Does the sun 'shine' on art prices?☆

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Abstract

This paper examines how variation in mood influences subjective risk and hence auction prices for art in London during the period 1990-2007. The private value of an object is closely related to taste and mood which is proxied for by the variation in weather. Using a unique data set that includes presale estimates for paintings sold through Sotheby's and Christie's auction houses as well as weather data for London from the British Atmospheric Data Centre we find that the lower part of the price distribution is populated with paintings with a relative high private value, whereas in the upper part, prices are driven primarily by the common value characteristics. Our findings have important implications for collectors and investors in the art market.

Keywords: Auctions, Private value, Common value, Mood, Emotions, Cartel.

1. Introduction

There has been an increasing interest in understanding the role of emotions in economic decision making. Experimental evidence has shown that mood affects economic decision making. For instance, Kirchsteiger et al. (2006) find that good mood implies greater generosity in a gift-exchange game. Psychologists have found similar effects of mood on decision making, and Loewenstein et al. (2001) show that when inducing subjects with a positive mood they become overoptimistic and overweight the probability of good outcomes. Similarly, Lerner et al. (2004) show that when inducing sadness and disgust subjects respond by changing their valuation for objects being traded.

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While there is plenty of experimental evidence from economics and psychology on the effect of mood on decision making, it has yet to be fully understood how the effect of mood carries over to economic behavior in the field. In this paper, we investigate the effect of mood in English auctions. In order to identify changes to mood we use the variation in the hours of daily sunshine as a proxy. Our approach enables us to compare our findings with those of Capra et al. (2010) which contributes to a better understanding of the effect of mood in auctions. We find that on the sunniest days, the prices obtained at auctions are higher for low priced paintings as compared to normal weather days during the winter and summer only. We control for seasonality, painting specific characteristics, and the auction house.

We collect data on art auction from both Sotheby's and Christie's over the period 1990-2007. London provides an ideal setting for studying the influence of weather on bidding behavior. First, in London the variation of sunshine is very high. The probability of rainfall is around 50%, providing us with a setting in which we can study the effect of relatively sunny days. Second, London is one of the leading markets for art auctions, providing us with both high quality artworks as well as consistently high auction room attendance rates. This implies that both supply and demand should remain stable over time.

The contribution of our paper to the current literature is threefold. First, our results provide suggestive evidence for emotional influences on market prices beyond the stock market. This contributes to the literature on stock returns and weather induced behavior (see Hirshleifer and Shumway, 2003; Saunders, 1993). Second, the results highlight the importance of location specific factors on willingness-to-pay for objects with a relative high private value component. Finally, we study the influence of emotions in auctions using field data, giving empirical support to some of the experimental findings. Most notably, our findings support Capra et al. (2010).

There are several known price anomalies in art auctions. Beggs and Graddy (1997) show that valuations are ordered from high to low throughout an auction, which coincides with the optimal strategy for selling heterogeneous items for the auctioneer. Mei and Moses (2005) show that price estimates are biased with respect to long-term performance. More recently, Beggs and Graddy (2009) show the effect from anchoring on art prices. We also contribute to this stream of literature by showing that there is a significant effect from mood present in the art market as captured by good weather days.

Our paper is organized as follows. In section two we discuss the private and common value components and how they relate to auction prices. We also describe the relationship and prior evidence on the weather and emotions in markets. We describe the data in section three and our results in section four. Finally, we discuss our findings and conclude the paper.

2. The value of art

The value of art is determined by on the one hand, its future resale value and on the other hand, the emotional utility derived from owning the object. For art traded at an auction both components play important roles. Interestingly, the two components have very different characteristics from an auction theory point of view. The investment value will at any point in time for a fixed horizon be identical to all bidders, even though they have different information about it. This resembles a common value good, where every bidder only receives a noisy signal of the true value of the good. The emotional utility on the other hand, is strictly personal. The value someone derives from viewing a painting is independent from that of all other bidders. Thus, the emotional value represents a private value good. Goeree and Offerman (2003) show that when private and common value signals are drawn from log-concave distributions the value of the item is an additive combination of these two components.[1] Thus, importantly every transaction price therefore has to be a combination of the private and common value components.

If the private value component makes up a relatively large part of the total value attached to a painting, we expect that variation in mood will affect auction prices. Paintings where this is the case carry a relatively lower common value component and hence the resale value is less important. On the other hand, if the common value component is relatively more important, then the variation in the private value component will have a very low impact on transaction prices and thus carry little significance in explaining prices. We expect that low value paintings carry a large private value component and a low common value component, which reverses as we move up the distribution of prices.

The aim of our paper is to uncover the importance of the private value component in art. In the following we focus on the mechanisms by which the private value component is affected. Our identification strategy relies on using insights from recent experimental evidence on the importance of emotions in private value auctions. We proxy for external variation in mood by using the variation in daily sunshine. The motivation stems from Howarth and Hoffman (1984) who show that sunshine has a positive impact on mood. Taken together, we therefore expect that when the private value component of art is relatively high and consequently the resale value is low, transaction prices will be affected by the variation in sunshine while when the importance of the private value component is low it will have no effect.

Emotions are important in decision making, and have been shown to impact the perceived riskiness of decisions (Johnson and Tversky, 1983; Rottenstreich and Hsee, 2001). Loewenstein et al. (2001) look at the role of affect on decision making. They draw on clinical psychology research and show that positive emotional reaction to risky situations often diverges from the cognitive assessment of those risks. They find that people in positive emotional states tend to make more optimistic judgments. Kuhnen and Knutson (2011), test this hypothesis in a financial market setting and find supportive experimental evidence that positive emotional states induce people to take on risk. The mechanism at play is that positive affect reduces the subjective probability distribution of returns. Risk is associated with subjective uncertainty whereby individuals reduce the subjective probability distribution of returns. People in positive emotional states tend to make optimistic judgments about the expected distribution of returns. Risk, as measured by the standard deviation of

[1] Among other distributions, the normal, uniform and exponential distribution satisfy this requirement.

the probability return distribution is less and subsequently the judgment on the valuation of the object changes.

Emotions have also been studied in auction settings, Capra et al. (2010) find that when inducing bidders with positive emotions in a random n^{th}-price auction experiment, there is a resulting bias in bidding upwards in the induced value condition. Bosman and Riedl (2004) investigate how emotions, induced by an economic shock translate into bidding behavior in a first-price auction. The authors show that inducing negative emotions, bidders bid more aggressively. However, their experimental findings do not lead to any significant difference in bidding behavior induced by positive shocks on subjects and conclude that bidders in a positive emotional state do not change their bidding behavior. The results are supportive of the affective regulation hypothesis, whereby people in a negative mood will take action to improve their mood, whereas people in a positive mood will refrain from changing behavior as a way to prevent changing their affective state. Capra et al. (2010) explain this in detail and look specifically at how mood influences choice. The authors distinguish between how mood can affect the valuation of the object being auctioned as well as affecting the bidding behavior itself. They find no evidence that mood effects willingness to pay, instead it does appear to affect bidding behavior. Thus, the experimental results from Capra et al. (2010) and Bosman and Riedl (2004) stand in partial contrast to each other, but cannot be directly compared since the auction mechanism differ between the two studies. The design of the art auctions studied in this paper, theoretically resemble second price auction and thus lays closer to the n^{th}-price auction studied in Capra et al. (2010).

Lerner et al. (2004) study the willingness-to-pay and accept under different emotions. The authors focus on the effect of sadness and disgust and find that inducing negative emotions result in subjects reducing their willingness-to-accept. They suggest that by triggering the emotions of sadness and disgust, subjects overtly want to expel and as a response reduce the willingness-to-accept.

Mood induced changes in behavior are not exclusively found in the laboratory, but several researchers also establish that mood, through local weather conditions, has a significant impact on returns in financial markets. Saunders (1993) studies the New York weather and stock market and shows that on very cloudy days, stock market returns are significantly lower. Hirshleifer and Shumway (2003) extend the sample and record cloud coverage in the morning at 26 international stock markets, and show that cloud coverage is negatively correlated with returns. They argue that since the effect is present and significant for the pooled sample of stock markets, it can be considered a genuine effect on returns. Interestingly, Goetzmann and Zhu (2005) show that the weather effects do not seem to stem from individual traders, but is instead driven by market makers. This finding is confirmed by Loughran and Schultz (2004) who show that there is no local weather bias with respect to the geographic location of the firm itself.

In addition to the weather effect, Kamstra et al. (2003) show that there is considerable seasonal variation in stock returns that correlate with the length of the day. The authors study several international stock markets at different latitudes that are located in both hemispheres. The evidence shows that the stronger the variation in the length of the day is, the more variation in returns are present. They label it as a seasonal affective disorder (SAD) effect. While it is not the focus of our study, the authors show that on shorter days (with less sunlight), around the winter solstice, depressed mood lowers stock market returns which return to higher levels as the days subsequently become longer again (Kamstra et al., 2003).

Similarly, behavioral changes due to the variation in weather could be driven by a projection bias. The projection bias captures a decision maker's exaggerated belief that his current taste also represents his future taste and therefore leads to biased decisions (Loewenstein et al., 2003). Conlin et al. (2007) study the relation between catalog orders for clothing and the local weather and find that the quantity of clothing returned is inversely related to temperature.

We can use the existence of the common value component to further test our hypothesis. The common value component represents the future, but unknown, resale value of the painting. The value of the common value component is independent of any temporary factor affecting the private value component. During the sample period that we study, the two major auction houses in London, Sotheby's and Christie's, formed a cartel to jointly set the commission rates received from sellers (Ashenfelter and Graddy, 2005). Christie's publicly announced the increase in commission rate in March 1995, and Sotheby's followed to make a similar announcement shortly thereafter. In 1996, the UK Office of Fair Trading announced that informal inquiries were being made and later it was decided that the two auction houses were in violation of Britain's Fair Trading Act of 1973 and the Competition Act of 1980 (Ashenfelter and Graddy, 2005). The cartel was active from September 1, 1995 to February 2, 2000.

Since the auction houses publicly announced the increased commission rates charged to sellers, all bidders were aware of the institutional change that they faced. Thus the sellers could pass the increased commission to buyers by increasing estimates. Bidders who buy for investment purposes, incorporate the auction house estimate information when bidding and should be bidding more aggressively as a result. This would shift prices upward as long as buyers put a large emphasis on the common value component. The private value component on the other hand will remain unaffected by variation in the resale value.

In sum, we expect to see two effects on auction prices. When the relative importance of the private value component is high, then good weather should capture variation in mood and thus also higher prices, in accordance with Capra et al. (2010). However, when the relative importance of the private value component is low, the prices of paintings transacted during the cartel should be significantly different from the non-cartel period.

3. Data

In this section we introduce our weather data as well as our auction records.

3.1. *Weather variables*

We collect intra-daily weather data for London from the British Atmospheric Data Centre (BADC)[2] that is associated with the Natural Environment Research Council (NERC). We choose to record weather data from the Heathrow weather station (station id 708), since this station has been in continued operation for over half a century. Other weather stations have either opened, closed, or do only record a subset of the weather variables used in our study. From the weather data we extract daily observations on the minimum, and maximum temperature (°C), precipitation (mm), and sunshine (hours).

The vast majority of the studies on weather effects on the stock market, use cloud coverage as their main weather indicator (see for instance Saunders, 1993; Loughran and Schultz, 2004; Kliger and Levy, 2003). These studies have shown that variation in cloud coverage is a good proxy for mood variation. Hirshleifer and Shumway (2003) further shows that after controlling for sunshine, rain and snow become irrelevant for returns. Since we do not observe cloud coverage through the weather data available to us, we use a comparable measure, the hours of sunshine as our main weather indicator. The hours of hours of sunshine should be strongly negatively correlated with cloud coverage.

In Figure 1 we plot the monthly average hours of sunshine during our sample period. The plot indicates that there is a significant cyclical behavior of the hours of sunshine in London. To control for seasonal changes in weather, we calculate the distribution of sunshine hours for each month of the year separately using weather data going back to 1957. We use the distribution of the month specific sunshine hours to determine a threshold that defines what a good day constitutes. Using this method, a good day in January will be different from a good day in e.g. June.

The surveyed literature clearly shows that there are much stronger mood effects on *exceptional* compared to just normal days (see for instance Saunders, 1993). As a consequence we define a good weather day, as opposed to a normal weather day, as being one of the 10% best days in each month in terms of the hours of sunshine. We set our constructed variable to 1 when a day is in the top category, and 0 otherwise.

The amount of rain in London is considerable, as can clearly be seen in Figure 2. To make our measure restrictive, we therefore interact our constructed variable with a dummy variable that takes 1 if there is no rain on that day and 0 otherwise. To sum up, our proxy for *good weather* throughout this paper takes value 1 when there is no rain and the day belongs to the top 10% sunshine days of that particular month of the year, and zero otherwise.

3.2. *Auction data*

We collect art auction records from the two major auction houses in Britain, Christie's and Sotheby's over the time period between 1990 and 2007. The observations collected are from paintings that have a previously recorded transaction. We record pre-sale estimates,

[2]The data as well as an overview of all variables can be accessed at http://badc.nerc.ac.uk/data/ukmo-midas/

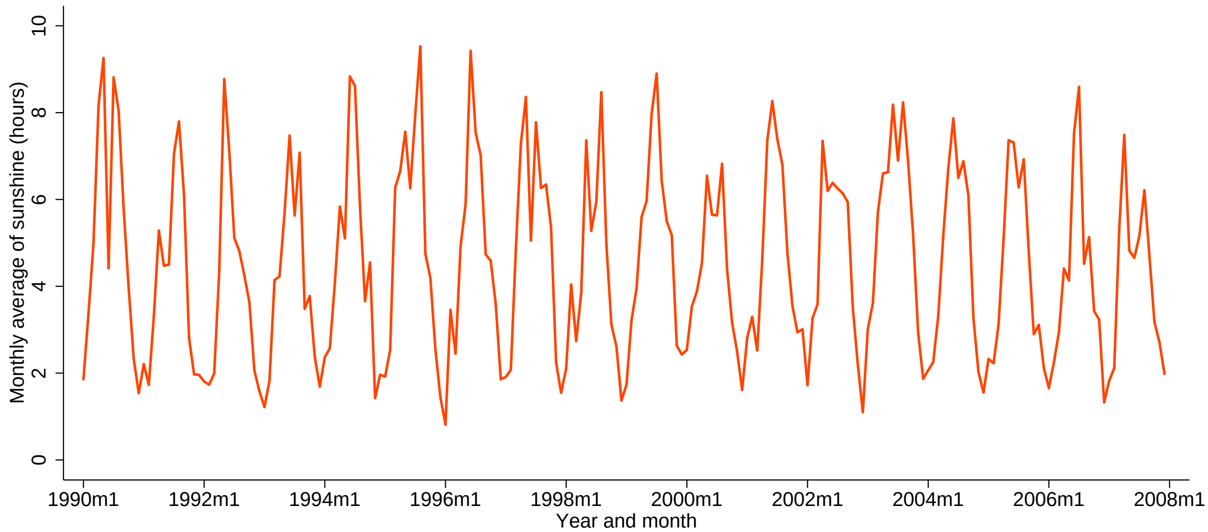


Figure 1: Monthly average of the daily hours of sunshine over our sample period.

the artist (if known), as well as the following characteristics associated with each object: motive, material, and school.

Due to the presence of some extreme outliers that could be incorrectly recorded values, we observe that the distribution of bids is skewed to the right in the upper tail. This is an empirical issue that is commonly reported in the literature (see, e.g., Marion, 2007, Guerre et al., 2000). One solution is to consider the data-driven scheme introduced by Guerre et al. (2000). By calculating an upper and a lower bound for auction prices using the optimal bandwidth obtained by Silverman's rule of thumb (see Silverman, 1986 and Härdle, 1990) this procedure results in a removal of 26 observations. The optimal width is the width that minimizes the mean integrated squared error if we use a Gaussian kernel and the standard normal distribution as the reference distribution. By this process we remove 26 observations.

In Table 1, we report simple summary statistics by weather, cartel and seasons. Results indicate that prices during bad weather days are about £46,000 higher than those on good weather days. In the next two rows, we report the price difference with and without cartel influence. Interestingly, the summary statistics indicate that the sale prices were lower during the cartel period, compared to the non-cartel period. The seasons show strong variation in prices indicating that there are strong seasonal patterns within the art market. The winter and summer display much higher prices than the spring and autumn. In relative prices however,[3] the differences are very small, showing that the markup above the estimate is stable across different painting price categories.

Figures 3(a), 3(b) and 3(c) plot the log transaction prices by weather, cartel, and

[3]Relative price $= \frac{\text{Price}}{\frac{\text{High estimate} + \text{Low estimate}}{2}}$.

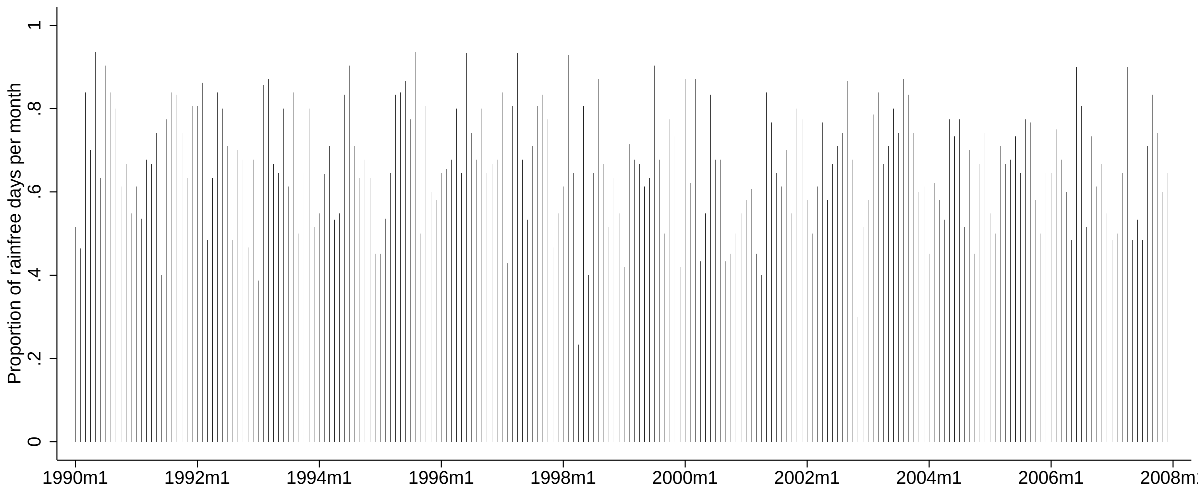


Figure 2: Proportion of rain free days per month.

seasons respectively. The figures reveal that there appears to be little differences between the cartel and non-cartel periods, whereas sales during good weather seem to fetch slightly lower prices. The differences between the four seasons are more pronounced, and sales during winter and summer seem to capture higher prices than those during spring and autumn. Note that these are unconditional densities and in the next section we empirically test the differences in sale prices due to good weather and the cartel.

4. Results

4.1. Number of Paintings sold

The art market suffers from selection and liquidity problems as noted frequently in the literature (for instance, Mei and Moses, 2002; Goetzmann, 1993). Some paintings that are put up for sale do not meet the reserve price and remain unsold. We therefore analyze the variation in the number of transacted paintings and how it is influenced by good weather days as well as the presence of the cartel. We define a session as all paintings that are observed and offered on a particular day for each of the auction houses in our study. We perform this analysis using the absolute number of paintings sold as well as the relative ratio of sold-to-offered. Our specifications are as follows,

$$sold_{at} = \phi offered_{at} + W\Gamma + M\Theta + \eta_{at} \tag{1}$$

where W and M are controls for the weather and the presence of cartels and the seasonal and market characteristics. The variables sold and offered are the number of paintings sold and the number of paintings offered for sale by an auction house a on a given day t respectively.

The results are presented in Table 3 and show three separate specifications. The first two columns concern the absolute number of paintings sold and are estimated by a negative

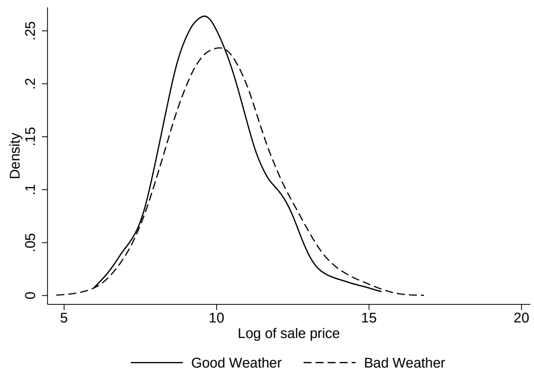
Variable	Number of Sessions	Paintings Sold		Sale price	Relative price
		Number	Percentage	Mean	Mean
Good weather	81	883	.669	92,151.79	1.398
			(.471)	(329,895.7)	(1.019)
Bad weather	708	9,095	.663	139,556.4	1.436
			(.473)	(540,063.9)	(1.535)
During cartel	204	2,147	.646	103,318.6	1.414
			(.478)	(355,332.3)	(2.148)
Pre- and post-cartel	585	7,831	.669	144,146.4	1.437
			(.471)	(562,387.6)	(1.261)
Spring	169	1,582	.710	36,899.49	1.459
			(.454)	(91,521.11)	(1.232)
Summer	277	4,166	.658	160,485.8	1.427
			(.474)	(583,141.9)	(1.377)
Autumn	204	1,652	.625	61,364.33	1.360
			(.484)	(169,690.5)	(1.030)
Winter	139	2,578	.673	202,599.9	1.470
			(.673)	(692,119.6)	(1.997)

Standard deviations are in parentheses.

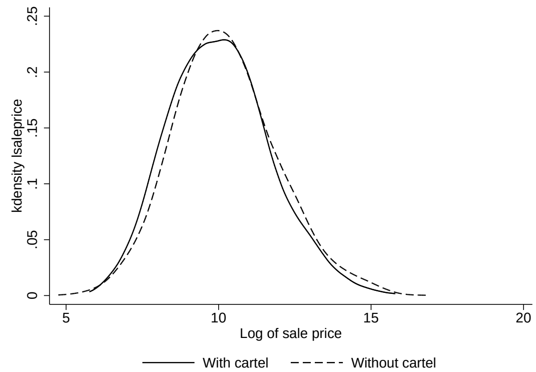
Table 1: Summary statistics by weather, cartel and season.

Variable	Mean	Std dev	Min	Max
Price	135,361	525,031	115	19,803,750
Mid-point estimate	106,194	415,207	150	16,000,000
Good weather	.088	.284	0	1
Cartel	.215	.411	0	1
Old master	.300	.458	0	1
European 19^{th} century	.099	.299	0	1
Modern impressionist	.322	.467	0	1
Other	.197	.398	0	1
Size (m^2)	.566	1.232	.002	40.649
Auction house 1	.563	.496	0	1
Auction house 2	.437	.496	0	1
Spring	.159	.364	0	1
Summer	.417	.493	0	1
Autumn	.166	.372	0	1
Winter	.258	.438	0	1
FTSE100	-.000	.005	-.026	.034

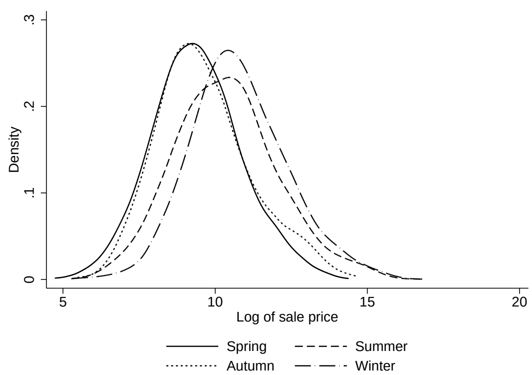
Table 2: Summary statistics of regression variables.



(a) Weather



(b) Cartel



(c) Season

Figure 3: Sale prices by weather, cartel and season.

binomial regression and OLS. The results show no sign of variation in the number of sold paintings arising from either good weather or the cartel. When we run our estimation using the relative number paintings sold, presented in column 3, we see that our good weather proxy is negative and significant at the 10% level. This shows some sign of good weather having a negative effect on the probability of sales and could signal that there are in fact outside opportunities resulting in less attendance and may lead to less aggressive bidding. While we cannot observe the number of actual or potential bidders in these auctions, Ashenfelter (1989) notes that there does not seem to be a link between then number of bidders and the percentage of items bought-in and argues that the actual buy-in rates are unlikely to be explained by the factors used in the optimal auctions literature. While we cannot fully rule out such effects, our main concern is the effect that mood has on prices. Further, if less paintings sell, due to less aggressive bidding, it should in general lower prices during good weather and thus works in the opposite direction to our hypothesis.

	Number of paintings sold		Proportion of paintings sold
	Negative binomial	OLS	OLS
Number of paintings offered for sale	0.043***	0.699***	
	(0.002)	(0.016)	
Good weather (β_1)	0.027	-1.203	-0.136*
	(0.224)	(1.539)	(0.078)
Cartel (β_2)	-0.032	-1.586	-0.047
	(0.226)	(1.142)	(0.087)
Spring (β_3)	0.032	1.110*	0.038
	(0.081)	(0.619)	(0.032)
Summer (β_4)	0.053	-0.284	-0.022
	(0.069)	(0.419)	(0.025)
Autumn (β_5)	-0.002	-0.147	-0.045
	(0.076)	(0.428)	(0.028)
Spring $\times$ Good weather (β_6)	-0.168	0.703	0.129
	(0.270)	(1.632)	(0.103)
Summer $\times$ Good weather (β_7)	0.072	2.045	0.174*
	(0.258)	(1.677)	(0.090)
Autumn $\times$ Good weather (β_8)	0.034	1.625	0.152
	(0.274)	(1.606)	(0.096)
Salehouse 2	-0.189***	-0.153	-0.010
	(0.049)	(0.254)	(0.018)
Constant	1.354***	-0.846	0.661***
	(0.114)	(0.610)	(0.041)
Year effects	Yes	Yes	Yes
F Test (p-value)			
$H_o : \beta_1 + \beta_6 = 0$	0.351	0.394	0.929
$H_o : \beta_1 + \beta_7 = 0$	0.434	0.182	0.410
$H_o : \beta_1 + \beta_8 = 0$	0.695	0.407	0.762
Observations	789	789	789
R-squared		0.96	0.064
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Table 3: Number of paintings sold per session.

4.2. The value of art

To assess whether there is an effect of mood on auction prices we take two approaches. First, we estimate the log price on the good weather and cartel dummies, with a set of controls using a linear regression model. Second, we employ quantile regression to study how the relative importance of the private and common value components vary with the distribution of prices. This approach also enables us to see whether in fact the cartel and mood affect different paintings through the relative importance of the private and common value components as discussed in Section 2.

Our first empirical specification is as follows:

$$y_i = WB + P\Gamma + M\Phi + \epsilon_i. \tag{2}$$

where our dependent variable, y_i, is the log of the sales price. The independent variables include three sets of variables. W contains the variables of interest, good weather and the cartel; P contains the controls for for painting characteristics; and M contains the control for seasonal and market characteristics. In specific, The painting characteristics consist of a set of dummy variables to identify if the painting was created by a 'top western painter', the dummy variables for the painting categories, the size of the painting in squaremeters, and an auction house dummy. For market controls we include FTSE100 returns and year effects. The logic behind controlling for three day past $FTSE100$ returns is that it can capture any potential outside variation in mood implied by short-term swings in the stock market. Detailed description of the construction of these variables are provided in Appendix B.

We report the results from the linear regressions in Table 4. All specifications are estimated using robust standard errors with different sets of controls. Through all specifications it is clearly visible that there is no effect from either the cartel or good weather. By interacting good weather with a particular season we analyze whether there are seasonal differences in the good weather effect. We do this since the weather pattern in London is highly seasonal, as shown in Figure 1. The base coefficient on good weather (β_1), thus only captures the good weather effect from sales occurring during winter. We test for significance of good weather during other seasons with an F-test on the sum of the season specific good weather coefficient and our base case, for instance for the spring this represents a test of $\beta_1 + \beta_6 = 0$. There does not appear to be any good weather effect. Looking at the type of art that is sold. European and 19th century art as well as modern and impressionist art yields low prices compared to the left out category, uncategorized or 'other' paintings. We also control for a selection of important painters in the last two columns. In our sample of sold paintings 14% or 1,370 out of 9,785 were attributed to top artists. The list of painters is presented in Appendix A.

Next, we employ quantile regression as proposed by Koenker and Basset (1982). The quantile regression allows us to assess how good weather, our proxy for good mood, affects log prices at different quantiles of the distribution. Table 5 reports the results of the quantile regression. In Panel A, the quantile regression reveals that in fact both good weather and the cartel have a significant impact on sales prices but in different quantiles.

	Log (sale price)			
	(1)	(2)	(3)	(4)
Log of midpoint estimate	0.970***	0.972***	0.971***	0.971***
	(0.004)	(0.004)	(0.004)	(0.004)
Good weather (β_1)	0.023	0.053	0.038	0.038
	(0.037)	(0.038)	(0.038)	(0.038)
Cartel (β_2)	0.092	0.087	0.084	0.084
	(0.061)	(0.060)	(0.061)	(0.061)
Spring (β_3)	-0.002	0.014	0.013	0.013
	(0.019)	(0.019)	(0.020)	(0.020)
Summer (β_4)	-0.034**	-0.025*	-0.024*	-0.024*
	(0.014)	(0.014)	(0.014)	(0.014)
Autumn (β_5)	-0.038**	-0.011	-0.01	-0.010
	(0.017)	(0.018)	(0.018)	(0.018)
Spring $\times$ Good weather (β_6)	-0.066	-0.094	-0.071	-0.070
	(0.057)	(0.057)	(0.057)	(0.057)
Summer $\times$ Good weather (β_6)	-0.008	-0.020	-0.004	-0.004
	(0.046)	(0.046)	(0.046)	(0.046)
Autumn $\times$ Good weather (β_6)	-0.048	-0.075	-0.061	-0.061
	(0.053)	(0.053)	(0.053)	(0.053)
Old master		0.087***	0.084***	0.084***
		(0.013)	(0.013)	(0.013)
European / 19th century		-0.012	-0.011	-0.011
		(0.018)	(0.018)	(0.018)
Modern / Impressionist		0.000	-0.001	-0.002
		(0.012)	(0.012)	(0.012)
Log size (m^2)		-0.002	-0.002	-0.002
		(0.004)	(0.004)	(0.004)
Salehouse 2		0.054***	0.053***	0.052***
		(0.012)	(0.012)	(0.012)
Lag log three day FTSE-100				-0.248
				(1.045)
Constant	0.478***	0.401***	0.399***	0.399***
	(0.049)	(0.055)	(0.055)	(0.055)
Year effects	Yes	Yes	Yes	Yes
Top artists			Yes	Yes
F Test	p-value			
$H_o : \beta_1 + \beta_6 = 0$	0.334	0.340	0.451	0.464
$H_o : \beta_1 + \beta_7 = 0$	0.561	0.216	0.198	0.199
$H_o : \beta_1 + \beta_8 = 0$	0.512	0.547	0.538	0.541
Observations	9978	9978	9978	9978
R-squared	0.910	0.910	0.911	0.911

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Regression results with robust standard errors.

In the low end of the price distribution we observe that good weather is significant at the 20^{th} and 30^{th} quantile, as well as marginally at the 60^{th} quantile during winter and at the 10^{th} and 20^{th} quantiles, as well as marginally at the 90^{th} quantile during summer, whereas the cartel remains insignificant. As we move up the price distribution we observe that the significance of good weather vanishes but at the same time that the coefficient of cartel picks up significance.

Adding additional controls for important painters in Panel B, we see that the magnitude of the good weather effect weakens, but that it remains significant at the low end during summer and winter. The cartel effect remains strongly significant. The cartel dummy should only pick up significance if paintings indeed are bought for investment purposes and therefore the common value component is strong enough. Further, our evidence for the weather effect support our hypothesis of paintings entailing both a private and a common value component.[4]

5. Discussion

In this paper we study how mood affects art auction prices, as proxied by variation in local weather. We find that mood affects the lower end of the price distribution. We use the existence of a cartel between the auction houses to proxy for variation in the common value component. Our evidence shows that it is only the upper end of the price distribution that is affected by the cartel. Our findings support the evidence by Capra et al. (2010) by showing that there is a, although relatively weak, mood effect on auction prices.

The role of emotions in economic decision making is not yet fully understood. Experimental evidence has shown that mood affects decision making. Our study identifies this effect also in a field setting. At the same time, we show that the effect of mood induced behavior disappears as we move up the price distribution and the cartel effect becomes significant. This does not suggest that the mood induced behavior vanishes when moving up the quantiles, instead it could be driven by the reduction of the importance of the private value component and thus we can no longer capture the effect of mood on auction prices.

Our research suggests that there are important insights to be made by understanding the role of emotions in auctions. The implications of our results are important to art auction participants. By understanding the nature of the good being sold, bidders can make informed judgments about the value that they attach to an item. Our findings highlight the importance of the source of the value attached to an item and its relation to the relative importance of the private and common value components. By understanding emotions in

[4] As a robustness check we rerun our regressions using a broader good weather definition. We redefine good weather to include the 15% best days in each month in terms of the hours of sunshine and no rain. Results indicate that coefficients of good weather in general show the same direction as in top 10% of days but is less statistically significant with as well as without artist dummies. The cartel effect remains statistically significant at the higher quantiles. We do not report these results but can be provided upon request.

Panel A

	Log (sale price)								
Variables	q10	q20	q30	q40	q50	q60	q70	q80	q90
Log of midpoint estimate	0.998***	0.998***	0.995***	0.986***	0.977***	0.975***	0.970***	0.966***	0.966***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.009)
Good weather (β_1)	0.032	0.074**	0.048**	0.067	0.056	0.087*	0.008	0.017	0.015
	(0.040)	(0.030)	(0.023)	(0.042)	(0.046)	(0.047)	(0.050)	(0.058)	(0.090)
Cartel (β_2)	-0.037	0.04	0.014	0.024	0.150*	0.203***	0.245***	0.193**	-0.016
	(0.090)	(0.039)	(0.034)	(0.068)	(0.081)	(0.061)	(0.094)	(0.098)	(0.122)
Spring (β_3)	-0.010	-0.002	0.001	0.01	0.021	0.045*	0.036	0.037	0.092*
	(0.015)	(0.011)	(0.011)	(0.018)	(0.022)	(0.023)	(0.025)	(0.029)	(0.047)
Summer (β_4)	-0.009	-0.017**	-0.027***	-0.031***	-0.032**	-0.032**	-0.033*	-0.019	0.007
	(0.011)	(0.008)	(0.009)	(0.011)	(0.016)	(0.016)	(0.018)	(0.022)	(0.028)
Autumn (β_5)	0.021*	0.000	-0.018*	-0.030*	-0.02	-0.018	-0.028	-0.023	-0.016
	(0.013)	(0.010)	(0.010)	(0.016)	(0.022)	(0.023)	(0.025)	(0.028)	(0.037)
Spring × Good weather (β_6)	-0.008	-0.054	-0.048	-0.049	0.003	-0.092	-0.014	-0.078	-0.196*
	(0.059)	(0.044)	(0.036)	(0.068)	(0.068)	(0.065)	(0.082)	(0.077)	(0.112)
Summer × Good weather (β_7)	0.013	-0.046	-0.024	-0.042	-0.047	-0.088	-0.022	-0.037	0.024
	(0.045)	(0.034)	(0.030)	(0.048)	(0.054)	(0.061)	(0.064)	(0.076)	(0.122)
Autumn × Good weather (β_8)	-0.027	-0.086**	-0.033	-0.061	-0.089	-0.118	-0.079	-0.007	-0.001
	(0.054)	(0.041)	(0.033)	(0.052)	(0.066)	(0.078)	(0.087)	(0.098)	(0.114)
Old master	0.015	0.019***	0.030***	0.042***	0.072***	0.081***	0.112***	0.126***	0.186***
	(0.010)	(0.007)	(0.008)	(0.011)	(0.013)	(0.015)	(0.020)	(0.017)	(0.029)
European / 19th century	-0.008	0.011	0.019*	0.015	0.011	0.014	0.011	-0.007	-0.050
	(0.016)	(0.010)	(0.010)	(0.015)	(0.022)	(0.026)	(0.027)	(0.029)	(0.035)
Modern / Impressionist	0.022*	0.009	0.012	0.014	0.005	0.001	-0.03	-0.060***	-0.090***
	(0.012)	(0.007)	(0.007)	(0.011)	(0.015)	(0.017)	(0.019)	(0.017)	(0.025)
Log size (m^2)	0.000	0.002	-0.003	-0.006	-0.004	-0.008	-0.010	-0.007	-0.015
	(0.003)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)	(0.009)
Salehouse 2	0.108***	0.079***	0.063***	0.060***	0.059***	0.045***	0.036*	0.021	-0.006
	(0.012)	(0.006)	(0.007)	(0.010)	(0.013)	(0.015)	(0.019)	(0.020)	(0.024)
Constant	-0.388***	-0.266***	-0.137***	0.045	0.218***	0.417***	0.633***	0.876***	1.272***
	(0.046)	(0.034)	(0.030)	(0.051)	(0.060)	(0.074)	(0.080)	(0.087)	(0.102)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F Test					p-value				
$H_o : \beta_1 + \beta_6 = 0$	0.518	0.490	0.997	0.753	0.280	0.917	0.927	0.252	0.013
$H_o : \beta_1 + \beta_7 = 0$	0.014	0.050	0.120	0.159	0.740	0.976	0.762	0.657	0.583
$H_o : \beta_1 + \beta_8 = 0$	0.877	0.659	0.478	0.849	0.459	0.620	0.278	0.894	0.851
Observations					9978				

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B

	Log (sale price)								
Variables	q10	q20	q30	q40	q50	q60	q70	q80	q90
Log of midpoint estimate	0.996***	0.999***	0.994***	0.986***	0.978***	0.975***	0.971***	0.967***	0.965***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.009)
Good weather (β_1)	0.046	0.060**	0.051**	0.059	0.068	0.072	0.009	0.014	-0.003
	(0.037)	(0.027)	(0.022)	(0.041)	(0.042)	(0.047)	(0.038)	(0.058)	(0.102)
Cartel (β_2)	-0.038	0.019	0.015	0.049	0.134*	0.194***	0.247***	0.190*	0.034
	(0.093)	(0.041)	(0.033)	(0.067)	(0.080)	(0.072)	(0.095)	(0.105)	(0.131)
Spring (β_3)	-0.010	-0.001	0.004	0.013	0.018	0.043	0.035	0.045	0.061
	(0.017)	(0.011)	(0.013)	(0.021)	(0.025)	(0.028)	(0.027)	(0.031)	(0.047)
Summer (β_4)	-0.008	-0.014*	-0.024***	-0.030**	-0.034**	-0.035**	-0.030	-0.013	-0.005
	(0.014)	(0.007)	(0.009)	(0.012)	(0.014)	(0.018)	(0.020)	(0.022)	(0.030)
Autumn (β_5)	0.020	0.001	-0.015	-0.028	-0.025	-0.018	-0.024	-0.022	-0.010
	(0.019)	(0.012)	(0.012)	(0.019)	(0.025)	(0.028)	(0.027)	(0.029)	(0.037)
Spring × Good weather (β_6)	-0.031	-0.028	-0.053	-0.028	-0.005	-0.075	-0.01	-0.066	-0.111
	(0.053)	(0.040)	(0.039)	(0.071)	(0.062)	(0.070)	(0.064)	(0.079)	(0.125)
Summer × Good weather (β_7)	0.008	-0.038	-0.023	-0.025	-0.055	-0.068	-0.024	-0.045	0.034
	(0.041)	(0.032)	(0.029)	(0.050)	(0.057)	(0.062)	(0.057)	(0.072)	(0.124)
Autumn × Good weather (β_8)	-0.036	-0.066**	-0.039	-0.067	-0.088	-0.086	-0.073	-0.056	-0.039
	(0.052)	(0.034)	(0.031)	(0.050)	(0.065)	(0.077)	(0.085)	(0.102)	(0.144)
Old master	0.013	0.016**	0.027***	0.036***	0.066***	0.079***	0.112***	0.130***	0.177***
	(0.013)	(0.008)	(0.009)	(0.012)	(0.014)	(0.018)	(0.019)	(0.021)	(0.031)
European / 19th century	0.000	0.009	0.018*	0.014	0.014	0.018	0.011	-0.004	-0.042
	(0.018)	(0.010)	(0.010)	(0.014)	(0.019)	(0.024)	(0.025)	(0.027)	(0.038)
Modern / Impressionist	0.025**	0.012*	0.013	0.011	0.006	0.001	-0.027	-0.058***	-0.096***
	(0.012)	(0.007)	(0.008)	(0.012)	(0.016)	(0.019)	(0.018)	(0.018)	(0.025)
Log size (m^2)	0.002	0.002	-0.003	-0.006	-0.004	-0.008	-0.007	-0.010	-0.012
	(0.004)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.009)
Salehouse 2	0.113***	0.081***	0.063***	0.062***	0.061***	0.046***	0.028	0.011	-0.032
	(0.011)	(0.008)	(0.007)	(0.010)	(0.013)	(0.016)	(0.018)	(0.017)	(0.027)
Constant	-0.388***	-0.272***	-0.131***	0.036	0.200***	0.409***	0.609***	0.883***	1.263***
	(0.051)	(0.033)	(0.029)	(0.050)	(0.059)	(0.070)	(0.077)	(0.078)	(0.110)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top artists	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Last 3 day log-return of FTSE100	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F Test					p-value				
$H_o : \beta_1 + \beta_6 = 0$	0.724	0.287	0.961	0.633	0.268	0.950	0.994	0.407	0.131
$H_o : \beta_1 + \beta_7 = 0$	0.011	0.173	0.121	0.157	0.638	0.916	0.698	0.476	0.671
$H_o : \beta_1 + \beta_8 = 0$	0.785	0.798	0.573	0.800	0.713	0.825	0.372	0.591	0.669
Observations					9978				

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Quantile regression results.

decision making better we can improve our understanding of individual behavior in markets beyond auctions.

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Appendix A. Artists

Important painters of the history of western painting

Albrecht Durer	Fra Angelico	James Ensor	Paul Gauguin
Amedeo Modigliani	Francis Bacon	James Mcneill Whistler	Paul Klee
Andrea Mantegna	Francisco de Goya	Jan van Eyck	Peter Paul Rubens
Andy Warhol	Francisco de Zurbaran	Jan Vermeer	Piero Della Francesca
Arshille Gorky	Frans Hals	Jasper Johns	Pierre-Auguste Renoir
Artemisia Gentileschi	Franz Marc	Jean Francois Millet	Piet Mondrian
Camille Corot	Frederick Edwin Church	Jean-Antoine Watteau	Pieter Bruegel the Elder
Caravaggio	Frida Kahlo	Jean-Auguste-Dominique Ingres	Raphael
Caspar David Friedrich	Georges Braque	Jean-Michel Basquiat	Rembrandt van Rijn
Cimabue	Georges de La Tour	Joachim Patinir	Rene Magritte
Claude Lorrain	Georges Seurat	Joan Miro	Roger van der Weyden
Claude Monet	Georgia O'Keefe	John Constable	Roy Lichtenstein
Dante Gabriel Rossetti	Gerhard Richter	Joseph Mallord William Turner	Salvador Dali
David Hockney	Giorgio de Chirico	Kazimir Malevich	Sandro Botticelli
Diego Velazquez	Giorgione	Leonardo da Vinci	Simone Martini
Duccio da Buonisegna	Giotto di Bondone	Lucio Fontana	Theodore Gericault
Edgar Degas	Gustav Klimt	Marc Chagall	Tintoretto
Edouard Manet	Gustave Courbet	Marcel Duchamp	Titian
Edvard Munch	Gustave Moreau	Mark Rothko	Tomasso Masaccio
Edward Hopper	Hans Holbein the Younger	Max Ernst	Umberto Boccioni
Egon Schiele	Hans Memling	Michelangelo Buonarroti	Uincent van Gogh
El Greco	Henri Matisse	Nicolas Poussin	Wassily Kandinsky
El Lissitzky	Hieronymus Bosch	Pablo Picasso	Willem de Kooning
Eugene Delacroix	Jackson Pollock	Paolo Uccello	William Blake
Fernand Leger	Jacques-Louis David	Paul Cezanne	William Hogarth
			Winslow Homer

Source:The Art Wolf (2011)

Appendix B. Construction of variables

In this appendix we describe the construction of our variables used in the empirical analysis.

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- **Good weather:** We construct the good weather dummy variable with the following procedure,

  1. Using daily data from the Heathrow weather station (id 708) from the period between 1957 to 2007, we construct month specific distributions of the hours of sunshine. From these distributions, we infer a 10% cutoff value to identify the requirement for a *good day*.
  2. We compare each auction sale day in our sample from 1990 to 2007 with these cutoff values to determine whether a sale was conducted on a good or bad day.
  3. To create the *good weather* variable, we interact *good sunshine* with a variable taking value 1 of there is *no rain* and zero otherwise.

- **Cartel:** The variable takes value 1 for every sale that occurs within the cartel period between September 1, 1995 and February 2, 2000.

- **Seasons:** We define the seasons as,

  - Winter: December, January, and February.
  - Spring: March, April, and May.
  - Summer: June, July, and August.
  - Autumn: September, October, and November.

- **Mid-point estimate dummies:** We calculate the mid point estimate for each painting. We then construct five dummy variables for the different ranges of estimates, from 0% to 20%, 21% to 40%, 41% to 60%, 61% to 80%, as well as 81% to 100%. We use these variables to make sure that paintings eith low and high estimates are not unevenly distributed across qunatiles in the qunatile regression.

- **Painting category:** We categorize the paintings on sale into one of the following categories,

  - Old master
  - European / 19th century
  - Modern / Impressionist
  - Other

- **FTSE100 returns (lagged 3 day average):** We calculate the one day lagged three day average daily log return of the FTSE100 to control for any outside opportunities that investors enjoy at the time of the sale.
- **Painting size:** We include two variables, *height* and *width* as further control variables. Both are measured in centimeter.
- **Top 101 artists:** To control for the effect of master pieces, we create dummy variables for a list (Appendix A) of top western painters.