# *Empirical Evidence of Anchoring and Loss Aversion from Art Auctions*

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# Empirical Evidence of Anchoring and Loss Aversion from Art Auctions

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**Abstract**

We find evidence for the behavioral biases of anchoring and loss aversion. We find that anchoring is more important for items that are resold quickly, and we find that the effect of loss aversion increases with the time that a painting is held. The evidence in favor of anchoring and loss aversion with a large new dataset validates previous results and adds to the empirical evidence a finding of increasing loss aversion with the length of holding. However, we do not find evidence that investors can take advantage of these behavioral biases.

**Keywords:** anchoring, loss aversion, endowment effect, art auctions

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# 1 Introduction

The seminal work of Daniel Kahneman and Amos Tversky has shown repeatedly that individuals use heuristics, such as anchoring on a previous sale price, when solving difficult problems and that these heuristics lead to biased judgement. Their work on loss aversion has demonstrated that individuals dislike monetary losses more than they enjoy monetary gains. Because works of art are unique and difficult to value and because there is a large amount of empirical data available from over a hundred years of art auctions, art prices are a good medium with which to study the behavioral biases of anchoring and loss aversion. As the same work of art can be sold repeatedly over many decades—or even centuries—and since auction sales are publicly recorded, it is also possible to shed light on whether or not investors could have taken advantage of these behavioral biases within our auction dataset.

Anchoring was first proposed by Tversky and Kahneman [1974]. Subjects were given a number—determined by the spin of a wheel—between one and 100. They were then subsequently asked the number of African countries in the United Nations. The subjects showed a bias towards the original number they were given. In general, anchoring refers to an irrelevant message having an effect on the outcome. Beggs and Graddy [2009] show that it matters whether a painting had been previously sold in a 'hot' vs. a 'cold' market using a limited dataset of repeat sales.

Loss aversion [Tversky and Kahneman, 1974] is related to anchoring, but with asymmetric effects depending upon whether the price has subsequently increased or decreased. Rather than expected utility where gains and loses are perceived with the same magnitude, losses weigh more heavily in the mind of individuals. In a classic demonstration of loss aversion, Genesove and Mayer [2001] show that home owners set higher asking prices for condominiums for which they have suffered nominal losses.

The time lapsed between two sales of an identical item can have an effect on the salience of the previous price as an anchor and can also have an effect on loss aversion. The tendency to place a larger value on an item in one's possession is called the endowment effect, which was introduced by Thaler [1980] and has been studied extensively since. Strahilevitz and Lowenstein [1998] find that for attractive items loss aversion tends to be greater the longer the good is held.

This research extends previous work on anchoring and loss aversion in three ways. First, it replicates previous results on anchoring and loss aversion using a *much larger* dataset of repeat art sales extending over a *much longer* period of time. This empirical study adds to a relatively small body of work that tests for behavioral biases using actual data rather than experimental data. Second, when using the previous sale price as an anchor, the research shows that the degree of anchoring and loss aversion may depend upon the time between repeat sales. Finally, we examine whether the behavioral biases of anchoring and loss aversion can be used to predict future returns.

This paper proceeds as follows. Section 2 discusses anchoring, loss aversion, and the variation of these behavioral biases over time. The model and the tests for behavioral anomalies are described in the section 3. In section 4 we present the data and summary statistics. Section 5 introduces the hedonic model for estimating predicted prices. In section 6 we discuss our empirical findings; section 7 discusses the predictability of returns and section 8 concludes our analysis.

# 2 Art Auctions and Behavioral Biases

## 2.1 Art Auctions

Art can be sold either through a dealer or through an auction house. The major auction houses are Christie's and Sotheby's, and the auction is conducted in the English, ascending auction format. Auction houses generally charge a buyer's premium of between 12.5 percent and 25 percent of the painting. The seller's premium is unknown and subject to negotiation.

Before the auction starts, the auctioneer will determine a pre-sale low and high estimate for the work of art and will publish the details of the work of art both online and in a catalogue. The pre-sale estimates are determined in conjunction with the seller; the seller also sets a secret reserve price that is equal to or below the pre-sale low estimate. If the bidding does not reach the secret reserve price, then a painting is said to be "bought in." The painting is not actually "bought in" by the auction house, but simply goes unsold and is returned to the seller. The seller can decide to list the item again at auction, take it to a dealer, or take it off the market. About 20 percent of paintings on average are "bought-in."

## 2.2 Anchoring

The anchoring heuristic was first introduced by Tversky and Kahneman [1974]. With few exceptions, most instances of anchoring have been introduced in laboratory or experimental settings. Some well known laboratory experiments in the field of economics include Ariely et al. [2003], Fudenberg et al. [2012] and Banerji and Gupta [2014]. Maniadis et al. [2014] demonstrate the limitations of experimental results on anchoring.

Northcraft and Neale [1987] were one of the first authors to use actual market data to demonstrate anchoring by investigating the effect of manipulating the alleged list price on valuations of properties by estate agents. This study, however, was not performed in a true market context as it involves valuations, not prices. Rajendran and Tellis [1994] and Greenleaf [1995] examine the importance of past prices when consumers repeatedly purchase the same commodity. Beggs and Graddy [2009] use actual market data on art auctions to demonstrate anchoring, and subsequently, anchoring has been studied in commercial real estate by Bokhari and Geltner [2011]. More recently, Dougal et al. [2014] have shown that anchoring influences the cost of capital.

When testing for anchoring or loss aversion, it is critical to separate out anchoring (where an 'irrelevant' message has an effect on the outcome) from rational learning (where past prices are important because they represent unobservable quality effects). The identification strategy we use in this paper is similar to the strategy used in Genesove and Mayer [2001] and again later in Beggs and Graddy [2009]. We can identify anchoring from other effects because the demand for art, which is captured by the average overall price index, changes over time, whereas the unobservable component of quality is assumed to remain constant between auctions. This allows us to control for unobserved quality characteristics. As long as something drastic has not happened between sales—such as a painting has been deemed a fake, which is a very rare occurrence—the assumption of constant quality is a realistic one.

It is worth noting that anchoring on a previous price can be applied to sellers, buyers, or auctioneers. For example, it is possible that buyers are directly influenced by previous sale prices or that auctioneers' pre-sale estimates anchor on previous sale prices, and the buyers (and sellers with their undisclosed reserves), are influenced by auctioneers' expert opinions. In many ways, art and real estate are natural goods in which to study anchoring on previous prices. Both types of markets involve goods that are unique and difficult to value. In these types of goods, it is natural that individuals use a heuristic when making decisions on price. There are, of course, many different prices on which participants in auctions can focus. These include estimates, reserve prices [Rosenkranz and Schmitz, 2007] and buy prices [Shunda, 2009], as well as endogenously determined reference prices [Lange and Ratan, 2010, Ahmad, 2013].

## 2.3 Loss Aversion

In a series of papers on prospect theory, Kahneman and Tversky [1979] show that the outcome of risky prospects are evaluated by a value function with three characteristics: first, gains and losses are dependent on a reference point; second, the value function is steeper for losses than for equivalently sized gains (loss aversion); and third, diminishing sensitivity to gains and losses. Loss aversion can result in a reluctance to realize a loss [Shefrin and Statman, 1985]. As loss aversion encourages owners to increase their secret reserve price, some items will not sell immediately at auction, resulting in these owners holding these items for a longer period of time.

The role of a "loss" was first studied in a number of experimental papers, providing strong evidence that people prefer to avoid realizing losses. The empirical evidence resulting from observing the outcomes of pairs of concurrent decisions is that the magnitude of the impact of losses over gains results in losses being weighted just over twice as heavily as gains.

Indeed loss aversion has been studied much more widely outside experimental settings than anchoring. In addition to Genesove and Mayer [2001] and Bokhari and Geltner [2011], loss aversion has been studied extensively in the finance literature including papers by Benartzi and Thaler [1995] and Barberis et al.

[2001] on the stock market, Hung and Wang [2011] on interest rates, and Froot et al. [2011] in currency markets. Eichholtz and Lindenthal [2012] look at loss aversion in real-estate markets over time and across generations. Jullien and Salanie [2000] look at the effect of loss aversion on race track betting. Our research is one of few attempts to measure differences in effects due to both loss aversion and anchoring.

The tendency to place a larger value on an item when it is in one's possession is called the "endowment effect", which was introduced by Thaler [1980]. Strahilevitz and Lowenstein [1998] take this one step further by studying the effect of ownership history on the valuation of objects. They find that one's valuation increases with the duration of ownership, in contrast to the "instant endowment" effect as labelled by Kahneman et al. [1990]. Ownership makes an individual increasingly averse to losses. This idea is reaffirmed and extended by Brenner et al. [2007] in a paper that shows that this effect is stronger for attractive items.

At first glance, loss aversion is an idea that applies to sellers; sellers are the individuals who are averse to realizing actual losses. However, much of the recent theoretical literature shows that buyers can be considered loss-averse relative to some endogenous reference point. In this case, the endogenous reference point could be influenced by the previous sale price. This literature draws on the expectations-based model of Kőszegi and Rabin [2006]. Applications of endogenously determined reference points in an auction context include Lange and Ratan [2010], Shunda [2009], and Ahmad [2013]. Furthermore, in art auctions sellers almost always set a secret reserve price. This secret reserve price can end up raising the auction price if the bidder with the second highest reservation value has a valuation below the secret reserve, and the highest bidder's valuation is above the secret reserve. In cases where the highest bidder's reservation value is below the secret reserve, the item will go unsold. In this paper, we do not try to identify the source of loss aversion.

# 3 Testing for Anchoring and Loss Aversion

This paper combines the loss aversion model of Genesove and Mayer [2001] and the anchoring model of Beggs and Graddy [2009] so that both of these behavioral biases can be studied at the same time in a single framework.

The equation which we estimate to test for anchoring and loss aversion for each painting sold at time t has the following form in log prices:

$$p_{it} = a_0 + a_1\pi_{it} + a_2(p_{it-1} - \pi_{it}) + a_3(p_{it-1} - \pi_{it-1}) + a_4\Phi(\phi, \tau) + \eta_{it} \qquad (1)$$

The first term of equation 1 above, $a_0$, is a constant. The second term, the predicted price, $\pi_{it}$, is constructed from a hedonic price model, $\pi_{it} = \mathbf{X_i}\mathbf{B} + \delta_t$, where $\mathbf{X_i}$ represents characteristics of work $i$, $\mathbf{B}$ is a vector of coefficients on these characteristics, and $\delta_t$ is a time effect.

The third term, $a_2(p_{it-1} - \pi_{it})$, captures the anchoring effect. If there is anchoring, then the final price will be adjusted by a proportion of the difference between the predicted price and the previous price. The adjustment will be identical whether the predicted price is above or below the previous price. The derivation of equation 1 is provided in the Appendix.

The fourth term, $a_3(p_{it-1} - \pi_{it-1})$, in equation 1 controls for unobservables. Because the econometrician cannot observe the actual predicted price, there is an unobservable effect in this term that is correlated with the previous sale price of the painting. The identifying assumption is that the characteristics stay the same over time. In this case, the unobservable effect will be equal to the difference between last period's price and last period's prediction.

The fifth term in the equation, $a_4\Phi(\phi, \tau)$, is the loss aversion effect, which captures the differential effect of a loss relative to a gain. The loss aversion term is the absolute value of the expected loss, if there is a loss; otherwise the term is zero. Because there is an unobservable quality effect in this nonlinear loss term, the quality effect cannot be easily factored out as it was in the anchoring term. Thus, a nonlinear estimate is required. As explained in more detail in the appendix, $\phi$ and $\tau$ are the parameters that define the distribution of the sellers' ex-ante expected loss. A significant and positive coefficient on this term indicates loss aversion. If the loss aversion effect is zero, then there is symmetry between gains and losses, and the term can be dropped; this is then equivalent to the simple model estimated in Beggs and Graddy [2009].

In addition to estimating the full nonlinear model below, we also estimate a linear version of the model where the unobservable effects in the anchoring term are ignored. Genesove and Mayer [2001] demonstrate theoretically that the linear coefficients on the anchoring effect in the linear model provide a lower bound for the anchoring effects in the nonlinear regression.

We estimate equation 1 with two different dependent variables: $\ln(price)$ and $\ln(estimate)$. We allow for heteroskedasticity of the error term, $\eta_{it}$.

## 4 Data and Summary Statistics

The data come from a database put together by Jianping Mei, Mike Moses and Rachel Pownall, and are used to construct the Mei Moses Fine Art Index®. Parts of the data have been used in various academic papers, including Mei and Moses [2002, 2005] and De Silva et al. [2012].

The data covers the American and European market, principally New York and London. It contains all Impressionist and Modern paintings sold at the main sales rooms of Sotheby's and Christies (and their predecessor firms) from

1950 to 2011. If a painting had listed in its provenance a prior public sale, at any auction house anywhere, that sale was also included. Some paintings had multiple resales over many years resulting in up to six resales for some works of art. Each resale pair was considered a unique point in the database. Some of the original purchase dates went back to the 17th century. If the art piece was sold overseas, the sale price was converted into US dollars using the long-term exchange rate data provided by Global Financial Data. The data has continuous observations since 1875.

The number of observations in our resale data by year of purchase and sale from 1875-2011 are depicted in Figure 1. For convenience, we will call the first price from each price pair "purchase price" and the second price "sale price" from the perspective of the collector for the time period between the two transactions corresponding to the price pair. The database for this time period contains 6411 price pairs. We can see that our data is rather spotty for the beginning of our sample but increases rapidly after 1940. We can also see that most artworks bought are held for long time periods (on average 16 years) so that not many purchases in the early years are sold right away. Since the data from Beggs and Graddy [2009] only cover a ten year period between 1980-1990, they left out most paintings that were held for long time periods. Moreover, our data contains 6411 repeated sales pairs, comparing to just 94 pairs by Beggs and Graddy [2009]. This significant increase in sample size allows us to examine a more complex model of behavioral bias that includes anchoring, loss aversion as well as the endowment effect.

Figure 1: Number of Observations by Purchase and by Sale

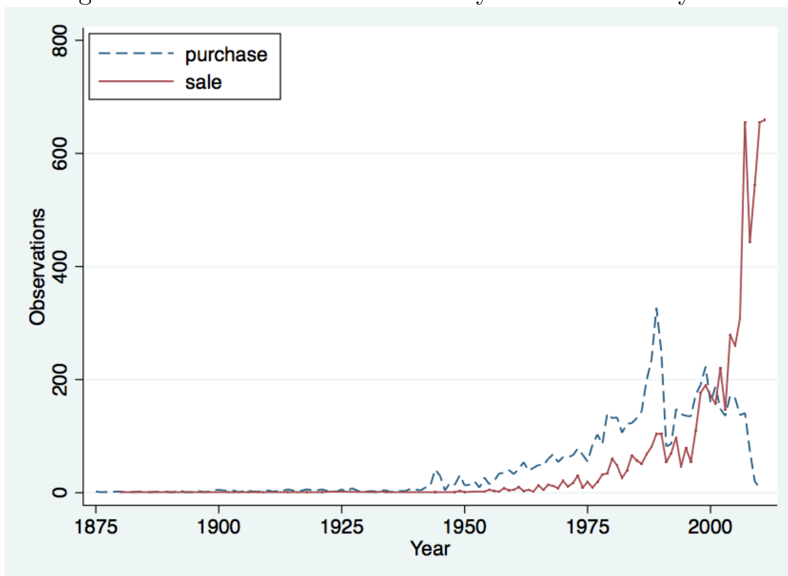



Table 1 provides summary statistics on the purchase price, the sale price, the high estimate and low estimate at purchase and sale, and the months since the last sale. All prices are in US dollars. (Note: all price pairs are converted to end of year US prices). Clearly the auction sales prices indicate that the paintings sold are from the high end of the market. Sotheby's and Christies, the two major art auction houses for the New York and London art markets, represent a large fraction of the data sample. The average sales price is $751,172 and the average purchase price is $289,406, with an average holding period of about 16 years. In addition to information on the sale price, date sold, and the auction house's low and high estimates, the dataset includes information about the artist such as birth year, death year and country. It also includes descriptive information about the painting, such as its dimensions, shape, medium, whether it was signed and dated and the date it was painted.

Note that a painting may have changed hands through a private sale or may have been bequeathed to a new owner between the first and second recorded

Table 1: Summary statistics

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| Purchase price | 289406 | 1172048 | 4 | 29150000 | 6411 |
| Sale price | 751172 | 2878625 | 23 | 80451176 | 6411 |
| Sale high estimate | 707047 | 2423097 | 735 | 59080000 | 5899 |
| Sale low estimate | 513670 | 1755471 | 441 | 44310000 | 5899 |
| Purchase high estimate | 386364 | 1164394 | 700 | 20000000 | 3306 |
| Purchase low estimate | 281085 | 854031 | 440 | 16000000 | 3318 |
| Sale year | 2001 | 12 | 1880 | 2011 | 6411 |
| Purchase year | 1985 | 19 | 1875 | 2010 | 6411 |
| Holding period | 16.4 | 13.8 | 0.6 | 123.3 | 6411 |

auction sales. It is also possible that a painting came to auction and did not sell between the two observed sales. To the extent that anchoring and loss aversion are driven by the seller's knowledge of the previous price, this could potentially provide a downward bias to the data, as the regressors would be conditioning on the "wrong" previous price. However, it is likely that any downward bias is small as the large majority of important sales of art (unlike violins!) take place at auction and the buy-in rate (the rate at which paintings go unsold because they do not meet their reserve price) is low in a sample of repeat sales that contain relatively important pieces. In addition, the buyer and the auctioneer may be using the published and readily accessible auction price as the reference, even in the presence of a previous sale. We therefore do not take account of this potential downward bias in our regressions or interpretations below.

Goetzmann (1993) also argues that the decision by an owner to sell a work of art (and consequently the occurrence of a repeat sale in the sample) could be conditional upon whether or not the value has increased. We also do not observe those paintings that have been bought in by the auction house due to high reservation prices set according to loss aversion. As a result, our data may suffer from a sample selection bias against loss aversion. As a result, we should interpret our estimate as a lower bound on the effect of loss aversion.

## 5 Hedonic Regressions

In order to conduct the empirical tests set out in section 3, it is first necessary to construct a predicted price for the current sale and a predicted price for the purchase. One method to construct a predicted price is by hedonic regression, in which the log price is regressed on various painting characteristics as well as year fixed effects. The characteristics that are used in the hedonic regressions are length, width, whether the painting is signed, whether the painting is dated, and fixed effects for the medium, the artist, and the year.

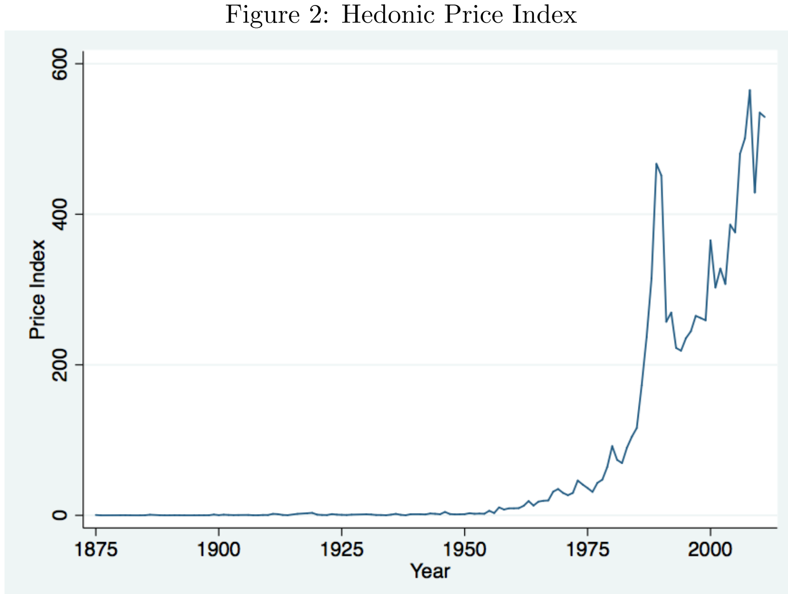
The regression results from the hedonic regression are presented in Table 2. The coefficients from this regression are used to construct a predicted price for each painting.

Table 2: Hedonic Regression

| Dependent Variable: ln (Sale Price) | |
|---|---|
| Painting is Dated | .196 |
| | (.023)*** |
| Log of Width (inches) | .628 |
| | (.031)*** |
| Log of Height (inches) | .799 |
| | (.031)*** |
| Painting is Signed | .149 |
| | (.037)*** |
| Medium Fixed Effects | yes |
| Artist Fixed Effects | yes |
| Year Fixed Effects | yes |
| Obs. | 12536 |
| $R^2$ | .793 |

The value of a painting increases as both the height and the width increases, and signed and dated paintings both have significant positive effects. The artist, medium and time fixed effects are each jointly statistically significant at the .001 level. Note that the number of observations is not quite twice as high as the number of observations when each painting is grouped as a purchase and a sale, as a repeat sale. This discrepancy is because some paintings are sold more than twice. Below is a graph of the price index, calculated as the exponential of the coefficients from the year fixed effects in the above hedonic regression, from 1875 to the present.[1]

Figure 2: Hedonic Price Index




Although the general trend has been up, the index indicates ample opportunity for both increases and decreases in price. The pattern is similar to other estimates of art price indices, such as Mei and Moses [2005] and Renneboog

[1] An interesting check would be to test whether individuals were anchoring on real prices or nominal prices by deflating prices by the art index (rather than CPI). However, it is changes in the art index that identify the anchoring and loss aversion effects from the unobservable term.

and Spaenjers [2013]. The bubble in the late 1980s is most often explained by the increase in wealth driven by asset prices. The subsequent fall in wealth and the withdrawal of the Japanese from the art market after the Japanese stock market crash is often cited for this decline. Goetzmann et al. [2011] provide a discussion and analysis of the relationship of art to income and wealth.

# 6 Empirical Results

In this section, we estimate equation 1 above and attempt to separate out anchoring from loss aversion using both the log sale price and the log of the low estimate as dependent variables. In Table 3 we present the regression results for the full sample, and in Table 4, we present results for the sample split at five years.

Note that this model, as in Genesove and Mayer [2001], Beggs and Graddy [2005, 2009], Bokhari and Geltner [2011], and other work relies on the assumption that the correct model for price in the absence of anchoring and loss aversion is a prediction of price, adjusted by the difference between the prediction the previous time the work was sold and the previous price:

$$p_{it} = b_1 \pi_{it} + b_2 (p_{it-1} - \pi_{it-1}) \tag{2}$$

We begin with this specification in columns 1 and 4 of Table 3 below.

## 6.1 Full Sample

As a preface to our main regression, we can see from column 1 of Table 3 that when we estimate equation 2, the coefficients on the predicted price are statistically significantly different from one, though they are very close to one in value. These coefficients are reassuring in the absence of other regressors as they indicate that modeling price as the predicted price plus an adjustment is at least consistent with the data.

In columns 2 and 5 we estimate a linear version of the regression where we ignore the unobservables in the loss aversion term, and in columns 3 and 6, we present our non-linear results. Our nonlinear estimation technique is described in detail in the Appendix. All standard errors reported are robust standard errors, and all variables are in natural logarithms.

Table 3: Linear and Nonlinear Regression Results

| | Sale Price | | | Low Estimate | | |
|---|---|---|---|---|---|---|
| | Linear | Linear | Nonlinear | Linear | Linear | Nonlinear |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Predicted Price | 1.005*** | 1.053*** | 1.058*** | 0.974*** | 1.070*** | 1.078*** |
| | (0.001) | (0.007) | (0.006) | (0.001) | (0.007) | (0.006) |
| Anchoring | | 0.011 | 0.088*** | | -0.009 | 0.065*** |
| | | (0.019) | (0.013) | | (0.019) | (0.013) |
| Loss Aversion | | 0.457*** | 0.533*** | | 0.444*** | 0.600*** |
| | | (0.037) | (0.044) | | (0.040) | (0.095) |
| Unobservable Quality | 0.664*** | 0.548*** | 0.518***[2] | 0.688*** | 0.599*** | 0.568*** |
| | (0.015) | (0.024) | | (0.016) | (0.025) | (0.026) |
| Holding Period | | 0.006** | 0.008*** | | 0.002 | 0.004*** |
| | | (0.002) | (0.001) | | (0.002) | (0.001) |
| Constant | | -0.727*** | -0.733*** | | -1.268*** | -1.308*** |
| | | (0.077) | (0.065) | | (0.087) | (0.070) |
| $1-\phi$ | | | 0.432***[3] | | | 0.392***[4] |
| $\ln(\tau)$ | | | -2.519 | | | -2.519 |
| Obs. | 6411 | 6411 | 6411 | 5899 | 5899 | 5899 |
| $R^2$ | * | 0.850 | 0.853 | * | 0.845 | 0.879 |

In this specification, the coefficient on the predicted price is close to one in magnitude, as it should be. Furthermore, the coefficient on unobservable quality

[2] 99 percent confidence interval based on bootstrapped percentiles: $[0.5063, 0.5871]$
[3] 99 percent confidence interval based on bootstrapped percentiles: $[0.3819, 0.4422]$
[4] 99 percent confidence interval based on bootstrapped percentiles: $[0.3216, 0.4146]$

is large and highly significant; if, for example, the price was 100 percent greater than the predicted price during the previous sale, then this in itself will raise the price for the current sale by a little over 50 percent. Finally, the longer the holding period for a work of art, the higher the price: each ten year increase in holding period increases the price by around 6 percent.

The regression results indicate that both anchoring effects and loss aversion effects are present, though the anchoring coefficient is only statistically significant in the nonlinear results. An interpretation of the anchoring and loss aversion results in the nonlinear regressions is that a 10 percent unrealized or expected loss (that is, a positive difference between the previous price and the current predicted price), results in a 6.2% increase in price relative to what the sale price would have been in the absence of anchoring and loss aversion. Of this difference, 0.9 percent is due to anchoring, and 5.3 percent of this difference is due to loss aversion. A 10 percent expected gain (that is, a negative difference between the previous price and the predicted price) results in a 0.9 percent decrease in price relative to what the sale price would have been in the absence of anchoring.

The larger loss aversion coefficient in the nonlinear regression is consistent with the Genesove and Mayer [2001] prediction.

Here it is not possible to tell whether the sale price adjustments result because of anchoring on the part of the buyer, the seller, or the "expert" auctioneer. Generally the pre-sales estimate is set by the seller in consultation with the auction house, which gives an indication of the extent of the anchoring on the sellers behalf. However, it is instructive to see if results using the pre-sale estimate are consistent with the above results.

We find that the results from regressions using the log of the pre-sale low estimate as the dependent variable are very similar to the regressions when price is used as a dependent variable. The effect of loss aversion on the low pre-sale estimate is not significantly different than when the sale price is used, though the point estimate is slightly larger. As the pre-sale low estimate is set in conjunction with the seller's secret reserve, this would be expected.

One initial interpretation of these regressions is that the pre-sale estimates are 'correct' (for items that are sold), and that auction house experts do a good job in predicting current prices. That is, the estimates accurately reflect the determinants of price. The hedonic pricing function is a good indicator of the pre-sale estimate and the coefficients are similar in magnitude to those in columns 1 and 2.

The coefficients of interest from the above table—the coefficients on anchoring and loss aversion—contrast with previous results of Beggs and Graddy (2005, 2009) who only find symmetric anchoring effects. In their study, the coefficient on loss aversion is not significantly different from zero. While we find anchoring effects in this paper in the nonlinear specification, we also find significant asymmetric effects that are attributable to loss aversion.

There are two primary differences between this dataset and the dataset used in Beggs and Graddy (2005, 2009). First, this dataset is much, much larger, with 6411 repeat sales observations as opposed to only 76 observations used in the anchoring regressions for the Impressionist Art dataset in Beggs and Graddy [2005, 2009]. The fact that Beggs and Graddy [2005, 2009] do not find significant loss aversion effects could very well be due to the very small sample size. A finding of anchoring in their study is notable given the small size of the sample. Second, this dataset covers a much longer sample period, from 1875-2011, while Beggs and Graddy (2005, 2009) only look at a short sample period of 1980-1990 for Impressionists. Thus, their data left out those sales with long holding periods, where the effect of loss aversion are likely to be more prominent.

## 6.2 Split Sample Results

The second primary difference between the two datasets is the holding period. In the dataset used in this paper, the average time between sales is about 16 years. In Beggs and Graddy [2005, 2009], the average time between sales is just over 3 years. When Beggs and Graddy [2009] restrict the time sample to sales that took place within a three and a half year period, the anchoring effects become stronger, especially in the very small (22 observations) Contemporary Art sample.

In Tversky and Kahneman [1982], salience is an important part of biases in judgement. One would expect an anchor to be more salient if a work was sold relatively recently rather than a long time ago. However, the endowment effect may become stronger if a painting is held for a long period of time, as noted by Strahilevitz and Lowenstein [1998].

Running the regression in equation 1 over the two subsamples, we observe the anchoring and loss aversion behavior for short and long holding periods. In Table 4, we present these two subsamples. When paintings are resold relatively quickly, within a 5 year period, we find the coefficient for anchoring to be significantly larger for shorter holding periods in both the linear and nonlinear regressions when the natural log of the sale price is used as the dependent variable. This result is consistent with salience: for the short term period, salience of the purchase price is likely to lead to the significantly larger coefficient. Interestingly, when the natural log of the low estimate is used as the dependent variable, the anchoring effects are not as large for the shorter time period, though the point estimates are still larger than the point estimates for the longer time period.

For loss aversion, for the linear regression we find that for both dependent

Table 4: Linear and Nonlinear Regression Results with One Break at 5 Years

| | Sale Price | | | | Low Estimate | | | |
|---|---|---|---|---|---|---|---|---|
| | Linear | Nonlinear | Linear | Nonlinear | Linear | Nonlinear | Linear | Nonlinear |
| | $< 5$ | $< 5$ | $\geq 5$ | $\geq 5$ | $< 5$ | $< 5$ | $\geq 5$ | $\geq 5$ |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Predicted Price | 1.021*** | 1.036 | 1.059*** | 1.065 | 1.043*** | 1.044 | 1.075*** | 1.087 |
| | (0.012) | 0.009 | (0.008) | 0.007 | (0.011) | 0.009 | (0.009) | 0.007 |
| Anchoring | 0.153* | 0.189*** | 0.010 | 0.085*** | 0.071 | 0.131*** | -0.004 | 0.065*** |
| | (0.068) | (0.059) | (0.020) | (0.014) | (0.071) | (0.064) | (0.021) | (0.015) |
| Loss Aversion | 0.233*** | 0.485***[5] | 0.458*** | 0.392***[6] | 0.200*** | 0.340[7] | 0.449*** | 0.475**[8] |
| | (0.064) | | (0.045) | | (0.057) | | (0.047) | |
| Unobservable Quality | 0.587*** | 0.611***[9] | 0.532*** | 0.510***[10] | 0.712*** | 0.708***[11] | 0.579*** | 0.574***[12] |
| | (0.065) | | (0.026) | | (0.072) | | (0.027) | |
| Holding Period | 0.021 | 0.004 | 0.006** | 0.008*** | -0.021 | -0.021*** | 0.003 | 0.005*** |
| | (0.015) | (0.012) | (0.002) | (0.001) | (0.012) | (0.012) | (0.002) | (0.001) |
| Constant | -0.300* | -0.402*** | -0.810*** | -0.827*** | -0.756*** | -0.734*** | -1.341*** | -1.427*** |
| | (0.136) | (0.112) | (0.091) | (0.078) | (0.140) | (0.120) | (0.102) | (0.082) |
| $1-\phi$ | | 0.246***[13] | | 0.442***[14] | | 0.186[15] | | 0.387***[16] |
| | | | | | | | | |
| $\ln(\tau)$ | | -2.519 | | -2.519 | | -2.519 | | -2.519 |
| Obs. | 1087 | 1087 | 5324 | 5324 | 946 | 946 | 4953 | 4953 |
| $R^2$ | 0.928 | 0.931 | 0.833 | 0.836 | 0.935 | 0.953 | 0.831 | 0.861 |

[5] 99 percent confidence interval based on bootstrapped percentiles: $[0.3841, 0.5405]$
[6] 99 percent confidence interval based on bootstrapped percentiles: $[0.3630, 0.4025]$
[7] 90 percent confidence interval based on bootstrapped percentiles: $[-0.0494, 0.7972]$
[8] 95 percent confidence interval based on bootstrapped percentiles: $[0.0592, 0.5548]$
[9] 99 percent confidence interval based on bootstrapped percentiles: $[0.4294, 0.7591]$
[10] 99 percent confidence interval based on bootstrapped percentiles: $[0.4467, 0.5979]$
[11] 99 percent confidence interval based on bootstrapped percentiles: $[0.0068, 0.9578]$
[12] 99 percent confidence interval based on bootstrapped percentiles: $[0.1691, 0.8373]$
[13] 99 percent confidence interval based on bootstrapped percentiles: $[0.1407, 0.3618]$
[14] 99 percent confidence interval based on bootstrapped percentiles: $[0.3668, 0.4975]$
[15] 99 percent confidence interval based on bootstrapped percentiles: $[0, 0.9678]$
[16] 99 percent confidence interval based on bootstrapped percentiles: $[0.1106, 0.7638]$

variables, the natural log of the sale price and the natural log of the low estimate, that loss aversion appears to have a statistically larger effect for the longer periods than for the shorter periods. However, we find no significant difference in coefficients for the nonlinear results, though for the low estimate, the point estimate on loss aversion only becomes statistically significant for the longer holding period. The strength of the low estimate results may be due to the fact the the low estimate is set in conjunction with the seller and must be at or above the seller's secret reserve price. The above results provide convincing evidence that the anchoring effect is stronger for shorter holding periods, and some evidence that the loss aversion effect is stronger for longer holding periods.

## 7 Prediction of Future Returns

In the previous section we identified the presence of an anchoring effect and a loss aversion effect. Does this mean that we can predict excess returns: can we identify those paintings which are likely to outperform the art market returns out of sample? We test this by putting together yet another unique dataset of items that have been sold three times or more. The dataset is summarized in Table 5 below.

Table 5: Summary statistics

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| Sale price 0 | 207364 | 898942 | 21 | 10780000 | 583 |
| Sale price 1 | 553771 | 1866588 | 23 | 22552500 | 583 |
| Sale price 2 | 1199527 | 4226424 | 75 | 68962496 | 583 |
| Sale year 0 | 1971 | 24 | 1875 | 2006 | 582 |
| Sale year 1 | 1986 | 18 | 1880 | 2009 | 583 |
| Sale year 2 | 2000 | 12 | 1886 | 2011 | 583 |
| Holding period 1 | 15 | 15 | 1 | 90 | 582 |
| Holding period 2 | 14 | 14 | -14 | 97 | 583 |

As what this dataset contains is a subset of our first dataset, we first reestimate equation 1. This replication is presented in column 1 of Table 6 below. The results are very similar to our previous results, with the exception that the point estimates of the anchoring effect and the holding period are smaller and not significant in this smaller sample.

Secondly, we test whether any of these components—the unobservable component, the anchoring and loss component, or the holding period—has an effect on future excess returns in an out-of-sample regression. Specifically our regression is as follows, where the prices at the three sales are denoted $p_0$, $p_1$, and $p_2$ respectively, and years between the first two sales and second two sales are denoted $T_1$ and $T_2$.

$$\begin{aligned}\frac{p_2 - p_1}{T_2} - \frac{p_2^m - p_1^m}{T_2} &= \beta_0 + \beta_1(\pi_1) \\ &+ \beta_2(p_0 - \pi_0) + \beta_3(p_0 - \pi_1) + \beta_4(p_0 - \pi_1)^+ + \beta_5(T_1) + \epsilon_\beta \quad (3)\end{aligned}$$

The results are presented in column 2 of Table 6. Despite the fact that loss aversion significantly increases price as shown in column 1, this increase in price does not translate into a decrease in returns.

However, if a painting trades for much higher than its predicted price in the first sale, this is likely to significantly decrease excess returns generated by the second sale. Likewise, if a painting trades for much lower than its predicted price in the first sale, this is likely to significantly increase excess returns generated by the second sale. Thus, we find strong evidence that over or underpayment, as defined by the difference between the actual price and the predicted price, provides a reliable predictor of future returns. Thus, the results seem to suggest that one should avoid those paintings over-paid by previous collectors and favor those paintings where previous collectors had a bargain. We replicated the regression in column 2 using the low pre-sale estimate for the predicted price, rather than our prediction. We did not find that the difference between the first price and the low pre-sale estimate was a predictor of future excess returns.

Table 6: Excess Returns

| | Saleprice | Excess |
|---|---|---|
| | (1) | (2) |
| Predicted Price 1 | 1.000 | .001 |
| | (.016)*** | (.003) |
| Anchoring | -.023 | .008 |
| | (.042) | (.006) |
| Loss Aversion | .529 | .003 |
| | (.090)*** | (.014) |
| Unobservable Quality | .434 | -.025 |
| | (.050)*** | (.009)*** |
| Holding Period 1 | .006 | .0007 |
| | (.004) | (.0006) |
| Const. | -.182 | -.016 |
| | (.178) | (.035) |
| Obs. | 496 | 496 |
| $R^2$ | .913 | .017 |

# 8 Conclusion

In this paper, we find new evidence for the behavioral biases of anchoring and loss aversion. We find that anchoring is more important for items that are resold quickly, and we find that the effect of loss aversion increases with the time that a painting is held. The evidence in favor of anchoring with this large new dataset validates previous results from Beggs and Graddy [2009] on anchoring and from Genesove and Mayer [2001] on loss aversion and adds to the empirical evidence a finding of increasing loss aversion with the length a painting is held.

A contribution of this paper is that not only can we identify behavioral biases, but we also have the data to test whether investors can take advantage of these behavioral biases. We do not find any evidence that this is the case. It does not appear to be the case that excess returns be earned by understanding these behavioral biases. However, we do find that paintings over-paid by previous collectors have a higher probability of earning lower returns. Equivalently, we find that those paintings where previous collectors had a bargain tend to earn higher returns.

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# Appendix: Motivation of Estimating Equation and Explanation of Nonlinear Least Squares (NLS) Estimation

We first explain the theory behing equation 1, the estimating equation, which is largely adapted from Beggs and Graddy [2005]. We then explain the details of the nonlinear least squares estimation, starting with the grid search and ending with the inference.

## The Estimating Equation

We start with the assumption that the auctioneer believes the true model for value of each painting i is given by:

$$p_{it} = \pi_{it} + u_i + \epsilon_t$$

Both $u_i$ (unobserved value) and $\epsilon_t$ (shocks to that particular period) are i.i.d. normal, and $\pi_{it} = \mathbf{X_i B} + \delta_t$,

The auctioneer observes $p_{it-1}$, $\pi_{it-1}$, and a signal $w_i$—representing the knowledge of the auctioneer. $w_i$ is jointly normally distributed with $u_i$.

In a world with perfect information, $w_i = u_i$. But in a world with imperfect information, we would expect the auctioneer's estimate to satisfy the following equation:

$$Est_{it} = \pi_{it} + v_i$$

where

$$v_i = E(u_i | \pi_{it-1}, p_{it-1}, w_i)$$

The econometrician does not observe the auctioneer's estimate of quality: $v_i$. Since $v_i$ depends on the painting's previous price and price estimate, this gives a conditional estimate of the unobserved quality:

$$E(v_i|\pi_{it-1}, p_{it-1}) = E(u_i|\pi_{it-1}, p_{it-1})$$

Furthermore, from joint normality of $w_i$ and $u_i$, we have:

$$E(u_i|\pi_{it-1}, p_{it-1}) = \phi(p_{it-1} - \pi_{it-1})$$

where $\phi$ is a constant. If the variance of $u_i$ and $\epsilon_t$ are $\sigma_u^2$ and $\sigma_\epsilon^2$ respectively, then $\phi = \sigma_u^2/(\sigma_u^2 + \sigma_\epsilon^2)$. The closer $\phi$ is to 1, the larger the uncertainty in unobserved quality in comparison to idiosyncratic shocks.

We can then write:

$$Est_{it} = \pi_{it} + \phi(p_{it-1} - \pi_{it-1}) + \omega_{it}$$

where $\omega_{it}$ is orthogonal to the other terms.

This equation is then updated to account for both anchoring and loss aversion. Similar techniques apply for including a term to account for anchoring, since it is linear. However, things become more complicated when accounting for loss aversion, because it is nonlinear.

The ideal equation to estimate is the following:

$$Est_{it} = \pi_{it} + v_i + \lambda(p_{it-1} - v_i - \pi_{it}) + v(p_{it-1} - v_i - \pi_{it})^+$$

Here the third term accounts for anchoring and the last term captures loss aversion. Without the loss aversion term, the equation can still be estimated using OLS by taking expectations of the equation conditional on observed variables and using properties of conditional expectations to rewrite the equation with $v_i$ in the error term.

However, because the loss aversion term is the positive part of a difference of observed and unobserved ($v_i$) variables, we cannot apply the same technique. Assuming the auctioneer observes quality perfectly, implying that $u_i = v_i$, we get:

$$(p_{it-1} - \pi_{it} - v_i)^+ = (\pi_{it-1} - \pi_{it} + \epsilon_{t-1})^+$$

Conditional on $p_{it-1}$ and $\pi_{it-1}$, $\epsilon_{t-1}$ is Normal with mean $(1-\phi)(p_{it-1} - \pi_{it-1})$.

The expectation of $(p_{it-1} - \pi_{it} - v_i)^+$ conditional on the observable variables is then equal to the expectation of $U^+$ where $U$ has a normal distribution with mean

$$\pi_{it-1} - \pi_{it} + (1-\phi)(p_{it-1} - \pi_{it-1})$$

and some variance $\tau^2$. Under the assumptions above $\tau = \sigma_\epsilon^2 \phi$. We denote the expectation of $U^+$ with $z(\phi, \tau)$. We add a constant to the equation to be estimated and rewrite the estimating equation as:

$$Est_{it} = a_0 + a_1\pi_{it} + a_2(p_{it-1} - \pi_{it}) + a_3(p_{it-1} - \pi_{it-1}) + a_4\Phi(\phi, \tau) + \eta'_{it}$$

where $\eta'_{it}$ is orthogonal to the other regressors and has zero conditional expected value. The above theory implies two restrictions on the coefficients: that $\phi$ lies between 0 and 1 and that the coefficient on the unobservable quality term $(p_{t-1} - \pi_{t-1})$, $a_3$ above, should equal $\phi(1 - a_2)$ where $a_2$ is the coefficient on the anchoring regressor above.

Finally, if we assume that the auctioneer's estimates are unbiased predictors of price and let $\Phi(\phi, \tau)$ be represented by $\Phi$, then our final result is equation 1 in the text:

$$p_{it} = a_0 + a_1\pi_{it} + a_2(p_{it-1} - \pi_{it}) + a_3(p_{it-1} - \pi_{it-1}) + a_4\Phi + \eta_{it}$$

Below we explain how this equation can be estimated using non-linear least squares. Consistency and asymptotic normality (and accounting for measurement error) of the estimator follows from Hsiao [1989].

## Non-linear Least Squares Estimation

### The Grid Search

We start by calculating $\Phi(\phi, \tau)$ for given values of $\phi$ and $\tau$. The value of $\Phi(\phi, \tau)$ is the expected value of $U^+$, which is the normal distribution $U$ truncated at zero: a value that depends on both $\phi$ and $\tau$. The values of the remaining parameters that minimize the sum of squared errors—$SSE(\phi, \tau)$—are determined by OLS. This procedure is repeated over a grid of different values of $\phi$ and $\tau$ to find the overall minimum SSE. The grid was set to have rectangular tiles of 0.05 for divisions of $\tau$ and 0.005 for $\phi$ with values of $\phi$ ranging between 0 and 1 and the values of $\ln(\tau)$ range between -10 and 2. The restriction on the coefficient for unobservable quality is imposed during the grid search.

The surface that results does not reveal an obvious minimum value for the value of $\tau$, but it provides a solid estimation for $\phi$. For this value of $\phi$, the SSE is almost entirely flat, but decreasing slowly as $\tau$ increases, with one bigger drop when $\tau$ is approximately equal to negative one. In addition to resulting in a higher SSE, the coefficient estimates for very small values of $\tau$ result in all zero estimates for the value of the expected loss term, which does not seem reasonable

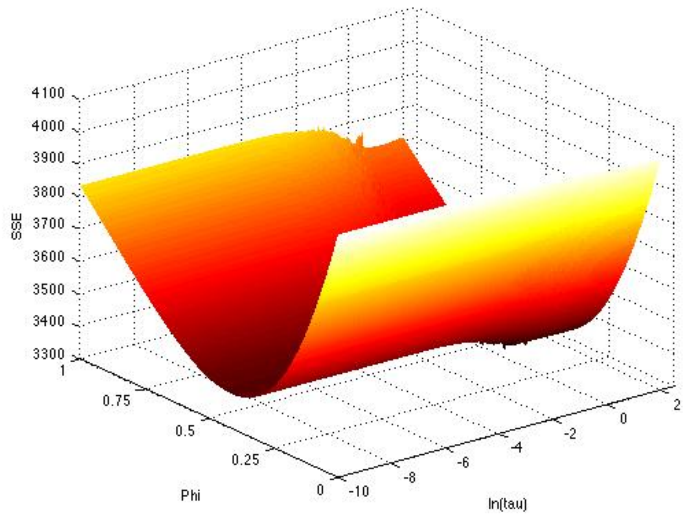


Figure 3: Grid search using the sale price as the dependent variable.

so we forgo very small values of $\tau$. High values of $\tau$ result in coefficients for the loss aversion term that do not make economic sense—although those coefficient values are higher and more significant than the values reported—so we forgo very high values of $\tau$. Since the SSE is slightly decreasing as $\tau$ increases, we choose a reasonable value of $\tau$— on the high end of our range for the grid search, but excluding the highest values—and report results for these values of $\phi$ and $\tau$. For the range of values of $\tau$ that produce reasonable results, the point estimates for the coefficients do not vary significantly, so the results are robust to values of $\tau$ over a fairly large range.

A hill climbing algorithm could have been used to further refine the value of $\phi$ once the grid search determined there weren't multiple minima. But this is unnecessary since we re-ran the grid search using a finer grid for $\phi$ and found no significant changes in the results.

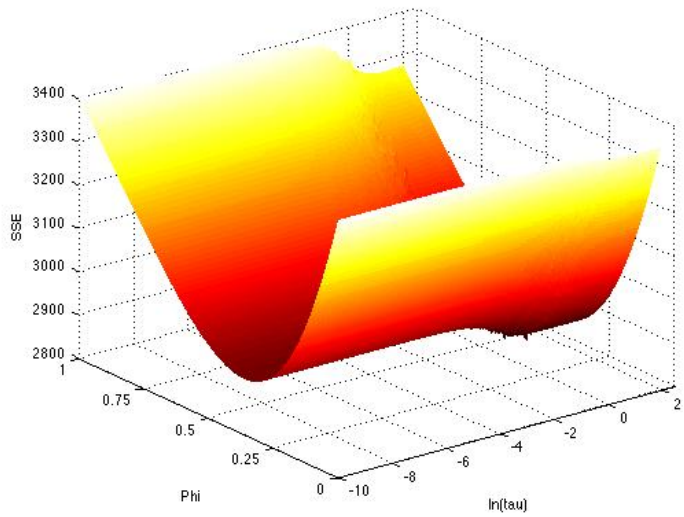


Figure 4: Grid search using the low estimate as the dependent variable.

# Inference

## Loss Aversion Regressor

We are interested in testing whether the $\beta$ value on the loss aversion regressor is significantly different from zero. This is complicated by the fact that when this coefficient is zero, $z(\phi, \tau)$ does not enter the regression and $\phi$ and $\tau$ are not identified. Standard asymptotic theory therefore does not apply, so we use the bootstrap to estimate a standard error or a confidence interval for the coefficient.

In order for a bootstrap to be reasonably accurate, the data generating process used for drawing bootstrap samples should be as close as possible to the true data generating process. Because the errors are heteroskedastic of unknown form, there are two options available: the pairs bootstrap and the wild bootstrap. The pairs bootstrap works by resampling observations with replacement, but it is only generally applicable when the observations are independent, which is not the case in our data. The wild bootstrap works by sampling $N$ numbers from a distribution with mean 0 and variance 1 and then transforming the residuals from the original regression by multiplying them by the random sampling: effectively randomly changing the signs on the residuals. Because It has been shown by Davidson and Flachaire [2008] and Flachaire [2005] that it is the preferred distribution to sample from in almost all practical situations, we sample from the Rademacher distribution:

$$\epsilon_t = \begin{cases} 1 & \text{with probability } 1/2 \\ -1 & \text{with probability } 1/2. \end{cases}$$

The regression is then run by subtracting the transformed residuals from the dependent variable and rerunning the grid search and then the robust regression. This procedure is repeated 2000 times and results in a distribution of 2000 coefficients on the loss aversion term. If that distribution is normal, we report its standard deviation as the standard error. Otherwise we report confidence intervals based on the percentiles of the distribution. The standard errors for the loss aversion regressor, the unobservable regressor, and the nuisance parameters are calculated via the bootstrap.

## Unobservable Quality Regressor

Because of the restriction on the coefficient of the unobservable quality regressor (that $a_3 = \phi(1 - a_2)$), it is not identified in the regression. The value of the coefficient is consequently calculated using the estimated values of $a_2$ and $\phi$, but the standard error or confidence interval must be calculated using a bootstrap in the same way as described above for the loss aversion coefficient.