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ABSTRACT

We study the impact of colors of paintings on prices in the art auction market and incorporate color attributes of non-figurative paintings in pricing models. A one standard deviation increase in the percentages of blue (red) hue leads to premiums of 10.63% (4.20%). We also conduct laboratory experiments in China, the Netherlands, and U.S., and elicit participants' willingness-to-pay and emotions (pleasure-arousal). Blue (red) paintings command 18.57% (17.28%) higher bids and stronger intention to purchase. Although abstract art is visually arousing, it is the emotional pleasure channel that relates colors and prices. Our results are consistent across all three cultures.

Keywords: Emotion, auction, art investment, cultural economics.

JEL Code: C91, D44, G02, G11, Z11

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"The final question is the most important, and the most elusive. Has the painting got 'wallpower', the visceral impact that makes people want to own it? This is a matter of factors such as composition, colour (blue and red tend to be good news) and emotional power."

–Philip Hook, What sells art? [1]

1. Introduction

Owning objects of art generates consumption value by means of an aesthetic dividend, as one usually enjoys having a painting or photograph on the wall or a sculpture in the garden. However, art is also often considered as an alternative asset class in its own right. High-net-worth individuals (HNWIs) hold on average 9% of their investment portfolios in art and other types of collectibles (such as Bordeaux wines, classic cars, superior watches, etc.). The total value of collectibles held by HNWIs is estimated at more than USD 4 trillion (Deloitte, 2013). Purchases of art through auction houses and internet-auctions have been growing rapidly over the past two decades (Deloitte, 2016) and global art sales are estimated to have exceeded USD 63 billion in 2018 (Art Basel, 2018). The relevant academic literature in finance has focused on the risk-return relationship of art (Mei and Moses (2002), Renneboog and Spaenjers (2013), Korteweg, Kräussl, and Verwijmeren (2015), Lovo and Spaenjers (2018)), its financial and macro-economic market drivers such as equity market evolution and income inequality (Goetzmann, Renneboog, and Spaenjers (2011), sentiment and hypes (Pénasse, Renneboog, and Spaenjers (2014)), and whether behavioral anomalies such as anchoring (Beggs and Graddy (2009), Graddy *et al.* (2015)) appear in the art market.

To study the determinants of art prices, a hedonic pricing model is often used to generate an index which depicts the risk and return of (schools of) art. The typical determinants of prices for paintings in particular include the reputation of the artist (e.g. his/her importance in art history as measured by a word count in an art encyclopedia or more simply by an indicator variable), physical characteristics of the painting (size, medium, signature, and date), subject matter (e.g. urbanscape, portrait), and transaction characteristics (auction house, sale location, lot number, and

[1] The Guardian, 18 Nov. 2013. Mr. Hook is a board member and senior director at Sotheby's in London with more than 45 years' experience, and particular expertise in Impressionist & Modern Art market.

auction seasonality). As pointed out in the above quotation by Mr. Hook of Sotheby's, composition and color may induce a visceral emotional impact on buyers. Throughout art history, a debate on color versus design/drawing (*colore* versus *disegno*) has regularly resurfaced.[2] Although the use of color has been recognized as a key component of the aesthetic value of a painting, there has been almost no research on colors and their emotional effects in an art pricing framework. This motivates the research questions addressed in this study: (1) Do a painting's color attributes affect its price? (2) If color attributes do affect the price, is it because color attributes trigger certain quantifiable emotional impacts which are reflected in the price? (3) Does the potential price impact of color differ across cultures?

Color systems, and in particular the effect of color on emotional states, have been discussed since Aristotle and this debate has led to various theories of color developed by artists, philosophers, physicists, and psychologists (Silvestrini (1994)). Color has also been shown to affect decision making. One strand of literature documents the effects of various interior colors in department stores on consumer purchase intentions and buying behavior (Bellizzi and Hite (1992), Brengman (2002)).[3] A few studies find that priming financial decision makers with red stimuli (background, logo, or text) increases risk avoidance (Kliger and Gilad (2012), Chan and Park (2015), Gnambs, Appel, and Oeberst (2015), and Bazley, Cronqvist, and Mormann (2017)). Colors on objects are also found to affect non-financial decisions such as voting (ballot colors, Garrett and Brooks (1987)), food intake (package colors, Genschow, Reutner, and Wänke (2012)), and customized configurations (product colors, Deng, Hui, and Hutchinson (2010)).

In this paper, we report the results of (1) an empirical estimation of pricing models in art markets, and (2) an experimental study in which we study the relationship between colors, emotions, and the valuation of art in the laboratory. Our research proceeds in two stages. First,

[2] E.g., the Venetian versus Florentine schools in Renaissance Italy, Rubenists versus Poussinists in the Baroque, and impressionists versus the French Academy des Beaux Arts (neo-classicism) in the 19th century. For details on color theories and color systems: see Online Appendix I.

[3] The literature on emotions and decision making has extended into investor psychology and asset pricing. Two examples are the following. (i) Specific weather conditions drive investor moods, which affect trading behavior and asset returns (Kamstra, Kramer, and Levi (2003), Hirshleifer and Shumway (2003), Loughran and Schultz (2004), De Silva, Pownall, and Wolk (2012), Goetzmann and Zhu (2005), Goetzmann *et al.* (2014)), and (ii) euphoria following sports victories seems to be related to asset prices and returns (Edmans, Garcia, and Norli (2011), Bollen, Mao, and Zeng (2011), Palomino, Renneboog, and Zhang (2011), Garcia (2013)).

we gather a large sample of high-quality images of 12906 oil paintings, watercolors, and color drawings produced by artists belonging to art schools of Color Field, Washington Color School, Abstract Expressionism, Abstract Imagist, Post-painterly Abstraction, and Bauhaus, that were sold through auction houses around the world during the 1994-2017 period. As we focus on color only and seek to eliminate potential contamination effects induced by a painting's figurative or symbolic meaning, we exclude paintings which contain figurative objects or abstract constructs (such as geometric patterns) or have non-rectangular shapes (e.g. diamond, round, oval, etc.). The retention decisions require consensus by at least three judges. We also exclude images corresponding to bought-in or withdrawn lots. This process resulted in 5482 images of non-figurative abstract paintings. We then study whether specific colors, color combinations, and the locations of colors on a painting's surface affect a painting's value, while controlling for many hedonic variables.

Second, in order to explain the relationships we find between color and prices, we develop a laboratory experiment to measure the emotions triggered by experiencing color in paintings (using the PA(D) approach, Panel A of Online Appendix II) and to examine which emotions relate to purchase intentions, rankings (Panel B of Online Appendix II), and auction bids (using the BDM approach, see infra). The experiment enables us to vary the three dimensions of color, namely hue, saturation, and luminosity, ceteris paribus. It also enables us to observe and relate color preferences, emotions, painting' rankings, purchase intentions, and willingness-to-pay for paintings at the individual subject level. As the emotional impact of color may be sensitive to culture, we perform our lab experiments with Chinese, European, and American participants, in Shanghai (China), Tilburg (the Netherlands), and Tucson (USA), respectively.

Our large sample hedonic pricing model reveals that a one standard deviation increase in the percentage of blue (red) hue in a painting leads to a significant premium of about 10.63% (4.20%), which is about USD 53,612 (21,183) more than the average price of an auctioned painting of the above schools of art. Second, the color combination of red-blue (followed by green-blue, and yellow-blue) trade at the highest premiums. Third, the dispersion of colors across the painting's surface does not in general affect the painting's valuation, with exception of color in the golden ratio areas. These areas on the painting are most salient, and here a small increase of 0.8

percentage point[4] of blue hue is related to premiums from 3.81% to 6.69%. Fourth, incorporating color attributes into a traditional hedonic pricing model increases the R^2 from 72.4% to 85.4%. The extra explanatory power is mainly contributed by variables capturing hue percentages rather than the degrees of saturation and luminosity.

Our laboratory experiments also yield consistent results. First, we find that single-color non-figurative abstract paintings (in the style of Mark Rothko) of blue and red hues carry significant value premiums of 18.57% and 17.28%, respectively, compared to the average willingness-to-pay. A non-monetary preference ranking and a purchase intention measurement yield the same preferences for blue and red over other colors. We thus observe a color-bidding hierarchy which puts blue and red on top, followed by green and purple, and with orange and yellow at the bottom. Saturation and luminosity variations do not affect the valuation ranking, which suggests that the hue dimension of color has a dominating impact. Second, the color hierarchy is largely the same for Chinese, European, and American participants. This pattern suggests that the preference for blue and red that we detect in the art auction data set is robust and may be universal. Third, we find that colors induce different emotions, as measured with the Pleasure-Arousal (PA) framework. The hues of blue and green are viewed as more pleasurable, and the hues red, green, and purple lead to more arousal, relative to the benchmark hue (yellow). Fourth, the pleasure emotion induced by viewing a painting serves as the main channel that relates colors to the monetary valuation. In contrast, the arousal emotion does not affect the valuation of paintings, with the exception of a trivial impact on purchase intention. Fifth, for two-color combination paintings (dual color Mark Rothkos), the bid price is strongly correlated with the average bid price of the constituent colors in single-color paintings. Again, blue and red, this time combined, receive the highest bids among all two-color combinations. The emotion of pleasure is highly correlated with the prices for dual-color abstract art. Sixth, all of the above results remain valid and are consistent when controlling for the weather conditions at the time of the experiment, the participants' gender, educational background, wealth, weather-induced mood, art exposure and education, cognitive

[4] Each of the golden ratio areas covers 4% of the painting surface and one standard deviation of the percentage blue is about 20% of the surface within a gold ratio area. Therefore, a one standard deviation increase of blue for a gold ratio area is 0.8% (=20%*4%) of the surface of the entire painting.

ability and color vision, and when we replace the participants' characteristics by subject fixed effects.

We contribute to the literature in three ways. First, we add an important set of hedonic variables to art auction pricing models. Second, we contribute to the growing literature of the roles of emotions in decision making, by clarifying the connection between colors and emotional states, as well as between emotional states and willingness-to-pay. Third, we add to the literature on cultural economics in that we reveal the important role of color in art prices and in the desirability of art works. We also show that the bidding preference for colors does not depend on the cultural background of the buyer, at least for the type of abstract art that we consider.

The paper proceeds as following. Section 2 describes the hedonic pricing methodology, the experimental design, and the data. Sections 3 and 4 present the empirical results from the auction data analysis and the laboratory experiments, respectively. Section 5 concludes.

2. Methodology, Experimental Design, and Data

2.1 Large Sample Analysis

2.1.1 Color and Valuation

From the Blouin database, we collected a large sample of high-quality images and transaction records of paintings auctioned during the 1994-2017 period in auction houses around the world.[5] We included oil paintings, watercolors, and colored drawings in our sample, and filtered out prints and collages. As we are primarily interested in the role of color on auction prices, we focus on six art schools in which color and color combinations are the essential, if not the dominant, elements. These schools are Color Field, Washington Color School, Abstract Expressionism, Abstract Imagist, Post-painterly Abstraction, and Bauhaus. We identified more than one hundred artists from exogenous art history sources (e.g. Oxford Grove Art Online) and collected all available auction records related to these artists as well as the corresponding images of their auctioned work. We obtained 12906 records with painting images.

We have addressed several potential sources of distraction from the pure color effects. First,

[5] Our earliest observations are in the year 1994, as digitalized images of paintings auctioned prior to 1994 are not available in the database.

as painters are usually active in multiple artistic styles (or have early work before they establish their "own style"), they may have made figurative work, which we exclude. Second, we also exclude paintings with patterns, such as geometric structures or symbols as they may induce meaning (beyond color). Third, less traditional shapes of paintings (e.g. oval, round, or diamond-shape) may also distract the viewer, which is why we only retain the most common, rectangular shape. In order to eliminate paintings that may be subject to the above contagion problems, we and several research assistants individually eyeballed all the 12906 images and removed any paintings where one of the above mentioned issues could be a concern. A painting is only included in our sample when all (at least three) viewers reached consensus, and the quality of the image is high enough for a color analysis at the pixel level. Furthermore, we only retain the auctioned paintings and exclude the ones bought-in or withdrawn. Our final sample comprises 5482 paintings by 66 artists.

In order to study the price impact of colors on prices, we estimate hedonic pricing models. We take the natural logarithm of real USD hammer prices[6] as the dependent variable and use various color measures as explanatory variables, while controlling for a wide range of hedonic characteristics. Our specification is:

$$\ln(Price_{kt}) = \alpha + \sum_{m=1}^{M} \beta_m \, Artist_{mkt} + \sum_{n=1}^{N} \beta_n \, Transaction_{nkt} + \sum_{p=1}^{P} \beta_p \, Physical_{pkt} + \sum_{q=1}^{Q} \beta_q \, Provenance_{qkt} + \sum_{z=1}^{Z} \beta_z \, Color_{zkt} + \varepsilon_{kt} \quad (1)$$

where $Price_{kt}$ represents the hammer price of art object k at time t, $Artist_{mkt}$ is an artist-specific attribute m of item k at time t, $Transaction_{nkt}$ is transaction-level attribute n, $Physical_{pkt}$ is physical attribute p, $Provenance_{qkt}$ is a provenance-related attribute q, and $Color_{zkt}$ is color attribute z. The coefficients β reflects the relative shadow prices of the corresponding characteristics. Thus, this model accounts for a set of attributes related to artist, transaction, physical art object, provenance information, and color.

[6] The Blouin database gives either the hammer prices or the premium price, which is the hammer price plus a commission averaging 15%, paid by the buyer. Given that the actual percentage of the commission is not available, we divide the premium price by 1.15 as an approximation of the hammer price.

First, the set of $Artist_{mkt}$ variables comprises:

1. *Artist dummies.* We include artist fixed effects to account for artists' reputation and other personal traits.

2. *Deceased artist dummy.* This dummy equals one for sales after the artist's death, as it is often assumed that prices for art works increase after the artist's death.

3. *Attribution dummy*. As attribution uncertainty can be an important factor discounting the price of art objects (especially of older works), we generate a dummy variable that captures doubts about the identity of the creator of the painting.[7]

Second, we include the dummy variables $Transaction_{nkt}$ that stand for transaction level attributes such as the timing of the sale, and the reputation and location of the auction house:

1. *Month dummies*. Important sales are often clustered in time, and the busiest months are May/June and November/December. January is omitted and serves as benchmark.

2. *Year dummies*. We include year fixed effects and the exponential of the coefficient of each year's fixed effect yields an index number for the corresponding year. Therefore, we can calculate index returns based on the index series.

3. *Auction house dummies*. We introduce auction house fixed effects for every auction house at the branch level. We distinguish among the different fine art auction houses based on reputation. For Sotheby's and Christie's, we introduce dummy variables for their London, New York, and other sales rooms (e.g., Soth_London, Soth_NYC, and Soth_Other). Together, these two institutions account for more than 60% of all sales in our sample. For two other big British auction houses, Bonhams and Phillips, we make a similar distinction among their London, New York, and other sales rooms (See Panel A of Appendix I). We also report the effect of selected smaller auction houses in our analysis.

Third, we include a vector of price-determining variables ($Physical_{pkt}$) capturing the physical characteristics of the painting. We use variables that capture the medium, size, and authenticity of the work of art:

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[7] Different levels of attribution are used in the art auction world: attributed to, studio of, circle of, school of, after, and in the style or manner of.

1. *Medium dummies*. We introduce dummies for Oil paintings, Watercolors (including gouaches), and Drawings.

2. *Size*. The height and width in centimeters are represented by Height and Width and their quadratic forms.

3. *Authenticity dummy*. The dummy equals one if the auctioned lot contains any of the physically identifiable markings - signature, date, or inscription - that confirm the authenticity of the art piece.

Fourth, we include a set of variables $Provenance_{qkt}$ containing provenance information offered in the auction catalogue.

1. *Provenance dummy*. This dummy equals one if there is textual information in the catalogue about the provenance (past ownership, previous sales information, etc.) of the auctioned lot.

2. *Literature dummy*. This dummy equals one if there is textual information in the catalogue about the literature coverage of the auctioned lot. Art-related literature include scholarly articles, art critics, art catalogues, *catalogue raisonné*, etc.

3. *Exhibition dummy*. This dummy equals one if there is textual information in the catalogue about the exhibition history of the auctioned lot.

Fifth, we introduce a set of color-related variables, $Color_{zkt}$, analyzed from high quality images of paintings at the pixel level, and we decompose colors according to the Hue-Saturation-Value method (HSV). [8] We classify these variables into color attributes and color controls.

1. *Color attributes*. These hue percentages are the key variables of interest: we assign the chromatic part of each pixel to one of six major hues according to the segments on the color wheel. We thereby obtain the percentages of Pct_Red, Pct_Orange, Pct_Yellow, Pct_Green, Pct_Blue, and Pct_Purple of the whole painting.

2. *Color controls*. We count the number of hues whose percentages exceed a 3% surface coverage threshold. We also calculate the average and the standard deviation of saturation and luminosity in the colored part of the painting. Furthermore, we calculate the achromatic black

[8] Saturation is often referred as chroma or intensity, and value is often referred as lightness, brightness, or luminosity in daily use and other color models. For consistency, we only use saturation and luminosity in this paper except for specific color models (e.g. HSV color model – See Online Appendix I).

percentage of the whole painting, as well as the percentage that is white (which is omitted as the benchmark).

2.1.2 Color and Returns

We construct two color return series based on (i) index returns and (ii) repeat sales returns. For the index return method, we first run the traditional hedonic regression, which is essentially equation (1) without the color attributes. This is our benchmark regression and we calculate the exponential of the coefficient of year fixed effects to obtain the index series, which enables us to calculate art returns. Then we add, one by one, the six Hue Percentages into the benchmark equation and calculate the exponential of the coefficient of year fixed effects as the new art index series. For instance, for the hue red, we estimate the model:

$$\ln(Price_{kt}) = \alpha + \sum_{m=1}^{M} \beta_m \, Artist_{mkt} + \sum_{n=1}^{N} \beta_n \, Transaction_{nkt} + \sum_{p=1}^{P} \beta_p \, Physical_{pkt} + \sum_{q=1}^{Q} \beta_q \, Provenance_{qkt} + \beta_{red} \, Pct_{red,kt} + \varepsilon_{kt} \quad (2)$$

The difference between the index series derived from the year fixed effects of equation (2) and the index series derived from the traditional hedonics model without any color variables, is the index series of the Hue Red.[9] In this example, the Hue Red index series enables us to calculate the Hue Red returns.

To obtain the repeat sales returns, we first identify pairs of repeat sales within our sample. We select repeat sales candidates for each artist based on the exact title and on similar height and width (a 10% discrepancy is allowed as measurement could have been done with and without including the frame). We then view the digitalized pictures of all candidate pairs to rule out false pairs. We calculate the returns based on hammer prices in USD from two adjacent auctions of the same painting. The repeat sales period is the number of calendar days between two auctions. We calculate the normalized returns as the geometric return in this period as

[9] We set the first year in our sample as the starting point (100) and the corresponding hue index series is then 100 plus the difference between the two art index series.

$$\text{Normalized Return}_{k,t} = \sqrt[\frac{365}{repeat\ sales\ period}]{\frac{Hammer\ Price_t}{Hammer\ Price_{t-1}}} - 1 \tag{3}$$

Similarly to equation (1), we regress the normalized return on a comprehensive set of hedonics including color attributes:

$$\begin{aligned}\text{Normalized Return}_{k,t} = \alpha + \sum_{m=1}^{M} \beta_m\, Artist_{mkt} + \sum_{n=1}^{N} \beta_n\, Transaction_{nkt} + \\ + \sum_{p=1}^{P} \beta_p\, Physical_{pkt} + \sum_{q=1}^{Q} \beta_q\, Provenance_{qkt} + \\ + \sum_{z=1}^{Z} \beta_z\, Color_{zkt} + Repeat\ Sales\ Period_{kt} + \varepsilon_{kt}\end{aligned} \tag{4}$$

2.2 Experimental Design

2.2.1 General Procedures

The experiments took place at three universities in three different countries: China, the Netherlands, and the United States. We conducted 14 experimental sessions at the Finance Lab at Shanghai University of Finance and Economics (China) with a total of 166 Chinese participants. Sixteen sessions were performed at the CentERlab at Tilburg University (the Netherlands) with 185 subjects. In this group, roughly half of the participants were Dutch and the other half were from other European countries (non-European participants were excluded). Another 15 sessions were conducted at the Economic Science Laboratory at the University of Arizona (Tucson, U.S.A.) with 132 US students taking part (Online Appendix III). All participants were university students who were enrolled in the local recruiting system for laboratory experiments and were aged between 18 and 28. Each person was allowed to participate in only one session. All sessions were conducted by the same experimenter in all three locations.

Each location was equipped with large computer screen monitors, which were calibrated so that they displayed equal brightness, saturation, and contrast across locations. The monitor vertical angle and position on the desk were also adjusted to be the same. Light conditions, lab layout, and lab decorations were also standardized across locations such that there was no eye-catching color inside the labs or in the corridors leading to the labs. The experimenter wore glasses with dark frames, a grey shirt, dark blue jeans, and white shoes in all sessions. The sessions were conducted in Chinese in Shanghai, and the Tilburg and Tucson sessions were in English. The interface was developed and shown in Z-tree 3.4.7 (Fischbacher (2007)), and the default background color of the screen was neutral grey.

In the experiment, we elicited participants' preferences for the different paintings by means of various measures (see below). Participants were clearly informed that they would see pictures of high quality prints on the experiment interface and that they would bid on the physical prints.[10] At the beginning of the session, the participants took part in three training rounds to familiarize themselves with the BDM auction method (Becker, DeGroot, and Marschak (1964)),[11] which we used to elicit their valuations for the paintings. The participants were aware that the practice rounds would not count towards their payment. Each session consisted of three training rounds, as well as two rounds (consisting of the evaluation of 6 paintings in each round) that could count toward the participants' earnings. The numbers of rounds and of pictures to be shown were not revealed to the participants beforehand. Each round consisted of viewing and evaluating a set of paintings. An evaluation consisted of (1) reporting one's emotions after viewing each painting, (2) indicating one's purchase intention for a large print of the painting shown on the screen, (3) ranking the set of paintings from the same round from most to least preferred, and (4) bidding between 0 and 100 ECU on each painting shown. Bidding zero was allowed and indicated that the participant had no interest in buying the corresponding painting.

Each participant's endowment was set at 100 ECU and he/she could bid from 0 to 100 ECU on every painting. At the end of the experiment, one bid out of all 12 bids was randomly selected to count for each individual participant. The random selection was revealed to the participant and compared to a randomly generated selling price.[12] This procedure was exactly the same as the one

[10] Bushong, King, Camerer, and Rangel (2010) use the BDM method to elicit willingness-to-pay in three different display settings (namely text display, image display, and physical goods display) and find that the average willingness-to-pays differs significantly in different display settings. In our experiment instruction and training rounds, we ensure that the participants are aware that they will bid on a high-quality physical print, which they will receive at the end of their session in the event that their bid is accepted.

[11] Miller *et al.* (2011) compare four common measurements to elicit consumers' willingness to pay (open-ended questions; choice-based conjoint analysis; BDM incentive-compatible mechanism; and incentive-aligned choice-based conjoint analysis) with real purchase data; BDM method yields the closest willingness-to-pay to the real purchase data.

[12] Under the BDM procedure, bidding one's true willingness to pay is optimal, by the same logic as bidding one's value is a dominant strategy in a second price sealed bid auction. Bidding lower than one's valuation reduces the

used to determine the hypothetical earnings in the three training rounds. The participant had a winning bid if her bid was no less than the randomly generated selling price. If the individual won an item, she paid the selling price (deducted from the 100 ECU endowment) and received a high quality physical print of A3 size of the corresponding auctioned painting, immediately after the experiment. The remainder of the initial monetary endowment was converted to and paid out in local currency at the exchange rate indicated above. If the bid was lower than the randomly generated selling price, the participant did not receive the print of the corresponding painting auctioned and received instead the entire initial endowment of 100 ECU, converted to and paid out in local currency at the above exchange rate. Participants did not know which one of the bids would count and how much would be her (individually) randomly generated selling price until the end of the session.

2.2.2. Timing of activity in each session

A session proceeded in the following manner. The experimenter read the instructions aloud to all participants (Online Appendix IV). The participants were then informed that they were endowed with 100 Experimental Currency Units (ECU). The exchange rates from ECU to local currencies were set to equal about two lunch meals in campus student restaurant: ECU 100 ECU equaled CNY 25, EUR 10, and USD 16, respectively. We used different methods across the locations to pay the participants after the experiment: Wechat Pay in China, bank transfer in the Netherlands, and cash in U.S.A.

After reading the instructions to the participants, the experimenter started the program for each individual. In the training rounds, only pictures of emotionally neutral items[13] were shown on the screen. Each picture of a painting was shown for 10 seconds and the participants were then asked to report the emotional states induced by this painting. They did so on scales constructed

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probability of winning the item at a profit and confers no benefit, over bidding one's valuation. Bidding in excess of one's valuation induces a positive probability of paying more than one's valuation for the item, and also brings no benefit relative to truthful bidding. Techniques on implementation of the BDM mechanism have been studied extensively in experimental economics (Noussair et al., 2004; Cason and Plott, 2014). To generate our selling prices, we used a triangular distribution with lower limit 0, mode 20, and upper limit 100.

[13] We carefully selected emotionally neutral items based on a pilot experiment to avoid the priming of emotions at the beginning of experiment.

on a four-item short version of a PA(D) scale.[14] The pairs of antonyms used to capture emotions are measured on a seven-point scale and they are Happy-Unhappy (Pleasure 1, P1), Pleased-Annoyed (Pleasure 2, P2), Stimulated-Relaxed (Arousal 1, A1), and Excited-Calm (Arousal 2, A2) (see Panel A of Online Appendix II for more detail). The sequence of these four items was randomized by painting. A gradation of seven points was placed between each pair of antonyms; a score of 7 (1) indicates that the participant feels very happy (unhappy), pleased (annoyed), stimulated (relaxed), or excited (calm), respectively.

Subsequently, the participants rated their purchase intention by responding to four questions by means of a scale from 1 to 7 (strongly disagree to strongly agree): "I would love to buy this painting." (PI1), "I may spend more than intended on buying this painting." (PI2), "I would like to buy this painting immediately." (PI3), and "I regard the purchase of this painting as a waste of money." (PI4) (Panel B of Online Appendix II). The score on question PI4 was reversed and subsequently the average of the four scores was calculated and taken as the measure of purchase intention.

Six paintings were viewed and evaluated in each round. The paintings differed from each other only in their color scheme. Participants were then asked to rank all six paintings, which appeared simultaneously on the screen. No.1 stands for the most favored painting and No.6 indicates the least favored. We allowed for tied ranking of multiple paintings. For example, one could rank both the red and blue painting to be No.1 (the most favored). In the regression analysis, the Rank variable will be reversed so that a higher rating represents a higher place in the hierarchy.

The BDM bidding process described above was then implemented. In the training rounds, participants were asked to bid on emotionally neutral items. In the rounds that could count toward participants' earnings, the first 6 paintings auctioned were single-color paintings by Mark Rothko. We created six hue variations of this painting, and did not include the original black Rothko painting in the experiment. The next six paintings were transformations of a dual-color Mark Rothko work. We created 6 dual-color combinations of that painting and did not use the original

[14] The dominance dimension was not used for two reasons. First, when compared to pleasure and arousal, the dominance dimension has only very limited power in explaining the variance of emotional reactions to environmental situations (Mehrabian and Russell (1974)). Second, the hue-dominance relation is weak and statistically insignificant (Valdez and Mehrabian (1994)).

in the experiment. The six paintings within each round were displayed in a sequence randomized at the level of the participant.

At the end of the session, the participants filled out an exit questionnaire (Online Appendix V) on personal information (gender, year of birth, nationality, education level, current study program), art background (preference for specific visual arts, favorite art genre, frequency of attending art-related activities, art-related education, number of paintings at the home the participant grew up, and whether a participant recognized any artists from a list of twenty artists),[15] color-related specific information (awareness of color blindness, and preference ratings of hues), financial situation (part-time job alongside studies, income per month, expenditure per month, and student loan amount), and some other control variables (related to whether or not they liked the weather that day, a cognitive reflection test (CRT, Frederick (2005)), and a color vision deficiency test. We excluded color-deficient participants from our experiment's analysis.

The preference rating of hues was conducted as follows: the participants gave a rating (strongly dislike, dislike, neutral, like, to strongly like) for the six major hues (red, orange, yellow, green, blue, and purple) as well as for three achromatic colors (white, black, and grey). A score from 1 to 5 was given with the higher number representing a greater preference for a hue. We also collected the weather information for the hour that the experimental session started, because several studies have shown that the weather can influence decision making at the individual and institutional level (De Silva, Pownall, and Wolk (2012), Goetzmann *et al.* (2014)). The weather information includes temperature, humidity, air pressure, cloud coverage (clear sky, scattered clouds, partly cloudy, mostly cloudy, overcast, or mist), and precipitation, which was also verified by the experimenter on site. We chose the nearest weather station to each laboratory and this distance was always less than 15 km. The experimenter also recorded whether it rained shortly before each session.

2.2.3. The stimuli

The modification of colors of the original single- and dual-color paintings (namely, the hue,

[15] The list comprises Paul Cézanne, Pieter Breughel, Damien Hirst, Jeff Koons, Marc Chagall, Henri Matisse, Joan Miro, Claude Monet, Mark Rothko, Ton Schulten, Pablo Picasso, Peter-Paul Rubens, Piet Mondriaan, Alberto Giacometti, Andy Warhol, Rembrandt Harmenszoon van Rijn, Vincent van Gogh, Pierre-August Renoir, Alfred Sisley, and Winslow Homer.

saturation, and luminosity) was performed using Matlab. We adopted the widely-used Munsell color system and used the HSV model to analyze high resolution pictures of the original paintings at the pixel level. Hence, for each pixel we considered three parameters corresponding to the pure color (hue), the saturation, and the luminosity. Saturation is higher when less neutral grey is added to the pure color, and a higher luminosity means that more pure white is added. We took the hues at 0, 30, 60, 120, 240, and 300 out of 360 degrees of the color wheel. These points represent the classic red, orange, yellow, green, blue, and purple, respectively.

As we also sought to examine whether it may not just be the hue that affects the evaluation of art but also the color dimensions saturation and luminosity, we adjusted the saturation and luminosity of the six colors and created the following saturation-luminosity combinations: High-High, High-Low, Low-High, and Low-Low. A high saturation is defined as 7 out of 10, and low saturation as 3 out of 10; a high (low) luminosity is defined as 8 (5). For the experiment, we ignored the Low-Low group because the images become very dark and it is then difficult for the human eye to discern the hue variations. As a consequence, we have six major hues with three combinations of saturation and luminosity for our experiment.

For dual-color Mark Rothko abstract art, we rotated the original picture to be left-right positioned and made the color segments equal in size in order to eliminate potential concerns of a color weight effect when two color segments were positioned up and down, and to cancel the area size effect of a hue.[16] To prevent the task from becoming too repetitive, we limited the number of paintings shown to the participants and showed six dual-color pictures arising from combinations of the four primary hues (red, yellow, green, and blue). We also applied the same method of hue, saturation, and luminosity modification that we used for the single-color art on both the left and right panels of the dual-color art. This resulted in red-yellow, red-green, red-blue, yellow-green, yellow-blue, and green-blue dual-color paintings, each of which were modified according to High-High, Low-High, and High-Low luminosity-saturation combinations. The position of a constituent hue on the left or the right panel was randomized and then fixed across

[16] A painting with a red half on top and a green half on the bottom appears visually different from the opposite combination. An average person would perceive red bottom as heavier. Furthermore, a green lower part combined with a blue upper part could be interpreted as landscape with blue sky over a green meadow.

all sessions. Our modified paintings preserved the specific brush strokes and texture of the original.

Each participant only saw the paintings in a fixed setting of saturation-luminosity combinations, so that we had a within-subject analysis of the hue effect and a between-subject analysis of saturation-luminosity effects. As a robustness check, we asked about half of the Tilburg and Tucson participants to rate the single-color Rothko abstract art in three saturation-luminosity settings of six hues as a within-subject analysis of saturation-luminosity effects.

3. Results from Large Sample Auction Data

3.1 Descriptive Statistics

We have obtained 5,482 abstract non-figurative paintings sold in auctions for which high quality images are available. The average hammer price is USD 504,349, the average height and width are both close to 96 centimeters. 81% of the paintings are oil paintings, 18% are watercolors (including gouaches), and 1% are colored drawings (Table I). More than 60% of the paintings are auctioned by one of Sotheby's or Christie's branches. 89% of the paintings in our sample carry a signature, date, or inscription authenticity marking, and in less than 1% there may be some doubt about authenticity as these paintings are attributed to specific artists. 54% of paintings have clear provenance information including past ownership, previous sales history, etc. 19% of paintings have been shown in exhibitions before their sale, and 12% have been covered in the literature (in scholarly articles, art critics, art catalogues, etc.). In terms of color attributes, on average 19% of the painting surface is red, 10% is orange, 15% is yellow, 7% is green, 14% is blue, and 2% is purple. The average saturation and luminosity are 0.43 and 0.64, respectively, and the average number of chromatic hues used in a painting is close to three. To proxy for the degree of scattering of a hue in the painting, we calculate a dispersion factor. The normalized dispersion of a specific hue is based on a pixel analysis. Dispersion is the average Euclidean distance of each (e.g. blue) pixel to the center pixel among the blue hues in the painting image, normalized by the painting's diagonal pixel length. Therefore, the larger the dispersion factor, the more scattered the dots of blue hues in a painting are. The average dispersion for each chromatic hue is quite homogenous at around 20%. Detailed definitions of all variables are given in Panel A of Appendix I.

[Insert Table I about here]

3.2 Regression Results

3.2.1 Hue Percentage and Valuation

We regress the natural logarithm of the hammer price in USD on the percentages of chromatic hues in the corresponding paintings. We set the percentage of white as the benchmark and add in controls for color, size, medium, authenticity, provenance, and artist death (Models 1-6 of Table II). All models include artist, year, month, and auction branch fixed effects and the standard errors are clustered at the auction branch level. Model 4 is our focal specification which shows strong evidence that a higher percentage of blue or red in the painting commands a higher premium in an auction. For a one standard deviation increase in the percentage of blue (20%) or red hue (22%), the value premiums are 10.63% and 4.20%, respectively.[17] For the average hammer price in our sample, this represents about USD 53,612 for blue and USD 21,183 for red, respectively. To address any potential concerns about whether our results are solely driven by single hue paintings, we split our sample into one group that contains paintings with only one chromatic hue, and another one that comprises paintings with multiple chromatic hues (Models 5 and 6). We find that the results are valid for both subsamples. For a single chromatic hue painting, a one standard deviation increase in the percentage of the surface area that is of blue or red hue (relative to benchmark white) will lead to premiums of 15.7% and 9.8%, respectively.[18]

[Insert Tables II and III about here]

3.2.2 Dual Color and Valuation

To study dual color combination effects, we follow the specification of model 4 of Table II

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[17] This is calculated, e.g. in the blue hue case, as exp(0.505*0.20) – 1 = 10.63%.

[18] As robustness checks, we change the boundary parameters between neighboring 6 major hues on the color wheel; we exclude pixels in the boundary regions on the color wheel; and we reparametrize the orange and yellow hues since the white surfaces of a canvas/paper, whether left blank intentionally or painted white, have a tendency to become yellowish with aging. Our results remain qualitatively and quantitatively similar. In order to investigate the impact of the hue percentages and color controls on the explanatory power of the pricing model, we run two additional (unreported) regressions based on Model 4 and exclude, respectively, (i) the hue percentages and (ii) both the hue percentages and color controls. The R^2 is 85.4% in Model 4 and drops to 72.4% when excluding hue percentages and to 72.0% after excluding both hue percentages and color controls. This indicates that hue percentages are indeed important contributors to the explanatory power of the hedonic pricing model while the average value of saturation and luminosity, as key members in color controls, have little impact.

and use the percentage of a specific dual-color, the summation of the percentages from dual combinations of the four primary hues (red, yellow, green, and blue), as the dependent variable. Panels A and B of Table III report the respective results of two subsamples comprising paintings with: (i) only two chromatic hues, and (ii) more than two chromatic hues. The column header indicates the constituent hues in the dual-combination and the benchmark is the sum of all other hues and thus varies by model. The estimates show that the percentages of dual-colors of red-blue, green-blue, and yellow-blue induce a significant premium compared to their corresponding benchmarks. We can thus infer that blue in combination with other primary hues is value-adding.

3.2.3 Hue Dispersion, Salient Area, and Valuation

The two preceding subsections reported that the percentages of blue and red hues in a painting are related to higher values. Follow-up questions that we investigate here are: (i) Do particular shapes or patterns of colors affect paintings' prices? (ii) Are there any particular blue and red locations on a painting that trigger higher premiums?

To answer the first question, we introduce a normalized dispersion measure for each hue, which is greater when the hue is more dispersed over the painting's surface. This normalized dispersion factor is the average Euclidean distance between each pixel of a specific hue to the center pixel of that hue in the painting, which is normalized by the diagonal pixel length of the painting image. We regress the logarithm of hammer price in USD on the percentages of six major hues and their dispersion factors, and split the sample into single and multiple chromatic hue subsamples (Models 1-3 of Table IV). We find that the blue and red premium effects still hold in these models while the dispersion generally is not significant for orange, blue, and purple. For red, a more clustered shape is value-adding in the single chromatic hue painting while the scattering of the red hue is insignificant in multiple chromatic hue paintings.[19] For yellow and green, it is preferable for the hue to be dispersed across the painting.

In order to determine a salient area for the hues, we have tried different segmentations of the paintings' surfaces and associated the value of the paintings with the color attributes within those

[19] Note that a single chromatic hue painting may also contain black and white.

specific areas. We have considered 2x2, 3x3, or 4x4 equal cuts of the paintings and hence 4, 9, or 16 areas (or mini-paintings). We then regressed the painting valuation on the color attributes within each of the mini-paintings or some combinations of the mini- paintings with the same specification as Model 4 of Table II. However, we cannot identify consistent results from these mini-paintings.

As the golden ratio (1.618) is aesthetically important in figurative painting, architecture, and nature (Livio (2008)), we conjecture that the golden ratio may also play this role in non-figurative abstract art. We mark the two golden ratio points on each of the four outlines of the painting and then link them by drawing two horizontal and two vertical lines. The four interception points are defined as the golden ratio points.[20] We then focus on four small squares centered at these golden ratio points in the same aspect ratio of the original painting; each of them covers a surface of 4% of the painting. Table V reports the regression results of the log hammer prices in USD on the hue percentages in the four golden ratio areas. We find consistent and strong evidence that the presence of blue in these small golden ratio areas leads to a significant premium. An increase of 20 percentage points of blue hue within one of these small golden ratio areas (which is only a 0.8 percentage point increase for the whole painting; 20%*4%), still induces a significant premium of between 3.81% and 6.69% (depending on the golden ratio square). On average, a blue dot in a golden ratio area has 10 times the impact relative of a blue dot in a random area. Among the four golden ratio squares, the right-top one carries the highest premium.

[Insert Tables IV and V about here]

3.2.4 Hue and Return

One potential concern for the positive effects of blue and red on prices is that a high valuation may negatively affect future return. We use two methodologies to investigate the relationship between hues and returns. The first method analyses the differences in the price index series derived from two regressions: the traditional hedonic regression without any color attributes and

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[20] If we denote the width and height of the painting as W and H respectively and set the left-lower corner of the painting as the origin (0,0), the coordinates of the four golden ratio points are: Left-Top (0.382W, 0.618H); Right-Top (0.618W, 0.618H); Left-Bottom (0.382W, 0.382H); and Right-Bottom (0.618W, 0.382H).

the same hedonic model including the percentage of a specific hue (see methodology section above). For the six major hues, we do not find statistically significant differences among annualized hue index returns. Blue generates an annualized return of 87 basis point as the highest hue return and red generates a negative 3 basis points as the lowest hue return (untabulated). The second method consists of a repeat sales return analysis. We can identify 63 pairs of repeat sales[21] and regress their normalized return on a comprehensive set of hedonic variables. We find little evidence of a relation between hues and returns (with one – statistically rather weak - exception that yellow lowers returns). The reason for this lack of relation may very well be the tiny subsample of repeat sales.

4. Results from Laboratory Experiments

4.1 Descriptive Results on the Valuation of Single-Color Abstract Art

After excluding the participants with color vision deficiency, we examine the preferences of the participants in our experiments in China, the Netherlands, and the USA, respectively. The average bidding results for the six major hues show that in each of the three cultures, single-color abstract paintings in red and blue hues receive the highest valuation with an average of more than ECU 18 in China, 17 in the Netherlands, and 18 in the U.S. (Table VI). The green hue comes third with an average between ECU 14 to 17 in the three countries; the hues orange, purple, and yellow are in the least-valued group (between ECU 11 to16). We find it remarkable that this color-bidding hierarchy is similar across cultures.[22]

[Insert Table VI about here]

4.2 Regression Results

While the descriptive statistics show clear patterns in color premiums for blue and red,

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[21] About 2% of our total sold observations are repeat sales. This is consistent with Renneboog and Spaenjers (2013).
[22] We also study whether people bid according to their personal color preferences. The results are given in Online Appendices VI and VII. In Online Appendix VII, the horizontal axis indicates the six hues, the depth axis displays the rating of a given hue from 1 to 5, and the height of each bar represents the average valuation of the corresponding hue at a specific level of affect towards it. For example, the height of the red bar located at the crossing of "red" and "5" is the average bid on the red single-color abstract art by the individuals who rated red at "5" (a strong liking). The figure depicts a positive relationship between bid prices and preference towards a hue. The table also shows that the correlation between color preferences and bids is significantly positive and ranges between 15% and 24%, so that the analysis of the bids on the paintings does not just pick up color preferences.

individual choices display considerable heterogeneity. We therefore regress the bids on colors while also controlling for either subject fixed effects or a broad set of control variables including personal traits and session characteristics. The definitions of all variables are given in Panel B of Appendix I.

4.2.1 Single Color and Valuation

We first regress the individual bids on the single-color paintings' hues (red, orange, green, blue, and purple whereby the omitted yellow serves as the benchmark) and include subject fixed effects (Model 1 of Table VII). A participant can only take part in one experimental session and will only view the hues in one of three saturation-luminosity combinations; the subject fixed effects are a strong control for any personal (and session) traits. We find that in all three locations, the hues blue and red always carry significant premiums. Red elicits bids by Chinese participants that are on average ECU 3.32 higher than yellow, and European (American) participants bid ECU 6.26 (4.59) more. Blue receives bids that are ECU 2.40, 5.91, and 6.97 higher in China, the Netherlands, and the U.S., respectively. Green also carries a significant positive premium in the Netherlands and the U.S. at ECU 2.80 and 2.91, respectively. Blue and red premiums are about 18.57% and 17.28% higher than the pooled average of all bids on the single color arts. In Models 2 and 3, the dependent variables are the Purchase Intention and the Rank of the paintings. Our results are largely consistent with those for bidding behavior: purchase intention and rank are higher for paintings that are blue and red.[23]

To study whether specific types of individuals value art differently, we replace the subject fixed effects with a long list of control variables capturing personal traits and session characteristics. We report, in Table VIII, that the results on color are upheld as blue and red carry a significant premium for all the three cultures. Also noteworthy is the impact of the two dummy

[23] To alleviate concerns that the sequence in which the paintings were displayed may affect our results, we do a robustness check in Model 4 by including the sequence in which the six major hues were displayed as regressors (recall that the sequence was randomized at the individual level). We label the hues red, orange, yellow, green, blue, and purple as No.1, No.2,…, No. 6, respectively. The Order of Appearance in Model 4 represents the display order for a specific individual. For example, 2-1-6-4-3-5 means the display sequence orange, red, purple, green, yellow, and blue. The Order of Appearance-parameter estimates are insignificant, which indicates that the order of display does not affect valuation. Robustness tests on Purchase Intention and Rank yield similar insignificant results for the Order of Appearance.

variables HL and LH, which capture the High-Saturation-Low-Luminosity and Low-Saturation-High-Luminosity combinations, respectively (the omitted benchmark is HH). The HL and LH combinations are insignificant in all three different cultures suggesting that the hue-bidding hierarchy remains unchanged under different Saturation-Luminosity settings in a between-subject design.

[Insert Tables VII and VIII about here]

As a robustness test on the Saturation-Luminosity setting, we performed an additional within-subject experiment. We asked 118 and 65 participants in our European and American experiments, respectively, to rate the three Saturation-Luminosity variations of six major hues of a single-color Mark Rothko in six additional experiment rounds. In each additional round, one painting in one hue but in three different Saturation-Luminosity variations was displayed on the same screen and positioned randomly on the left, middle, and right panel. Participants then rated these variations on a scale from 1 to 5 where 1 indicates a strong dislike and 5 a strong preference. A joint F-test on the average rating differences among Saturation-Luminosity variations within each hue does not indicate any statistically significant differences (in any of the locations) (Online Appendix VIII). As shown above, these rating comparisons are informative because rankings and ratings are strongly correlated to actual bidding results. Both our between-subject and within-subject analyses on the valuation/rating effects of Saturation-Luminosity combinations suggest that hue is the predominant characteristic affecting valuation.

Table VIII also shows that bidding is not affected by gender or age. The Cognitive Reflection Test Score has little impact; only European participants with higher cognitive scores are inclined to bid less. The weather conditions (as measured by the Temperature, Humidity, Air Pressure, Rain Before, and Cloud Coverage) do not significantly affect the participants' valuations. One (weak) exception is the rain that fell shortly before a session started in China, which seems to have negatively affected the willingness to pay, but this effect is only significant at the 10% level. The weather-induced mood is significantly positive for the Chinese and US experiments. Art Appreciation by a participant in China increases his/her valuation of single-color paintings, but we do not find an effect in the other locations. Similarly, Art Background does not affect bids.[24] The variables capturing whether the participant has a favorite type of art (such as Old Masters, or Modern & Contemporary, relative to No Preference) do not affect the valuation (with exception of the European participants whose favorite style is Modern & Contemporary art and who bid more for single-color abstract art - at a significance level of 10%).

We also control for the financial status of the participants by capturing whether or not they had a student loan, and their annual expenditure (sum of spending on accommodation, transportation, food and drinks, tuition fee, and other expenses). We use reported expenditure rather than reported income, due to the concerns about misreporting of income and subsidies, and potential ambiguity about what constitutes one's own income and what is family aid. These expenditures do not explain the willingness to pay, with exception of the US participants, where wealthier individuals bid more on the art works.

4.2.2 Color and Emotion

To investigate the potential emotional channel relating color stimuli and art valuation, we first study whether the hues trigger specific emotions. We use the (dis)pleasure and (non)arousal dimensions to classify the main emotional states. Pleasure is calculated as the average response of scales of being happy/unhappy and pleased/annoyed. Arousal is calculated as the average on scales of being stimulated/relaxed and excited/calm. Each dimension ranges from 1 to 7, and a higher number stands for a stronger emotional state. We regress Pleasure and Arousal on hue fixed effects (yellow is the omitted benchmark) and include subject fixed effects (Table IX). Blue and green stand out significantly in terms of inducing pleasure (for Europe and the US), whereas orange is strongly negatively related to pleasure in each of the three locations. The response to red is not dissimilar from the response to yellow across all three locations. When we turn to arousal, we find that red, purple, and green are more effective in inducing arousal, whereas orange is more soothing (all relative to yellow). Blue is negatively correlated with arousal, but only

[24] Art Background is a comprehensive index constructed by normalizing and equally weighting the responses to four questions about the frequency with which individuals attend cultural events, whether they have had an art-related education, training in painting, or grew up in a family with an artistic background (see Panel B of Appendix I).

significantly so in the US. Other than a few minor exceptions, Table IX shows similar patterns across the three locations/cultures.

[Insert about here Tables IX and X]

4.2.3 Emotions and Bidding Behavior

Art is usually considered as an emotional asset, which we confirm with this research relating color in abstract paintings to specific emotions. We have also documented above that a paintings' color affects consumers' willingness-to-pay. We now investigate which specific (color-induced) emotions play a role in the valuation and purchase process by regressing bid, purchase intention, and rank on the pleasure and arousal emotions in Table X. We find that the key emotional channel (at a significance level of 1 %) relating color stimulus to valuation of single-color abstract art is pleasure. When a painting is making people happier, they are willing to pay more for it (Model 1), have a higher propensity to purchase it (Model 2), and they rank the painting more highly (Model 3). Increasing one notch on the pleasure scale results in a bid increase of ECU 4.63 in China, 6.24 in the Netherlands, and 5.30 in the U.S, which correspond to respective increases of 28.0%, 44.0% and 31.7%, respectively. In contrast, arousal has no significant impact on the bid and ranking of paintings (Models 1 and 3). The purchase intention increases slightly when people are feeling aroused, but the economic impact of arousal on purchase intention is small in magnitude (only 12% and 17% of the pleasure impact for the Netherlands and the US, respectively, in Model 2 of Table X) and Model 1 shows that arousal does not translate into actual purchase decisions. Our regressions control for subject fixed effects in all models.

All of our evidence suggests that pleasure is indeed the dominant emotional channel relating color stimulus to valuation. To investigate the robustness of the above findings, we adopt a two-stage model. In the untabulated first stage, we regress pleasure (and arousal) on the rating for the corresponding hue and, in the second stage, we regress the respective bid, purchase intentions, and rank on the predicted pleasure and predicted arousal, respectively (Online Appendix IX). Again, we find strong evidence (at the level of significance of 1%) that color-induced pleasure is the emotional channel leading to higher bid values, purchase intentions, and ranks.

4.3 Dual-Color Paintings and their Constituent Colors

4.3.1 Descriptive Statistics of Dual-color Abstract Art

In Table XI, we present the bidding results for the dual-color abstract paintings. The red-blue dual-color paintings attract the highest average bid of ECU 15.35, followed by an average bid of 13.43 for the green-blue combination. The least valued combination is red-green with a mean of only ECU 11.10. The average bid on all six dual-color abstract art paintings is ECU 12.93 (a discount of 18% compared to the average bid in the single-color round (15.71) with a standard deviation of 20.29.

[Insert about here Tables XI and XII]

4.3.2 Dual-color and Its Constituent Colors

We now turn to the relationship between the bids on dual-color works and single-color paintings of the same constituent colors. We find that the bid, purchase intention, and rank as well as the pleasure and arousal emotional states induced by the dual-color abstract art are all highly positively correlated with the average of the corresponding measurements of the single-color paintings with the constituent colors (at a 1 % significance level) (Panel A of Table XII) . The correlation amounts to 79% for the bids, 64% for the purchase intentions, and 37% for the ranking. The correlation coefficients for the emotional states induced by the combined colors and the average emotional states induced by the single constituent colors are approximately 50% (49% for Pleasure and 51% for Arousal). In Panel B, we report the regression results with the bids on dual-color paintings as the dependent variable and the average bid on the single-color paintings of the constituent colors as independent variables (Panel B of Table XII). As the average bid of certain constituent colors from the single-color round is given for an individual, we cannot include subject fixed effects. We do, however, include the comprehensive list of control variables used in Table VIII. We find that the bids on the color combinations are largely explained by the bids on the single colors: for example, 85% of the bid price variation in the red-blue combinations is explained by the average of the bids on red and blue. The explanatory power of the single colors amounts to between 69% and 85%.

To determine the color-bidding hierarchy, we regress bid, purchase intention, and rank on the dual-color combination fixed effects (whereby the least favored combination red-green is the omitted benchmark) and include subject fixed effects (Model 1 to Model 3 of Table XIII). We find that the combination of red-blue does indeed induce the highest bid premium, the strongest purchase intention, and the highest rank. The next favored color combination is blue-green. The difference in the bid between the least favored combination (RG) and the most favored one (RB) amounts to ECU 4.26, which is about one third increase of the average bid (ECU 12.93) on the dual-color painting. Green-glue, red-yellow, and yellow-blue dual-color abstract paintings carry significant premiums compared to red-green in all three measurements (bid, purchase intention, and rank). In terms of the emotional impact, red-blue and green-blue combinations significantly increase the pleasure level (at the 1% level of statistical significance), by 0.38 and 0.34 units, respectively, relative to the baseline red-green (Models 4 and 5 of Table XIII). With regard to the arousal dimension, no other dual-color combinations attains a greater level of arousal than the baseline red-green combination.

[Insert about here Tables XIII and XIV]

4.3.3 Emotional Channels

We regress the three measures of preference: (1) bid, (2) purchase intention, and (3) rank, on our emotion measures in Models 1 to 3 of Table XIV. The estimates show that the reported pleasure is strongly positively related to bid prices, purchase intentions, and rank. As in the single-color analysis, arousal does not affect bid value and rank, though it has a statistically significant, but economically trivial, impact on purchase intention.

As a robustness check, we regress bid prices, purchase intention, and rank on the predicted emotions in a two-stage framework. In the first stage (untabulated), we regress pleasure (arousal) induced by dual-color paintings on the ratings for two constituent hues. In the second stage, we regress our three dependent variables on predicted pleasure and arousal while also including subject fixed effects (Online Appendix Table X). We confirm that the color-induced emotion of pleasure is the channel whereby color influences bids, ranks and purchase intention (at the level of significance of 1%). As before, arousal has no effect on the preference measures.

5. Conclusion

The psychological and aesthetic roles of colors in artwork have been discussed among psychologists, scientists, and painters for centuries, but the economic effects of colors have not been analyzed to date. This study attempts to isolate the effect of color on the value of paintings by means of both art auction data and laboratory experiments. In addition, the experiments enable us to investigate which emotional channels connect colors and a painting's auction value.

We find that color is indeed an important determinant of the market prices of paintings and their private valuations. We demonstrate that blue and red hues command significant premiums in the field and in the laboratory: in the auction prices of abstract paintings and their private valuations, as well as increase the purchase intention of paintings and their relative rankings. The effects emerge for both single-color abstract paintings and dual-color abstract art, where the blue-red combination is valued the most among the color combinations we have studied. In terms of art returns, we find supportive evidence that blue leads to the highest return among the six primary hues. Of the three dimensions of color, it is the hue affects prices, bids, and purchase intention. Saturation and luminosity levels do not add much explanatory power to the hedonic regression model, nor do they affect the art valuation in the laboratory experiments.

By inquiring about the participants' emotional states after they have viewed a painting in a laboratory setting, we can measure the emotional response induced by a particular color in a painting. Among the basic emotional states (PA(D)), we confirm that the emotion of pleasure is strongly positively correlated to bid, amplifies the purchase intention, and leads to a higher ranking of a painting. The arousal level only affects the purchase intention and then only to a limited extent. Arousal does not translate to a higher or a lower bid. We find that the hues blue and green, as well as the dual-color combinations of red-blue and green-blue induce higher "pleasure". The valuations of dual-color abstract art, as well as the emotional states evoked by dual-color abstract art, are strongly and significantly correlated with the valuations and emotional states associated with the constituent single-color abstract art pieces.

All of the major results from our laboratory experiments are consistent across three locations, despite the different cultural backgrounds of participants. It is indeed remarkable that individuals from China, Europe, and the U.S. are all willing to offer higher bid premiums for blue and red colors. In view of the generality of these results, it is only natural that the premiums also appear in auction houses in different parts of the world.

This paper contributes to the literature in three principal ways. First, we verify and add the color dimensions of an artwork as an important missing class of variables to the hedonic pricing models in art auction markets. We confirm the importance and the consistency of the effects of hue in a large sample with both field and experimental data. Second, we contribute to the growing literature on the role of emotions in decision making, and provide another case showing the association between emotions and willingness-to-pay. Third, we provide the first cross cultural comparison of art preferences. The consistent patterns in the color-bidding hierarchy and in the emotional channel of decision making across three diverse cultures suggests that our results may be universal.

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Table I Descriptive Statistics of Auctioned Paintings

This table reports descriptive statistics for hedonics used in the regression analysis. Detailed variable descriptions are provided in Panel A of Appendix I.

Variable	N	Mean	SD	P25	Median	P75
Hammer Price	5,482	504,349	3,269,296	10,326	30,000	130,000
Pct_Red	5,482	0.19	0.22	0.02	0.12	0.26
Pct_Orange	5,482	0.10	0.16	0.01	0.03	0.11
Pct_Yellow	5,482	0.15	0.20	0.01	0.07	0.19
Pct_Green	5,482	0.07	0.14	0.00	0.02	0.07
Pct_Blue	5,482	0.14	0.20	0.00	0.06	0.18
Pct_Purple	5,482	0.02	0.05	0.00	0.00	0.02
Pct_White	5,482	0.22	0.24	0.00	0.12	0.37
Pct_Black	5,482	0.11	0.19	0.00	0.04	0.18
Sat_Avg	5,482	0.43	0.19	0.29	0.41	0.56
Lum_Avg	5,482	0.64	0.16	0.53	0.65	0.75
Sat_Std	5,482	0.08	0.11	0.00	0.03	0.12
Lum_Std	5,482	0.08	0.10	0.00	0.04	0.11
Nbr_Hue	5,482	2.86	1.30	2.00	3.00	4.00
Disp_Red	5,482	0.22	0.09	0.18	0.24	0.28
Disp_Orange	5,482	0.23	0.09	0.19	0.25	0.29
Disp_Yellow	5,482	0.23	0.09	0.19	0.25	0.29
Disp_Green	5,482	0.19	0.11	0.12	0.21	0.27
Disp_Blue	5,482	0.19	0.11	0.10	0.22	0.27
Disp_Purple	5,482	0.16	0.11	0.02	0.19	0.26
Disp_Black	5,482	0.19	0.11	0.13	0.22	0.27
Disp_White	5,482	0.23	0.12	0.17	0.27	0.31
Height	5,482	96.1	65.7	45.7	76.2	127.0
Width	5,482	96.1	78.0	45.7	75.6	121.9
Oil	5,482	0.81	0.39	1	1	1
Watercolor	5,482	0.18	0.38	0	0	0
Drawing	5,482	0.01	0.12	0	0	0
Authenticity	5,482	0.89	0.32	1	1	1
Attributed	5,482	0.01	0.03	0	0	0
Literature	5,482	0.12	0.32	0	0	0
Exhibited	5,482	0.19	0.4	0	0	0
Provenance	5,482	0.54	0.5	0	1	1
Deceased	5,482	0.78	0.42	1	1	1
Soth_London	5,482	0.05	0.22	0	0	0
Soth_NYC	5,482	0.20	0.40	0	0	0
Soth_Other	5,482	0.03	0.16	0	0	0
Chr_London	5,482	0.05	0.22	0	0	0
Chr_NYC	5,482	0.23	0.42	0	0	0
Chr_Other	5,482	0.05	0.23	0	0	0
Bon_London	5,482	0.01	0.08	0	0	0
Bon_NYC	5,482	0.01	0.10	0	0	0
Bon_Other	5,482	0.03	0.17	0	0	0
Phi_London	5,482	0.00	0.07	0	0	0
Phi_NYC	5,482	0.01	0.11	0	0	0
Phi_Other	5,482	0.00	0.02	0	0	0

Table II Painting Valuation and Hue Percentage

Pct_Red, Pct_Orange, Pct_Yellow, Pct_Green, Pct_Blue, and Pct_Purple are the percentages of six major hues analyzed in the images of non-figurative abstract art works at the pixel level. Pct_White is omitted as the benchmark. Color controls are color-specific control variables consisting of: 1) the number of hues exceeding a 3% coverage threshold, 2) the average and the standard deviation of saturation and luminosity in the colored part of the painting, 3) the percentage of black hue in the painting. Size controls are width and height, and their quadratic forms. Medium controls include dummy variables for oil paintings and watercolors (the category of colored drawings is the benchmark). Authenticity controls comprise: 1) an authenticity dummy for whether a painting contains verifiable attributes (signature, date or inscription), 2) an attribution dummy for whether a painting is attributed to the artist, or produced in his studio, by his circle, or in the style of the artist or his school. Provenance controls are: 1) a provenance dummy for whether past ownership is documented in the catalogue, 2) an exhibition dummy for whether the art work has been exhibited in the past, 3) a literature dummy indicating if the art work has been covered in the art literature at the time of the sale. The deceased dummy equals one if auction took place after the artist had passed away. All models include artist, year, month, and auction branch fixed effects. The percentage of white hue is left out as the benchmark category. Models 5 and 6 are subsample analyses with the number of chromatic hues equaling one and greater than one, respectively. Panel A reports the coefficients of hue percentages. Panel B reports the coefficients of the month fixed effects, Panel C reports the coefficients of a selected number of prominent auction houses (with Clarke Auction, Larchmont as the benchmark), Panel D reports the coefficients of color, size, and medium controls, Panel E reports the coefficients of Authenticity, Attribution, Provenance, and Deceased controls. Panels B, C, D and E are based on Model 4 in Panel A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors (S.E.) are reported in parentheses and clustered at the auction branch level.

Dependent Variable: Ln(Price)	Model 1	Model 2	Model 3	Model 4	Model 5 # of Hues =1	Model 6 # of Hues >1
Panel A: Hue Percentages						
Pct_Red	0.170**	0.169**	0.176**	0.187**	0.468**	0.163*
	(0.077)	(0.080)	(0.078)	(0.079)	(0.186)	(0.097)
Pct_Orange	-0.113	-0.105	-0.089	-0.098	0.408	-0.077
	(0.075)	(0.074)	(0.074)	(0.069)	(0.398)	(0.104)
Pct_Yellow	0.088	0.087	0.102	0.121	0.237	0.149*
	(0.079)	(0.079)	(0.078)	(0.078)	(0.187)	(0.078)
Pct_Green	0.110	0.101	0.113	0.130	0.242	0.185*
	(0.085)	(0.085)	(0.081)	(0.086)	(0.182)	(0.097)
Pct_Blue	0.483***	0.472***	0.496***	0.505***	0.731***	0.478***
	(0.103)	(0.103)	(0.093)	(0.093)	(0.220)	(0.097)
Pct_Purple	-0.283	-0.273	-0.261	-0.211	0.200	0.082
	(0.253)	(0.251)	(0.253)	(0.241)	(0.318)	(0.263)
Color Controls	YES	YES	YES	YES	YES	YES
Size Controls	YES	YES	YES	YES	YES	YES
Medium Controls		YES	YES	YES	YES	YES
Authenticity Controls			YES	YES	YES	YES
Provenance Controls				YES	YES	YES
Deceased Dummy				YES	YES	YES
Artist FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Auction Branch FE	YES	YES	YES	YES	YES	YES
Observations	5,482	5,482	5,482	5,482	821	4,507
R-squared	0.845	0.849	0.850	0.854	0.901	0.853

Panel B: Month Fixed Effects in Model 4

January	[Left Out]	April	0.463*** (0.149)	July	0.222 (0.145)	October	0.382** (0.157)
February	0.397** (0.154)	May	0.821*** (0.159)	August	-0.073 (0.320)	November	0.823*** (0.163)
March	0.284** (0.135)	June	0.432*** (0.153)	September	0.260* (0.133)	December	0.476*** (0.149)

Panel C: Selected Prominent Auction Branch Fixed Effects in Model 4

Sotheby's, Hong Kong	3.676*** (0.643)	Christie's, London	3.492*** (0.566)	Bonhams, London	3.091*** (0.580)	Phillips, London	3.090*** (0.599)
Sotheby's, London	3.491*** (0.566)	Christie's, New York	3.284*** (0.565)	Bonhams, New York	2.639*** (0.573)	Phillips, New York	2.916*** (0.576)
Sotheby's, New York	3.176*** (0.565)	Auctionata, New York	3.991*** (0.944)	Kornfeld, Bern	3.702*** (0.574)	Aguttes, Paris Drouot	4.297*** (0.713)
Porro & C., Milan	3.817*** (0.775)	Thomaston Place, Thomaston	3.702*** (0.809)				

Panel D: Color, Size, Medium Controls in Model 4

Nbr_Hue	0.052*** (0.015)	Sat_Std	-0.237* (0.138)	Height	0.013*** (0.001)	Width^2	-0.001*** (0.000)
Sat_Avg	0.573*** (0.113)	Lum_Std	-0.081 (0.113)	Width	0.008*** (0.001)	Oil	0.770*** (0.121)
Lum_Avg	0.564*** (0.149)	Pct_Black	0.492*** (0.116)	Height^2	-0.001*** (0.000)	Watercolor	0.488*** (0.126)

Panel E: Authenticity, Attribution, Provenance, Deceased Controls in Model 4

Authenticity	0.061** (0.031)	Literature	0.407*** (0.086)	Provenance	0.040 (0.045)	Deceased	0.055 (0.043)
Attribution	-2.638*** (0.305)	Exhibition	0.124*** (0.033)				

Table III Painting Valuation and Dual-Color Hue Percentage

Pct_Dual_Color is the sum of dual-color hue percentages corresponding to the column header. The model specification follows Model 4 of Table II. Panel A reports the analysis of the subsamples where the number of hues (that exceed a 3% threshold) is equal to two. Panel B reports the estimates for the subsample where the number of hues (that exceed the 3% coverage threshold) is greater than one. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors (S.E.) are reported in parentheses and clustered at the auction branch level.

Panel A: # of Hues = 2

Dependent Variable: Ln(Price)	Red-Blue	Green-Blue	Red-Yellow	Yellow-Blue	Yellow-Green	Red-Green
Pct_Dual_Color	0.208**	0.333***	0.032	0.190**	0.069	0.075
	(0.086)	(0.065)	(0.061)	(0.077)	(0.070)	(0.089)
Color Controls	YES	YES	YES	YES	YES	YES
Size Controls	YES	YES	YES	YES	YES	YES
Medium Controls	YES	YES	YES	YES	YES	YES
Authenticity Controls	YES	YES	YES	YES	YES	YES
Provenance Controls	YES	YES	YES	YES	YES	YES
Deceased Dummy	YES	YES	YES	YES	YES	YES
Artist FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Auction Branch FE	YES	YES	YES	YES	YES	YES
Observations	1,186	1,186	1,186	1,186	1,186	1,186
R-squared	0.888	0.888	0.887	0.888	0.887	0.887

Panel B: # of Hues >1

Dependent Variable: Ln(Price)	Red-Blue	Green-Blue	Red-Yellow	Yellow-Blue	Yellow-Green	Red-Green
Pct_Dual_Color	0.202***	0.297***	-0.051	0.215***	0.012	-0.028
	(0.049)	(0.053)	(0.047)	(0.045)	(0.044)	(0.056)
Color Controls	YES	YES	YES	YES	YES	YES
Size Controls	YES	YES	YES	YES	YES	YES
Medium Controls	YES	YES	YES	YES	YES	YES
Authenticity Controls	YES	YES	YES	YES	YES	YES
Provenance Controls	YES	YES	YES	YES	YES	YES
Deceased Dummy	YES	YES	YES	YES	YES	YES
Artist FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Auction Branch FE	YES	YES	YES	YES	YES	YES
Observations	4,507	4,507	4,507	4,507	4,507	4,507
R-squared	0.852	0.852	0.852	0.852	0.852	0.852

Table IV Painting Valuation, Hue Percentage, and Hue Dispersion

Pct_Red, Pct_Orange, Pct_Yellow, Pct_Green, Pct_Blue, and Pct_Purple are the percentages of the six major hues analyzed in the images of non-figurative abstract art works at the pixel level. Pct_White is omitted as the benchmark. Disp_Red, Disp_Orange, Disp_Yellow, Disp_Green, Disp_Blue, Disp_Purple are the dispersions of the six major hues proxied by the average Euclidean distance between each pixel of a corresponding hue to the center pixel of that hue, normalized by the painting diagonal pixel length. The model specifications follow Model 4 of Table II. Models 2 and 3 are subsample analyses with the number of hues equal to one and greater than one, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors (S.E.) are reported in parentheses and clustered at the auction branch level.

Dependent Variable: Ln(Price)	Model 1	Model 2 # of Chromatic Hues =1	Model 3 # of Chromatic Hues >1
Pct_Red	0.267***	0.673***	0.195*
	(0.092)	(0.177)	(0.100)
Pct_Orange	-0.084	0.419	-0.049
	(0.074)	(0.437)	(0.106)
Pct_Yellow	0.066	0.066	0.108
	(0.080)	(0.165)	(0.077)
Pct_Green	0.029	0.176	0.098
	(0.088)	(0.240)	(0.096)
Pct_Blue	0.468***	0.804***	0.425***
	(0.111)	(0.202)	(0.116)
Pct_Purple	-0.162	0.412	0.062
	(0.232)	(0.362)	(0.264)
Disp_Red	-0.304	-0.624**	-0.092
	(0.222)	(0.271)	(0.144)
Disp_Orange	0.094	0.396	0.095
	(0.167)	(0.295)	(0.188)
Disp_Yellow	0.345**	0.780***	0.325*
	(0.148)	(0.265)	(0.166)
Disp_Green	0.416***	0.566	0.473**
	(0.150)	(0.520)	(0.183)
Disp_Blue	0.239	-0.018	0.258
	(0.150)	(0.307)	(0.220)
Disp_Purple	-0.116	0.024	0.002
	(0.146)	(0.405)	(0.163)
Color Controls	YES	YES	YES
Size Controls	YES	YES	YES
Medium Controls	YES	YES	YES
Authenticity Controls	YES	YES	YES
Provenance Controls	YES	YES	YES
Deceased Dummy	YES	YES	YES
Artist FE	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
Auction Branch FE	YES	YES	YES
Observations	5,482	821	4,507
R-squared	0.855	0.903	0.854

Table V Painting Valuation and Hue Percentage in Golden Ratio Area

This table reports regressions of the log hammer price of the paintings on the hue percentages in four golden ratio areas covering a surface size of 4% each. Pct_Red, Pct_Orange, Pct_Yellow, Pct_Green, Pct_Blue, and Pct_Purple are the percentages of the six major hues analyzed in the corresponding four golden ratio squares. Pct_White is omitted as the benchmark. The model specifications follow Model 4 in Table I. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors (S.E.) are reported in parentheses and clustered at the auction branch level.

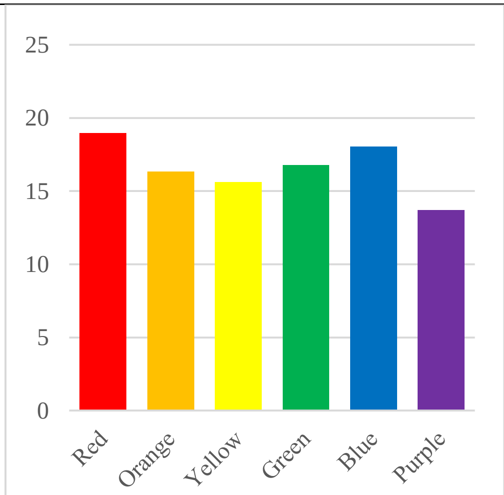
Dependent Variable:	Model 1	Model 2	Model 3	Model 4
Ln(Price)	Left-Top	Right-Top	Left-Bottom	Right-Bottom
Pct_Red	0.100	0.076	-0.001	-0.029
	(0.089)	(0.060)	(0.062)	(0.048)
Pct_Orange	-0.069	0.026	-0.177***	-0.113*
	(0.054)	(0.061)	(0.053)	(0.067)
Pct_Yellow	0.018	0.096	-0.009	0.014
	(0.064)	(0.068)	(0.053)	(0.056)
Pct_Green	0.075	0.037	-0.089	-0.004
	(0.087)	(0.091)	(0.069)	(0.080)
Pct_Blue	0.227**	0.324***	0.187***	0.238***
	(0.093)	(0.067)	(0.067)	(0.080)
Pct_Purple	0.074	-0.363**	-0.064	-0.491***
	(0.188)	(0.147)	(0.170)	(0.164)
Controls	YES	YES	YES	YES
Observations	5482	5482	5482	5482
R-squared	0.847	0.852	0.848	0.851

Table VI Bidding Results for Single-Color Abstract Art

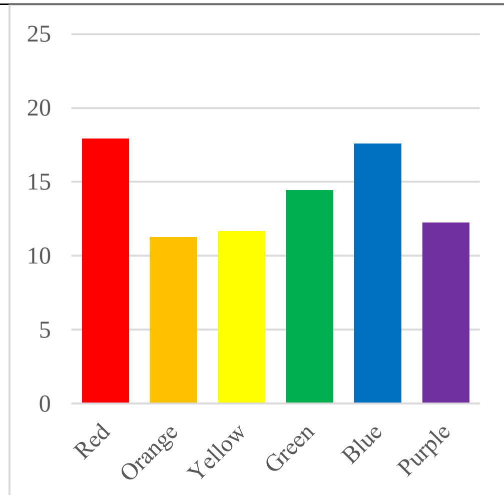
This table illustrates the average of the bids elicited via the BDM method (Becker, DeGroot, and Marschak (1964)) for single-color abstract art in the six hues (red, orange, yellow, green, blue, and purple). Each participant can bid any integer number from 0 to 100 ECU (experimental currency units) on each painting with a specific hue.

Panel A: Average of Biddings on Single-color Abstract Art of Six Major Hues in Three Countries

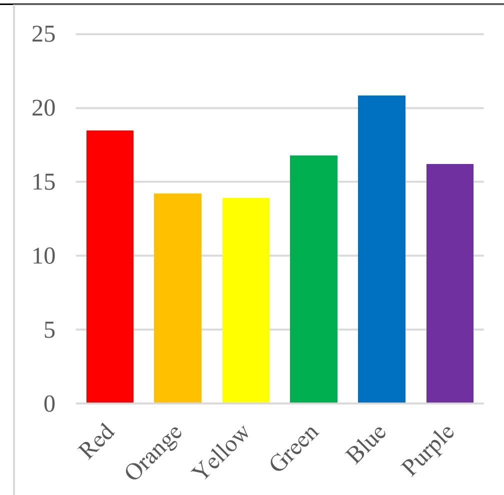
Shanghai, China (N=161)



Tilburg, the Netherlands (N=175)



Tucson, U.S.A. (N=129)



Panel B: Descriptive Statistics of Bids on Single Color Abstract Art by Six Major Hues in Three Countries

Shanghai, China (N=161)								**Tilburg, the Netherlands (N=175)**								**Tucson, U.S.A. (N=129)**							
Hue	Avg	STD	Min	25%	Med	75%	Max	Hue	Avg	STD	Min	25%	Med	75%	Max	Hue	Avg	STD	Min	25%	Med	75%	Max
Red	18.95	22.08	0	1	10	30	100	Red	17.92	23.57	0	0	7	30	100	Blue	20.84	25.19	0	0	10	30	90
Blue	18.02	22.14	0	1	8	30	95	Blue	17.57	23.30	0	0	8	30	100	Red	18.47	23.41	0	0	10	30	100
Green	16.78	21.76	0	0	7	25	100	Green	14.46	21.90	0	0	5	20	100	Green	16.78	23.15	0	0	5	25	90
Orange	16.35	21.09	0	0	6	25	100	Purple	12.23	21.80	0	0	1	12	100	Purple	16.19	22.10	0	0	6	25	95
Yellow	15.63	19.76	0	0	10	25	100	Yellow	11.66	18.25	0	0	3	20	100	Orange	14.21	20.53	0	0	4	20	90
Purple	13.70	19.98	0	0	5	15	100	Orange	11.23	18.63	0	0	1	15	100	Yellow	13.88	21.08	0	0	5	20	90

Table VII Hue and Valuation with Subject Fixed Effects

Red, Orange, Green, Blue, and Purple are fixed effects corresponding to the hues of the paintings that the participants bid on. Yellow is the omitted baseline category. PI stands for the Purchase Intention, calculated as the equally weighted average of four purchase intention ratings (on a scale from 1 to 7). The higher the rating, the higher the reported purchase intention. Rank is a rating from 1 to 6 of the single-color abstract paintings of the six hues (1 stands for the most favored painting and 6 for the least favored). We allow for tied rankings of multiple paintings. For example, one can rank both the red and blue painting to be No.1 (the most favored). In the regression analysis, Rank is reversed, in that a higher rating represents a higher place in the hierarchy. Order of Appearance in Model 4 is the display number of the painting: the six paintings within each round were displayed in a randomized sequence at the level of the participant. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses and clustered at the subject level.

	Model 1 Depend Variable: Bid			Model 2 Depend Variable: PI			Model 3 Depend Variable: Rank			Model 4 Depend Variable: Bid		
	CHN	NLD	USA	CHN	NLD	USA	CHN	NLD	USA	CHN	NLD	USA
Red	3.323**	6.263***	4.589***	0.0699	0.306***	0.200*	0.348*	1.189***	1.295***	3.343**	6.300***	4.568***
	(1.435)	(1.306)	(1.B)	(0.124)	(0.0927)	(0.110)	(0.191)	(0.166)	(0.188)	(1.438)	(1.304)	(1.490)
Orange	0.720	-0.423	0.333	-0.284**	-0.180**	-0.178**	-0.0683	-0.154	0.155	0.708	-0.407	0.317
	(1.172)	(1.050)	(1.366)	(0.116)	(0.0881)	(0.0893)	(0.174)	(0.163)	(0.181)	(1.166)	(1.048)	(1.368)
Green	1.149	2.800**	2.907**	0.144	0.0771	0.138	0.143	0.286	0.659***	1.155	2.837**	2.888**
	(1.317)	(1.188)	(1.409)	(0.118)	(0.0817)	(0.0960)	(0.191)	(0.173)	(0.187)	(1.313)	(1.198)	(1.413)
Blue	2.398*	5.914***	6.969***	0.179	0.399***	0.359***	0.304	1.160***	1.729***	2.384*	5.970***	6.881***
	(1.345)	(1.287)	(1.795)	(0.121)	(0.0912)	(0.109)	(0.204)	(0.191)	(0.211)	(1.347)	(1.292)	(1.802)
Purple	-1.932	0.577	2.318	-0.205	-0.0143	0.178	-0.578***	-0.194	0.736***	-1.926	0.626	2.305
	(1.513)	(1.474)	(1.760)	(0.131)	(0.0915)	(0.118)	(0.210)	(0.200)	(0.244)	(1.512)	(1.454)	(1.753)
Order of Appearance										0.117	-0.122	0.270
										(0.238)	(0.247)	(0.222)
Constant	15.63***	11.66***	13.88***	2.696***	2.010***	1.959***	3.509***	3.943***	4.357***	14.98***	12.29***	12.42***
	(0.851)	(0.765)	(0.966)	(0.0755)	(0.0534)	(0.0655)	(0.121)	(0.111)	(0.126)	(1.516)	(1.550)	(1.383)
Observations	966	1,050	774	966	1,050	774	966	1,050	774	966	1,050	774
R-squared	0.021	0.054	0.039	0.027	0.056	0.044	0.034	0.118	0.133	0.022	0.054	0.040
Number of Subjects	161	175	129	161	175	129	161	175	129	161	175	129
Subject FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table VIII Hue and Valuation with Control Variables

Red, Orange, Green, Blue, and Purple are hue fixed effects corresponding to the hue of the single-color paintings that the participants bid on. Yellow is the omitted benchmark. Gender equals 1 if the participant is female. Cognitive Score is the number of correct answers to the three questions of the Cognitive Reflection Test. Age is reported in the exit survey. Weather-induced mood is the rating of how one likes the weather on the day of the experiment (1 stands for "dislike very much" and 5 for "like very much"). Temperature, Humidity, Air Pressure, and Cloud Coverage are collected from the website Weather Underground (https://www.wunderground.com) at the time that a session started. Rain Before equals 1 if it rained shortly before the session and is recorded by the experimenter. Art Appreciation is the degree of affinity towards visual arts (1 stands for "dislike very much" and 5 for "like very much"). Art Background is the average of scaled responses to questions on the frequency of attending art-related events (0 is "almost never", 1 is "once or twice per week, 2 is "once or twice per month", and 3 is "once or twice per year"), and as to whether or not a participant has an art-related education (0 is "No", and 1 is "Yes"), has had painting classes (0 is "No", and 1 is "Yes"), or comes from a family with an art background (0 is "No", and 1 is "Yes"). Old Master equals 1 if the participant has a preference for the genre of Medieval, Renaissance and Baroque Art. Contemporary & Modern equals 1 if the participant prefers Impressionism, Modern Art, or Contemporary Art (the omitted benchmark is "No preference"). Expense is the sum of a participant's annual expenses on accommodation, transportation, food and drinks, tuition fee, and other expenses. Have A Loan equals 1 if the participant has a student loan. LH and HL are dummy variables indicating the Low-Saturation-High-Luminosity and High-Saturation-Low-Luminosity combinations, respectively (with the High-Saturation-High-Luminosity combination as benchmark). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors (S.E.) are reported in parentheses and clustered at the subject level.

Dependent Variable: Bid	CHN		NLD		USA	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Red	3.323**	(-1.448)	6.299***	(-1.324)	4.544***	(-1.543)
Orange	0.72	(-1.182)	-0.253	(-1.051)	0.4	(-1.426)
Green	1.149	(-1.329)	2.759**	(-1.204)	2.752*	(-1.453)
Blue	2.398*	(-1.357)	6.092***	(-1.292)	6.816***	(-1.85)
Purple	-1.932	(-1.527)	0.782	(-1.48)	1.968	(-1.799)
Gender	-5.142	(-3.326)	1.269	(-2.575)	5.327	(-4.813)
Cognitive Score	-0.93	(-1.817)	-4.942***	(-1.192)	-1.732	(-1.58)
Age	-0.292	(-1.266)	0.79	(-0.536)	0.449	(-0.717)
Weather-Induced Mood	3.618**	(-1.486)	2.861	(-2.333)	3.324*	(-1.937)
Temperature	1.988	(-4.398)	-2.849	(-2.12)	-0.509	(-1.791)
Humidity	0.592	(-1.098)	-0.289	(-0.242)	-0.391	(-0.619)
Air Pressure	-0.501	(-0.853)	-0.29	(-0.606)	0.328	(-0.906)
Rain Before	-6.768*	(-3.56)	-1.922	(-5.301)	6.143	(-6.691)
Cloud Coverage	-1.795	(-2.722)	5.647	(-3.744)	1.352	(-3.498)
Art Appreciation	5.003**	(-2.155)	0.149	(-1.322)	-2.124	(-2.728)
Art Background	-0.555	(-13.27)	-2.888	(-15.4)	-20.8	(-16.07)
Old Master	4.448	(-4.123)	2.886	(-3.023)	-4.944	(-5.475)
Modern & Contemporary	4.232	(-2.651)	5.748*	(-3.473)	0.65	(-3.839)
Expense	-3.099	(-2.094)	2.147	(-4.782)	7.992**	(-3.084)
Have A Loan	7.988	(-6.019)	-0.537	(-2.766)	-1.369	(-3.642)
HL	-3.379	(-5.845)	1.507	(-3.233)	4.215	(-5.082)
LH	-2.609	(-4.509)	1.095	(-3.736)	2.529	(-5.327)
Constant	406.8	(-815.5)	331	(-665.5)	-313.1	(-953.3)
Observations	966		1,044		750	
R-squared	0.133		0.164		0.105	
Subject FEs	No		No		No	

Table IX Hue and Emotions

Red, Orange, Green, Blue, and Purple are the hues of the single-color paintings that the participants bid on. Yellow is omitted as the benchmark. In Model 1, the dependent variable Pleasure is the average of pleasure measurements (1/2*P1+1/2*P2). In Model 2, the dependent variable Arousal is the average of arousal measurements (1/2*A1+1/2*A2) (see Online Appendix II). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses and clustered at the participant level.

Dependent Variable	Model 1 Pleasure			Model 2 Arousal		
	CHN	NLD	USA	CHN	NLD	USA
Red	0.001	0.189	0.109	0.553***	0.609***	0.186
	(0.123)	(0.116)	(0.144)	(0.137)	(0.109)	(0.129)
Orange	-0.278**	-0.386***	-0.217*	-0.294**	-0.374***	-0.492***
	(0.113)	(0.112)	(0.126)	(0.114)	(0.104)	(0.125)
Green	0.201	0.326***	0.477***	0.208	0.351***	0.295**
	(0.130)	(0.118)	(0.146)	(0.126)	(0.0992)	(0.132)
Blue	0.128	0.466***	0.523***	-0.0901	-0.0286	-0.442***
	(0.123)	(0.109)	(0.147)	(0.122)	(0.120)	(0.144)
Purple	-0.171	0.0686	0.267*	0.432***	0.566***	0.345**
	(0.147)	(0.116)	(0.150)	(0.125)	(0.109)	(0.139)
Constant	3.998***	3.586***	3.667***	3.431***	3.146***	3.372***
	(0.0792)	(0.0720)	(0.0931)	(0.0783)	(0.0654)	(0.0840)
Observations	928	1,050	774	928	1,050	774
R-squared	0.024	0.069	0.060	0.076	0.114	0.101
Number of Subjects	161	175	129	161	175	129
Subject Fes	YES	YES	YES	YES	YES	YES

Table X Emotions and Single-color Abstract Art Valuations

Red, Orange, Green, Blue, and Purple are the hues corresponding to the single-color paintings that the participants bid on. Yellow is omitted as the benchmark. The dependent variable PI is the Purchase Intention, calculated as the equally weighted average of four purchase intention ratings (from 1 to 7). The higher the rating, the higher is the reported intention to buy a specific painting. The dependent variable Rank is the rating from 1 to 6 of the single-color abstract paintings. No.1 stands for the most favored painting and No.6 indicates the least favored. We allow for tied rankings for multiple paintings; for example, one can rank both the red and blue painting to be No.1 (the most favored). In the regression analysis, Rank is reversed such that a higher rating represents a higher place in the hierarchy. Pleasure is the average of the pleasure measurements (1/2*P1+1/2*P2) and Arousal is the average of the arousal measurements (1/2*A1+1/2*A2) (see Online Appendix II). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses and clustered at the subject level.

Dependent variable:	Model 1 Bid			Model 2 PI			Model 3 Rank		
	CHN	NLD	USA	CHN	NLD	USA	CHN	NLD	USA
Pleasure	4.634***	6.235***	5.301***	0.650***	0.536***	0.477***	0.855***	0.943***	0.831***
	(0.557)	(0.607)	(0.622)	(0.0486)	(0.0393)	(0.0398)	(0.0507)	(0.0442)	(0.0501)
Arousal	-0.472	0.597	-0.378	0.0602	0.0625**	0.0804**	-0.0429	-0.0185	-0.0995*
	(0.497)	(0.462)	(0.518)	(0.0416)	(0.0307)	(0.0326)	(0.0510)	(0.0425)	(0.0536)
Constant	-0.357	-10.85***	-2.463	-0.144	-0.0798	-0.0343	0.266	0.0142	0.534**
	(2.036)	(2.845)	(2.785)	(0.188)	(0.169)	(0.188)	(0.211)	(0.229)	(0.253)
Observations	928	1,050	774	928	1,050	774	928	1,050	774
R-squared	0.172	0.309	0.208	0.490	0.460	0.430	0.285	0.330	0.276
Number of Subjects	161	175	129	161	175	129	161	175	129
Subject FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table XI Bidding Results on Dual-color Abstract Art

This table documents the summary statistics of the bidding results on dual-color abstract art. RB is the combination of Red-Blue, GB of Green-Blue, RY of Red-Yellow, YB of Yellow-Blue, YG of Yellow-Green, and RG of Red-Green. All dual-color paintings combine four primary hues (Red, Yellow, Green, and Blue) and the two constituent hues are configured in the same saturation-luminosity setting of one of the three possible combinations of High-High, High-Low, and Low-High. The two colors are positioned left and right in the dual-color abstract art and are equal in terms of the area size.

	Color Left	Color Right	Number of Observations	Mean	SD	Min	25%	Med	75%	Max
RB	Red	Blue	465	15.35	22.16	0	0	5	20	100
GB	Blue	Green	465	13.43	20.26	0	0	4	20	100
RY	Yellow	Red	465	13.25	20.16	0	0	5	20	100
YB	Blue	Yellow	465	12.91	20.44	0	0	3	17	100
YG	Green	Yellow	465	11.56	19.35	0	0	2	15	100
RG	Green	Red	465	11.10	19.06	0	0	1	11	100
Pooling			2,790	12.93	20.29	0	0	3	20	100

Table XII Dual-color Abstract Art and Constituent Colors

This table documents the relationship between bid, purchase intention, and rank (the dependent variables), and emotional states (pleasure and arousal) for the color combinations in the dual-color abstract art and its constituent colors. RB is the combination of Red-Blue, GB is Green-Blue, RY is Red-Yellow, YB is Yellow-Blue, YG is Yellow-Green, and RG is Red-Green. All dual-color paintings are made from the combinations of four primary hues (Red, Yellow, Green, and Blue) and the two constituent hues are configured in the same saturation-luminosity setting of one of the three possible combinations of High-High, High-Low, and Low-High. The two colors are positioned left and right in the dual-color abstract art and are equal in terms of the area size. Bid_Avg, PI_Avg, and Rank_Avg are the average of – respectively – bids on, purchase intentions of, and rankings of single-color paintings of the constituent colors. For example, Bid_Avg for the Red-Blue dual-color abstract art is the average of the bids on the red and blue single-color abstract art. Pleasure_Avg and Arousal_Avg are the averages of the respective Pleasure and Arousal states induced by viewing single-color paintings of the constituent colors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The control variables in Panel B are the same as in the regressions of Table VII (gender, Cognitive Reflection Test score, age, weather-induced mood, weather conditions, art appreciation, art background, old master, modern & contemporary, expense, having a loan, HL, and LH). Standard errors are reported in parentheses and clustered at the participant level.

Panel A: Correlation between Valuation and Emotional Influences of Dual-color Abstract Art and Its Constituent Colors

	Bid		PI		RANK		Pleasure		Arousal
Bid_Avg	0.786***	PI_Avg	0.640***	RANK_Avg	0.368***	Pleasure_Avg	0.487***	Arousal_Avg	0.505***

Panel B: Relationship of Bidding Results on Dual-color Abstract Art and Its Constituent Colors

Dependent Variable: Bid	RB	YB	RY	GB	YG	RG
Bid_Avg	0.852***	0.820***	0.791***	0.784***	0.779***	0.690***
	(0.028)	(0.031)	(0.032)	(0.026)	(0.030)	(0.030)
Observations	460	460	460	460	460	460
R-squared	0.696	0.639	0.606	0.698	0.636	0.578
Constant	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES

Table XIII Valuations and Emotional Influences of Dual-color Abstract Art

This table documents the relationship between the dependent variables bid, purchase intention, rank and the emotional states of pleasure and arousal for the color combinations in the dual-color abstract art and its constituent colors. RB is the combination of Red-Blue, GB is Green-Blue, RY is Red-Yellow, YB is Yellow-Blue, YG is Yellow-Green, and RG is Red-Green which is omitted as the benchmark. All dual-color paintings are made from the combinations of four primary hues (red, yellow, green, and blue) and the two constituent hues are configured in the same saturation-luminosity setting of one of the three possible combinations of High-High, High-Low, and Low-High. The two colors are positioned left and right in the dual-color abstract art and are equal in terms of the area size. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses and clustered at the participant level.

	Valuations			Emotional Influences	
Dependent variable:	Model 1 Bid	Model 2 PI	Model 3 Rank	Model 4 Pleasure	Model 5 Arousal
RB	4.258***	0.348***	1.019***	0.377***	-0.0688
	(0.718)	(0.0577)	(0.105)	(0.0667)	(0.0592)
GB	2.335***	0.233***	0.591***	0.341***	-0.268***
	(0.624)	(0.0529)	(0.101)	(0.0672)	(0.0678)
RY	2.153***	0.102*	0.458***	0.0871	-0.0538
	(0.662)	(0.0545)	(0.115)	(0.0704)	(0.0639)
YB	1.811**	0.0946*	0.303***	0.0656	-0.527***
	(0.710)	(0.0553)	(0.115)	(0.0739)	(0.0693)
YG	0.462	0.0616	0.0860	0.0323	-0.292***
	(0.687)	(0.0562)	(0.113)	(0.0706)	(0.0657)
Constant	11.10***	2.088***	2.910***	3.456***	3.746***
	(0.437)	(0.0341)	(0.0686)	(0.0435)	(0.0420)
Observations	2,790	2,752	2,790	2,790	2,790
R-squared	0.021	0.021	0.044	0.022	0.039
Number of Subjects	465	465	465	465	465
Subject FEs	YES	YES	YES	YES	YES

Table XIV Emotions and Dual-color Abstract Art Valuation

This table illustrates the emotional channel linking color to bid value, purchase intention, and rank of the dual-color abstract art. The dependent variable PI is the Purchase Intention calculated as the equally weighted average of four purchase intention ratings (from 1 to 7). The higher the rating, the higher the reported intention to buy a specific painting. The dependent variable Rank is the rating from 1 to 6 of the dual-color abstract art of the six combinations whereby No.1 stands for the most favored painting and No.6 indicates the least favored. We allow for tied rankings for multiple paintings. In the regression analysis, Rank is reversed such that a higher rating represents a higher place in the hierarchy. Pleasure is the average of the pleasure measurements (1/2*P1+1/2*P2) and Arousal is the average of the arousal measurements (1/2*A1+1/2*A2) (see Online Appendix II). RB is the combination of Red-Blue, GB is Green-Blue, RY is Red-Yellow, YB is Yellow-Blue, YG is Yellow-Green, and RG is Red-Green which is omitted as the benchmark. All dual-color paintings are made from combinations of two of the four primary hues (red, yellow, green, and blue) and the two constituent hues are configured in the same saturation-luminosity of either High-High, High-Low, or Low-High described earlier. The two colors are positioned on the left and right halves of the dual-color painting and are equal in terms of area size. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parentheses and clustered at the participant level.

Dependent Variable:	Model 1 Bid	Model 2 PI	Model 3 Rank
Pleasure	4.055***	0.538***	0.858***
	(0.311)	(0.023)	(0.033)
Arousal	0.140	0.065***	-0.031
	(0.312)	(0.020)	(0.037)
Constant	-2.187	0.059	0.336**
	(1.485)	(0.100)	(0.143)
Observations	2,790	2,752	2,790
R-squared	0.188	0.503	0.284
Number of Subjects	465	465	465
Subject FEs	YES	YES	YES

Appendix I Variable Definitions

Panel A Variable Definitions for the Hedonic Pricing Model

Variable	Definition
Ln(Price)	Ln(Price) is the natural logarithm of hammer price in US Dollars.
Pct_Red	Pct_Red is the percentage of red pixels among all pixels in the image of the painting.
Pct_Orange	Pct_Orange is the percentage of orange pixels among all pixels in the image of the painting.
Pct_Yellow	Pct_Yellow is the percentage of yellow pixels among all pixels in the image of the painting.
Pct_Green	Pct_Green is the percentage of green pixels among all pixels in the image of the painting.
Pct_Blue	Pct_Blue is the percentage of blue pixels among all pixels in the image of the painting.
Pct_Purple	Pct_Purple is the percentage of purple pixels among all pixels in the image of the painting.
Pct_Black	Pct_Black is the percentage of black pixels among all pixels in the image of the painting.
Pct_White	Pct_White is the percentage of white pixels among all pixels in the image of the painting.
Sat_Avg	Sat_Avg is the average of pixel-level saturation on the colored part (excluding white and black hues) of the image of the painting.
Lum_Avg	Lum_Avg is the average of pixel-level luminosity on the colored part (excluding white and black hues) of the image of the painting.
Sat_Std	Sat_Std is the standard deviation of pixel-level saturation on the colored part (excluding white and black hues) of the image of the painting.
Lum_Std	Lum_Std is the standard deviation of pixel-level luminosity on the colored part (excluding white and black hues) of the image of the painting.
Nbr_Hue	Nbr_Hue is the number of chromatic hues exceeding 3% of painting surface.
Disp_Red	Disp_Red is the normalized dispersion of red hues based on pixel level. Dispersion is the average Euclidean distance of each red pixel to the center pixel of red hues in the painting image, normalized by the diagonal pixel length of the painting image.
Disp_Orange	Disp_Orange is the normalized dispersion of orange hues based on pixel level. Dispersion is the average Euclidean distance of each orange pixel to the center pixel of orange hues in the painting image, normalized by the diagonal pixel length of the painting image.
Disp_Yellow	Disp_Yellow is the normalized dispersion of yellow hues based on pixel level. Dispersion is the average Euclidean distance of each yellow pixel to the center pixel of yellow hues in the painting image, normalized by the diagonal pixel length of the painting image.
Disp_Green	Disp_Green is the normalized dispersion of green hues based on pixel level. Dispersion is the average Euclidean distance of each green pixel to the center pixel of green hues in the painting image, normalized by the diagonal pixel length of the painting image.
Disp_Blue	Disp_Blue is the normalized dispersion of blue hues based on pixel level. Dispersion is the average Euclidean distance of each blue pixel to the center pixel of blue hues in the painting image, normalized by the diagonal pixel length of the painting image.
Disp_Purple	Disp_Purple is the normalized dispersion of purple hues based on pixel level. Dispersion is the average Euclidean distance of each purple pixel to the center pixel of purple hues in the painting image, normalized by the diagonal pixel length of the painting image.
Disp_Black	Disp_Black is the normalized dispersion of black hues based on pixel level. Dispersion is the average Euclidean distance of each black pixel to the center pixel of black hues in the painting image, normalized by the diagonal pixel length of the painting image.
Disp_White	Disp_White is the normalized dispersion of white hues based on pixel level. Dispersion is the average Euclidean distance of each white pixel to the center pixel of white hues in the painting image, normalized by the diagonal pixel length of the painting image.
Height	The height of a painting measured in centimeters.
Width	The width of a painting measured in centimeters.
Oil	Oil refers to the Oil/Acryl Painting category based on the medium of a painting.

Watercolor	Watercolor refers to the Watercolor (or gouache) category based on the medium of a painting.
Drawing	Drawing refers to the Colored Drawing category based on the medium of a painting.
Authenticity	Authenticity is a dummy variable equaling one if the auctioned object contains any physically identifiable markings such as signature, date, or inscription, which help to confirm the authenticity of the art piece. Signature includes various types of signature including full names, monograms, initials, countersignatures, and stamps.
Attributed	Attributed is a dummy variable equaling one if the auctioned object had been recognized and disclosed by the auction house at any of the following levels: 1) attributed to the artist, 2) from the studio of the artist, 3) from the circle of the artist, 4) from the school of the artist, 5) after the artist, or 6) in the style or manner of the artist.
Literature	Literature is a dummy variable equaling one if there is textual information in the catalogue about literature covering the auctioned lot.
Exhibited	Exhibited is a dummy variable equaling one if there is textual information in the catalogue about the exhibition history of the auctioned lot.
Provenance	Provenance is a dummy variable equaling one if there is textual information in the catalogue about the provenance information (past ownership, previous sales information, etc.) of the auctioned lot.
Deceased	Deceased is a dummy variable equaling one if the artist is dead before the sale of the auctioned lot.
Soth_London	Soth_London is a dummy variable that equals one if the sale takes place at Sotheby's London.
Soth_NYC	Soth_NYC is a dummy variable that equals one if the sale takes place at Sotheby's New York.
Soth_Other	Soth_Other is a dummy variable that equals one if the sale takes place at one of Sotheby's other branches.
Chr_London	Chr_London is a dummy variable that equals one if the sale takes place at Christie's London.
Chr_NYC	Chr_NYC is a dummy variable that equals one if the sale takes place at Christie's New York.
Chr_Other	Chr_Other is a dummy variable that equals one if the sale takes place at one of Christie's other branches.
Bon_London	Bon_London is a dummy variable that equals one if the sale takes place at Bonham's London.
Bon_NYC	Bon_NYC is a dummy variable that equals one if the sale takes place at Bonham's New York.
Bon_Other	Bon_Other is a dummy variable that equals one if the sale takes place at one of Bonham's other branches.
Phi_London	Phi_London is a dummy variable that equals one if the sale takes place at Phillips' London.
Phi_NYC	Phi_NYC is a dummy variable that equals one if the sale takes place at Phillips' New York.
Phi_Other	Phi_Other is a dummy variable that equals one if the sale takes place at one of Phillips' other branches.

Panel B Variable Definitions for Laboratory Experiment

Variable	Definition
Bid	Bid is the willingness to pay, elicited by means of the BDM method (Becker, DeGroot, and Marschak (1964)) for a painting. It ranges from 0 to 100 ECU (Experimental Currency Unit). Bidding 0 ECU indicates unwillingness to participate in the auction.
Purchase Intention (PI)	The Purchase Intention (PI) is the equally weighted average of the responses to four questionnaire items measuring the intention to purchase a painting (constructed following Dodds, Monroe, and Grewal (1991)). The four items are "I would love to buy this painting." (PI1), "I may spend more than intended on buying this painting." (PI2), "I would like to buy this painting immediately." (PI3), and "I regard the purchase of this painting as a waste of money." (PI4, reversed scale). Each item ranges from 1 to 7, where a higher value of the measurement indicates a stronger intention to purchase.
Rank	Rank is the ranking preference for the six paintings in each round. No.1 stands for the most favored painting and No.6 indicates the least favored. We allow for tied rankings for multiple paintings. For example, one can rank both the red and blue painting to be No.1 (the most favored). In the regression analysis, Rank is reversed such that a higher rating represents a higher position in the hierarchy.
Pleasure	Pleasure is the Pleasure-Displeasure dimension in the PAD emotional state model (Mehrabian and Russell (1974)). It responds to judgments of evaluation, with higher evaluations of stimuli being associated with greater pleasure induced by these stimuli (Mehrabian (1996)). Pleasure is the average

	of two items, "Unhappy-Happy" and "Annoyed-Pleased", each ranging from 1 to 7. A higher rating indicates more Pleasure.
Arousal	Arousal is the Arousal-Nonarousal dimension in the PAD emotional state model (Mehrabian and Russell (1974)). It responds to judgments of high-low stimulus activity in terms of level of mental alertness and physical activity (Mehrabian (1996)). Arousal is the average of two items: "Relaxed-Stimulated" and "Calm-Excited", each ranging from 1 to 7. A higher rating indicates greater Arousal.
Red	Red is the hue defined in the Munsell system with the parameter 0/360 in the HSV method.
Orange	Orange is the hue defined in the Munsell system with the parameter of 30/360 in the HSV method.
Yellow	Yellow is the hue defined in the Munsell system with the parameter of 60/360 in the HSV method.
Green	Green is the hue defined in the Munsell system with the parameter of 120/360 in the HSV method.
Blue	Blue is the hue defined in the Munsell system with the parameter of 240/360 in the HSV method.
Purple	Purple is the hue defined in the Munsell system with the parameter of 300/360 in the HSV method.
Hue Preference	Hue Preference is the individual rating of six hues (as reported in the exit survey). A rating of 1 means strongly dislike, 2 means dislike, 3 means neutral, 4 means like, and 5 means strongly like.
High-Saturation-High-Luminosity (HH)	In the Munsell system, color is decomposed into hue, chroma (saturation), and value (luminosity). Hue is the pure color. Higher saturation indicates that less neutral grey is added to the pure color, and a higher luminosity indicates that more pure white is added to the pure color. We define a representative example of the *High-Saturation-High-Luminosity (HH)* combination at 7 out of 10 in saturation and 8 out of 10 in luminosity according to the HSV method.
High-Saturation-Low-Luminosity (HL)	In the Munsell system, color is decomposed into hue, chroma (saturation), and value (luminosity). Hue is the pure color. Higher saturation means that less neutral grey is added to the pure color, and lower luminosity means that more pure black is added to the pure color. We define a representative example of the *High-Saturation-Low-Luminosity (HL)* combination at 7 out of 10 in saturation and 5 out of 10 in luminosity according to the HSV method.
Low-Saturation-High-Luminosity (LH)	In the Munsell system, color is decomposed into hue, chroma (saturation), and value (luminosity). Hue is the pure color. Lower saturation indicates that more neutral grey is added to the pure color, and higher luminosity indicates that more pure white is added to the pure color. We define a representative example of the *Low-Saturation-High-Luminosity (LH)* combination at 3 out of 10 in saturation and 8 out of 10 in luminosity according to the HSV method.
Order of Appearance	We assign a number from 1 to 6 to the red, orange, yellow, green, blue, and purple hues of the single-color paintings, respectively. The sequence of this number for each individual represents the order of appearance in which the paintings were displayed. For example, 2-1-6-4-3-5 means that the sequence of display is orange, red, purple, green, yellow, and blue. The order of appearance of the paintings is randomized at the participant level.
Gender	Gender equals 1 if the participant is female.
Cognitive Score	Cognitive Score is the number of correct answers to the three questions comprising the Cognitive Reflection Test (Frederick (2005)).
Age	Age is the participant's age as reported in the exit questionnaire.
Weather-Induced Mood	Weather-induced mood captures the degree to which a participant liked the weather on the day of the experiment; 1 is "dislike very much", 2 is "dislike", 3 is "neutral", 4 is "like", and 5 is "like very much".
Temperature	Temperature is gathered from Weather Underground (https://www.wunderground.com) in the hour when a session started and measured in Celsius (°C). The weather station chosen was the nearest to the corresponding experiment location and always within a distance of 15km.
Humidity	Humidity is gathered from Weather Underground (https://www.wunderground.com) in the hour when a session started and measured as a percentage from 0% to 100%. The weather station chosen was the nearest to the corresponding experiment location and always within a distance of 15km.
Air Pressure	Air Pressure is the atmospheric pressure gathered from Weather Underground (https://www.wunderground.com) in the hour when a session started and measured in Pascal (Pa). The

	weather station chosen was the nearest to the corresponding experiment location and always within a distance of 15km.
Cloud Coverage	Cloud Coverage is the degree of cloud coverage gathered from Weather Underground (https://www.wunderground.com) on the hour when a session started. 1 is “clear sky”, 2 is “scattered clouds”, 3 is “partly cloudy”, 4 is “mostly cloudy”, and 5 is “overcast or misty.” The weather station chosen was the nearest to the corresponding experiment location and always within a distance of 15km.
Rain Before	Rain Before equals 1 if it had rained shortly before a session. This was recorded by the experimenter.
Art Appreciation	Art Appreciation is the degree of affinity towards visual arts. 1 indicates “dislike very much”, 2 “dislike”, 3 “neutral”, 4 “like”, and 5 “like very much”.
Art Background	Art Background is an aggregate index composed of the answers to four questions about the frequency of attending art-related events (0 is “almost never”, 1 is “once or twice per week, 2 is “once or twice per month”, and 3 is “once or twice per year”), whether a participant has an art-related education (0 is “No”, and 1 is “Yes”), whether he/she has had painting classes (0 is “No”, and 1 is “Yes”), and whether he/she comes from a family with an artistic background (0 is “No”, and 1 is “Yes”).
Old Master	Old Master is a dummy variable gauging a subject’s art taste. Old Master equals to 1 if the participant favors the genre of old masters. The participants can also indicate “No preference”.
Modern & Contemporary	Contemporary & Modern is a dummy variable gauging a subject’s art taste. Contemporary & Modern equals 1 if the participant prefers impressionism, modern art, or contemporary art. The participants can also indicate “No preference”.
Expense	Expense is the annualized sum of the expenses related to accommodation, transportation, food and drinks, tuition fee, and other living expenses. It serves as a measure of participant’s wealth level.
Have A Loan	Have A Loan equals 1 if the participant had a student loan at the time of experiment and 0 otherwise.

Online Appendix

Online Appendix I Color Theories and Decision Making

1. Color Theories

Theories of colors have been proposed and developed through the ages, starting with Empedocles and Aristotle, by painters, physicists, philosophers, psychologists, and recently neuroscientists. These theories have mainly focused on color systems, the emotional impacts of colors, and vision processing.

1.1 Color Systems

A color system consists of three major aspects: the composition of primary colors, color relationships, and their fundamental attributes. Primitive color systems can be traced back to the classical period, specifically to Empedocles in 5th century BC and to Aristotle who included an analysis of color in his *De Sensu et Sensibilibus* (On Sense and the Sensible) and *De Coloribus* (On Color). Primitive color systems in the classical period and the Middle Ages used subjective definitions of primary colors, which were often linked to physical substances such as the elements (air, water, earth, fire), or to minerals and stones which were allotted medical qualities. The theory of color was taken up again in the Renaissance in treatises by e.g. Leon B. Alberti with *Della Pittura* (*On Painting*), and Leonardo da Vinci in *A Treatise on Painting* (Hoeppe (2007), Sorabji (1972)).

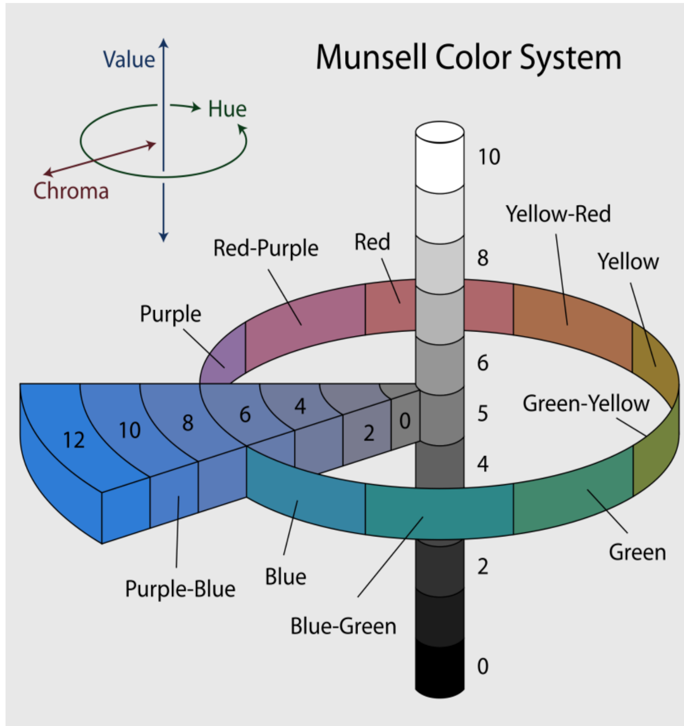
In 1666, Sir Isaac Newton decomposed natural light by means of two prisms and proposed a color system with seven primary colors. Johann Wolfgang von Goethe (1840) studied the psychological effects of colors. He also proposed a color wheel with the primary colors of red, yellow, and blue (RYB), and the secondary colors orange, violet, and green. In his framework, the semi-circle from green through yellow and orange to red are on the Plus Side, which stands for action, brightness, warmth, repulsion, etc. The other semi-circle, consisting of blue and violet is on the Minus Side and represents shadow, darkness, coldness, and distance. Around the same time, physicists Thomas Young (1802) and Hermann von Helmholtz (1852) advocated the three primary colors, red, green and blue, based on the different types of photoreceptors in the human eye (the Young-Helmholtz or

Trichromatic Theory). Helmholtz also introduced three dimensions of color that have remained in use: Hue, Saturation (also called Intensity or Chroma), and Brightness (also called Luminosity, Lightness, or Value).

James Clerk Maxwell (1857) laid the foundation of the quantitative measurement of color, colorimetry. He realized that the three colors from the RGB system were sufficient to produce the entire color space, and this insight led to the CIE color system (*Commission Internationale de l'Eclairage* / International Commission on Illumination). Physiologist Ewald Hering proposed in 1892 the Color Opponent theory, which stressed that yellow, then regarded as a mixture of red and green, was actually an elementary color in human experience. He therefore proposed to expand the group of primary colors to four (RYGB), which led to the Natural Color System (NCS) standard. Maxwell also conjectured that red was complementary to green, yellow to blue, and white to black.[1] In order to arrange colors on perceived equidistance, the American painter Albert Henry Munsell (1905, 1915) introduced a color-tree system. Hue, Chroma (Saturation), and Value (Luminosity) are the three fundamental coordinates in the Munsell system with red, yellow, green, blue and purple qualified as primary colors. The Munsell system is structured in the form of an asymmetric spindle (Figure 1, below). Along the vertical coordinate is the luminosity, representing the ratio of white to black added to a hue. On each horizontal disc, the hues red, yellow, green, blue and purple, and their five intermediate hues (such as yellow-green), appear in a circle. For a given hue of a certain luminosity, saturation is 0 in the innermost part of the spindle and the color increases in intensity as saturation increases (moving outwards). The Munsell color tree blossomed and was refined over time and is probably the most popular color system in use today. This framework also guides our choice of six major hue families (red, orange, yellow, green, blue, and purple), and further decomposes a color by means of two more dimensions (saturation, and luminosity).

[1] Hurvich and Jameson (1957) performed a hue cancellation experiment with quantitative data that supported the opponent-process theory.

Figure 1. Munsell Color System[2]



1.2 Color Processing and Perception

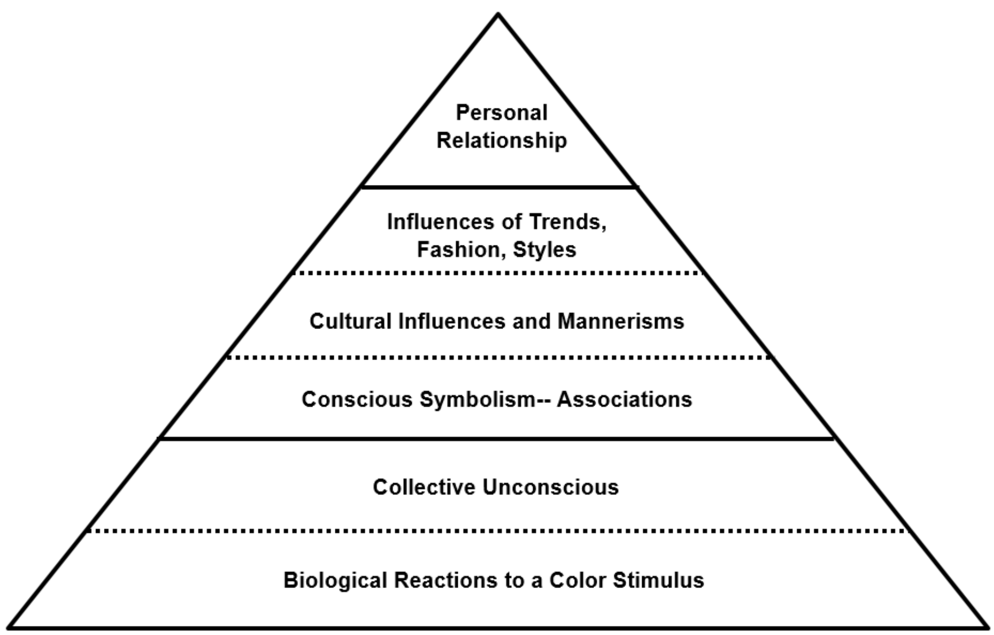
There are three types of cones in the human eye, which have peak sensitivity to long, medium, and short wavelength light, respectively termed as the L-cones, M-cones, and S-cones. The colors arousing the highest sensitivity in each are red, green, and blue (in this order). A combination of all three types of cones is needed to distinguish black and white. The L-cone and M-cone are both needed to differentiate red and green. Yellow is detected by the combination of L- and M-cones, and blue is recognized by the S-cone along with a weak but necessary stimulus to the L- and M-cones (Hunt (2004)).

Color perception is both an objective and subjective process: although color is nothing other than a form of energy, it can influence mental and emotion states. Mahnke (1996) argues that color perception induces visual, associative, synesthetic, symbolic, emotional, and physiological effects, based on how the color is experienced. He proposes a color experience pyramid with six levels of factors describing this experience (Figure 2, below).

[2] Released under the Creative Commons Attribution ShareAlike 3.0 license. Copyright: Jacob Rus.

The basic layer results from biological or physiological actions beyond our control, to color stimuli that have traces of our evolutionary heritage. An example consists of the production and release of hormones after a neural pathway carries color or light stimulation to the hypothalamus, and the pineal and pituitary glands. The second level is composed of associations not controlled for or caused by reason. The third level consists of a range of symbols related to color. At the fourth level are the color characteristics of specific cultures, while the fifth layer represents influential trends, styles, and fashions. The sixth level reveals personal preferences of color.

Figure 2. Color Experience Pyramid (by Frank H. Mahnke)



1.2.1 Single-color Effects

While the psychological effect of color is complex, some studies find commonalities in reactions to color across individuals (Evans (1974), Birren (1945, 1978), Hilbert (1987), Dove (1992), Crozier (1996), Feisner (2001)), which Cheng (2002) summarizes. Red is associated with being adventurous, aggressive, social, powerful, protective, brave, arousing, passionate, sexy, and exiting. Orange, as a mixture of red and yellow, is energetic, motivated, and jovial. Yellow is cheerful, affectionate, and impulsive. Green is associated with being stable, peaceful, calm, quiet, natural, and restful, and blue with dignity, conservatism, poise, and reserve but also with being relaxed, comfortable, soothing, and intellectual. Purple or violet arouses, as a blend of red and blue, sensations of elegance, mysticism, and magic. White is usually regarded as an achromatic "color" and is connected to spirituality, hope, holiness, purity, cleanness, and innocence. The other achromatic "color", black, is related to power, protection, status, elegance, richness, and dignity. Grey refers to being conservative, quiet, tired, passive, and lifeless.

Valdez and Mehrabian (1994) quantitatively test the emotional effects of color by means of the Pleasure-Arousal-Dominance (PAD) emotion model. They find that blue, green, and purple induce pleasure, whereas yellow, green-yellow, and yellow-red decrease the pleasure level (with red being a neutral color in terms of pleasure). On the arousal scale, green-yellow, green, and blue-green lead to greater arousal levels, but purple-blue and yellow-red decrease arousal. There is little relation of color to the Dominance emotion. With regard to the other dimensions of color, namely luminosity and saturation, pleasure is positively associated with both luminosity and saturation, and both arousal and dominance are negatively related with luminosity but positively with saturation. Colors of high saturation tend to be perceived as warm while colors of high luminosity tend to be viewed as cool.

1.2.2 Color Combinations

An early study on color combinations is by Chevreul (1839), who documents that color interactions induce different visual effects than single colors. Washburn, Haight, and Regensburg (1921) report that whether or not a color combination is experienced as pleasant is strongly correlated with how the constituent colors are experienced, an insight confirmed by Guilford (1931, 1934), Lo (1936), Hogg (1969), and Ou *et al.* (2004a, 2004b).

2. Colors and Decision Making

The number of studies of the effects of color on decision making is growing in the fields of consumer behavior, risk attitude, and financial decisions. For instance, Bellizzi and Hite (1992) show that changing colors in a shopping environment affects purchase behavior through the emotional channel of affection/pleasure (rather than arousal). Similarly, Brengman (2002) studies how different color combinations, in terms of hue, saturation, and luminosity, influence customers' emotional states in a department store setting, which then also affects purchasing behavior. In a financial setting, most studies focus on the avoidance effect induced by red stimuli. Kliger and Gilad (2012) prime subjects with a text on either a green or red background, and find that red background priming significantly increases the risk aversion in subjects' investment decisions. Chan and Park (2015) find that red in a business plan reduces the favorable decisions in venture investment. Gnambs, Appel, and Oeberst (2015) demonstrate that subjects make less risky decisions in an online test when shown a red university logo than subjects facing a grey logo. Bazley, Cronqvist, and Mormann (2017) show that portfolio losses and negative stock paths displayed in red lead to reductions in risk-taking and lower return expectations, respectively. There is also research on color effects regarding non-financial decisions. Garrett and Brooks (1987) find that ballot color influences voting results and is gender dependent. Genschow, Reutner, and Wänke (2012) document that the package color red serves as a stop sign and discourages food intake. Deng, Hui, and Hutchinson (2010) find that consumers ignore color lightness (luminosity) and focus on hue when customizing shoe colors online.

However, only very few papers touch on color attributes as pricing factors in an art auction context, or on pricing colors directly. Etro and Pagani (2012) document that the market for paintings and painted altarpieces is affected by the scarcity of pigment needed to make specific colors such as ultramarine blue, a supply-side rather that a demand-side effect, which was reflected in the sales prices of those art objects. Pownall and Graddy (2016) use RGB color decomposition to study 178 figurative prints of Andy Warhol's Monroe and Chairman Mao sold in 2012. Garay and Pérez (2018) apply a similar methodology to 1627 non-abstract paintings of 5 Latin-American painters. Both studies find that, without differentiating among the actual hues, higher intensity and lower lightness positively affect the art works' prices.[3] Charlin and Cifuentes (2018) study color attributes in 169 Mark Rotho's paintings and find that RGB color decomposition is inferior to HSV color decomposition in terms of precision and can miss important information.

[3] A problematic aspect of both studies is that averaging the RGB values of the whole art work's surface blurs the results (e.g. a painting that is one half blue and one half yellow, is considered as green). Furthermore, when analyzing figurative paintings, one cannot isolate any hue effects as hues "interact" with the painted objects (or subjects).

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Online Appendix II Emotion Measurement and Purchase Intention

This table shows the four-item short version of Pleasure-Arousal-(Dominance) emotion scale (PA(D)) and purchase intention scale (PI) that we used to measure the participants' self-reported emotions after they viewed a painting. We elicited evaluations of emotions and purchase intention by asking "How do you feel when looking at this painting?" and "To what extent do you agree or disagree?" and instructed the participants to click on one button per item. The middle point of each item was labeled "Neutral" above. The Pleasure emotion is calculated as the average of scores from P1 and P2, the Arousal emotion as the average of scores from A1 and A2, the Purchase Intention is calculated as the average of scores from PI1, PI2, PI3, and PI4 (reversed). The sequence of emotion scale from up to down was randomized and fixed as A2, P1, A1, and P2 across all rounds and all sessions. The scores assigned were not shown on the experiment interface.

Panel A: Emotion Measurement

How do you feel when looking at this painting?

Dimension	Item		Neutral	
Pleasure	P1	Unhappy	■ ■ ■ ■ ■ ■ ■	Happy
	P2	Annoyed	■ ■ ■ ■ ■ ■ ■	Pleased
Arousal	A1	Relaxed	■ ■ ■ ■ ■ ■ ■	Stimulated
	A2	Calm	■ ■ ■ ■ ■ ■ ■	Excited
Score Assigned			1 2 3 4 5 6 7	

Panel B: Purchase Intention (Continued)

To what extent do you agree or disagree?

Question	Item		Neutral	
I would like to buy this painting.	PI1	Disagree	■ ■ ■ ■ ■ ■ ■	Agree
I may spend more than intended on buying this painting.	PI2	Disagree	■ ■ ■ ■ ■ ■ ■	Agree
I would like to buy this painting immediately.	PI3	Disagree	■ ■ ■ ■ ■ ■ ■	Agree
I regard the purchase of this painting as a waste of money. (Reversed)	PI4	Disagree	■ ■ ■ ■ ■ ■ ■	Agree
Score Assigned			1 2 3 4 5 6 7	

Online Appendix III Overview of Experiment Sessions

This overview of the experimental sessions includes the locations, laboratories, number of sessions, number of subjects who showed up, number of non-color-blind subjects, endowment exchange rates, and payment methods. Subjects who failed the color vision impairment test are classified as color vision deficient.

Location	Laboratory Name	Number of Sessions	Number of Participants		Endowment Exchange Rate (100 ECU =)	Payment Method (subsequent to the lab experiment)
			Total	Without Color Vision Deficiency		
Shanghai, China	Finance Lab	14	166	161	25 CNY	Wechat Pay
Tilburg, the Netherlands	CentERlab	16	183	175	10 EUR	Bank Transfer
Tucson, U.S.A.	Economic Science Laboratory	15	132	129	16 USD	Cash

Online Appendix IV Experiment Instructions

Welcome to this experiment!

If you follow these instructions carefully, and make good decisions, you can make some money and also receive a high quality physical print in A3 size of a painting.

In the experiment, you will give your opinion about, and bid for high quality prints of different paintings. You will see images of these paintings on the screen during the session.

Our experiment consists of two parts. The first part is for practice and does not count. This part is to familiarize you with our procedures. The second part is similar to the first, except that it does count toward your final outcome.

You will see a number of prints.

- First, you give your opinion about these prints.
- Second, you also bid some money to buy the print.

How does this work? You will start the experiment with 100 ECU (Experiment Currency Units). The exchange rate is 10 ECU=1 Euro.

The print will be sold in the following way. You are required to bid an amount from 0 to 100 ECU on every print. If you do not want to bid for it, you can input 0. The sequence of events is as follows

1. You type in your bid for a print.
2. The selling price for each print is generated by the computer. The selling price will be taken from a range of typical prices of the print.

3.1 If your bid is equal to or higher than the selling price, you get the print and only pay the selling price for it.
3.2 If your bid is less than the selling price, you do not get the print and you pay 0.

Under this procedure, it is in your best interest to bid the amount that you think the print is worth to you. Let us call this amount your valuation. The two examples below illustrate what can happen if you bid less or more than your valuation.

Case 1, you bid too low:
Suppose your valuation for an item is 80 ECU and you bid only 40 ECU for it. The selling price turns out to be 50 ECU. Since your bid is less than the selling price, you do not buy the print.
On the other hand, suppose you had bid your valuation of 80 ECU. In that case, you would have received the print and paid only 50 ECU (the selling price). So you would have received a print with the value of 80 ECU to you while paying 50 ECU, and therefore a payoff of 30 ECU. That means you would have been 30 ECU better off than you were by bidding 40 ECU.

Case 2, you bid too high:

Suppose your valuation for an item is 20 ECU and you bid 80 ECU for it. The selling price turns out to be 30 ECU. Since your bid is higher than the selling price, you will get the print and pay the selling price of 30 ECU. So, you buy a print for 30 ECU but it is worth only 20 ECU to you. This means that you incur a loss of 10 ECU.
On the other hand, suppose you had bid your valuation of 20 ECU. In that case, you would have not received the print and not paid the 30 ECU. So, you would have avoided a loss of 10 ECU. That means you would have been 10 ECU better off by bidding 20 ECU.

In the bidding process, it is in your best interest to think about your valuation for the print, and then to make a bid equal to your valuation. You are on average worse off by bidding either higher or less than your own valuation.

- You don't need to think about the allocation of your funds (ECU) over different prints because for every print you can bid between 0 and 100 ECU.

- At the end of the experiment, **only one** of the prints for sale in Part 2 will be randomly selected and it is then revealed whether you have made a successful bid and receive the print.

    - If you had made a bid equal to or higher than the selling price, you will pay the selling price and will get the print. You will keep the rest of your 100 ECU which will be paid out to you.

    - If you had made a bid less than the selling price for that print, you do not get a print, and you keep your 100 ECU which will be paid out to you.

(The End)

Online Appendix V Exit Questionnaire

1. What's your gender?
   ☐ Female ☐ Male

2. In which year were you born?
   ____

3. What's your nationality (*Please include original and acquired if any.*)?
   ____________/____________/____________

4. What level of education are you currently following? (*Please mark only one.*)
   ☐ Bachelor or Equivalent
   ☐ Pre-Master or Master
   ☐ Research Master, MPhil or Doctoral Degree

5. What is (was) the name of your study program?
   ____

6. How much do you like visual arts (painting, prints)?
   ☐ Very much
   ☐ A lot
   ☐ Neutral
   ☐ Dislike
   ☐ Highly Dislike

7. What's your most favorite art genre? (*Please mark only one.*)
   ☐ Old Masters
   ☐ Impressionist and Modern
   ☐ Contemporary
   ☐ No preference

8. How often do you participate in art-related events (*E.g. exhibitions, auctions, and galleries' openings*), read art magazines, and watch art documentaries?
   ☐ Once or twice per week
   ☐ Once or twice per month
   ☐ Once or twice per year
   ☐ Almost Never

9. Do you have an art-related education?
   ☐ Yes ☐ No
   Do you have a degree of BA/MA in fine arts or art history?

☐ Yes ☐ No

Do (Did) you have painting classes in an academy or private art tuition?

☐ Yes ☐ No

Do you come from a family with an art background?

☐ Yes ☐ No

10. How many paintings or prints are (were) there in your parents' house?

☐ More than 10
☐ 7 to 10
☐ 4 to 6
☐ 1 to 3
☐ None

11. Have you ever realized or been informed that you are color blind?

☐ Yes ☐ No

12. What's your most favored color? (*Please mark <u>only one</u>.*)

☐ Red
☐ Yellow
☐ Purple
☐ White
☐ Grey
☐ Green
☐ Blue
☐ Orange
☐ Black

13. What's your least favored color? (*Please mark <u>only one</u>.*)

☐ Red
☐ Yellow
☐ Purple
☐ White
☐ Grey
☐ Green
☐ Blue
☐ Orange
☐ Black

14. How much do you like the color…? (*Please check the appropriate box for each row.*)

Color	Strongly Dislike	Dislike	Neutral	Like	Strongly Like
Red	☐	☐	☐	☐	☐
Green	☐	☐	☐	☐	☐
Yellow	☐	☐	☐	☐	☐
Blue	☐	☐	☐	☐	☐
Purple	☐	☐	☐	☐	☐
Orange	☐	☐	☐	☐	☐
White	☐	☐	☐	☐	☐
Black	☐	☐	☐	☐	☐

Grey	☐	☐	☐	☐	☐
Scores Assigned[28]	1	2	3	4	5

15. Do you have a part-time job?

☐ Yes ☐ No

16. Do you have a full-time job?

☐ Yes ☐ No

17. How much money do you receive per month from working, work study, your parents, and other sources?

____

18. What's your average monthly expenditure in the term of euro on the following aspects? (*Please Round up to 100 euro.*)

Accommodation (including rent) or Mortgage ____________

Transportation (including bus, car payment and insurance, flight, etc.) ____________

Food and Drinks ____________

Tuition Fee (including the amount that parents or others pay and loans) ____________

Others ____________

19. Do you currently have a student loan?

☐ Yes ☐ No

20. How do you like the weather today?

☐ I like it very much
☐ I like it
☐ Neutral
☐ I do not like it
☐ I dislike it very much

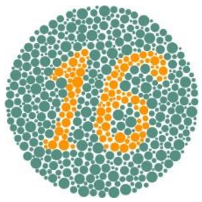
21. Did you recognize any painter of the art works shown earlier in this experiment?
Please write down the serial number before the artist name.

____

[28] Scores assigned were not shown on experiment interface to subjects.

1. Paul Cezanne, 2. Pieter Breughel, 3. Damien Hirst, 4. Jeff Koons,
5. Marc Chagall, 6. Henri Matisse, 7.Joan Miro, 8. Claude Monet,
9. Mark Rothko, 10. Ton Schulten, 11. Pablo Picasso, 12. Peter-Paul Rubens,
13. Piet Mondriaan, 14. Alberto Giacometti, 15. Andy Warhol,
16. Rembrandt Harmenszoon van Rijn, 17. Vincent van Gogh,
18. Pierre-August Renoir, 19. Alfred Sisley, and 20. Winslow Homer.

22. Please fill in the number shown on each picture.



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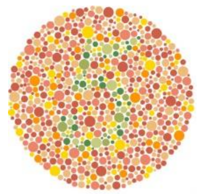

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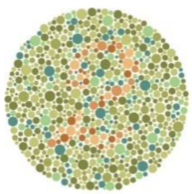

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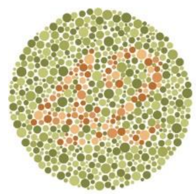

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23. Please calculate and answer the question below.

A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball.
How much does the ball cost? ____________ cents

If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? ____________ minutes

In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? ____________ days

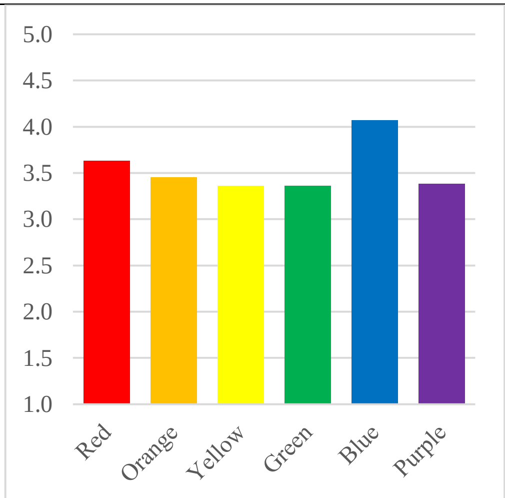
(The End)

Online Appendix VI Hue Rating by Country (from Exit Survey)

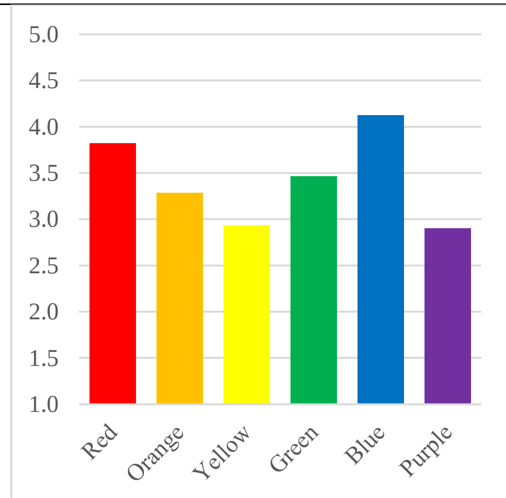
This table illustrates the average of the ratings given to the six major hues (red, orange, yellow, green, blue, and purple) by the participants in the exit survey. A rating of 1 signifies a strong dislike, 2 expresses a dislike, 3 is the neutral stance, 4 refers to a liking, and 5 represents a strong preference.

Panel A: Average Ratings of Six Major Hues in Three Countries

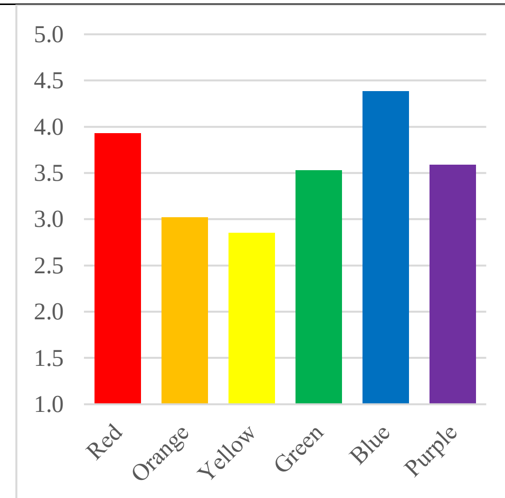
Shanghai, China (N=161)



Tilburg, the Netherlands (N=175)



Tucson, U.S.A. (N=129)



Panel B: Descriptive Statistics of Ratings by Six Major Hues in Three Countries

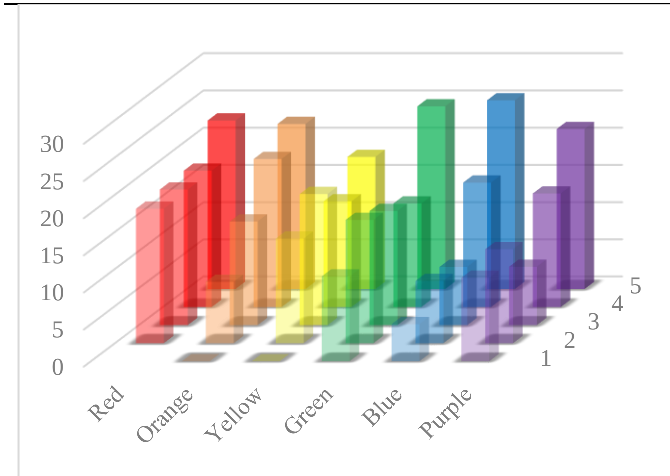
Shanghai, China (N=161)								**Tilburg, the Netherlands (N=175)**								**Tucson, U.S.A. (N=129)**							
Hue	Avg	STD	Min	25%	Med	75%	Max	Hue	Avg	STD	Min	25%	Med	75%	Max	Hue	Avg	STD	Min	25%	Med	75%	Max
Blue	4.07	0.95	1	4	4	5	5	Blue	4.13	0.85	1	4	4	5	5	Blue	4.39	0.79	1	4	5	5	5
Red	3.63	0.86	2	3	4	4	5	Red	3.82	0.82	1	3	4	4	5	Red	3.93	0.80	1	4	4	4	5
Orange	3.45	0.87	1	3	4	4	5	Green	3.46	1.24	1	3	4	4	5	Purple	3.59	1.16	1	3	4	5	5
Purple	3.39	1.13	1	3	3	4	5	Orange	3.30	1.09	1	2	4	4	5	Green	3.53	1.05	1	3	4	4	5
Green	3.36	1.12	1	3	3	4	5	Yellow	2.93	1.13	1	2	3	4	5	Orange	3.02	1.14	1	2	3	4	5
Yellow	3.36	0.88	1	3	3	4	5	Purple	2.90	1.23	1	2	3	4	5	Yellow	2.85	0.99	1	2	3	4	5

Online Appendix VII Bidding Results for Single-Color Abstract Art and Hue Preferences

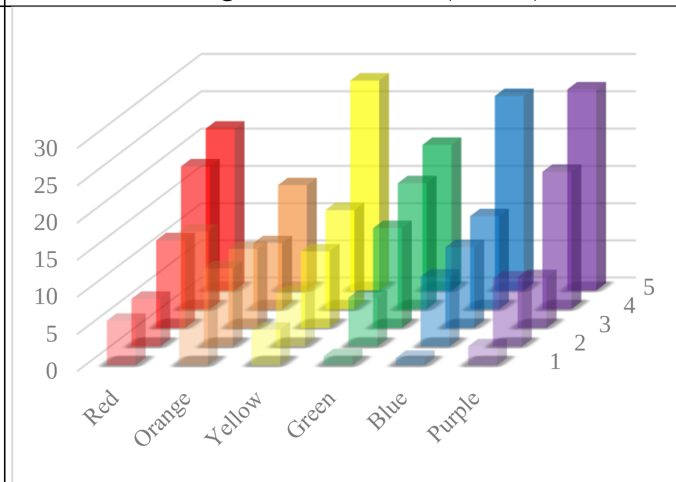
This table illustrates the average bids for each of the five ratings for each hue as shown in two-way bar charts. The horizontal axis shows the six hues, while the depth axis (labeled from 1 to 5) indicates the rating of a given hue. The height of each bar represents the average valuation of the corresponding hue (from 1 to 5). For example, the height of the red bar located at the crossing of "Red" and "5" is the average bid on the red single-color abstract art piece among participants who rated red to be "5" (a strong liking).

Panel A: Average Bid for Single-color Abstract Art of Six Major Hues Grouped by Corresponding Affect Level

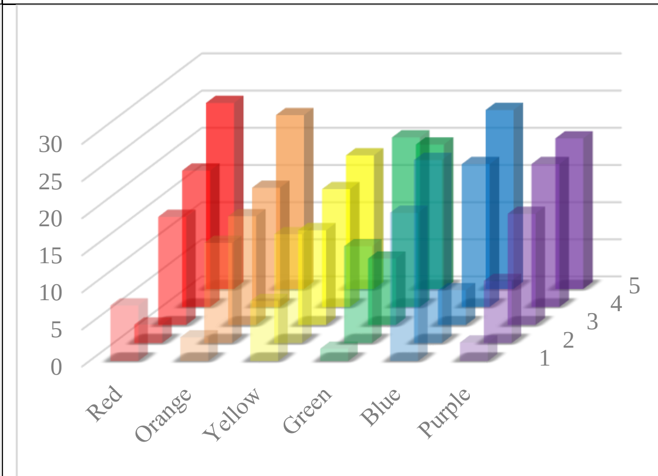
Shanghai, China (N=161)



Tilburg, the Netherlands (N=175)



Tucson, U.S.A. (N=129)

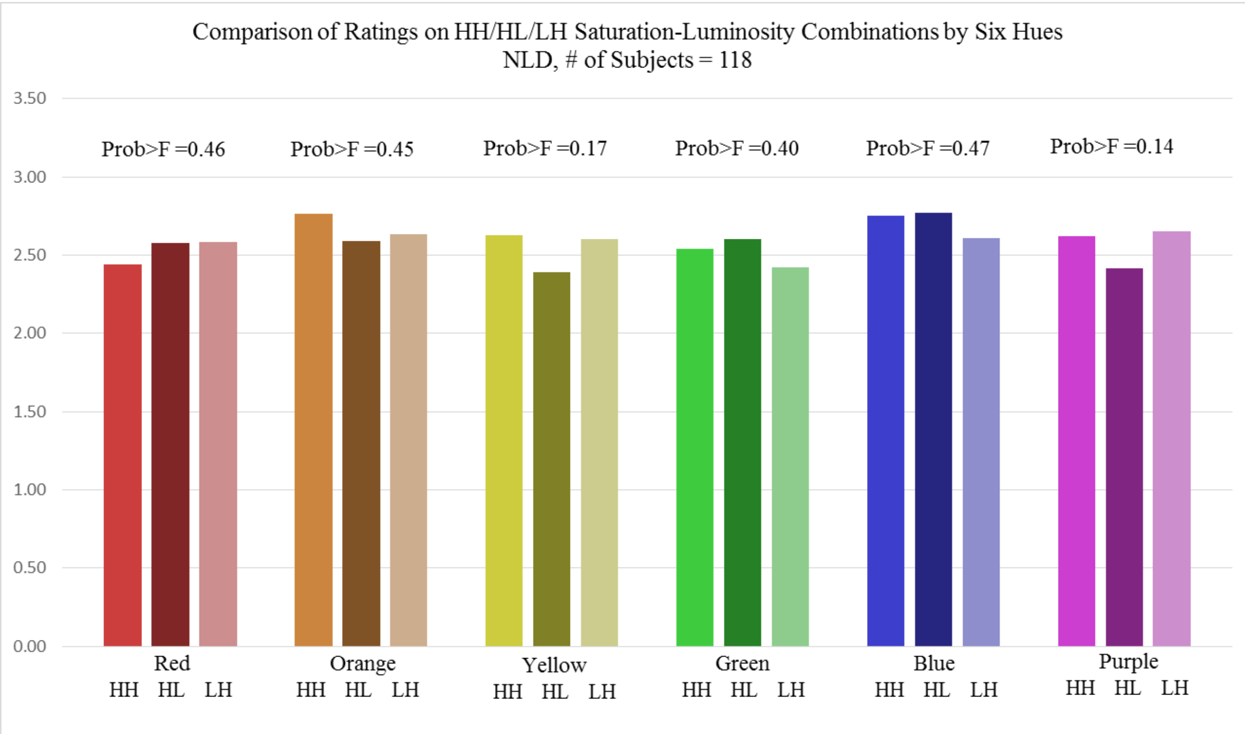


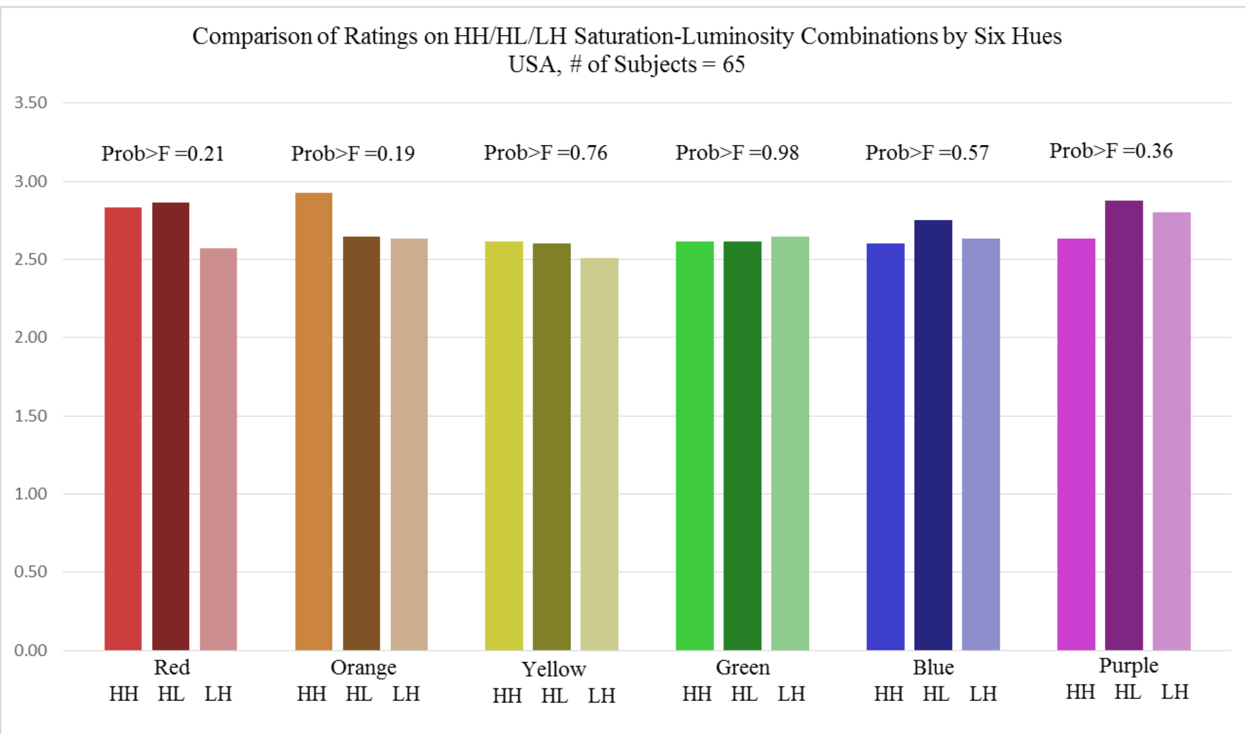
Panel B: Pearson Correlation Coefficients between Hue Preferences and Bids in the Three Countries

Shanghai, China (N=966)		Tilburg, the Netherlands (N=1050)		Tucson, U.S.A. (N=774)	
Coefficient	0.15	Coefficient	0.24	Coefficient	0.20
P-Value	<0.0001	P-Value	<0.0001	P-Value	<0.0001

Online Appendix VIII Saturation-Luminosity Variations

These two graphs report the comparisons of ratings on HH/HL/LH Saturation-Luminosity combinations for each of the six hues of the single-color Mark Rothko paintings in experiments performed in the Netherlands and the U.S. A rating of 1 signifies a strong dislike, a rating of 2 expresses a dislike, a rating of 3 is the neutral stance, a rating of 4 means a liking, and a rating of 5 represents a strong liking. The bar height indicates the average of the ratings on the corresponding Hue-Saturation-Luminosity as labeled below. The joint F-tests of whether the three rating averages are equal within each hue are reported as above the corresponding hues.





Online Appendix IX Predicted Emotions and Single-color Abstract Art Valuation

This table reports results of a two-stage model. In the untabulated first stage, we regress the emotion pleasure (arousal) on the rating of the corresponding hue (from the exit questionnaire). In the second stage, we regress Bid, Purchase Intention (PI), and Rank on the predicted emotions $\widehat{Pleasure}$ and $\widehat{Arousal}$ from the first stage.

Dep. Var.:	Model 1 Bid			Model 2 PI			Model 3 Rank		
	CHN	NLD	USA	CHN	NLD	USA	CHN	NLD	USA
$\widehat{Pleasure}$	9.559***	10.02***	10.76***	1.059***	0.720***	0.692***	1.720***	2.033***	2.088***
	(1.938)	(1.073)	(1.745)	(0.134)	(0.0640)	(0.0860)	(0.251)	(0.171)	(0.235)
$\widehat{Arousal}$	-0.850	-0.350	-2.607*	-0.0418	-0.0264	0.00846	-0.312	-0.262	-0.515**
	(1.711)	(1.187)	(1.374)	(0.123)	(0.0640)	(0.0680)	(0.231)	(0.183)	(0.229)
Constant	-18.61**	-21.70***	-16.07**	-1.407***	-0.466	-0.624*	-2.216**	-3.205***	-2.927***
	(7.647)	(4.470)	(6.437)	(0.488)	(0.305)	(0.335)	(0.920)	(0.727)	(0.867)
Observations	928	1,050	774	928	1,050	774	928	1,050	774
R-squared									
Number of Subjects	161	175	129	161	175	129	161	175	129
Subject FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES

Online Appendix X Predicted Emotions and Dual-color Abstract Art Valuation

This table reports results of a two-stage model. In the untabulated first stage, we regress the emotion measurement of pleasure (arousal) on the ratings for the corresponding two constituent hues (from the exit questionnaire). In the second stage, we regress Bid, Purchase Intention (PI), and Rank on the predicted emotions $\widehat{Pleasure}$ and $\widehat{Arousal}$ from the first stage.

Dep. Var.:	Model 1 Bid	Model 2 PI	Model 3 Rank
$\widehat{Pleasure}$	7.283***	0.686***	1.875***
	(0.933)	(0.0579)	(0.169)
$\widehat{Arousal}$	-0.316	-0.0210	0.142
	(1.122)	(0.0682)	(0.232)
Constant	-12.21**	-0.171	-3.946***
	(4.803)	(0.309)	(1.018)
Observations	2,790	2,752	2,790
R-squared			
Number of Subjects	465	465	465
Subject Fes	YES	YES	YES