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**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]](#footnote-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]](#footnote-2)[[3]](#footnote-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]](#footnote-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 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]](#footnote-5). Some studies show that people formulate estimates more quickly when provided with numbers to anchor on[[6]](#footnote-6), while others show that anchoring decreases – but does not altogether vanish – with increased cognitive ability[[7]](#footnote-7). Other studies demonstrate that anchoring is extremely difficult to avoid, even if the anchors are obviously incorrect.[[8]](#footnote-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]](#footnote-9) [[10]](#footnote-10). The bias appears in many fields from accounting[[11]](#footnote-11) to neuroscience[[12]](#footnote-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]](#footnote-13), while another study discusses a how a higher “Buy Now” price in online auctions can induce people to bid significantly higher[[14]](#footnote-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]](#footnote-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]](#footnote-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 painting significantly impacts its current sale due to anchoring[[17]](#footnote-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]](#footnote-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]](#footnote-19). None of this work examines anchoring between substitute goods (specifically, similar art pieces), which is the primary contribution of this paper.

**How Auctions for Art Work**

**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[[20]](#footnote-20) and are already described in detail elsewhere[[21]](#footnote-21), 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[[22]](#footnote-22).

<Table 1>

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.

<Table 2>

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 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.

<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 the below figure, 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.

<Pic: artists, logprice, salesvolume, price / # of works on same plot>

**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 for paintings as a function of their characteristics, while also controlling for temporal effects. 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.

This is fitted for observations where a first sale and a second sale 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:

Above, the term refers to the sale price of either the past sale of a painting at time or the current sale (resale) at time. Beggs and Graddy fit several regressions where the response represents either the sale price, an indicator for whether the item sells, or the presale estimate. The anchoring effect is captured in the term, which specifies how the past price (the anchor) impacts the current hedonic price, and thus the dependent variable. The last term controls for unobservable non-hedonic effects on price. For example, if

After identifying painting resales, they fit a model that regresses sales price on

1. Tversky, Amos, and Daniel Kahneman. "Availability: A heuristic for judging frequency and probability." *Cognitive psychology* 5.2 (1973): 207-232. [↑](#footnote-ref-1)
2. http://www.christies.com/about/press-center/releases/pressrelease.aspx?pressreleaseid=7712 [↑](#footnote-ref-2)
3. <http://www.xe.com/currencyconverter/convert/?From=GBP&To=USD> accessed 2/20/2015 [↑](#footnote-ref-3)
4. Beggs, Alan, and Kathryn Graddy. "Anchoring effects: Evidence from art auctions." *The American Economic Review* 99.3 (2009): 1027-1039. [↑](#footnote-ref-4)
5. Tversky, Amos, and Daniel Kahneman. "Judgment under uncertainty: Heuristics and biases." *science* 185.4157 (1974): 1124-1131. [↑](#footnote-ref-5)
6. http://soco.uni-koeln.de/files/jpsp73.pdf [↑](#footnote-ref-6)
7. Bergman, Oscar, et al. "Anchoring and cognitive ability." *Economics Letters*107.1 (2010): 66-68. [↑](#footnote-ref-7)
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. [↑](#footnote-ref-8)
9. Rajendran & Tellis (1994); Greenleaf (1995); Geltner (2011); Dougal et al. (2012). [↑](#footnote-ref-9)
10. Furnham, Adrian, and Hua Chu Boo. "A literature review of the anchoring effect." *The Journal of Socio-Economics* 40.1 (2011): 35-42. [↑](#footnote-ref-10)
11. Kinney Jr, William R., and Wilfred C. Uecker. "Mitigating the consequences of anchoring in auditor judgments." *Accounting Review* (1982): 55-69. [↑](#footnote-ref-11)
12. Logvinenko, Alexander D. "The anchoring effect in lightness perception in humans." *Neuroscience letters* 334.1 (2002): 5-8. [↑](#footnote-ref-12)
13. http://digitalcommons.uconn.edu/cgi/viewcontent.cgi?article=1190&context=econ\_wpapers [↑](#footnote-ref-13)
14. Dodonova, Anna, and Yuri Khoroshilov. "Anchoring and transaction utility: evidence from on-line auctions." *Applied Economics Letters* 11.5 (2004): 307-310. [↑](#footnote-ref-14)
15. http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6758989 [↑](#footnote-ref-15)
16. https://www.researchgate.net/profile/Rachel\_Pownall/publication/257004491\_Does\_the\_sun\_shine\_on\_art\_prices/links/0912f51126bf976f32000000.pdf [↑](#footnote-ref-16)
17. Beggs, Alan, and Kathryn Graddy. "Anchoring effects: Evidence from art auctions." *T, e American Economic Review* 99.3 (2009): 1027-1039. [↑](#footnote-ref-17)
18. Graddy, Kathryn, et al. "Anchoring or loss aversion? Empirical evidence from art auctions." (2014). [↑](#footnote-ref-18)
19. Bruno, Brunella, and Giacomo Nocera. "Investing in art: The informational content of Italian painting pre-sale estimates." *Available at SSRN 1179183*(2008). [↑](#footnote-ref-19)
20. Richardson (2002); Abowd & Ashenfelter (1989); Beggs & Graddy (1997); Ashenfelter & Graddy (2003); Beggs & Graddy (2009) [↑](#footnote-ref-20)
21. http://www.jstor.org/stable/pdf/2556028.pdf?acceptTC=true [↑](#footnote-ref-21)
22. For more info: http://www.jstor.org/stable/pdf/2556028.pdf?acceptTC=true [↑](#footnote-ref-22)