‘The missing Pink’: Color as a price determinant among the Color Field Painters

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I. Introduction

In *Drunk Pink Tank*, author Adam Alter outlines the history of using the color pink to calm bus riders, away football teams, patients in psych wards, and misbehaving school children. The bright bubblegum pink color has been proven to have a physical effect on human bodies. Adrenaline is less likely to flood into the capillaries. Muscles are more prone to relaxation. The bubblegum pink color makes people feel at ease. Studies have proven certain colors affect how people feel and behave (Boyatzis and Varghese 1993; Hemphill 1995; Singh et al. 2011; Labrecque and Milne 2011). Advertisers know that blue is a calming, secure presence –aligned with the values and logos of corporate America– and red is a cue for danger and passion. Red grabs our attention daringly and says, “Look at me!” But how does color affect how we view art? And does color relate to how much we are willing to pay for art?

This paper follows the trend of placing color as a significant factor in the pricing models of paintings (Stepanova 2015; Pownall and Graddy 2016; Charlin and Cifuentes 2020). Stepanova’s research on color and art price concludes that “color analysis is an essential part of a hedonic pricing model” (Stepanova 2015, 15). This paper compares the effect of color among the Color Field painters, using Rothko as the standard. Color in Rothko paintings was found to have significant price differences in Stepanova’s research. Hence, I would hypothesize that certain colors and features of a color palette have significant differences among the Color Field artists. As blue has been generally shown in studies to be a color of trust (Singh et al. 2011) and around 54% of people state blue as their favorite color (Hemphill 1995), blue should have a significant positive effect on price as blue would be a preferred characteristic of a painting. Black may have an effect to price between painters as it has been shown to be a sign of luxury goods and sophistication (Singh et al. 2011). Pink should have a significant effect to price between painters, given Alter's research into the significance of the color pink on human decision-making. Red may also have a significant effect on price (Puccinelli et al. 2013; Labrecque and Milne 2011). Color palette variance should have a significant relationship to price between painters if color diversity is significant (see Charlin and Cifuentes 2020).

Results show that Green, Grey and Brown have significant effects on price when their composition is altered in a painting. Pink and Violet have the most positive effect on price when generally added to the color palette *or* their proportion is increased of a painting. Color palette groupings and variance have no significant effect on changing the price of a painting.

II. Literature and Studies on Color and Price

Psychological studies into the impact of color in marketing and decision-making are numerous and widespread (Boyatzis and Varghese 1993; Hemphill 1995; Singh et al.

2011; Labrecque and Milne 2011; Greenberg 2020; among others). There have also been many studies done on how color affects financial decision-making and pricing (Kilger and Gilad 2012; Puccinelli et al. 2013; Ben and Marianne 2020; among others). However, studies on the impact of color palettes on prices of paintings are sparser and more recent (Stepanova 2015; Pownall and Graddy 2016; Veronika 2018; Charlin and Cifuentes 2020).

Studies tend to suggest that humans have positive reactions to brighter colors–pink, yellow, blue and red. In 1993, Boyatzis and Varghese conducted a study with sixty children who were each shown nine different colors in a random order. The children were asked to verbally respond to each color and their responses demonstrated distinct color-emotion associations. For brighter colors such as blue, red, and pink the children had positive emotions such as happiness and excitement. For darker colors such as grey, brown, and black, the children expressed more negative emotions such as sadness. Boyatzis and Varghese conclude that the children had a positive emotional preference towards brighter colors. In 1996, Hemphill conducted a study among 40 undergraduate students (20 men and 20 women) where he found that again bright colors have mainly positive associations, with 53% of men, and 55% of women citing blue as their favorite color. In contrast to the Boyatzis and Varghese study, men and women were more negative towards pink than brown (Hemphill 1995, 278).

These positive emotional responses to certain colors may translate into a pricing determinant.

Alongside the emotional psychology studies, marketing psychology research has shown that various colors lead to how humans assign characteristics to products or companies. Labrecque and Milne hypothesize that black and purple stands for “sophistication and glamour,” red for “excitement,” blue and brown for “competence” (Labrecque and Milne 2011, 714). Their results found that black was significant at the 1% level for brand sophistication, red was significant at the 1% level for excitement, and blue significant at the 5% level for competence. Singh provides an overview, using case studies and literature, on the significance of colors in daily life and marketing; red shows importance and excitement, blue symbolizes truthfulness and dependability, black professionalism and sophistication, pink health and peace, violet artistic creativity, and yellow weakness or friendship (Singh et al. 2011 201-202).

Moving from the marketing realm into the financial realm, studies have disagreed upon the use of color in economics. A recent paper from Ben and Marianne, published in 2020, tested the effects of the colors red and blue on decision-making in an

Ultimatum Game[1] experiment and found no statistically significant effects. The pair hypothesized that in red color conditions (using light screens) participants would be more likely to provide higher offers to their opposing player and reject offers more frequently. In blue conditions they hypothesized that there would be lower offers and a lower rejection threshold. Since their hypothesis was nullified, Ben and Marianne concluded that decision makers are not affected by the color of their surroundings. However, Ben and Marianne, unlike other studies, were varying the color of the environment (through light screens) not the color of the good or brand logo. In contrast, Kilger and Gilad find that color priming with either red and/or green can significantly change how individuals perceive financial gains and losses. Participants exposed to more red assigned lower valuations and higher probabilities of loss while those exposed to green saw higher returns to the same asset. Also, looking at the effect of red on financial decisions, Puccinelli, Chandrashekaran, Grewal, and Suri demonstrated that men tend to perceive greater consumer savings when sale prices are in red.

Looking specifically at the art market, research has shown that more intense colors, more color variation, reds, and blues are preferred. A 2016 paper by Pownall and Graddy analyzed Andy Warhol's prints, differentiating between intensity and

[1] A Proposer chooses how to split an amount of money between themselves and another player. If the other player agrees the percentage split, they both receive the offered amount. If the other player rejects the offer, neither receive any money.

lightness using RGB values. The pair found that intensity and darker colors are preferred. In 2015, Stepanova explored the color variants in Picasso's paintings and the Color Field Abstract Expressionists (i.e. Color Field painters). She found that contrastive paintings (those that place colors dissimilar in the RGB spectrum together) get higher prices. Specifically, among the Color Field artists, the distance of the color palette from the black/grey spectrum in Rothko's work was a significantly positive determinant – with a 1% movement away from black/grey leading to a 0.34% increase in price (Stepanova 11, 2015). The model used to estimate the results found in this paper is similar to the hedonic pricing model found in Stepanova.

In addition to Stepanova's research, Charlin and Cifuentes published a framework in 2020 to analyze the relationship between color and auction price. Charlin and Cifuentes focus on dominant colors, features of the color palette such as contrast and diversity, color harmony ("the pleasant effect produced by a certain combination of colors" Charlin et al. 2020) and color emotion. The pair apply the framework to Rothko paintings and find that results demonstrate a preference for red over green, blue over yellow, and lighter hues.

III. Dataset

In order to test the hypothesis that certain colors and the variance of colors have a significant effect on the pricing of artworks depending on which Color Field painter, I constructed a dataset of 224 observations from Christie's and Sotheby's auction records that were analyzed for color palette composition. This dataset was constructed from scratch.

The dataset compiled includes artworks made by various painters from the Color Field movement. The term Color Field painting is applied to a group of abstract painters that appeared around the 1950s and 1960s. Their work is generally defined by large areas of a single color (Tate 2017). The painters included in the dataset are Helen Frankenthaler (1928-2011), Clyfford Still (1904-1980), Barnett Newman (1905-1970), and Mark Rothko (1903-1970). Still, Newman, and Rothko are generally considered the central figures in the first decade of this movement from the '50s. Their abstract work entails elements of mythic or even religious context. However, from the '60s onwards, Helen Frankenthaler and artists such as Morris Louis, Kenneth Noland, and Sam Gillian moved away from any associated mythic or religious context and instead began to create "purely abstract" forms (Tate 2017). For my research, Frankenthaler is the only artist taken from the second period of the Color Field movement.

My observations were taken from auction records procured from askArt.com. AskArt is a company that specializes in auction records, art pricing, and verifying artist signatures. The company has an online database with millions of auction results, including over 350,000 artists. Each auction record includes the name of the artwork, the artist's full name, the year of artwork completion (or year thereabouts), the low estimate, the high estimate, the final price (which includes buyer's fees), the date of the auction, the location of the auction, the size of the painting, the medium of the painting, notes, and an official image of the painting. Auction houses in this paper are restricted to Christie's and Sotheby's. For each observation taken from the online database, I noted the final price of the painting (including buyer's fees), the date of the auction, the name of the painting, the name of the artist (Newman, Still, Rothko, or Frankenthaler), the low estimate (in the case of Frankenthaler and Rothko), the medium, the size of the painting (in square inches), and downloaded fully rendered images for color extraction. Price was adjusted according to CPI, using a 2020 US Dollar base and transformed into the natural logarithm of price for interpretation.

Color extraction identifies the color palette of any image. For my color extraction process, I used an algorithm developed by TinEye, an image search and recognition company. As their website states, TinEye "are experts in computer vision, pattern recognition, neural networks, and machine learning." (TinEye) Their color extraction tool, named MulticolorEngine, provided a method for analyzing the percentage proportion of colors in any given painting. The user can simply upload an image into the tool and the algorithm will provide the percentages of the colors Grey, Brown, Black, White, Green, Pink, Violet, Red, Orange, Yellow, and Blue[2]. These are colors from the X11 HTML spectrum[3]; colors formed by combining red, green and blue pixels.

Figure 3.1. Helen Frankenthaler's *Giant Step* (1975)

To begin color extraction, I would upload a downloaded .jpg or .png file into the MulticolorEngine. The MulticolorEngine would then provide the distribution of the color palette in a given painting by percentages. An example color extraction of *Giant Step* (1975) (Figure 3.1) and *After Hours* (1975) (Figure 3.3) by Helen Frankenthaler is provided. Figure 3.5 demonstrates the color composition breakdown for *Giant Step*

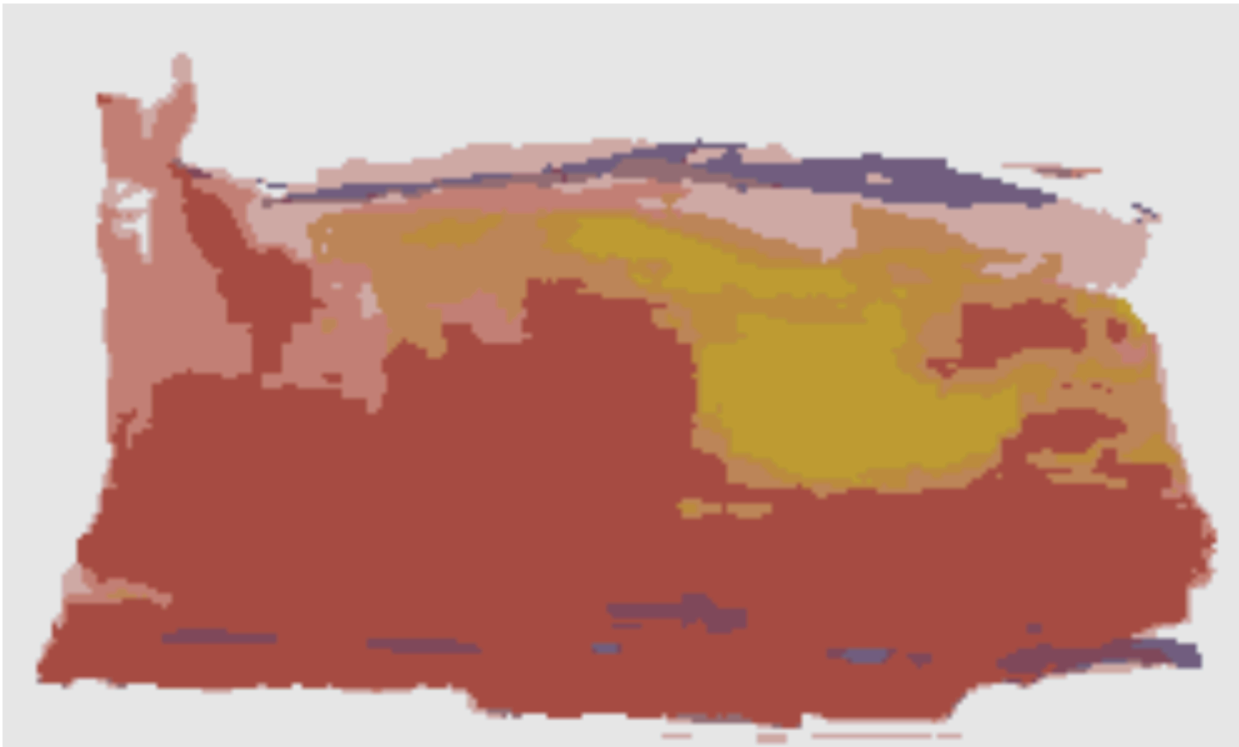
[2]Since these colors are specifically the categories from the X11 HTML spectrum, I will capitalize the names of the colors.
[3] For online and world wide web use.

rendered as a single vertical column; the proportional areas in the rectangle correspond the percentage each color covers in the painting. Figure 3.5 performs the same transformation for *After Hours*. Table 3.1 displays the percentage of each color (from the categories of the X11 HTML color chart) present in each painting. As Table 3.1 displays, Frankenthaler's painting *Giant Step* is composed of 49.6% Brown pigments, 37.1% Grey, 10.1% Pink, and 3.3% Violet. In comparison, After Hours is composed of 25.3% Brown, 37.3% Blue, 9.7% Grey, and 27.9% Violet. The distribution of these percentages represents the spread of the color palette. Due to rounding errors, not all of the observations color percentages sum to 100. However, the mean of the summed color palette of all observations is 100, suggesting that the rounding errors cancel each other out in the dataset at large.

Table 3.1. Color Extraction

Artist	Helen Frankenthaler	Helen Frankenthaler
Artwork	Giant Step	After Hours
Grey	37.1	9.7
Blue	0	37.3
Pink	10.1	0
Brown	49.6	25.3
Yellow	0	0
Black	0	0
Red	0	0
Orange	0	0
Violet	3.3	27.9
White	0	0
Green	0	0
	100.1	100.2

Figure 3.2. Frankenthaler's *Giant Step* After Color Extraction



Two main issues with using an algorithmic color extraction tool to construct a dataset is that digital image files of paintings are not the real thing and are often already color quantized. Since the images that the color palette is being extracted from is not the real painting, the colors in the image may not actually reflect the real colors in the painting. For example, if the photograph is taken in reduced light, color extraction may result in the image having a greater percentage of grey which in reality is not the truth. In addition to this 'not real life' color issue, images of paintings are often already compressed into HTML colors. That is to say, the image of the painting has already been broken down into groups of colors to reduce file size. In order to try and minimize the errors created by these issues, I made sure that every image was taken from auction reports from askArt.com and there were no extra steps involved between downloading the image and uploading the image file to TinEye's MulticolorEngine. Any extra steps may have re-rendered the image file again. Furthermore, part of the reason why Color Field painters were chosen is to ensure that any ambiguity and uncertainty in the color palettes could be minimized; if the paintings are only composed of several blocks of color, there should be less error in identifying these colors.

The final dataset contains observations from 224 auction results from Rothko, Still, Newman, and Frankenthaler, all broken down into their various color compositions with descriptions of final price, auction date, size in square inches, and other pieces of information from askArt.com. As Table 3.2 illustrates, Frankenthaler has the most datapoints at 80, then Rothko at 61, Newman at 45, and Still at 38. Rothko has both the highest average price of a painting, at over $15 million, and the highest average price per square inch, at $5,537.51 per square inch. In contrast, Frankenthaler has the lowest average price per painting ($777,487.00) and per square inch ($259.50). Frankenthaler's artwork is also painted the most recently, with her work being dated to as recently as 2002. Every artist has auction records from 2020 with Still and Newman's auction records both dating back to the start of the '90s.

Table 3.2 Summary of Observations

Artist	Mark Rothko	Clyfford Still	Barnett Newman	Helen Frankenthaler
Observations	61	38	45	80
Average Price	$15,351,795.00	$9,737,685.00	$5,439,622.00	$777,487.00
Average Price per Square Inch	$ 5,537.51	$ 2,183.92	$ 4,338.59	$ 259.50
Auction Date Range	2008-2020	1990-2020	1989-2020	2012-2020
Year Painted Range	1937-1970	1937-1976	1944-1969	1952-2002
Mean Standard Deviation of Color	32.62	37.78	34.06	37.05

Looking at the dataset from a color palette standpoint, interestingly Rothko has the lowest mean standard deviation of color (32.62); this figure is calculated from the variance of the distribution of the color palette. Although Rothko has the highest value for his paintings per square inch, the distribution of his color palette also varies the least. Still and Frankenthaler have fairly similar standard deviations of color (37.78 and 37.05). A curious observation after color extracting all paintings is that the percentage of Browns and Greys in paintings seem inordinately high. Taking the example from Table 3.1, both *Giant Step* and *After Hours* have Grey and Brown pigments, with Brown being the dominating color in *Giant Step* (49.6%). While the colors may appear to the naked eye as 'more red' or 'a light blue,' categorization by the HTML X11 color spectrum places many colors from painters within the Grey and Brown categories. This is a categorization bias since other metrics may not label

Greys and Browns with the Grey and Brown categories. The most common color used in all the observed paintings is Grey (38.89%), then Black (37.22%), and then Brown (36.22%).

Figure 3.3 Helen Frankenthaler's *After Hours* (1975)

Figure 3.4 Helen Frankenthaler's *After Hours* After Color Extraction

Figure 3.5. Color Extraction in Vertical Columns

Columns represent the relative percentage of each X11 HTML Color category in each painting after color extraction. On the left-hand side is Frankenthaler's painting *After Hours* (1975) and the right-hand side *Giant Step* (1975)

IV. Estimation and Results

i. Estimation

The model that I estimate is similar to the hedonic pricing model used by Stepanova in her paper on the effect of color palettes (Stepanova 4, 2015),

$$p_{\mathrm{it}} = \sum_m \alpha_m x_{imt} + \sum_t \gamma_t d_t + e_{it} \text{ , (Eq. 4.1)}$$

where p_{it} is the price of an artwork i (i = 1, … I) at time t and m (m = 1, …, M) is the set of measurable characteristics of the artwork i. x_{imt} represents the value of the independent variables measured at time t as part of a measurable characteristic of the artwork. $\sum_t \gamma_t d_t$ represents the time dummy variable included to account for market-wide price effects; d_t takes the value of 1 in year t and 0 otherwise. There are 32 time dummies for years 1989-2020. The dependent variable p_{it} is the natural logarithm of price paid by the bidder, including buyer's fees. Since the dependent variables is log(*price*), the coefficients of the independent variables can be interpreted as percentage change in price with a unit change of a particular characteristics (transformed by exp(α_m) - 1).

Control variables used in the model are dummy variables for each artist, Newman, Still, Frankenthaler – Rothko is omitted because of multicollinearity where all artist dummies are 0 – size in square inches, age of artist, medium dummy variables, and the time dummy variables to control for market price trends. The independent variables are observations on color as described in the dataset.

To analyze the dataset in line with the pricing model, I have divided the regression results into four sections, as the independent variables change. (i) The first section looks at the results of how altering the percentage of colors already within paintings can change the prices between artworks. The significant colors from this section are Green, Grey, and Brown. (ii) The second section looks at how color groupings are related with price between artists. I divided the colors into two color groupings: Primary Colors, which only looks at the sum of Red, Blue, and Yellow, and Cool Colors, which adds the percentages of Blue, Grey, Green, White, Violet, and Black. Since the percentage of color adds to 100% (or thereabouts), the group defined as Warm Colors is the inverse of this operation; Warm Colors are Pink, Brown, Red, and Orange. Both of these categories need not be included because of multicollinearity. (iii) The third section looks at the variation of colors in the observed paintings by taking the variance of the color palette used. (iv) The fourth set of estimation results places all colors extracted – Blue, Red, Pink, White, Violet, Green, Orange, Yellow, Black, Grey, Brown – as independent variables into the model. Results show every color to be significant, some more significant than others.

i. Altering Composition of Individual Colors

The only individual colors that significantly effect log(*price*) (Log Price) when their composition is altered in my hedonic model are Green, Grey, and Brown. These relationships can be interpreted as the effect of changing the amount of a color in a painting that already has that color in its color palette. In the dataset of 224 observations, Green accounts for 2.8% of all canvas space. As demonstrated in Table 4.1.1, the coefficient for Green is very finely significant between the Color Field painters at the 10% level (p-value = 0.099). Table 4.1.1 shows the regression results for all observations with Green as the individual color independent variable; observations are only taken for the individual color regression results if a painting has the color Green in the painting, along with some other color or not. For estimation results in Table 4.1.1. observations number 32 since Green only appears in these 32 paintings. The control variables – Size in Inches^2 and the dummy variables for Frankenthaler and Still – are also significant in this regression. Size in Inches^2 and Frankenthaler are significant at the 1% level. This suggests that there should be a 93% decrease in price if the painting is a Frankenthaler and not a Rothko. The coefficient of Green has the value .0113723 which can be interpreted as: a 1% increase in the color Green (since color extraction is already in percentage units) leads to a 1.1% USD increase (exp(0.0113723) - 1) in price in Rothko paintings, 92% USD decrease in price in Frankenthaler paintings, and a 380% USD increase in Still paintings. The R-squared value for this regression is 0.84, which also suggests that 84% of the variation in Log Price–of artworks observed with Green in them–is explained by these variables.

Table 4.1.1. Regression Results (Green)

Log Price ($)	Time Dummies: 32	R-squared: 0.84		
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Green*	.0113723	.0065704	1.73	0.099
Still**	1.569915	.5831268	-2.69	0.014
Newman	0	(omitted)		
Frankenthaler***	-2.575647	.4949188	-5.20	0.000
Oil	.3731163	.5257337	0.71	0.487
Size in Inches^2***	.0003363	.0000624	5.39	0.000
Constant***	11.39872	1.103921	10.33	0.000

***Significant at the 1% Level
** Significant at the 5% Level Obs. 32
*Significant at the 10% Level

Looking to Table 4.2, using Grey and Brown in the regression as the independent variables, the coefficients for Grey and Brown, are significant at the 5% level and 10% level (p-value = 0.014 and 0.065, respectively). Observations for these estimations number 132. The dependent variable remains the same: *Log* Price. The control variables – Size in Inches^2, the dummy variables for Frankenthaler and Oil – are also significant in this regression. Size in Inches^2 , Frankenthaler, and Oil are all significant at the 1% level. In this model, when the painting's medium is Oil, price increases by 167% USD. Similar to Table 4.1.1, if the painting is a Frankenthaler and not a Rothko, price is expected to decrease by 93% USD. The coefficient for Grey can be interpreted as for every 1% increase of the use of Grey in the color palette, Rothko painting price decreases by 1.2% USD (1 - exp(-0.0117078)) and Frankenthaler paintings decrease by 94% USD. The coefficient for Brown can be interpreted as for every 1% increase of the use of Brown in the color palette, Rothko painting price decreases by 0.8% USD (1 – exp(-0.0078925)) and Frankenthaler by 93.8% USD.

Table 4.1.2. Regression Results (Grey and Brown)

Log Price ($)	Time Dummies: 32	R-squared: 0.7832		
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Grey**	-.0117078	.0046816	2.50	0.014
Brown*	-.0078925	.0042313	-1.87	0.065
Still	-.7622375	.5290228	-1.44	0.153
Frankenthaler***	-2.669664	.4589027	-5.82	0.000
Oil***	.9832078	.3448746	2.85	0.005
Size in Inches^2***	.0002711	.0000446	6.08	0.000
Newman	-.629283	.5494366	-1.15	0.255
*** 1% ** 5% * 10%		Obs. 132		

Altering the composition of Red, Black, White, Violet, Blue, Yellow, Pink, and Orange in paintings–assuming the color is already part of the color palette– has no significant effect on price as independent variables according to the estimated results for this dataset.

ii. Color Groupings

The groupings used as independent variables in the estimations are Primary Colors, as the summation of Blue, Red, and Yellow, and Cool Colors, the sum of Blue, Green, Grey, White, Violet, and Black. Table 4.2.1. exhibits the regression results from using Primary Colors as the independent variables affecting price changes. The control variables – Size in Inches^2, the dummy variables for Frankenthaler, and Oil – are also significant in this regression. Size in Inches^2 and Frankenthaler are significant at the 1% level. Oil is significant at the 5% level. The coefficient for Primary Colors is not significant at any level and therefore should not be interpreted as having any significant effect on price between the painters. Interestingly, a Frankenthaler work is again expected to achieve 92% USD (similarly to 93%) less than a Rothko painting.

Table 4.2.1. Regression Results (Primary Colors)

Log Price ($)	Time Dummies: 32 R-squared: 0.6366			
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Primary Colors	.0008216	.0051131	0.16	0.873
Still	-.0661073	.4439518	-1.15	0.882
Newman	-0.7159181	.4660845	-1.54	0.126
Frankenthaler***	-2.437807	.4135259	-5.90	0.000
Oil**	.8653565	.3668804	2.36	0.019
Size in Inches^2 ***	.0001205	.0000451	6.67	0.008
Constant***	9.043777	.4771787	18.95	0.000
***1 % **5% *10%		Obs. 224		

Clustering the color palette into the summation of Cool Colors, and using this grouping as the independent variable, yields no significant coefficient. Table 4.2.2. displays the estimations from the regression using Cool Colors as the independent variable. In this regression, the control variables – Size in Inches^2, the dummy variables for Frankenthaler and Oil – are all significant at the 1% level (with p-values = 0.008; 0.000; and 0.008 respectively). In this estimation, Frankenthaler works are expected to achieve 91.2% USD less than a Rothko work.

Table 4.2.2. Regression Results (Cool Colors)

Log Price ($)	Time Dummies: 32	R-squared: 0.6367		
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Cool Colors	.0008894	.00271	0.33	0.873
Still	-.0860212	.4300544	-0.20	0.882
Newman	-.7391133	.4855382	-5.86	0.000
Frankenthaler***	-2.435553	.415396	2.68	0.000
Oil**	.8849182	.3304029	2.68	0.008
Size in Inches^2 ***	.0001214	.0000454	6.39	0.008
Constant***	8.999649	.4866744	18.49	0.000
***1 % **5% *10%		Obs. 224		

iii. Color Variation

Table 4.3.1. displays the estimation results by using Color Standard Deviation as the independent variable. The estimated coefficient between the variance of color composition and price is not significant and therefore should not be interpreted as having an effect on price between the painters. Once again, Oil, Size in Inches^2, and

Frankenthaler are all significant. A Rothko Oil painting is expected to achieve a 143% USD higher price than if a different medium. If a painting is a Frankenthaler, it can be expected to decrease by 91.2% USD in price. Regardless of these results, the variation of color palette composition is not significantly related to price.

Table 4.3.1. Regression Results

Log Price ($)	Time Dummies: 32	R-squared: 0.6370		
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Color Standard Deviation	.0029466	.006918	0.43	0.671
Still	-.0964069	.4178165	-0.23	0.818
Newman	-.700155	.4862593	-1.44	0.152
Frankenthaler***	-2.432748	.4098143	-5.94	0.000
Oil***	.888332	.3222292	2.76	0.006
Size in Inches^2***	.0001211	.0000448	2.70	0.008
Constant***	8.968957	.5091091	17.62	0.000
***1% **5% *10%		Obs. 224		

iv. All Colors

The final estimation places all colors extracted from the Color Field artworks as independent variables into the model. These results differ from the (i) *Individual Color* results as this model replaces non-observation datapoints for colors (i.e. where artworks are not observed to have *m* where *m* may be 'Red') with the numeric value 0 (representing 0%). This allows all colors to be compared as independent variables affecting *Log* Price, the dependent variable. Table 4.4.1. displays the results from this regression.

Table 4.4.1. Regression Results (All Colors)

Log Price ($)	Time Dummies: 32	R-squared: 0.6585		
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Blue*	.0660119	.0358112	1.84	0.067
Red*	.0723996	.0368624	1.96	0.051
Pink**	.07665	.0343746	2.23	0.027
White**	.0752421	.0356216	2.11	0.036
Violet**	.0847264	.0352526	2.40	0.017
Green**	.0752031	.0351316	2.14	0.034
Orange**	.0720517	.0354158	2.03	0.043
Yellow**	.0758659	.0347033	2.19	0.030
Black**	.0713728	.0349226	2.04	0.042
Grey**	.0662704	.0334993	1.98	0.049
Brown*	.0644591	.0342045	1.88	0.061
Still	.037986	.4587228	0.08	0.934
Newman	-.700155	.4862593	-1.44	0.152
Frankenthaler***	-2.351922	.4897009	-4.80	0.000
Oil**	.9266777	.4003852	2.31	0.022
Size in Inches^2***	.0001205	.0000435	2.77	0.006
Constant	4.761787	3.657499	1.30	0.195
***1% **5% *10%		Obs. 224		

As Table 4.4.1. demonstrates, every color coefficient is judged to be significant in these results at either the 5% or 10% level. The coefficients for Blue, Red, and Brown are significant at the 10% level. For every 1% increase of Blue in the color palette, price is expected to increase by 6.8% USD. For every 1% increase of Red in the color palette, price is expected to increase by 7.5% USD and for Brown a 6.6% USD increase. The coefficients for Pink, White, Violet, Green, Orange, Yellow, Black, and

Grey are all significant at the 5% level. Their relative translations into % USD increase are: Pink +8.0%, White +7.8%, Violet +8.8%, Green +7.8%, Orange +7.5%, Yellow +7.9%, Black +7.4%, and Grey +6.9%. Frankenthaler, Oil, and Size in Inches^2 are all also significant.

V. Interpretation and Critique

Results suggest that increasing specifically Green and decreasing Greys and Brown (in paintings that already contain these colors) can have significant effects in increasing price among the Color Field painters. According to the estimation given in Table 4.1.1., a 1% increase in the use of Green can (curiously) increase the price of a Still painting by 380% USD and a Rothko by 1.1%. For Greys and Browns, the price effect is negative, with a 1.1% decrease. As Table 4.4.1 demonstrates, increasing the colors used in a color palette also increases price. Among all colors, increasing the percentage of Pink, White, Violet, Green, Orange, Yellow, Black, and Grey are strongly significant in increasing price. However, neither grouping by Primary Colors or Cool Colors has a significant effect nor does estimating differences in price suggested by color variance.

It is clear Color Field paintings have other more significant factors affecting their price. Individual characteristics of paintings, such as medium, size of paintings, and age of painting, may be more fit within a hedonic pricing model for fine art. In general, estimation results yielded 1% significance for the control variables. Therefore, medium and size of painting are two of many significant factors in determining painting price among the Color Field painters (though this was obviously true). In addition to other variables, there is a possibility that a preference for individual characteristics of a particular painting – such as color – is less relevant among these high-priced goods.

Nevertheless, while most of the coefficients for individual color relationships have no significance to price among the painters, Green, Greys and Browns do. The 380% estimation increase for Clyfford Still for Greens seems to be an anomaly. This can be explained by the fact Green is only extracted from one of Still's paintings – the painting PH-351 (1940). This estimation result is therefore inaccurate. However, the fact that altering the composition of Green in artworks is a significant factor in changing price agrees with the research from Kilger and Gilad which suggests green color priming leads to higher estimation of asset prices. In this case, the assets are artworks. Green makes a difference between the Color Field painters as people are willing to pay more for an additionally greener canvas – the high 0.8404 R-squared value affirms the power of this model. The result for Greys and Browns agrees with Stepanova's findings. Stepanova found that Rothko works were expected to increase in price the further the colors were away from the black/grey spectrum. Inversely, estimation results in this paper demonstrate that a increasing the percentage of

Greys and Browns already in a color palette is associated with a decrease in price (on the assumption that Greys and Browns are closer to non-color saturation).

In contrast to the estimations for individual colors, the estimated results found in Table 4.4.1. have a slightly more confusing interpretation. If it is the case that increasing the percentage of any color in the Color Field paintings increases the price, then surely maximizing the percentage of all colors used would result in the highest price painting? To test this dilemma, I estimated the model using squared values for the colors. The results demonstrated that the color White has diminishing marginal returns (p-value = 0.003). None of the other color squared coefficients were significant and therefore none other show diminishing marginal returns. While the estimated coefficients for this regression are all positive and significant, no Color Field painting observed in this dataset paints colors in a perfect, maximized color palette distribution (nor any painting that I know of). Given the philosophical approach behind the movement, to paint in large areas of single colors (Tate 2017), this would be a very unlikely occurrence in a Color Field painting.

Although all the colors are positive in the estimations from Table 4.4.1., offering the aforementioned issue, Pink and Violet have the greatest effect on price (8.0% and 8.8%). Alter's presentation of pink as a tranquilizing effect on the body may have an indirect effect, through altering human emotion and encouraging decisiveness, on the decision for consumers to pay more for paintings with more pink in them. Singh describes violet as the color, “used to portray elegance, grace, and artistic creativity.” (Singh et al. 2011, 203). It seems entirely apt that among all colors analyzed in artworks from the Color Field painters, increasing the percentage of or adding Violet in a painting has the largest effect on increasing price.

There are several critiques of my approach to this paper that I would like to outline. In regard to the data collection, there is a selection bias since the constructed dataset was taken from askArt.com and although I would have liked to note every observation for each color painter, unfortunately the size of that dataset was not within the scope of this paper. The estimations are limited in that way because not all the artworks by the Color Field painters Newman, Still, Frankenthaler, and Rothko have been used.

In addition to the selection bias, the method of color extraction via TinEye differs the method of color extraction used by other scholars in this field. Stepanova, Pownall and Graddy, Charlin and Cifuentes all use the RGB color spectrum or L* a* and b* as color variables: L* relates to the lightness of a color, a* to how red or green, and b* to how blue or yellow. This paper did not use this method of extraction. On the one hand, this is a limitation. Variables for luminosity or intensity could not be used in the model. On the other hand, the results demonstrate that when the X11 HTML categories are used – perhaps a more simplified method of color extraction – the results differ from previous research. This difference could point to the need for more detailed methods of color extraction.

VI. Conclusion

Color has been shown to be a significant variable in effecting the price of paintings among the Color Field painters. This affirms Stepanova's wish that color should be included in the hedonic pricing model and confirms Agnello and Pierce's suggestion that color be placed alongside medium as a price determinant for paintings (Agnello et al. 1996). Furthermore, not only do certain colors affect price more than others – Pink and Violet – altering the composition of colors already in paintings – such as Green – can affect price.

The strength of this paper lies in the differentiation between total color palette composition and the alteration of an individual color within a certain painting: making a piece Greener vs. making it, at least, Green. There is a significant difference between the colors which affect price when their proportion is altered within a painting (Green, Grey and Brown) and those that significantly affect price when generally added to a painting (Pink and Violet). This is demonstrated by the change in which colors are significant; the difference between replacing null color observation values with 0 percentage values.

However, weakness to this paper lie in methodology and data compilation. The amount of data used in this paper is limited and more observations are needed to have balanced estimation results. Furthermore, the usage of TinEye as a tool for color extraction is different than other research papers in the same field. For that reason, it is difficult to compare the results of this paper to others since the aesthetic definition of the extracted colors – like Pink and Violet – are not the same.

For future research, I would like to see the results of how color affects artwork outside of the Color Field painters. While the simplicity of color palette composition among the Color Field movement makes the pieces prime targets for price determinant modelling, subtle shifts in color in other artistic pieces from different periods may also have interesting effects on price.

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VIII. Tables

Table 3.1. Color Extraction

Artist	Helen Frankenthaler	Helen Frankenthaler
Artwork	Giant Step	After Hours
Grey	37.1	9.7
Blue	0	37.3
Pink	10.1	0
Brown	49.6	25.3
Yellow	0	0
Black	0	0
Red	0	0
Orange	0	0
Violet	3.3	27.9
White	0	0
Green	0	0
	100.1	100.2

Source: data for observations taken from askArt.com. Color extraction in 'MulticolorEngine' tool, tineye.com

Table 3.2 Summary of Observations

Artist	Mark Rothko	Clyfford Still	Barnett Newman	Helen Frankenthaler
Observations	61	38	45	80
Average Price	$15,351,795.00	$9,737,685.00	$5,439,622.00	$777,487.00
Average Price per Square Inch	$ 5,537.51	$ 2,183.92	$ 4,338.59	$ 259.50
Auction Date Range	2008-2020	1990-2020	1989-2020	2012-2020
Year Painted Range	1937-1970	1937-1976	1944-1969	1952-2002
Mean Standard Deviation of Color	32.62	37.78	34.06	37.05

Source: data for observations taken from askArt.com and 'MulticolorEngine' tool, tineye.com

Table 4.1.1. Regression Results (Green)

Log Price ($)	Time Dummies: 32	R-squared: 0.84		
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Green*	.0113723	.0065704	1.73	0.099
Still**	1.569915	.5831268	-2.69	0.014
Newman	0	(omitted)		
Frankenthaler***	-2.575647	.4949188	-5.20	0.000
Oil	.3731163	.5257337	0.71	0.487
Size in Inches^2***	.0003363	.0000624	5.39	0.000
Constant***	11.39872	1.103921	10.33	0.000

***Significant at the 1% Level
** Significant at the 5% Level Obs. 32
*Significant at the 10% Level

Source: data for observations taken from askArt.com and 'MulticolorEngine' tool, tineye.com

Table 4.1.2. Regression Results (Grey and Brown)

Log Price ($)	Time Dummies: 32	R-squared: 0.7832		
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Grey**	-.0117078	.0046816	2.50	0.014
Brown*	-.0078925	.0042313	-1.87	0.065
Still	-.7622375	.5290228	-1.44	0.153
Frankenthaler***	-2.669664	.4589027	-5.82	0.000
Oil***	.9832078	.3448746	2.85	0.005
Size in Inches^2***	.0002711	.0000446	6.08	0.000
Newman	-.629283	.5494366	-1.15	0.255

*** 1% ** 5% * 10% Obs. 132

Source: data for observations taken from askArt.com and 'MulticolorEngine' tool, tineye.com

Table 4.2.1. Regression Results (Primary Colors)

Log Price ($)	Time Dummies: 32 R-squared: 0.6366			
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Primary Colors	.0008216	.0051131	0.16	0.873
Still	-.0661073	.4439518	-1.15	0.882
Newman	-0.7159181	.4660845	-1.54	0.126
Frankenthaler***	-2.437807	.4135259	-5.90	0.000
Oil**	.8653565	.3668804	2.36	0.019
Size in Inches^2 ***	.0001205	.0000451	6.67	0.008
Constant***	9.043777	.4771787	18.95	0.000
***1 % **5% *10%		Obs. 224		

Source: data for observations taken from askArt.com and 'MulticolorEngine' tool, tineye.com

Table 4.2.2. Regression Results (Cool Colors)

Log Price ($)	Time Dummies: 32 R-squared: 0.6367			
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Cool Colors	.0008894	.00271	0.33	0.873
Still	-.0860212	.4300544	-0.20	0.882
Newman	-.7391133	.4855382	-5.86	0.000
Frankenthaler***	-2.435553	.415396	2.68	0.000
Oil**	.8849182	.3304029	2.68	0.008
Size in Inches^2 ***	.0001214	.0000454	6.39	0.008
Constant***	8.999649	.4866744	18.49	0.000
***1 % **5% *10%		Obs. 224		

Source: data for observations taken from askArt.com and 'MulticolorEngine' tool, tineye.com

Table 4.3.1. Regression Results

Log Price ($)	Time Dummies: 32	R-squared: 0.6370		
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Color Standard Deviation	.0029466	.006918	0.43	0.671
Still	-.0964069	.4178165	-0.23	0.818
Newman	-.700155	.4862593	-1.44	0.152
Frankenthaler***	-2.432748	.4098143	-5.94	0.000
Oil***	.888332	.3222292	2.76	0.006
Size in Inches^2***	.0001211	.0000448	2.70	0.008
Constant***	8.968957	.5091091	17.62	0.000
***1% **5% *10%		Obs. 224		

Source: data for observations taken from askArt.com and 'MulticolorEngine' tool, tineye.com

Table 4.4.1. Regression Results (All Colors)

Log Price ($)	Time Dummies: 32	R-squared: 0.6585		
	Coefficient	Robust Std. Err.	T-Statistic	P-Value
Blue*	.0660119	.0358112	1.84	0.067
Red*	.0723996	.0368624	1.96	0.051
Pink**	.07665	.0343746	2.23	0.027
White**	.0752421	.0356216	2.11	0.036
Violet**	.0847264	.0352526	2.40	0.017
Green**	.0752031	.0351316	2.14	0.034
Orange**	.0720517	.0354158	2.03	0.043
Yellow**	.0758659	.0347033	2.19	0.030
Black**	.0713728	.0349226	2.04	0.042
Grey**	.0662704	.0334993	1.98	0.049
Brown*	.0644591	.0342045	1.88	0.061
Still	.037986	.4587228	0.08	0.934
Newman	-.700155	.4862593	-1.44	0.152
Frankenthaler***	-2.351922	.4897009	-4.80	0.000
Oil**	.9266777	.4003852	2.31	0.022
Size in Inches^2***	.0001205	.0000435	2.77	0.006
Constant	4.761787	3.657499	1.30	0.195
***1% **5% *10%		Obs. 224		

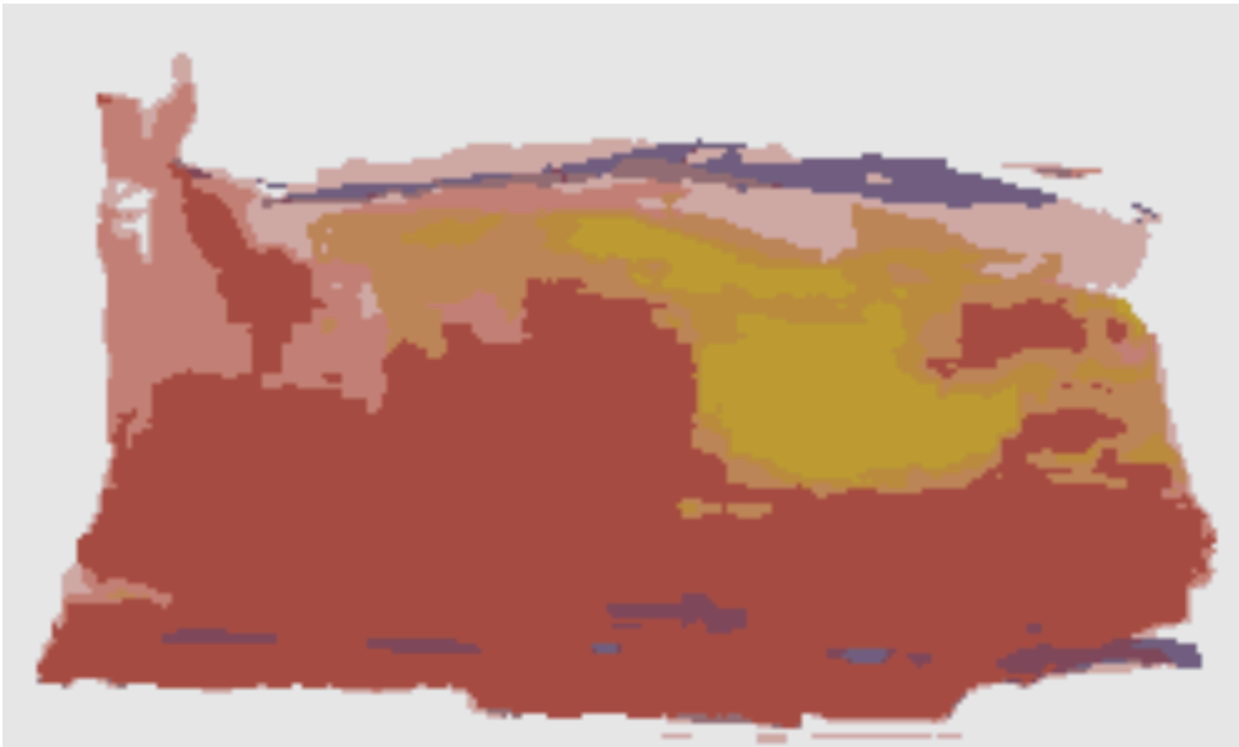
Source: data for observations taken from askArt.com and 'MulticolorEngine' tool, tineye.com

IX. Figures

Figure 3.1. Helen Frankenthaler's *Giant Step* (1975)

Source: figure downloaded from askArt.com

Figure 3.2. Frankenthaler's *Giant Step* After Color Extraction



Source: figure downloaded from askArt.com and re-rendered from 'MulticolorEngine' tool, tineye.com

Figure 3.3 Helen Frankenthaler's *After Hours* (1975)

Source: figure downloaded from askArt.com

Figure 3.4 Helen Frankenthaler's *After Hours* After Color Extraction

Source: figure downloaded from askArt.com and re-rendered from 'MulticolorEngine' tool, tineye.com

Figure 3.5. Color Extraction in Vertical Columns

Columns represent the relative percentage of each X11 HTML Color category in each painting after color extraction. On the left-hand side is Frankenthaler's painting *After Hours* (1975) and the right-hand side *Giant Step* (1975)

Source: re-rendered vertical columns from 'MulticolorEngine' tool, tineye.com

X. Equations

Equation 4.1:

$$p_{\mathrm{it}} = \sum_m \alpha_m x_{imt} + \sum_t \gamma_t \, d_t + e_{it}$$

Equation based off hedonic pricing model from Stepanova, Elena. 2015. “The Impact of Color Palettes on the Prices of Paintings.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2807443. p.4