PRICE, ANCHORING, & SUBSTITUTION

IN

THE MARKET FOR FINE ART AUCTIONS

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ABSTRACT

Joan Miro and Salvador Dali are two Surrealists painters often featured together at auction. Can the past price of a Miro painting drive up the current price of a Dali piece? We examine the existence and behavior of these "anchoring" cross-effects between prices of related art pieces sold at auction. My research generalizes the anchoring model of Beggs & Graddy (2009) in order to study related art pieces. We draw upon insights from conversations with art specialists and experts at Sotheby's, and construct a new dataset of recent auction sales for assorted art (2006-2015). We find significant evidence of anchoring cross-effects. Our findings are of interest to art researchers, auction house specialists, and those who wish to understand where price signals travel in the art auction world.

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1. INTRODUCTION

Imagine you are heading to Christie's to bid on a Monet painting, which experts believe is worth $1 million based on its size and medium. However, you're unaware of those experts' estimates and you have no idea how much the Monet is worth, so you look up recent sales of other Impressionist paintings. You find out a Van Gogh sold for $20 million last week. With that number in mind, you start to believe the Monet is also worth $20 million, and that's how much you bid – even if that amount reflects more the price of the Van Gogh than the Monet itself.

This is known as the *anchoring effect* - a well-studied cognitive bias in which the first value you hear (the "anchor") can shape your perception of what sorts of values are normal. This was first demonstrated in a landmark experiment by Tversky & Kahneman (1974)[1]. In that study, participants were given five seconds to mentally calculate the product of the numbers 1 through 8, visually written out for them on a blackboard. It was found that if the numbers were displayed as "1x2x3x4x5x6x7x8", participants would read the lower numbers first and give a median estimate of 512 for the product. On the other hand, if the numbers were displayed as "8x7x6x5x4x3x2x1", then participants would first see the higher numbers and give a much higher median estimate of 2250. Thus, it seems that first impressions do affect judgement, at least in quantitative scenarios.

This bias also appears in the market for fine art auctions, which in 2014 saw a sales volume of approximately $7.35 billion.[2] To the best of our knowledge, Beggs & Graddy (2009) were the first to formally study anchoring in the context of art auctions. In their model, the hedonic value of an artwork, say a painting, is assumed to be determined by its hedonic characteristics such as the artist,

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

[2] http://www.christies.com/about/press-center/releases/pressrelease.aspx?pressreleaseid=7712 http://www.xe.com/currencyconverter/convert/?From=GBP&To=USD accessed 2/20/2015

medium, and degree of authenticity. These features do not change over time[3], which means that if buyers were perfectly rational, they would pay only according to their (time-dependent) demand for these features. If however, buyers learn that the painting previously sold for a very high price, they may internalize that previous high price as a reference point – the “anchor” – and be willing to pay much more as a result. Past price could legitimately inform current price since it reflects hedonic value, as well as other relevant, non-hedonic influences such as bidder wealth and artwork reputation. However, if we control for those, then past price becomes an irrelevant signal in this context, and its impact on current price can be interpreted as an anchoring effect. Thus, anchoring is said to occur when past price biases current price, controlling for hedonic value and non-hedonic price determinants.

Of course, the ways in which auction participants internalize and act upon past price cannot be inferred from just observing prices. Hence in our research and in much of the literature, including Beggs & Graddy (2009), this is treated as a black box. The mere observation of this effect, i.e. past price biasing current price, suffices for our definition of anchoring (discussed further in Section <>).

Using a regression model that carefully separates out anchoring, Beggs & Graddy (2009) identified and analyzed resales of Impressionist and Contemporary paintings, finding significant evidence of anchoring effects. However, as mentioned in their paper, it is very difficult to identify multiple sales of the same art piece. This method of testing for anchoring effects cannot be applied to new works or works that have never been brought to auction. Moreover, in practice, it turns out that auction specialists appraise an art piece based primarily on past sales of related pieces[4]. The anchoring research of Beggs & Graddy (2009) is limited in its analysis and applicability.

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[3] Age is not considered a hedonic feature, because for us it represents time-dependent demand for art rather than intrinsic characteristics of the work.

[4] Interview with Raphaelle Benabou

In this paper, we study whether the sales of similar paintings (substitutes) display anchoring cross-effects – for example, whether the past price of a Monet can bias the current price of a Van Gogh. Our data consists of two datasets of Impressionist and Contemporary art, used not only in Beggs & Graddy (2009) but also in many other econometric papers on art auctions, as well as a new dataset of assorted art sales (2006-2015) specifically collected for this project. We begin by successfully replicating the general anchoring findings from Beggs & Graddy (2009). Our success is surprising and noteworthy because, as discussed later in Section <>, we do not know exactly which observations in their data were originally used. Next, we introduce our expanded version of their model, which tests for anchoring cross-effects by controlling for similarity across pieces. We introduce two quantitative measures of similarity. Running our model on these three datasets, we discover significant evidence of anchoring cross-effects for Impressionist and assorted art. To experiment further, we also run our regressions on a subset of our assorted art dataset for three artist pairs: Joan Miro & Salvador Dali, Pablo Picasso & Marc Chagall, and Edvard Munch & Henri de Toulouse-Lautrec. We explain this selection of artists in Section <>. We find the strongest and most significant evidence of anchoring cross-effects between works by Picasso and Chagall.

This research makes several major contributions to the existing literature on art auctions. First, to the best of our knowledge, no econometric work has attempted to quantify hedonic similarity between art pieces. Thus, this study is useful not only for appraising art, but also for other tasks where art pieces must be compared, such as constructing price indices across heterogeneous artworks. We hope our two measures of similarity may provide a starting point for such analysis. Second, much of the econometric work on art auctions has relied on the same two Impressionist and Contemporary art datasets that only include sales until 1991 and 1994, respectively. Our new dataset of approximately 500,000 assorted art sales (2006-2015), constructed by writing a Python program to scrape Blouin ArtInfo for 10 straight days, is a larger and more up-to-date collection of

auction data. Lastly, our discovery of anchoring cross-effects is notable because it adds to the growing body of research on how price signals implicitly propagate around the art auction market. Our work allows researchers to account for hidden biases such as anchoring when comparing sales of different art pieces, and demonstrates how Beggs & Graddy's original anchoring model may be successfully customized. For auction houses and professionals, our work provides a practical regression model for estimating an artwork's price in light of related sales. Beggs & Graddy's original model has been extensively applied in other domains such as corporate finance[5], real estate[6], and horse racing[7]. Our approach is more general than theirs, and may find application in other fields as well.

As part of our research, we conducted interviews with several specialists and experts in the field. To learn about the art market and how auction specialists appraise pieces, we talked with Mark Best, a former financial analyst who is now a specialist in American, Modern, and Contemporary prints at Sotheby's NYC. For insight into artistic similarity, we talked with Hadley Newton, who formerly worked at Sotheby's with Impressionist art. The three artist pairs we examine in Section <> were suggested by Hadley. We also talked extensively with Raphaelle Benabou, who is an administrator of art collections, estates, and valuations at Bonham's in London. Raphaelle provided us with many of our anecdotes and fact-checked our description of the auction system. We draw upon these interviews for both our discussion and our quantitative analysis.

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[5] Dougal, Casey, et al. "Anchoring on credit spreads." *The Journal of Finance* 70.3 (2015): 1039-1080.

[6] Leung, Tin Cheuk, and Kwok Ping Tsang. "Anchoring and loss aversion in the housing market: implications on price dynamics." *China Economic Review* 24 (2013): 42-54.

[7] McAlvanah, Patrick, and Charles C. Moul. "The house doesn't always win: Evidence of anchoring among Australian bookies." *Journal of Economic Behavior & Organization* 90 (2013): 87-99.

Determining artistic similarity is not trivial: we were told that no two art pieces are the same[8]. Even in the case of prints, where 100-200 copies (editions) of the same art piece are manufactured and numbered in order of production, an edition with a lower number (i.e. produced earlier) may sell for more than an edition with a higher number. Furthermore, drivers of similarity can vary at different price points, and whether art is purchased as a decoration or as an investment. In this paper, we provide a starting point for quantitatively measuring similarity between pieces, but acknowledge that better measures could be constructed.

This thesis proceeds as follows. In Section I, we give a brief overview of the art auction system and process, followed by a discussion of anchoring and its role in this market. Section II surveys the literature relevant to anchoring in the art market and explains the importance of our research. Section III describes our methodology, which includes the original regressions of Beggs & Graddy (2009), our expanded regression models, and our measures of substitution. Section IV describes the original data of Beggs & Graddy, as well as our new dataset, and explains the motivation behind constructing the latter. Section V gives our results. This includes our replication of the anchoring work of Beggs & Graddy, followed by our findings on anchoring cross-effects. We then present the results of our experiments on the three artist pairs suggested to us by Hadley Newton. Finally, Section VII concludes with a summary of our research and directions for future work.

[8] Interview, Mark Best.

2. OVERVIEW OF ART AUCTIONS

In perhaps one of the world's oldest duopolies, approximately 42% of the global art auction market is controlled by two major houses, Christie's (est. 1766) and Sotheby's (est. 1744)[9]. The former, headquartered in London, is privately held by French multibillionaire Francois-Henri Pinault and so only reports sales figures twice a year[10]. Sotheby's on the other hand is headquartered in New York City and publicly traded, and is thus required to report revenue and costs in detail[11]. While both houses deal in art, often sourced from museum or private collections, in recent years Christie's has become the larger player in this domain. In the first six months of 2015, Christie's realized $4.5 billion in art sales, while Sotheby's only pulled $3.5 billion[12]. Over the years, both houses have enjoyed their share of record-breaking auctions: Picassso's *Les Femmes d'Alger ("Version O")* sold for $179 million at Christie's in 2015, while Pollock's *No. 5, 1948* went for $164 million at Sotheby's in 2006. The whole spectrum of art can be found at Christie's and Sotheby's, ranging from European sculptures and Impressionist oil paintings to Chinese ceramics and modern prints. Auctions are usually themed around a certain artist, medium, time period, or represent a private collection. Often individual events are part of a series, such as Christie's "First Open" series (launched in 2005) for post-war and contemporary art[13]. In recent decades, one sees the rise of other innovations. For example, Sotheby's and Christie's offer telephone and online bidding for clients who cannot attend

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

10 http://www.bloombergview.com/articles/2014-12-03/how-sothebys-and-christies-went-wrong

11 http://www.wikinvest.com/stock/Sotheby's_Holdings_(BID)

12 http://www.nytimes.com/2015/08/17/arts/international/sothebys-and-christies-jostle-for-sales.html

13 http://www.christies.com/auctions/first-open-september-2014/#specialist-picks-section

in person (the latter, however, suffers from greater time lag)[14]. Both houses also offer art-backed loans, allowing collectors to borrow money against their own artwork – a highly illiquid asset. Finally, some other smaller but well-known auction houses include Bonham's and Phillip's, both headquartered in the United Kingdom.

In addition to fine art, both houses run auctions for other luxury goods such as jewelry, automobiles, and furniture – and so many believe these houses play to different strengths. To sell photographs, go to Sotheby's; to sell books and manuscripts, go to Christie's[15]. For classic automobiles, go to Bonham's or Sotheby's[16]. Specialization is not limited to products, either. According to Raphaelle Benabou, the smaller house Bonham's is appealing to many sellers because lower sales volume (smaller lots) ensures art pieces will be better noticed at auction. Competition between these houses is fierce, and each tries to capture the best consignments and expand market share by luring prospective sellers with benefits such as higher guaranteed prices and waived house commission fees[17]. Putting one's own money on the line means profit margins are thin for both Sotheby's and Christie's, and both have lost millions as a result[18]. Despite this ongoing cut-throat battle, the two houses have cooperated – and even colluded – at times. For example, according to an auctioneer interview in Hong et al. (2015), Sotheby's and Christie's have an agreement to take turns leading New York City's annual Auction Week, a major event which saw $1.5 billion in art

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[14] http://www.sothebys.com/en/news-video/auction-essays/sothebys-digital-features/2015/01/online-bidding-regis.html

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

[16] http://www.nytimes.com/2015/08/17/arts/international/sothebys-and-christies-jostle-for-sales.html

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

[18] http://www.nytimes.com/2015/01/08/arts/design/sothebys-and-christies-return-to-guaranteeing-art-prices.html

sales in 2014[19]. The early 2000's saw an infamous scandal where both houses fixed commission prices charged to sellers, and once convicted, were required to pay back $256 million to customers (and for Sotheby's, shareholders)[20].

The auction process is as follows. First, a client (prospective seller) will begin by requesting an auction estimate from the auction house for their item of interest, either by submitting photographs or scheduling an in-person appointment with a specialist. After assessing whether the item is appropriate for auction, the house will negotiate with the seller (e.g. for the reserve price) and draw up a seller's contract. The item then goes to the house to be officially photographed, catalogued, and stored before the auction event[21]. Of course, many clients visit more than one auction house to compare arrangements.

Three quantities are determined by the seller and the house before any auction: a low and a high presale estimate for the art piece, and a reserve price. The low and high estimates represent the range of possible values the piece might go for, and are usually decided upon by a committee of in-house art experts. As shown empirically by Ashenfelter (1989), these estimates do generally seem to accurately predict the item's sale price[22]. Some significant cross-house differences may exist: Bauwens and Ginsburgh (2000) show that in certain art categories, Sotheby's tends to undervalue expensive pieces and overvalue inexpensive ones, while Christie's does the opposite[23]. In negotiations, the seller and the house also determine a secret reserve price known only to those two parties. The reserve

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19 http://www.artspace.com/magazine/news_events/the_heat_index/how_to_understand_new_york_record_auction_week-52310

20 http://www.wsj.com/articles/SB969829620926708015

21 http://www.sothebys.com/en/news-video/videos/2014/10/how-to-sell-at-auction.html

22 Ashenfelter, Orley. "How auctions work for wine and art." *The Journal of Economic Perspectives* 3.3 (1989): 23-36.

23 http://www.jstor.org/stable/pdf/40724283.pdf?_=1459015351227

price is a closely guarded secret in the art auction world, but according to estimates by Ashenfelter, Graddy and Stevens (2004), the reserve price may be set around 70-80% of the low estimate. It is unclear why the reserve is concealed, but Vincent (1995) also suggests that under certain circumstances, announcing the reserve may discourage potential bidders from participating and could lower overall bids[24].

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. In addition to the presale estimates, 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 who previously owned the work (provenance). Houses also host pre-auction viewings where both potential bidders and the public can examine the art pieces in person. Bidders must register before an auction, and for particularly opulent auctions, must show proof of their assets.

Auctions are almost always conducted in an ascending first price format. Unless starting bids have already been pre-placed, the auctioneer starts low (somewhere below the secret reserve price[25]) and calls increasing prices[26] 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 20% to 25% of the hammer price, before the winning bidder receives the item[27]. At Sotheby's and Christie's, the seller receives payment approximately 35

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[24] Vincent, Daniel R. "Bidding off the wall: Why reserve prices may be kept secret." *Journal of Economic Theory* 65.2 (1995): 575-584.

[25] Ashenfelter, Orley. "How auctions work for wine and art." *The Journal of Economic Perspectives* 3.3 (1989): 23-36.

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

[27] Interview with Raphaelle Benabou, also http://www.ppge.ufrgs.br/giacomo/arquivos/econ-cultura/ashenfelter-graddy-2003.pdf

days after the auction, minus a "seller's premium" fee which is often around 10% of the hammer price[28] [29]. If an item does not meet its reserve price, 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 at a lower estimate, or taken off the market. Historically, auction houses did not publish records of whether items went unsold. However, since the 1980's auction houses in NYC have been legally required to report this, and according to Ashenfelter & Graddy (2003) houses in other locations are following this trend[30].

HOW ANCHORING AFFECTS ART AUCTIONS

The auction market is particularly prone to unobserved psychological and behavioral biases, because on both sides of the market, participants must rely on subjective judgement, past experience, and personal preferences to evaluate artwork. The ever-changing heterogeneity of art pieces, buyers, and sellers makes it intractable for both auction houses and economists to perfectly estimate demand for art. The auction format, designed to set prices by discovering private valuations, is a natural way to tackle this issue. Yet auctions are perhaps shaped the most by behavioral phenomena: the thrill of winning, for example, can spark bidding wars that drive up sale prices far beyond an artwork's estimated value[31].

Anchoring is one of the most-studied biases in the behavioral sciences: it is at once trivial to demonstrate and difficult to explain away. This effect occurs when first (quantitative) impressions

28 http://www.christies.com/features/guides/selling-guide/selling-at-christies/after-the-sale/

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

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

31 http://video.cnbc.com/gallery/?video=3000504214

distort future outcomes – even when the initial information is irrelevant[32] [33] or obviously mistaken[34]. For instance, a record high sale price for an Edgar Degas ballerina sculpture in March may induce buyers in April to pay more for other Degas ballerinas, even if the hedonic value of Degas ballerina pieces does not change month-to-month. It is important to understand that anchoring differs from rational learning, in which past prices do correspond to shifts in hedonic quality and thus are legitimately informative for predicting future prices[35]. Beggs & Graddy (2009) argue that demand for art changes over time, but underlying hedonic quality remains constant, thus allowing anchoring to be identified.

If the quality changes, then we can still identify anchoring, given we control for those differences[36]. This allows us to generalize the work of Beggs & Graddy (2009) beyond resales of the same good to sales of similar (substitute) goods. We define anchoring as follows: *when past observed quantities bias future quantities beyond hedonic factors, which either remain constant or whose changes are controlled for*. Even after controlling for such factors, the mechanism by which past quantities impact future ones is still a black box: this impact may be attributed to buyers, sellers, auctioneers, or some combination of all three[37]. For instance, the knowledge of a past price may affect buyers not only directly, but indirectly through the presale estimates set by auction house

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[32] Tversky, A.; Kahneman, D. (1974). "Judgment under Uncertainty: Heuristics and Biases" (PDF). Science 185 (4157): 1124–1131. doi:10.1126/science.185.4157.1124. PMID 17835457.

[33] Sugden, Robert, Jiwei Zheng, and Daniel John Zizzo. "Not all anchors are created equal." *Journal of Economic Psychology* 39 (2013): 21-31.

[34] Edward Teach, "Avoiding Decision Traps", CFO (1 June 2004). Retrieved 29 May 2007.

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

[36] Observation from MB 00 about how even the same work can change over time?

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

researchers. Hence, the mere observation of this effect suffices for our definition of anchoring. Next, we outline just a few ways in which anchoring can impact auctions for art.

Bidders may anchor on numbers provided prior to auction: this can include presale estimates and past sale prices for a work of art, as well as estimates and prices for related pieces. The former is expected to anchor bidder perceptions, because the purpose of presale estimates is to provide a baseline idea of how much an art piece is worth. Past sales prices may reflect not only the hedonic value of an art piece, but also unobserved characteristics such as bidding activity, the wealth of individual customers, and even exogenous factors such as the weather[38]. It is worth noting that anchoring is extremely difficult to avoid and can bias even experts in the field, though more expertise does guard against anchoring[39]. Additionally, anchoring effects tend to weaken when the value of goods is well-known.

Sellers, when setting reserve prices, may anchor on past sales prices. Past economic psychology research[40] finds that anchoring is more powerful for sellers than for buyers, though anchoring is weaker with more experience selling the goods of concern[41]. While sellers may experience anchoring when setting reserve prices, auctioneers can actively anchor bidder perceptions of value through what numbers they call out, particularly at the start of an auction. Hence, quickly

[38] De Silva, Dakshina G., Rachel AJ Pownall, and Leonard Wolk. "Does the sun 'shine'on art prices?." *Journal of Economic Behavior & Organization*82.1 (2012): 167-178.

[39] Northcraft, Gregory B., and Margaret A. Neale. "Experts, amateurs, and real estate: An anchoring-and-adjustment perspective on property pricing decisions." *Organizational behavior and human decision processes* 39.1 (1987): 84-97.

[40] Sugden, Robert, Jiwei Zheng, and Daniel John Zizzo. "Not all anchors are created equal." *Journal of Economic Psychology* 39 (2013): 21-31.

[41] Alevy, Jonathan E., John A. List, and Wiktor L. Adamowicz. "How can behavioral economics inform nonmarket valuation? An example from the preference reversal literature." *Land Economics* 87.3 (2011): 365-381.

calling out numbers at the start can be a powerful tool for the auctioneer, but one veteran auctioneer warns against setting anchors too high (to drive up future bids) or too low (to attract starting bids)[42]. Go too high, and your numbers lose credibility; go too low, and bidders will suspect something is wrong with the good.

We learned from our interviews that auction houses are aware of anchoring effects. For example, when internal departments need to determine presale estimates for a work of art, a single specialist will research past sales of comparable pieces (same artist, medium, etc.) to get an idea of how much revenue to expect. Next, the specialist tells others in the department about the current work of art – but without revealing any prices from related past sales (which, if done, would introduce anchoring). Every person volunteers an estimate for the current work, and only then does the specialist reveal what related works went for in the past. From there presale estimates are formed, presumably as a combination of past sales information (the anchors) and more up-to-date expert knowledge of the art piece in question.

The question of what makes two art pieces similar (i.e. substitute goods) is therefore of enormous interest to those in the field. Before one can appraise a piece of art, one must identify past sale precedents, which requires understanding what makes art pieces similar. Only then is it possible to properly analyze anchoring and other biases that can drastically alter prices and sales.

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[42] https://mikebrandlyauctioneer.wordpress.com/2015/04/13/value-anchoring-in-the-auction-business/

3. REVIEW OF THE LITERATURE

ANCHORING

Anchoring is a cognitive bias that has been studied in psychology and behavioral sciences for over 40 years.[43] The seminal work on anchoring was first authored by Tversky & Kahneman (1974), who conducted the experiment described in the introduction to this paper[44]. The anchoring effect is extremely complex, and many studies have attempted to understand its nature and implications. For instance, some research shows people formulate estimates more quickly when provided with numbers to anchor on[45]. Some studies show that anchoring decreases, but does not altogether vanish, with increased cognitive ability[46]. Other work demonstrates that anchoring is extremely difficult to avoid, even if the anchors are obviously incorrect.[47] For a comprehensive survey of the vast anchoring literature, see Furnham & Boo (2011)[48].

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

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

45 http://soco.uni-koeln.de/files/jpsp73.pdf

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

47 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.

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

Within economics, much of the anchoring work focuses on historical market data. Some studies test for anchoring by examining changing prices and demand for unchanging goods[49] [50]. Much of the anchoring research in economics uses experiments, surveys, or multiple-choice tests to find out how individuals form estimates and judgments in the presence of an anchor[51] [52] [53]. Anchoring has been studied in many socioeconomic contexts such as accounting[54], real estate[55], the courtroom[56], public goods[57], and international finance[58].

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

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

51 Frykblom, Peter, and Jason F. Shogren. "An experimental testing of anchoring effects in discrete choice questions." *Environmental and resource economics* 16.3 (2000): 329-341.

52 Winter, Joachim. "Bracketing effects in categorized survey questions and the measurement of economic quantities." (2002).

53 Flachaire, Emmanuel, and Guillaume Hollard. "Starting point bias and respondent uncertainty in dichotomous choice contingent valuation surveys."*Resource and energy economics* 29.3 (2007): 183-194.

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

55 Bucchianeri, Grace W., and Julia A. Minson. "A homeowner's dilemma: Anchoring in residential real estate transactions." *Journal of Economic Behavior & Organization* 89 (2013): 76-92.

56 Mussweiler, Thomas. "Sentencing Under Uncertainty: Anchoring Effects in the Courtroom1." *Journal of applied social psychology* 31.7 (2001): 1535-1551.

57 Green, Donald, et al. "Referendum contingent valuation, anchoring, and willingness to pay for public goods." *Resource and Energy Economics* 20.2 (1998): 85-116.

58 Nianhang, Xu, and Wu Shinong. "A Study on Anchoring Effect for Non-tradable Share Reform of Listed Companies in China [J]." *Economic Research Journal* 1 (2007): 009.

In addition, anchoring has been researched in the context of auctions[59] [60]. For example, one bizarre experiment was conducted by Prelec and Ariely (2006). Students were first asked to write down the last two digits of their Social Security number, then bid for various items such as chocolate, computer equipment, or a textbook[61]. The students who had higher digits submitted significantly higher bids, even when explicitly reminded that Social Security numbers are random quantities that carry no inherent meaning. Wolk and Spann (2008) study bidding for online auctions in the presence of an anchor[62]. They found that bidders respond strongly to internalized anchors such as knowledge of past prices for a good, while they respond to external anchors (such as advertiser-suggested bids) just moderately, and only when those numbers are not implausibly high.

ANCHORING AND ART AUCTIONS

Anchoring is also present in the art market. The literature shows that first numerical impressions do impact prices, auctioneer estimates, and sale volume. Here, we provide an overview of research that studies anchoring in the art market, which is still a highly nascent topic.

To our knowledge, a discussion paper by Beggs & Graddy (2005) is the first to examine anchoring effects (i.e. "reference dependence")[63] in the art auction market. This paper is described

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[59] Lucking-Reiley, David, et al. "Pennies from ebay: The determinants of price in online auctions*." *The Journal of Industrial Economics* 55.2 (2007): 223-233.

[60] Ku, Gillian, Adam D. Galinsky, and J. Keith Murnighan. "Starting low but ending high: A reversal of the anchoring effect in auctions." *Journal of Personality and social Psychology* 90.6 (2006): 975.

[61] Ariely, Dan, George Loewenstein, and Drazen Prelec. "Tom Sawyer and the construction of value." *Journal of Economic Behavior & Organization* 60.1 (2006): 1-10.

[62] Wolk, Agnieszka, and Martin Spann. "The effects of reference prices on bidding behavior in interactive pricing mechanisms." *Journal of Interactive Marketing* 22.4 (2008): 2-18.

[63] Beggs, Alan, and Kathryn Graddy. "Testing for reference dependence: An application to the art market." (2005).

as a working paper for Beggs & Graddy (2009). To identify anchoring, they examine resales within two datasets of Impressionist and Contemporary paintings, which contain not only hammer price but also hedonic characteristics such as artist and medium. Both the Impressionist and Contemporary art datasets are used in our research, and are described in detail in Section <>. As described earlier, the regression model of Beggs & Graddy (2005) detects anchoring by first controlling for hedonic value and non-hedonic biases on price, then testing for the impact of past price on current price. This model is formalized in Beggs & Graddy (2009), except that this model tests separately for positive (gains) and negative impacts (losses) of anchoring on current price. The authors find strongly significant evidence for anchoring in both Impressionist and Contemporary genres. They find no evidence that positive impacts of anchoring are significantly different from negative ones. [64]

Beggs & Graddy (2009), using the same resale approach and data, dive deeper into the impact of anchoring effects on price, presale estimates, and the probability of a sale[65]. Their model, which we apply and expand, does not test asymmetrically for gains and losses. For price, they find that anchoring effects are stronger for Impressionist art pieces than for Contemporary ones, particularly for items that are resold quickly after a first sale. They also find significant anchoring effects for the presale low estimates, noting that low estimates tend to gravitate toward past price as the anchor. Beggs & Graddy do not find anchoring significantly affects the probability of sale (estimated with a probit transformation). The anchoring models developed by Beggs & Graddy

[64] Loss aversion is another behavioral bias that says losses are felt more strongly than equivalent gains.

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

(2009) have been used in later anchoring research such as Leung et. al (2013)[66], and forms the basis of our own approach. We attempt to replicate selected results from Beggs & Graddy (2009) in a later section. Beggs & Graddy believe anchoring effects on the sale price may primarily be attributed to the buyers, since buyers primarily determine price, but beyond that treat anchoring as a black box. Graddy et al. (2014) use more data and mostly corroborate the anchoring results of Beggs & Graddy (2009). However, they express more uncertainty about whether anchoring effects should be attributed to buyers, sellers, or auctioneers.

Bruno & Nocera (2008) study how anchoring affects presale estimates using a unique dataset of nearly 1,000 Italian paintings that have been sold at least twice (1985-2006)[67]. They regress the range of presale estimates on a multi-level dummy variable for anchoring to account for multiple past prices (anchors). The authors find significant evidence of anchoring. First, the existence of past prices makes the presale estimate range narrower, presumably because auction houses become more confident in their estimates of the item's value[68]. Second, Bruno & Nocera find that if a past price exists for an item, the presale estimate range will be more closely centered on actual sale price. Hence, both the bias and variance of the presale estimate range, an estimator of the actual sale price, seem to decrease in the presence of anchors. These findings are consistent with what we heard through interviews, namely, that specialists at auction houses research past sales before formulating estimates.

[66] Leung, Tin Cheuk, and Kwok Ping Tsang. "Anchoring and loss aversion in the housing market: implications on price dynamics." *China Economic Review* 24 (2013): 42-54.

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

[68] Specifically, both the relative and absolute range between low and high estimates.

Even the order in which art pieces are auctioned can beget anchoring effects, as shown in Hong et al. (2015)[69]. For the semiannual Auction Week, a two-week auction series held every spring and fall across New York City[70], Sotheby's and Christie's have a handshake arrangement to alternate who holds their auction first. Using 26 years of Auction Week data and an adapted version of the resale model in Beggs & Graddy (2009), Hong et al. find that average opening sale revenues significantly anchor later sales during the rest of an Auction Week. Specifically, they discover that if more expensive paintings are sold first, then Sotheby's and Christie's will pull in higher total revenue (+21% higher), and more works will sell overall (+11% more sales). They state that their anchoring coefficients are quantitatively comparable to those from Beggs & Graddy (2009). This is the only work we found that does not examine anchoring across resales of the same art piece. However, since they only analyze mean revenues of auction houses and do not consider individual art pieces, their approach cannot be applied in our context.

Other behavioral research on art auctions exists, though much of it is more tangential to anchoring. In the art trade, there is the belief that if an art piece goes unsold at auction, it becomes "burned" and will sell for less in the future. To test this quantitatively, Beggs & Graddy (2008)[71] use an even smaller sample of repeat sales from the Impressionist and Contemporary datasets in Beggs & Graddy (2005). The authors find that on average, burned paintings do seem to sell for significantly less (-30%), particularly if they are resold at the same auction house within 2 years (-37%). Whether

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69 Hong, Harrison, et al. "Ordering, revenue and anchoring in art auctions." *The RAND Journal of Economics* 46.1 (2015): 186-216.

70 http://www.artspace.com/magazine/news_events/the_heat_index/how_to_understand_new_york_record_auction_week-52310

71 Beggs, Alan, and Kathryn Graddy. "Failure to meet the reserve price: The impact on returns to art." *Journal of Cultural Economics* 32.4 (2008): 301-320.

this is directly due to buyer perceptions of failure, however, is ambiguous. Sentiment, emotion, and mood are also growing areas of research. For instance, Canals-Cerda (2012) analyze art auctions and seller reputations on eBay, and discover that negative feedback significantly lowers sale price and the probability of sale[72]. Penasse et al. (2014) collect survey data on sentiment toward selected artists in the art community, and find that strong confidence on the part of auction houses and art collectors can predict art returns in the short run[73]. Furthermore, De Silva et al. (2012) examine if weather, a proxy for mood, significantly impacted art auctions at Sotheby's and Christie's during the period 1990-2007[74]. They find a weakly significant effect, suggesting that external emotional shocks do affect art auction activity.

In the aforementioned literature, the exact process by which past quantities anchor future ones is treated as a black box: only the impact is noted. This is what we described earlier, and the view of anchoring we adopt in this research.

CONTRIBUTION OF THIS RESEARCH

It is clear that anchoring is pervasive in the art auction market, especially since psychological and behavioral factors seem to be significant drivers of auction activity. However, the research to date (except Hong et al. 2015; see above) has studied anchoring only in the context of resale. This is problematic because as Beggs & Graddy (2009) acknowledge, it is extremely uncommon to encounter multiple sales of the same artwork. This is further limited by large time gaps between

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[72] Canals-Cerdá, José J. "The value of a good reputation online: an application to art auctions." *Journal of Cultural Economics* 36.1 (2012): 67-85.

[73] Pénasse, Julien, Luc Renneboog, and Christophe Spaenjers. "Sentiment and art prices." *Economics Letters* 122.3 (2014): 432-434.

[74] De Silva, Dakshina G., Rachel AJ Pownall, and Leonard Wolk. "Does the sun 'shine'on art prices?." *Journal of Economic Behavior & Organization*82.1 (2012): 167-178.

sales, which weaken anchoring effects[75]. Additionally, it is difficult to show resale observations refer to the same art piece, since an artist may create multiple pieces with the same medium, dimensions, and so forth. Beggs & Graddy (2009) manually cross-checked their resale data against presale catalogs.

More importantly, a shared but flawed assumption across much of the aforementioned literature on anchoring is that hedonic quality does not change across auction sales. In talking with Mark Best at Sotheby's, we were surprised to hear how much artwork can deteriorate over time. Prints may tear accidentally, fade under glass, or become punctured, if tacked to the wall for decoration. The canvas of a painting can weaken over time, and must be "relined" with a new canvas attached to the back for extra support. Restoration (often by an unwitting owner) can also harm the value of an art piece: protective glaze must be scraped off, retouched paintings must be scrutinized under ultraviolet light, and so forth. We suspect these factors explain why Beggs & Graddy (2009) find stronger anchoring effects for Impressionist artworks than for Contemporary ones. Paintings in the former category mostly belong to renowned Impressionists artists such as Renoir and Monet, and are an order of magnitude more valuable in both presale estimates and prices[76]. Thus, they are probably far better maintained, which better preserves their hedonic quality, allowing past sales to better anchor future ones.

If the hedonic quality of a painting changes across sales, then we can still identify anchoring, given we control for those intertemporal differences.[77] Yet, if we have to control for hedonic differences anyway, why not look at different art pieces altogether? This observation allows us to generalize the anchoring work of Beggs & Graddy (2009) beyond resales of the same good to sales

[75] See Graddy et al. (2014); Hong et al. (2015).

[76] See Table 1 and 2 – sample means – in Beggs & Graddy (2009).

[77] Observation from MB 00 about how even the same work can change over time?

of related (substitute) goods. In all previous literature we are aware of, the anchor is always a previous sale of the same good. However, if we control adequately for quality changes between the anchor and the current art piece, then we may use sales of a related piece as the anchor instead of a past sale. We introduce this formally in the next section.

4. DATA

I use three datasets on auction sales in this paper: Impressionist art (1980-1991), Contemporary art (1982-1994), and recent assorted art sales (2006-2016). The Impressionist and Contemporary art datasets have been used extensively in the literature[78] and are already described in detail elsewhere[79]. Both of those datasets are available on the Brandeis academic website of Kathryn Graddy[80]. However, the last is a new dataset constructed specifically for this paper.

IMPRESSIONIST ART (1980-1991)

The Impressionist art dataset (1980-1991) was constructed by Orley Ashenfelter and Andrew Richardson in 1992, and covers sales at Christie's and Sotheby's in both London and New York. [81] There are well over 16,000 observations of art piece sales, which were compiled by manually scouring presale catalogs. 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. In-depth attribute details are unavailable in this dataset: for example, dimensions are called "DIM_A" and "DIM_B". The dataset contains 58 major artists whose work is often featured at auction, and among the most frequent are Pablo Picasso (1,155 sales), Pierre Renoir (829 sales), and Raoul Dufy (763 sales). Approximately half the auction sales in this dataset are split between Christie's and Sotheby's, as well

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78 Richardson (2002); Abowd & Ashenfelter (1989); Beggs & Graddy (1997); Ashenfelter & Graddy (2003); Beggs & Graddy (2009)

79 http://www.jstor.org/stable/pdf/2556028.pdf?acceptTC=true

80 http://people.brandeis.edu/~kgraddy/data.html

81 Richardson, Andrew. 1992. "An Econometric Analysis of the Auction Market for Impressionist and Modern Pictures, 1980-1991." Senior thesis, Department of Economics, Princeton University.

as between London and New York. Table 1 shows summary statistics for selected attributes. The highest sale in this dataset goes to Vincent Van Gogh's *Portrait of Dr. Gachet* (1890), which netted approximately $82.5 million on May 15, 1990. Conversely, the lowest sale is a work by Paul Cesar Helleu that went for a mere $1,888 on March 25, 1986.

Many of these quantities have distributions that are roughly log-normal (i.e., without the log transformation, skewed heavily right), showed in Figure 1. In general, we see very high variation: sales price, for example, reflects both works with record-high sales as well as works that sold for minimal amounts or were bought in. This is because the majority of paintings exhibit middle-market sale price, estimates, size, and so forth, while relatively few reach the highest ranges. The two painting dimensions have the most irregular distributions, particularly in the middle ranges. However, as seen in Figure 2, the large portion of paintings do not tend to be lopsided in their physical dimensions. Finally, we see that auction sales in this dataset have generally risen over time (Figure 3), though there are some years with record numbers of sales.

CONTEMPORARY ART (1982-1994)

The Contemporary art dataset represents every Contemporary art piece sold from 1982 to 1994 at Christie's primary King Street location in London, for a total of approximately 4,500 observations. [82] The dataset was compiled by Kathryn Graddy, who manually examined auction catalogs and sifted through internal data in the archives of Christie's. 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

[82] Beggs, Alan, and Kathryn Graddy. "Testing for reference dependence: An application to the art market." (2005).

quantities are given in thousands of pounds. The data comes with a STATA .do file, which gives more detailed information on the attributes. Nearly 600 artists are represented, with Lucio Fontana (157 sales), Karel Appel (151 sales), and Alexander Calder (141 sales) being the most frequent.

Table 2 gives summary statistics for this dataset. As with the Impressionist dataset, and shown in Figure 4, quantitative dimensions such as sale price and size also show roughly a log-normal shape, though auctions sales seem to be more uniform over time (Figure 5). As shown in Figure 6, Impressionist pieces are generally far more expensive than Contemporary pieces. However, Contemporary pieces do tend to be physically larger (Figure 7) and have far more unbalanced dimensions, though as with Impressionist pieces large width and length do seem to scale together (Figure 8).

RECENT ASSORTED ART (2006-2015)

A major contribution of this research is the construction of a large dataset of 500,000 recent auctions sales of assorted artworks[83] (2006-2015). To do this, we wrote a Python program to scrape recent listings on the Blouin Art Sales Index, an up-to-date online database of art auction sales[84]. We ran our program for 10 nonstop days in December 2015. The motivation behind collecting and using a new dataset is threefold. First, the time gaps between auction sales in this dataset are much shorter, compared to our other datasets. The average time gap between sales in the Impressionist and Contemporary art datasets are 5.57 and 0.98 days, respectively, while the average gap here is only 0.0072 days – indicating most sales occur on the same day. This is more conducive to studying anchoring. Second, this dataset consists of a very wide range of artists and artistic styles, while the

83 The collected raw data also includes prints, drawings, and other mediums, but since we wish to compare against our other two datasets, we only use paintings here.

84 http://artsalesindex.artinfo.com

Impressionist and Contemporary datasets are more limited in their artistic scope. More variety allows us to identify more substitutes, and better test our measures of substitution. Finally, as mentioned earlier, sales in this dataset are more recent and could better reflect the current auction climate.

The full, raw dataset consists of approximately 500,000 observations (paintings and non-paintings), covering primarily 19^{th} and 20^{th} century art. It also includes some works from earlier time periods, going back to 1000 CE for works by Song Dynasty artist Yi Yuanji. Nearly 90,000 artists are included, with the best represented being Pablo Picasso (3,440 sales), Andy Warhol (2,573 sales), and Salvador Dali (1,508 sales). However, we did not identify any resales. We only examine paintings, of which there are approximately 250,000 observations. 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 before, sale prices and other quantitative characteristics seem to follow a roughly log-normal distribution (Figure <>). 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. It is clear that artists who sell more works through auction will enjoy higher revenue on average (regression slope: 0.52. p-val: <2E-16), as they become better-known in auction circles through higher representation (Figures 9-12).

Each observation in this new dataset 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. Information on the materials were given in the form of unstructured text data, which might be attributed to freeform data entry on the part of Blouin. Hence, 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.

5. METHODOLOGY

ANCHORING

A two-stage regression model for detecting anchoring is specified in Beggs & Graddy (2009). The same model is used to detect anchoring effects in later papers such as Hong et al. (2015), and in general, may be estimated for goods that exhibit unchanging hedonic quality over time. That hedonic quality for artwork would not change is thus a key assumption of their work. Intuitively, their model identifies anchoring by looking at two sales of an item, say a painting, at different points in time. After controlling for hedonic value and non-hedonic price biases at all time points, current price may be regressed on past price. That impact of past price is identified as the anchoring effect.

Hedonic regressions are commonly used to estimate demand for highly heterogeneous items such as art, wine, and real estate as a function of their constituent attributes[85] [86]. For example, the value of a painting may depend on its dimensions and authenticity, while a bottle of wine may be appraised based on its age and where it was grown. In the first stage of the model, Beggs & Graddy (2009) regress the sale prices $P \in R^{[n,1]}$ of n resold paintings[87] on their k hedonic and temporal variables $\boldsymbol{X} \in R^{[n,(k+1)]}$[88], while also including temporal effects $\delta_t \in R^{[n,1]}$. This yields a hedonic

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[85] Edmonds, Radcliffe G. "A theoretical basis for hedonic regression: A research primer." *Real Estate Economics* 12.1 (1984): 72-85.

[86] Costanigro, Marco, Jill J. McCluskey, and Ron C. Mittelhammer. "Segmenting the wine market based on price: hedonic regression when different prices mean different products." *Journal of agricultural Economics* 58.3 (2007): 454-466.

[87] The data here consists of all sale observations that correspond to the set of paintings that have been resold multiple times. Beggs & Graddy have painstakingly verified each observation against presale catalogs. Because those are not available, in my replication analysis I make the assumption that duplicate observations in their Impressionist and Contemporary data refer to multiple sales of the same item.

[88] Each sale observation includes the auction date, hence the $k + 1$ dimensions in the data.

price prediction $\pi_t \in R^{[n,1]}$ for each observation of a painting sale. The resulting equation, which both Beggs & Graddy and we use, is given below. We denote the current period as t and the previous period as $t-1$.

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

For my replication work on the Impressionist and Contemporary datasets, I use the same hedonic variables that Beggs & Graddy used. For Impressionist art this includes painting date, length, width, medium of the artwork, indicators of authenticity (signed, monogrammed, stamped), and artist.[89] For Contemporary art this includes painting date, length, width, medium, and artist. The temporal effects are modelled by half-year time dummies.

In the same manner as Beggs & Graddy, I use the natural log of prices and hedonic price predictions, which allows us to interpret the regression results as relative effects (percent changes). For unsold items, we proxy value with 80% of the low estimate as they do. It is important to note that hedonic price predictions for a single painting $\pi_t, t \in \{1, 2, 3 \ldots\}$ may vary with respect to time, since these are estimated based on prices for the painting at different times. These prices reflect demand for art, which may change over time. The k hedonic variables, however, are assumed to remain constant across sales.

[89] Besides the artist's hand-drawn signature, monograms and stamps may also be used to mark an artwork as authentic. A monogram is a stylized symbol of the artist (sometimes an artistic rendering of their initials) that may be put onto a work. Artists may also have a custom stamp for their work, which may include their printed name.

In the second stage of the model, Beggs & Graddy specify the following regression – for each unique painting – in order to separate out anchoring from other effects. Their equation (which we also use) is given below.

$$\omega = a_0 + a_1\pi_t + a_2(P_{t-1} - \pi_t) + a_3(P_{t-1} - \pi_{t-1})$$

- ω is the response variable. Beggs and Graddy fit several regressions where the response ω represents either the hammer price, the presale estimator, or an indicator for whether the item sells, which involves a probit transformation. In our replication work, we only examine ω as hammer price.
- π_t is the current hedonic valuation of bidders, i.e. the hedonic price prediction in the current period t. To detect anchoring effects, hedonic valuations π_t must be controlled for. Otherwise, one would not be able to separate hedonic and non-hedonic influences in the current period.
- $(P_{t-1} - \pi_t)$ identifies the anchoring effect. This specifies how past hammer price P_{t-1}, the anchor, differs from π_t, the current hedonic valuations of bidders. Since we have already controlled for the latter, as well as non-hedonic components of past price that could possibly affect current price – see $(P_{t-1} - \pi_{t-1})$ below – this term measures the extent to which past price irrelevantly impacts current price.

- $(P_{t-1} - \pi_{t-1})$ is the past residual, i.e. non-hedonic inputs into past price. This controls for any other components of past price that could, conceivably, affect current price.[90] For example, past price might be a function of unobservable bidder excitement for the work. This would not only drive up past price, but could also drive up current price. Hence, we control for such non-hedonic price biases in this term.

In the case of the dependent variable P_t (i.e., when ω is hammer price), we see that those non-hedonic inputs, usually captured by $(P_t - \pi_t)$, would instead be contained in the residuals. One should also note that because hedonic prices may vary over time, $(P_{t-1} - \pi_t)$ is distinct from $(P_{t-1} - \pi_{t-1})$. Additionally, the intercept a_0 represents the value of ω in the absence of other predictors. For example, if ω represents hammer (sale) price, then a high intercept could suggest a high average price for paintings across the given market.

IDENTIFYING SUBSTITUTES

As we discussed earlier and as Beggs & Graddy (2009) note, it is extremely difficult to track down multiple sales of the same item. The same art piece can become a drastically different hedonic object within its lifetime due to deterioration or restoration. Also, many years or decades may elapse between sales of the same art piece – far too long to reliably measure anchoring biases.

It is reasonable to believe that buyers, when bidding on an artwork, make judgments based not only on that piece's past sales, but also what similar pieces went for. This allows for more versatile

[90] One example would be a work's reputation, which could drive up both past and current price. This component of quality, however, cannot be modeled as another hedonic attribute like size, medium, etc., since reputation is not an intrinsic property of an art piece.

approach to identifying anchoring effects, or if between different goods, cross-effects, as long as we control adequately for hedonic differences. Before measuring similarity, however, we must identify related pieces for the current good, since many pieces may be entirely irrelevant. Thus, to identify substitutes for the sale of an art piece, we search through our data for past sales of other pieces with the same artist, medium, and signs of authenticity. I also omit observations where no substitutes were found. This gives us a list of related sales to consider for the current good. Only then may we proceed to measure similarity and test for anchoring cross-effects, as described below.

ANCHORING AND SUBSTITUTION

Here, we build on the two-stage regression model presented earlier.

Suppose, as before, we have our same design matrix $\boldsymbol{X} \in R^{[n,k+1]}$ and our hammer prices $P_t \in R^{[n,1]}$. We run the first hedonic regression as before, except that we are not concerned specifically with resale.

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

We next depart from the original model. Denote the sale observation of our current good as x_c and the sale observation of a single substitute as x_s, such that the hedonic predictions estimated above are π_c, π_s, and P_c, P_s are the respective hammer prices. Then our second regression is:

$$\omega_c = b_0 + b_1\pi_c + b_2(P_s - \pi_c) + b_3(P_s - \pi_s) + b_4 Q$$

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. In other words, instead of considering a current sale and past sale of the same painting (which corresponds to hedonic matrices $\boldsymbol{X_t}$ and $\boldsymbol{X_{t-1}}$), we consider the current sale of the painting and the past sale of a substitute (thus replacing $\boldsymbol{X_t}$ and $\boldsymbol{X_{t-1}}$ with $\boldsymbol{X_c}$ and $\boldsymbol{X_s}$). The previous regression model assumed that there was no unobserved quality changes in the painting across sales, such that $\boldsymbol{X}_t = \boldsymbol{X_{t-1}} = \boldsymbol{X}$. Hedonic prices π_t could still change due to time-dependent demand. However, in this generalized framework, we assume that characteristics do differ across goods, such that $\boldsymbol{X_c} \neq \boldsymbol{X_s}$. Thus, we control for those hedonic differences by including a measure of substitution Q in our regression model, which may be constructed from either π or $\boldsymbol{X}$. This allows us identify anchoring effects in $(P_s - \pi_c)$, as before.

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:

$$w_c = b_1\pi_c + b_{i2}(P_{RS} - \pi_c) + b_{i3}(P_{RS} - \pi_{RS}) + b_3 Q$$

$$P_{RS} = \frac{1}{d}\sum_{i=1}^{d} P_{si} \qquad \pi_{RS} = \frac{1}{d}\sum_{i=1}^{d} \pi_{si}$$

Two goods c_1 and c_2 may have different numbers of substitutes d_1, d_2, which is why for our regression model it is necessary to aggregate them into a "representative substitute" via a summarizing function such as the mean or maximum (we use the former). This produces a representative price P_{RS} and hedonic prediction π_{RS}. Hence, this multivariate regression tests whether there exists anchoring effects for the sale of the current good with respect to the "average" substitute – a conglomerate of all substitutes together. The marginal effect of Q on w_c, then, represents how

strongly the dependent variable (such as price) is affected by our quality of substitution. The measure of substitution Q may be calculated from the multivariate π or $\boldsymbol{X}$. Finally, if we omit Q and use the current good's previous sale instead of its average substitute, this reduces to the original model of Beggs & Graddy.

MEASURING SUBSTITUTION (SIMILARITY) ACROSS ART PIECES

In this paper, we experiment with two simple measures of substitution Q_1 and Q_2 between art pieces. The first is derived from the hedonic predictions, and represents unobserved quality differences. The second is formulated from our interviews with art experts and specialists. These measure do not and cannot perfectly capture differences between artworks, but they do provide a starting point for quantitatively measuring art similarity.

MEASURE #1: SECOND MOMENT OF HEDONIC PRICE DIFFERENCES

Consider the current good x_c and d substitute art pieces $X_s = \{x_{s1}, x_{s2}, \dots x_{sd}\}$, which are aggregated into an "average substitute." One way we can measure substitution is by examining how much, on average, the hedonic price predictions of the substitutes differ from that of the current good. This corresponds to hedonic value differences that are not captured in our hedonic regression model. It is not, however, sufficient to just capture the average magnitude of these hedonic differences. If some substitutes have hedonic values below that of the current good, and some have hedonic values above, then our "average substitute" may have the same hedonic value as the current good, indicating perfect substitution! It is preferable to have uniformly substitutable goods rather than a polarized mix of good substitutes and bad substitutes. Thus, we use the following measure of

similarity, which is essentially a second moment estimator about the current good's hedonic prediction[91]:

$$Q_1 = -\log \frac{1}{d} \sum_{i=1}^{d} (\pi_c - \pi_{si})^2$$

This measure captures both the hedonic differences $(\pi_c - \pi_{si})$ as well as the variability of such differences (indicated in the squared term). As described before, we work in logs for relative effects, and the negative sign allows a higher Q_1 (smaller hedonic differences and lower variation in those differences) to correspond to higher substitutability.

MEASURE #2: DOMAIN KNOWLEDGE

For our second measure of substitution, we draw upon domain knowledge from our expert interviews. We found the most commonly mentioned and important determinants of artwork similarity (substitutability) were artist, medium, signs of authenticity, size of the artwork, and how recently the artwork was auctioned. The opinions of our interviewees on more complex factors, such subject matter and artistic style, seemed to be mixed: some said these were key to measuring similarity between pieces, while others did not believe they were as relevant[92]. One thing we were surprised to learn about size in particular was that its importance in determining similarity varies at different price points. For the lower and middle price ranges, people usually purchase art as a

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[91] We do not subtract the other term $E[X = (\pi_c - \pi_s)]^2$ typically used in calculating variance $V[X] = E[X^2] - E[X]^2$, since that (squared) mean term reflects the absolute hedonic differences $X = (\pi_c - \pi_s)$. Our measure represents $E[X^2]$, the summation of $V[X]$ and $E[X]^2$, and this is how we account for both spread and magnitude.

[92] For further discussion: http://www.jstor.org/stable/pdf/20715780.pdf?acceptTC=true

decoration, and usually purchase pieces of similar sizes that can be displayed side-by-side. As price increases, people tend to value artwork more as an investment, and so the importance of size in determining similarity decreases.

To capture these anecdotal observations about art similarity, we present a second measure of substitution between a current piece x_c and its substitutes $X_s = \{x_{s1}, x_{s2}, \ldots x_{sd}\}$. This measure of substitution depends on size S_i, hedonic price π_i, and auction date t_i.

$$Q_2 = -\log\frac{1}{d}\sum_{i=1}^{d}\left[\frac{(S_c - S_{si})^2}{1 + (\pi_c + \pi_{si})} + \Delta days(t_c, t_{si})\right]$$

Greater differences in size between the current good and its substitutes correspond to decreased similarity and thus decreased substitutability[93]. However, this effect decreases as the hedonic values of the current good or its substitutes rise. Consistent with the anchoring literature discussed earlier, the farther the anchor (the sale of a substitute) is in the past, the weaker the anchoring effect is. Note that we use hedonic prices to indicate increasing value. This is because P_{si} and P_c can reflect not only π_{si} and π_c but also non-hedonic determinants of price, and furthermore, P_c is the dependent variable to be determined in our main anchoring regression. No possible past anchoring effects are considered with the hedonic prices here: we assume buyers are myopic, as captured in the time difference effect, and assess similarity primarily based on hedonic factors.

The hedonic price predictions enter into both Q_1 and Q_2, but the two measures are considerably different. Hedonic differences are the primary focus of Q_1, while for Q_2 they only serve

[93] We add one in the denominator of the first term to protect against results exploding toward infinity. Empirically, however, this is negligible compared to the magnitude of our hedonic prices.

the implicit purpose of scaling size. The measure Q_2 also includes temporal differences, which do not explicitly enter into the hedonic regressions. Hence, we may consider Q_1 a very broad measure of hedonic similarity, while Q_2 is a narrower measure formulated from domain knowledge. It is surprising that these two divergent measures yield similar evidence of anchoring effects, and given that we apply these broadly, detect anchoring effects at all. We show this in the next section.

6. RESULTS

I begin by fitting a hedonic regression model to all three datasets. Next, I replicate Beggs & Graddy's (2009) original anchoring findings for their two Impressionist and Contemporary datasets. Then, I apply their same model to my new dataset of assorted art sales. Finally, I run my anchoring cross-effects regression on all three datasets. As a final experiment, I also run my cross-effects regressions on three selected pairs of artists.

HEDONIC REGRESSION

We begin by fitting a hedonic regression model to our three datasets in order to construct a measure of artistic value for each piece. 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 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 may 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 as a whole. 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. Despite a high R^2 value for

Impressionist art, the intercept is highly significant. This suggests that non-hedonic factors likely play a large role in determining value for Impressionist pieces, which is understandable given the relatively more pronounced age and renown of those works. Additionally, the presence of a signature specifically, rather than other signs of authenticity such as a monogram, generally seems to be more important to determining hedonic value. We do note that signature is more significant for Impressionist art auctioned in NYC, while medium is more significant factor for that auctioned in London. As a further note, regressing on only artist and time dummies corresponds to a reduction in R^2 in the Impressionist and Contemporary datasets, as noted in Beggs & Graddy (regressions not included). Generally, it is clear that hedonic factors such as size and medium do play a large role in determining value for the works we examine.

REPLICATION: BEGGS & GRADDY (2009)

Here, we attempt to replicate some of the work of Beggs & Graddy (2009), who analyze the same Impressionist and Contemporary datasets to test whether the first sale of a painting produces an anchoring effect on its later sales. In this research we only consider sale price, but Beggs & Graddy did also run regressions for presale estimate and the probability of sale. As mentioned earlier, they identified resale observations in the Impressionist and Contemporary datasets by cross-checking them against presale catalogs, which we do not have. Hence, we make the assumption that duplicate hedonic observations refer to multiple sales of the same item, which is clearly too lenient since even different art pieces may have the same characteristics. However, as discussed below, we are still able to reproduce their general findings even without knowing which exact observations were originally used.

Tables 8 and 9 show our results, alongside the original tables of Beggs & Graddy. We were able to reproduce the discovery of highly significant anchoring effects in Impressionist art, and the

more weakly significant effects in Contemporary art. However, our anchoring coefficients are not nearly as large as theirs. For Impressionist art, a 10% increase in the difference between past price and current hedonic prediction (anchoring) only corresponds to a 1.7% increase in the current sale price (Beggs & Graddy: 6.2-8.5%), while for Contemporary art the same 10% increase only corresponds to a 1.3% predicted increase in current sale price (Beggs & Graddy: 5%). On the other hand, our regressions show that the residuals from past price (unobserved inputs into past price, such as the thrill of bidding) are much strong than anchoring in the case of Impressionist art (5% increase for Impressionist), which differs from the results of Beggs & Graddy. One explanation could be that the reputation of Impressionist pieces grows over time as these pieces trade ownership across collectors and museums, so that reputation effects tend to drive up buyer demand beyond hedonic value or even past price anchors. This would be captured in the past residuals.

We do find a weaker impact of the past residuals on current price in the case of Contemporary art, a result which is shared by Beggs & Graddy. They attribute this to the heavy time-dependent variation in prices in this Contemporary art dataset (not shown here), which suggests past prices would not serve as meaningful anchors. We also replicated their discovery of relatively small time coefficients, particularly for Contemporary art. This indicates that the specific number of months between sales seems to not be a major influence in determining the current price of a work (at least in the context of resale). Finally, our anchoring regressions also share the very high R^2 and adjusted R^2 values of Beggs & Graddy, indicating that much of the variation in hammer prices is explained by this model.

In addition to Impressionist and Contemporary art, we also ran Beggs & Graddy's original anchoring regression on our new dataset of recent assorted painting sales (Table 10). Because our dataset does not seem to have identifiable multiple sales of the same item, we used the average substitute of an item (constructed as described in our methodology) instead of a past sale as a point

of comparison for the anchoring effect. This reduces to running our regression for anchoring cross-effects without the measure of substitution, i.e. the control term Q. Despite this simplistic approach that does not control for substitution, we can still discover some insight.

We discovered strong and highly significant anchoring effects in this context (5.9% increase), although, just as in our findings for Contemporary art, the residual from past price seemed to be relatively unimportant. This preliminary evidence suggests, although we have not controlled for substitution yet, anchoring is at work in this dataset. The R^2 value is much lower due to the very high variation in our data, but the F-statistic is extremely high indicating that our regression variables do seem to be relevant. As in both the original results of Beggs & Graddy and our replication of their work, we found that time effects seemed to be relatively weak, though they are highly significant. Hence, our next Q_1 and Q_2 regressions, designed to control for substitution, should yield more precise and accurate insight into anchoring effects.

ANCHORING CROSS-EFFECTS

In this section, we describe our regression results that control for substitution. We employ our measures Q_1, Q_2 which describe how similar a current good is to its "average substitute," a representative good constructed from all other identified substitutes. As discussed earlier, the measure Q_1 represents the (log) second moment of hedonic prices of substitutes about that of the current good. This allows Q_1 to capture both the spread of hedonic differences as well as the magnitude of those differences. Conversely, the variable Q_2 measures similarity across art pieces according to insight from our interviews, and represents the importance of size, price, and time effects.

Q1: SECOND MOMENT OF HEDONIC PRICE DIFFERENCES

$$\omega_c = b_1\pi_c + b_2(P_s - \pi_c) + b_3(P_s - \pi_s) + b_4\left[Q_1 = -\log\frac{1}{n}\sum_{i=1}^{d}(\pi_c - \pi_{si})^2\right]$$

Tables 11 through 13 show the results of running the above regression for our Impressionist, Contemporary, and assorted art datasets. There are several results particularly worth noting here.

First, after controlling for substitution, anchoring effects lose significance for Contemporary art, and only retain significance for Impressionist and recent assorted art. It is possible that anchoring is no longer significant for Contemporary art because it tends to be especially diverse. For instance, based on our interviews, we learned that over time the boundaries between art mediums have become finer as mediums are combined in "mixed media" formats. These unusual Contemporary artworks do seem to fetch competitive sums at auction[94] [95]. As a result, a Contemporary artwork to be auctioned may lack obvious precedents for the determination of its value. Thus, current price will be determined by the piece's own characteristics as well as unobserved inputs into price such as general demand for Contemporary art. This seems to be confirmed by the highly significant hedonic price prediction, as well as the highly significant, non-negative substitute residual. The lack of anchoring effects for Contemporary art goes hand-in-hand with the insignificance of the substitution measure, which indicates that price does not seem to be determined by substitution phenomena.

On the other hand, anchoring effects and substitution are significant for Impressionist art. In general, Impressionist works tend to have better-defined mediums such as oil and watercolor, which likely makes it easier to identify similar sale precedents. Hence, anchoring is significant (though not particularly strong): a 10% gap between the substitute's sale price and the current piece's hedonic

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[94] http://www.christies.com/lotfinder/paintings/invader-alias-hk-59-5875653-details.aspx

[95] For instance, Matt Lamb's "Figures" fetched $24K at Christie's, London on June 22, 2010. http://www.christies.com/lotfinder/paintings/matt-lamb-figures-5332422-details.aspx

value corresponds to 0.3% change in the current price. More impactful is the substitute sale residual, which exhibits a highly significant and stronger coefficient. We believe this may be due to reputation effects. Impressionist pieces, which tend to be much older, scarcer, and well-known, seem to be purchased more as an investment rather than a decoration.[96] [97] Hence, we would expect their non-hedonic value to rise as their provenance and auction history becomes more and more illustrious over time. As a result, the sale prices of these pieces begin to reflect their historical reputation more than their hedonic value. Historical reputation may be tied to general attributes such as the artist and provenance, which may of course be shared by multiple works. Thus, we should expect buyers of a piece to draw upon price signals from sales of similarly reputable works, which are captured in the significant substitute residual here.

Finally, our assorted art dataset exhibits strong and highly significant anchoring effects. We believe this is partially due to the far smaller time gaps between sales, which as discussed in our literature review, seem to be more conducive to anchoring. However, in addition to containing both Impressionist and Contemporary works, the assorted art dataset is much larger and diverse. This means that for a given art piece, it may be possible to find more appropriate substitutes, which is suggested here by the highly significant coefficient for the substitution measure. < need to work hard on this section. Maybe go into data, .Rdata, or regression here >

Time effects (months since last sale) have small coefficients across the board, and are insignificant for Impressionist art. From our interviews, we learned that buyers of art tend to be myopic, in that they do not tend to internalize the full range of historical prices (only recent prices, e.g. anchoring). This seems to be confirmed by the price indices and small time coefficients in Beggs

[96] http://pierrebittar.com/why-invest.html

[97] Impressionist price index in Beggs & Graddy (2009)

& Graddy (2009), which suggest that prices can climb up dramatically over long stretches of time. Here, for assorted art, a 100 month (8.3 year) time interval between sales only corresponds to an 8% decrease in the current price. For Contemporary art, the same gap corresponds to a 5% decrease, while for Impressionist art the association is almost nonexistent. Nevertheless, the fact Contemporary and assorted art have somewhat larger coefficients suggest that smaller time intervals between sales can counteract buyer nearsightedness.

The R^2 values are generally in line with our results for the original anchoring regression: there is much less variation in the Impressionist and Contemporary datasets than in our assorted art one. High F-statistics confirm the relevance of our variables, as before.

Q2: DOMAIN KNOWLEDGE

$$\omega_c = b_1\pi_c + b_2(P_s - \pi_c) + b_3(P_s - \pi_s) + b_4\left[Q_2 = -\log\frac{1}{n}\sum_{i=1}^{n}\left(\frac{(S_c - S_s)^2}{1 + (\pi_c + \pi_s)} + \Delta days(t_c, t_s)\right)\right]$$

Tables 14 through 16 show the results of using Q_2 as a control for substitution. Even though the design and focus of Q_2 is considerably different from those of Q_1, we reach similar results, which further confirms our overall discovery of anchoring effects.

First, as in the Q_1 case, anchoring is significant for Impressionist and assorted art, but insignificant for Contemporary art. This is what we found in the Q_1 case, which is surprising since Q_2 only focuses on a couple of key variables (size, time) that were carefully suggested by our experts. Nevertheless, anchoring coefficients are weaker across the board, which suggests that Q_1 might be a more stringent control.

Although Q_2 becomes a significant predictor of price across all three datasets, the impact of Q_2 on price is mixed, compared to the Q_1 case. For Impressionist art, Q_2 has a larger coefficient (in absolute value) than Q_1 did; on the other hand, for Contemporary art Q_2 is weaker. This suggests that when buyers of a given art piece research sales of comparable pieces, they base their hedonic value judgments primarily on size, and do not delve into sales too far in the past. For Contemporary art, we see that Q_2 is significant as opposed to the Q_1 case, indicating that domain knowledge of artistic similarity does seem to be legitimately helpful in predicting price. This is consistent with our discussion of Contemporary art pieces in the Q_1 case, and the lower R^2 for Impressionist art in our hedonic regression model (Table 5 and 6). Compared to Impressionist pieces, Contemporary art pieces do seem to generally have a more limited provenance and history, and so derive much of their value from hedonic factors. That said, here the quality of substitution Q_2 is still comparatively

stronger for Impressionist art than for Contemporary art. This is because time effects are stronger for Contemporary art than for Impressionist art: some of the predictive ability of Q_2 is sapped by the significant time coefficient also included in the regression (-0.05039). Prices for Impressionist pieces generally seem to be somewhat resistant to long intervals between sales, as indicated by the lower and nonsignificant time coefficient (0.8457).

While both Q_1 and Q_2 are significant for assorted art, Q_2 is a hugely more impactful measure of substitution: a 10% improvement in substitution quality corresponds to a 3.0% increase in sales price. Focusing on size and time duration seems to be far more effective as a control, since for this assorted art dataset, it is possible that Q_1 (as a more general hedonic measure of similarity) may capture too much noise to be helpful for measuring substitution. Nevertheless, regardless of which measure we use, we are still accounting for a lot of variation in the data, as evidenced by moderate-low R^2 values.

THREE EXPERIMENTS

Hadley Newton (formerly of Sotheby's) helped us to sift through our assorted art dataset for pairs of artists to compare. This includes Joan Miro & Salvador Dali, Pablo Picasso & Marc Chagall, and Edvard Munch & Henri de Toulouse-Lautrec. The first two artist pairs produced artistically similar work, and so should be expected to exhibit anchoring cross-effects. However, while they were historically similar (as explained below), Munch and Toulouse-Lautrec had fairly divergent artistic styles. Thus, they should not be expected to display anchoring effects. This allows us to ensure our model does not falsely detect anchoring in light of non-artistic similarity.

In this section, we run our Q_1 and Q_2 regressions on those three pairs of artists for comparison. Specifically, we test whether one artist serves as an anchor for the other, and vice-versa: an artist may not be their own anchor. This allow us directly test our anchoring regressions on known substitutes, and evaluate our results more thoroughly.

SUBSTITUTION EXPERIMENT #1:

JOAN MIRO (1893-1983) AND SALVADOR DALI (1904-1989)

Miro and Dali were two of the most iconic Spanish Surrealists, and created pieces that are at once abstract, imaginative, and occasionally absurd. The work of Miro draws heavily on well-defined geometric shapes and lines, filled with bright colors and political overtones[98]. Dali's work, which ranges from bizarre scenes to nightmarish landscapes, is dreamlike yet shows an appreciation for the realistic nature of classical and Renaissance art[99]. Overall, their artistic styles only seem to be moderately similar, given Miro's focus on geometry and Dali's emphasis on realism. That said, works by both Surrealists have sold at auction for 6- and 7-figure sums, and the two Surrealists are

98 http://joanmiro.com/style-of-joan-miro/

99 http://www.theartstory.org/artist-dali-salvador.htm

sometimes paired together at museum and gallery exhibitions[100]. We were also told that works by these two artists tend to also attract the same kinds of clients.

Tables 18 and 19 show the anchoring regression results for Miro and Dali (in our assorted art dataset) with our respective controls Q_1 and Q_2. First, it is notable that anchoring is entirely insignificant with Q_1, but gains a highly significant p-value and becomes much stronger when Q_2 is used. However, the substitution measure in the Q_1 case is highly significant and impactful while that in the Q_2 case is not. This relationship between the anchoring effect and the measure of substitution in this dataset suggests that Q_2 is not an appropriate control, which would indicate that the anchoring effects in the Q_2 case may be illusory. Either way, there is a large amount of variation that our model cannot explain, as evidenced by our low R^2 values. It is also surprising that the hedonic price predictions are relatively weak and insignificant, and that unobserved inputs into the substitute's price (the substitute's residual) are impactful and highly significant. Even further, the intercept term is very large and significant. Together, all these observations suggest that there are other influential inputs at work (in the error term) beyond our identified variables. Thus, a substitution control better tailored to Dali and Miro might be required in this scenario, as anchoring effects between Dali and Miro pieces are inconclusive here. However, this experiment does highlight the importance of controlling for substitution to prevent anchoring effects from being falsely detected.

As confirmed by our earlier regressions, time effects are significant and influential for both Dali and Miro who (as Surrealists) may be classified as Contemporary artists. Despite the variation in our data, high F-statistics in both the Q_1 and Q_2 cases ensures the relevance of our model. However, we cannot say there are conclusive anchoring effects between Dali and Miro – which makes sense given their somewhat divergent styles, even within the larger Surrealist movement.

[100] http://www.galeriemichael.com/current-exhibitions/miro-dali-poetic-visions-two-catalan-surrealists/

SUBSTITUTION EXPERIMENT #2:

PABLO PICASSO (1881-1973) AND MARC CHAGALL (1887-1985)

Picasso and Chagall, former friends turned opponents[101] and two of the best-known Contemporary artists, spanned multiple artistic traditions. The works of Picasso range from Cubist nude portraits to Neoclassical and Surrealist paintings, and frequently depict real life in abstract forms. Chagall drew upon a variety of movements including Surrealism, Cubism, and Expressionism for his works, many of which focus on scenes from Eastern Europe[102] [103]. Overall, the styles of Picasso and Chagall seem to be relatively similar, and some research even suggests that price indices for those two artists tend to move together[104]. The two painters are frequently featured together at exhibitions[105] [106], more often than Dali and Miro are, and the works of Picasso and Chagall often fetch 7- and even 8-figure sums at auction.

Overall, for this comparison we see similar results whether we use Q_1 or Q_2 (Tables 20 and 21). Anchoring is strong and significant in this comparison between Picasso and Chagall. It is also associated with the presence of significant control terms this time, which suggests that even after controlling for substitution, anchoring is still very much at play. Also, the coefficients are large: if the price of the substitute is 10% higher than the hedonic value of the current good, we should expect to see a 15% increase in the current good's price due to anchoring (if we use Q_1; 25% increase if we use Q_2). In the Q_2 case, the intercept is also much stronger and highly significant, compared to that

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101 http://www.pablopicasso.org/picasso-and-chagall.jsp

102 http://www.theartstory.org/artist-chagall-marc.htm

103 http://www.infoplease.com/encyclopedia/people/chagall-marc.html

104 http://digitalcommons.iwu.edu/cgi/viewcontent.cgi?article=1040&context=uauje

105 http://www.operagallery.com/catalogues/picasso_chagall_dubai/cata.pdf

106 http://pueblopulp.com/picasso-matisse-chagall

of Q_1. There is a lot of variation in the data, as evidenced by the extremely low R^2 values. This indicates that for Picasso and Chagall, prices for their artwork are probably affected by other influences, and that our two measures of substitution, although significant and generally a step in the right direction, could be improved. Time effects are fairly small, and do not seem to affect price much if at all.

While anchoring effects were less conclusive for Miro and Dali than for Picasso and Chagall, we do see here highly significant evidence of strong anchoring cross-effects, which makes sense given their artistic similarity. Thus, we should expect prices for one artist's works to noticeably impact those for the other's pieces.

SUBSTITUTION EXPERIMENT #3:

EDVARD MUNCH (1863) AND HENRI DE TOULOUSE-LAUTREC (1864-1901)

We were suggested to pair together Munch and Toulouse-Lautrec because, as contemporaries in Europe, they met with similar levels of economic and critical success during their lifetimes. However, their artistic styles seem to somewhat differ. Munch, a Norwegian artist associated with Expressionism and Symbolism, is known for the intensely psychological and brooding themes he imbued into his paintings and prints[107]. On the other hand, Toulouse-Lautrec is known for his Post-Impressionist, drawing-like depictions of people, often those from lower-class, urban environments[108]. It seems that Munch and Toulouse-Lautrec are featured together less frequently: a quick Google search only turns up a 1965 exhibition at the Metropolitan Museum of Art[109]. Nevertheless, both artists pull in hefty sums: Toulouse-Lautrec's work "Au Lit: Le Baiser" fetched $16.3 million at Sotheby's in early 2015[110], and Munch's Internet-famous "The Scream" sold for nearly $120 million at Sotheby's in 2012[111].

Tables 22 and 23 show the respective Q_1 and Q_2 anchoring regression results for Munch and Toulouse-Lautrec in our assorted art dataset. As expected, no significant or strong anchoring effects appear this time, regardless of whether we use Q_1 or Q_2. Even if the two artists did enjoy comparable success during their concurrent lifetimes, which would be reflected in similar prices, their artistic styles seem to be too different to permit anchoring cross-effects. Our measure of substitution is insignificant in both the Q_1, Q_2 cases, which seems to further suggest that Munch and Toulouse-

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107 http://www.theartstory.org/artist-munch-edvard.htm

108 http://www.toulouse-lautrec-foundation.org/biography.html

109 http://libmma.contentdm.oclc.org/cdm/ref/collection/p16028coll12/id/1460

110 http://www.theguardian.com/artanddesign/2015/feb/04/sothebys-auction-highest-sales-total-ever

111 http://www.nytimes.com/2012/05/03/arts/design/the-scream-sells-for-nearly-120-million-at-sothebys-auction.html?_r=0

Lautrec are not particularly close hedonic substitutes. That said, Q_2 has a somewhat larger coefficient, which could be due to its inclusion of near-significant time effects (p-value: 5.38). The R^2 value indicates that we do seem to explain more variation in the data than we did for other artist pairs, but relatively low F-statistics confirms that anchoring is not at play between the Munch/Toulouse-Lautrec pair. In fact, the only significant variable is the hedonic price prediction. Hence, we do not find any evidence of anchoring between Munch and Toulouse-Lautrec – which is understandable, given their relatively divergent artistic styles. This is encouraging, because it means our model is relatively robust and does not detect anchoring too leniently.

7. CONCLUSION AND FUTURE DIRECTIONS

If a Picasso painting fetches a high sum at auction, will a similar painting by Dali also sell for more? In this research, we set out to examine the existence of these anchoring cross-effects, building upon the original anchoring work of Beggs & Graddy (2009). To accomplish this, we developed a more general model to control for similarity between art pieces, effectively allowing us to consider related goods instead of past sales of an item. With modern computer programming tools, we also constructed a new dataset consisting of 500,000 recent auction sales of assorted art (including 250,000 paintings) spanning the years 2006-2015. This is itself a major contribution to the art economics literature, much of which has relied on the same Impressionist and Contemporary auction data compiled in the 1990's.

We were able to replicate the general findings of Beggs & Graddy (2009) on their original dataset, despite not knowing exactly which observations they used. This included the discovery of significant anchoring effects across the resales of Impressionist and Contemporary art pieces, as well as various other results (similarly high R^2 values, insignificant time coefficients, etc.). Such replication work ensured we were applying their model correctly before modifying it for our substitution work.

Our model, which generalizes the original model of Beggs & Graddy (2009), allows one to test for anchoring cross-effects across sales of similar art pieces. For our model, we introduced two quantitative measures of similarity (substitution) between art pieces, drawing upon insights from our interviews with experts and specialists in the art world. Quantitative measures of artistic similarity, to our knowledge, has not previously appeared in the art econometric literature. Running our model, we were able to find significant evidence of anchoring cross-effects in our Impressionist and assorted art datasets. Furthermore, in our experiments with known pairs of similar artists, we identified strong and significant anchoring between Picasso and Chagall, inconclusive effects between Miro and Dali,

and no significant anchoring between Munch and Toulouse-Lautrec. This showed that our anchoring model successfully accounts for artistic similarity when it is clearly strong (Picasso and Chagall), and is robust against false detection of anchoring when there is clear artistic dissimilarity (Munch and Toulouse-Lautrec).

Overall, our discovery of anchoring cross-effects was surprising given that the similarity measures we constructed were considerably different, broadly applied, and admittedly imperfect. Measuring similarity across art pieces is an enormously difficult challenge, even for art experts. In our interviews, we sometimes received very divergent opinions on the relative importance of various hedonic characteristics. Yet assessing artistic similarity is vital to properly appraising works, and according to Mark Best, something that those in the field must continually address. Hence, there are a myriad of directions for future work.

First, the exact mechanism by which past price can bias current price is still a black box. The mere observation of this sufficed for our definition of anchoring, but it would be worthwhile to dig deeper into this regard in order to understand how price signals flows across auction sales. To better understand how past price biases current price, it may be useful to conduct further interviews with buyers, auctioneers, and sellers to understand how they formulate their estimates of pieces.

Second, one could further develop measures of similarity between art pieces. While in this research we have optimized for breadth and generality, one should examine the art market more closely to understand how similarity is defined for different styles, artists, and price points. It is well-known that many artists pass through multiple artistic phases during their careers, and their styles can often change dramatically. Hence, future research may wish to take a complementary approach to our general survey by focusing on several artists in depth, and studying how anchoring cross-effects between them change based on different points in their careers.

Finally, one could examine other applications of anchoring. While we have only focused on the impact of anchoring on sale (hammer) price, Beggs & Graddy (2009) also discuss how it can impact auctioneer presale estimates for a piece, as well as the probability of even selling the work. As in their paper, our regression model can easily be adapted for these by changing the dependent variable or applying a probit transformation. One could also test for asymmetric anchoring cross-effects between similar pieces, i.e. if gains in the price of a substitute affects a good's sale price differently than losses do. However, when Beggs & Graddy (2005) examined this for resales of the same work, they found no significant evidence of asymmetric effects.

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FIGURES

Figure 1: Distribution of selected quantities in the Impressionist art dataset.

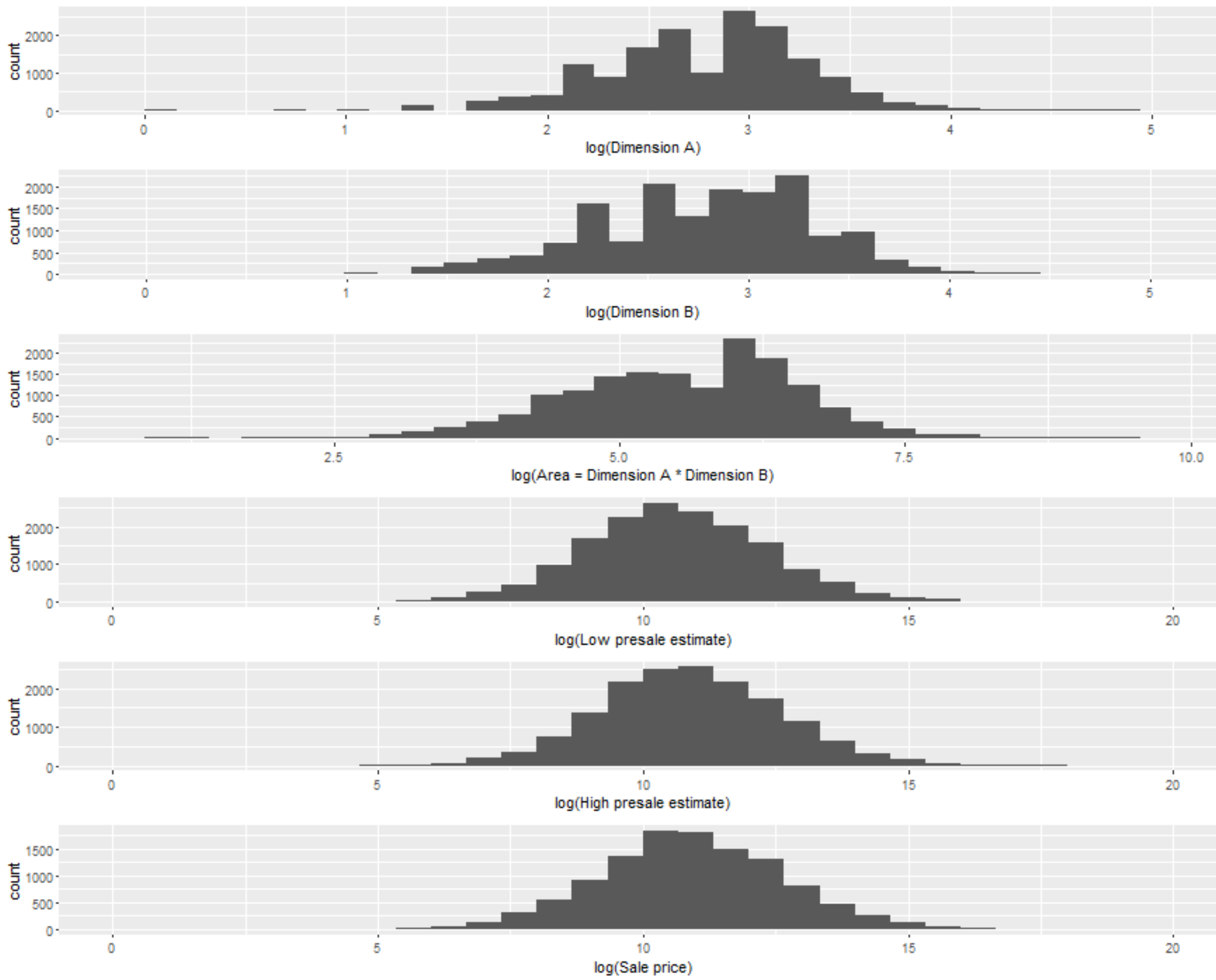


Figure 2: Comparison of painting dimensions, Impressionist art.

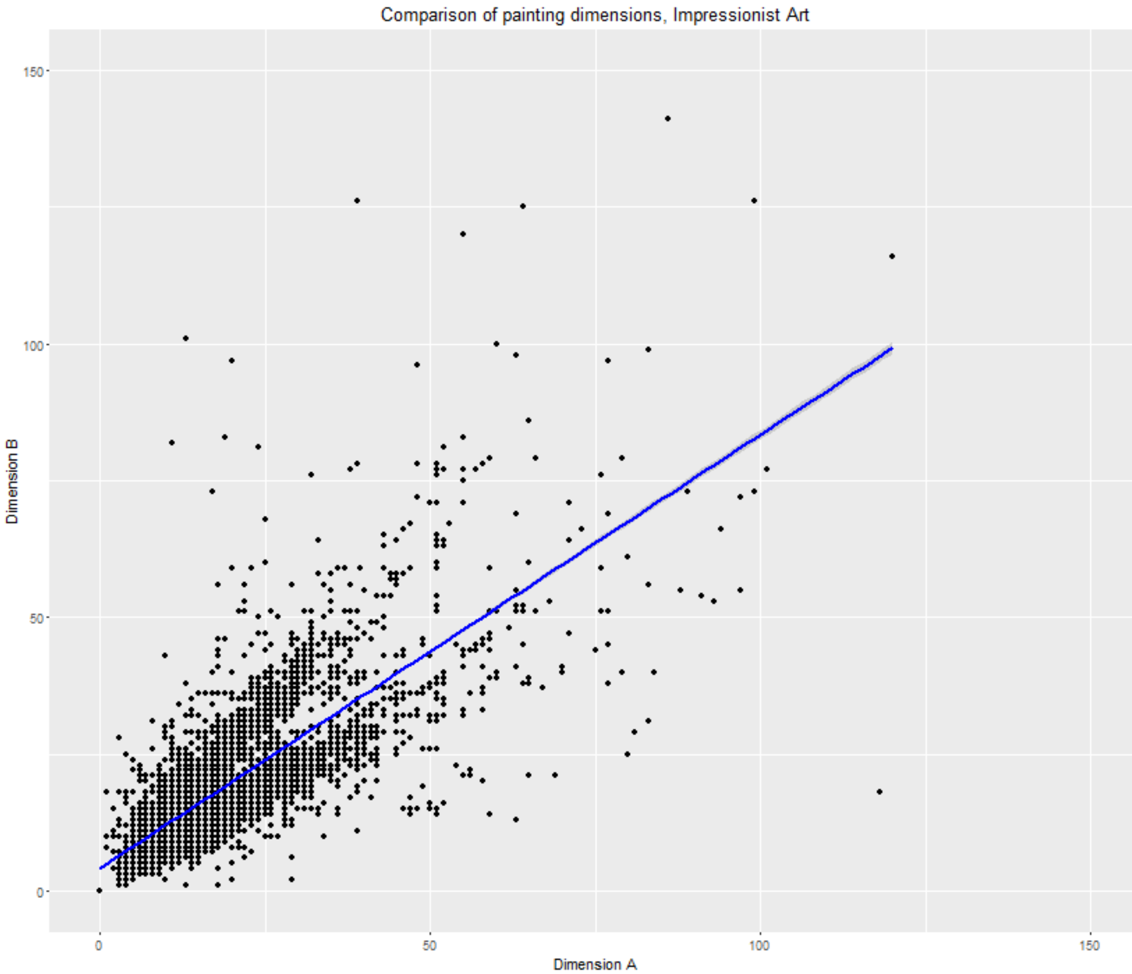


Figure 3: Impressionist art, auction sales over time.

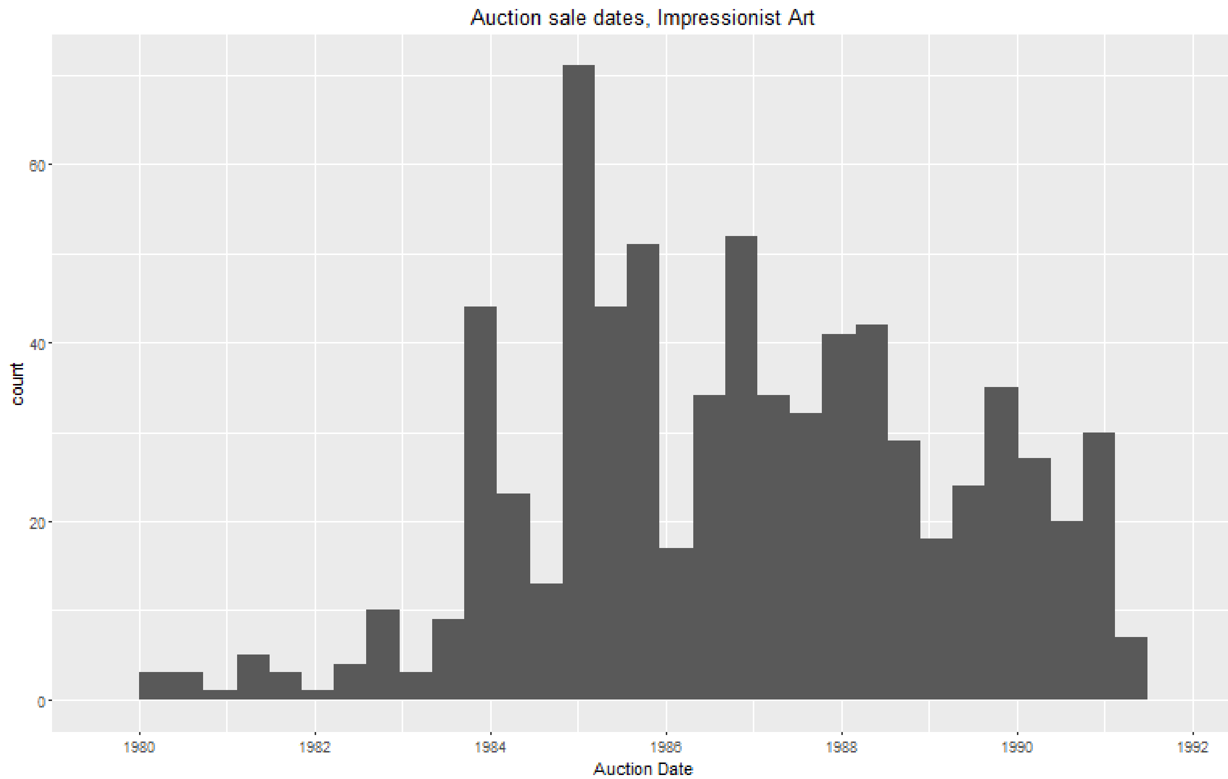


Figure 4: Distribution of selected quantities in the Contemporary art dataset.

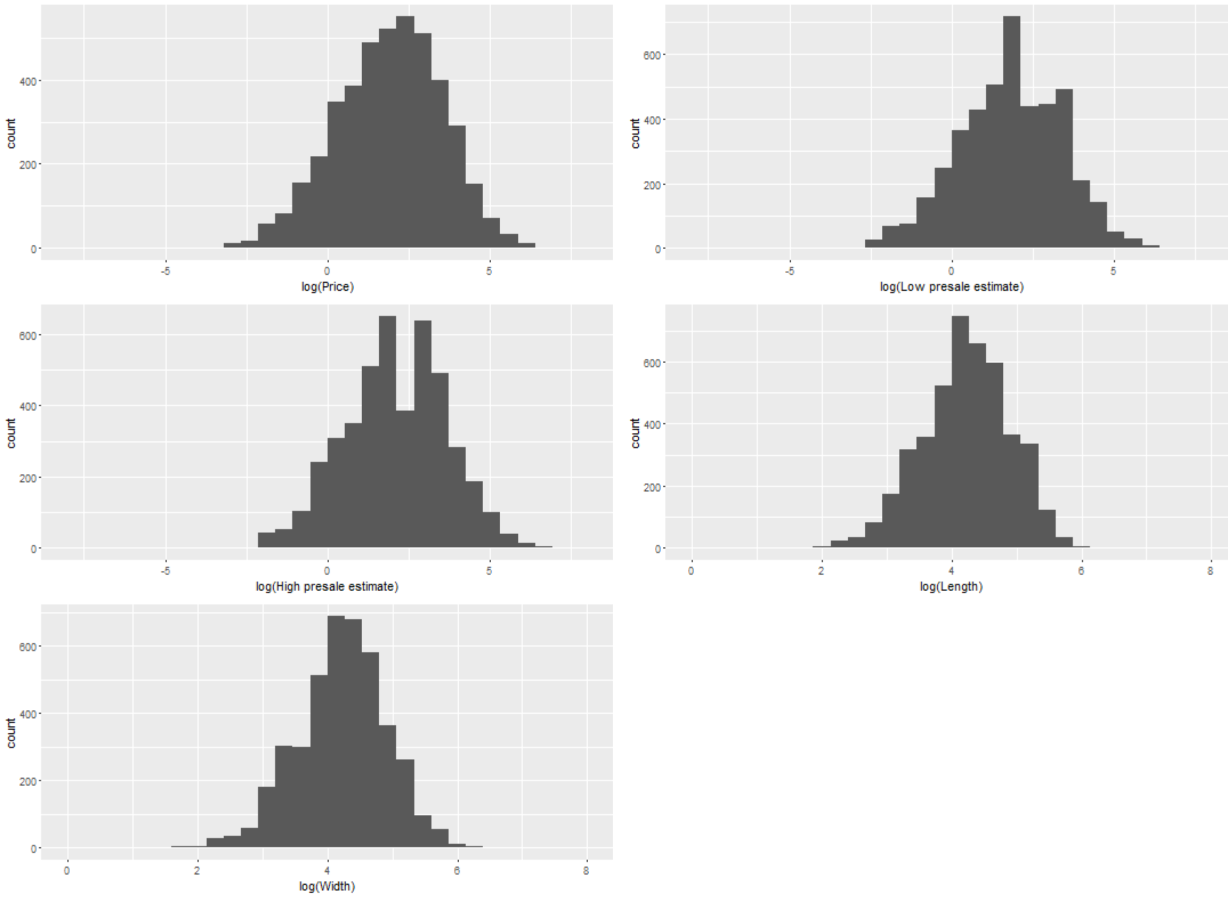


Figure 5: Auction sales over time, Contemporary art.

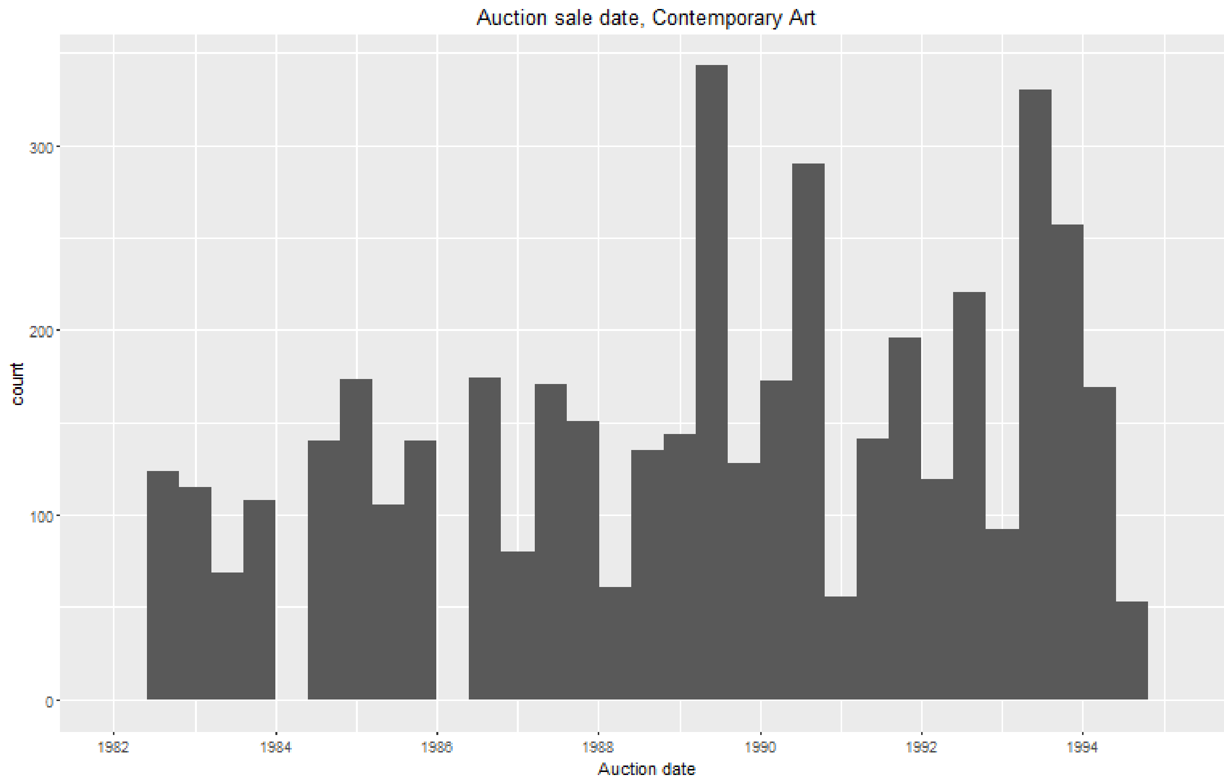


Figure 6: Comparison of log prices, Impressionist and Contemporary art.

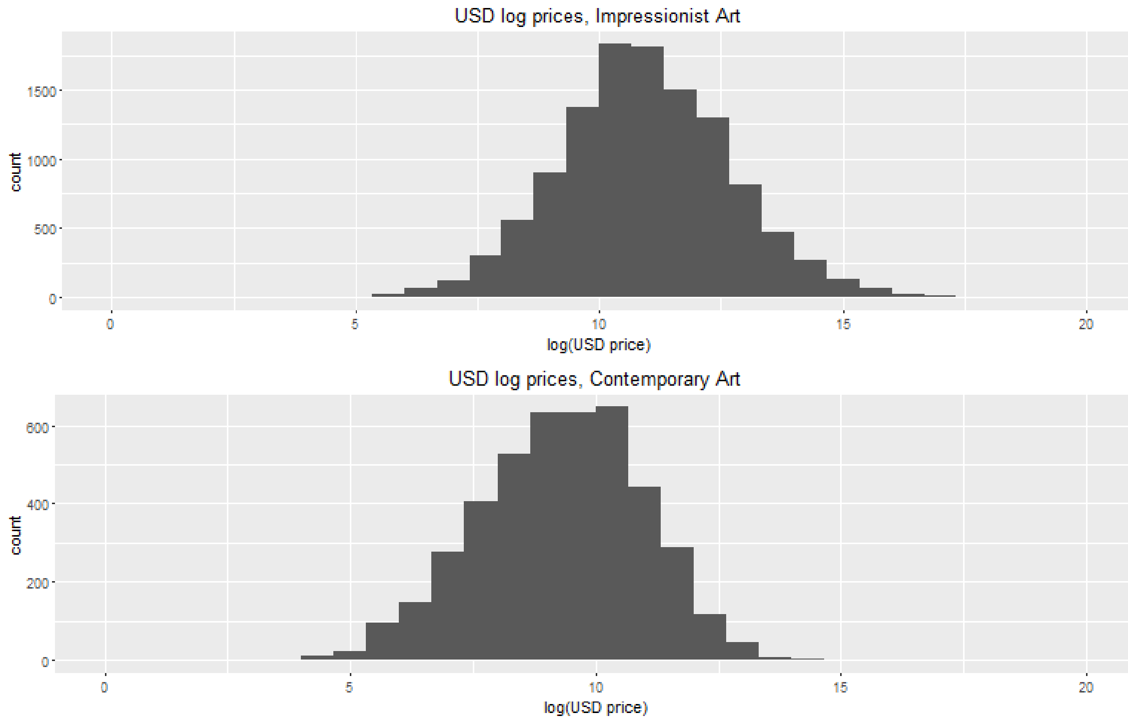


Figure 7: Comparison of log area, Impressionist and Contemporary art.

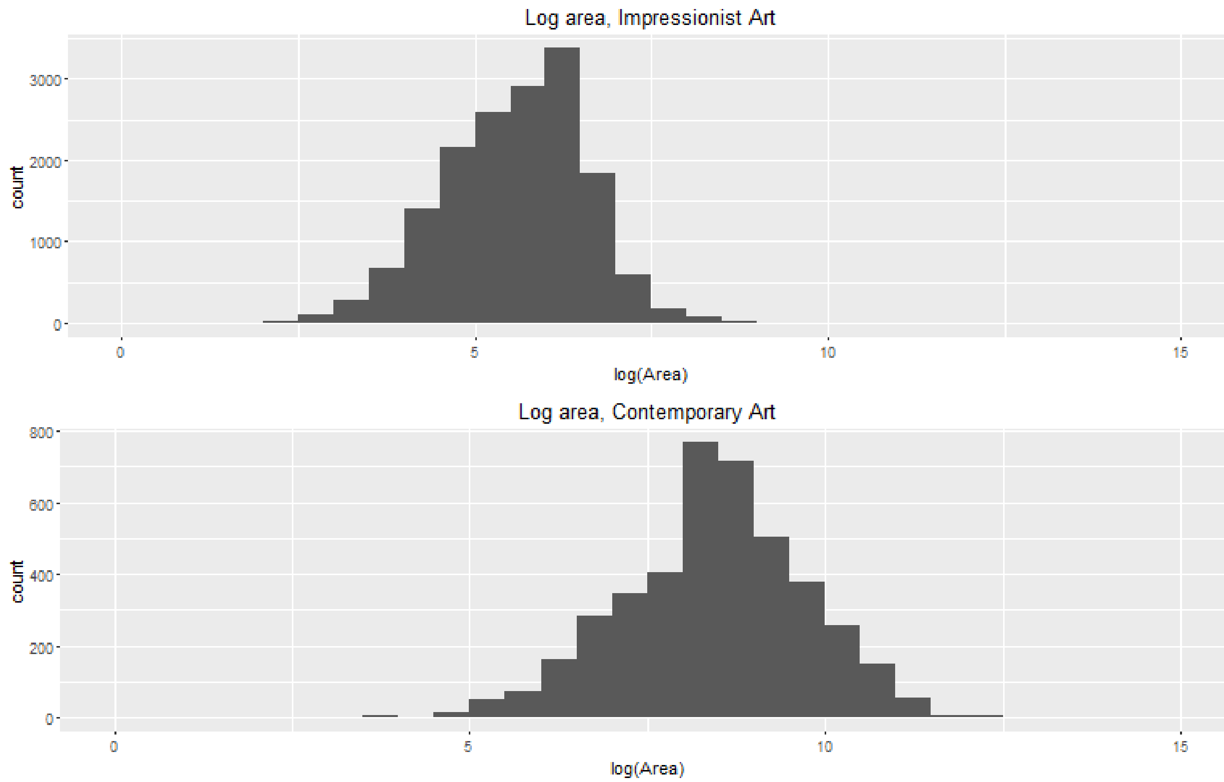
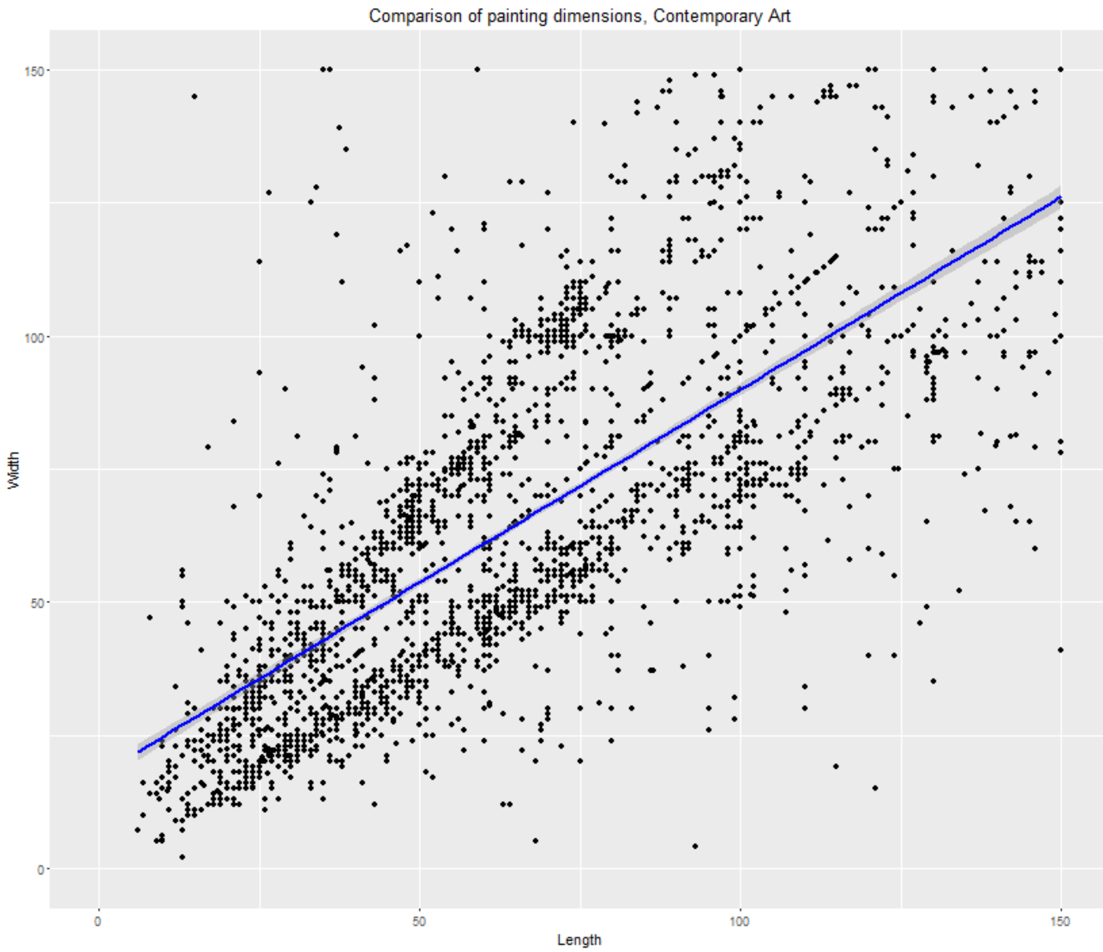
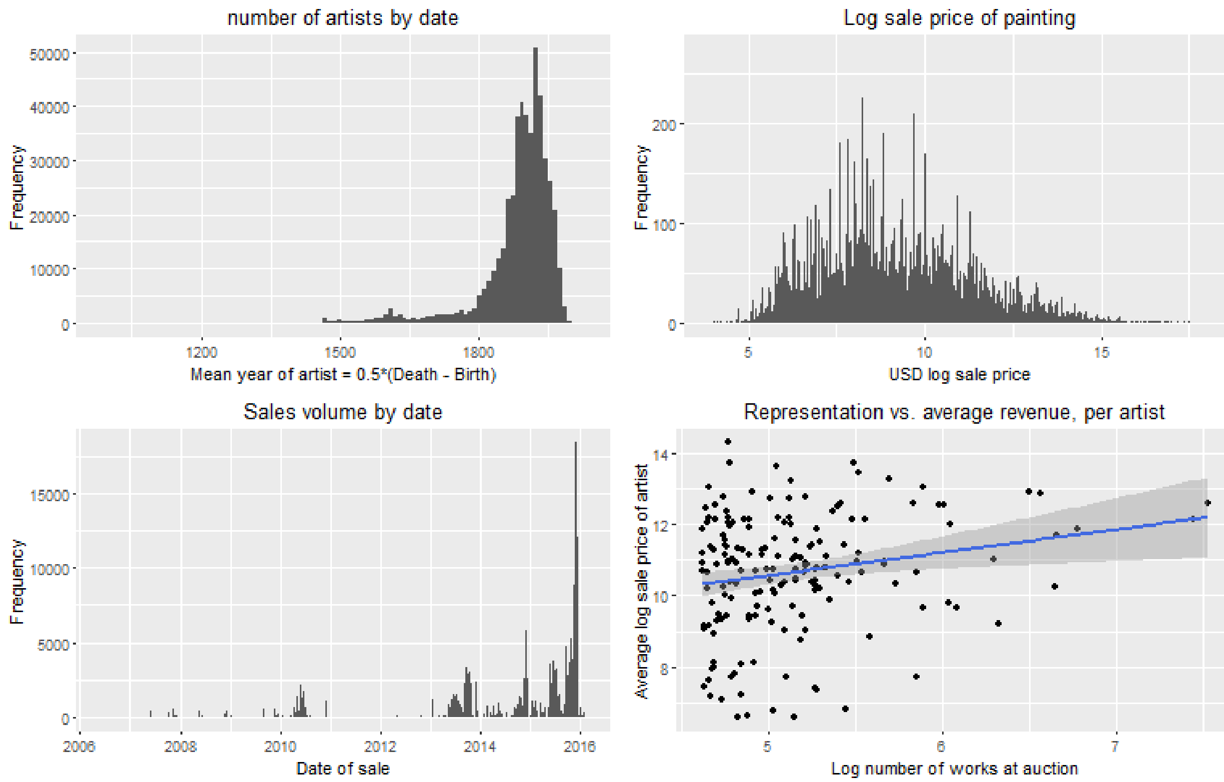


Figure 8: Comparison of painting dimensions, Contemporary art.



Figures 9-12: Plots for recent assorted art dataset.



TABLES

SUMMARY STATISTICS

Table 1: Impressionist art, summary statistics for continuous features.

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

S_PRICE	CNV_RATE	DATE_PTG
Min. : 126	Min. :0.0000	Min. :1823
1st Qu.: 18700	1st Qu.:0.0000	1st Qu.:1902
Median : 53856	Median :1.2400	Median :1922
Mean : 285428	Mean :0.8639	Mean :1921
3rd Qu.: 176000	3rd Qu.:1.6800	3rd Qu.:1938
Max. :82500000	Max. :2.3610	Max. :1983
NA's :4696		NA's :3950

DATE_FLG	DIM_B	DIAM
Min. :0.0000	Min. : 0.00	Min. : 1.00
1st Qu.:0.0000	1st Qu.: 11.00	1st Qu.: 6.75
Median :0.0000	Median : 18.00	Median :11.50
Mean :0.3538	Mean : 18.69	Mean :15.10
3rd Qu.:1.0000	3rd Qu.: 24.00	3rd Qu.:24.50
Max. :1.0000	Max. :141.00	Max. :36.00
	NA's :37	NA's :16243

PND_FLG
Min. :0.0000
1st Qu.:0.0000
Median :1.0000
Mean :0.5127
3rd Qu.:1.0000
Max. :2.0000
NA's :4

Table 2: Contemporary art, summary statistics.

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

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

Table 3: Assorted art, summary statistics.

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

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

HEDONIC REGRESSION

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					

ANCHORING EFFECTS (REPLICATION)

Table 8: Replicated 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: Replicated 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 (original regression from Beggs & Graddy (2009))

	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					

ANCHORING CROSS-EFFECTS (Q1)

Table 11: Anchoring cross-effects (Q_1) for Impressionist art.

```
Call:
lm(formula = log_sale_price ~ log_hed_pred + anchoring + sub_price_hed_pred +
    substitute_measure + avg_months_since_sub_sale, data = df.anchor.sub.impress)

Residuals:
    Min      1Q  Median      3Q     Max
-5.2368 -0.4767  0.0007  0.4753  3.2939

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)              -0.1049942  0.0673771  -1.558   0.1192
log_hed_pred              1.0203528  0.0120905  84.393   <2e-16 ***
anchoring                 0.0342261  0.0141471   2.419   0.0156 *
sub_price_hed_pred        0.2836732  0.0211621  13.405   <2e-16 ***
substitute_measure        0.0084785  0.0041261   2.055   0.0399 *
avg_months_since_sub_sale -0.0006209  0.0006000  -1.035   0.3008
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.773 on 11608  degrees of freedom
Multiple R-squared:  0.7752,	Adjusted R-squared:  0.7751
F-statistic:  8004 on 5 and 11608 DF,  p-value: < 2.2e-16
```

Table 12: Anchoring cross-effects (Q_1) for Contemporary art.

```
Call:
lm(formula = log_sale_price ~ log_hed_pred + anchoring + sub_price_hed_pred +
    substitute_measure + avg_months_since_sub_sale, data = df.reg.sub)

Residuals:
     Min       1Q   Median       3Q      Max
-2.96495 -0.33364  0.02062  0.35064  1.66091

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                0.059521   0.090352   0.659 0.510202
log_hed_pred               1.034162   0.024752  41.781  < 2e-16 ***
anchoring                 -0.030017   0.028887  -1.039 0.299009
sub_price_hed_pred         0.298056   0.043888   6.791 1.95e-11 ***
substitute_measure        -0.013093   0.008939  -1.465 0.143340
avg_months_since_sub_sale -0.050238   0.014234  -3.529 0.000436 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5653 on 952 degrees of freedom
Multiple R-squared:  0.8313,	Adjusted R-squared:  0.8304
F-statistic:   938 on 5 and 952 DF,  p-value: < 2.2e-16
```

Table 13: Anchoring cross-effects (Q_1) for assorted art.

```
Call:
lm(formula = log_sale_price ~ ., data = df.anchoring[complete.cases(df.anchoring),
    ])

Residuals:
    Min      1Q  Median      3Q     Max
-7.3357 -1.1534 -0.0891  1.0304  7.7630

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       -1.994594   0.220561  -9.043  < 2e-16 ***
log_hed_pred       1.240644   0.025869  47.959  < 2e-16 ***
anchoring          0.661090   0.025028  26.414  < 2e-16 ***
sub_price_hed_pred -0.102460   0.026481  -3.869  0.00011 ***
substitute_measure  0.026968   0.005026   5.366 8.16e-08 ***
avg_mon_subdiff    -0.088799   0.015873  -5.594 2.25e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.616 on 17693  degrees of freedom
Multiple R-squared:  0.4613,	Adjusted R-squared:  0.4611
F-statistic:  3030 on 5 and 17693 DF,  p-value: < 2.2e-16
```

ANCHORING CROSS-EFFECTS (Q2)

Table 14: Anchoring cross-effects (Q_2) for Impressionist art.

```
Call:
lm(formula = log_sale_price ~ log_hed_pred + anchoring + sub_price_hed_pred +
    substitute_measure + avg_months_since_sub_sale, data = df.anchor.sub.impress)

Residuals:
    Min      1Q  Median      3Q     Max
-5.2351 -0.4763  0.0000  0.4755  3.2843

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                0.0085722  0.0741016   0.116   0.9079
log_hed_pred               0.9988786  0.0061643 162.044   <2e-16 ***
anchoring                  0.0262716  0.0133724   1.965   0.0495 *
sub_price_hed_pred         0.2861356  0.0210827  13.572   <2e-16 ***
substitute_measure         0.0150060  0.0080184   1.871   0.0613 .
avg_months_since_sub_sale -0.0001465  0.0007528  -0.195   0.8457
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.773 on 11608  degrees of freedom
Multiple R-squared:  0.7752,	Adjusted R-squared:  0.7751
F-statistic:  8004 on 5 and 11608 DF,  p-value: < 2.2e-16
```

Table 15: Anchoring cross-effects (Q_2) for Contemporary art.

```
Call:
lm(formula = log_sale_price ~ log_hed_pred + anchoring + sub_price_hed_pred +
    substitute_measure + avg_months_since_sub_sale, data = df.reg.sub)

Residuals:
     Min       1Q   Median       3Q      Max
-2.95880 -0.33439  0.02226  0.34534  1.67089

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              -0.091648   0.114989  -0.797 0.425642
log_hed_pred              1.055614   0.018161  58.124  < 2e-16 ***
anchoring                -0.021001   0.027097  -0.775 0.438519
sub_price_hed_pred        0.291614   0.043657   6.680 4.07e-11 ***
substitute_measure       -0.011917   0.005894  -2.022 0.043486 *
avg_months_since_sub_sale -0.050393   0.014217  -3.545 0.000412 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5647 on 952 degrees of freedom
Multiple R-squared:  0.8316,	Adjusted R-squared:  0.8307
F-statistic: 940.3 on 5 and 952 DF,  p-value: < 2.2e-16
```

Table 16: Anchoring cross-effects (Q_2) for assorted art.

```
Call:
lm(formula = log_sale_price ~ ., data = df.anchoring[complete.cases(df.anchoring),
    ])

Residuals:
    Min      1Q  Median      3Q     Max
-7.1890 -1.0271  0.0846  1.0769  7.9026

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        -2.03647    0.17645 -11.541  < 2e-16 ***
log_hed_pred        1.27157    0.01920  66.215  < 2e-16 ***
anchoring           0.51926    0.02197  23.632  < 2e-16 ***
sub_price_hed_pred  0.08111    0.02262   3.586 0.000337 ***
substitute_measure  0.29640    0.01520  19.504  < 2e-16 ***
avg_mon_subdiff     0.07226    0.01019   7.093 1.34e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.658 on 29784 degrees of freedom
Multiple R-squared:  0.3979,	Adjusted R-squared:  0.3978
F-statistic:  3936 on 5 and 29784 DF,  p-value: < 2.2e-16
```

Table 17: Summary of anchoring results.

	Anchoring under Q_1	Anchoring under Q_2
Impressionist Art	0.034 *	0.026 *
Contemporary Art	-0.03	-0.02
Assorted Art	0.66 ***	0.52 ***

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Table 18: Miro vs. Dali (Q_1)

```
Call:
lm(formula = log_sale_price ~ ., data = df.anchoring[complete.cases(df.anchoring),
   ])

Residuals:
    Min      1Q  Median      3Q     Max
-3.2922 -1.0052 -0.1560  0.8208  8.4440

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)         7.15043    2.16084   3.309 0.000959 ***
log_hed_pred        0.51936    0.27060   1.919 0.055144 .
anchoring          -0.37001    0.25243  -1.466 0.142918
sub_price_hed_pred  0.48840    0.25445   1.919 0.055125 .
substitute_measure  0.18523    0.02024   9.149  < 2e-16 ***
avg_mon_subdiff    -0.08254    0.04425  -1.865 0.062339 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.483 on 1458 degrees of freedom
Multiple R-squared:  0.1255,	Adjusted R-squared:  0.1225
F-statistic: 41.84 on 5 and 1458 DF,  p-value: < 2.2e-16
```

Table 19: Miro vs. Dali (Q_2)

```
Call:
lm(formula = log_sale_price ~ ., data = df.anchoring[complete.cases(df.anchoring),
   ])

Residuals:
    Min      1Q  Median      3Q     Max
-3.0733 -1.0296 -0.1694  0.7886  8.2793

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)         8.67695    2.23295   3.886 0.000107 ***
log_hed_pred       -0.06076    0.27531  -0.221 0.825343
anchoring          -0.97311    0.25364  -3.836 0.000130 ***
sub_price_hed_pred  1.03215    0.25775   4.005 6.53e-05 ***
substitute_measure  0.01170    0.03687   0.317 0.751092
avg_mon_subdiff    -0.10641    0.04740  -2.245 0.024933 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.525 on 1458 degrees of freedom
Multiple R-squared:  0.07533,	Adjusted R-squared:  0.07216
F-statistic: 23.76 on 5 and 1458 DF,  p-value: < 2.2e-16
```

Table 20: Picasso vs. Chagall (Q_1)

```
Call:
lm(formula = log_sale_price ~ ., data = df.anchoring[complete.cases(df.anchoring),
    ])

Residuals:
    Min      1Q  Median      3Q     Max
-4.6215 -1.0532 -0.1586  0.8661  7.3545

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        -2.88027    3.35265  -0.859 0.390372
log_hed_pred        2.02669    0.34011   5.959 2.92e-09 ***
anchoring           1.54597    0.32518   4.754 2.11e-06 ***
sub_price_hed_pred -1.12558    0.32794  -3.432 0.000609 ***
substitute_measure  0.36201    0.02246  16.116  < 2e-16 ***
avg_mon_subdiff    -0.05674    0.03661  -1.550 0.121289
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.686 on 2359 degrees of freedom
Multiple R-squared:  0.179, Adjusted R-squared:  0.1773
F-statistic: 102.9 on 5 and 2359 DF,  p-value: < 2.2e-16
```

Table 21: Picasso vs. Chagall (Q_2)

```
Call:
lm(formula = log_sale_price ~ ., data = df.anchoring[complete.cases(df.anchoring),
    ])

Residuals:
    Min      1Q  Median      3Q     Max
-4.7629 -1.0573 -0.2084  0.8451  8.3682

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        -21.89473    3.22978  -6.779 1.52e-11 ***
log_hed_pred         3.47944    0.34053  10.218  < 2e-16 ***
anchoring            2.53673    0.33207   7.639 3.16e-14 ***
sub_price_hed_pred  -2.24188    0.33296  -6.733 2.08e-11 ***
substitute_measure   0.55122    0.08374   6.582 5.69e-11 ***
avg_mon_subdiff      0.20532    0.05785   3.549 0.000394 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.76 on 2359 degrees of freedom
Multiple R-squared:  0.1051,    Adjusted R-squared:  0.1032
F-statistic: 55.39 on 5 and 2359 DF,  p-value: < 2.2e-16
```

Table 22: Munch vs. Toulouse-Lautrec (Q_1)

```
Call:
lm(formula = log_sale_price ~ ., data = df.anchoring[complete.cases(df.anchoring),
    ])

Residuals:
    Min      1Q  Median      3Q     Max 
-5.2478 -0.9364 -0.0661  1.0238  7.1826 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)         2.21191    2.30155   0.961    0.337    
log_hed_pred        0.85602    0.20483   4.179 3.83e-05 ***
anchoring          -0.21898    0.19898  -1.101    0.272    
sub_price_hed_pred  0.14003    0.21334   0.656    0.512    
substitute_measure  0.04258    0.04577   0.930    0.353    
avg_mon_subdiff     0.05321    0.07060   0.754    0.452    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.567 on 305 degrees of freedom
Multiple R-squared:  0.2927,	Adjusted R-squared:  0.2811 
F-statistic: 25.24 on 5 and 305 DF,  p-value: < 2.2e-16
```

Table 23: Munch vs. Toulouse-Lautrec (Q_2)

```
Call:
lm(formula = log_sale_price ~ ., data = df.anchoring[complete.cases(df.anchoring),
    ])

Residuals:
    Min      1Q  Median      3Q     Max 
-5.2282 -0.9288 -0.0752  0.9997  7.0301 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)          2.7240     2.1874   1.245   0.2140    
log_hed_pred         0.8145     0.2060   3.953 9.59e-05 ***
anchoring           -0.2728     0.2016  -1.353   0.1770    
sub_price_hed_pred   0.1956     0.2151   0.909   0.3639    
substitute_measure   0.3686     0.2114   1.744   0.0822 .  
avg_mon_subdiff      0.2615     0.1351   1.936   0.0538 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.562 on 305 degrees of freedom
Multiple R-squared:  0.2977,	Adjusted R-squared:  0.2862 
F-statistic: 25.86 on 5 and 305 DF,  p-value: < 2.2e-16
```