Evan Chow
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Department of Economics
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Advised by Dr. Stephen Morris

Anchoring Cross-Effects in Auctions for Fine Art

Abstract. This paper studies the strength and existence of anchoring effects between substitute goods in the context of fine art auctions. We first attempt to replicate past anchoring research for resale of art pieces. Then, we construct a new, more recent dataset and also run new regressions that specifically capture cross-substitute anchoring. We show that ....

Introduction

Imagine for a moment you are heading to Christie's to bid on a Monet oil painting, which based on its characteristics, might usually sell for around $5 million. You're unaware of that, and so when you learn that a very similar oil painting by Van Gogh (a peer of Monet) fetched $10 million just the week before, $8 or $9 million for the Monet seems like a bargain – even if that reflects more of the Van Gogh than the Monet.

You've been a victim of the *anchoring effect* - a well-known cognitive bias in which the first number you hear (the "anchor") can shape your perception of what is normal. This was demonstrated in a famous clinical experiment by Tversky & Kahneman[1], where participants were given only 5 seconds to calculate the product of numbers 1 through 8, shown either in increasing or decreasing order. It was found those who saw the lower numbers first gave a median estimate of 512, whereas those who saw higher numbers first gave a median estimate of 2250 – a very large difference due to first impressions.

This bias translates naturally into the fine art auction market, which in 2014 enjoyed a sales volume of £5.1 billion (approximately $7.35 billion in today's exchange rate)[2][3]. The primary work on anchoring in art auctions is conducted by Beggs & Graddy (2009), who study this bias across multiple sales of Impressionist and Contemporary art pieces[4]. The main idea is that past sale(s) of a painting should serve to bias its current sale, and the authors do indeed find evidence of these anchoring effects (particularly for Impressionist art). However, as they note, it is very difficult to find two identifiable sales of the same art piece, which is required for their regression model. Hence, Beggs & Graddy use only 1-2% of their original data on all painting sales – but do find a strong anchoring effect with their carefully constructed regression model.

This research generalizes the model of Beggs & Graddy to capture anchoring effects across related art pieces (substitutes). I present a new dataset of recent auction sales (2006-2015) of assorted art pieces constructed for this purpose, and discuss measures of hedonic similarity between non-identical works. I replicate the past research of Beggs & Graddy by

[1] Tversky, Amos, and Daniel Kahneman. "Availability: A heuristic for judging frequency and probability." *Cognitive psychology* 5.2 (1973): 207-232.
[2] http://www.christies.com/about/press-center/releases/pressrelease.aspx?pressreleaseid=7712
[3] http://www.xe.com/currencyconverter/convert/?From=GBP&To=USD accessed 2/20/2015
[4] Beggs, Alan, and Kathryn Graddy. "Anchoring effects: Evidence from art auctions." *The American Economic Review* 99.3 (2009): 1027-1039.

running their original anchoring regressions on their original data and my new data. Next, I run my new cross-anchoring regressions on their original data and my new data. I find that _____. Finally, I discuss how these quantitative results match up against observational evidence, namely conversations with art experts and notes from live auctions.

Review of the Literature

Anchoring is a well-studied bias in psychology and behavioral sciences. The seminal work on anchoring was first conducted by Tversky & Kahneman (1974), who conducted the experiment described above[5]. Some studies show that people formulate estimates more quickly when provided with numbers to anchor on[6], while others show that anchoring decreases – but does not altogether vanish – with increased cognitive ability[7]. Other studies demonstrate that anchoring is extremely difficult to avoid, even if the anchors are obviously incorrect.[8] Within economics, some work has been conducted with historical market data, examining past prices and indices for unchanging goods and current demand to evaluate potential anchoring[9] [10]. The bias appears in many fields from accounting[11] to neuroscience[12], and auctions are no exception.

Within an auction, there are many potential sources for anchoring. For example, some work shows how buyers may anchor on low reserve prices by reducing their range of bids[13], while another study discusses a how a higher “Buy Now” price in online auctions can induce people to bid significantly higher[14]. While buyers may anchor on the starting bids of other buyers and instant buy prices, sellers may anchor on expert estimates and prices set by other sellers. During the bustle of real-time auctions, it is likely that anchoring is even more prevalent in how bidders might anchor on each other’s bids, since some research suggests that emotions play a strong role in driving the auction process[15]. A growing body of literature studies the role of emotions within auctions for art: De Silva et al. (2012), for instance, use weather data as a proxy for mood, and find a significant positive association between favorable weather and art prices[16].

Some work has been conducted specifically on anchoring within art auctions. The primary work is that of Beggs & Graddy (2009), who find that the previous sale price of a

[5] Tversky, Amos, and Daniel Kahneman. "Judgment under uncertainty: Heuristics and biases." *science* 185.4157 (1974): 1124-1131.

[6] http://soco.uni-koeln.de/files/jpsp73.pdf

[7] Bergman, Oscar, et al. "Anchoring and cognitive ability." *Economics Letters* 107.1 (2010): 66-68.

[8] Strack, Fritz; Mussweiler, Thomas (1997). "Explaining the enigmatic anchoring effect: Mechanisms of selective accessibility.". Journal of Personality and Social Psychology 73 (3): 437–446. doi:10.1037/0022-3514.73.3.437.

[9] Rajendran & Tellis (1994); Greenleaf (1995); Geltner (2011); Dougal et al. (2012).

[10] Furnham, Adrian, and Hua Chu Boo. "A literature review of the anchoring effect." *The Journal of Socio-Economics* 40.1 (2011): 35-42.

[11] Kinney Jr, William R., and Wilfred C. Uecker. "Mitigating the consequences of anchoring in auditor judgments." *Accounting Review* (1982): 55-69.

[12] Logvinenko, Alexander D. "The anchoring effect in lightness perception in humans." *Neuroscience letters* 334.1 (2002): 5-8.

[13] http://digitalcommons.uconn.edu/cgi/viewcontent.cgi?article=1190&context=econ_wpapers

[14] Dodonova, Anna, and Yuri Khoroshilov. "Anchoring and transaction utility: evidence from on-line auctions." *Applied Economics Letters* 11.5 (2004): 307-310.

[15] http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6758989

[16] https://www.researchgate.net/profile/Rachel_Pownall/publication/257004491_Does_the_sun_shine_on_art_prices/links/0912f51126bf976f32000000.pdf

painting significantly impacts its current sale due to anchoring[17]. This result is further confirmed with more data in Graddy et al. (2014), who find that anchoring among buyers is stronger for items that are resold quickly[18]. Hong et al. (2015) examine aggregated painting sales for Sotheby's and Christie's, who take turns opening NYC's "auction week" twice a year. They find evidence of anchoring: higher opening sales at one house drive up prices and sales volume at the other institution. On the seller side, Bruno and Nocera (2008) find in a dataset of Italian paintings that even though presale estimates are not a reliable predictor of prices, past prices can nevertheless serve as an anchor for presale estimates[19]. None of this work examines anchoring between substitute goods (specifically, similar art pieces), which is the primary contribution of this paper.

Auctions for Fine Art

The two oldest auction houses are Sotheby's (est. 1744) and Christie's (est. 1766), which together control nearly half of the global market for art auctions[20]. The former has been a publicly traded company since 1988, while the latter is privately owned by *Groupe Artémis*, the holding company of French billionaire François-Henri Pinault. To those in the know, the houses play to different strengths: for instance, some believe that Sotheby's is better at selling American furniture and photographic pieces, while Christie's is better at selling European furniture and books[21]. In recent years, though, Christie's has consistently turned higher revenues[22].

Before an auction, the house will typically put out a presale catalog for the art pieces, which is usually available both online and in print. The description of each piece can include information such as the artist, the materials and a condition report, various signs of authenticity such as a signature, and how the work was acquired (provenance). Also included are a low and high presale estimate, usually by a specialist, which represents the range of possible values the art might go for. Additionally, houses often host pre-auction viewings where both potential bidders and the public can view the pieces in person. Potential bidders must register before an auction, and for particularly opulent auctions, must show proof of their assets. Furthermore, prior to the sale, the seller will inform the house of their reserve price, or their minimum acceptable price for a sale. Reserve prices are closely guarded secrets (perhaps due to potential seller collusion or decreased participation[23]), though some literature for related auctions suggests the optimal reserve price has a lower bound of 75% of the appraised value.

Auctions are almost always conducted in an ascending first price format. Bidding begins low, and the auction calls out increasing prices[24] until the bidding stops, at which the item is declared to be "knocked down" or "hammered down." The final price is the "hammer price," on top of which the house adds a commission or "buyer's premium," usually 10% to 17.5% of the hammer price, before the winning bidder receives the item. If an item does not meet its reserve,

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[17] Beggs, Alan, and Kathryn Graddy. "Anchoring effects: Evidence from art auctions." *T, e American Economic Review* 99.3 (2009): 1027-1039.

[18] Graddy, Kathryn, et al. "Anchoring or loss aversion? Empirical evidence from art auctions." (2014).

[19] Bruno, Brunella, and Giacomo Nocera. "Investing in art: The informational content of Italian painting pre-sale estimates." *Available at SSRN 1179183*(2008).

[20] http://www.bloomberg.com/news/articles/2015-06-21/auction-wars-christie-s-sotheby-s-and-the-art-of-competition

[21] http://www.forbes.com/2001/11/14/1114connguide.html

[22] http://www.nytimes.com/2015/08/17/arts/international/sothebys-and-christies-jostle-for-sales.html?_r=0

[23] Ashenfelter 1989; Vincent 1995

[24] Typically, the auctioneer will call out prices that are approximately 10% higher than the current bid. http://www.sothebys.com/en/Glossary.html

it goes unsold and is said to have been "bought in." The auction house, however, rarely purchases the item: instead, it may be resold later or taken off the market. Historically, auction houses have concealed whether items go unsold. However, since the 1980's houses in NYC have been legally required to report this, and according to Ashenfelter & Graddy (2003) houses in other locations are following this trend[25].

< notes on behavioral aspects of auctions would be great here >

Data

I use three datasets on auction sales in this paper: Impressionist art (1980-1991), Contemporary art (1982-1994), and assorted art sales (2006-2016). The Impressionist and Contemporary art datasets have been used extensively in the literature[26] and are already described in detail elsewhere[27], while the latter is a new dataset constructed specifically for this paper.

The Impressionist art dataset (1980-1991) was constructed by Orley Ashenfelter and Andrew Richardson, and covers sales at Christie's and Sotheby's in both London and New York. There are approximately 16,000 observations of art piece sales, which were compiled by manually scanning auction house catalogs that are typically published before pieces go to sale. Each observation contains the painting title, the artist name, the sale price and date, the auction house and location, the presale low and high estimates, and hedonic characteristics such as the piece dimensions and the presence of a signature. The dataset contains 58 major artists whose work is often featured at auction, and among the most frequent are Pablo Picasso (1881-1973), Raoul Dufy (1877-1953), and Pierre Renoir (1841-1919). Approximately half the auction sales are split between Christie's and Sotheby's, as well as between London and New York. Table 1 shows summary statistics for selected attributes; the highest sale in this dataset goes to Paul Gauguin's *Mata Mua*, which netted approximately $24.2 million on May 9, 1989[28].

Next, the Contemporary art dataset (1982-1994) represents every Contemporary art piece sold from 1980 and 1994 at Christie's primary King Street location in London, for a total of approximately 4,500 observations. Similar to the Impressionist dataset, each observation lists the artist, the auction sale price and date, the presale low and high estimates, the lot number, whether or not the item sold, and hedonic characteristics such as the artist and medium. Various currency exchange quantities are included, such as the UK CPI at the time, and monetary quantities are given in thousands of pounds. Nearly 600 artists are represented, with Lucio Fontana (1899-1968), Karel Appel (1921-2006), and Alexander Calder (1898-1976) being the most frequent. Table 2 gives summary statistics for this dataset.

The dataset of assorted art sales (2006-2016) is a new contribution of this research, and was collected by scanning recent listings on the Blouin Art Sales Index, a database that hosts a large collection of art auction data (http://artsalesindex.artinfo.com/). The raw dataset consists of almost 500,000 observations, covering mostly 19th and 20th century art with some works from earlier time periods (earliest: approx.. 1000 CE, for works by Song Dynasty artist Yi Yuanji). Each observation includes the artwork title, the artist, artwork category as described by the auction house, a textual description of the materials, the lot number, sale date, auction house, and the USD sale price. Because information on the materials were given in the form of

[25] http://www.ppge.ufrgs.br/giacomo/arquivos/econ-cultura/ashenfelter-graddy-2003.pdf

[26] Richardson (2002); Abowd & Ashenfelter (1989); Beggs & Graddy (1997); Ashenfelter & Graddy (2003); Beggs & Graddy (2009)

[27] http://www.jstor.org/stable/pdf/2556028.pdf?acceptTC=true

[28] For more info: http://www.jstor.org/stable/pdf/2556028.pdf?acceptTC=true

unstructured text data, which might be attributed to freeform data entry by Blouin, simple keyword extraction was used to extract hedonic characteristics such as height and width; more sophisticated textual extraction methods should be employed in future work. Some summary statistics for the full raw dataset are provided in Table 3.

In this dataset I analyze paintings, of which there are approximately 260,000 observations, for the purposes of comparison with the two other datasets. Nearly 60,000 artists are included, with the best represented being Pablo Picasso (1,868 works), Andy Warhol (1,712 works), and Joan Miro (880 works). However, the most expensive sale is an untitled crayon work by Cy Twombly (1928-2001), which went for $70.5 million at Sotheby's in NYC in November 2015. The artists whose works sell for the most, on average, include Kazimir Malevich of the Suprematist movement (1879-1935), the Abstract Expressionist Mark Rothko (1903-1970), Vincent Van Gogh (1853-1890), and also Song Dynasty artists such as Emperor Huizong (1082-1135) and Yi Yuanji. As seen in Figure 1, the (log) sale price for paintings in this dataset is somewhat bell-shaped with a moderate right skew. This is because most of the paintings in this dataset sell for low 5 or 6 figure sums, while only a minority sell for higher figures reflected in the gradually diminishing right tail. Furthermore, record-breaking highs (and lows) seem to be associated primarily with artists who sell very few works. Conversely, artists who sell more works through auction will enjoy higher revenue on average (regression slope: 0.52. p-val: <2E-16), but will find it more difficult to sell for a record sum.

Methodology

A simple two-part regression model for detecting anchoring effects between two consecutive sales of the same painting is specified in Beggs & Graddy (2009) who themselves cite Genesove & Mayer (2001). They use the two Impressionist and Contemporary datasets described previously.

First, a hedonic regression is fitted in order to estimate prices π_t for paintings as a function of their characteristics $\boldsymbol{X}$, while also controlling for temporal effects δ_t. I use the same variables as Beggs & Graddy for the same Impressionist and Contemporary datasets. For Impressionist art this includes painting date, length, width, medium of the artwork, indicators of authenticity (signed/monogrammed/stamped), and artist. For Contemporary art this includes painting date, length, width, medium, and artist. The temporal effects are modelled by half-year time dummies.

$$\pi_t = \boldsymbol{XB} + \delta_t$$

This is fitted for observations where a first sale x_{t-1} and a second sale x_t are identified. Beggs & Graddy carefully confirmed resale observations against actual presale catalogs, but this research only examines the data for duplicate observations. Next, an anchoring regression is fitted in order to isolate the anchoring bias:

$$\omega = a_1\pi_t + a_2(P_{t-1} - \pi_t) + a_3(P_{t-1} - \pi_{t-1})$$

Above, P_{t-1} is the past sale (resale) of a painting at time $t-1$ and P_t is the current sale at time t. Beggs and Graddy fit several regressions where the response ω represents either the sale price, an indicator for whether the item sells, or the presale estimate. The anchoring effect is captured in the term $(P_{t-1} - \pi_t)$, which specifies how the past price (the anchor) P_{t-1} impacts the current hedonic price prediction π_t, and thus the dependent variable ω. The last term $P_{t-1} - \pi_{t-1}$ controls for unobservable non-hedonic effects on price. For example, if the past price was not only a function of the painting's hedonic characteristics, but was also a function of bidding activity at the time, this difference will be captured in the $P_{t-1} - \pi_{t-1}$ term. Otherwise, $P_{t-1} - \pi_t$ will not only reflect the impact by strictly past price on current hedonic prediction, but also past bidding activity and other non-hedonic inputs into P_{t-1}.

I propose an extension to the second (anchoring) regression to allow for a substitute – for example, a related painting - which replaces the past sale at time $t-1$, since the sale of substitute must still occur before in order to impact the sales of the current good. As before, we fit a hedonic price regression for every observation, not considering substitutes.

$$\pi = \boldsymbol{XB} + \delta_t$$

However, we add one additional term to the second regression in order to control for omitted hedonic differences between the current and substitute good. Denote our current good as x_c and our substitute as x_s, where the hedonic predictions π_c and π_s are estimated by the first regression above. Then our second regression is:

$$\omega_c = b_1\pi_c + b_2(P_s - \pi_c) + b_3(P_s - \pi_s) + b_4(\pi_c - \pi_s)$$

Here, the subscripts for the past and current sales $t-1$ and t are replaced by subscripts for the substitute s and current good c. The previous regression model assumed that there was no unobserved quality changes in the painting (e.g. was shown to be a fake) between its past and current sale, i.e. $\pi_{t-1} = \pi_t$. However, because we cannot assume our hedonic characteristics (length, width, signature, etc.) can capture all possible differences between two related goods, despite their similarity. Hence, the last term is intended to control for quality differences between the current good and its substitute.

What if a painting has multiple substitutes – the multivariate case? Let a given good x_c have a vector of substitutes $X_s = \{x_{s1}, x_{s2}, \dots x_{sd}\}$. We can write:

$$w_c = b_1\pi_c + \sigma(g_1, g_2, g_3 \dots g_d) \quad : \quad g_i = b_{i2}(P_{si} - \pi_c) + b_{i3}(P_{si} - \pi_{si}) + b_{i4}(\pi_c - \pi_{si})$$

Two goods c_1 and c_2 may have different numbers of substitutes s_1 and s_2. Hence, it is necessary to introduce an aggregation function $\sigma(.)$, such as the mean or the maximum with respect to a quantity. Here, I take the mean of the $g_i's$, so that the anchoring effect is calculated for a good with respect to its "average" substitute.

To detect substitutes for a given painting, a variety of methods may be used. As a relatively simple approach, I look for works that share the same artist, artistic medium, auction house and location, and were auctioned before or on the same day as the given observation. An observation cannot be its own substitute, though a past sale can. Hence, in my regression for anchoring cross-effects I omit observations for which there are no substitutes (just as Beggs & Graddy omit paintings that do not have at least two sales). However, there exists a variety of qualitative and quantitative research to identify the key features of art pieces (and thus their similarity). One study, for instance, suggested metrics such as subject matter and painting style were among the most important[29]. Given the visual nature of paintings, a computational approach may perhaps be worth investigating in future work: one could conceivably encode m x n images of paintings as vectors in R^{mn}-dimensional space, then calculate similarity between those vectors.

[29] http://www.jstor.org/stable/pdf/20715780.pdf?acceptTC=true

I begin by replicating Beggs & Graddy's original anchoring regression for their two Impressionist and Contemporary datasets, then apply it to my new dataset of assorted art sales. Then, I run my modified anchoring cross-effects regression on all three datasets. I find significant evidence of anchoring effects and cross-effects.

Results: Hedonic Regressions

The same sets of hedonic price predictions are used for both anchoring regressions. Specifically, I fit hedonic predictions for all three datasets, though for Impressionist art (as Beggs & Graddy do) predictions are fit separately for observations in London and in New York due to currency differences, then recombined for the anchoring regressions. Tables 4-7 below show the results of the hedonic predictions.

Overall, hedonic characteristics such as the painting dimensions, the presence of a signature, medium, and artist and time effects (both omitted for brevity; both highly significant) have a significant impact on the sale price of the painting. It is surprising that a painting's date of creation is generally not significant, which can be explained by the importance of artist variables. For Impressionist Art and Contemporary Art, much of the variation in price is explained by our regression model, indicated by generally high R^2 values. For our new dataset, however, the R^2 value is extremely low although variables are significant. This is to be expected: our dataset covers a very large variety of paintings, and so we should see very high variance across prices in our regression model (though far lower bias, as indicated by our highly significant hedonic variables). The F-statistic is extremely significant in all cases, which shows that our regression variables are relevant. In general, the most impactful variables are those for the art medium and the dimensions. This may be attributed to large pieces and pieces from specialized mediums selling for more, as indicated by large, significant coefficients for certain mediums and not for others. As a final note, regressing on only artist and time dummies corresponds to a reduction in R^2, as noted in Beggs & Graddy (regressions not included).

Results: Anchoring Effects and Cross-Effects

This research was able to reproduce the general findings of Beggs & Graddy (2009) for both the Impressionist and the Contemporary Art datasets. Strong and significant anchoring effects were rediscovered in the Impressionist Art dataset, while weaker and less significant anchoring appeared in the Contemporary Art case. It is worth noting in both cases that anchoring, though at least weakly significant, is not as impactful as past unobserved non-hedonic inputs to price $(P_{t-1} - \pi_{t-1})$, which suggests that other biases such as the thrill of bidding may be at work. As one would expect, the current hedonic prediction has a much larger impact by itself on price than anchoring, though anchoring is stronger than the time elapsed (in months) since the last sale. In neither case does time elapsed wield a particularly strong influence on price.

For assorted art, anchoring effects and cross-effects are strong and significant between a given good and its "average" substitute. In this scenario, however, unobserved hedonic inputs to the substitute $(P_s - \pi_s)$ are not nearly as significant as anchoring effects, or even as the time difference between the given good's sale and the average substitute. Hence, as long as a good is successfully identified as a substitute, we can infer that bidders tend to anchor primarily on a substitute's final price rather than its dimensions, authenticity, and other hedonic signals of value. This suggests that bidders may not conduct serious hedonic analysis when considering related goods, or do not know how to properly appraise those substitutes. The moderate R^2 in this regression, can again be primarily attributed to the large variation in sales prices across the wide assortment of paintings.

Anchoring cross-effects are prevalent in the regression for Impressionist Art, though they tell a different story. Similar to our previous regression with resale, anchoring cross-effects here are not as significant as unobserved inputs to the substitute. For Impressionist art pieces whose hedonic and artistic qualities have been well-known for decades, the actual auction process may be more influential in determining the final price. Furthermore, as these pieces appreciate over decades, demand for these goods (a non-hedonic driver of price) may increase. This would be expected to carry across related pieces, especially if demand increases for certain art categories as a whole. However, the average time difference between sales of an art piece and its substitute is neither significant nor impactful. Time may not be an important factor if similar art pieces (anchors) are continually being brought to auction, whereas this might be influential if one is anchoring only on the previous sale of a painting. The drop in R^2 from the previous regression, in this case, may be due to our method of averaging across substitute goods, which would naturally lose much of the cross-substitute variance in prices and predictions.

In our analysis of Contemporary Art, anchoring cross-effects are more significant than the resale case. The presence of these effects may be due to lack of information for newer Contemporary artists who are less established: before purchasing from a relatively unknown artists, savvy buyers may research their other works and auction sales thoroughly. However, as with Impressionist pieces, anchoring cross-effects are not nearly as significant and impactful as unobserved inputs into the substitutes. In general for newer Contemporary pieces, it is likely that the value of their hedonic characteristics such as the presence of a signature is not as well understood, which means that these factors – while still significant – will not be as impactful as unobservable factors such as auction activity, artist reputation, or how well these newer works are publicized.

Hence, across the board we see significant anchoring effects and cross-effects. These phenomena are stronger and more significant for Impressionist Art than for Contemporary Art, though in our new dataset of assorted artwork anchoring cross-effects are highly significant and influential.

Conclusion

This work is of interest to art researchers who wish to understand how biases travel across diverse art sales, as well as to auctioneers and potential buyers. Future work should talk with bidders, auction experts, and specialists to understand unobservable factors that impact sales price, and perhaps incorporate these factors into our regression model.

TABLES

Table 1: Impressionist art, summary statistics.

	DIM_A	LOW_EST	HIGH_EST
Min.	0.00	102	128
1st Qu.	11.00	14000	18000
Median	17.00	40000	50000
Mean	18.31	196023	257967
3rd Qu.	23.00	132800	168300
Max.	120.00	40000000	50000000
NA's	37		

	S_PRICE	CNV_RATE	ARTIST
Min.	126	0.0000	620
1st Qu.	18700	0.0000	2420
Median	53856	1.2400	4820
Mean	285428	0.8639	4791
3rd Qu.	176000	1.6800	6860
Max.	82500000	2.3610	8460
NA's	4696		

	DATE_PTG	DATE_FLG	SHAPE
Min.	1823	0.0000	0.0000
1st Qu.	1902	0.0000	0.0000
Median	1922	0.0000	0.0000
Mean	1921	0.3538	0.0029
3rd Qu.	1938	1.0000	0.0000
Max.	1983	1.0000	3.0000
NA's	3950		2307

	DIM_B	DIAM	SIGNED
Min.	0.00	1.00	0.000
1st Qu.	11.00	6.75	1.000
Median	18.00	11.50	1.000
Mean	18.69	15.10	1.188
3rd Qu.	24.00	24.50	1.000
Max.	141.00	36.00	39.000
NA's	37	16243	5

	ART_MED	ILLUS	PND_FLG
Min.	1.00	0.0000	0.0000
1st Qu.	18.00	1.0000	0.0000
Median	18.00	1.0000	1.0000
Mean	21.03	0.9944	0.5127
3rd Qu.	27.00	1.0000	1.0000
Max.	700.00	2.0000	2.0000
NA's	18	44	4

Table 2: Contemporary art, summary statistics.

	Auction_date	mdate	ddate	ydate
Min.	1982-06-29	2.000	1.00	1982
1st Qu.	1986-06-26	6.000	5.00	1986
Median	1989-06-29	6.000	22.00	1989
Mean	1989-05-15	7.831	17.07	1989
3rd Qu.	1992-07-02	12.000	26.00	1992
Max.	1994-06-30	12.000	30.00	1994

	lot	sold	price	low_est
Min.	1.0	0.0000	0.00	0.05
1st Qu.	87.0	1.0000	1.90	2.00
Median	423.0	1.0000	7.00	6.00

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 Mean   : 397.7   Mean   :0.7745   Mean   :  21.23   Mean   :  19.53  
 3rd Qu.: 601.0   3rd Qu.:1.0000   3rd Qu.:  20.00   3rd Qu.:  20.00  
 Max.   :1164.0   Max.   :1.0000   Max.   :1700.00   Max.   :1800.00  
                                   NA's   :2         NA's   :45       
    high_est         date_ptg          len               wid         
 Min.   :   0.1   Min.   :26.00   Min.   :  5.40   Min.   :  2.00  
 1st Qu.:   3.0   1st Qu.:60.00   1st Qu.: 44.50   1st Qu.: 46.00  
 Median :   8.0   Median :67.00   Median : 70.00   Median : 70.00  
 Mean   :  26.1   Mean   :68.24   Mean   : 84.53   Mean   : 84.71  
 3rd Qu.:  25.0   3rd Qu.:77.00   3rd Qu.:105.00   3rd Qu.:105.00  
 Max.   :2600.0   Max.   :91.00   Max.   :957.00   Max.   :602.00  
 NA's   :45       NA's   :449     NA's   :73       NA's   :293     
    artist             medium             CNV_RATE         ukcpi      
 Length:4456        Length:4456        Min.   :1.210   Min.   :239.6  
 Class :character   Class :character   1st Qu.:1.482   1st Qu.:286.4  
 Mode  :character   Mode  :character   Median :1.610   Median :339.3  
                                       Mean   :1.609   Mean   :342.9  
                                       3rd Qu.:1.722   3rd Qu.:407.1  
                                       Max.   :1.954   Max.   :423.0  

     ukinf            uktb            uscpi           usinf      
 Min.   : 1.270   Min.   : 4.900   Min.   :181.6   Min.   :1.280  
 1st Qu.: 3.050   1st Qu.: 8.800   1st Qu.:204.1   1st Qu.:3.050  
 Median : 4.710   Median : 9.630   Median :231.7   Median :3.920  
 Mean   : 5.061   Mean   : 9.832   Mean   :232.7   Mean   :3.848  
 3rd Qu.: 6.520   3rd Qu.:11.990   3rd Qu.:261.9   3rd Qu.:4.600  
 Max.   :10.430   Max.   :14.540   Max.   :276.8   Max.   :6.220  

      ustb            japcpi            dj              ftse       
 Min.   : 2.970   Min.   :149.3   Min.   : 812.2   Min.   : 736.2  
 1st Qu.: 3.990   1st Qu.:160.6   1st Qu.:1776.5   1st Qu.:1588.4  
 Median : 6.990   Median :168.2   Median :2458.3   Median :2182.0  
 Mean   : 6.157   Mean   :169.9   Mean   :2438.5   Mean   :2078.3  
 3rd Qu.: 7.760   3rd Qu.:182.3   3rd Qu.:3174.7   3rd Qu.:2546.6  
 Max.   :10.320   Max.   :185.4   Max.   :3753.5   Max.   :3223.9  

      VAT        
 Min.   :0.0000  
 1st Qu.:0.0000  
 Median :0.0000  
 Mean   :0.2949  
 3rd Qu.:1.0000  
 Max.   :1.0000  
```

Table 3: Assorted art, summary statistics.

```
     height          width           area.inches        artist.startdate
 Min.   :      0   Min.   :       0   Min.   :0.000e+00   Min.   :1000
 1st Qu.:     12   1st Qu.:      12   1st Qu.:1.520e+02   1st Qu.:1869
 Median :     19   Median :      20   Median :3.920e+02   Median :1904
 Mean   :     64   Mean   :      78   Mean   :2.270e+08   Mean   :1886
 3rd Qu.:     29   3rd Qu.:      29   3rd Qu.:8.160e+02   3rd Qu.:1932
 Max.   :7700281   Max.   :10197670   Max.   :7.852e+13   Max.   :2015
 NA's   :4000      NA's   :31325      NA's   :86729       NA's   :19411

 artist.enddate    lot.number       sale.date          usd.sale.price
 Min.   :1016    Min.   :     0   Min.   :2006-06-09   Min.   :       1
 1st Qu.:1930    1st Qu.:    81   1st Qu.:2013-10-15   1st Qu.:     905
 Median :1956    Median :   205   Median :2015-06-02   Median :    3009
 Mean   :1941    Mean   :  1195   Mean   :2014-08-27   Mean   :   50275
 3rd Qu.:1983    3rd Qu.:   599   3rd Qu.:2015-11-11   3rd Qu.:   12188
 Max.   :2015    Max.   :221186   Max.   :2016-02-04   Max.   :70530000
 NA's   :19411   NA's   :275      NA's   :275          NA's   :209591
```

Table 4: Hedonic predictions, Impressionist Art (London). Half-year time dummies omitted for brevity.

```
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 10.667134   6.703545   1.591 0.112783
DATE_PTG    -0.002122   0.003513  -0.604 0.546317
DIM_A        0.026975   0.007665   3.519 0.000512 ***
DIM_B        0.016575   0.006388   2.595 0.010018 *
SIGNED1      0.266633   0.350862   0.760 0.447990
SIGNED2     -0.064880   0.434096  -0.149 0.881308
SIGNED3     -0.429974   0.413009  -1.041 0.298822
ART_MED6     1.779714   0.677907   2.625 0.009178 **
ART_MED9     0.348789   0.684150   0.510 0.610622
ART_MED12    2.270866   0.674249   3.368 0.000874 ***
ART_MED15    1.473253   0.698082   2.110 0.035791 *
ART_MED18    2.952254   0.642515   4.595 6.80e-06 ***
ART_MED24    1.457382   0.771532   1.889 0.060030 .
ART_MED27    1.093956   0.661039   1.655 0.099170 .
ART_MED30    0.490681   0.658584   0.745 0.456923
ART_MED33    1.278982   0.846104   1.512 0.131866
ART_MED39    1.767484   0.660349   2.677 0.007918 **
R^2:                                  0.8664
Adjusted R^2:                         0.8251
F-statistic: 21.01 on 79 and 256 DF,  p-value: < 2.2e-16
```

Table 5: Hedonic predictions, Impressionist Art (NYC). Half-year time dummies omitted for brevity.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	20.536155	5.799675	3.541	0.000458	***
DATE_PTG	-0.006033	0.002998	-2.013	0.044995	*
DIM_A	0.040589	0.007452	5.447	1.03e-07	***
DIM_B	0.012602	0.007114	1.771	0.077433	.
SIGNED1	1.059125	0.156739	6.757	6.69e-11	***
SIGNED2	0.301338	0.245387	1.228	0.220348	
SIGNED3	0.203128	0.217131	0.936	0.350234	
ART_MED6	-0.364772	0.687000	-0.531	0.595814	
ART_MED9	-0.060186	0.642117	-0.094	0.925382	
ART_MED12	1.014323	0.618434	1.640	0.101960	
ART_MED15	-0.131242	0.665053	-0.197	0.843687	
ART_MED18	1.248101	0.615153	2.029	0.043296	*
ART_MED21	0.773179	0.877041	0.882	0.378669	
ART_MED24	0.361094	0.661262	0.546	0.585401	
ART_MED27	-0.342484	0.656519	-0.522	0.602264	
ART_MED30	-0.075431	0.646362	-0.117	0.907170	
ART_MED38	-0.404069	0.807695	-0.500	0.617227	
ART_MED39	0.645365	0.630585	1.023	0.306876	
R^2:				0.8377	
Adjusted R^2:				0.8	

F-statistic: 22.24 on 74 and 319 DF, p-value: < 2.2e-16

Table 6: Hedonic predictions, Contemporary Art. Half-year time dummies omitted for brevity.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.54229	1.91849	-0.804	0.422029	
log(date_ptg)	-0.67160	0.42660	-1.574	0.116371	
log(len)	0.59158	0.11574	5.111	5.42e-07	***
log(wid)	0.61585	0.11764	5.235	2.94e-07	***
mediuma	0.37892	0.36754	1.031	0.303314	
mediumbr	-1.00407	0.47045	-2.134	0.033555	*
mediumchk	-0.51240	0.50577	-1.013	0.311749	
mediumcol	-2.01051	0.54342	-3.700	0.000253	***
mediumcr	-0.85626	0.37571	-2.279	0.023304	*
mediumf	-1.19646	0.49004	-2.442	0.015148	*
mediumg	-0.92343	0.40669	-2.271	0.023817	*
mediumik	-0.66618	0.38336	-1.738	0.083193	.
mediumo	0.33903	0.31500	1.076	0.282582	
mediumpas	-0.76427	0.55061	-1.388	0.166063	
mediumpg	3.84267	0.64429	5.964	6.33e-09	***
mediumph	-2.97383	0.71974	-4.132	4.57e-05	***
mediumpl	1.43608	0.66003	2.176	0.030281	*
mediumpn	0.73305	0.79588	0.921	0.357696	
mediums	-0.30325	0.49084	-0.618	0.537122	
mediumsk	2.78109	0.57888	4.804	2.36e-06	***
mediumt	-0.77276	0.39024	-1.980	0.048510	*
mediumtp	0.25322	0.55431	0.457	0.648099	
mediumw	-0.41915	0.36663	-1.143	0.253758	
R^2				0.9232	
Adjusted R^2				0.8892	

F-statistic: 27.17 on 146 and 330 DF, p-value: < 2.2e-16

Table 7: Hedonic predictions, assorted art. Half-year time dummies omitted for brevity. Artist and medium were omitted due to computational constraints.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	6.224144	0.018000	345.782	<2e-16	***
log(height)	0.614017	0.008031	76.454	<2e-16	***
log(width)	0.230060	0.008092	28.431	<2e-16	***
signed	-0.634735	0.008009	-79.255	<2e-16	***
monogrammed	-0.203214	0.022359	-9.089	<2e-16	***
stamped	0.086423	0.016030	5.391	7e-08	***
R^2				0.1006	
Adjusted R^2				0.1006	

F-statistic: 5907 on 5 and 264109 DF, p-value: < 2.2e-16

Table 8: Anchoring effects, Impressionist Art

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.338390	0.192857	-1.755	0.0802	.
curr_hed_pred	1.018156	0.019093	53.327	< 2e-16	***
anchoring	0.174402	0.072377	2.410	0.0165	*
past_control	0.503147	0.077019	6.533	2.29e-10	***
months_since_last_sale	0.007903	0.001873	4.219	3.13e-05	***
R^2				0.9231	
Adjusted R^2				0.9222	

F-statistic: 1047 on 4 and 349 DF, p-value: < 2.2e-16

Table 9: Anchoring effects, Contemporary Art

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.1152982	0.0499920	-2.306	0.0223	*
curr_hed_pred	1.0344742	0.0203640	50.799	<2e-16	***
anchoring	0.1312881	0.0740504	1.773	0.0780	.
past_control	0.1914626	0.0952936	2.009	0.0460	*
months_since_last_sale	-0.0009164	0.0026884	-0.341	0.7336	
R^2				0.9407	
Adjusted R^2				0.9394	

F-statistic: 698 on 4 and 176 DF, p-value: < 2.2e-16

Table 10: Anchoring effects, assorted art

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.598781	0.096913	-16.497	<2e-16	***
log_hed_pred	1.147787	0.011706	98.054	<2e-16	***
anchoring	0.590709	0.011442	51.626	<2e-16	***
sub_price_hed_pred	-0.020331	0.012078	-1.683	0.0923	.
avg_mon_subdiff	-0.042259	0.004782	-8.837	<2e-16	***
R^2				0.4144	
Adjusted R^2				0.4144	

F-statistic: 3.046e+04 on 4 and 172189 DF, p-value: < 2.2e-16

Table 11: Anchoring cross-effects, Impressionist art

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.1661272	0.0637779	-2.605	0.009206	**
log_hed_pred	1.0096589	0.0060636	166.510	< 2e-16	***
anchoring	0.0542330	0.0152373	3.559	0.000374	***
sub_price_hed_pred	0.2609712	0.0208044	12.544	< 2e-16	***
curr_sub_hed_diff	NA	NA	NA	NA	
avg_months_since_sub_sale	-0.0004658	0.0005206	-0.895	0.370999	
R^2				0.7791	
Adjusted R^2				0.779	

F-statistic: 9710 on 4 and 11014 DF, p-value: < 2.2e-16

Table 12: Anchoring cross-effects, Contemporary Art

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.1110567	0.0261522	-4.247	2.25e-05	***
log_hed_pred	1.0223990	0.0094342	108.371	< 2e-16	***
anchoring	0.0451416	0.0189840	2.378	0.0175	*
sub_price_hed_pred	0.3056918	0.0305144	10.018	< 2e-16	***
curr_sub_hed_diff	NA	NA	NA	NA	
avg_months_since_sub_sale	-0.0005511	0.0005588	-0.986	0.3241	
R^2				0.8430	
Adjusted R^2				0.8428	

F-statistic: 3437 on 4 and 2560 DF, p-value: < 2.2e-16

Table 13: Anchoring cross-effects, assorted art. Same as previous assorted art table, since both regressions test for anchoring in the presence of a substitute; no resales yet identified for the first regression.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.598781	0.096913	-16.497	<2e-16	***
log_hed_pred	1.147787	0.011706	98.054	<2e-16	***
anchoring	0.590709	0.011442	51.626	<2e-16	***
sub_price_hed_pred	-0.020331	0.012078	-1.683	0.0923	.
curr_sub_hed_diff	NA	NA	NA	NA	
avg_mon_subdiff	-0.042259	0.004782	-8.837	<2e-16	***
R^2				0.4144	
Adjusted R^2				0.4144	

F-statistic: 3.046e+04 on 4 and 172189 DF, p-value: < 2.2e-16

FIGURES

Figure 1: Assorted art.