**INTRODUCTION**

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

This is the *anchoring effect* - a well-studied cognitive bias in which the first number you hear (the “anchor”) can shape your perception of what is normal, even if that number is irrelevant. This was first demonstrated in a landmark experiment by Tversky & Kahneman (1974)[[1]](#footnote-1). Participants were given five seconds to mentally calculate the product of numbers 1 through 8, visually written out for them on a blackboard. It was found that if the numbers were displayed as “1x2x3x4x5x6x7x8”, participants would read the lower numbers first and give a median estimate of 512 for the product. On the other hand, if the numbers were displayed as “8x7x6x5x4x3x2x1”, then participants would first see the higher numbers and give a much higher median estimate of 2250. First (quantitative) impressions do affect judgment.

This bias appears in the market for fine art auctions, which in 2014 saw a sales volume of approximately $7.35 billion.[[2]](#footnote-2) To the best of our knowledge, Beggs & Graddy (2009) are the first to formally study anchoring in the context of art auctions, describing it as follows. The true (hedonic) value of an artwork, say a painting, is assumed to be determined by its intrinsic characteristics such as artist and medium. These features do not change over time, which means that if buyers were perfectly rational, they would pay only according to their (time-dependent) demand for those hedonic characteristics. If however, buyers learn the painting previously sold for a very high price, they may internalize that previous high price as a reference point (the anchor) and drive up the current price from there. This internalization of past price may be interpreted as an anchoring bias, because past price is actually an irrelevant signal. Specifically, if we account for the painting’s (unchanging) true value by subtracting it from past price, the resulting past residual will only include past bidding activity and other unobserved inputs into past price, which are not helpful in determining hedonic value. In other words, anchoring (identified in that past residual) is said to occur when past price biases current price beyond hedonic factors.

Of course, the exact behavioral mechanism by which auction participants internalize and act upon past price cannot be inferred from just observing prices. Hence in our research and in much the literature, including Beggs & Graddy (2009), the process is treated as a black box. The mere observation of this effect, i.e. past price biasing current price, suffices for our definition of anchoring (discussed further in Section 5).

Using a regression model that carefully identifies anchoring, Beggs & Graddy (2009) analyze resales of Impressionist and Contemporary paintings and do find significant evidence of anchoring effects. However, as mentioned in their paper, it is very difficult to identify multiple sales of the same art piece. This method of testing for anchoring effects cannot be applied to new works or works that have never been brought to auction. Moreover, even in practice, auction specialists appraise an art piece based primarily on sales of related pieces rather than previous sales[[3]](#footnote-3). The anchoring research of Beggs & Graddy (2009) thus seems to be limited in both 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 Van Gogh. To show we understand the original regression model of Beggs & Graddy (2009), we begin by successfully replicating their general anchoring findings. Our success is surprising because, as discussed later in Section <>, we do not know exactly which observations in their data were originally used. Next, we introduce our expanded version of their model, which tests for anchoring cross-effects by controlling for similarity across pieces. We introduce two quantitative measures of similarity. 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) 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 artist pairs: Joan Miro & Salvador Dali, Pablo Picasso & Marc Chagall, and Edvard Munch & Henri de Toulouse-Lautrec. We explain this selection of artists in Section <>. We find the strongest and most significant evidence of anchoring cross-effects between works by Picasso and Chagall.

This research makes several major contributions to the existing literature on art auctions. First, to the best of our knowledge, no econometric work has attempted to quantify hedonic similarity between art pieces. This is useful not only for appraising art, but also for other tasks where art pieces must be compared, such as forecasting returns to art and constructing price indices. We hope our two measures of similarity may provide a starting point for such analysis. Second, much of the econometric work on art auctions has relied on the same two Impressionist and Contemporary art datasets that only include sales until 1991 and 1994, respectively. Our new dataset of approximately 500,000 assorted art sales (2006-2015), constructed by writing a Python program to scrape Blouin ArtInfo for 10 straight days, is a larger and more up-to-date collection of auction data. Lastly, our discovery of anchoring cross-effects is notable because it adds to the growing body of research on implicit price signals in the art auction market. For researchers, our work allows one to account for hidden biases (including anchoring) when comparing sales of different art pieces, and demonstrates how Beggs & Graddy’s original anchoring model may be successfully customized. For auction houses and professionals, our work provides a practical regression model for estimating an artwork’s price in light of related sales. Our approach is more general than Beggs & Graddy’s original model, which has been extensively applied in other domains such as corporate finance[[4]](#footnote-4), real estate[[5]](#footnote-5), and horse racing[[6]](#footnote-6).

As part of our research, we conducted interviews with several specialists and experts in the field. To learn about the art market and how auction specialists appraise pieces, we talked with Mark Best (Princeton ‘00), a former financial analyst who is now a specialist in American, Modern, and Contemporary prints at Sotheby’s NYC. For insight into artistic similarity, we talked with Hadley Newton (Princeton ’16), who formerly worked at Sotheby’s with Impressionist art. The three artist pairs we examine in Section <> were suggested by Hadley. We also talked extensively with Raphaelle Benabou (Princeton ’15), who is an administrator of art collections, estates, and valuations at Bonham’s in London. Raphaelle provided us with many of our anecdotes and fact-checked our description of the auction system. We draw upon these interviews for both our discussion and our quantitative analysis.

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

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

1. Tversky, Amos, and Daniel Kahneman. "Judgment under uncertainty: Heuristics and biases." *science* 185.4157 (1974): 1124-1131. [↑](#footnote-ref-1)
2. <http://www.christies.com/about/press-center/releases/pressrelease.aspx?pressreleaseid=7712>

   <http://www.xe.com/currencyconverter/convert/?From=GBP&To=USD> accessed 2/20/2015 [↑](#footnote-ref-2)
3. Interview with Raphaelle Benabou [↑](#footnote-ref-3)
4. Dougal, Casey, et al. "Anchoring on credit spreads." *The Journal of Finance*70.3 (2015): 1039-1080. [↑](#footnote-ref-4)
5. 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. [↑](#footnote-ref-5)
6. 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. [↑](#footnote-ref-6)