**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.

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[[1]](#footnote-1) [[2]](#footnote-2). For example, the value of a painting may depend on its dimensions and authenticity, while a bottle of wine may be appraised based on its age and where it was grown. In the first stage of the model, Beggs & Graddy (2009) regress the sale prices of resold paintings[[3]](#footnote-3) on their hedonic and temporal variables, while also controlling for temporal effects. This yields a hedonic price prediction 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.

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. It is important to note that multiple hedonic price predictions at different times may differ for the same painting, since these are estimated based on the price index. The price index reflects demand for art, which varies over time. The hedonic variables, however, are assumed to remain constant across sales.

In the second stage of the model, Beggs & Graddy specify the following regression in order to separate out anchoring from other effects. They for each unique painting.

Above, is the previous hammer price of a painting at time and is the currents sale at time. Beggs and Graddy fit several regressions where the response 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, which specifies how information from the past price (the anchor) differs the later hedonic price prediction and thus the dependent variable. The last term 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 term. Otherwise, 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. In the case of the dependent variable (for a regression for hammer price), we see that those non-hedonic inputs, usually captured by, would instead be contained in the residuals. One should also note that because hedonic prices may vary over time, is distinct from.

**ANCHORING AND SUBSTITUTION**

As we discussed earlier and as Beggs & Graddy (2009) note, it is extremely difficult to track down multiple sales of the same item, to the extent that even auction house specialists formulate estimates from researching sales of related goods (substitutes) instead. The same art piece can become a drastically different hedonic object within its lifetime. And, many years or decades may elapse between sales of the same art piece – far too long to reliably measure anchoring biases.

It is reasonable to believe that buyers (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 identifying anchoring effects, or if between different goods, cross-effects – given that we control adequately for hedonic differences. Here, we build on the two-stage regression model presented earlier.

Suppose, as before, we have our same design matrix and our historical hammer prices. 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.

We next depart from the original model. Denote our current good as and our substitute as, such that the hedonic predictions estimated above are, and are the respective hammer prices[[4]](#footnote-6). Then our second regression is:

Here, the subscripts for the past and current sales and are replaced by subscripts for the substitute and current good. The previous regression model assumed that there was no unobserved quality changes in the painting (e.g. was shown to be a fake) between its past and current sale, i.e.. However, because we cannot assume our hedonic characteristics (length, width, signature, etc.) can capture all possible differences between two related goods, despite their similarity. Hence, the last term is intended to control for quality differences between the current good and its substitute.

Here, we propose

From here we depart from the original model.

Substitution – the hedonic predictors for 🡨 do not stay the same.

**MEASURING SUBSTITUTION ACROSS ART PIECES**

1. Edmonds, Radcliffe G. "A theoretical basis for hedonic regression: A research primer." *Real Estate Economics* 12.1 (1984): 72-85. [↑](#footnote-ref-1)
2. 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. [↑](#footnote-ref-2)
3. 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. [↑](#footnote-ref-3)
4. 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. [↑](#footnote-ref-6)