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. Using the hours of daily sunshine as a proxy for the variation in mood, we collect 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. Our quantile regression findings indicate that extraordinarily good weather results in an upward bidding bias during the winter and across the distribution. This paper complements previously reported experimental findings on the role of emotions in decision making.

Keywords: Auctions; Risk preferences; Mood; Emotions;

JEL Classification: D44; Z11;

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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. Kirchsteiger, Rigotti, and Rustichini (2006) find that good mood implies greater generosity in a gift-exchange game. Capra, Lanier, and Meer (2010) show through a series of auction experiments that positive mood generates an upward bidding bias. Psychologists have found similar effects of mood on decision making. Loewenstein, Hsee, Weber, and Welch (2001) show that when inducing subjects with a positive mood they become overoptimistic and overweight the probability of good outcomes. Similarly, Lerner, Small, and Loewenstein (2004) show that when inducing sadness and disgust subjects respond by changing their valuation for objects being traded.

While there is plenty of experimental evidence from economics and psychology on the effect of mood on decision making, it has yet to be studied how the effect of mood carries over to economic behavior in the field. In this paper, we investigate the effect of mood on ascending auction prices. Our purpose is to study the mood effects that are induced by extraordinarily good weather in an ascending auction. Our approach enables us to directly compare our findings with those of Capra et al. (2010) which contributes to a better understanding of the effect of mood in auctions.

We collect data on art auction from both Sotheby's and Christies over the period 1990-2007. London provides an ideal setting for studying the influence of weather on bidding behavior. In order to identify changes to mood we use the the variation in the hours of daily sunshine as a proxy. First, 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 attendance rates.

This implies that both supply and demand should remain stable over time.

We collect intra-daily weather data from the Natural Environment Research Council in the United Kingdom. We do not only study the effect of weather conditions on art auction prices, but also the seasonal variation in prices. Our results are striking. We find that on the sunniest days, the prices obtained at auction are 2-3% higher than on normal weather days during the Winter. We control for seasonality, painting specific characteristics, and the auction house, among other things. Due to the low level of sunshine during Winter our results show support towards a more pronounced affect during the Winter months.

The contribution of our paper to the current literature is fourfold. First, our results provide supportive evidence for emotional influences on market prices beyond the stock market. This contributes to the literature on stock returns and weather induced emotions (see Hirshleifer & Shumway, 2003; Saunders, 1993). Second, the results highlight the importance of location specific factors on willingness-to-pay (WTP). This relates to the local bias found in financial markets where investors are willing to pay more for stocks with headquarters in close proximity (Loughran & Schultz, 2004). An important third contribution is that 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). Finally, our approach allows us to disentangle the effect of selling an artwork on a good weather day from the seasonal variation in prices.

There are several known anomalies affecting prices 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 good weather effect present in the art market.

Our paper is organized as follows. In section two we introduce a theoretical framework that captures the effect of mood, and how it relates to auction prices. In section three we describe the relationship and prior evidence on the weather and emotions in markets. We describe the data in section four and our results in section five. Finally, we discuss our findings and conclude the paper.

2 Emotions and the winner's curse

Emotions have been shown to impact the perceived riskiness in decision making (Rottenstreich & Hsee, 2001). The process is facilitated by the cognitive evaluation in combination with an emotional reaction to the risk involved (see Loewenstein et al., 2001). If, and as shown by Howarth and Hoffman (1984), sunshine significantly impacts optimism, it could temporarily alter an individual's perceived risk attitudes and thereby also affect auction prices. This argument is supported by Capra et al. (2010) who find that when inducing bidders with positive emotions in a random nth-price auction experiment WTP rises slightly. Bosman and Riedl (2004) investigate how emotions, as induced by an economic shock translates into bidding behavior in a first-price auction. The authors show that inducing negative emotions, bidders bid more aggressively. This finding is supported by Lerner et al. (2004) who show that when inducing sadness as a negative emotion WTP increases.

To exemplify the effect of variation in risk attitudes on auction prices, consider the following setting. Art has an unknown future resale value and is auctioned in an English auction setting. Thereby, we model the auction as a common value ascending button auction with irreversible exit.

The winner's curse is a well known phenomenon in common value auctions (see Kagel & Levin, 1986; Levin, Kagel, & Richard, 1996). It arises since the true value of the painting being auctioned is unobserved. Instead every bidder only observes a noisy signal of the true value. As a result, if every bidder would bid their own signal, it is likely that the highest bidder will have drawn a signal that lies above the true value. If the bidders do not adjust for this possibility by discounting their bids, the winner will end up paying a price above the value, the 'winner's curse'.

In equilibrium, bidders will adjust their bids so that *ex ante* they do not bid above the expected value of the item. By varying risk preferences of the bidders', the expected value that the bidders' assign to the item will vary as well. Thus, the more risk averse, or less risk seeking, that the bidders are, the less revenue the auction will generate *ex ante*.

Following Krishna (2002), let R be the revenues generated from the auction. With N symmetric bidders each receiving a signal $X_1, X_2, \ldots, X_N$. If we define the random variables $Y_1, Y_2, \ldots, Y_{N-1}$ to be $X_2, X_3, \ldots, X_{N-1}$ ordered from large to small, then given that bidder 1 receives the highest signal the *ex ante* expected revenues generated by a common value English auction are,

$$\begin{aligned} E[R] &= E[\beta^2(Y_1, Y_2, \ldots, Y_{N-1}] \\ &= E[u(Y_1, Y_1, Y_2, \ldots, Y_{N-1})|X_1 > Y_1] \end{aligned}$$

With risk neutral bidders the expected payoff is the difference between the value and the price paid. Introducing variation in risk preferences, the dropout prices, which are calculated as expectations, are replaced with their certainty equivalents (Levin et al., 1996). Thus, average prices must fall with risk aversion, and increase with risk seeking preferences. Hence,

$$E[R^{RL}] > E[R] > E[R^{RA}],$$

where the superscripts RA and RL represent symmetric risk averse and risk seeking bidders

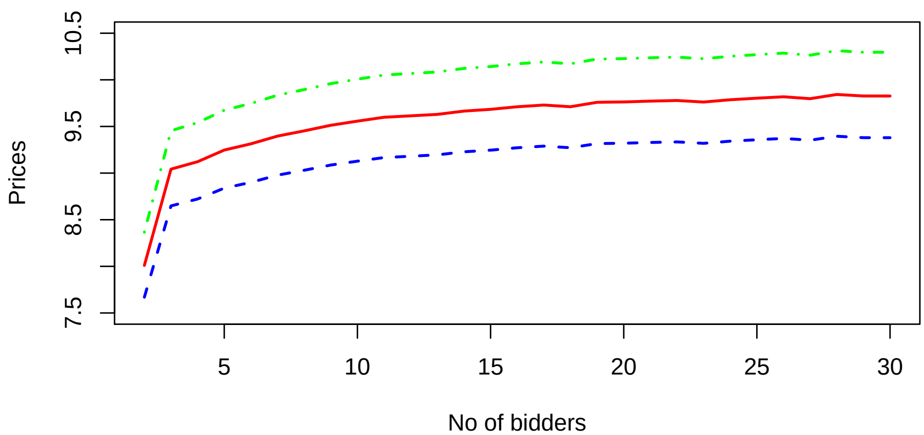


Figure 1: English auctions with varying number of bidders. The upper line shows $\alpha = 1.02$ (risk seeking), the middle line shows $\alpha = 1.0$ (risk neutral) and the dashed line shows $\alpha = 0.98$ (risk averse).

respectively. Thus if weather alters the perception of the uncertainty in estimating the value of an item, then positive emotions, as induced by good weather, in the common value English auction, should drive prices upward. Thus we expect a positive relationship between good weather and art auction prices. Apart from variation in risk preferences also variation in the number of bidders could drive price changes. We therefore simulate the English auction, following the setup described in Levin et al. (1996). The model allows us to easily simulate the effect of varying risk attitudes as well as varying the number of bidders.[1] These results are presented in Figure 1, and show clearly that whenever there are more than five bidders price changes due to variation in the number of bidders are very small. Instead, varying risk attitudes show a much larger impact on prices. The line shows how a population of risk neutral bidders would bid, and the dashed line shows how slightly risk averse bidders would bid. For simplicity we assume a power utility function

[1] Our setup mimics the one presented in Levin et al. (1996), except that we use different bounds for the distribution from which we draw values. In specific we draw the value of the item x_0 from $U[5, 15]$, and subsequently the signals from $U[x_0 - 5, x_0 + 5]$. Thus all valuations are strictly positive.

of the form $U(v) = v^{\alpha}$. Where α is the risk parameter. For example $\alpha = 1$ indicates risk neutrality and $\alpha < 1$ shows risk aversion. For a risk averse bidder, the certainty equivalent of the value of the item will be less than what he would expect it to be if he would have been risk neutral.

3 Emotions and the weather

Mood induced changes in behavior is not exclusively found in the laboratory, but several researchers also establish that local weather conditions have a significant impact on asset prices in financial markets. Saunders (1993) study 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. The authors 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, Kramer, and Levi (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. The authors label it as a seasonal affective disorder (SAD) effect.

In many settings preferences have shown to vary depending on the method of preference elicitation (Slovic, 1995). Such violations of the elicitation invariance of preferences, can be driven by emotions (Elster, 1996). In this paper we use field data to test how WTP is affected by exogenous variation in a known driver of emotion, the weather.

Early research in psychology has shown that mood is connected to weather conditions. Howarth and Hoffman (1984) study subjects over time, and show that the hours of sunshine directly influences an individual's level of optimism, one of the categories that define mood. Similarly, later research into economic decision making under different mood conditions have shown that inducing changes to a persons mood significantly alter individual WTP (Lerner et al., 2004).

4 Data

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

4.1 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 & Schultz, 2004; Kliger & Levy, 2003). These studies have shown that variation in cloud

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

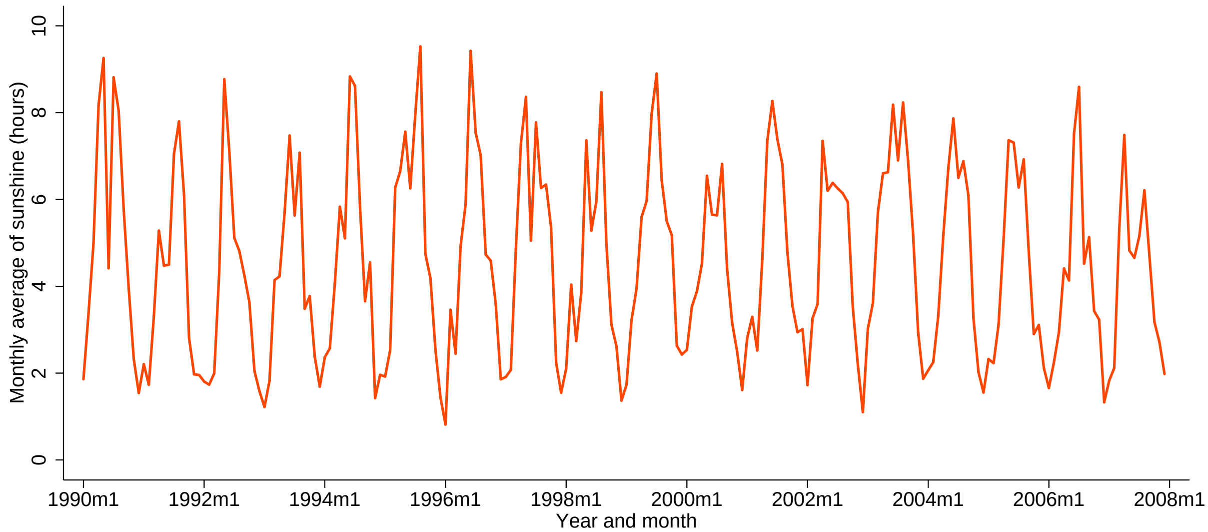


Figure 2: Monthly average of the daily hours of sunshine over our sample period.

coverage is a good proxy for mood variation. Hirshleifer and Shumway (2003) further shows that after controling for sunshine, rain and snow become irrelevant for returns. We follow this stream of literature and use a comparable measure, the hours of sunshine as our main weather indicator. In Figure 2 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 than a good day in e.g. June.

The surveyed literature clearly shows that there are much stronger mood effects on *exceptional* compared to just average days (see for instance Saunders, 1993). As a consequence we define a good 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.

Figure 3: Proportion of rain free days per month.

The amount of rain in London is considerable, as can clearly be seen in Figure 3. 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.

4.2 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. We record pre-sale estimates, 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, we drop the top and bottom 1% of the relative prices. Since paintings are heterogeneous we focus on relative prices throughout this paper. The relative prices are calculated using by,

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

Our study is complicated by the fact that, during our sample period Sotheby's and Christie's were accused of collusive behavior by fixing sellers' commission rates. 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 & Graddy, 2005). It was later determined that the cartel was active from September 1, 1995 to February 2, 2000. Note that in March, Christie's made an announcement stating as of September 1, 1995 they would charge a non-negotiable commission form sellers on the sale price. On April 13, 1995 Sotheby also announced a similar non-negotiable sliding-scale commission on the sale price for sellers. Therefore, we treat the cartel as an exogenous shock to the market since it was publicly known (Ashenfelter & Graddy, 2005; Ginsburgh, Legros, & Sahuget, 2010). We control for this period using a dummy variable.

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 more 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, the differences are very small, showing that the markup above the estimate is stable across different painting price categories.

The art market suffers from selection and liquidity problems as noted frequently in the literature (for instance, Mei & Moses, 2002; Goetzmann, 1993). Some paintings that are put up for sale do not meet the reserve price and remain unsold. This could introduce a selection bias in the sense that weather does not only affect prices, but also the probability of a sale. Also, any differences in the sales rates between the different seasons will complicate our study. In column four of Table 1 we present the differences in sale rates between different weather regimes, the cartel period and the the different seasons. The result shows that weather does not affect the probability of sale and thus, if there are any weather effects present we expect these to appear in the auction prices. The full results are available in Appendix C.[3]

Variable	Number of	Paintings Sold		Sale price	Relative price
	Sessions	Number	Percentage	Mean	Mean
Good weather	81	866	.654	92,155.73	1.333
			(.263)	(331,083.10)	(.677)
Bad weather	708	8,919	.648	138,322.30	1.354
			(.243)	(539,717.60)	(.732)
During cartel	204	2,105	.632	102,409.00	1.323
			(.229)	(354,910.50)	(.749)
Pre- and post-cartel	585	7,680	.654	142,595.90	1.360
			(.250)	(562,134.80)	(.721)
Spring	169	1,537	.684	34,517.69	1.367
			(.279)	(86,800.69)	(.737)
Summer	277	4,081	.645	159,012.70	1.344
			(.228)	(581,104.40)	(.737)
Autumn	204	1,627	.612	61,203.12	1.302
			(.237)	(169,897.80)	(.678)
Winter	139	2,540	.665	201,551.60	1.388
			(.238)	(693,195.80)	(.725)

Standard deviations are in parentheses.

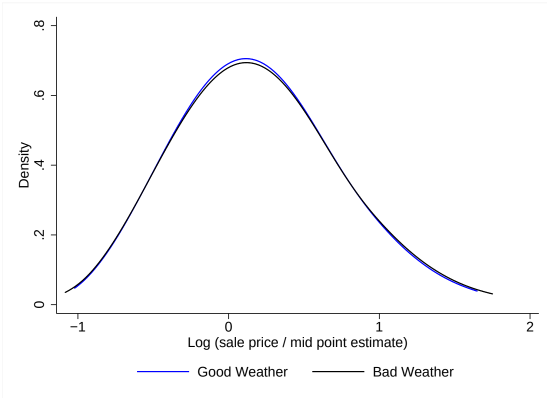
Table 1: Summary statistics by weather, cartel and season.

Figures 4(a) and 4(b) represent log of relative prices by weather and cartel respectively. These figures indicate that relative prices distributions are not different due to weather but slightly lower during cartel period. Figure 4(c) show the distribution of log relative prices by seasons. However, we also need to be cautious in interpreting these figures since the distributions are unconditional on any painting, sales, or market characteristics. Therefore,

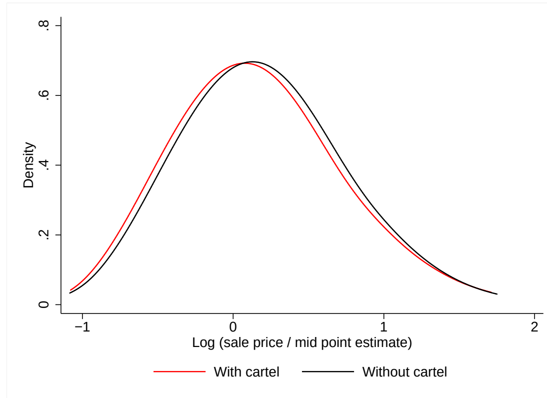
[3]When considering seasons, in only two cases, between autumn and summer and autumn and spring we reject the null hypothesis of equal sale rates.

Variable	Mean (Standard deviation)
Good weather	.089
	(.284)
Cartel	.215
	(.411)
Old master	.299
	(.460)
European 19^{th} century	.100
	(.300)
Modern impressionist	.323
	(.468)
Other	.197
	(.398)
Size (m^2)	.566
	(1.234)
Auction house 1	.561
	(.496)
Auction house 2	.439
	(.496)
Spring	.157
	(.364)
Summer	.417
	(.493)
Autumn	.166
	(.372)
Winter	.260
	(.438)
FTSE100	-.000
	(.005)

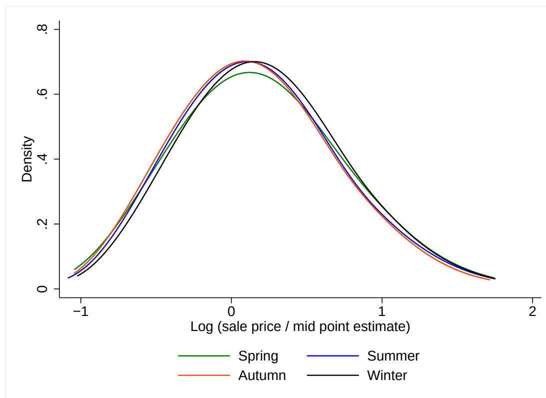
Table 2: Summary statistics of regression variables.



(a) Weather



(b) Cartel



(c) Season

Figure 4: Relative prices by weather, cartel and season.

our next section presents some basic regression models that will be used to describe more fully the differences in prices due to weather. Summary statistics of regression variables are presented in Table 2.

5 Results

5.1 Number of Paintings offered

To be able to determine whether the weather significantly affects relative prices, we fist have to show that the weather and the presence of the cartel do not alter the pattern of the number of paintings offered for sale. If the supply of paintings is adversely influenced by bad weather days or by the presence of the cartel, it could influence relative prices. To aid our analysis, we use a simple count data model to test whether good weather days as well as the cartel significantly alters the number of paintings offered for sale in a session. We use a negative binomial model to estimate the number of items per day.[4] In the negative binomial regression, our dependent variable is the number of paintings offered for sale on a given day and the independent variables are weather, cartel, seasonal, and year effects. Note that general negative binomial regression has a difficulty with zero-truncated data since it tries to predict zero counts even though there are no zero values. Since we do not observe any zeros, we also use a zero truncated negative binomial model to estimate the effects of weather and cartel on number of paintings for sale.

The results are reported in Table 3 and indicate that the number of items offered for sale is not affected by weather or the presence of the cartel. Note that β_1 captures the effect of the number of paintings offered for sale during winter good weather days, we see that the coefficient is insignificant, and thus there are no unusual patterns during good weather days in winter compared to other winter days. Concerning seasons, we observe that during spring (β_3) and autumn (β_5) the number of paintings for sale are less as when compared to winter. However, we also observe that during good weather days in spring, summer, and autumn, the number of paintings offered for sale is not statistically different from good weather days in winter. $\beta_1+\beta_6$, $\beta_1+\beta_7$, and $\beta_1+\beta_8$ provide the total effect for good weather days in spring, summer and autumn. P-values, provided in Table 3, show that they are not statistically significant different from the baseline category (winter). Therefore, we can conclude that the weather and the presence of the cartel has not adversely (or favorably) affected the supply of paintings, thereby increasing (or decreasing) prices. We can thus confidently estimate weather effects on the full sample of paintings, including the cartel

[4]We first test whether a Poisson model is appropriate. The goodness of fit test rejects the Poisson model.

period.

Variable	Negative binomial			Zero truncated negative binomial		
	(1)	(2)	(3)	(4)	(5)	(6)
Good weather (β_1)	.288		.291	.299		.303
	(.329)		(.329)	(.387)		(.387)
Cartel (β_2)		.492	.491		.529	529
		(.336)	(.338)		(.393)	(.396)
Spring (β_3)	-.588**	-.607**	-.578**	-.639**	-.657**	-.628**
	(.119)	(.113)	(.119)	(.140)	(.133)	(.140)
Summer (β_4)	-.106	-.135	-.093	-.111	-.140	-.096
	(.104)	(.101)	(.104)	(.122)	(.118)	(.123)
Autumn (β_5)	-.581**	-.614**	-.596**	-.625**	-.660**	-.641**
	(.111)	(.108)	(.112)	(.131)	(.126)	(.131)
Spring $\times$ Good weather (β_6)	-.404		-.365	-.418		-.375
	(.396)		(.396)	(.465)		(.465)
Summer $\times$ Good weather (β_7)	-.518		-.530	-.535		-.549
	(.381)		(.381)	(.448)		(.447)
Autumn $\times$ Good weather (β_8)	-.254		-.273	-.260		-.270
	(.403)		(.403)	(.474)		(.473)
Auction house 2	-.310**	-.305**	-.305**	-.340**	-.334**	-.334**
	(.074)	(.074)	(.074)	(.087)	(.087)	(.087)
Year effects	yes	yes	yes	yes	yes	yes
Number of Obs.	789	789	789	789	789	789
LR χ^2	170.93	170.69	173.10	140.91	140.88	142.75
χ^2 *Test*				p-value		
$H_o : \beta_1 + \beta_6 = 0$	.597		.739	.641		.780
$H_o : \beta_1 + \beta_7 = 0$	.238		.220	.302		.281
$H_o : \beta_1 + \beta_8 = 0$	.885		.937	.885		.932

Robust stranded errors are in parentheses. ** denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level.

Table 3: Number of paintings per session.

5.2 Relative Prices

With the above conclusion, we now examine log relative prices due to the weather. Our empirical approach will be to first estimate the differences in log relative prices due to weather, using a linear regression model controlling for the presence of the cartel, painting characteristics, and other market characteristics. We will then examine how weather conditions affect across the log relative price distribution by employing a quantile regression analysis.

The basic structure of the regression model is as follows:

$$y_i = W\mathbf{B}+P\mathbf{\Gamma}+M\mathbf{\Phi} + \varepsilon_i. \tag{1}$$

Our dependent variable is the logarithm of the relative price. The independent variables include three sets of controls–the W's control for the weather and the presence of cartels, the P's control for painting characteristics, and the M's control for seasonal and market characteristics. The first set of regression results are reported in Table 4. In the first column, we do not include interactions terms of good weather with seasons and painting-specific characteristics (other than the size of the painting), while, in other columns, we include these. Analyzing the results from column one we see that in general good weather has no effect on relative prices. In column two, where we use interaction terms, we observe that during winter, the relative prices are about two percent higher during good weather (β_1), whereas for the other three seasons the effect is insignificant (e.g. $\beta_1 + \beta_6$).

In the next three columns we include other painting and market controls. These columns indicate that that 'European & 19th century' and 'Modern impressionist' yields low prices compared to the left out category, uncategorized or 'other' paintings. In none of our specifications the presence of the cartel has a significant effect on the log relative prices. All columns indicate that as the auction house estimate increases (four mid-point estimate dummies) the relative prices increases and it is monotonic. We also control for 101 most important painters of the history of western painting in the last two columns. In our full sample, out of 15,427 offered for sale, 2,168 (14.05%) were painted by these top artists. In the regression sample 14.00% or 1,370 out of 9,785 were attributed to top artists. The list of painters is presented in Appendix A. In the last column we include lagged three day *FTSE100* average return. If one considers investing in art is an alternative investment to the stock market then we expect to see an inverse relationship between log relative

Variable	Log (sale price / mid-point of the estimate)				
	(1)	(2)	(3)	(4)	(5)
Good weather (β_1)	-.007	.021*	.027**	.021*	.021*
	(.005)	(.011)	(.011)	(.011)	(.011)
Cartel (β_2)	-.014	-.016	-.013	-.012	-.012
	(.018)	(.018)	(.018)	(.018)	(.018)
Spring (β_3)	-.003	.000	.001	.002	.002
	(.005)	(.006)	(.006)	(.006)	(.006)
Summer (β_4)	-.001	-.000	.001	.002	.002
	(.004)	(.004)	(.004)	(.004)	(.004)
Autumn (β_5)	-.001	.000	.002	.002	.002
	(.005)	(.005)	(.005)	(.005)	(.005)
Spring $\times$ Good weather (β_6)		-.032*	-.040**	-.032**	-.031**
		(.016)	(.016)	(.015)	(.015)
Summer $\times$ Good weather (β_7)		-.013	-.018	-.012	-.012
		(.014)	(.014)	(.014)	(.014)
Autumn $\times$ Good weather (β_8)		-.015	-.022	-.016	-.016
		(.017)	(.017)	(.017)	(.017)
Mid-point estimate (>20% $-$ 40%)	.235***	.235***	.233***	.233***	.233***
	(.004)	(.004)	(.004)	(.004)	(.004)
Mid-point estimate (>40% $-$ 60%)	.419***	.419***	.418***	.418***	.418***
	(.004)	(.004)	(.004)	(.004)	(.004)
Mid-point estimate (>60% $-$ 80%)	.708***	.708***	.706***	.706***	.706***
	(.004)	(.004)	(.004)	(.004)	(.004)
Mid-point estimate (>80%)	1.201***	1.201***	1.199***	1.197***	1.197***
	(.007)	(.007)	(.007)	(.007)	(.007)
Old master			.006	.005	.005
			(.004)	(.004)	(.004)
European 19^{th} century			-.011**	-.010**	-.011**
			(.005)	(.005)	(.005)
Modern impressionist			-.006**	-.006**	-.006**
			(.003)	(.003)	(.003)
Auction house 2			.012***	.012***	.012***
			(.003)	(.003)	(.003)
Lag log three day *FTSE*-100					-.119
average return					(.299)
Log of painting size	yes	yes	yes	yes	yes
Year effects	yes	yes	yes	yes	yes
Top 101 artist effects				yes	yes
Number of Obs.	9785	9785	9785	9785	9785
Adj R^2	.880	.880	.881	.881	.881
F Test			p-value		
$H_o : \beta_1 + \beta_6 = 0$		.295	.254	.336	.356
$H_o : \beta_1 + \beta_7 = 0$		.339	.257	.266	.270
$H_o : \beta_1 + \beta_8 = 0$		.627	.703	.696	.691

Robust stranded errors are in parentheses. ** denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level.

Table 4: Regression results.

prices and *FTSE100* three day average return. As expected our results indicate that the coefficient is negative but it is statistically insignificant.

We test for season specific good weather effects by adding the coefficients of the interaction terms to our base case (winter). Thus, e.g. $\beta_1 + \beta_6$, gives the good weather in spring effect. Our tests clearly show that only during winter we observe significant good weather effects. This is only partly consistent with the theoretical predictions developed in Section 2. We would expect that weather would influence the perceived risk attitudes on extremely good days regardless of the season in which the auction is held. Interestingly, only during the season with the lowest hours of sunshine, additional sunshine has a positive effect on prices. This suggests that there are diminishing marginal returns to one additional hour of sunshine.

In order to verify our findings hold across the log relative price distribution we implement a quantile regression method proposed by Koenker and Basset (1982). The quantile regression allows us to assess whether the good weather effect that we identify at the mean also is present at other quantiles of the distribution of the dependent variable. We estimate coefficients at three quantiles of the distribution, 25th quantile, median, and the 75th quantile. Table 5 reports the results using quantile regression. We observe that good weather during winter increases relative prices throughout the distribution. This verifies our findings from the linear regression and it indicates that on good weather days during winter bidders' perceived risk is lower than when compared to other winter days. Total effects of good weather days in other seasons indicate that they do not affect the relative prices of paintings. All p-values calculated for post estimation test fail reject that the total effect is zero. For two of the three models, we cannot reject the hypothesis that the effect is constant for all three points at which we estimate.

We do not observe a significant cartel effect, indicating that price fixing did not affected buyers. To check the robustness of our results, we re-estimate our models excluding the cartel period. These results are presented in Table 6. The results are similar to the ones presented in Table 5.

6 Discussion

We find that during the winter season, there is a significant weather effect on the art market. This is robust across the distribution of artworks. The effect is insignificant for other seasons. The significance during winter only suggests that while bidders' in general do not react to extraordinarily good weather, under certain conditions they do, and hence WTP above the pre-sale estimate goes up with about 2%-3% during such days. Our findings support the evidence by Capra et al. (2010) by showing that there is a mood effect on auction prices.

Our results are robust to a number of different specifications, both in a linear regression and a quantile regression framework. In addition, the sale rate during winter is no different from the sale rate of other seasons (see Appendix C) suggesting that the weather effect is genuine, and does not act as a force that compensates for low attendance. Further, the absence of seasonal effects on relative prices shows that buyers value items similarly regardless of season and the seasonal variation in transaction prices therefore seem to stem largely from variation in pre-sale estimates and not demand or supply factors that vary with season.

One possible explanation for the absence of the good weather effect during spring, summer and autumn, is that additional hours of sunshine result in diminishing marginal returns to sunshine, which in seasons with enough sunshine would make the good weather effect disappear. One possibility to examine this explanation would be use empirical data from auctions held at different latitudes.

Further, the type of object auctioned can also influence the results. Paintings are com-

	Log (sale price / mid-point of the estimate)								
Variable / Quantile	(.25)	(.50)	(.75)	(.25)	(.50)	(.75)	(.25)	(.50)	(.75)
Good weather (β_1)	.036**	.035**	.014**	.036**	.025**	.018**	.036**	.024**	.018**
	(.011)	(.010)	(.006)	(.010)	(.011)	(.006)	(.010)	(.010)	(.006)
Cartel (β_2)	-.015	.005	-.000	-.011	.005	-.002	-.009	.005	-.001
	(.015)	(.016)	(.006)	(.017)	(.016)	(.010)	(.016)	(.016)	(.009)
Spring (β_3)	-.003	.002	-.001	-.002	.003	-.003	-.002	.001	-.003
	(.005)	(.006)	(.002)	(.004)	(.006)	(.003)	(.004)	(.005)	(.003)
Summer (β_4)	-.000	-.002	-.000	-.001	-.003	-.000	-.001	-.004	-.000
	(.003)	(.005)	(.002)	(.003)	(.004)	(.002)	(.003)	(.004)	(.002)
Autumn (β_5)	.002	.001	-.001	.002	.002	-.001	.002	-.000	-.001
	(.004)	(.005)	(.003)	(.005)	(.005)	(.003)	(.004)	(.005)	(.003)
Spring × Good weather (β_6)	-.035**	-.043**	-.017*	-.034**	-.034**	-.022**	-.034**	-.031**	-.022**
	(.014)	(.016)	(.010)	(.013)	(.015)	(.010)	(.014)	(.015)	(.011)
Summer × Good weather (β_7)	-.032*	-.028**	-.010	-.030**	-.021	-.013	-.031**	-.020	-.013
	(.013)	(.012)	(.008)	(.012)	(.013)	(.007)	(.013)	(.012)	(.007)
Autumn × Good weather (β_8)	-.037*	-.043**	-.011	-.032**	-.030*	-.016	-.033**	-.030*	-.017*
	(.014)	(.017)	(.008)	(.015)	(.015)	(.010)	(.014)	(.016)	(.009)
Painting estimate effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Log of painting size	yes	yes	yes	yes	yes	yes	yes	yes	yes
Painting category effects				yes	yes	yes	yes	yes	yes
Auction house effects				yes	yes	yes	yes	yes	yes
Top 101 artist effects							yes	yes	yes
Lag log three day FTSE-100 average return							yes	yes	yes
Number of Obs.	9785	9785	9785	9785	9785	9785	9785	9785	9785
Pseudo R^2	.683	.711	.736	.685	.713	.738	.685	.713	.738
F Test					p-value				
$H_o : \beta_1 + \beta_6 = 0$	.880	.513	.711	.793	.331	.622	.843	.552	.633
$H_o : \beta_1 + \beta_7 = 0$	.475	.299	.453	.420	.567	.396	.488	.509	.290
$H_o : \beta_1 + \beta_8 = 0$	.950	.545	.778	.675	.681	.872	.749	.678	.868
$H_0 : \beta_1^{25} = \beta_1^{50} = \beta_1^{75}$		.020			.226			.221	

Stranded errors are in parentheses. ** denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level.

Table 5: Quantile regression results.

	Log (sale price / mid-point of the estimate)					
Variable / Quantile	(.25)	(.50)	(.75)	(.25)	(.50)	(.75)
Good weather (β_1)	.034**	.036**	.021**	.032**	.029**	.022**
	(.011)	(.011)	(.008)	(.012)	(.012)	(.007)
Spring (β_3)	-.004	.000	-.000	-.003	.002	-.000
	(.005)	(.006)	(.003)	(.005)	(.007)	(.003)
Summer (β_4)	.000	-.001	-.000	.000	-.002	-.000
	(.004)	(.004)	(.002)	(.003)	(.005)	(.002)
Autumn (β_5)	.003	.005	.000	.003	.004	-.000
	(.005)	(.005)	(.003)	(.005)	(.006)	(.004)
Spring × Good weather (β_6)	-.033**	-.053**	-.023	-.032**	-.047**	-.027**
	(.014)	(.019)	(.014)	(.014)	(.016)	(.013)
Summer × Good weather (β_7)	-.031**	-.033**	-.019**	-.027*	-.027**	-.019**
	(.014)	(.015)	(.009)	(.014)	(.013)	(.008)
Autumn × Good weather (β_8)	-.026	-.016	-.020	-.023	-.010	-.020
	(.020)	(.023)	(.014)	(.019)	(.027)	(.016)
Painting estimate effects	yes	yes	yes	yes	yes	yes
Log of painting size	yes	yes	yes	yes	yes	yes
Painting category effects	yes	yes	yes	yes	yes	yes
Auction house effects	yes	yes	yes	yes	yes	yes
Top 101 artist effects				yes	yes	yes
Number of Obs.	7680	7680	7680	7680	7680	7680
Pseudo R^2	.684	.710	.734	.687	.712	.736
F Test			p-value			
$H_o : \beta_1 + \beta_6 = 0$	.868	.235	.854	.999	.123	.684
$H_o : \beta_1 + \beta_7 = 0$	.649	.674	.656	.509	.686	.591
$H_o : \beta_1 + \beta_8 = 0$	.576	.298	.918	.566	.423	.864
$H_0 : \beta_1^{25} = \beta_1^{50} = \beta_1^{75}$		.337			.644	

Stranded errors are in parentheses. ** denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level.

Table 6: Quantile regression results without cartel period.

mon value objects for which emotions with a future, but unknown, resale price. Studying the effect of good weather on private value objects could further enhance the understanding of where the effect arises from.

The role of emotions in economic decision making is not yet fully understood. Experimental evidence has shown that mood affects decision making. Our study successfully identifies this effect also in a field setting.

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A Artists

Most 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

B Construction of variables

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

- **Relative price:** The relative price is constructed as,

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

  The high and low estimate is provided by the auction house to the public well in advance of the auction. In our linear and quantile regressions, we use the logarithm of the relative price as the dependent variable.

- **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.

C Sale rate t-tests

	Bad weather	Before and after cartel	Summer	Autumn	Winter
Good weather	.2213				
	(.8253)				
During cartel		-1.1775			
		(.2397)			
Spring			1.5636	2.6676	-.6544
			(.1189)	(.0080)	(.5133)
Summer				1.5113	.8429
				(.1314)	(.4001)
Autumn					2.0334
					(.0429)

Table 7: Unpaired Welch's t-test with unequal variances on the sale rate between weather, cartel and season. The p-value is calculated using a two-sided alternative hypothesis.