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The impact of color palettes on the prices of paintings

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Abstract We emphasize that color composition is an important characteristic of a painting. It impacts the auction price of a painting, but it has never been considered in previous studies on art markets. By using Picasso's paintings and paintings of *Color Field Abstract Expressionists* sold in Chrisite's and Sotheby's auctions in New York between 1998 and 2016, we demonstrate the method to analyze color compositions: How to extract color palettes from a painting image and how to measure color characteristics. We propose two measures: (1) the surface occupied by specific colors, (2) color diversity of a painting composition. Controlling for all conventional painting and sale characteristics, our empirical results find significant evidence of contrastive paintings, i.e., paintings with high diversity of colors, carrying a premium than equivalent artworks which are performed in monochromatic style. In the case of Picasso's paintings, our econometric analysis shows that some colors are associated with high prices.

Keywords Art markets · Hedonic pricing · Picasso · Rothko · Visual perception · Color · Color quantizing

JEL Classifications: Z11 · C810

"Colors, like features, follow the changes of the emotions." Pablo Picasso

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All images of artworks used in the paper are obtained from free online database artvalue.com.

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1 Introduction

As the art market bids new price records every year, the question of the main determinants of the prices of artworks returns in the focus of economics literature. Conventional price determinants can be classified into three main categories: the intrinsic characteristics of an artwork, sale conditions (country of sale, auction house and time) and acquired characteristics (provenance of an artwork, whether it was exhibited before or mentioned in art catalogs). The intrinsic characteristics of an artwork are supposed to measure its quality. Up to now the standard set of intrinsic characteristics includes size, support and the presence of the artist's signature. And there are no characteristics which measure visual appeal of an artwork. We suppose that this is caused by the inability to analyze a painting image.[1] In particular, we know little about the value or premium that individuals put on color—one of the principal components of our visual perception of an artwork. This paper analyzes color palettes of artworks. We propose a method to quantify color composition of an artwork. We show that color composition is an important characteristic of an artwork, and that it has an influence on a price of an artwork.

The importance of colors is confirmed in marketing literature and in psychology. There is evidence that different colors trigger different human emotions (Hemphill 1996; Boyatzis and Varghese 1994; Cimbalo et al. 1978). This has been extensively exploited in marketing science where researchers have found the relation between the color of products and consumer behavior (Hagtvedt and Brasel 2017; Labrecque and Milne 2012; Puccinelli et al. 2013; Deng et al. 2010). The visual sense is the strongest sense developed in humans. Therefore, it is only natural that 90% of an assessment of a product is made by color alone. This has motivated us to study whether color perception has an impact on the price of a very particular good—a painting.[2]

Combining different colors to create more appealing color scheme is an important artifice used by artists, especially in Modern and Contemporary Art. We propose to measure the colorfulness of artworks. Some artworks are executed in polychromatic style and have few different colors, while other artworks have many different colors. Intuitively, a painting with too few colors may seem to be flat, while big diversity of colors makes the work more contrastive and catchy. We find higher prices for paintings with a high diversity of colors than for paintings in a monochromatic style. Additionally, on the example of one artist we show that some particular colors can be important in determining the price of an artwork. But this finding is artist-specific and we do not claim to find a universal result which is applicable to the whole art market. As each artist uses colors differently, each artist must be considered separately.

[1] In several studies, the subject of a painting (landscape, portrait, etc.) or the number of figures [in the case of figurative works] has been considered as price explanatory variables (Etro and Pagani 2012, 2013; Etro and Stepanova 2016, 2017). But these studies focus on the *Old Masters* where the classification of subjects is unambiguous. Modern Art, in turn, presents a puzzle for defining subjects. A possible solution is to use the artist's age [under the assumption that paintings done in the same year are close in style] (Galenson 2000; Hodgson 2011; Hellmanzik 2009).

[2] Neuroscientists who studied human reaction to the abstract art confirm that color characteristics of paintings play crucial role (Mallon et al. 2014).

The relation between color composition of an artwork and its price is still a new research area. We did not find any previous work on it to our best knowledge. The only exception is Pownall (2014).[3] Using the example of Andy Warhol's color prints, she demonstrates that darker colors carry a premium. Although it is impossible to compare our results to hers due to the difference in methodologies and measures applied, we believe that the novel technique to quantify color compositions which we use in the current paper gives deeper insight into the "color–price" relation, and that our findings complement Pownall's work.[4]

The paper is organized as follows. In the next section, we explain the hedonic pricing model used to measure the impact of painting characteristics on prices of paintings. In the same section, we explain our choice of the dataset and explanatory variables. We introduce the color variables, and how they are estimated from the digital images taken from electronic auction catalogs. We briefly review computer science literature on color quantization to advocate the chosen methodology of image color analysis. In Sect. 3, we discuss the results of our analysis and Sect. 4 provides concluding remarks.

2 The hedonic pricing model and the data

2.1 The hedonic pricing model

A vast majority of studies on price determinants have been based on a hedonic pricing model (Chanel et al. 1996; Agnello and Pierce 1996; Higgs and Worthington 2005), so we have adopted it as our workhorse. A hedonic price function can be used when a good has a number of elements which all add value to the price of the good. We use the hedonic function to estimate the degree to which artworks characteristics explain art prices.

The price of an artwork is regressed on a set of measurable characteristics: the intrinsic characteristics of a painting, sale characteristics, etc. The estimated regression coefficients represent the buyer's willingness to pay a premium for a particular characteristic. Here we run a hedonic regression of the (natural logarithm of) price p_{it} of work $i (i = 1, \ldots, I)$ at time t on the set of measurable characteristics m $(m = 1, \ldots, M)$ of an artwork $i (i = 1, \ldots, I)$ at time $t - x_{imt}$:

$$p_{it} = \sum_m \alpha_m x_{imt} + c(t) + e_{it},$$

where $c(t)$ is the market-wide price effect. It can be represented by a time trend or by a set of time dummies: $c(t) = \sum_t \gamma_t d_t$, where d_t is a time-dummy variable of value 1 if the work is sold in period t, or otherwise zero.

e_{it} is an error term, and α_m's and γ_t's are parameters to be estimated in the OLS regression.

[3] We thank our referee for pointing this out to us. Later version of this paper is published as Pownall and Graddy (2016).

[4] Further discussion of Pownall (2014) follows in the next section.

The dependent variable—p_{it}—is the (natural logarithm of) price paid by the successful bidder.[5] As the dependent variable is the natural logarithm of the price, the coefficient of a particular independent variable is interpreted as the percentage change in price due to a unit change in a particular characteristic, while other characteristics are held constant. For example, if the variable *canvas* has a coefficient equal to α_{canvas}, this means that the price of a painting on canvas is $exp(\alpha_{canvas}) - 1$ percent more expensive than the price of a painting on a *wooden support*—omitted from the regression to avoid linear dependency ($\alpha_{wooden\ support} = 0$ and $exp(\alpha_{wooden\ support}) = 1$).

Regression coefficients γ_t are interpreted as the prices of the characteristic-free works of each period. They are used to construct a price index. However, if the construction of a price index is not the main research question, then the set of time dummies, d_ts, can be replaced by a continuous time variable representing a price time trend.

2.2 The data

In this paper we will consider two models: One focuses on one particular artist, Picasso, and another—on the group of artists belonging to *Color Field Abstract Expressionism* movement in art. By focusing on one particular artist, we are able to control for a large part of the heterogeneity which occurs in pricing the cross section of artworks. But to avoid creating the impression that color analysis is only important for the market of Picasso's works, we consider another interesting example—the school of *Color Field Abstract Expressionism*.

(a) Picasso

We have chosen Picasso for our econometric exercise for two reasons. Firstly, color was immensely important to Picasso. He always experimented with color palettes during his working life, and we can study whether particular colors and the ways they are combined impact prices. The second reason for our choice is that he produced an enormous number of works during his life and they are always present in the semiannual Modern Art sales at Christie's and Sotheby's in New York. There is enough turnover in the market and market liquidity such that we have enough variation in the type of artworks and images which were sold during the time period under investigation. For this reason several cultural economists tested new methods or hypotheses on a set of Picasso's artworks (Pesando 1993; Czujack 1997; Scorcu and Zanola 2011). Czujack (1997) is of special interest because the set of painting characteristics used in the paper is the largest across studies of art markets which apply the hedonic methodology. We use the same set of painting characteristics to be able to compare our results to her findings.

Our set of explanatory variables includes three major categories: sale characteristics, intrinsic characteristics of a painting and acquired painting characteristics. As our intention is to focus on intrinsic painting characteristics, we want to maintain the sample as homogenous as possible with respect to other explanatory variables. That is why we have only two major auction houses—Christie's and Sotheby's in New York

[5] The price is equal to the auction hammer price plus the buyer's premium. The buyer's premia are included as these differ from period to period and, more importantly, between auction houses.

to avoid price variance due to the fact that works were sold in different locations by different auction houses. At the same time, Christie's and Sotheby's in New York are principal marketplaces for Picasso's works. (They have the largest market share of his sold works in the world.)

Sale characteristics are the following: (1) the year of sale (we take the time frame: 1998–2016); (2) the auction house and (3) the evening auction dummy. (Sales of important artworks take place in the evening, and indeed, the average price of an item from an evening auction is eight times higher than the average price of an item from a day auction in our sample.)

Acquired characteristics represent the history of a particular painting and include (1) how many times the work was publicly exhibited and (2) how many different art books mentioned it. (We define a variable "mentioned in more than 2 art books").[6] This information is provided in auction catalogs.

The intrinsic characteristics of a painting include: (1) canvas or wooden support (we have selected only oil paintings executed on a canvas or wooden support in order to have a homogeneous sample; this leaves out Picasso's works on paper, collages and mixed techniques[7]); (2) size; (3) signature and date; (4) to proxy the painting genre we have attributed his paintings to eight major working periods (as defined in Czujack 1997). The eight periods differ according to quality, number of paintings produced and their genres. The 127 sold items in our sample (37%) belong to the last and longest period—*the Old Picasso* period which lasted from 1954 to 1973 in which Picasso produced many paintings that were not new conceptually and the themes repeated each other. The highest prices are associated with *the Blue and Rose Period* (1902–1906), and we have 7 items from this period in our dataset. This period lasted 4 years, and it is associated with the first paintings in Picasso's style. In an alternative regression, we use a continuous variable, the artist's age, instead of working periods.

The list of the intrinsic characteristics of a painting also includes color variables which we will define in the next section after explaining how we quantify color.

Summary statistics for all explanatory variables are given in "Appendix Table 3".

(b) Color Field Abstract Expressionism

The works of artists who belong to *Color Field Abstract Expressionism* are freed from the subjective and objective contexts. Color composition is the only subject. The Color Field painters sought to rid their art of superfluous rhetoric. Their works present abstraction as an end in itself. Any recognizable imagery is eliminated. Only flat

[6] In the period 1942–1978, Christian Zervos produced 34 volumes of *catalogue raisonnee*, in which most of Picasso's works are registered. This registration is considered to be a proof of authenticity, and it is assumed to influence prices. In our case, Christie's and Sotheby's only auction authentic works and in the Provenance indicate, apart from Christian Zervos *catalogue raisonnee*, other important art catalogs. So the variable "mentioned in more than 2 art books" means that the painting is mentioned not only in Christian Zervos *catalogue raisonnee* but in some other art catalogs. Pre-auction catalog information refers to extremely prominent and influential publications. It is reasonable to expect that Christie's and Sotheby's use valuable catalog space to report the fact that the piece has been reproduced in a book only if it is perceived as an important work of reference. We expect such references to have a positive effect on prices.

[7] Works on paper and collages are usually drafts of his oil paintings with prevailing use of black and white colors to sketch the objects, so we do not want to consider these works in our analyses of Picasso's color palette.

areas of color are present, which these artists considered to be the essential nature of visual abstraction (Anfam 1990; Sandler 1976; Landau 2005). Very influential artists, Adolph Gottlieb, Robert Motherwell, Clyfford Still, Hans Hofmann and Mark Rothko, are classical representatives of this art direction, and this is without mentioning the sensational prices that their works have recently obtained. We have a sample of 371 observations of their paintings sold at NY Christie's and Sotheby's in the period 1998–2016. For each observation, we have information on size, signature, type of support and date of creation (summary statistics of variables is given in "Appendix Table 4"). This art direction represents an interesting case for testing our hypothesis that color composition influences painting price.

2.3 Quantifying color

For each observation, we have a digital image of a painting. We obtained the image from the auction catalogs that are available on the Web sites of the auction houses.[8] We believe that this is a precious source of information, but it has been disregarded in the economic analysis of art market prices.

Digital images are represented by pixels. Each pixel has a color which is a coordinate in the three-dimensional integer R–G–B space (red–green–blue). The R–G–B space is the conventional way to represent color in electronic systems, computers, cameras, etc., and it is grounded on the theory of the human perception of colors. The RGB scale goes from 0 to 250 where R 0 G 0 B 0 is pure black and R 250 G 250 B 250 is pure white. It distinguishes between 15.6 million (250^3) different colors.

In our sample, an image contains 2000 different RGB colors on average, but most of them are just brightness and gradient variations of the principal colors. We are faced with the classical statistical problem of dimensionality reduction, where for each observation [each image] we want to reduce the number of RGB colors to the principal ones, i.e., those that occupy the most space on the image.

Facing the same problem of dimensionality reduction, Pownall (2014) calculates average values of red-R, green-G and blue-B for each observation [each image]. These average values are significant in her hedonic regression models. But each of her regressions includes only one variable: or average value of red-R, or average value of green-G or average value of blue-B. There is no regression where all three variables appear together, so we do not know how their mutual behavior impacts the price. The significance of the average values allows to conclude that color is an important painting characteristics, and that darker colors, i.e., smaller values of average red-R (green-G or blue-B), carry a premium. This is very simple solution to the problem of dimensionality reduction. But as nothing is mentioned about mutual behavior of the color variables it is hard to give visual interpretation of the result: Does the finding mean that absolutely black painting—R 0 G 0 B 0—will have the highest price?

The interpretation of the results impedes us from employing principal components analysis frequently used for the dimensionality reduction problems. Instead, we use

[8] In a small number of cases, auction catalogs on Web sites are not available for free. Alternative solutions are the online databases artvalue.com and artsalesindex.artinfo.com

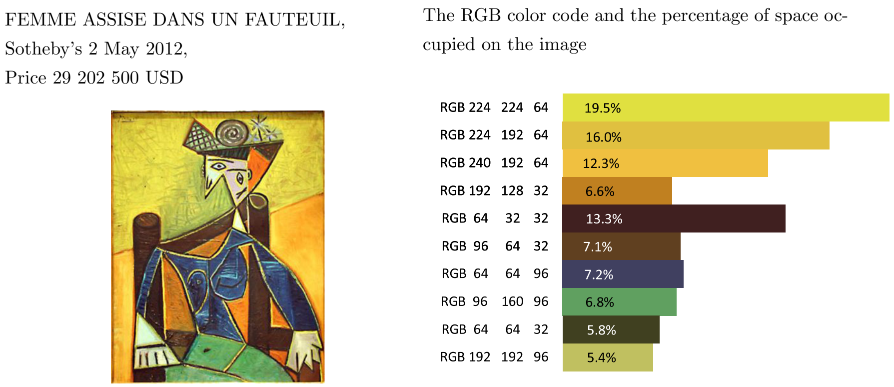


Fig. 1 Quantizing colors. (Color figure online)

clustering approach which allows us to construct explanatory variables with nice visual interpretation. The three-dimensional clustering algorithm is applied (also known in computer science as color quantizing algorithm, Orchard and Bouman (1991); Brun and Trémeau (2003)). It rounds up the colors that are close to each other in the sense of the Euclidian distance in the RGB space. For each image, we identify 10 principal colors that occupy the most space and the percentage of space occupied by each color. (An example is provided in Fig. 1.)[9] Color clustering is the main technique used in computer science for image data compression, that is, the reduction of the amount of data (number of pixels) needed to display an image while preserving the main color characteristics so that the human eye cannot see the number of colors reduced (Orchard and Bouman 1991; Brun and Trémeau 2003). The same principles are used (1) in image search engines, where only the main color characteristics of an image are needed to identify whether an image corresponds to the search query (Niblack et al. 1993); (2) in robot vision—to identify objects by their color characteristics (Swain and Ballard 1991).

We propose two approaches to characterize the color composition of a painting: (a) presence of specific colors, (b) color diversity.

(a) Color clusters

A possible approach to quantify the impact of color on a price of an artwork is the identification of colors which carry a premium if they are present on an artwork. But this approach is artist-specific. We demonstrate it on Picasso's artworks, and we do not claim to find a universal result which is applicable to the whole art market.

Figure 2a displays all of the 200 principal colors that were found on Picasso's paintings weighted by how many times we encountered each color. Figure 2b, in turn, displays the same colors but weighted by the average price of the paintings on which

[9] As color brightness and gradients are rounded off, it is not critical that there may be differences in the brightness of an image due to the amount of external light hitting the object. We also do not need high image resolution, i.e., a larger amount of pixels (a color is associated with each pixel), because we round off colors to the principal ones. Actually, the color quantizing algorithm is a workhorse tool in computer science used to reduce the memory weight of an image (image resolution) while preserving its color characteristics.

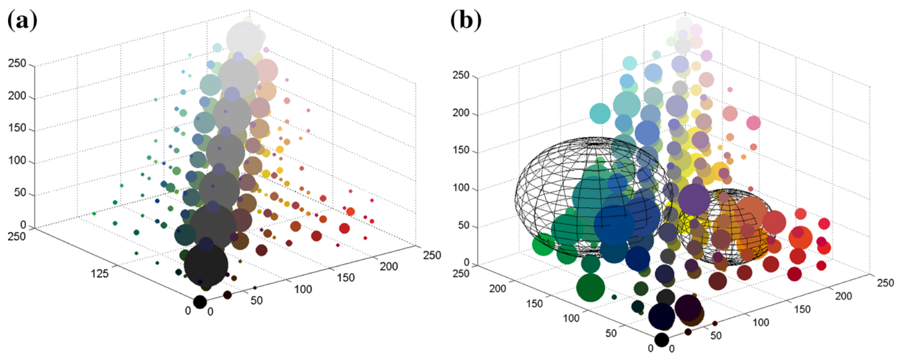


Fig. 2 Distribution of colors encountered on the paintings of Picasso. **a** Weighted by the encounter frequency and **b** weighted by the average price of works on which we encounter the color, with 2 clusters of high priced colors. (Color figure online)

we found the color. From Fig. 2a, we notice that colors from the main diagonal [which connects full black with full white and goes through all variations of gray]—black/gray spectrum, and colors close to the black/gray spectrum (ochers, cream and brown) are frequently used and we find them on a large number of works. But the main diagonal loses all its weight in Fig. 2b. The weight, in terms of average prices, moves to colors that are distant from the main diagonal.

In Fig. 2b, one can see two concentration areas: the blue-teal colors and the orange colors. We identify these two concentration areas by specifying two spheres centered in the most "heavy" [in price terms] points and with a radius big enough to cover the concentration area of high priced colors (Fig. 2b). We call them the blue-teal cluster and the orange cluster. The blue-teal cluster is centered in R 32 G 128 B 128, and it has a radius of 72 points. The orange cluster is centered in R 192 G 128 B 32, and it has a radius of 45 points.

In total, 116 paintings from our dataset (or 40% of the dataset) have colors from the blue-teal cluster (see Fig. 5 for examples of these paintings), and, on average, these colors cover 14% of the surface of the paintings and the average price for them is 7 mln. USD. (This is 30% higher than the average price of a painting in our dataset.) In total, 38 paintings from our dataset (or 12% of the dataset) have colors from the orange cluster (see Fig. 6 for examples of these paintings), and, on average, these colors cover 12% of the surface of the paintings and the average price for them is 8 mln. USD. (This is 48% higher than the average price of a painting in our dataset.) We introduce two variables for these two clusters—the surface of a painting occupied by colors from the given cluster.

(b) Color diversity of a painting composition

For each painting, we define *the diversity of colors* as an average Euclidean distance in the RGB space between the colors that are on the painting. We suppose that the bigger the diversity of colors is, the more catchy and more contrastive is the painting. We expect higher prices for paintings with a high diversity of colors than for paintings in a monochromatic style. A painting composed of pure blue (R 0 G 0 B 250) and yellow (R 250 G 250 B 0), colors that are the most distant from each other on the RGB space, will have the highest color diversity. Figure 4 presents the distribution of color diversity for Picasso paintings and for *Color Field Abstract Expressionists*. We see left-skewed distribution in the case of *Color Field Abstract Expressionists*. This can be explained by the presence of many monochromatic works (one of them is presented in Fig. 3): two, three colors similar to each other occupy all space of a painting.

Figure 3 gives examples of paintings: with high and low color diversity.

3 Empirical results

The results of our hedonic pricing models are discussed in this section. First, we discuss the general results of hedonic models and then we study how the differences in art prices across paintings are influenced by color.

We start by verifying results commonly seen in the literature. In particular, we refer to the study of Czujack (1997). Although her sample is heterogeneous in geographical locations, auction houses, types of artworks (collages and works on paper are considered together with oil paintings) and the time span is twice as long as ours (1963–1994), we can compare results for several explanatory variables: size, signature and—most importantly—the working periods. Table 1 shows the empirical results for four regressions: (1) and (2) are regressions on a full data sample, and they differ by color variables included; (2) regression with observations from the "Blue and Red Period" being excluded from the sample; (3) reduced form regression when working periods are replaced by a continuous variable, the artist's age, and time-period dummies are replaced by a continuous variable, year of sale. All regressions deliver similar results. All versions have a high 70% R^2.

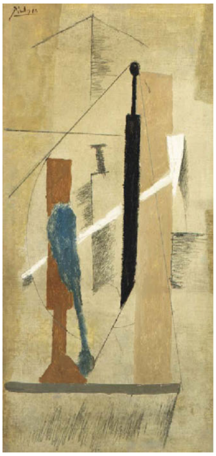
We find price difference between a canvas and a wooden support in line with (Czujack 1997). A canvas is on average 28% ($exp(0.25) - 1$) more expensive than a wooden support. Also in line with her findings, we do not observe that the artist's signature has a significant influence on prices. Fame has a positive impact on price, and a painting that is mentioned in several art books has, on average, a 60% higher sale price ($exp(0.47) - 1$). We observe significant price differences between sales in Christie's and Sotheby's auctions in line with Pesando (1993) and Pesando and Shum (1996) who find significant price differences between Christie's and Sotheby's auctions in New York in the case of Picasso's prints. This is a puzzle because these results do not confirm the "law of one price" which states that, in the absence of different transaction costs, no systematic price differences should exist between distinct market places for the same good (Ashenfelter and Graddy 2003). We confirm the presence of the afternoon effect (Beggs and Graddy 1992) with expensive works being sold in the evening sessions. Prices are positively correlated with the size of the paintings. There is a nonlinear increase in price with an increase in the size of the painting as captured by the negative and significant coefficient of the squared size of the work. In other words, evidence shows the expected results of a typical hedonic regression.

Using the time dummies, we built a biannual price index for the market of Picasso's works (Fig. 8) which indicates a strong increase. Indeed, reduced form regression (Table 1, column 4) shows that the annual price increase is on average 6.7%.

Pablo Picasso

Low diversity

average distance between colors is 53 points in the RGB space



Bouteille, verre et pipe, 1914
Christie's 10 Nov 1999
Price 167 500 USD

High diversity

average distance between colors is 165 points in the RGB space

Buste de femme assise sur une chaise, 1939
Christie's 9 May 2000
Price 4 736 000 USD

Mark Rothko

Low diversity

average distance between colors is 54 points in the RGB space

Untitled, 1968
Sotheby's 14 Nov 2007
Price 7 881 000 USD

High diversity

average distance between colors is 175 points in the RGB space

NO.6(Yellow, White, Blue over Yellow on Gray), 1954
Sotheby's 9 Nov 2004
Price 17 368 000 USD

Fig. 3 Diversity of the painting colors. (Color figure online)

Table 1 Picasso's paintings at auctions—regression results

Dependent variable: *log* price	Full sample		Full sample		Excluded "Blue and Red Period"		Reduced form regression	
Time dummies (see Fig. 8)	Yes		Yes		Yes		–	
Year of sale							0.067***	(0.009)
log Diversity of colors (point distance in RGB space)			0.579***	(0.171)	0.585***	(0.164)	0.568***	(0.165)
Surface occupied by colors in the blue-teal cluster (in 1000 cm^2)	0.210***	(0.066)	0.195***	(0.064)	0.140**	(0.063)	0.247***	(0.066)
Surface occupied by colors in the orange cluster (in 1000 cm^2)	0.360**	(0.145)	0.345**	(0.142)	0.342**	(0.136)	0.450***	(0.144)
Surface (in 1000 cm^2)	0.141***	(0.026)	0.154***	(0.026)	0.168***	(0.025)	0.136***	(0.026)
Surface squared	−0.003***	(0.001)	−0.004***	(0.001)	−0.004***	(0.001)	−0.004***	(0.001)
Canvas *versus wooden support*	0.254**	(0.129)	0.245*	(0.127)	0.263**	(0.123)	0.258**	(0.127)
Signed	0.092	(0.099)	0.076	(0.097)	0.016	(0.094)	0.070	(0.100)
Dated	0.073	(0.138)	0.040	(0.135)	0.041	(0.129)	0.072	(0.136)
Mentioned in more than 2 art books	0.475***	(0.105)	0.434***	(0.103)	0.397***	(0.099)	0.429***	(0.101)
Exhibited	0.021	(0.015)	0.019	(0.015)	0.020	(0.014)	0.028*	(0.015)
Evening sale	1.013***	(0.122)	0.974***	(0.120)	0.947***	(0.116)	1.089***	(0.119)
Sotheby's *versus Christie's*	0.200**	(0.102)	0.153	(0.101)	0.116	(0.097)	0.184*	(0.101)
Artist's age							−0.007**	(0.003)

Table 1 continued

Dependent variable: *log* price	Full sample		Full sample		Excluded “Blue and Red Period”		Reduced form regression	
Working periods (see Fig. 7)								
(1881–1901) Child and youth	Omitted		Omitted		Omitted			
(1902–1906) Blue and Rose Period	0.484	(0.331)	0.642*	(0.328)	–			
(1907–1915) Analytical and synthetic cubism	− 0.207	(0.271)	− 0.122	(0.267)	− 0.158	(0.254)		
(1916–1924) Camera and classicism	− 0.269	(0.238)	− 0.349	(0.235)	− 0.426*	(0.225)		
(1925–1936) Juggler of the form	0.078	(0.238)	− 0.062	(0.237)	− 0.128	(0.226)		
(1937–1943) Guernica and the “Style Picasso”	0.313	(0.251)	0.162	(0.250)	0.090	(0.239)		
(1944–1953) Politics and art	− 0.128	(0.269)	− 0.272	(0.267)	− 0.349	(0.256)		
(1954–1973) The Old Picasso	− 0.277	(0.262)	− 0.448*	(0.262)	− 0.544**	(0.251)		
Constant	12.028***	(0.279)	12.647***	(0.329)	12.749***	(0.316)	− 107.305***	(19.535)
Observations	296		296		289		296	
Variables	27		28		27		14	
R^2	0.704		0.716		0.737		0.671	

Standard errors in parentheses; * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

By examining Picasso's working periods, we confirm Czujack (1997) finding that the most expensive period is the "Blue and Red Picasso" and the cheapest one is the "Old Picasso." She finds that the second highest prices are obtained by works from the "Cubism Period," while we find that the second highest prices are associated with the "Guernica and the Style Picasso"—symbolism that made him famous all over the world. The age–price profile of Picasso (Fig. 7) is referred in Galenson (2011) as a canonical example of *conceptual innovator* or young genius who make radical innovations in the field at a very early age.

(a) Color clusters

Our main finding is the existence of a strong positive correlation between the price of a work and its surface occupied by colors from the blue-teal and orange clusters. A 1000-cm^2 increase of surface painted in blue-teal colors (which is 15% of the average size of a painting in our dataset) gives a 23% ($exp(0.21) - 1$) increase in the sale price. The same holds for orange colors which give a 43% increase. One can suppose that the presence of colors from the blue-teal cluster on a painting is correlated with the painting being produced during Picasso's *Blue Period*—the most expensive one. However, the correlation is only 7% and, as shown in Fig. 7, Picasso was using blue in all his working periods. Additionally, as shown in Fig. 5, the "blue" painting from 1953 (i.e., from Picasso's *Politics and Art* period) was sold at twice the price than the average price in our sample. We confirm our results even after the exclusion of observations from *the Blue Period* from the regression (Table 1, column 3).

(b) Color diversity of a painting composition

The presence of contrastive colors on the same painting is strongly and positively correlated with price. We log-transformed the explanatory variable, so the result should be interpreted as follows: a 1% increase of the average distance between colors of the same painting increases the price by 58% (the second column of Table 1). Table 2 presents the regression for the group of artists—*Color Field Abstract Expressionists*. We confirm our finding that the higher is the diversity of colors on an artwork, the higher is its price. Table 2 also contains the reduced form regression for Picasso. So we can confront the magnitude of the regression coefficient for the color diversity. We see that the value of the coefficient is higher in the case of Picasso than in the case of the *Color Field*.

4 Conclusion

The paper builds a connection between human aesthetic assessment of artworks reflected, at least in part, in prices and visual characteristics of artworks—color palettes, which we are able to extract thanks to computational advances in image processing. The framework proposed in the paper can be a useful tool for art experts, art appraisers and art collectors interested in precise valuations of artworks. Our work is not meant to provide full answers, but rather to inspire more interest in this new and amazing research direction. In the examples of Picasso's works and the works of the *Color Field Abstract Expressionists*, we show that the analysis of color palettes is a fruitful research direction toward explaining the price variation of artworks. It is

Table 2 Diversity of colors—regression results

Dependent variable: *log* price	Picasso		Color Field Abstract Expressionism	
Time dummies (see Fig. 8)	Yes		Yes	
Artists dummies	–		Yes	
log Diversity of colors (point distance in RGB space)	0.711***	(0.177)	0.435***	(0.155)
Surface (in 1000 cm^2)	0.196***	(0.025)	0.081***	(0.006)
Surface squared	– 0.005***	(0.001)	– 0.001***	(0.00005)
Canvas *versus wooden support*	0.218*	(0.129)	0.485***	(0.140)
Signed	0.044	(0.104)	0.221	(0.144)
Sotheby's *versus Christie's*	0.098	(0.107)	– 0.043	(0.105)
Artist's age	– 0.012***	(0.003)	0.021***	(0.005)
Constant	35.259***	(5.304)	– 32.037***	(10.499)
Observations	296		371	
Variables	16		20	
R^2	0.649		0.774	

Standard errors in parentheses; * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

especially important for Modern Art where intrinsic painting characteristics that can be used to explain price variation are limited. In turn, the role of color in Modern Art is conceptual, that is why color analysis is an essential part of a hedonic pricing model for the market of a particular artist or a particular art direction in Modern and Contemporary Art. We show that, in the case of Picasso, the premium is paid for paintings with contrastive colors and with blue-teal and orange colors. In the case of *Color Field Abstract Expressionism*, the premium is paid for works with contrastive colors.

Apart from Modern Art, there is another application for color analysis in the primary market for paintings of the Renaissance and Baroque periods. In those times, the production of some pigments was expensive then and the colors used to execute an artwork were an important price component. Therefore, our method will be of use in the studies of historical markets for paintings as well.

Compliance with ethical standards

Conflict of interest The author declares that they have no conflict of interest.

Appendix

See Tables 3, 4 and Figs. 4, 5, 6, 7, 8.

Table 3 Descriptive statistics (Picasso's paintings sold in New York in 1998–2016)

	Mean	SD	Min.	Max.	Av. price (USD)
Price (in USD)	5,704,449	8,382,733	101,500	67,450,000	
Diversity of painting colors (average distance between colors in RGB space)	105.4	28.43	50.5	184.5	
Surface occupied by colors in blue-teal cluster (in 1000 cm^2)	0.26	0.7	0	5.8	
Surface occupied by colors in orange cluster (in 1000 cm^2)	0.07	0.35	0	3.7	
Surface (in 1000 cm^2)	6.00	6.12	0.25	26.68	
Canvas	0.85	0.36	0	1	6,040,644
Wooden support	0.15	0.36	0	1	3,980,460
Signed	0.74	0.44	0	1	5,809,454
Dated	0.68	0.47	0	1	5,593,500
Mentioned in 0–2 art books	0.54	0.5	0	1	2,690,265
Mentioned in $>$ 2 art books	0.46	0.5	0	1	8,843,358
Exhibited	2.32	3.31	0	20	
Evening sale	0.78	0.41	0	1	7,095,347
Day sale	0.22	0.41	0	1	857,380
Sotheby's	0.37	0.48	0	1	7,439,886
Christie's	0.63	0.48	0	1	4,805,582
Working periods					
Child and youth (1881–1901)	0.06	0.23	0	1	6,531,605
Blue and Rose Period (1902–1906)	0.02	0.16	0	1	14,094,071
Analytical and synthetic cubism (1907–1915)	0.05	0.2	0	1	3,187,738
Camera and classicism (1916–1924)	0.12	0.33	0	1	2,743,730
Juggler of the form (1925–1936)	0.14	0.36	0	1	8,119,268
Guernica and the "Style Picasso" (1937–1943)	0.11	0.31	0	1	7,945,514
Politics and art (1944–1953)	0.12	0.32	0	1	4,006,710
The Old Picasso (1954–1973)	0.37	0.49	0	1	5,197,254

Table 4 Descriptive statistics (*Color Field Abstract Expressionists* paintings sold in New York in 1998–2016)

	Mean	SD	Min.	Max.	Av. price (USD)
Price (in USD)	5,704,449	8,382,733	101,500	67,450,000	
Diversity of painting colors (average distance between colors in RGB space)	92.8	28.43	24.1	186.7	
Artists					
Adolph Gottlieb (1903–1974)	0.06	0.24	0	1	1,024,315
Hans Hofmann (1880–1966)	0.37	0.48	0	1	607,604
Robert Motherwell (1915–1991)	0.25	0.43	0	1	572,450
Mark Rothko (1903–1970)	0.26	0.44	0	1	13,473,714
Clyfford Still (1904–1980)	0.05	0.23	0	1	14,166,000
Surface (in 1000 cm^2)	17.00	20.15	0.21	177.75	
Canvas	0.67	0.47	0	1	6,708,166
Wooden support	0.33	0.47	0	1	560,223
Signed	0.80	0.40	0	1	5,809,454
Sotheby's	0.47	0.50	0	1	4,330,850
Christie's	0.53	0.50	0	1	5,021,202

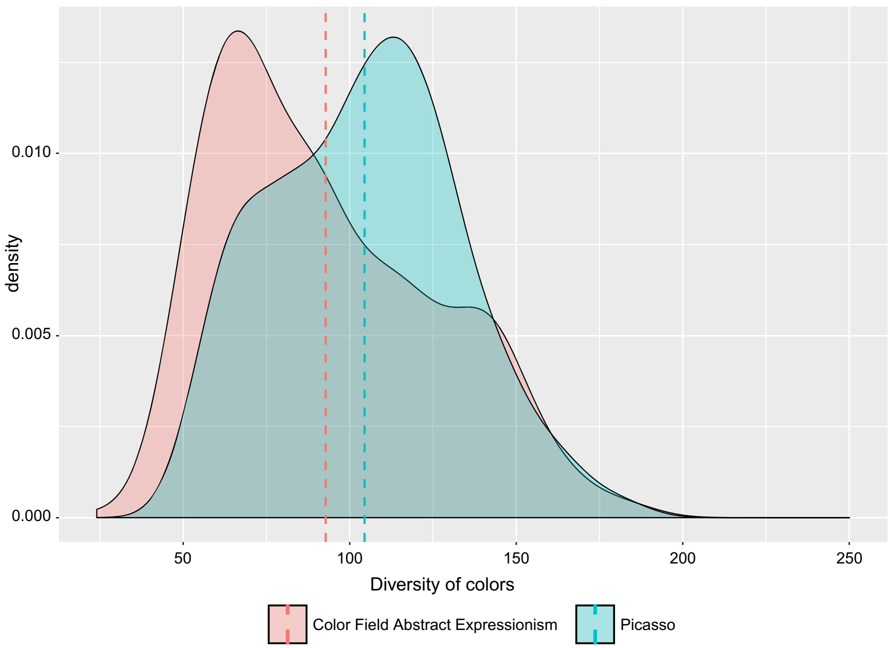


Fig. 4 Distribution of the *diversity of the painting colors* (Picasso and *Color Field Abstract Expressionists* artworks). (Color figure online)

FEMME AUX BRAS CROISES, 1902

Christie's 8 Nov 2000
Price 55 006 000 USD

FEMME ASSISE EN COSTUME ROUGE SUR FOND BLEU, 1953
Christie's 8 May 2013
Price 8 523 750 USD

TETE DE FEMME (PORTRAIT DE FRANCOISE), 1946
Sotheby's 2 May 2012
Price 6 914 500 USD

Fig. 5 Example of paintings that belong to the blue-teal cluster. (Color figure online)

FEMME AU CHAPEAU VERT, 1947

Sotheby's 4 Nov 2009
Price 8 146 500 USD

FEMME ASSISE DANS UN FAUTEUIL, 1953

Sotheby's 7 May 2014
Price estimate 8 000 000 USD

JEUNE FILLE AUX CHEVEUX NOIRS (DORA MAAR), 1939
Sotheby's 8 May 2007
Price 8 216 000 USD

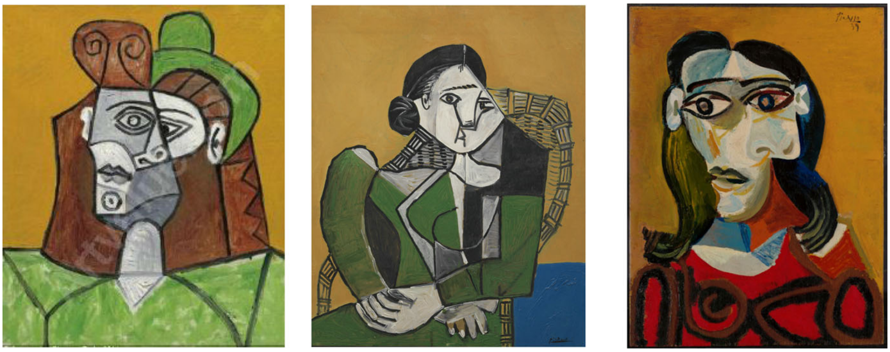


Fig. 6 Example of paintings that belong to the orange cluster. (Color figure online)

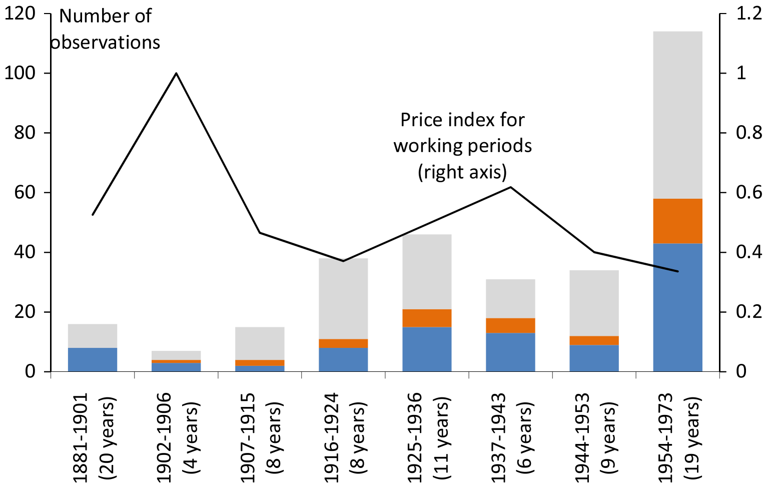


Fig. 7 Fixed effects of Picasso's working periods (Table 1) and the number of artworks from each period in our dataset. Note: The reference period, the Blue and Rose Period (1902–1906), is set up to 1. Bars indicate the number of works belonging to a particular working period. The works that belong to the blue-teal cluster are in blue, the works that belong to the orange cluster are in orange, the rest of the works from a particular period that do not belong to neither of the two clusters are in gray. (Color figure online)

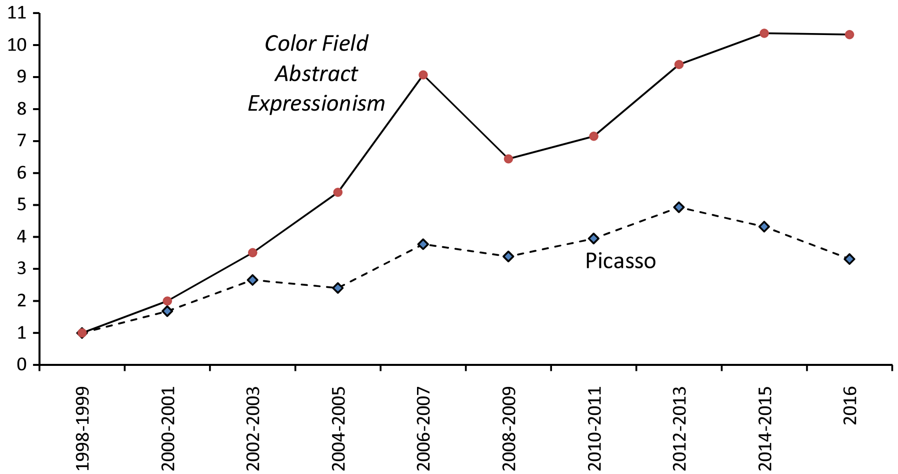


Fig. 8 Price indexes of Picasso's paintings and paintings of *Color Field Abstract Expressionists* sold in New York. Note: Reference period is 1998–1999, and it is set up to 1. (Color figure online)

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