**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.

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]](#footnote-1), where participants were given only 5 seconds to calculate the product of numbers 1 through 8, shown either in increasing or decreasing order. It was found those who saw the lower numbers first gave a median estimate of 512, whereas those who saw higher numbers first gave a median estimate of 2250 – a huge difference due to first impressions.

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]](#footnote-2) [[3]](#footnote-3). To our knowledge, Beggs & Graddy (2009) are the first to formally study anchoring in the context of art auctions, and describe it as follows. First, the true value of a 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 as a reference point (the “anchor”) and drive up price even more, even if that 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 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, 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]](#footnote-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. To show we understand the original anchoring model of Beggs & Graddy (2009), we begin by successfully replicating their general anchoring findings. Next, we introduce our expanded version of their model, which 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 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 pairs of artists identified as similar: Joan Miro & Salvador Dali, Pablo Picasso/ & Marc Chagall, and Edvard Munch & Henri de Toulouse-Lautrec. 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 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 500,000 assorted art sales (2006-2015), constructed by writing a Python program to scrape Blouin ArtInfo for 10 straight days, 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]](#footnote-5), real estate[[6]](#footnote-6), and horse racing[[7]](#footnote-7).

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 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 sell for more. Furthermore, drivers of similarity may 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 deeper discussion on 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.

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 [↑](#footnote-ref-2)
3. <http://www.xe.com/currencyconverter/convert/?From=GBP&To=USD> accessed 2/20/2015 [↑](#footnote-ref-3)
4. Interview with Raphaelle Benabou [↑](#footnote-ref-4)
5. Dougal, Casey, et al. "Anchoring on credit spreads." *The Journal of Finance*70.3 (2015): 1039-1080. [↑](#footnote-ref-5)
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. [↑](#footnote-ref-6)
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. [↑](#footnote-ref-7)