Pricing Colour Intensity in Contemporary Art

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Abstract

Colours affect us in different ways. From the psychology and marketing literature we know that colours have an affect on us and influence our decision making process. However, little is known about how colours and the intensity of colour drive prices observed in auction markets for art. Using a unique set of data for Contemporary artworks, which include Warhol prints which in some cases differ only by their combination of colours, we are able to observe the influence of colour and intensity using RGB values and luminosity as explanatory variables on prices achieved at auction. Controlling for other hedonic characteristics, empirical results find significant evidence of darker colours carrying a premium than equivalent artworks which are less intense in colour.

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1 Introduction

Sensational prices achieved recently at Contemporary Evening auction sales for Andy Warhol's artworks have hit the headlines. In 2007 his Green Car Crash sold for an auction record price of $71.72 million dollars, only to be superseded by his Silver Car Crash, selling in November 2013, for $104.5 million dollars. His iconic vivid images have reached sensational prices, but to what extent is it the color whose sensualness affects us and drives the prices reached at auction? Fashion, tastes and fads play a role. In this paper we use prices of Warhol paintings which appeared at auction during 2012 such that we can focus on the current market for Warhol's artworks, and determine which colors, and their corresponding intensity, are currently favoured in the art auction market.

During the 1950s Pop Art emerged in the US and Andy Warhol was a leading artist in this movement. He used nonrepresentational colour and form to convey different sensations. In the 1960s he created, amongst other work, a large number of 'mass-produced' silkscreen images. He often focused on a number of iconic celebrities, such as Marilyn Monroe, Chairman Mao, and Elizabeth Taylor for his artworks. Many of these prints belonged to a number of limited editions and hence has the advantage that they can be compared to each other at different times of sale, and also can be compared to other artworks of the same image, but which differ only in their use of color. This begs the research question as to how much prices for these contemporary artworks differ between these various color editions, and which colours and intensity attract a higher price?

Little is known about the value or premium that individuals put on the color of artworks. Roger de Piles (1673) set about ranking artworks according to a number of attributes, one of them being color. Recently Graddy (2013) analyses the scores which de Piles at the time gave to various paintings during the 17th century, to see how well his ranking of attributes has stood the test of time. She finds fascinating evidence that contrary to conventional thought on fashion and the Masterpiece effect, the paintings which he ranked most highly, in terms of composition, drawing, color and expression, have outperformed the price increase of their contemporary's of the time.

The outline of the paper is as follows. In the following section we outline how we can quantify color through the use of color pixels, tonal values, and the intensity of color. In section three we introduce the contemporary art sample for Andy Warhol prints sold and the hedonic pricing model for pricing. In section four we provide empirical results to test the contribution which color has on the variation in contemporary art prices for Warhol paintings. Section five concludes.

1.1 Contemporary Art Sample

The artist is the most predominant and important factor influencing the price of art. The variation in price across a particular artists paintings depends on other defining characteristics of his or her work. For example the genre, the medium, the size, the time during his or her life when the artwork was painted. Other factors which also play a role are whether the artwork was exhibited and where the artwork was auctioned. These factors influence the quality and the reputation associated with the artwork.

Since we are interested in analysing the influence of color and intensity on art prices, we decided to focus on a single artist. We also chose to focus on contemporary art, which is vibrant in color and of which there are a variety of different color combinations occurring of the same image. Furthermore we collect information on the number of editions of the artwork which were produced at the time. This means that we can control the price at auction for the relative scarcity of the work. Uniqueness has a value. Generally speaking, the greater the number of the edition printed at the time of creation the lower the price obtained at auction. For every artwork sold in our database we also collect information on the maximum number of editions associated with the artwork.

Warhol paintings are not only iconic, well-known and reach high prices, but there is also enough turnover in the market, and hence market liquidity such that we have enough variation in the type of artworks and images which were sold during the time period under investigation[1]. They also offer us an ideal control group to work with. Many of the images are produced using different colours on the same image, hence we are easily able to ascertain the influence of color on prices obtained at auction. We condition our data sample to all Warhol artworks, which have been sold at major auction houses during 2012, since data is available from the major auction houses. We are not able to obtain prices of Warhol paintings sold by dealers or privately for the sample period [2]. We also have information on the location of the auction houses as well as the name of the house. This means that we are able to control for repetitional effects and potential quality effects for sales occurring at the more well-known and prestigious auction houses globally. As mentioned earlier an important factor in the determinant of price is the number of editions which were printed at the time of creation. All sales include the maximum number of prints in the edition. For this variable there is a minimum of 1 and a maximum of 2000 in our sample of 178 paintings. The average auction price for our sample during 2012 is just over $40,000 US dollars. The highest price obtained in our sample at auction is $218,500 and the lowest price was $2,250. For sales not occurring in USD the exchange rate was used on the day of the sale and all prices are compared in US dollars. We also have information on the size of the artworks, and the material used. The larger the size of the artwork, typically the higher the value, and hence the greater the price. The artworks are also categorised into oil on canvas, silk print and serigraphy. The majority of the artworks are oil prints. See Table 1 for summary statistics. Later, in the empirical section we return to our findings, where we expect the price to be negatively influenced by the number of prints in the edition.

Insert Table 1 here.

To investigate how colour influences prices for Andy Warhol artworks, we control for the artwork characteristics and focus on how colour is represented. In the

[1] At this stage we limit ourselves to analysing images of sales occurring during the one year period only. We could also include time dummies and increase the datasample as and when required.

[2] Thank you to Anna Butz a research assistant at Maastricht University for help in collecting auction price results for this sample.

following section we introduce the color variables, and how they are estimated from the digital images analysed from the online auction catalogues.

2 Quantifying Color

2.1 Digital image pixel tone and RGB color

Digital images are represented by pixels, the larger the number of pixels, the higher the quality of the image. Each pixel is expressed as a vector of the three colors, denoted RGB color for red (R), green (G) and blue (B); stored as 8-bit RGB matrices. With RGB color expressed as an integer between 0 and 255, colors are formed from various combinations or red (R), green (G) and blue (B). For example for yellow we would need equal amounts of red and green (255 255 0). The lower the RGB colour the darker the image. For a darker shade of yellow, we would lower the amount of red and green by an equal amount i.e. (220R 220G 0B). Likewise, the larger the RGB number the whiter the image. However, to achieve a lighter yellow than that produced by (225 225 0), we need to increase the amount of blue.

Insert Figure 1 here.

An RGB histogram can be used to illustrate the tonal values for each of the three RGB color channels. We take the average of the R, G, and B pixel tonal values over the whole painting as a proxy for the amount of red, green and blue in the artwork. This gives us a first indication of how color differs across our database of artworks. This estimate expresses the amount of RGB color in each image. We therefore take the simple average of the R, G, and B, pixel values over all pixels in the image. Using the minimum definition of at least 200 x 200 pixel images. Hence the average R, G and B values are determined from using at least 4000 pixels per image.

Insert Figure 2 here.

Figure 2 gives an example of one of the Marilyn images which was taken from the data sample using the clustering approach of the three colours, red, green and blue.

2.2 Grayscale

When the color numbers of a pixel are equal we obtain a grayscale image; ranging from pure black (0R 0G 0B) through to (127R 127G 127B), to pure white (255R 255G 255B). Again we will also use the average of the grayscale obtained from all pixels. Since this is a 1 dimensional matrix of pixels we can also estimate the standard deviation of these grayscale pixels. The average grayscale gives an indication of the color intensity in the overall artwork. The higher the number the lighter the artwork and the less intense the color.

2.3 Luminosity

Humans perceive colour differently than depicted by digital tonal values. Since, the human eye is more sensitive to green, and less sensitive to blue, to take into account how this representation of the visual brightness differs to the human eye, we apply the NTSC standard coefficients related to the eye's sensitivity to RGB colours. We further use these values as a proxy for quantifying color. This use of luminosity, taking into consideration if this approximation that the human eye, should provide a better approximation of the true value of color when applied later to the price of the artworks in the contemporary art sample.

2.4 $L * a * b$ Layers

A further color representation of color is captured by using the three dimensional planes $L*a*b$. L again represents luminosity. The second plane is a, which indicates where the color falls alone the red-green axis. The b layer indicates where the color falls along the blue-yellow axis. Using the Image-Processing software in Matlab we are able to determine the average values of these values for the three layers. We effectively transform the image from RGB colorspace to the $L * a * b$ colorspace and estimate the average over all the pixels of the variables for the Luminosity layer, (L-mean), the red-green layer (a-mean) and the blue-yellow axis (b-mean). These three layers are shown for the Marilyn print depicted in Figure 1 in Figure 3.

Insert Figure 2 here.

3 Design and Methodology

Using our sample of 178 images for all global auction houses which auctioned artworks by Andy Warhol during 2012, we are able to estimate the various color values, tones, intensity and luminosity for the various images. This is all completed in Matlab.

We estimate an hedonic pricing model which attributes values to a number of hedonic characteristics. An hedonic price function can be used when a item or product has a number of elements which all add value to the price of the item. The price of a painting can (to a certain extent), be broken up into a number of various constituents, or bundles of characteristics, which are valued separately. This approach enables us to use quantitative models to analyse art prices.

The approach of using hedonic regression was first used on farm land prices by G. Haas in 1922; and later to obtain a price index the hedonic function was applied to farmland values by Wallace in 1926. Another early application, as, Olav Velthuis (2005) points out, is in the late 1920's by Frederick Waugh, who applied the hedonic technique to the market for asparagus. Later, the hedonic price index was also applied to cars in 1939 by A. Court. and has been since used for a wide variety of goods and services.

We use the hedonic function to estimate the amount that paintings characteristics help explain art prices. It assumes that art buyers value a number of characteristics separately and the 'function expresses the price of a good in terms of all its relevant factors' (See Velthuis (2005, page 99)). For example it can help explain why a large painting demands a higher price on average than a smaller painting by the same artist, or the premium that buyers are willing to pay for an oil painting over a watercolour. Olav Velthuis provides an excellent comprehensive study using data from galleries for The Netherlands.

The method enables us to decompose the prices paid for paintings into a number of characteristics related to the artwork itself, such as size, genre, technique, date, and also characteristics of the artist, such as age, reputation, etc. which we write compactly, in a semi-logrithmic functional form, with the characteristics listed in a vector, X.

$$P = \exp^{x\beta\epsilon} \tag{1}$$

Taking logs,

$$ln(P) = X\beta + \epsilon, \tag{2}$$

since β and ϵ are unknown true parameters, we can estimate these by running a regression of the various characteristics on price as

$$ln(P) = Xb + e \tag{3}$$

For example if we have three factors in our hedonic price function, so the vector X contains the variables 'artist', 'size', and 'medium', then we would estimate the following equation:

$$ln(P) = \alpha + \beta_1 Artist + \beta_2 Size + \beta_3 Medium + e \tag{4}$$

The appeal from using a semi-log model is in the interpretation of the coefficients. The coefficients from the hedonic regression are approximately the percentage change in the price of the artwork given a unit change in the independent variables. [3]. The estimated coefficients represent the consumer's willingness to pay a premium for a particular characteristic. For example the implicit price for a particular painting characteristic.

For example. If the log price of a painting is given by the equation

$$\hat{ln(p)} = \alpha + \beta(X). \tag{5}$$

and that the price of a different painting differs to the first painting by one unit. That is to say that $P_1 = P_2 + 1$, then

$$\hat{ln(p_1)} = \alpha + \beta(X_1). \tag{6}$$

[3]Technically a better approximation of the percentage change is given by $\exp^b - 1$, where b is the estimated coefficient and e is the base of the natural logarithm

and,

$$ln(\hat{p_2}) = \alpha + \beta(X_2). \tag{7}$$

so subtracting from each other, we have,

$$ln(\hat{p_1}) - ln(\hat{p_2}) = (\alpha - \alpha) + (\beta(X_1) - \beta(X_2)). \tag{8}$$

which from the properties of logs, and since $(X_1) - (X_2) = 1$, the above can be written as:

$$ln(p_1)\hat{/}ln(p_2) = \beta. \tag{9}$$

So exponentiating both sides gives,

$$(p_1)/\hat{l}n(p_2) = e^{\beta}. \tag{10}$$

In the literature, a number of hedonic studies have taken this approach to analyze art prices. The main hedonic studies are Anderson (1974), Frey and Pommerehne (1989), Rouget et al, (1991), Beulens and Ginsburg (1993), Agnello and Pierce (1996) and Galenson (1999). Renneboog and Houte (2002) and Velthuis (2003). Some interesting findings which these studies claim are as follows. Firstly, paintings are more expensive than artworks made in edition. This supports the general hypothesis that consumers value artworks according to the proximity to the creator. Larger paintings are on average more expensive. The number of works an artist sells has a positive effect on price (Velthuis). Living artists have a premium. Life dummy is always positive (Beulens and Ginsburgh). An artists death impacts negatively on art prices. (Ursprung and Wiermann). Changing tastes: The coefficients vary over time. (Beulens and Ginsburg). Portraits more expensive than landscapes (Beulens and Ginsburgh). Sales at Christie's were on average 10% less than at Sotheby's. (Chanel et al.)

Indicator variables which assign a value of 1 if positive of *zero* otherwise are also included, such as signature, evening sale. Further indicative variables, (dummy variables) which can take a value of 1 if assigned to a particular artist, auction house, medium. Studies have even included the subject, prominence in the artists career, exhibited, condition. Although some factors are hard to quantify, such as who attends a sale, or prominence in the collection, they can indirectly be incorporated into the estimate. Indeed the inclusion of price estimates in hedonic price regressions, since their introduction in the mid-1970's, means that not only can indexes be created over time, but also they have significantly improved the ability of these models to explain the heterogeneity of art prices. We further add to this literature by studying how the differences in art prices across paintings are influenced by color. 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.

4 Empirical Results

The artist is namely, the most important variable in the determination of prices, and since we are only estimating the hedonic pricing function across one artist using 178 observations the R^2 is likely to be lower than found for other studies which have a larger number of observations.

In Table 2 we present the results from the hedonic regression outlined in the previous section without including any explanatory variables associated with color. For our sample we find support for the size and the number of editions printed in line with previous literature. Sotheby's has attracted slightly higher sales, and the difference with Christies is significant at the 1% level only. There is no difference for the material used, so we find no evidence of a premium for silk over oil. The date of creation is highly significant, indicating that his earlier works are worth more than Warhols later creations.

In columns two to four respectively, we include the average pixel values for the RGB factors. We find that the coefficient on all RGB factors to be statistically significant at the 5% level for all three colours. The negative coefficient represents that the lower the RGB values, the higher the log art price. Since the variables are denoted in logs, we can express the value in terms of percentages. The estimated coefficient from the hedonic regression range from -0.003 from red to -0.004 for green and blue. This means that a 1 unit reduction in the mean value of the RGB colors is approximately worth an additional 0.3% more in price. Since the maximum value of the RGB colors is 255, a 10 point reduction in color tone, results in a 3-4% increase in price.

Insert Table 2 here.

Using the luminosity scale which represents how the human eye associates color, the coefficients increase significantly. As outlined earlier (in section 2), the human eye is more sensitive to green than red or blue. The more intense the red color the greater the price paid. The coefficient is -0.1 which represents a 1% increase in price per unit pixel change. This means all else constant a 10% reduction in the color intensity on the RGB scale is equal to 25.5 pixies, which is worth an extra 25.5% in price.

The coefficient on blue is the highest of the three colours tones, with an estimated 3% increase in art prices per 1 unit reduction in the value for blue. The coefficient on green is the lowest, with a 0.6% increase in price per 1 unit reduction in green color, G. Although the human eye is the most sensitive to green. The color that the human eye is least sensitive too, is the color for which the greatest price increase is paid: in this case blue.

Insert Table 3 here.

When using the three-dimensional layering scale which represents luminosity (L), and then the red-green plane, (a) and the blue-yellow plane we find that only the luminosity layer is priced in the hedonic function. The coefficient is statistically significant at the 5% level and the value for the coefficient is -.004, which represents a 0.4% increase in price per unit reduction in the level of the luminosity. Luminosity also ranges from 0 to 255, which reflects a 4% increase in price for a 10% reduction in color intensity.

Insert Table 4 here.

Using the grayscale variables in the hedonic function we again find a significant coefficient on the average value for the gray value. Since we have one dimension of values, we can include the measure for the standard deviation of the gray value. This represents the variation in the gray shading in the artwork. This, however is not statistically significant. The average gray value is, but not the variation in the gray values.

Insert Table 5 here.

To gage this color difference in Figure 4 we show the scale from white to black, with each 10% range representing 25.5 units on the RGB color scale. A movement from one block to the next, from light to dark, as depicted in Figure 4, is worth an additional 4% in price. Given that the average price of paintings sold in the sample is just above $41,000 dollars, this represents an additional cost of $1250 per block of shading.

Finally, we also include a dummy variable for the prints which occur most frequently in the sample. From the 178 images, we have 19 Marilyn prints and 14 Mao prints which differ only in the color representation of the image. Including dummies for these two particular images increases the R^2 of the regressions to 0.37 for the Marilyn images. The dummy on the Marilyn image is highly significant in Table 6. The dummy for Mao himself is not significant, thus there is no premium paid for this particular image. The date variable becomes insignificant when the Marilyn dummy is included, highlighting that it was his earlier work using this particular image for this data sample which drove the significantly higher prices for the Warhol works that we see in the earlier tables. For the color variables, including the dummy variables, we still find the coefficient value is similar in size, but the level of significance drops from the 5% to the 10% level for Marilyn, yet remains significant at the 5% level for Mao. The luminosity variables and degree of color intensity remain signficant. From including the dummy variables on the images Marilyn and Mao, we find that the importance of color is worth more for the Mao paintings than for the Marilyn images; however in both sets of images luminosity and color intensity remain important and significant variables.

Insert Table 6 & 7 here.

The current analysis is still in its infancy. Ideally we would like a larger sample to analyze the affect of color on price in greater detail. In particular we would like to have a large sample of prints of the same image which are replicated and only differ in terms of color. This would enable more precise estimation of the influence and affect of color intensity, and luminosity on prices realised at auction. The disadvantage of taking a longer time period into the analysis is the role that taste and fashion have on prices in the longer term. Focusing on a one year sample period enables us to gain a snapshot of which colors, and the intensity of these colours, currently in vogue. The larger the subsample of icons such as Marilyn, Mao and even the $ sign images, the more precise we can be. Even if only in terms of Andy Warhol's iconic dollar signs, in one sense we are able to put a price on the the color of money.

5 Conclusion

Using a unique set of images for contemporary art sales in 2012, for Andy Warhol artworks sold at auction, we find significant evidence that color intensity influences price. Interesting when analysing the data using the luminosity factors which are more representative of the way the human eye processes color, we find the model increases in explanatory power and the value of the coefficients increase. The color that the eye is least sensitive to is the color which is worth the most in terms of price increase per unit of reduction in the RGB color intensity. This paper is the first to assess how the digital representation of color images and in particular the luminosity of colour drive prices observed in auction markets for contemporary art. Controlling for other hedonic characteristics, empirical results find significant evidence of darker colours carrying a significant and robust premium than equivalent artworks which are less intense in colour.

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Table 1: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Price $	41095.251	42892.651	2250	218500
Log Price	10.165	0.975	7.72	12.29
Edition max	187.494	193.844	1	2000
Red	145.039	49.211	24	236
Green	128.219	43.998	22	224
Blue	118.483	41.264	22	225
N		178		

Table 2: Log Art Prices and RGB Pixels

	(1)	(2)	(3)	(4)
Rmean		-.003		
		(.001)**		
Gmean			-.004	
			(.002)**	
Bmean				-.004
				(.002)**
Log Print Editions	-.080	-.091	-.097	-.095
	(.051)	(.052)*	(.052)*	(.051)*
Log Size	.637	.552	.558	.588
	(.179)***	(.184)***	(.174)***	(.167)***
Log Date	1.215	1.274	1.303	1.300
	(.419)***	(.419)***	(.414)***	(.412)***
London	.336	.335	.379	.348
	(.216)	(.216)	(.215)*	(.215)
NYC	.097	.090	.109	.118
	(.218)	(.217)	(.219)	(.218)
Christies	.100	.120	.107	.116
	(.184)	(.179)	(.182)	(.181)
Sotheby's	.170	.171	.145	.185
	(.187)	(.187)	(.186)	(.185)
Oil	-.115	-.117	-.154	-.177
	(.392)	(.427)	(.364)	(.367)
SP	.002	.076	.064	.070
	(.272)	(.338)	(.272)	(.272)
Silk	-.284	-.195	-.153	-.197
	(.315)	(.368)	(.313)	(.314)
Const.	.468	1.407	1.307	1.020
	(2.465)	(2.453)	(2.384)	(2.354)
Obs.	178	178	178	178
R^2	.2	.218	.221	.221

luminosity

Table 3: Log Art Prices and Luminosity: Human Eye Sensitivity to Color

	(1)	(2)	(3)	(4)
LumRMean		-.010		
		(.005)**		
LumGmean			-.006	
			(.003)**	
LumBmean				-.032
				(.015)**
Log Print Editions	-.080	-.091	-.097	-.095
	(.051)	(.052)*	(.052)*	(.051)*
Log Size	.637	.552	.558	.588
	(.179)***	(.184)***	(.174)***	(.167)***
Log Date	1.215	1.274	1.303	1.300
	(.419)***	(.419)***	(.414)***	(.412)***
London	.336	.335	.379	.348
	(.216)	(.216)	(.215)*	(.215)
NYC	.097	.090	.109	.118
	(.218)	(.217)	(.219)	(.218)
Christies	.100	.120	.107	.116
	(.184)	(.179)	(.182)	(.181)
Sotheby's	.170	.171	.145	.185
	(.187)	(.187)	(.186)	(.185)
Const.	.468	1.407	1.307	1.020
	(2.465)	(2.453)	(2.384)	(2.354)
Obs.	178	178	178	178
R^2	.2	.218	.221	.221

Table 4: Log Art Prices and L*a*b Layers

	(1)	(2)	(3)	(4)	(5)
l-mean		-.004			-.004
		(.002)**			(.002)**
a-mean			-.0008		-.003
			(.006)		(.006)
b-mean				.0009	.005
				(.006)	(.006)
Log Print Editions	-.080	-.097	-.080	-.080	-.098
	(.051)	(.052)*	(.051)	(.051)	(.052)*
Log Size	.637	.550	.636	.641	.561
	(.179)***	(.177)***	(.180)***	(.177)***	(.172)***
Log Date	1.215	1.305	1.213	1.216	1.310
	(.419)***	(.417)***	(.420)***	(.420)***	(.416)***
London	.336	.371	.332	.334	.349
	(.216)	(.215)*	(.217)	(.219)	(.219)
NYC	.097	.102	.097	.100	.112
	(.218)	(.218)	(.218)	(.219)	(.217)
Christies	.100	.111	.101	.100	.116
	(.184)	(.180)	(.185)	(.184)	(.181)
Sotheby's	.170	.154	.173	.173	.178
	(.187)	(.186)	(.193)	(.186)	(.191)
Const.	.468	1.454	.586	.300	1.028
	(2.465)	(2.395)	(2.540)	(2.523)	(2.491)
Obs.	178	178	178	178	178
R^2	.2	.223	.2	.2	.227

Table 5: Log Art Prices and Grayscale

	(1)	(2)
gray-mean		-.004
		(.002)**
gray-stdev		.003
		(.004)
Log Print Editions	-.080	-.098
	(.051)	(.052)*
Log Size	.637	.533
	(.179)***	(.178)***
Log Date	1.215	1.308
	(.419)***	(.419)***
London	.336	.402
	(.216)	(.216)*
NYC	.097	.127
	(.218)	(.219)
Christies	.100	.103
	(.184)	(.179)
Sotheby's	.170	.153
	(.187)	(.186)
Oil	-.115	-.179
	(.392)	(.386)
SP	.002	.074
	(.272)	(.294)
Silk	-.284	-.150
	(.315)	(.330)
Const.	.468	1.368
	(2.465)	(2.385)
Obs.	178	178
R^2	.2	.227

Table 6: Log Art Prices and Image Title: Marilyn

	One	Red	Blue	Green	Luminosity	Grayscale
	(1)	(2)	(3)	(4)	(5)	(6)
LumRMean		-.008				
		(.004)*				
LumBmean			-.021			
			(.014)			
LumGmean				-.004		
				(.003)		
l-mean					-.003	
					(.002)**	
gray-mean						-.003
						(.002)*
Log Print Editions	-.102	-.110	-.111	-.113	-.115	-.113
	(.048)**	(.049)**	(.048)**	(.049)**	(.049)**	(.049)**
Log Size	.630	.561	.597	.576	.559	.566
	(.102)***	(.108)***	(.101)***	(.105)***	(.105)***	(.106)***
Log Date	.251	.315	.337	.339	.345	.344
	(.381)	(.388)	(.384)	(.389)	(.389)	(.389)
London	.348	.348	.356	.378	.377	.369
	(.195)*	(.195)*	(.196)*	(.197)*	(.196)*	(.196)*
NYC	.054	.049	.069	.063	.059	.060
	(.197)	(.196)	(.198)	(.199)	(.197)	(.198)
Christies	.103	.118	.114	.107	.112	.113
	(.171)	(.168)	(.169)	(.170)	(.168)	(.169)
Sotheby's	.086	.087	.098	.071	.074	.078
	(.166)	(.166)	(.166)	(.165)	(.164)	(.165)
Oil	.256	.248	.203	.218	.206	.221
	(.353)	(.378)	(.349)	(.347)	(.352)	(.356)
SP	-.110	-.048	-.061	-.064	-.060	-.051
	(.222)	(.278)	(.240)	(.242)	(.249)	(.255)
Silk	-.298	-.225	-.238	-.207	-.206	-.204
	(.263)	(.305)	(.274)	(.273)	(.279)	(.284)
Marilyn	1.437	1.412	1.394	1.396	1.407	1.395
	(.184)***	(.186)***	(.182)***	(.184)***	(.181)***	(.185)***
Const.	4.021	4.720	4.287	4.496	4.756	4.618
	(1.717)**	(1.676)***	(1.676)**	(1.682)***	(1.655)***	(1.671)***
Obs.	178	178	178	178	178	178
R^2	.366	.378	.376	.376	.381	.378

Table 7: Log Art Prices and Image Title: Mao

	One	Red	Blue	Green	Luminosity	Grayscale
	(1)	(2)	(3)	(4)	(5)	(6)
LumRMean		-.010				
		(.005)*				
LumBmean			-.031			
			(.016)**			
LumGmean				-.006		
				(.003)**		
l-mean					-.004	
					(.002)**	
gray-mean						-.004
						(.002)**
Log Print Editions	-.078	-.088	-.092	-.095	-.094	-.094
	(.051)	(.052)*	(.052)*	(.053)*	(.052)*	(.053)*
Log Size	.618	.537	.572	.540	.533	.531
	(.181)***	(.184)***	(.168)***	(.175)***	(.178)***	(.177)***
Log Date	1.144	1.211	1.236	1.235	1.238	1.239
	(.444)***	(.445)***	(.438)***	(.439)***	(.443)***	(.441)***
London	.316	.318	.331	.360	.352	.346
	(.218)	(.218)	(.217)	(.217)*	(.217)	(.217)
NYC	.102	.094	.121	.113	.106	.108
	(.220)	(.218)	(.219)	(.220)	(.219)	(.219)
Christies	.122	.137	.135	.127	.131	.133
	(.188)	(.183)	(.185)	(.186)	(.184)	(.184)
Sotheby's	.198	.194	.208	.171	.180	.181
	(.189)	(.189)	(.186)	(.187)	(.187)	(.187)
Oil	-.060	-.069	-.128	-.101	-.115	-.098
	(.420)	(.457)	(.396)	(.395)	(.413)	(.415)
SP	.045	.111	.105	.104	.099	.116
	(.312)	(.373)	(.307)	(.310)	(.325)	(.332)
Silk	-.250	-.167	-.168	-.121	-.143	-.126
	(.349)	(.401)	(.343)	(.345)	(.357)	(.363)
Mao	.228	.197	.198	.217	.211	.205
	(.188)	(.190)	(.176)	(.179)	(.182)	(.181)
Const.	.808	1.680	1.306	1.625	1.759	1.728
	(2.568)	(2.540)	(2.444)	(2.473)	(2.485)	(2.478)
Obs.	178	178	178	178	178	178
R^2	.203	.221	.224	.224	.226	.226

Figure 1: Andy Warhol Marilyn Print

Figure 2: Andy Warhol Marilyn Print

Figure 3: Andy Warhol Marilyn Print

Figure 4: Grayscale Color Range from White to Black