PRICE, ANCHORING, AND SUBSTITUTION

IN

THE MARKET FOR FINE ART AUCTIONS

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ABSTRACT

Given Joan Miro and Salvador Dali were both Surrealist painters, can the past price of a Miro painting bias 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.

INTRODUCTION

Imagine you are heading to Christie's to bid on a Monet oil painting, which experts believe is worth $5 million based on its medium, artist, and so forth. You're unaware of that, and so when you learn that a very similar oil painting by Van Gogh fetched $10 million just the week before, $8 or $9 million for the Monet seems like a bargain – even if that reflects more of the Van Gogh than the Monet.

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

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This bias appears in the fine art auction market, which in 2014 enjoyed a sales volume of £5.1 billion (approximately $7.35 billion in today's exchange rate)[2] [3]. To the best of our knowledge, Beggs & Graddy (2009) are the first to formally study anchoring in the context of art auctions, ~~and~~ describinge it as follows. First, the true value of a

Commented [J3]: Footnotes go on the outside of periods and you can combine these two footnotes into one.

[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

[3] http://www.xe.com/currencyconverter/convert/?From=GBP&To=USD accessed 2/20/2015

painting is determined by its hedonic characteristics: the artist, the medium, the presence of authenticity, and so forth. These intrinsic features do not change over time, which means buyers should pay based on their (time-dependent) demand for those hedonic features. If, however, buyers learn the painting previously sold for a very high price, they may internalize that previous price as a reference point (the "anchor") and drive up price even more, even if that price reflects irrelevant past circumstances (such as past bidding activity) rather than the painting's intrinsic value. This impact of past price, an irrelevant signal in this context, on current price can thus be interpreted as an anchoring effect. It is important to note the exact behavioral mechanism by which auction participants internalize and act upon past price, however, is complex and cannot be inferred from just observing prices. Hence in our research and in much of our surveyed literature, including Beggs & Graddy (2009), the process is treated as a black box. The mere observation of past price biasing current price suffices for our definition of anchoring (discussed further in Section 5).

Using a regression model that isolates this phenomenon, Beggs & Graddy (2009) identify and analyze resales of Impressionist and Contemporary paintings, and do find significant evidence of anchoring effects. However, as they note in their research, it is very difficult to identify multiple sales of the same art piece, and they use only 1-2% of their original data. This method of studying anchoring only across resales cannot be applied to new works or works that have never been brought to auction. Moreover,

Commented [J4]: Current price? Future price?

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even in practice, it turns out that auction specialists not only appraise an art piece based on its previous sales, but also on sales of related art pieces.[4]~~.~~ Hence, the anchoring research of Beggs & Graddy (2009) seems to be somewhat limited in its analysis and application.

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 similar piece by Van Gogh. We begin by successfully replicating the general anchoring findings of Beggs & Graddy (2009). Next, we introduce an expanded version of their original anchoring regression model that controls for similarity across pieces and allows us to detect anchoring cross-effects. As part of this regression model, we introduce two measures to quantity similarity between art pieces. Our data includes two datasets of Impressionist and Contemporary art that are often used in the econometric literature on art auctions, and a new dataset of assorted art sales (2006-2015) ~~collected by us~~ specifically collected for this project. Running our model on these three datasets, we discover significant evidence of anchoring cross-effects. To experiment further, we also run our regressions on a subset of our assorted art dataset for three known pairs of similar artists: Joan Miro/Salvador Dali, Pablo Picasso/Marc Chagall, and Edvard Munch/Henri de Toulouse-Lautrec. We

[4] Interview with Raphaelle Benabou

find the strongest and most significant evidence of anchoring cross-effects between Picasso and Chagall.

This research makes several major contributions to the existing literature on art auctions. First, to our knowledge no econometric work has focused on quantifying hedonic similarity between art pieces. Understanding hedonic similarity is important not only for appraising art, but also for other contexts where art pieces must be compared, such as forecasting returns to art and constructing price indices for art. We hope the two measures of similarity we introduce may provide a starting point for such analysis. Second, much of the art auction econometric work has relied on the same two Impressionist and Contemporary art datasets that only cover auction sales until 1991 and 1994, respectively. Our new dataset of approximately 250,000 assorted painting sales (2006-2015), constructed by writing a Python program to scrape Blouin ArtInfo, provides a larger and more up-to-date reference for auction sales. Lastly, our discovery of anchoring cross-effects is important because it adds to the growing body of research on how price signals implicitly propagate around the art auction market. For researchers, our work allows one to account for hidden biases (such as anchoring) when estimating price or other quantities, and may facilitate the discovery of other biases that travel across sales of different artworks. For auction houses and professionals, our work provides a practical regression model for estimating an artwork's price in the light of related sales. Our approach is more general than the original anchoring model of Beggs

& Graddy (2009), which has been extensively applied in other domains such as corporate finance,[5] real estate,[6] and horse racing.[7]

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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 art pieces, we talked with Mark Best (Princeton '00), a former financial analyst who now works as a specialist in American, Modern, and Contemporary prints at Sotheby's NYC. To gain insight into artistic similarity, we talked with Hadley Newton (Princeton '16), who formerly worked at Sotheby's with Impressionist art. We also talked extensively with Raphaelle Benabou (Princeton '15), who works as an administrator of art collections at Bonham's in London and provided us with many of our auction anecdotes. We draw upon insight from these interviews both for our discussion of the art auction system and for our applied quantitative analysis.

Determining artistic similarity is not trivial: ~~we were told by~~ Mark Best noted that no two art pieces are the same. Even in the case of prints, where 100-200 identical copies (editions) of the same art piece are manufactured and numbered in order of production, an edition with a lower number may fetch a higher price than an edition

[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.

with a higher number~~sell for more~~. Furthermore, drivers of similarity may vary depending on~~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 deeper discussion of~~n~~ anchoring and its role in this market. Section II surveys the relevant literature on anchoring in the art market, and shows how our research fits in. Section III describes our methodology, which includes the original regressions of Beggs & Graddy, our expanded regression models, and our measures of substitution. Section IV is a description of the original data of Beggs & Graddy, and explains the motivation behind and nature of our new dataset. Section V gives our results. This includes our replication of the anchoring work of Beggs & Graddy, followed by our findings pertaining to anchoring cross-effects. We then present the results of our three experiments conducted on known pairs of “similar” artists, as suggested by Hadley Newton. Section VI discusses directions for future work. Finally, Section VII concludes with a summary of our findings.

A BRIEF 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).[8]~~.~~ The former, headquartered in London, is privately held by French multibillionaire Francois-Henri Pinault and ~~so~~ only reports sales figures twice a year[9]. 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.[10]~~.~~ 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.[11]~~.~~ 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, or time period~~,~~ or represent a private collection. Often individual events are part of a series, such as

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

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

[10] http://www.wikinvest.com/stock/Sotheby's_Holdings_(BID)

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

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Christie's "First Open" series (launched in 2005) for post-war and contemporary art.[12]~~.~~ 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 in person (the latter, however, suffers from greater time lag).[13]~~.~~ 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. M~~— and so m~~any believe, however, that these houses play to different strengths. To sell photographs, for example, go to Sotheby's; to sell books and manuscripts, go to Christie's.[14]~~.~~ For classic automobiles, go to Bonham's or Sotheby's[15]. Specialization is not limited to products, either. According to Raphaelle Benabou, Bonham's, the smaller house ~~Bonham's is~~ appeals~~ing~~ to many sellers because lower sales volume (smaller lots) ensures art pieces will be better noticed at auction. Competition between these auction houses is fierce, and each tries to capture the best consignments and expand market share by luring prospective sellers with benefits such

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

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

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

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

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as higher guaranteed prices and waived house commission fees.[16]~~.~~ 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.[17]~~.~~ 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~~ that saw art sales as high as $1.5 billion ~~in art sales~~ in 2014.[18]~~.~~ In another instance, t~~T~~he early 2000~~'~~s saw an infamous scandal where both houses fixed the commission prices that were charged to sellers.~~,~~ O~~and o~~nce convicted, they were required to pay back $256 million to customers (and for Sotheby's, shareholders, as well).[19]~~.~~

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The actual 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.

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

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

[18] http://www.artspace.com/magazine/news_events/the_heat_index/how_to_understand_new_york_record_auction_week-52310

[19] http://www.wsj.com/articles/SB969829620926708015

The item then goes to the house to be officially photographed, catalogued, and stored before the auction event.[20]~~.~~ 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.[21]~~.~~ Some significant cross-house differences may exist: Bauwens and Ginsburgh (2000), for instance, show that in certain art categories, Sotheby's tends to undervalue expensive pieces and overvalue inexpensive ones, while Christie's does the opposite.[22]~~.~~

In negotiations, the seller and the house also determine a secret reserve price known only to those two parties. The reserve 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,

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

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

[22] http://www.jstor.org/stable/pdf/40724283.pdf?_=1459015351227

announcing the reserve may discourage potential bidders from participating and could lower overall bids[23].

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[24]) and calls increasing prices[25] until the bidding stops, at which time 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

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

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

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

the item.[26]~~.~~ At Sotheby's and Christie's, the seller receives payment approximately 35 days after the auction, minus a "seller's premium" fee which is often around 10% of the hammer price.[27] [28]~~.~~ 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 information~~,~~. A~~and a~~ccording to Ashenfelter & Graddy (2003), houses in other locations are following this trend as well.[29]~~.~~

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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

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

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

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

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

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[30].

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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 distort future outcomes – even when the initial information is irrelevant[31] [32] or obviously mistaken.[33] 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.[34] Beggs & Graddy (2009) argue that demand for art changes over time, but underlying hedonic quality remains constant, thus allowing anchoring to be identified.

Commented [J15]: Combine footnotes.

[30] http://video.cnbc.com/gallery/?video=3000504214

[31] 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.

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

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

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

If the quality changes, then we can still identify anchoring, given we control for those differences[35]. 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.[36] For instance, the knowledge of a past price may affect buyers not only directly, but indirectly through the presale estimates set by auction house 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.

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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,

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

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

and even exogenous factors such as the weather[37]. 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.[38] 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[39] finds that anchoring is more powerful for sellers than for buyers, though anchoring is weaker with more experience selling the goods of concern.[40] 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 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).[41] Go too high, and your numbers lose credibility; go too low, and bidders will suspect something is wrong with the good.

[37] 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.

[38] 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.

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

[40] 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.

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

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.

REVIEW OF THE LITERATURE

ANCHORING

Anchoring is a well-studied bias with over 40 years of research in psychological and behavioral fields.[42] The seminal work on anchoring was first conducted by Tversky & Kahneman (1974), who conducted the experiment described in the introduction to this paper.[43] The anchoring effect is extremely complex, and many studies have attempted to understand its nature and implications. For instance, some studies show that people formulate estimates more quickly when provided with numbers to anchor on,[44] while others show that anchoring decreases, but does not altogether vanish, with increased cognitive ability.[45] Other work demonstrates that anchoring is extremely difficult to avoid, even if the anchors are obviously incorrect.[46] A myriad of studies exist on

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

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

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

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

[46] 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.

anchoring: for a comprehensive survey of the anchoring literature, see Furnham & Boo (2011).[47]

Within economics more generally, various work has been conducted with historical market data by examining prices for unchanging goods with shifting demand to assess potential anchors.[48] [49] Much of the anchoring research in economics uses experiments, surveys, or multiple-choice tests to understand questions about how individuals form estimates and judgments in the presence of an anchor.[50] [51] [52] The bias has been studied in many socioeconomic contexts such as accounting,[53] real estate,[54] the courtroom,[55] public goods,[56] and international finance.[57] Of course, anchoring has

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

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

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

[50] 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.

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

[52] 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.

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

[54] 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.

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

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

been researched in the context of auctions as well.[58] [59]~~.~~ For example, one bizarre experiment, ~~was~~ conducted by Prelec and Ariely (2006), ~~who~~ first asked students 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.[60]~~.~~ 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. In the case of a '98 Cotes du Rhone wine, the high-digit students submitted bids that were, on average, over three times what the low-digit students had submitted. Wolk and Spann (2008) study bidding in online auctions in the presence of an anchor.[61]~~.~~ They find that bidders tend to 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.

Commented [J19]: Combine

Commented [J20]: You mostly talk about literature in the present tense, but you use past tense here. Be sure to be consistent.

ANCHORING AND ART AUCTIONS

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[57] 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.

[58] 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.

[59] 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.

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

[61] 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.

The art auction market is no exception to anchoring effects, and the literature shows that first numerical impressions do seem to significantly 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") as well as loss aversion[62] in the art auction market. To identify anchoring – specifically, the marginal impact of past price on current price (which is our definition) – they first use two datasets of repeat auction sales of Impressionist and Contemporary paintings, including not only hammer price but also hedonic characteristics such as artist and medium. The Impressionist dataset was originally collected by Orley Ashenfelter and Andrew Richardson at Princeton University in 1992, while the Contemporary dataset was constructed by Kathryn Graddy from the archives of Christie's; we use both datasets in our research.[63] [64]. The regression model of Beggs & Graddy (2005) isolates anchoring effects on the price for a second sale by controlling for hedonic characteristics as well as unobserved inputs into price such as bidder behavior. Beggs & Graddy in this paper, believe

Commented [J21]: Combine footnotes

Commented [J22]: Give some examples of this

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

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

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

anchoring effects on the sale price can primarily be attributed to the buyers. The authors find strongly significant evidence for anchoring in both Impressionist and Contemporary genres, though no significant asymmetry between gains and losses appears for anchoring (and loss aversion is not evident either)[65].

The anchoring analysis in that discussion paper is formalized further in Beggs & Graddy (2009), which using the same resale approach and data but~~,~~ dives deeper into anchoring effects on price, presale estimates, and the probability of a sale.[66]~~.~~ 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 an association between presale low estimates and anchoring, although anchoring does not seem to significantly affect the probability of sale (which is estimated with a probit model). The anchoring models developed by Beggs & Graddy (2009) has been used in later anchoring research such as Leung et. al (2013),[67]~~,~~ and forms the basis of our own approach. We attempt to replicate selected results from Beggs & Graddy (2009) in a later section.

Commented [J23]: You should be more specific here. Does a low presale estimate lead to a lower sale price, as explained by anchoring?

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

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

[67] 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.

Graddy et al. (2014) further extends the work in Beggs & Graddy (2009) and Beggs & Graddy (2005) by studying anchoring (as well as loss aversion[68]) with more data.[69] The anchoring part of their model is mostly unchanged from Beggs & Graddy (2009). They again find significant evidence of anchoring, and validate the original paper's finding that anchoring effects are stronger for items that are resold more quickly. However, they express more uncertainty on who to attribute anchoring effects to, whether to buyers, sellers, or auctioneers.

Commented [J24]: The phrasing here is pretty awkard

Bruno and 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)[70]. They regress the range of presale estimates on a multi-leveled dummy variable for anchoring to account for multiple past prices (anchors). Subsequently, the authors find significant evidence of anchoring. First, the existence of past prices makes the presale estimate range narrower, presumably because the auctioneer grows more confident.[71] Second, Bruno and Nocera find that the existence of a past price corresponds to the presale estimate range being more closely centered on the true hammer price. Hence, both the bias and variance of the presale estimate range seem to

Commented [J25]: Confident in what? His own ability to accurately determine an item's price?

[68] See also Mei, J., et al. "Loss Aversion? What Loss Aversion? Some Suprising Evidence from the Art Market." *Working Paper*. 2010.

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

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

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

decrease in the presence of anchors. These findings are consistent with what we learned through interviews, namely, that specialists at auction houses do research past sales before formulating estimates (as described earlier).

Even the order in which art pieces are auctioned can beget anchoring effects, as shown in (Hong et al. 2015)[72]. For the semiannual Auction Week, a two-week auction series held every spring and fall across New York City[73], Sotheby's and Christie's have an arrangement to alternate who holds their auction first – a natural experiment. 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 revenues averaged across many works, their model cannot be applied in our context.

Commented [J26]: You've already described this, so I think you can skip it and go straight into the next sentence.

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

[73] http://www.artspace.com/magazine/news_events/the_heat_index/how_to_understand_new_york_record_auction_week-52310

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 is bought ~~in~~ at auction, it becomes "burned" and will sell for less in the future. To test this quantitatively, Beggs & Graddy (2008)[74] use a 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 this is directly due to buyer perceptions of failure, however, is ambiguous. Sentiment, emotion, and mood are also topics of research. For instance, Canals-Cerda (2012) analyze art auctions and seller reputations on eBay, and discover that negative feedback very significantly lowers sale price and the probability of sale.[75]~~.~~ Penasse et al. (2014) collect survey data on sentiment toward selected artists in the art community, and find that strong confidence can predict art returns in the short run.[76]~~.~~ Furthermore, De Silva et al. (2012) examine if weather, a proxy for mood, significantly impacts art auctions at

Commented [J27]: Whose confidence? The auctioners'? The buyers'?

[74] 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.

[75] 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.

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

Sotheby's and Christie's during the period 1990-2007.[77]~~.~~ They find a weakly significant effect, suggesting that external emotional shocks do affect art auction activity.

In the aforementioned literature, the exact mechanism by which past quantities anchor future ones is treated as a black box; only the impact is noted. This is consistent with our definition of anchoring earlier, as the details of transmission need not involve purely psychological factors. Rather, in this context it is enough to say anchoring occurs when past quantities bias future ones, even though hedonic factors should be the only determinants.

Commented [J28]: Be sure to establish earlier why hedonic factors should be the only determinants.

ON THIS RESEARCH

It is clear that anchoring is pervasive in the art auction market, especially since empirically and anecdotally, psychological and behavioral factors seem to be significant inputs into 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 sales, which tend to weaken possible anchoring effects[78]. Additionally, it is difficult to show resale observations refer to the same art piece, since an artist may create multiple

[77] 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.

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

pieces with the same medium, dimensions, and so forth. Beggs & Graddy (2009) manually cross-checked their resale data against presale catalogs.

Most importantly, a shared (flawed) assumption across much of our aforementioned anchoring literature is that hedonic quality does not change much across auction sales. Thus, 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 if tacked to the wall for decoration will have holes in the corners. 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 come from classic Impressionists artists such as Renoir and Monet, are an order of magnitude more valuable in both presale estimates and prices,[79], and are thus probably far better maintained. This preserves their hedonic quality and better allows past sales to anchor future ones.

If an art piece can change over time, how can we test for anchoring? The key is to control for quality differences between an anchor and the current good. In all existing

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

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 related artwork (substitutes) as the anchor instead of past sales. This is the intuition behind our generalization of the original anchoring model in Beggs & Graddy (2009), which we introduce in the next section.

Commented [J29]: These last few paragraphs are super solid! I completely understand how your study fits into the existing research. I think you could have an extra sentence in this paragraph to more fully explain why substitutes can be used to assess anchoring effects, but otherwise this is great!

METHODOLOGY

ANCHORING

A two-stage regression model for detecting anchoring is specified in Beggs & Graddy (2009) who themselves cite Genesove & Mayer (2001). 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 – 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. By controlling for hedonic characteristics (artist, medium, etc.) and unobserved inputs into the past price (bidding behavior), the difference between past price and hedonic quality can be isolated, and identified as the anchoring effect on current price.

Commented [J30]: Why is this relevant?

Commented [J31]: This is not very clear to me, but also this type of research is not more forte…

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[80] [81]. 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

Commented [J32]: Combine footnotes

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

[81] 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.

prices $P_t \in R^{[n,1]}$ of n resold paintings[82] on their k hedonic and temporal variables $\boldsymbol{X} \in R^{[n,(k+1)]}$[83], while also controlling for temporal effects $\delta_t \in R^{[n,1]}$. This yields a hedonic price prediction $\pi_t \in R^{[n,1]}$ for each observation of a painting sale. For my replication work, I use the same variables that Beggs & Graddy use on the Impressionist and Contemporary datasets, respectively. For Impressionist art, this includes painting date, length, width, medium of the artwork, indicators of authenticity (signed, monogrammed, stamped), and artist. For Contemporary art, this includes painting date, length, width, medium, and artist. The temporal effects are modelled by half-year time dummies.

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

Commented [J33]: Is this the equation that Beggs and Grady use? You should make it more explicity by saying "This gives us a final equation: ____"

In the same vein 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 multiple hedonic price predictions at different times $\pi_t, t \in \{1, 2, 3 \ldots\}$ may differ for the same painting, since these are estimated based on the price index $P_t, t \in \{1, 2, 3 \ldots\}$. The price index reflects demand for art, which

[82] 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.

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

varies over time. The k hedonic variables, however, are assumed to remain constant across sales.

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: ~~. They do this for each unique painting.~~

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

Above, P_{t-1} is the previous hammer price of a painting at time $t-1$ and P_t is the currents sale at time t. Beggs and Graddy fit several regressions where the response ω represents either the hammer price, an indicator for whether the item sells (which involves a probit transformation), or the presale estimate. The anchoring effect is captured in the term $(P_{t-1} - \pi_t)$, which specifies how information from the past price (the anchor) P_{t-1} differs the later hedonic price prediction π_t and thus the dependent variable ω. The last term $P_{t-1} - \pi_{t-1}$ controls for unobservable non-hedonic effects on price. For example, if the past price was not only a function of the painting's hedonic characteristics, but was also a function of bidding activity at the time, this will be controlled for in the $P_{t-1} - \pi_{t-1}$ term. Otherwise, $P_{t-1} - \pi_t$ not only reflects the impact by past price on the later hedonic prediction, but also past bidding activity and other non-hedonic factors inputted into P_{t-1}. In the case of the dependent variable P_t (for a regression for 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

Commented [J34]: I wonder if this section wouldn't be easier to read if you made it into a list?

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.

Commented [J35]: You might wanna ask someone else to read this section as well because this stuff is super difficult for me to understand >.<

ON 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. Furthermore~~And~~, many years or decades may elapse between sales of the same art piece – far too long to reliably measure anchoring biases.

Commented [J36]: Is this because of how paintings can be damaged? You might wanna explain that again just to be clear.

It is reasonable to believe that buyers (and specialists), when bidding on an artwork, make judgments based not only on that artwork's past sales, but also what similar pieces went for as well. This allows for a much more versatile approach to identify~~ing~~ anchoring effects, or if between different goods, cross-effects – given that we control adequately for hedonic differences. Before measuring similarity, however, we must identify related pieces for the current good, since many other pieces may be entirely irrelevant. Thus, to identify substitutes for the sale of a current 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 art 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 and simply treat auction date as another explanatory variable:~~.~~

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

We next depart from the original model. Denote the sale observation of our current good as x_c and the 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[84]. Thus~~en~~ our second regression is:

$$\omega_c = b_1\pi_c + b_2\left(P_s - \pi_c\right) + b_3\left(P_s - \pi_s\right) + b_4Q$$

Here, the subscripts for the past and current sales $t-1$ and t are replaced by subscripts for the substitute s and current good c. The previous regression model assumed that there was no unobserved quality changes in the painting across sales, such that $\boldsymbol{X}_t = \boldsymbol{X}_{t-1} = \boldsymbol{X}$ (though hedonic prices π_t could still change). However, in this generalized

[84] As with resale, we add the temporal constraint that the sale of a substitute must occur before the sale of the current good – in this context, one can only anchor on the past.

framework, we assume that characteristics do differ across goods, that is $\boldsymbol{X_c} \neq \boldsymbol{X_s}$. Thus, we need to 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:

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

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

Here, P_{RS} and π_{RS} are price and hedonic prediction for a representative substitute. 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 via a function such as the mean or maximum (I use the former). Hence, this multivariate regression tests whether there exists anchoring effects for the sale of the current good with respective to the "average" substitutive – 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. As before, the measure of substitution Q may be calculated from the multivariate π or $\boldsymbol{X}$.

Commented [J37]: You're so smart. I have no idea what is happening.

MEASURING SUBSTITUTION (SIMILARITY) ACROSS ART PIECES

In this research, we experiment with two simple measures of substitution Q_1, 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 do not and cannot perfectly capture differences between artworks, but do provide a starting point for quantitatively measuring art similarity.

MEASURE #1: SECOND MOMENT OF HEDONIC PRICE DIFFERENCES

For a current good x_c and other 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 differences between the hedonic price predictions. These correspond to unobserved quality differences. We use the following measure, which is essentially a second moment estimator about the current good's hedonic prediction[85]:

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

As described before, we work in logs for relative effects, and the negative sign allows a higher Q_1 (smaller hedonic differences) to correspond to higher substitutability. The squared term is used instead of absolute value so that the estimator also captures the variability of hedonic differences, which corresponds to lower substitutability. This is

[85] We do not subtract the other term $\left(E\left[X = |\pi_c - \pi_s|\right]\right)^2$ typically used in calculating variance $V[X] = E[X^2] - E[X]^2$, since that (squared) first moment term reflects absolute hedonic differences $X = |\pi_c - \pi_s|$ between pieces which we still wish to account for. Hence, our measure captures both spread and mean.

important because substitutability may differ drastically across goods: it is preferable to have uniformly substitutable goods rather than a polarized mix of good and bad ones.

MEASURE #2: DOMAIN KNOWLEDGE

For our second measure of substitution, we draw upon domain knowledge from our expert interviews. We found some of the most commonly mentioned and important determinants of artwork similarity (substitutability) are 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 as subject matter and artistic style, seemed to be mixed: some said these were key to measuring similarity between pieces, while others looked more to the factors above.[86] One thing we were surprised to learn about artwork 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 decoration, and tend to purchase pieces of similar sizes to display next to each other. As price increases, people tend to value artwork more as an investment, and so the importance of size in determining similarity decreases.

Commented [J38]: This is a very interesting point! And very clearly explained as well.

To capture these anecdotal observations about art similarity, we present a second measure of substitution between a current piece x_c and a substitute piece x_s, here

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

formulated as two sale observations at different points in time. This measure of substitution depends on size S_i, hedonic price π_i, and auction date t_i. Artist, authenticity, and medium are categorical variables and thus used primarily to filter for substitutes, as we describe later. This leaves us with:

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

Greater differences in size between the two goods correspond to decreased similarity and thus substitutability[87]. However, this effect decreases as the hedonic values of the pieces rise. Consistent with the anchoring literature discussed earlier, the farther the anchor (the substitute here) is in the past, the weaker the anchoring effect is. Note that we use hedonic prices to indicate increasing value. This is because P_c, P_s can reflect not only π_s but also non-hedonic determinants of price. F~~, and f~~urthermore, 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.

Although hedonic features enter into both Q_1 and Q_2, the two measures are considerably different because Q_2 includes temporal effects (which do not enter into the

[87] 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.

hedonic regressions), and focuses ~~for~~ on the relative differences in size between works, which are not captured in the individual π terms. It is surprising, then, that these two diverse measures yield relatively similar evidence of anchoring effects. We show this in the next section.

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[88] and are already described in detail elsewhere.[89] Both of those datasets are available on the Brandeis academic website of Kathryn Graddy.[90] 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. 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 information on these, however, seems to be unavailable: for example, the dimensions are described as "DIM_A" and

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

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

[90] http://people.brandeis.edu/~kgraddy/data.html

"DIM_B". The dataset contains 58 major artists whose work is often featured at auction, and among the most frequent are Pablo Picasso (1881-1973), Raoul Dufy (1877-1953), and Pierre Renoir (1841-1919). Approximately half the auction sales in this data set are split between Christie's and Sotheby's, as well as between London and New York. Table 1 shows summary statistics for selected attributes. The highest sale in this dataset goes to 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 paintings with record-high sales, as well as paintings 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 tended to grow over time (Figure 3), though there are clearly some huge years with record numbers of sales.

Commented [J39]: Is this for the entire dataset? Or just some pieces?

Commented [J40]: I just thought of this, but do you adjust for inflation in these data sets?

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. 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 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 (1899-1968), Karel Appel (1921-2006), and Alexander Calder (1898-1976) being the most frequent.

Commented [J41]: In the next section, you provide the specific number of observations when you list frequently seen artists. You should maintain consistency and do the same here or not at all.

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 tend to be far more expensive than Contemporary pieces, which can be attributed to age. 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 generally 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 recent auctions sales of assorted paintings[91] (2006-2015). To do this, we wrote a Python program to scrape recent listings on the Blouin Art Sales, a database that hosts a large collection of art auction data.[92] We ran our program for 10 straight 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 on the much shorter scale of months, weeks, or even days, rather than years as in the previous datasets. This is far more conducive to studying anchoring. Second, this dataset consists of a very wide variety of artistic pieces, which is ideal for exploring substitutability across pieces. The Impressionist and Contemporary datasets tend to be more limited in their artistic scope, and so do not seem to be as conducive for studying substitution. Finally, as mentioned earlier, the sales in this dataset are far more up-to-date, and could better reflect the current auction climate.

Commented [J42]: Wow you're so intense

Commented [J43]: In terms of what? Art style?

[91] 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.

[92] http://artsalesindex.artinfo.com

The raw dataset consists of approximately 500,000 observations, covering both 19th and 20th century art with some works from earlier time periods (earliest: approx. 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 works), Andy Warhol (2,573 works), and Salvador Dali (1,508 works). However, 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. Appendix A describes a more sophisticated computational approach to text extraction that could be applied. Some summary statistics for the full raw dataset are provided in Table 3.

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 apply their same model to my new dataset of assorted art sales. Then, I run my anchoring cross-effects regression on all three datasets. I also run my cross-effects regressions on three pairs of artists identified as similar, under the recommendation of Hadley Newton.

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. For Impressionist art (as in Beggs & Graddy (2009)), though, predictions are fit separately for observations in London and in New York due to currency differences, then recombined for the anchoring regressions. Tables 4-7 below show the results of the hedonic predictions.

Overall, hedonic characteristics such as the painting dimensions, the presence of a signature, medium, and artist and time effects (both omitted for brevity; both highly significant) have a significant impact on the sale price of the painting. It is surprising that a painting's date of creation is generally not significant, which can be explained by the importance of artist variables. For Impressionist Art and Contemporary Art, much of the variation in price is explained by our regression model, indicated by generally high R^2 values. For our new dataset, however, the R^2 value is extremely low although variables are significant. This is to be expected: our dataset covers a very large variety of paintings, and so we should see very high variance across prices in our regression model (though far lower bias, as indicated by our highly significant hedonic variables). The F-statistic is extremely significant in all cases, which shows that our regression variables are relevant 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 observe that signature is more significant for Impressionist art auctioned in NYC, while medium is probably a 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 determine 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 they also run regressions for presale estimate and the probability of sale. As mentioned earlier, they identified resale observations by cross-checking against presale catalogs, so it is not possible for us to entirely replicate their work. We make the assumption that duplicate hedonic observations refer to multiple sales of the same item, and run our regressions for the full datasets each.

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 coefficients are not nearly as large, although significant. 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 (original: 6.2-8.5%), while for Contemporary art this is only a 1.3% predicted increase (original: 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 suggests that bidders may not conduct serious hedonic analysis when considering related goods, or do not know how to properly appraise those substitutes. 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. 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 their 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 an item's average substitute (constructed as described in our methodology) instead of a past sale. This corresponds to running our regression for anchoring cross-effects without the measure of substitution, i.e. the control term Q. Despite this naïve approach that does not control for substitution, we can still discover some insight.

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. We discovered strong and highly significant anchoring effects in this context (5.9% increase), although as in Contemporary art the residual from past price seemed to be relatively unimportant and less significant. This suggests that, although we have not properly controlled for substitution, anchoring is at work in this dataset. 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 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 because Contemporary art tends to be especially diverse. As a result, a piece to be auctioned may lack obvious precedents for its value, which means that 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. These seem to be confirmed by the highly significant, non-negative substitute residual, as well as the insignificant measure of substitution. For Impressionist art, we would expect past prices of substitutes, and unobserved inputs into those substitutes, to significantly affect the price for a current piece since as Beggs & Graddy (2009) show, Impressionist art prices have steadily risen over the decades. Here, while no doubt hedonic characteristics such as authenticity and artist do help determine value, the auction history of an Impressionist piece and its relatives are also informative. However, the anchoring coefficient for Impressionist art is small, suggesting that other factors into value (e.g. publicity for a well-known Impressionist work) are more influential. Finally, our assorted art dataset exhibits strong and highly significant anchoring effects. This could be due to the vastly larger and more diverse range of artworks, which could yield a higher chance of finding appropriate substitutes and other pieces that have closer hedonic price predictions.

Furthermore, while time effects (months since last sale) seem to be relatively strong (and significant) for Contemporary and assorted art sales, they are weaker for Impressionist art. From our interviews, we learned that buyers of art tend to be relatively myopic, in that they do not tend to internalize the full range of historical prices (only recent prices, i.e. anchoring). This is confirmed here by small coefficients. For example, in the assorted art dataset, 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. This finding is corroborated for Impressionist art by the price indices in Beggs & Graddy (2009), who find small time coefficients for both Impressionist and Contemporary art. It seems that myopic buyers do not internalize earlier, lower prices which allows prices to climb up over time.

It is clear that our Q_1 measure of substitution is a stronger and more relevant predictor of price for Impressionist and assorted art than for Contemporary art. As we discussed earlier, it is more difficult to identify substitutes for Contemporary goods, which tend to be far more heterogeneous in their hedonic characteristics. 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[93] [94]. Conversely, Impressionist works tend to have better-defined mediums such as oil and watercolor, which makes it easier to accurately assess substitution. Though significant, the coefficients are overall still relatively small, which indicates that price may not be hugely impacted by our measure Q_1. In the case of assorted art, a 100% increase in substitution quality only corresponds to a 2% increase in sale price, through the channel of anchoring.

The R^2 values are generally in line with our results for the original anchoring regression: there is generally 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.

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

[94] 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

Q2: DOMAIN KNOWLEDGE

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

Tables 14 through 16 show the results of using Q_2 as a control for substitution. We see many similar results since both artwork size and hedonic price prediction enter into both measures of substitution, but some differences are apparent.

First, the measure of substitution becomes significant for Contemporary art. Size, which was already significant in our hedonic regression results, plays a much larger role in Q_2 and may be key behind this result. Unlike Impressionist art, which seems to be purchased more as an alternate investment or showpiece rather than for its hedonic characteristics, Contemporary art which is often newer seems to be evaluated more based on hedonic characteristics. This is demonstrated in our hedonic regression results: the much higher intercept for Impressionist art suggests that non-hedonic factors such as buyer wealth and general demand for Impressionist pieces are at play. Thus for Contemporary art, based on our results, focusing on major hedonic characteristics such as size may be a more appropriate measure of similarity for Contemporary art. For Impressionist art, Q_2 is less significant and may be less relevant than our previous measure Q_1. We suspect this is because time effects seem to be more impactful for Contemporary art than for Impressionist art (though the coefficients are still relatively small). Prices for Impressionist pieces, in general, seem to be somewhat resistant to long intervals between sales.

For our assorted art dataset, Q_2 is a hugely more impactful measure of substitution than Q_1: a 10% improvement in substitution quality corresponds to a 3.0% increase in sales price. Hence, we see that the quality of substitution is highly relevant to sale price, in that the former shapes the latter through anchoring (which remains roughly as impactful across Q_1 and Q_2). Focusing on size, hedonic price, and time duration seems to be far more effective as a control, since for this assorted art dataset, it is possible that the hedonic price predictions in Q_1 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. This is as expected: the measure Q_2 invokes a smaller subset of hedonic variables than Q_1 does.

We see generally similar anchoring results regardless of whether we use Q_1 which is expected since the two measures invoke some of the same variables. We do see a decrease in the anchoring coefficients across the board when we use Q_2, which indicates that Q_2 might be a more stringent measure of substitution. Overall, even when controlling for quality of substitution we see significant anchoring cross-effects in the Impressionist and assorted art datasets. Anchoring cross-effects are vastly stronger in our assorted art dataset, which we attribute to our diversity of works. We can thus conclude that the price of a given art piece is indeed biased by the past sale prices of related goods (anchoring effect), although the exact mechanism by which this occurs remains a black box.

THREE EXPERIMENTS

One domain expert in the art history department here (Princeton University) helped us to identify pairs of “similar” artists in our assorted art dataset. In the next section, we run our Q_1 and Q_2 regressions on three pairs of artists for comparison. Specifically, we test whether one artist serves as an anchor for the other, and vice-versa. This allow us directly test our anchoring regressions on known substitutes, and evaluate our results more thoroughly. Only Contemporary artist pairs were provided for us.

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[95]. Dali’s work, which ranges from bizarre scenes to nightmarish landscapes, is dreamlike yet shows an appreciation for the realistic nature of classical

[95] http://joanmiro.com/style-of-joan-miro/

and Renaissance art[96]. Works by both Surrealists have sold at auction for 6- and 7-figure sums, and the two Surrealists are occasionally paired together at museum and gallery exhibitions[97]. We were 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, Q_1 is highly significant and impactful, but Q_2 is not. This negative association 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

[96] http://www.theartstory.org/artist-dali-salvador.htm

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

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, a high F-statistic ensures the relevance of our model. Nevertheless, due to our mixed results, we cannot say that our Q_1 and Q_2 regressions detect significant anchoring between Dali and Miro.

SUBSTITUTION EXPERIMENT #2:

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

Picasso and Chagall, former friends turned opponents[98] 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[99] [100]. The two painters are featured together at exhibitions[101] [102],

[98] http://www.pablopicasso.org/picasso-and-chagall.jsp

[99] http://www.theartstory.org/artist-chagall-marc.htm

[100] http://www.infoplease.com/encyclopedia/people/chagall-marc.html

[101] http://www.operagallery.com/catalogues/picasso_chagall_dubai/cata.pdf

[102] http://pueblopulp.com/picasso-matisse-chagall

apparently more often than Dali and Miro are, and the works of Picasso and Chagall frequently fetch 7- and even 8-figure sums at auction.

Overall, Q_1 and Q_2 give very similar results for this comparison (Tables 20 and 21). Anchoring seems to be much stronger and detectable 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 of Q_1. We are also explaining a huge amount of variation in the data: the R^2 values are extremely low. This indicates that for Picasso and Chagall, other influences are probably at work, 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, for Picasso and Chagall we see highly significant evidence of strong anchoring cross-effects. 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)

Munch and Toulouse-Lautrec were contemporaries in Europe who, as we learned in our interviews, met with comparable levels of economic and critical success during their lifetimes. However, their artistic styles differ somewhat. 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[103]. On the other hand, Toulouse-Lautrec is known for his Post-Impressionist, drawing-like depictions of people, often those from lower-class, urban environments[104]. 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[105]. 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[106], and Munch's Internet-famous "The Scream" sold for nearly $120 million at Sotheby's in 2012[107].

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. No significant or strong

[103] http://www.theartstory.org/artist-munch-edvard.htm

[104] http://www.toulouse-lautrec-foundation.org/biography.html

[105] http://libmma.contentdm.oclc.org/cdm/ref/collection/p16028coll12/id/1460

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

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

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, their artistic styles may be too different to permit anchoring cross-effects. It is also possible that the comparison between Munch and Toulouse-Lautrec is less conducive to anchoring in light of even more renowned artists during the same time period, such as Vincent Van Gogh (1853-1890) and Paul Gauguin (1848-1903). Works by Toulouse-Lautrec, in particular, seems to be auctioned off alongside those Impressionist artists[108]. Our measure of substitution is insignificant in both the Q_1, Q_2 cases, which seems to further suggest that Munch and Toulouse-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 suggest that our model is not as relevant for 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.

[108] http://www.bloomberg.com/news/articles/2015-02-05/here-s-why-sotheby-s-and-christie-s-just-sold-444-8-million-in-impressionist-art

FUTURE DIRECTIONS

Measures of substitution (similarity) across art pieces is an enormous difficult problem from both an economic and an artistic point of view. Even in our interviews, we received sometimes divergent opinions on the relative importance of certain hedonic characteristics. 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 financial capital flows between 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 qualitatively understand where their price signals come from. Some theoretic work could also be formulated to account for such price signals.

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.

Third, one could examine other applications of anchoring. While we have only focused on the impact of anchoring on sales (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. Beggs & Graddy (2005) examined this for resale and found no significant evidence of asymmetry.

CONCLUSION

Can the past price of a Miro painting bias the current price of a Dali piece? In this research, we set out to examine the existence of 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. We proposed two measures of similarity, drawing upon insights from our interviews, and also constructed a new dataset of recent auction sales for assorted art.

We found <to be finished, summarize your results etc. >

FIGURES

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

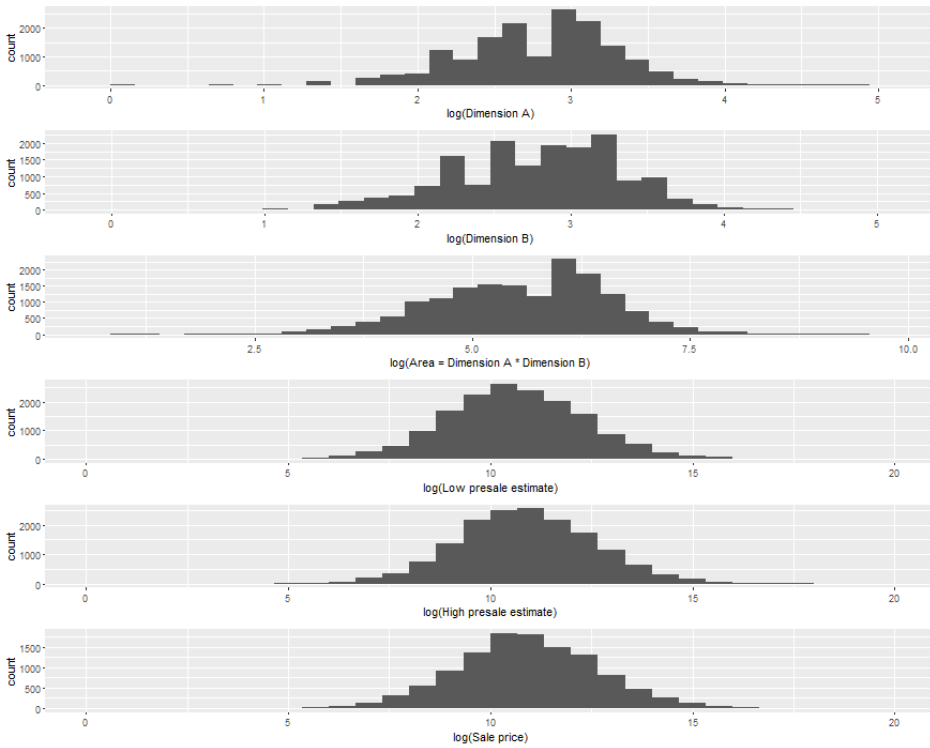


Figure 2: Comparison of painting dimensions, Impressionist art.

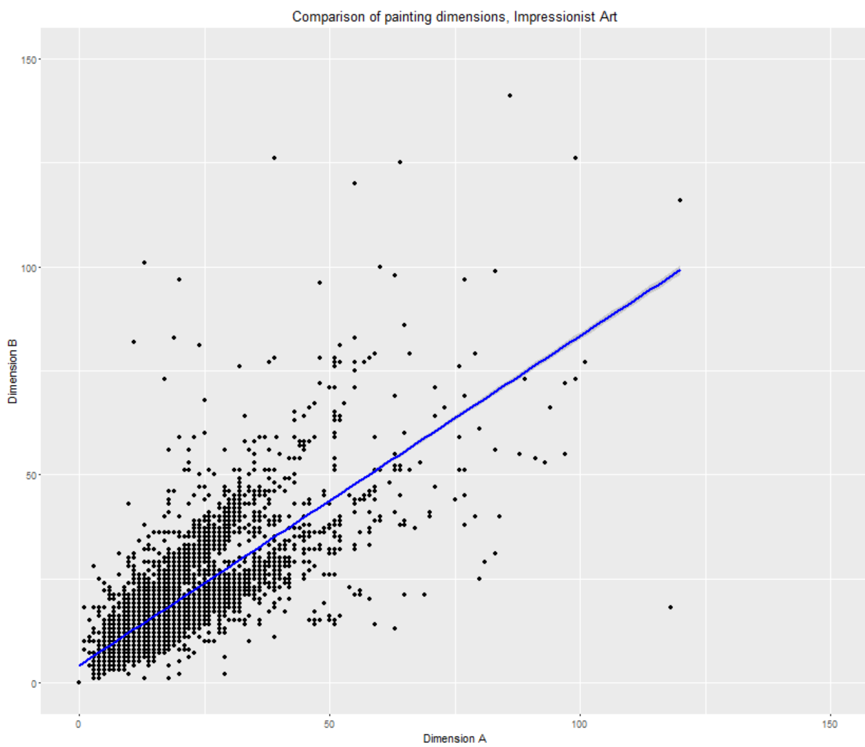


Figure 3: Impressionist art, auction sales over time.

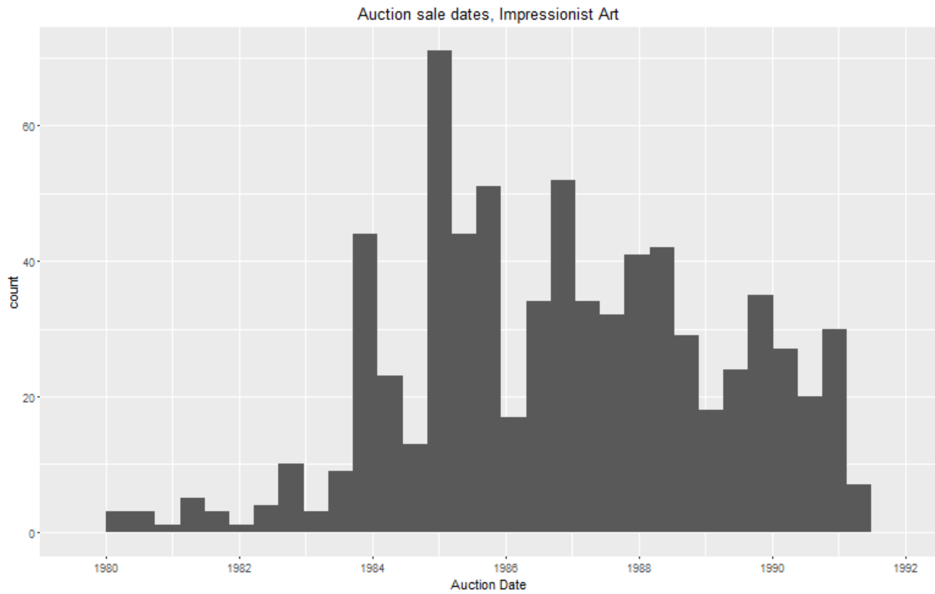


Figure 4: Distribution of selected quantities in the Contemporary art dataset.

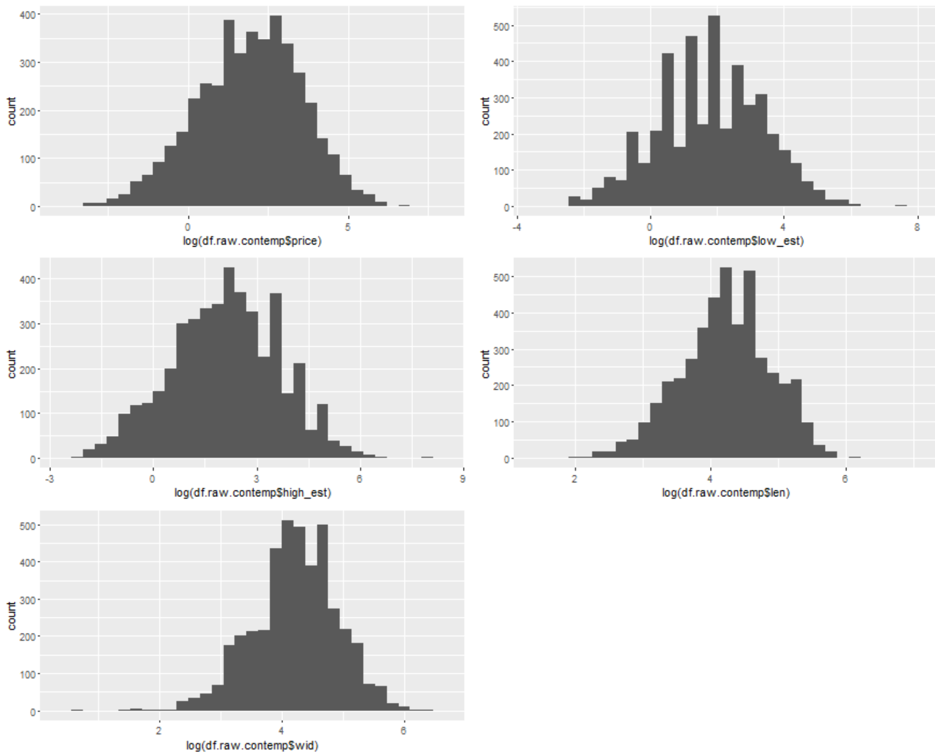


Figure 5: Auction sales over time, Contemporary art.

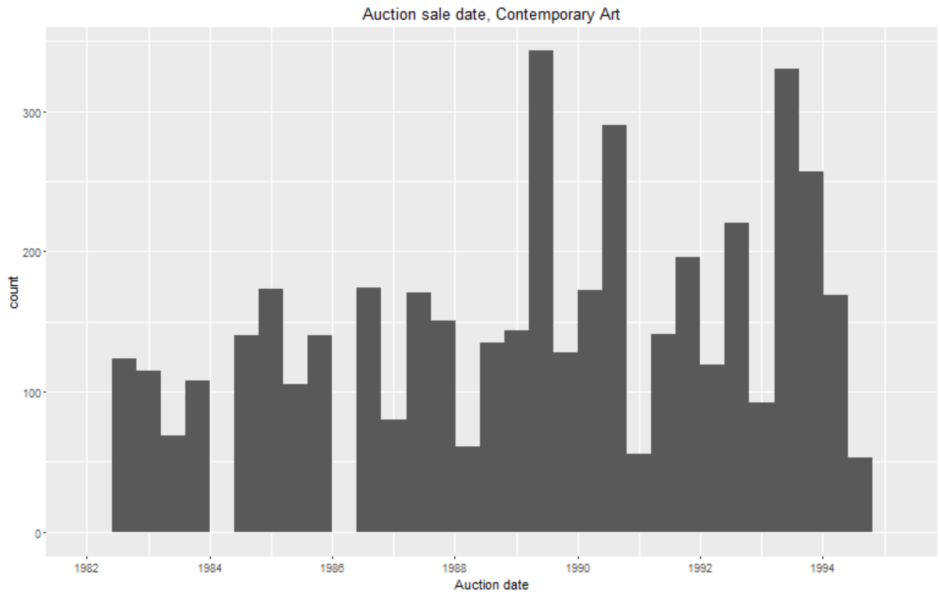


Figure 6: Comparison of log prices, Impressionist and Contemporary art.

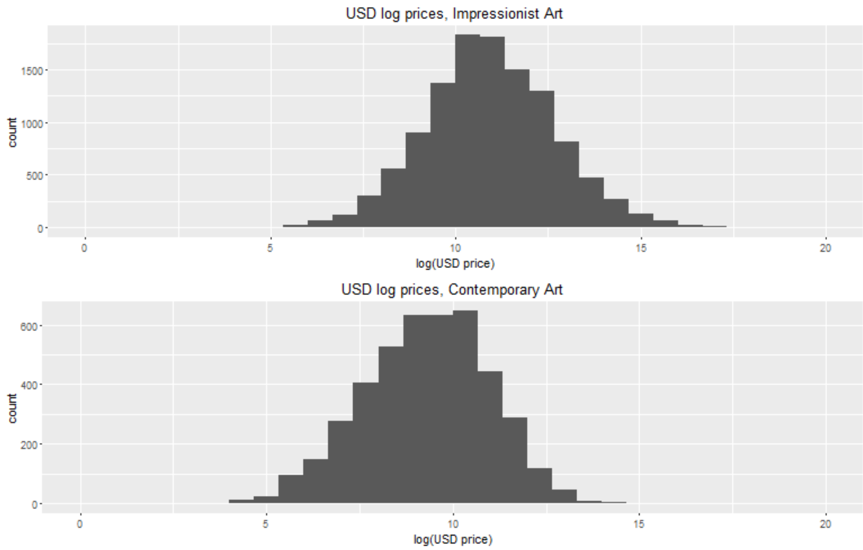


Figure 7: Comparison of log area, Impressionist and Contemporary art.

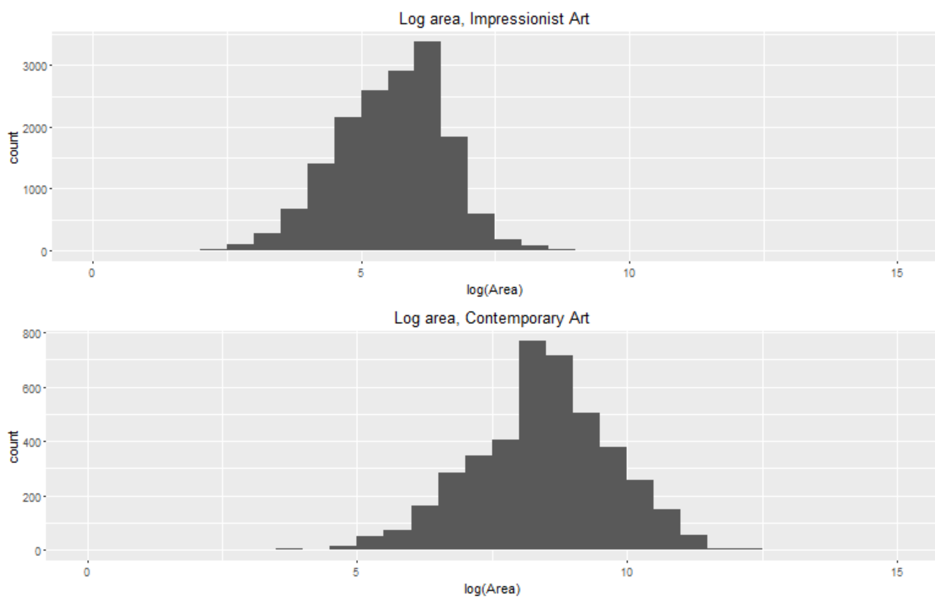
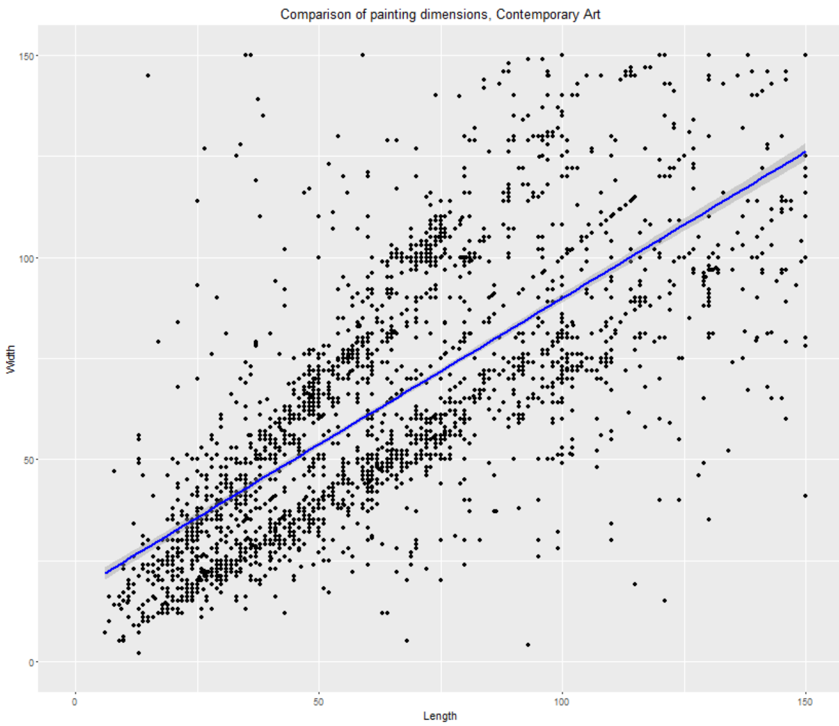
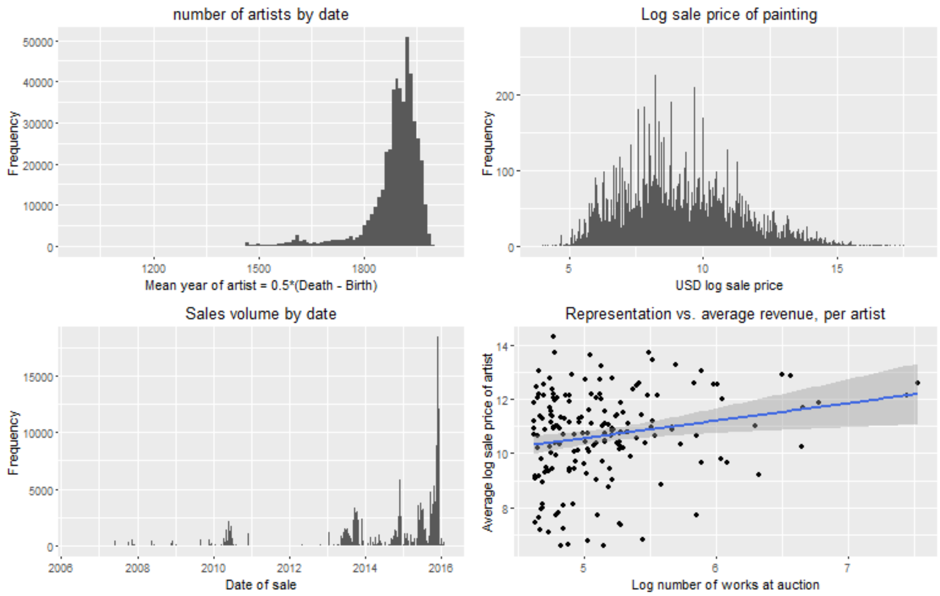


Figure 8: Comparison of painting dimensions, Contemporary art.



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

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

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 ***

THREE EXPERIMENTS

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
```