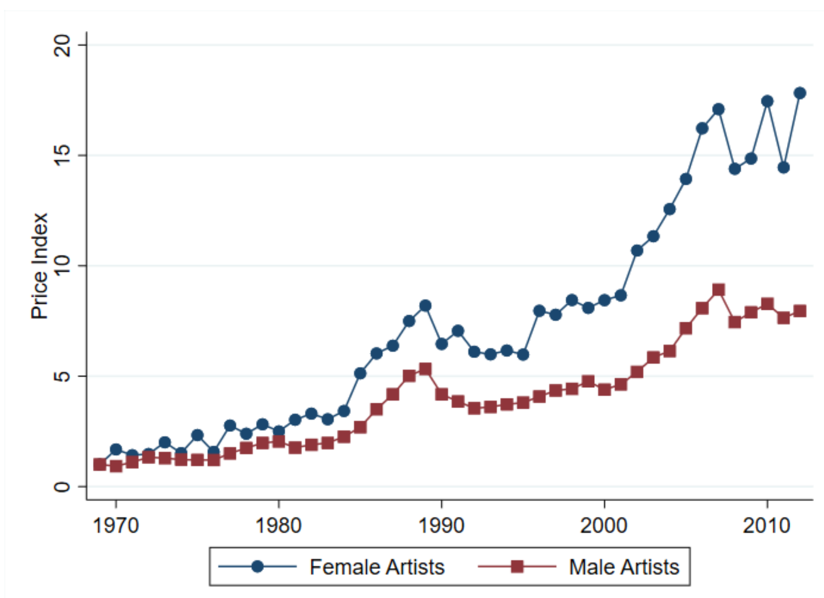
Notes: The graph shows the predicted price gender discount (in %) for different countries derived from the OLS regression of the (natural log of) inflation-adjusted sale price on a gender dummy, its interaction with the country-fixed effects, and a series of control variables detailed in Table 1. The regressions include style, year and country fixed effects. Countries with fewer than 60,000 transactions are lumped into "Others". The model corresponds to adding interactions between geographic dummies and the gender indicator to the regression in column 4 of Table 5.

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	
Female Painter	Dummy variable equal to one when the artist is female, and zero if male.
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.
Log(Age)	Natural logarithm of the age of the artist at the time of the auction in years. The variable is calculated regardless of whether the artist is dead or alive at the time of the auction.
Deceased	Dummy variable equal to one when the artist is deceased at the time of the auction.
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, Other.
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, Tempera.
Price	Sale price of the painting in 2016 US$. In regression frameworks we consider the natural logarithm of this quantity labelled as Log (Price).
Prob (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.
Female-prevalent Topic	A dummy variable equal to one if the estimated probability the painting was produced by a woman (given the words of the title) is greater than 50%.
Log (GDP)	Natural logarithm of per capita GDP in constant dollars from the World Bank (code NY.GDP.PCAP.KD).
Panel B. Proxies for gender culture	
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 2000, 2005, 2010 and 2013. We use linear interpolation between the available years and use the 2000 value for all the previous years. The index is scaled between 0 and 1 and 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 increasing 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. We use the first available value for each country for all the previous years. The index is decreasing in inequality.
% 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.
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.
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.

Panel C. Variables in experiments

Score	Artistic appreciation of a painting expressed on a scale from 0 to 10.
Affluent	Household income of US $100,000 or more.
Mature	Age of 45 years or more.
Art Expert	Self-reports visiting a museum or art gallery at least “few times a year”.
College Educated	Self-reported attainment of an associate degree or higher.
Male	Gender of the respondent.
Female Name	Painting associated with a female artist name (Experiment #1).
Female Guess	Respondent guess about the gender of the artist (Experiment #2).
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.
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.

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	-21,246***	-42.1%
	(719,946)	(293,789)	(743,627)	(1,992)	
Price (Excluding Mega Transactions)	22,467	18,382	22,796	-4,414***	-19.4%
	(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)	
Female-prevalent Topic	0.322	0.462	0.310	0.151***	
	(0.467)	(0.499)	(0.463)	(0.001)	

Panel B: Gender Culture Variables

	Mean	St. Dev.	Percentiles		
			10	50	90
UN Gender Inequality Index	0.791	0.127	0.576	0.820	0.913
WEF Gender Gap Index	0.696	0.050	0.636	0.691	0.758
% 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 Force Participation Ratio	0.725	0.121	0.558	0.753	0.853

Notes: Our sample consists of Blouin Art Sales Index (BASI) auction 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 a number of relevant characteristics of our dataset. 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). Panel B reports descriptive statistics for our gender culture proxy variables. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively.

Table 3. Gender discount in space and time

Panel A: Gender Price Gap by Sub Period

Sub Period	Full Sample: Number of Transactions	Full Sample: % of Trans. involving female artists	Full Sample: Gender Gap (2016 US$)	Full Sample: Gender Gap (%)	Excluding Mega Transactions: % of Mega Transactions	Excluding Mega Transactions: Gender Gap (2016 US$)	Excluding Mega Transactions: Gender Gap (%)
1970 - 1979	92,075	4.03%	-10213***	-39.1%	0.14%	-7895***	-33.1%
			(1,536)			(1,026)	
1980 - 1989	260,582	5.73%	-16202***	-39.0%	0.45%	-4470***	-17.3%
			(4,401)			(640)	
1990 - 1999	410,380	6.76%	-18468***	-50.3%	0.41%	-6500***	-31.6%
			(3,204)			(409)	
2000 - 2009	648,989	8.13%	-19861***	-43.0%	0.60%	-4782***	-21.9%
			(2,671)			(323)	
2010 - 2016	486,823	8.62%	-35125***	-45.1%	1.00%	-2027***	-8.4%
			(5,565)			(418)	

[Panel B follows on next page]

[Panel A on previous page]

Panel B: Gender Price Gap by Geographic Area

Area	Full Sample				Excluding Mega Transactions		
	Number of Transactions	% of Trans. involving female artists	Gender Gap (2016 US$)	Gender Gap (%)	% of Mega Transactions	Gender Gap (2016 US$)	Gender Gap (%)
Australia	69,643	13.32%	-8,796***	-43.1%	0.13%	-6,626***	-36.6%
			(909)			(576)	
Belgium	63,465	4.16%	-263	-4.7%	0.00%	-180	-3.3%
			(506)			(308)	
France	262,116	5.70%	-7,622***	-30.4%	0.23%	-4,642***	-25.6%
			(2,531)			(482)	
Germany	123,632	5.31%	2,072**	13.5%	0.08%	3,138***	22.7%
			(954)			(597)	
Italy	159,268	2.45%	-7,791***	-52.6%	0.07%	-6,828***	-49.3%
			(981)			(757)	
Others	392,995	8.88%	1,436	8.9%	0.09%	-326	-2.4%
			(1,253)			(247)	
Sweden	82,749	9.04%	1,567*	10.4%	0.07%	2,286***	16.7%
			(886)			(522)	
Switzerland	66,241	4.95%	-14,828***	-62.9%	0.26%	-8,699***	-49.9%
			(2,675)			(1,060)	
United Kingdom	375,242	8.95%	-72,087***	-56.3%	1.62%	-11,346***	-29.6%
			(8,167)			(595)	
United States	303,498	8.11%	-49,722***	-56.1%	1.37%	-12,220***	-32.7%
			(4,952)			(675)	

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 (Panel B). The gender discount is calculated as the difference between the average sale price (in 2016 US$) of paintings of female and male artists. We also provide the result of a *t*-test on this difference (standard errors in parentheses). We repeat the analysis both including and excluding transactions with price above one million (mega transactions) of 2016 US$. 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***		-0.287***	-0.197***	-0.095***	-0.184***	-0.094***
	(-5.250)		(-5.608)	(-4.415)	(-4.163)	(-4.271)	(-4.139)
Female-Prevalent Topic		0.118***	0.130***	0.077***	0.030***	0.077***	0.029***
		(6.761)	(7.524)	(5.779)	(4.881)	(5.960)	(4.724)
Log(Surface)				0.377***	0.249***	0.351***	0.245***
				(45.818)	(55.218)	(41.723)	(53.552)
Marked				-0.522***	-0.040***	-0.470***	-0.038***
				(-26.868)	(-5.777)	(-27.499)	(-5.559)
Log(Age)				1.022***	0.777***	0.959***	0.763***
				(13.036)	(19.073)	(13.316)	(19.204)
Deceased				0.249***	0.115***	0.232***	0.112***
				(5.091)	(5.183)	(5.664)	(5.337)
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	0.103	0.106	0.255	0.649	0.243	0.623
Only painters with at least 20 sales							
Female Painter	-0.135**		-0.156**	-0.100*	-0.032	-0.088*	-0.030
	(-2.129)		(-2.463)	(-1.824)	(-1.129)	(-1.652)	(-1.073)
Female-Prevalent Topic		0.142***	0.148***	0.089***	0.037***	0.089***	0.036***
		(7.347)	(7.717)	(6.061)	(5.310)	(6.221)	(5.137)
Only deceased painters							
Female Painter	-0.229***		-0.254***	-0.193***	-0.078***	-0.180***	-0.078***
	(-3.506)		(-3.904)	(-3.302)	(-2.576)	(-3.174)	(-2.597)
Female-Prevalent Topic		0.144***	0.156***	0.101***	0.047***	0.100***	0.045***
		(6.757)	(7.384)	(6.119)	(6.345)	(6.219)	(6.097)

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 individual artist and auction 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 (backfilled)	WEF Gender Gap Index (backfilled)	% of Women in Parliament	Tertiary Education Enrolment Ratio	Labor Force Participation Ratio
Period Covered	1970 - 2016	1970 - 2016	1990 - 2016	1970 - 2016	1990 - 2016
Female Painter	1.697**	0.099	1.750*	0.132	1.333
	(2.222)	(0.123)	(1.953)	(0.190)	(1.533)
Female-Prevalent Topic	1.082***	0.003	1.008***	0.288	0.674***
	(4.709)	(0.011)	(3.555)	(1.159)	(2.713)
Culture Proxy	-5.698***	1.912***	-0.024***	0.429***	1.971***
	(-17.435)	(5.681)	(-13.782)	(6.152)	(7.481)
Female x Culture Proxy	1.827***	2.063***	0.019***	0.181	0.514
	(3.200)	(2.857)	(4.688)	(1.432)	(0.973)
Fem-Prev Topic x Culture Proxy	0.990***	1.037***	0.007***	0.252***	-0.300**
	(5.975)	(5.162)	(6.101)	(6.774)	(-2.046)
Log (GDP)	0.681***	-0.002	0.103**	-0.092**	-0.125***
	(13.916)	(-0.044)	(2.420)	(-2.503)	(-3.093)
Female x Log (GDP)	-0.318***	-0.164**	-0.219**	-0.046	-0.179*
	(-3.522)	(-2.133)	(-2.563)	(-0.695)	(-1.766)
Fem-Prev Topic x Log (GDP)	-0.169***	-0.058***	-0.094***	-0.040*	-0.029
	(-6.085)	(-2.590)	(-3.495)	(-1.657)	(-1.115)
Log(Surface)	0.378***	0.382***	0.424***	0.379***	0.400***
	(43.627)	(41.617)	(43.296)	(40.819)	(42.548)
Marked	-0.561***	-0.607***	-0.713***	-0.478***	-0.678***
	(-25.774)	(-24.922)	(-25.056)	(-18.830)	(-25.543)
Log(Age)	1.003***	0.945***	0.999***	1.010***	0.922***
	(12.319)	(10.993)	(10.848)	(11.154)	(10.480)
Deceased	0.248***	0.225***	0.260***	0.244***	0.247***
	(4.827)	(4.097)	(3.999)	(4.772)	(4.064)
Year, Style, Medium FE	Y	Y	Y	Y	Y
N	1,889,202	1,889,300	1,305,075	1,333,917	1,545,949
adj. R-sq	0.223	0.195	0.199	0.204	0.191
Marginal effects of changes in country culture on gender discount					
Mean Culture Proxy - 1 SD	-29.27%	-25.48%	-31.26%	-18.59%	-20.09%
Mean Culture Proxy	-14.75%	-16.71%	-13.80%	-14.26%	-16.21%
Mean Culture Proxy + 1 SD	-0.24%	-7.95%	3.67%	-9.93%	-12.34%
Only painters with at least 20 sales					
Female x Culture Proxy	1.193	2.320***	0.019***	0.235	0.540
	(1.630)	(2.615)	(4.009)	(1.409)	(0.841)
Fem-Prev Topic x Culture Proxy	0.927***	1.191***	0.007***	0.252***	-0.201

	(4.990)	(5.398)	(5.715)	(6.095)	(-1.254)
Only deceased painters					
Female x Culture Proxy	1.856**	2.812***	0.021***	0.059	1.321*
	(2.512)	(2.796)	(3.823)	(0.351)	(1.803)
Fem-Prev Topic x Culture Proxy	0.679***	0.998***	0.006***	0.203***	0.016
	(3.502)	(4.158)	(4.493)	(4.717)	(0.099)

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 year of the transaction, style and medium of the painting, and a series of control variables detailed in Table 1. We report the marginal effect of a (±1 SD) change in the gender culture proxy on the price gender discount (in %), calculated as the difference between the predicted (log) prices for paintings of female and male artists. 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 individual artist and auction 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 (Backfilled)	WEF Gender Gap Index (Backfilled)	% of Women in Parliament	Tertiary Education Enrolment Ratio	Labor Participation Ratio	UN Gender Inequality Index (Backfilled)	WEF Gender Gap Index (Backfilled)	% of Women in Parliament	Tertiary Education Enrolment Ratio	Labor Participation Ratio
Period Covered	1970 - 2016	1970 - 2016	1990 - 2016	1970 - 2016	1990 - 2016	1970 - 2016	1970 - 2016	1990 - 2016	1970 - 2016	1990 - 2016
Female-Prevalent Topic	-0.099	-0.511***	0.097	-0.325***	0.061					
	(-1.078)	(-5.155)	(1.080)	(-3.178)	(0.730)					
Culture Proxy	-1.731***	-1.014***	-0.010***	0.185***	-0.521***	-2.139***	-1.578***	-0.012***	0.199***	-0.496***
	(-19.776)	(-6.915)	(-15.159)	(6.530)	(-5.046)	(-18.640)	(-8.177)	(-10.197)	(4.800)	(-2.693)
Female x Culture Proxy	0.536*	0.626*	0.008***	0.246***	0.827***	0.916**	0.389	0.010***	0.297***	0.573
	(1.872)	(1.825)	(4.197)	(2.805)	(2.922)	(2.296)	(0.911)	(3.477)	(3.269)	(1.534)
Fem-Prev Topic x Culture Proxy	0.435***	0.647***	0.004***	0.100***	0.107**	0.746***	1.227***	0.006***	0.096**	0.527**
	(8.657)	(8.284)	(9.710)	(5.630)	(2.160)	(4.431)	(5.404)	(4.456)	(1.996)	(2.391)
Log (GDP)	0.127***	-0.001	-0.034**	-0.066***	0.018	0.192***	0.065***	0.017	-0.015	0.074***
	(7.162)	(-0.065)	(-2.163)	(-3.185)	(1.033)	(8.519)	(3.162)	(0.692)	(-0.561)	(2.650)
Female x Log (GDP)	0.130**	0.164***	0.042	0.121**	0.036	0.127*	0.219***	0.033	0.105	0.050
	(2.116)	(3.062)	(1.139)	(2.327)	(0.774)	(1.757)	(3.186)	(0.687)	(1.585)	(0.837)
Fem-Prev Topic x Log (GDP)	-0.024**	0.005	-0.017**	0.021**	-0.013	-0.058*	-0.049*	-0.006	-0.078**	-0.088**
	(-2.332)	(0.633)	(-2.002)	(2.207)	(-1.537)	(-1.943)	(-1.947)	(-0.187)	(-2.346)	(-2.402)
Log(Surface)	0.499***	0.503***	0.521***	0.500***	0.518***					
	(133.005)	(130.246)	(133.721)	(129.151)	(134.893)					
Marked	-0.129***	-0.133***	-0.155***	-0.088***	-0.151***					
	(-17.038)	(-17.417)	(-21.162)	(-10.200)	(-20.320)					
Log(Age)	1.795***	1.758***	2.449***	1.704***	2.330***	2.319***	2.241***	3.035***	1.957***	2.901***
	(9.818)	(9.632)	(11.143)	(8.951)	(10.884)	(8.437)	(8.116)	(8.082)	(7.339)	(7.590)
Deceased	0.061***	0.063***	0.142***	0.055**	0.127***	0.043**	0.045**	0.122***	0.032	0.086***
	(3.019)	(3.138)	(6.875)	(2.406)	(5.921)	(2.193)	(2.250)	(4.892)	(1.548)	(3.653)
Year, Medium, Artist FE	Y	Y	Y	Y	Y	N	N	N	N	N
Year, Painting FE	N	N	N	N	N	Y	Y	Y	Y	Y
N	1,872,418	1,872,518	1,288,523	1,319,023	1,529,155	454,807	454,810	274,922	310,818	338,799
adj. R-sq	0.741	0.740	0.772	0.743	0.759	0.806	0.805	0.826	0.807	0.818

					Marginal fffects of changes in country culture on gender discount					
Mean Culture Proxy - 1 SD	-17.85%	-15.47%	-7.83%	-17.27%	-9.08%	-25.46%	-25.47%	-18.02%	-12.10%	-3.08%
Mean Culture Proxy	-13.59%	-12.81%	-0.50%	-11.41%	-2.85%	-18.00%	-23.79%	-8.48%	-4.98%	1.78%
Mean Culture Proxy + 1 SD	-9.33%	-10.15%	6.83%	-5.55%	3.38%	-10.54%	-22.12%	1.05%	2.14%	6.64%
					Only painters with at least 20 sales					
Female x Culture Proxy	0.822**	1.109***	0.011***	0.303***	1.315***	1.084**	0.530	0.011***	0.313***	0.845**
	(2.315)	(2.738)	(4.796)	(3.073)	(3.857)	(2.531)	(1.180)	(3.641)	(3.401)	(2.162)
Fem-Prev Topic x Culture Proxy	0.449***	0.666***	0.004***	0.110***	0.114**	0.745***	1.266***	0.006***	0.106**	0.554**
	(8.043)	(7.898)	(9.027)	(5.761)	(2.109)	(4.323)	(5.478)	(4.245)	(2.169)	(2.465)
					Only deceased painters					
Female x Culture Proxy	0.342	0.715*	0.008***	0.239**	0.939***	0.137	0.196	0.010***	0.394***	0.351
	(1.267)	(1.841)	(3.604)	(2.440)	(2.878)	(0.328)	(0.405)	(3.009)	(3.708)	(0.742)
Fem-Prev Topic x Culture Proxy	0.280***	0.558***	0.003***	0.100***	0.053	0.619***	1.013***	0.003**	0.094*	0.392
	(4.835)	(6.327)	(6.683)	(4.854)	(0.953)	(3.524)	(3.906)	(2.097)	(1.763)	(1.446)

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 year of the transaction and a series of control variables detailed in Table 1. We report the marginal effect of a (±1 SD) change in the gender culture proxy on the price gender discount (in %) calculated as the difference between the predicted (log) prices for paintings of female and male artists. 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 individual artist and auction level (columns 1-5) or at the individual painting and auction level (columns 6-10). The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics in parentheses.

Table 8. Gender culture and percentage of transactions involving female artists

Panel A: Year-Country observations with more than 100 transactions

	(1)	(2)	(3)	(4)	(5)
	UN Gender Inequality Index	WEF Gender Gap Index	% of Women in Parliament	Tertiary Education Enrolment Ratio	Labor Force Participation Ratio
Period Covered	1970 - 2016	1970 - 2016	1990 - 2016	1970 - 2016	1990 - 2016
Culture Proxy	-5.691	37.645***	0.022	0.887	16.026*
	(-0.712)	(2.874)	(0.274)	(0.561)	(1.910)
Log (GDP)	0.558	-1.075	0.109	-0.240	-1.282
	(0.521)	(-1.527)	(0.141)	(-0.418)	(-1.265)
Year FE	Y	Y	Y	Y	Y
N	924	924	531	696	684
adj. R-sq	0.144	0.259	0.027	0.145	0.123

Panel B: Year-Country observations with more than 1000 transactions

	(1)	(2)	(3)	(4)	(5)
	UN Gender Inequality Index	WEF Gender Gap Index	% of Women in Parliament	Tertiary Education Enrolment Ratio	Labor Force Participation Ratio
Period Covered	1970 - 2016	1970 - 2016	1990 - 2016	1970 - 2016	1990 - 2016
Culture Proxy	-20.450	32.128**	-0.047	5.567**	26.455***
	(-1.725)	(2.299)	(-0.516)	(2.495)	(3.436)
Log (GDP)	3.511	0.525	1.043	2.135	-1.421
	(1.277)	(0.277)	(0.379)	(0.923)	(-0.699)
Year FE	Y	Y	Y	Y	Y
N	455	455	286	327	358
adj. R-sq	0.286	0.309	0.084	0.218	0.292

Notes: The table reports results for the OLS estimation of the fraction of transactions involving female artists in each year/country on a country/year-level proxy for gender culture and the (natural logarithm of) inflation-adjusted per-capita GDP for the specific country/year. We control for year of the transaction. The analysis is repeated for the sub-samples of country/year observations with a minimum of 100 transactions (Panel A) and a with a minimum of 1,000 transactions (Panel B). All models include year fixed effect and standard errors are clustered at the country level. The asterisks ***, **, * indicate significance at the 1%, 5% and 10%, respectively. *t*-statistics are given in parentheses.

Table 9. 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 painters of the 10 listedartworks. The table reports the actual gender of the artist and the estimated probability the painting was painted 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 10. 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 painted one of the 10 artworks listed in Table 9. 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 11. Perceived gender and artistic appreciation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female Guess	0.185**		0.121	0.259***	0.275***	0.444***	-0.055	0.110	0.450***	0.422***
	(2.334)		(1.562)	(2.915)	(2.904)	(3.982)	(-0.491)	(0.892)	(2.701)	(2.636)
Female-Prevalent Topic		0.802***	0.792***	0.739***	0.771***	0.884***	0.968***	0.574***	0.828***	
		(10.952)	(10.759)	(8.391)	(7.884)	(8.592)	(8.763)	(4.642)	(4.623)	
Affluent	-0.178	-0.181	-0.179	-0.111	-0.177	-0.181	-0.183	-0.175	-0.143	-0.061
	(-1.526)	(-1.546)	(-1.529)	(-0.671)	(-1.515)	(-1.544)	(-1.562)	(-1.498)	(-0.870)	(-0.454)
Art Expert	0.401***	0.392***	0.394***	0.397***	0.505***	0.402***	0.392***	0.393***	0.573***	0.522***
	(3.771)	(3.679)	(3.700)	(3.727)	(3.290)	(3.770)	(3.682)	(3.697)	(3.750)	(4.237)
Male	0.065	0.061	0.060	0.059	0.063	0.441***	0.062	0.060	0.451***	0.341***
	(0.632)	(0.588)	(0.581)	(0.573)	(0.606)	(2.971)	(0.597)	(0.581)	(3.031)	(2.845)
Mature	-0.055	-0.052	-0.047	-0.045	-0.045	-0.046	0.022	-0.047	0.053	-0.168
	(-0.511)	(-0.483)	(-0.435)	(-0.419)	(-0.417)	(-0.427)	(0.145)	(-0.440)	(0.344)	(-1.362)
College Educated	-0.384***	-0.392***	-0.390***	-0.387***	-0.387***	-0.399***	-0.388***	-0.601***	-0.653***	-0.449***
	(-3.400)	(-3.468)	(-3.443)	(-3.424)	(-3.427)	(-3.528)	(-3.428)	(-3.722)	(-4.047)	(-3.533)
Female Guess x Affluent				-0.474***					-0.465***	-0.316*
				(-2.679)					(-2.598)	(-1.833)
Female-prevalent Topic x Affluent				0.169					0.214	
				(1.109)					(1.376)	
Female Guess x Art Expert					-0.371**				-0.354**	-0.299**
					(-2.313)				(-2.254)	(-1.967)
Female-prevalent Topic x Art Expert					0.043				-0.067	
					(0.305)				(-0.465)	
Female Guess x Male						-0.672***			-0.663***	-0.649***
						(-4.388)			(-4.377)	(-4.442)
Female-prevalent Topic x Male						-0.215			-0.228	
						(-1.528)			(-1.629)	
Female Guess x Mature							0.338**		0.385**	0.331**
							(2.183)		(2.503)	(2.236)
Female-prevalent Topic x Mature							-0.326**		-0.399***	
							(-2.296)		(-2.802)	
Female Guess x College Educated								0.018	0.107	0.185
								(0.117)	(0.690)	(1.237)
Female-prevalent Topic x College Educated								0.339**	0.367**	
								(2.274)	(2.433)	
Family Background	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Guessed Country	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Guessed Period	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
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	4354	4354	4354	4354	4354	4354	4354	4354	4354	4354
adj. R-sq	0.057	0.078	0.079	0.080	0.079	0.083	0.080	0.079	0.088	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 12. 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 A on previous 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 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	-0.201***	-0.186	-0.644***	-0.315*	0.102	-0.178***
	(-4.305)	(-1.351)	(-4.558)	(-1.717)	(0.562)	(-3.848)
Female-Prevalent Topic	0.068***	0.152***	0.011	-0.083	-0.034	0.081***
	(4.928)	(4.190)	(0.125)	(-1.587)	(-0.698)	(6.063)
Log(Surface)	0.386***	0.395***	0.426***	0.354***	0.490***	0.417***
	(44.417)	(14.195)	(8.574)	(9.146)	(14.148)	(45.272)
Marked	-0.526***	-0.483***	-0.768***	-0.836***	-0.324***	-0.588***
	(-26.084)	(-14.034)	(-8.705)	(-10.573)	(-5.471)	(-26.740)
Log(Age)	0.997***	1.225***	1.259***	0.798**	1.109***	1.134***
	(12.042)	(5.555)	(2.758)	(2.163)	(2.976)	(14.221)
Deceased	0.247***	0.305***	0.240	0.514	0.177	0.251***
	(4.702)	(2.603)	(1.117)	(1.558)	(0.920)	(3.730)
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	0.253	0.300	0.332	0.370	0.387	0.249

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 "Oxford Art Online - Grove Art Online" or "The Getty Research Institute - Union List of Artist Names Online" (Link: http://www.getty.edu/research/tools/vocabularies/ulan/?find=&role=&nation=&page=1). 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 1250 in Western Europe or North America and 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-Inflation Adjusted Log-Prices	Only Transactions less than 100,000 US$	Quantile Regression
Female Painter	-22,191.721***	-0.095***	-0.153***	-0.205***
	(-3.435)	(-4.149)	(-4.594)	(-45.226)
Female-Prevalent Topic	6,756.203*	0.030***	0.081***	0.089***
	(1.917)	(4.862)	(8.068)	(34.481)
Log(Surface)	38,738.100***	0.256***	0.285***	0.358***
	(7.006)	(55.741)	(39.703)	(281.563)
Marked	-69,894.996***	-0.041***	-0.338***	-0.432***
	(-6.579)	(-5.915)	(-24.795)	(-117.175)
Log(Age)	92,066.298***	0.778***	0.717***	0.855***
	(4.500)	(19.107)	(12.862)	(145.604)
Deceased	25,987.981*	0.115***	0.204***	0.235***
	(1.666)	(5.193)	(6.942)	(58.137)
Constant				0.435***
				(8.082)
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	0.203	

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 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 art 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 women, 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 art 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 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 artwork (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 art 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, 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, we first show that differences in results do not stem from differences in regression specifications across papers.

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 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.: 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 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. (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 women. 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).

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. sample restrictions, for different style subsamples. While we generally document a discount for female artists, we document a premium for female artists in a small sample of Latin American transactions. We also document a premium for paintings by female Old Masters, which is consistent with Bocart et al..

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. Bocart et al.'s sample 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.

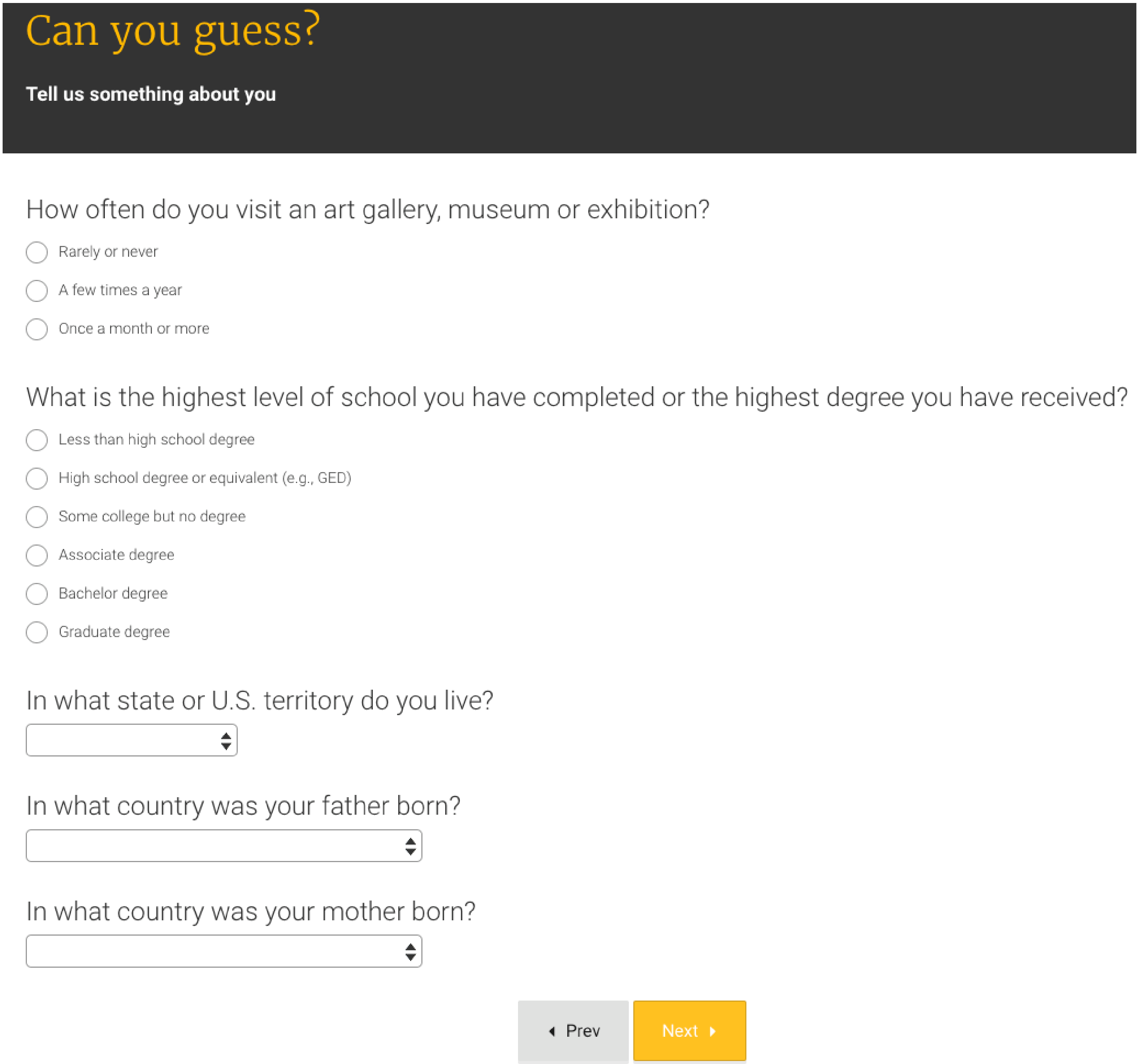
If you agree to be part of the research and to research data gathered from this survey to be published in a form that does not identify you, please continue with answering the survey questions.

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?

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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.

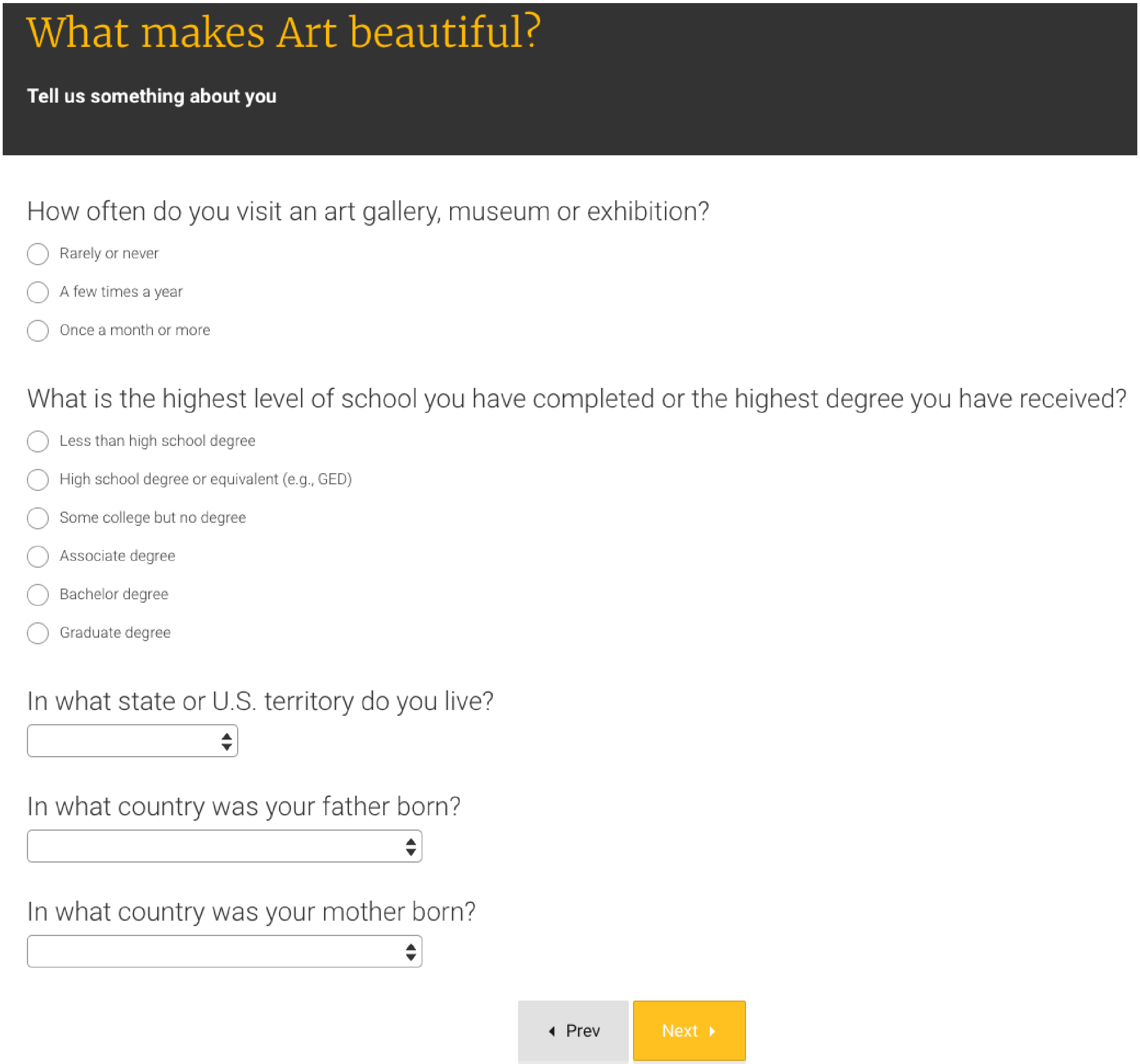
If you have concerns about the research that you think I can help you with, please feel free to contact me on +[redacted] or [redacted] You can also contact SurveyMonkey directly at http://help.surveymonkey.com/contact

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?

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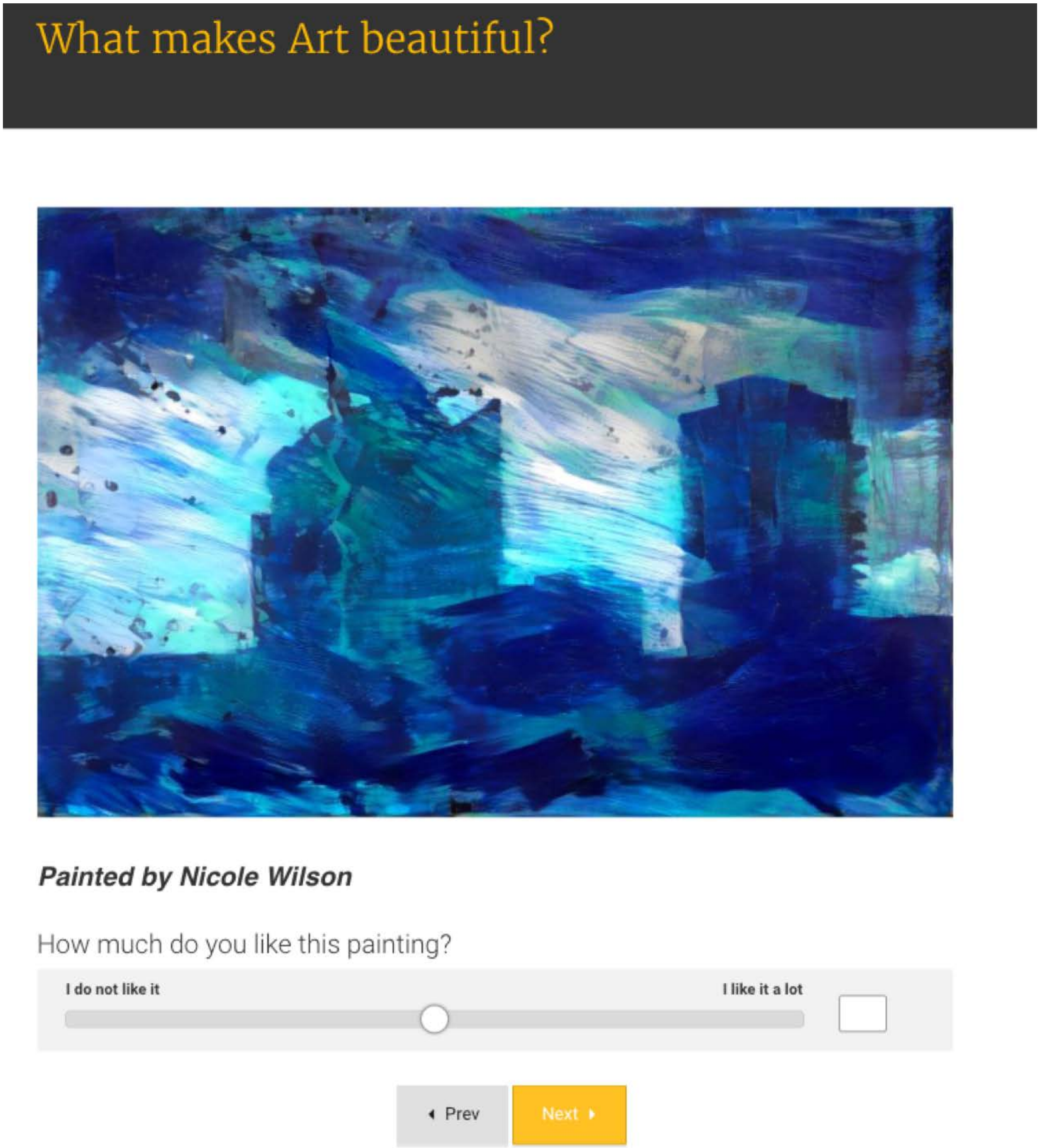
Steps 3 to 12 – The experiment

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 1-10 scale.



Step 13 – Conclusion

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

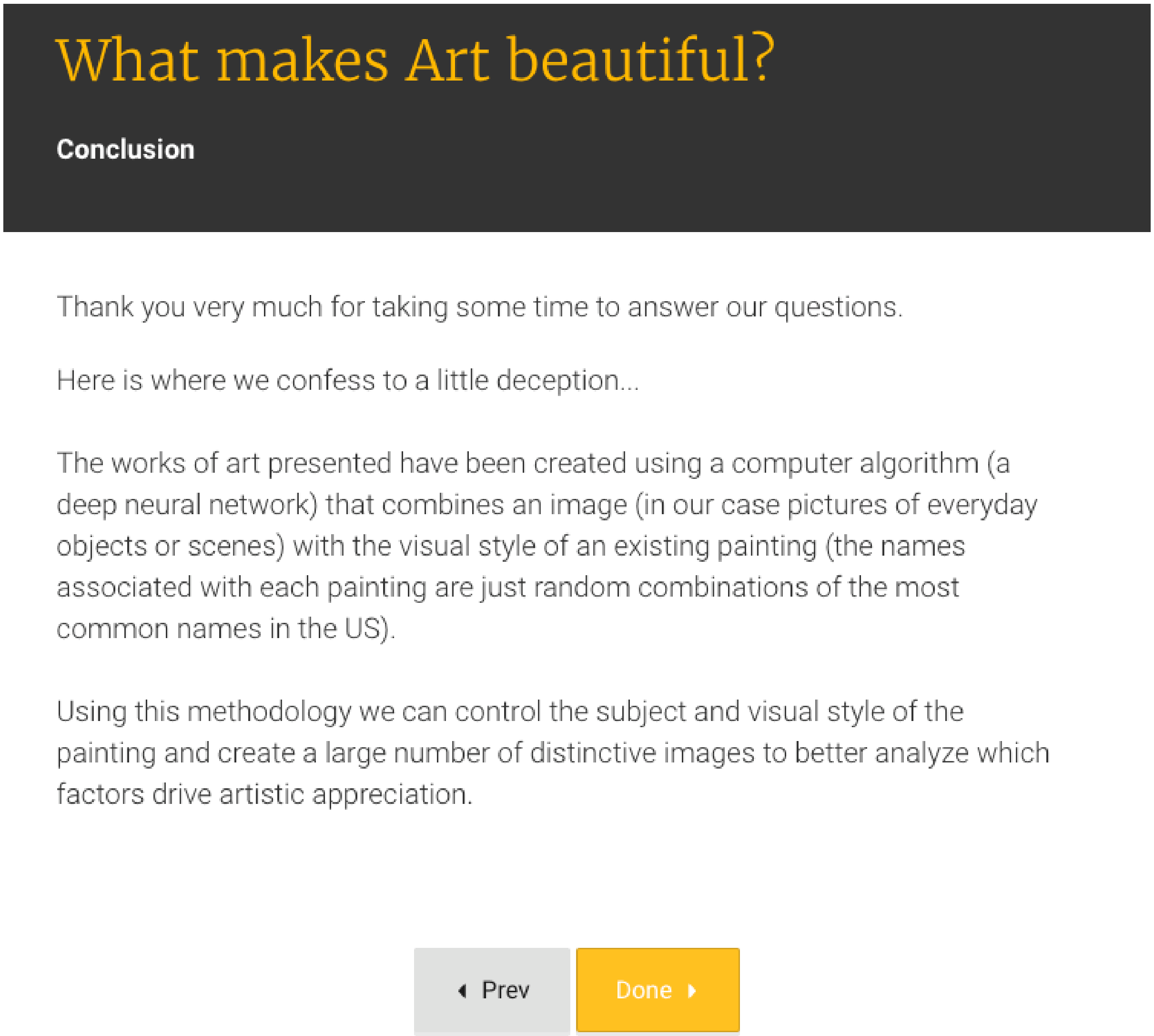


Table OA2.1 Summary statistics for experimental data

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.