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Bubbles & Bought-Ins: Reevaluating Price Movements in the Art Market

Silas Wuerth
Bowdoin College

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By Silas Wuerth

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1. Introduction

In December 2019, performance artist David Datuna ate a $120,000 banana duct-taped to the wall of a public exhibition at Art Basel Miami Beach. The duct-taped banana was not Datuna's creation, and he had not paid $120,000 for it. Videos of his intrepid stunt soon circulated around the internet with captions like "Datuna's actions have inspired me." News outlets weighed in with simmering disgust for price movements in the art market. The *Financial Times* professed that "the sale of a piece of fruit for $120,000 is a symptom of a world untethered from reality," NPR quipped "This art is bananas," and *Business Insider* journalist Alec Recinos argued the banana illustrates "that the market-driven world of contemporary art is driven not by merit or quality, but instead by financial speculation."

Intentionally or not, Recinos's complaint about art prices uses the economic definition of a bubble to diagnose the art market's problems. A bubble in a given asset class is generally defined as "a deviation of prices above fundamental value," in which price increases are sustained by "speculative trading activity" (Botsch and Jalil, 2018). So, if each piece of art has some "merit or quality" that dictates its fundamental value, and art prices exhibit a sustained rise due to speculative purchases instead of changes in the "merit or quality" of the art being sold, the art market would be in a bubble. A bubble in the art market would have important implications. The art market is large – it likely accounts for almost ten percent of the wealth of high income households (Barclays, 2012). This paper will examine whether Recinos is correct and there is an art market bubble.

Several recent papers have attempted to identify art market bubbles. Kräussl et al. (2016), Assaf (2018), and Li et al. (2020) have all evaluated data on sold art to construct price indexes, and then employed different varieties of augmented Dickey-Fuller tests to check for explosiveness in art prices. Kräussl et al. (2016) are the first to employ this blueprint and find evidence of a speculative bubble in several 2013 art markets: "Impressionist and Modern," "Post-War and Contemporary," "Old Masters," and "American." Assaf (2018) finds less evidence for bubbles since the Great Recession but identifies bubbles in a range of markets before 2008. Li et al. (2020) identify bubbles in the Chinese art market from 2004 to 2005 and 2010 to 2011.

Instead of testing new art markets for bubbles, my paper reevaluates price movements in the "Impressionist and Modern," "Post-War and Contemporary," "American," "Old Masters," and "19th Century European" painting markets. My study makes two fundamental changes to the framework that Kräussl et al., Assaf, and Li et al. use: First, it assigns unsold (or "bought-in") paintings a market price and includes them in the indexes. More than 30% of paintings go unsold at auction, and recent theoretical models of buyer behavior in the art market suggest that failing to price unsold paintings might bias price indexes (Lovo and Spaenjers, 2018). This paper tests both whether that bias exists, and whether accounting for that bias changes the outcome of tests for bubbles. Second, my analysis employs two tests for the presence of bubbles: the conventional augmented Dickey-Fuller test, and a second "significant year" test that proxies for changes in the underlying demand for art and then checks whether art prices have risen significantly in any years after controlling for this demand. Both tests are estimated over indexes based on sold paintings only, as well as indexes based on sold and bought-in paintings.

This paper's findings suggest that there is no current art market bubble, but that there is strong and consistent evidence for a bubble in the Post-War and Contemporary painting market shortly before the Great Recession. While both the augmented Dickey-Fuller and the "significant year" tests identify a bubble in 2008, the "significant year" test suggests that the bubble may have also persisted for several years after 2008. Including bought-ins in index construction reduces but does not eliminate both tests' evidence for this bubble. Finally, as might be expected, the results indicate that bought-ins reduce the index returns of high performing markets.

2. Theoretical Framework

A. The nature of asset-price bubbles

It is widely accepted that speculation can drive asset prices above their fundamental value (Tirole (1985), Gürkaynak (2008), and Botsch and Jalil (2018)). However, whether "pure bubbles" – episodes in which speculative factors alone sustain price increases – have ever existed is unclear (Botsch and Jalil, 2018). There is even evidence that fundamentals drove prices during several infamous "bubbles." Garber (1989, 1990) argues that the "Tulip Mania" and "South Sea Bubble" episodes were driven by an increased probability of future cash flows. Michael Lewis (2002) offers a similar explanation for the dot-com bubble. However, there has been considerable pushback to these explanations: Kindleberger (2000) notes that while Garber provides a fundamentals-based justification for the price increases of exotic tulips, he cannot explain why garden-variety tulips soared in price during the Dutch tulip craze of 1636 and 1637. Perez (2009) contends that extreme price to earnings ratios of technology stocks in the 1990s were driven by "excess confidence in the paper economy." After thoroughly surveying literature on the nature of bubbles, Botsch and Jalil (2018) argue that fundamental and speculation-based changes in asset prices often occur alongside one another. For example, in the 1920s land prices in Florida spiked, partially due to a population influx that contributed to underlying demand for land, and partially due to "feverish" buying and reselling on the part of investors who drove prices to "fictitious" levels (Botsch and Jalil, 2018). This speculative buying and reselling does not necessarily have to be "irrational." Investors might drive the prices of assets above their fundamental value because they are overconfident or make purchases based on just their intuition (i.e., irrationality), but they might also act rationally and drive prices above their fundamental value due to a market imperfect, such as different priors (Tirole (1982) and Barlevy (2007)).

Given that a bubble is an episode in which prices in an asset class exceed their fundamental value for a sustained period, it is crucial to determine what the "fundamental value" of an asset means. Economic theory provides that the value of an asset is equal to the present discounted value of an asset's future cash flows:

$$P_t^* = \frac{D+P_{t+1}}{1+r},$$

where P_t^* is the price of an asset at time t, r is the real interest rate, and D is the constant dividend an asset yields every period until the asset's sale in period t+1. P_{t+1} must then also be a function of D, r, and P_{t+2}, so that for P_{t+n}, as $n \rightarrow \infty$ (i.e. an infinite time horizon), P_t^* becomes entirely a function of D and r. Assuming P_t^* is the price of an asset that corresponds with its fundamental value, the price, P_t, of an asset at any given time, can be written as:

$$P_t = P_t^* + B_t,$$

where B_t is the "bubble component" of P_t that may or may not be equal to zero. If a bubble does not exist, $B_t = B_0 = 0$, so that $P_t = P_t^*$. If a bubble does exist, $B_t = (1+r)^t B_0 > 0$, for each period of the bubble. It is important to note that the existence of any B_t does not require that prices eventually collapse – prices have gradually "fizzled out" instead of collapsing (Botsch and Jalil, 2018).

B. What is "the fundamental value" of art?

Determining the fundamental value of art is notoriously difficult due to the heterogeneity of different pieces sold, and the buyer's heterogeneous preferences. Ultimately, the value of a work is a function of the utility that people might receive from ownership, but measuring utility, or the potential for future utility, is nearly impossible. Formally, V_{ijt}^*, the "fundamental value" of a piece of art, i, at time t, to individual j, is:

$$V_{ijt}^* = \frac{V(ED_{ij}) + V(P_{it'} - AF)}{1 + R},$$

where $ED_{i,j}$ are the "emotional dividends" (i.e. utility) that individual j receives from owning the painting i, $P_{it'} - AF$ is the difference between the price of painting i at time of resell t' and any fees AF that may go into maintaining or reselling the painting. $V(.)$ is simply an operator that converts both emotional dividends and prices to units that measure value generally. V_{ijt}^* can thereby be converted to P_{ijt}^*, a price that corresponds with the fundamental value of piece of art, i, at time t, to individual j. Lastly, $1/(1 + R)$ is some discount on future utility. Similar to traditional financial assets, on an infinite time horizon, $P_{i,j,t}^*$ becomes entirely a function of ED, AF, and R, but whereas D and r are constant across individuals for traditional assets, ED and R vary based on the heterogenous preferences of each owner i, making $P_{i,t}^*$ difficult to determine with accuracy. In a perfectly efficient market, the buyer who receives the highest discounted value at time t from owning painting i would own i at t, maximizing V_{it}^* and thereby also maximizing P_{it}^*.

The term "emotional dividends" is used by Spaenjers et al. (2015), but the same idea is presented by both Campbell (2008) who calls them "dividends of enjoyment" and Gerard-Varet (1995) who terms them "aesthetic pleasure." While the concept is cloaked in odd phrases, it is simple: people enjoy owning art, and this enjoyment constitutes art's value. In this regard, the value of art is no different from the value of any durable consumable good. Art is distinct from some consumable goods though, because its value can appreciate even as it is "consumed," and thus it shares characteristics of financial assets (Stein 1977).

Art is therefore not some inherently "bubbly" asset with no real value: If someone receives $120,000 worth of utility from owning a banana duct-taped to a wall by a famous artist, then the fundamental value of the duct-taped banana is at least $120,000. However, if buyers are consistently paying more for art than the amount that corresponds with the "emotional dividends" they receive from owning it plus the sum of the discounted emotional dividends that all future buyers might receive from owning it (i.e., $P_{it'}$), then prices would exceed P_t^* and some B_t greater than zero would exist.[1] This process does not require that art bubbles dissipate immediately – an investor might misjudge the discounted utility all future buyers will receive from owning a piece of art, but another investor might make the same mistake and repurchase the art at a $P_{it'}$ that rewards the first investor. Some investors might recognize that the discounted emotional dividends of all future buyers are less than the purchase price of a painting but nonetheless know that other investors will misjudge future emotional dividends more severely. Accordingly, as in other markets, art bubbles can be driven by irrational speculators who are too confident about their estimation of the future utility people might receive from owning a painting, or bubbles may be driven by speculators who are acting rationality in an imperfect market. Because the art market is particularly imperfect – it is illiquid and there are great asymmetries of information (Penasse and Renneboog, 2016) – it is particularly prone to bubbles.[2]

C. Identifying bubbles in the art market

i. The SADF Approach

Given the difficulty of determining the "fundamental value" of art across an entire market, attempting to test for the presence of bubbles in the art market might strike one as foolhardy. However, Kräussl et al. (2016) suggest bubbles in the art market might be detected using modified

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[1] A bubble could also exist if art investors accurately gauge the discounted future emotional dividends buyers will receive from owning a painting but underestimate the auction fee necessary to resell the painting However, this scenario is unlikely because while there are asymmetries of information about "seller's commissions" these fees have empirically been constant (see section 2Ciii.).

[2] See Barlevy (2007) for a description of how such imperfection can prompt bubbles even when investors act rationally. Penasse and Renneboog contextualize these imperfections to the art market.

augmented Dickey-Fuller tests. This approach is also used by Assaf (2018) and Li et al. (2020). Without having to gauge the fundamental value of art in a market, we know the price of art, P_t, equals $P_t^* + B_t$. A wealth of literature[3] suggests that if $B_t > 0$ in a given market, asset prices will exhibit explosive behavior, because the presence of B_t will lead to a stochastic process in which the expected value of prices in period t+1 will be greater than or equal to prices in t (Areal, 2013).

Kräussl et al. (2016) uses a recent approach developed by Philips et al. in two papers (2011, 2014) to test for non-stationarity. This paper employs a similar test:

$$H_0 : y_t = \tilde{\alpha}T^{-\eta} + \delta y_{t-1} + \varepsilon_t,\ \delta=1$$

$$H_A : y_t = \delta y_{t-1} + \varepsilon_t,\ \delta>1\ ,$$

where y_t is some measure of prices at time t, $\tilde{\alpha}T^{-\eta}$ is an intercept that converges to zero as $T \rightarrow \infty$, ε_t is the error term, and δ is an autoregressive coefficient that will = 1 if prices have a unit root but will exceed 1 if price movements are explosive. Therefore, rejecting H_0 suggests that a market is exhibiting bubble-like behavior. $\tilde{\alpha}T^{-\eta}$ is included in H_0 to allow for some drift in the data and depends on a population parameter $\eta \in [0,1]$.

Instead of using a single augmented Dickey-Fuller (ADF) test to find a single δ for the entire index, this paper follows Philips et al. (2014) and Kräussl et al. (2016) and uses a series of forward recursive calculations of ADF statistics. Forward recursive calculations require choosing an initial fraction of observations, r_0: $0 < r_0 < 1$, and expanding r until running the ADF regression for every possible recursive sample and obtaining the full sequence of test statistics, ADF_r: $r \in (r_0,1)$. Using ADF_r as opposed to a single ADF statistic for the entire model, helps to both identify the start and end date of episodes and to identify multiple bubbles. These forward recursive regressions are called

[3] Campbell and Shiller (1987) Diba and Grossman (1988) Evans (1991) Phillips et al. (2011)

a "Sup ADF test" or "SADF," because they generate a test statistic, $SADF(r_0) := \sup_{r \in [r0,1]} ADF_r$, where sup is synonymous with "max." The augmented Dickey-Fuller test used to recursively calculate ADF_r for any sample window size follows:

$$y_t = \alpha + \delta y_{t-1} + \sum_{i=1}^{k} \emptyset_i \Delta y_{t-i} + \varepsilon_t,$$

where α is an intercept, k is the lag order, δ is the unit root, $\emptyset_i$ is the coefficient on each lagged regressor Δy_{t-i}, ε_t is the error term, and the model is estimated using ordinary least squares. The ADF test statistic, $ADF_{r0} = \hat{\delta} / SE(\hat{\delta})$, and after finding ADF_{r0} the process is repeated for all ADF_r: $r \in (r_0,1)$.

Philips et al. (2014) provides asymptotic critical values for the SADF statistics based on η (Table 4), which this paper uses to determine the presence of a bubble.[4] If H_0 is rejected, Phillips et al. (2011) recommends using a separate set of critical values to determine the start and end date of a bubble, such that if rn is the origination date and rc is the collapse of a bubble, rn > rc, $ADF_{rn} > CV_{rn}$, and $ADF_{rc} < CV_{rc}$, where CV standards for critical value. The separate critical values come from the asymptotic ADF test statistic distribution, which this paper derives through 100,000 Monte Carlo simulations. They are found in table 4.

ii. The "Significant Year" Test

This paper also employs a separate test for the presence of bubbles, which uses equity market performance to control for portions of aggregate art demand. An abundance of literature has demonstrated that equity market movements affect art prices. In a sweeping analysis of art prices from 1830 to 2007, Goetzmann et al. (2010) find a weak relationship between total income (GDP)

[4] The paper estimates η for each market it tests in Appendix 21A

and art price trends, but strong evidence for a positive lagged relationship between equity market and art market movements. Similarly, Hiraki et al. (2009) discover a robust correlation between Japanese stock prices and demand for art in more recent periods. Renneboog and Spaenjers (2015) also find that risk in international art markets is positively related to risk in international equity markets.

Art prices are positively correlated with equity markets because fluctuations in equity markets affect the income of the wealthy – the potential art buyers.[5] Potential art buyers are more likely to buy art if they are wealthier. Risk-averse individuals' willingness to pay for "irreplaceable goods" (goods like art for which there is no perfect substitute) increases with their wealth (Cook and Graham 1977). Additionally, several empirical studies have shown that the marginal utility of consuming luxury goods is correlated positively with wealth creation (Aït-Sahalia et al. 2004 and Hiraki et al. 2009). Lovo and Spaenjers (2018) frame these as reasons the "emotional dividends" of art ownership increase with wealth. Using this framework, we can think of emotional dividends (ED) across an art market as

$$ED_{m,t} = f\,((\text{Stock Market Performance})_{t-1}, (\text{buyer tastes})_t, (\text{painting quality})_t\,),$$

for all agents in market *m* at time *t*. Beyond these variables – different tastes, different qualities of paintings, and a measure of wealth accumulation – there is very little anecdotally or in literature on the art market that indicates any other factors might affect how much art is "enjoyed" aggregately in a market. Given that supply is fixed in non-contemporary art markets (artists are dead), controlling for how much buyers might aggregately enjoy paintings offered in a given period (*t*) relative to a previous period should control for everything that might affect P^*_{tm} – the "fundamental" price of art

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[5] Art buyers are more likely to be wealthy (Barclays, 2012), and the wealthy earn a bigger share of income from investing (Austin and Williams, 2015).

in market m in period t.[6] In contemporary art markets, this relationship is different because aggregate supply might increase between periods as artists produce new work. Assuming the demand curve for art slopes downward, after effectively controlling for the heterogenous qualities of these new works (along with the other determinants of demand), prices should slowly decrease in contemporary art markets over time.

To test for the presence of bubbles, this paper constructs a pricing index that controls for stock market performance and for heterogenous qualities of paintings across time.[7] It then tests the following null and alternative hypothesis:

$$H_0: (\tilde{P}_{m,\, y+n} - \tilde{P}_{m,y}) = 0$$

$$H_a: (\tilde{P}_{m,\, y+n} - \tilde{P}_{m,y}) > 0,$$

where $\tilde{P}_{m,\, y+n}$ is a measure of prices in art market m at year $y + n$ after controlling for both heterogenous qualities of paintings in year y + n relative to base year y and stock market performance since some year y, and $\tilde{P}_{m,y}$ is a measure of prices in some reference/base period y.

Rejecting H_0 indicates that prices in market m have risen even after the wealth of buyers in market m and the quality of paintings in market m is held constant, and thus suggests a bubble is present. $\tilde{P}_{y,\, t+n} - \tilde{P}_{m,y}$ can therefore be thought of as some approximation of B_t in the equation $P_t = P_t^* + B_t$. This paper repeats the test for all years $y + n$. A bubble may thereby manifest over a single year, if $\tilde{P}_{y,\, t+n} - \tilde{P}_{y,t}$ is statistically significant for any year y+n.[8]

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[6] This assumes that for $V_{ijt}^* = \frac{V(ED_{ij}) + V(P_{it'} \cdot AF)}{1 + R}$, AF is constant. This assumption is addressed on the following page.
[7] Development of this index is described in "Data and Index Construction." I use a version of the index that controls for heterogenous painting qualities but does not control for stock market performance to run SADF tests.
[8] While a single year might seem like a short time for sustained speculative movements to drive prices over their fundamental value, many historic bubbles have manifested over a single year. Botsch and Jalil (2018) identify bubbles in the railroad stock (1885), Silver (1890), Cotton (1903), war stocks (1915), sugar (1920), and grain (1924) markets that only lasted a year.

In addition to the assumption that controlling for stock market performance controls for art demand due to increases in wealth, this test requires three other assumptions. First, the aggregate “taste” of buyers for art in a given market is constant after controlling for stock market performance and painting quality. For example, if 1995 is the base year t, $t+n$ is 2005, and m is the Old Masters market, then I am assuming that buyers in aggregate will not receive any bigger or smaller emotional dividends from purchasing Old Masters art in 1995 than they did in 2005, after controlling for stock market performance since 1995 and any differences in the quality of Old Master paintings sold in 1995 versus 2005. This assumption would be violated by “fads” that affect aggregate taste for paintings in a market. However, many of the fads that have been discovered for various art markets seem to be a function of changes in wealth – for example, Hiraki et al. (2009) shows that strong stock market performance in Japan in the 1980s led to preferences for Impressionist and Modern Art. Additionally, each genre that this paper examines encompasses many art movements and may thereby be less sensitive to fads than ultra-specific markets. For example, it is true that in the 1980s, Japanese art buyers increasingly enjoyed “Impressionist and Modern” art. However, “Impressionist and Modern” art includes impressionist, post-impressionist, expressionist, fauvist, cubist, surrealist, and art deco movements (and others). Intuitively, fads that affect the market for one of these movements must not necessarily affect the markets for all.

Second, I assume that the anticipated fees required to maintain and resell a piece of art are constant. The fundamental value of art as described previously is a function of both emotional dividends and anticipated fees, so if fees are decreasing, the fundamental value of a piece of art should increase and vice versa. Fortunately, while “buyer’s premiums” – the fee buyers have to pay an auction house for purchasing a painting – have incrementally increased in auction markets Spaenjers et al. (2015), the “seller’s commission” – the fee sellers have to pay auction houses – have hovered at around 10% (Ashenfelter and Graddy, 2006). Furthermore, “seller’s commissions” are not publicized by auction houses, and are often negotiated individually with sellers (Ashenfelter and Graddy, 2006), so it seems unlikely that on aggregate buyers in two different periods would expect seller's commissions to differ. Furthermore, there is no empirical or anecdotal evidence that fees paid to maintain art are have increased or decreased relative to the value of the art itself.

Lastly, the test requires that the art market is not in a bubble in base year *t*. If a market's base year were a bubble year, the tests would be subject to type II errors. This paper uses existing literature to identify a base year in which art markets acted normally. [9]

If these assumptions hold, any difference between $P_{m,t+n}$ and $P_{m,t}$ would indicate the presence of a bubble – price movements not due to underlying demand for art, but due to speculation about future resale prices. However, because the assumptions do not have a robust basis in existing art market literature, the paper employs the "significant year" test as a complement to its SADF tests rather than a be-all check for bubbles.

D. Bought-Ins

A crucial omission in previous art market literature is that researchers have paid little attention to bought-in paintings. This paper evaluates whether accounting for bought-ins in art price index construction changes the outcome of tests for bubbles. Paintings are "bought-in" when bidding does not reach a confidential reserve price set by the seller and the auction house. In art auctions, the reserve price is set at or below the auctioneer's low estimate of a painting's value (Ashenfelter and Graddy, 2011). Potential buyers see the low estimate, but not the reserve price.

A substantial portion of auctioned art is bought-in. However, there is little research on studying bought-in rates and their impact on art pricing (Ashenfelter and Graddy, 2011). In fact,

[9] More in "Data and Index Construction"

while surveying art market literature for this paper, I found no estimates of overall buy-in rates.[10] This paper finds 32% of paintings in its sample of auction sales across five art genres were bought-in between 1995 and the end of 2019. Prestigious auction houses are not immune to buy-ins: according to the Artnet database, 29% of painting sales at Sotheby's and 25% at Christie's New York auction houses have been bought-in between 1995 and the end of 2019, respectively.

Some papers have found that buy-ins can "burn" the value of a piece of art and temporarily make it difficult to resell at a high price (Beggs and Graddy, 2008). Ashenfelter and Graddy (2011) estimate the average reserve price to be 70% of the low estimate and find that price shocks and auction sale rates are correlated. Other papers have used buy-in rates to extrapolate other findings, for example whether expert appraisals of art before auctions are unbiased indicators of market value (McAndrew et al., 2012). But art market index construction has typically failed to price bought-in paintings. Kräussl et al. (2016), Assaf (2018), and Li et al. (2020) employ indexes of sold paintings to test whether there is a bubble in the art market, and do not speculate about the effect of leaving out bought-ins. Similarly, none of the other recent art market indexes – constructed by Hiraki et al. (2009), Goetzmann et al. (2010), Renneboog and Spaenjers (2015), and Spaenjers et al. (2015) – account for the effect of bought-ins on art price movement.

Although there are few attempts to quantify the effect of unsold paintings on art market indexes, a paper on the real estate market attempts to account for the effect of unsold houses on real estate prices. Goetzman and Peng (2006) estimate the "reservation" (reserve) prices that owners who choose not to sell their houses hold, and incorporate these prices into their indexes. Their model is specific to the housing market, and they attempt to account for all privately held reserve

[10] I could find no estimates of overall bought-in rates in academic literature. However, the art database ArtPrice estimates that 38% of total art went unsold in 2018 and 2019. This unsold rate may differ from the paper's because it is across all art markets – not only the five in the paper – and includes sales of non-paintings.

prices on the market, not just the reserve prices of houses that go on the market and fail to sell. Still, some of their findings have important implications for the art market. They find that after building a "reserve-conditional" index – which accounts for the reserve prices of unsold houses – and testing it against a conventional index, "reserve-conditional" indexes are more volatile especially during downturns, have smaller autoregressive coefficients, and have lower returns when trading volume decreases.[11] This suggest that SADF t-statistics – which quantify the likelihood of stochastic trends – might be negatively impacted by developing indices that price bought-ins at their privately held reserve price.

Recent art market literature has also suggested that failing to account for bought-in art will bias indexes. When a painting fails to sell, the market is pricing it below the lowest price for which its seller is willing to sell. Intuitively, failing to account for the prices of bought ins will lead to an inflated estimate of art prices. This is confirmed by Lovo and Spaenjers' (2018) theoretical model of trading in the art market, who describe the exclusion of bought-in paintings a "sample selection bias." Their model also suggests that failing to account for bought-ins could lead to inflated estimates of art market returns. They build a model of art buyers and sellers with two basic participants: "collectors" and "flippers."[12] Collectors are standard art buyers. For a collector, *j*, the value of painting *i* is:

$$V_{ijt}^{*} = \frac{V(ED_{ij}) + V(P_{it'} - AF)}{1 + R},$$

as defined in section 2B. In other words, collectors buy art because they enjoy the art itself, but they might resell if they believe the value of reselling is greater than future emotional dividends they will

[11] Interestingly, they find that reserve-conditional indexes have higher returns overall than conventional indexes, but suggest this might be because they are overestimating trading volume as housing stock grows.
[12] Their full model includes four types of participants: flippers, collectors, investors (who are between flippers and collectors), and super-collectors (who receive only emotional dividends from art and never try to resell).

receive from owning the art. Collectors are likely to resell during liquidity shocks, which simultaneously reduce their enjoyment of owning art and increase the marginal utility they receive from each dollar they earn.

On the other hand, flippers treat art exclusively as a financial investment, such that for a flipper, *f*, the value of a painting i is

$$V_{ift}{}^{*} = \frac{V(P_{it'} - AF)}{1 + R}.$$

In other words, flippers receive little to no "emotional dividends" from art and are investors whose sole objective is to profit from the asset. In Lovo and Spaenjers' (2018) model, flippers are not subject to liquidity shocks. Accordingly, they can wait for the opportune time to sell paintings, although in Lovo and Spaeners' model they generally resell quickly. Flippers will only buy painting *i* if they believe they can resell it for more than their purchase price, and therefore they will generally set higher reserve prices when they resell paintings than collectors.

An index based on "sold" paintings will include the successful attempts of flippers to "flip" art, and exclude unsuccessful attempts, and therefore result in indexes that often overstate returns during certain periods. This is illustrated by both Figure 1p and 2p. Both models consist of only flippers who use reserve prices close to the original purchase price of their painting. Indexes that price bought-ins capture negative variation in the market value of paintings better than indexes that ignore bought-ins.

Correcting for this sample selection bias requires pricing bought-ins. Pricing bought-ins for collectors, who enjoy the art they own and sell during liquidity shocks, is relatively straightforward. Because the reserve price of a painting is the lowest possible amount a collector is willing to receive for a painting, a collector's "bid" on a painting is some marginal amount less than the reserve price.

Figure 1p

Shows a theoretical market for a single painting. After a flipper purchases painting *i,* its market value dips. The flipper unsuccessfully tries to resell, and only later, after underlying demand for the painting has changed, successfully resells. The index excluding bought-ins fails to capture any of the negative variation in market prices for painting *i.*

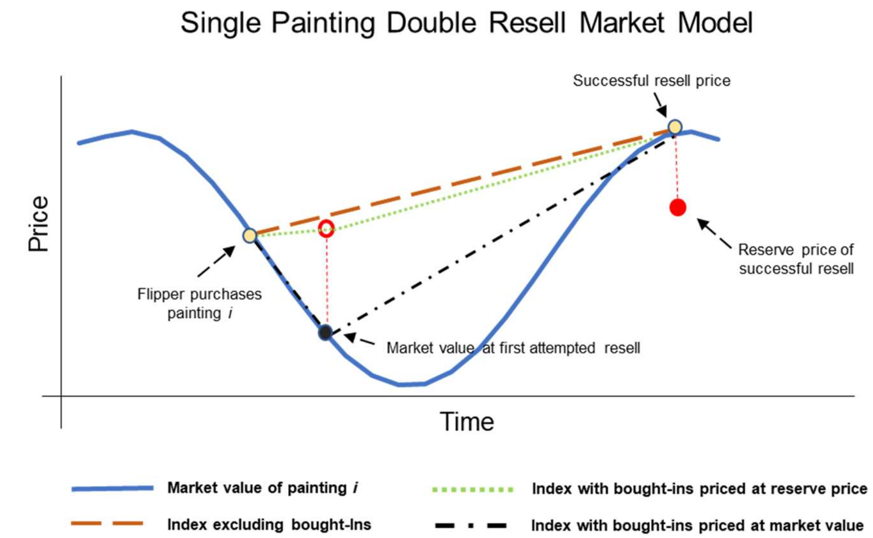
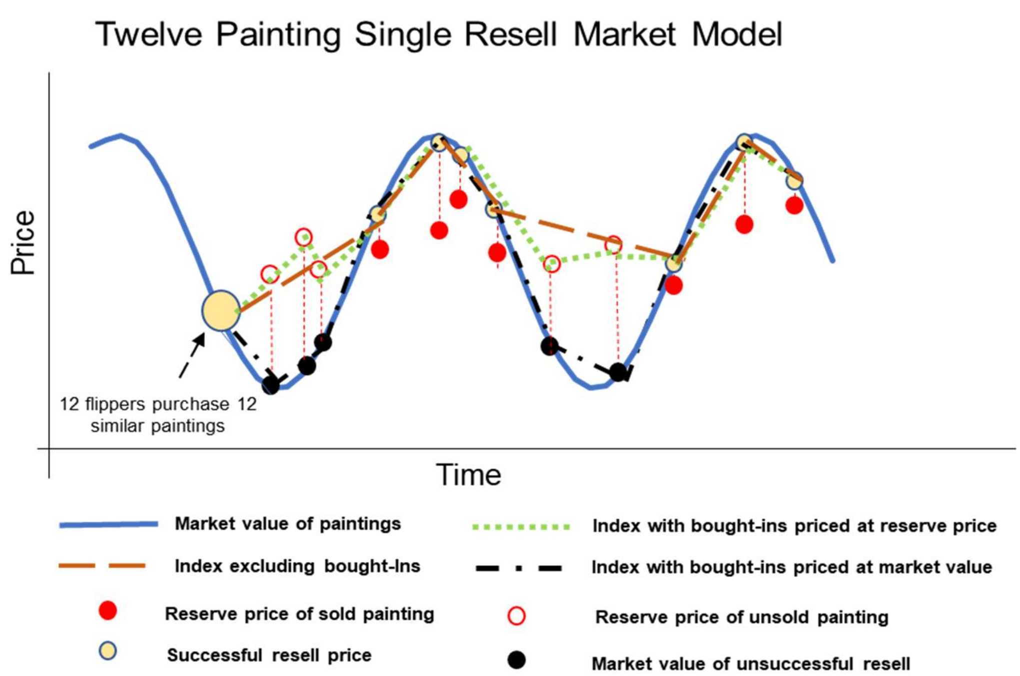


Figure 2p

Shows a theoretical market in which 12 flippers buy similar paintings and each attempt to resell once. The market value of these paintings varies together over time. Indexes that include bought-ins capture more negative variation in the market value of these paintings.



However, owners must also pay a seller's commission, so collector's actual bid is marginally less than the reserve price minus auction fees:

$OB_i = RP_i(1 – SC_h) - ε$

Where OB_i is the "owner's bid" on painting *i*, RP_i is the reserve price for painting *i,* SC_j is the auction house *h*'s seller's commission rate, and ε is some very small number. Using Ashenfelter and Graddy's estimate of the reserve prices of paintings (70% of the low estimate), and their findings regarding seller's commissions (10%), OB for any painting i is estimated as:

$OB_i = (LE_i)(.7) (1 – .1) - ε$

$OB_j = (LE_i)(.63) – ε,$

or 63% of the low estimate for painting *i*, LE_i, minus some negligible constant.

While a collector's reserve price is an indication of how much they value the art that they are trying to sell, flippers will strategically choose a reserve price based on how they believe the market will price their art. Because of this, the reserve price that flippers set is simply an upward bound for how they value a painting. Furthermore, as illustrated in Figures 1p and Figure 2p, for flippers the market value of unsold paintings is not a constant multiple of the reserve price they choose. Because flippers will maintain reserve prices close to the original price at which they bought a painting, the reserve prices they set will not necessarily vary with the highs and lows of the market value of their painting.

This makes pricing bought-ins difficult. While in a market of all collectors, 63% of every low estimate would provide a good estimate of bought-ins, 63% is simply an upward bound for flippers, for which the true value of an unsold painting *i* at time *t* is $X_{it} * LE_{it}$, where $.63 \geq X \leq 0$, and X_{it} is some function of how the rest of the market values painting *i* at time *t*. My study does not try to estimate which paintings are resold by flippers or an X_{it} for each of these painting in each period. [13] Instead, it prices every unsold painting at 50% of its low estimate.[14] This is an imperfect measure, one based on the assumption that flippers exist and therefore, on average, the true value of each unsold painting is somewhere below 63% of its low estimate. The estimate does not account for the changes in X_{it} across periods, and therefore will be unable to capture the same negative variation in index prices due to bought-ins that an index that consistently prices bought-ins at their true market price would. However, pricing bought-ins close to their reserve price will capture some true negative variation in prices, as demonstrated by figure 2p. Therefore, this paper's pricing of bought-ins will capture some of their impact, but will likely underestimate their entire effect.

3. Data and Index Construction

A. The Hedonic Index Model

To test for the presence of bubbles and evaluate the effect of pricing bought-ins, this paper constructs five art market indexes that extend from 1995 to 2019 for five art genres – "Impressionist and Modern," "Post-War and Contemporary," "American," "Old Masters," and "19th Century European."[15] It also constructs an "Aggregate" index that combines all five genres. Using these

[13] This is because I have data on a relatively small portion of the market, and therefore cannot identify which bought-ins were unsuccessful resells. Furthermore, even if I it could identify each bought-in resell, it would be difficult to gauge which resold paintings were attempted flips. One could maybe do this by using the ratio of each bought-in's low estimate to its original purchase price and the time between purchase and resell attempt. Lovo and Spaenjers' model suggests that bought-ins of quick attempted resells with high low estimate: original purchase price ratios might have reserve prices that don't reflect their true market value. This is an interesting area for the future exploration of economists with full samples of sales in an art market.

[14] Robustness checks ultimately show that pricing bought-ins at 75%, 50% or 25% of their low estimate does not significantly alter the effect of bought-ins on index returns. This is not because bought-ins are unimportant – they are. It is because indexes of all bought-ins which are priced at constant multiples of their low estimate are all the same (see 3ci for a more thorough discussion of this).

[15] See "Other Methodology" in the appendix for discussion and definition of each market.

genres helps the paper directly build on the work of Kräussl et al., who examine the same five genres.[16]

Because paintings are heterogenous assets, any index of art prices must control for the heterogeneity in the quality of paintings between periods. Simply using the average prices of paintings sold over time will result in biased estimates of art index returns, because it will capture variability in prices that are due to the variations in the quality of paintings offered at different times. For example, it is likely that "better" paintings are sold during boom periods. If so, average price indexes would overstate true art market returns (Ashenfelter and Graddy, 2006).

Art economists have employed two methods of index construction to avoid this issue. Some studies have employed "repeat-sales" indexes, which resolves the problem of heterogeneity by estimating returns based on only the purchase and selling price of art pieces that traded twice (Spaenjers et al., 2015). Economists have also developed hedonic pricing models, which use all available data on art sales (i.e., not just art pieces with repeated sales) and estimate returns between periods after controlling for the "hedonic" characteristics of each painting sold. Both index methods are flawed. Paintings may only return to the market if their original buyer believes they have appreciated in value (Goetzman, 1996), and studies have shown that repeat sales indexes might have to be adjusted downwards (Korteweg et al., 2015). On the other hand, hedonic models might not be able to control for all the idiosyncratic characteristics that dictate the "quality" of paintings (Ashenfelter and Graddy ,2006). The direction of any inherent bias in hedonic models is unclear (Spaenjers et al., 2015).

[16] Kräussl et al. also examine a sixth genre – Latin American art. However, the Latin American genre is often grouped with either Impressionist and Modern or Post-War and Contemporary art (this is the case at leading auction house Sotheby's, for example), and so due to the ambiguity of this genre, I decide not to include it.

This paper constructs a hedonic index instead of a repeat-sale index for two reasons. First, repeat sales data requires a much larger sample, since most paintings only sell once. Second, this paper examines the same markets as Kräussl et al. 2016, who use a hedonic model. A hedonic approach in this paper thereby allows for a more direct comparison with Kräussl et al.'s results.

This paper follows the same general hedonic model specification as Kräussl et al.:

$$\ln P_{iy} = a + \sum_{f=1}^{F} \beta_f X_{if} + \sum_{t=2}^{T} \lambda_y D_{iy} + \varepsilon_{iy},$$

where *a* is an intercept, F is the number of factors, Y is the number of years, and the natural log of the price, *P*, of painting *i* at year *y* is a function of the sum of its characteristics, X_{if}, with coefficients β_f, as well as a function of an annual time dummy variable D_{iy} and slope coefficient λ_y.

X_{if} consists of controls for a painting's artist, the auction house at which it was sold, whether the painting is signed, stamped or inscribed by its artist, the size and squared size of the painting, the medium (Oil, Pastel, Graphite/Chalk, Fresco, Watercolor, Acrylic, or Other), the material (Canvas, Panel, Paper/Cardboard, Metal, or Other). It also controls for whether the painting was certainly made by the artist listed, the painting was attributed to that artist, in the manner of that artist, or where it was done by a follower of that artist. Other variables include the length of the painting's title and whether it is untitled or titled "composition." These are all standard controls, and mirror many of Kräussl et al.'s hedonic controls. They do include more robust controls for the auction houses and artists of paintings offered than Kräussl et al., though. The appendix contains a more detailed list of controls with the theoretical motivation behind each.

I run the regression for all painting sales in each market, and use the estimated coefficients of the time dummy variables to construct an art price index for each market from 1995 to 2019. The base or reference year is 1995. Because the dependent variable is the natural log of prices, coefficients for each annual dummy variable represents a percentage increase in prices since 1995. 1995 is a suitable reference year because there is little evidence of a bubble in either the art market or stock market during this period. For each market this regression is run twice: first with prices of all sold paintings in a given market, and then with prices of all sold paintings and all bought-in paintings, which are each priced at 50% of their low estimate. To finalize each index, I exponentiate the estimated coefficients of the time dummy variables, so that the index is set to 100 in 1995.

This paper uses these indexes for the "SADF Approach" to test for bubbles. However, as explained previously, the "Significant Year" test requires controlling for both quality and wealth accumulation across periods. Accordingly, to test for significant years the paper employs a hedonic model with the addition of a control for stock market performance:

$$\ln P_{iym} = a + \sum_{f=1}^{F} \beta_f X_{if} + \delta \ln I_{m-1} + \sum_{y=2}^{Y} \lambda_y D_{iy} + \varepsilon_{iy},$$

where all the variables are the same as in the original hedonic model, and I_{m-1} is a stock market index that measures aggregate market returns between January 1995 (the base month of the sample) and the month preceding the month of the sale of painting *i*.[17] Whereas D_{iy} is a dummy variable for the year *y* in which painting i was sold, I_{m-1} corresponds with months in order to control for variation in stock market performance within a given year and avoid perfect collinearity between the dummy variable for each year and continuous measures of stock market performance.

B. Data and Sampling

To construct five art market indexes from 1995 to 2019, I sample over 50,000 auction results from 50 separate auction houses using both the Artnet and Askart databases. This leaves roughly 10,000 auction results for each genre, which are distributed evenly between the sample's 25 years, so

[17] I use the Center for Research in Security Prices database of US stocks to construct this index.

that each genre has roughly 400 painting sale results per year. The paper opts to only use painting sales for two reasons. First, sampling other types of art – like sculptures – would make running a single hedonic model impossible, because the hedonic characteristics that help determine the price of a painting are different than those that help to determine the price of a sculpture. Second, paintings are auctioned more frequently than any other type of art and have made up nearly 60% of art transactions since the 1970s according to the Blouin Art database (Kräussl et al, 2016).

The paper's sample consists of publicly auctioned sales. Private transactions constitute a substantial portion of the art market, but there is little reliable data on them. My study's indexes might therefore not completely capture price movements across an entire art market if there are differences between prices in primary art markets and dealer art markets. However, since the mid-twentieth century there is evidence that some differences between private and public market prices have dissipated (Saltzman, 2009).

Roughly 25% of the final sample consists of auction sales from Christie's, 25% from Sotheby's, 25% from "large" auction houses, and 25% from "medium/small" auction houses.[18] Christie's and Sotheby's are often deemed a duopoly and together account for more than 50% of global art market turnover. In 2019, Christie's accounted for 27.4% of global art market turnover and Sotheby's accounted for 27.0%.[19] This is not a recent trend: Christie's and Sotheby's have dominated global turnover for 250 years (Casadesus-Masanell and Wise, 2010). Auction sale turnover declines sharply after Christie's and Sotheby's. The next thirteen largest auction houses together accounted for 23.0% of global turnover in 2019, and while the third largest (Poly Auctions) accounts for 4.6%, the fifteenth largest (Ketterer Kunst) accounts for merely 0.46%.

[18] Large and medium/small defined in the "Other Methodology" section of the appendix
[19] Data based on Artprice.com's "The Art Market in 2019" report

I employ cluster sampling to choose auction houses, and then a "first relevant sale" approach to sample sales within auction houses. The first "cluster" consists exclusively of Christie's and Sotheby's because they are clear market leaders (i.e., no true "sampling" is done to choose them). Christie's and Sotheby's both have departments specializing in each of the five genres this paper evaluates and multiple auctions every year under each genre name. I aim for 400 painting sale results per genre per year, with 25% of these Christie's and 25% Sotheby's. Accordingly, for each genre, I sample the first 100 sale results every year that appear under the genre name for both Sotheby's and Christie's in their New York auction houses.[20] For example, both Sotheby's and Christie's held sales titled "Old Master Paintings" in 2015. I sample the first 100 results of the first Christie's "Old Masters" sale in 2015 and the first 100 results of the first Sotheby's "Old Masters" sale in 2015. Sampling the first sales of each year is done to help create a consistent gap of time between sales in different years. E.g., if I only sampled auctions in April, then the time gap between years would always be twelve months. I sample from Christie's and Sotheby's New York auction houses because they consistently hold the most sales in the paper's five genres. While this might result in some western bias in the sampling of each genre, four of the paper's five genres are by nature European or American. Furthermore, Christie's and Sotheby's New York are big enough to attract bidders from across the globe: New York auctions at Sotheby's[21] and Christie's[22] often attract bidders from 30+ countries. [23]

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[20] There are two years for which I sample sales from both Christie's and Sotheby's London auction houses instead of New York auction houses. The first was because Christie's and Sotheby's New York auction houses did not have Old Masters sales for a given year in the Artnet or Artprice database, and the second was because Christie's and Sotheby's did not have 19th Century European sales for a given year in the Artnet or Artprice database. Despite the differences between Christie's and Sotheby's New York and London locations, I do not use location controls because there would be perfect collinearity between the annual dummy variables and the dummy variables for Christie's London and Sotheby's London in each genre-based hedonic regression.

[21] A 2016 Sotheby's New York Contemporary Art Auction of 44 works attracted bidders from 34 different countries.

[22] A 2019 Christie's New York "interiors" sale registered bidders from 43 countries.

[23] In addition to attracting bids from a wide range of countries, recording breaking sales often take place in New York and feature foreign buyers. A Saudi Arabian Prince bought the "Salvatore Mundi" for a record-breaking price at a Christie's New York sale in 2017, a Qatari politician bought "Les Femmes d'Alger" for a record-breaking price in 2015

I then take a random sample of large auction houses. After taking this sample, I calculate how "specialized" each large auction-house is in a given genre, and for each genre choose a set of auction houses that are the most specialized. This generates five separate groups of large auction houses, each of which is used to draw a sample of auction sale results for the genre in which the group is specialized. [24]As with Christie's or Sotheby's, for each large auction house group, I sample the first 100 auction results with sale titles that mention the name of the group's genre. There are sometimes no sales within a year with titles that mention the name of a group's genre. In these cases, I use the first 100 auction results regardless of a sale title in a given year for the group, in which case I classify the genre of each painting manually.[25]

I repeat this process for medium/small auction houses. The only notable difference is that smaller auction houses are less likely to label their sales with the name of a given genre (e.g., many smaller auction houses simply have "emporium" or "premier" auctions). Because of this, medium/small auction house sale sampling generally results in choosing the first 100 auction sale in a given year, irrespective of sale title. This is why a group of "specialized" auction-houses are chosen for each genre – doing so increases the chances that paintings are classified under the genre to which their group of auction houses corresponds, and accordingly helps generate a similar number of auction results for each genre. This also why results are not distributed exactly evenly between genres: when there were no genre-labeled sales in a given year, overall paintings were more likely to be manually classified as some genres (Post-War & Contemporary and Impressionist & Modern) than other genres (Old Masters, 19th Century European, and American).

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at a Christie's New York sale, and later that year a Chinese investor bought "Nu couché" for another record-breaking price at a Christie's New York sale. This isn't a recent phenomenon. For example, in 1987, a Japanese investor bought Van Gogh's "Vase with Fifteen Sunflowers" for a record breaking $39.7 million at a Sotheby's New York auction.

[24] Brief explanation for the motivation behind the "specialization metric" in the next paragraph; additional details in the appendix "Other Methodology" section.

[25] Description of classification methodology in appendix "Other Methodology" section.

4. Results

A. Index Returns

The paper's art indexes exhibit modest positive returns, largely driven by price increases in the Post-War & Contemporary market. Returns are highly volatile in each market. Returns are lower in high performing markets after accounting for bought-ins, but bought-ins have a mixed effect on lower performing markets. Overall, the effect of pricing bought-ins is not completely consistent with the theory.

Since 1995, art prices have risen across all five genres (see Table 2 and Figure 1). In aggregate, when excluding bought-in paintings, the five indexes averaged a modest 3.45% annual return over the course of 25 years before accounting for inflation. These returns are largely driven by the Post-War & Contemporary market (henceforth PW&C), in which prices appreciated at an average 7.78% annual clip. PW&C's outperformance of the aggregate market is consistent with both Kräussl et al.'s findings, indexes developed through the entire Artprice database,[26] and anecdotal evidence. [27] The Old Masters market exhibits moderate returns at 3.26%. American art market averages 2.69% returns, but this number is biased by two anomalous years. The 19th Century European and Impressionist & Modern markets average 1.62% and 0.24% returns respectively. The underperformance of older markets may be due to a selection effect: collectors are more likely to hold on to older high quality works, as are museums. So lower quality works are more likely to be trading in these markets, whereas high quality contemporary works still trade (Pogrebin, 2016). This does not inherently bias returns – lower quality works could appreciate in price at the same rate as higher quality works – but it certain suggests a bias might exist.

[26] See Assaf (2018) or Artprice's "The Contemporary Art Market Report 2018."
[27] See Alec Recinos's "A banana taped to a wall sold for $120,000 at a Miami art fair. Here's why it wasn't good."

After including bought-ins in index construction, aggregate annual returns drop to 3.08%. In the two highest performing markets – PW&C and Old Masters – returns fall to 6.95% and 2.64%. This is consistent with both the theory and the intuition that suggests failing to account for bought-ins will positively bias index returns. In lower performing markets, 19th Century European returns drop to 1.38%, but returns in the American and Impressionist & Modern markets rise to 2.81% and 0.68%, respectively. This may be because these markets are less subject to speculation and flipper-like activity than higher performing markets. Accordingly, accounting for bought-ins in these markets might have a smaller negative effect on returns than in markets with frequent failed attempts to flip paintings. However, there are some inconsistencies between the expected effect of pricing bought-ins (see figures 1A and 2A), and the actual effect on returns. In theory, pricing bought-ins accurately should help capture negative price variation and lead to sharper dips in returns during market-wide contractions. However, after pricing bought-ins, the minimum values for market returns increase in PW&C, Impressionist & Modern, and Old Masters markets. This is likely because the paper is pricing bought-in paintings closer to their reserve price than their true market price, and thereby not capturing the entire negative effect of bought-ins on returns.

B. Bubble Detection

The two tests that this paper employs to identify bubbles both show strong evidence for an episode in the PW&C market before the Great Recession. Bought-ins reduce but do not eliminate evidence for this bubble. This is consistent with the negative effect of bought-ins on high performing indexes. The tests find little evidence for any bubbles in other markets. The effect of bought-ins on these less "bubbly" markets is inconsistent.

i. SADF Bubble Detection

SADF t-stats provides evidence of explosive price movements in the Post-War & Contemporary art market from 2004 to 2008 at 95% confidence level, and from 2005 to 2008 at a 99% confidence level. This suggests the PW&C market exhibited a pre-Great Recession bubble. Bought-ins slightly reduce the statistical significance of this bubble. The PW&C SADF score drops from 2.17 to 1.95 after accounting for bought-ins, but still meets the SADF >99% critical value of 1.77. Additionally, the ADF stats that this paper tests against a separate set of critical values to determine the start and end date of the bubble do not change after accounting for bought-ins enough to alter the start and end dates of SADF-based bubbles.

SADF output is statistically insignificant in the 19^{th} Century European, American, Impressionist & Modern, and Old Masters market (Tables III and IV). This suggests these markets have not been subject to speculative bubbles since at least 2004 and is consistent with their relatively low index returns. Accounting for bought-ins in these markets has an inconsistent effect on SADF t-stats: Bought-ins reduces the SADF score for the American market but slightly increases SADF scores in the Impressionist & Modern, 19th Century European, and Old Masters markets. This is unexpected. Bought-ins reduce average annual returns in the 19th Century European and Old Masters market (as described in section 4.A), which one would expect to correlate with lower SADF scores. However, SADF scores only correspond with one year of the index, so indexes with higher average returns might still happen to have a single year in which the ADF regression yields a particularly high score.

The SADF test finds no evidence of bubbles after 2008 in PW&C, American, Old Masters, and Impressionist & Modern markets. These results differ from those of Kräussl et al. for two primary reasons. First, while this paper follows Kräussl et al.'s general hedonic approach to index construction, it includes additional controls for the effect of artists on prices (dummy variables for each artist with paintings sold in more than one year) and further controls for the effect of auction houses on prices (dummy variables for each auction house with significant observations across more than one year). Kräussl et al. include a dummy variable for whether a painting's artist was alive at the time of sale, and a dummy variable for whether the painting was sold at Christie's or Sotheby's, but otherwise do not attempt to capture the variation in prices due to the heterogenous effects of artists or auction houses across years. Second, their index uses 1970, not 1995, as a base year. Because art prices were much higher in 1995 than in 1970, changes in prices in the 2000s are bigger relative to prices in 1970 than to prices in 1995. Using 1970 as a base year might thereby make price movements in the 2000s look more explosive and trigger higher SADF statistics than using 1995.

Other literature helps confirms the validity of this paper's results. The only other paper to run a SADF test on a genre that Kräussl et al. and my study both examine – Assaf et al. (2018), who tests the Old Masters market – finds no evidence for a bubble before 2008 or since 2008. [28] Furthermore, while Kräussl et al. find consistent, strong, upward price movement between 2009 and 2014 in each of the genres they test, Spaenjers et al. (2016) find that aggregate art prices declined slightly between 2009 and 2013.[29] Spaenjers and Lovo (2018) update this index and find that aggregate art prices have leveled off since 2009. Similarly, this paper finds some upward price movement between 2009 and 2014, primarily in the PW&C market, but overall returns are inconsistent and relatively flat compared to Kräussl et al., even before controlling for bought-ins. This suggests that my study's lack of SADF-based evidence for bubbles in the PW&C, American, Old Masters, and Impressionist &

[28] Assaf (2018) also tests the Contemporary, Post-War, and Modern markets for bubbles. He finds no evidence for a Contemporary bubble since 2008, but finds some evidence that a Post-War bubble and a Modern bubble formed around 2011. However, these genres are defined differently than the genres that Kräussl et al. and this paper examine. Furthermore, he uses quarterly price data, and lower critical SADF t-scores. The SADF t-stats he does obtain for these periods are lower than the critical values Phillips et al. (2014) recommends and this paper uses, and lower than the critical values Kräussl et al. (2016) use.

[29] Renneboog and Spaenjers (2015) use the same index as Spaenjers et al. (2015)

Modern since the Great Recession is more consistent with other existing indexes than Kräussl et al's.

ii. "Significant year" bubble detection

Overall, the "significant year" test provides little relevant evidence for bubbles in four of this paper's five genre-based markets, but supports evidence of a bubble in the PW&C market before the Great Recession. It also suggests that this bubble continued through 2009. This demonstrates the importance of the "significant year" test: while ADF scores fell in 2009, PW&C art prices had a relatively good year: prices were high after controlling for how stock market performance should have curbed demand. Including bought-ins also reduces the number of "significant years" for bubbles in the PW&C market. This strengthens the evidence from SADF tests that accounting for bought-ins diminishes the explosiveness of price increases in high performing markets.

It might initially appear as if the "significant year" approach has helped detect a multitude of bubbles across different markets (see Table 6). This is not the case. Contrary to what this paper's theoretical framework would suggest, the variable it uses to control for stock market performance is statistically insignificant in the Old Masters, 19th Century European, and Impressionist & Modern markets (see Appendix tables 4A and 5A). In these markets, the stock performance variable often varies negatively with the natural log of painting prices, thereby leading to higher annual dummy variables and inflating the indexes. This occurs in the 19th Century European (excluding bought-ins), Impressionist & Modern (including bought-ins), and Old Masters (excluding bought-ins) markets.

Because the stock market performance variable is statistically insignificant in these markets, its positive or negative effect on prices (and thereby positive or negative effect on index returns) can be attributed to chance, not any proven relationship. An unclear relationship between the stock performance control variable and art prices negates the point of "significant variable" test, which is to control for some clear, underlying component of art demand. This invalidates test results for Old Masters, 19th Century European, and Impressionist & Modern markets. The discrepancy between theory and results in these markets may be due to the measure of "stock market performance" that the paper uses: The Center for Research in Security Prices (CRSP) index is only constructed using US stocks. I assumed that this would effectively proxy for global stock performance, but using another variable that also accounts for European and Asian stock performance might help better control for demand in Old Masters, 19th Century European, and Impressionist & Modern markets.

The only two genre-based markets for which the stock performance control variable is statistically significant (American and PW&C), have bolded numbers in Table 6. As expected, in both of these markets higher stock prices are correlated with higher prices for art. Controlling for stock market performance thereby deflates these indexes. This is most apparent for the American art index, in which controlling for stock market performance completely deflates art index performance (see Figure 16). Controlling for stock performance also deflates the PW&C index, but leaves annual dummy variables on the years 2005 through 2018 statistically significant at a 95% confidence level before accounting for bought-ins, and dummy variables for 2006-2013 statistically significant after accounting for bought-ins. At a 99% confidence level, 2007-2012 are statistically significant before accounting for bought-ins, and 2008, 2009, and 2012 are statistically significant after controlling for bought-ins. Bought-ins thereby have a more important effect on the "significant year" test results than on the SADF test results.

C. Robustness checks

i. Repricing Bought-Ins

This paper prices bought-ins at a default of 50% of their low estimate. However, this is just an estimate of their true market price (see 2D). Repricing bought-ins at 25%, 75%, or 100% instead of 50% has a very minimal effect on the aggregate art market index, which is consistently lower than the aggregate market index that excludes bought-ins (figure 20). The general effect of bought-ins is shown in figure 21: regardless of how bought-ins are priced, an aggregate index of all bought-ins significantly underperforms an aggregate index that excludes bought-ins.

Pricing bought-ins differently has a consistent effect on SADF t-stats. In markets where including bought-ins originally had a positive effect on SADF t-stats (19th Century European, Impressionist & Modern, and Old Masters), pricing bought-ins higher results in lower SADF t-stats. In markets where including bought-ins originally had a negative effect on SADF t-stats (PW&C and American), pricing bought-ins higher results in higher SADF t-stats. This may be because data points for bought-in prices hold more power in the OLS regressions used to generate each index if they are lower (and are thereby bigger negative outliers). So in markets where SADF t-stats are negatively impacted by bought-ins, pricing them higher and thereby decreasing the power of bought-in data points in the OLS regressions used to create market indexes, leads to higher SADF t-stats – and vice versa in markets where SADF t-stats are negatively impacted by bought-ins. Overall, repricing bought-ins does not change the statistical significance of any SADF t-stats, except in the PW&C index, where pricing bought-ins at 25% of each bought-in painting's low estimate makes the SADF statistic no longer significant at a 99% confidence level. However, pricing bought-ins at 25% of their low estimate would only make sense if a high percentage of the market were flippers, and flippers were wildly overestimating the resell value of their paintings and setting very high reserve estimates.

ii. Defining Genres Differently

This paper uses an auction "sale-title" based approach to classify the genres of its paintings. However, some auction house sales classify paintings under genres that do not correspond with the year they were painted. For example, some paintings in the "19th Century European" were painted after 1900. This is likely because they follow a "19th Century European" style. As a robustness check, this the paper tests what happens if paintings were reclassified into genres based on the year painted. All paintings before 1800 are reclassified as "Old Masters," all paintings originally classified as "19th Century European" and painted after 1900 are classified as "Impressionist & Modern," and all paintings painted after 1945 are reclassified as "PW&C." Reclassifying genres does not have a statistically significant effect on any SADF t-stats, and the general effect of including bought-ins on SADF t-stats does not change.

iii. Excluding Paintings with Adjusted "Hammer Prices"

Roughly 30% of paintings in the sample had prices listed as the "hammer price" for which they were bought at auction. The remaining paintings were priced at "premium prices" – their hammer prices plus some auction premium. To derive a "premium price" for all paintings, I reprice the paintings with "hammer prices," using estimated auction fees (see 24A). McAndrew et al. (2012) and Spaenjers et al. (2015) convert hammer prices to premium prices in a similar fashion. To test whether this "repricing" leads to biased results, I rerun all SADF tests using indexes built only using paintings originally priced at their "premium price" – i.e., excluding all paintings I had to "reprice." This leads to slightly lower SADF t-stats in all genres besides Old Masters. It also reduces the significance of PW&C SADF t-stats from a >99% confidence level to a >95% confidence level, but the effect of pricing bought-ins on SADF t-stats remains the same.

iv. Trimester-based indexes

Because not all paintings are sold at the same day in each year, the data pools across different 12-month periods. For example, if some paintings are sold in January one year and others are sold in February the next year, the index accidentally includes an "extra" month of growth for that year. Geltner (1993) calls this the "working effect" and shows that in theory this should result in an estimated index with returns that are too smooth (i.e., the estimate SD > population SD), as well as positive serial correlation between years that leads to misplaced index peaks and valleys. Estimating the index with multiple time-based dummy variables a year – e.g., three trimesters – and using only one of these dummy variables a year – e.g., the first trimester every year – to estimate an index should help resolve this. However, Appendix table 22A and 23A shows no evidence for the "working effect" problem, because returns exhibit no positive serial correlations between years. It also shows that estimating the index using multiple time-series dummy variables a year does not significantly change serial correlation or the standard deviation of returns. Just to be thorough, I rerun all of the SADF tests using a trimester-based index. This has mixed effects and reduces the significance of PW&C SADF t-stats from a >99% confidence level to a >95% confidence level. Otherwise this test does not affect the statistical significance of t-stats but does diminish the negative effect of including bought-ins on SADF t-stats. There is no theoretical account that explains this. It is likely simply a function of random variance introduced by using a small sample to build indexes.

5. Conclusion

In this paper, I use both a SADF test and a "significant year" test to examine speculative bubbles in the 19th Century European, American, Post-War & Contemporary, Impressionist & Modern, and Old Masters art markets. Both tests find strong and consistent evidence for a bubble in the Post-War & Contemporary market before 2009. The "significant year" test – a novel contribution to art market literature that controls for demand to identify art market bubbles – indicates that this bubble may have persisted for several years. Overall, test results contrast with Kräussl et al. (2016), who find evidence for several bubbles in 2014 in the markets that this paper tests. The difference is likely because this paper employs more robust controls for artists and auction houses to create its indexes.

Kräussl et al. and other attempts to test for bubbles in the art market have employed SADF tests on price indexes of purchased art, but theoretical models of buyer behavior in the art market suggest that such tests might be biased, because failing to account for unsold art could bias indexes. This paper evaluates whether this is the case. As might be expected, the effect of bought-ins varies according to the nature of the market. In lower performing markets, accounting for bought-ins has an inconsistent effect on index returns and bubble-test results. At the same time, the exclusion of bought-in art from empirical estimation leads to a marked bias in higher performing markets, which exhibit lower returns and weaker test-based evidence for bubbles after accounting for bought-ins. This bias might be even greater than the paper estimates, because I price bought-ins at a constant multiple of their low estimate. This may lead to an underestimation of negative deviations in the market prices of bought-ins. Future papers should continue evaluating the best way to price bought-ins to ensure they do not overestimate price movements in art markets.

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Results

Summary Statistics

Table 1

Summary statistics for painting sales in each art genre the paper tests. Unclassified paintings are sampled paintings that did not fit into any of the genres. Here, "Total" is the combination of all five genres and unclassified paintings.

	Total	19th Century European	American	Post-War & Contemporary	Impressionist & Modern	Old Masters	Unclassified
# of Painting Sales	50,842	9,378	8,609	11,541	11,070	9,650	595
# of Sold Paintings	34,645	5,876	6,580	8,531	7,478	5,837	343
# of Unsold Paintings	16,197	3,502	2,029	3,010	3,592	3,813	252
Sale Rate	68%	63%	76%	74%	68%	60%	58%
Unique Artists	14,517	3,499	2,259	3,190	2,299	3,434	523
Mean Price	$471,033	$92,228	$84,985	$894,346	$802,433	$234,401	$639,445
Median Price	$25,000	$21,850	$11,875	$33,350	$40,302	$36,270	$10,000
5% Percentile Price	$1,055	$1,230	$793	$831	$1,045	$2,868	$1,363
95% Percentile Price	$1,497,000	$375,325	$314,000	$3,274,500	$3,515,710	$855,000	$325,000
Mean Year of Painting	1917	1873	1911	1976	1924	1695	1888
% Dated	60%	52%	55%	91%	73%	21%	38%
Average Height (Inches)	28	25	31	39	23	27	29
Average Width (Inches)	29	27	24	40	24	28	28
Average Size (Sq Inches)	1,189	863	1,029	2,266	648	973	895
Unique Auction Houses	50	43	37	44	46	43	48
%Signed	75%	89%	88%	84%	88%	27%	58%
%Oil	81%	94%	89%	50%	88%	93%	68%
%Canvas	66%	73%	69%	61%	71%	58%	53%
% Hammer Price	34%	35%	19%	32%	43%	36%	53%
%Untitled	4%	0%	1%	18%	1%	0%	7%

Table 2

Summary statistics for returns on each genre-based market's index before and after accounting for bought-ins. Here, "Aggregate" is an index based on a hedonic regression with data from all five genres. The "Aggregate" index does not include unclassified paintings.

	Excluding Bought-Ins				Including Bought-Ins			
	Mean	**Std. Dev**	**Min**	**Max**	**Mean**	**Std. Dev**	**Min**	**Max**
Aggregate	3.45%	17.68%	-38.83%	43.81%	3.08%	17.57%	-38.30%	41.23%
19th Century European	1.62%	15.08%	-23.02%	38.97%	1.38%	15.69%	-27.29%	44.51%
American	2.69%	33.28%	-48.97%	73.39%	2.81%	33.86%	-50.51%	67.13%
Post-War & Contemporary	7.78%	19.70%	-47.66%	47.04%	6.95%	19.87%	-45.20%	42.86%
Impressionist & Modern	0.24%	29.70%	-79.19%	50.36%	0.68%	26.20%	-55.22%	49.94%
Old Masters	3.26%	36.35%	-71.65%	69.34%	2.64%	30.03%	-54.20%	58.60%

Table 3

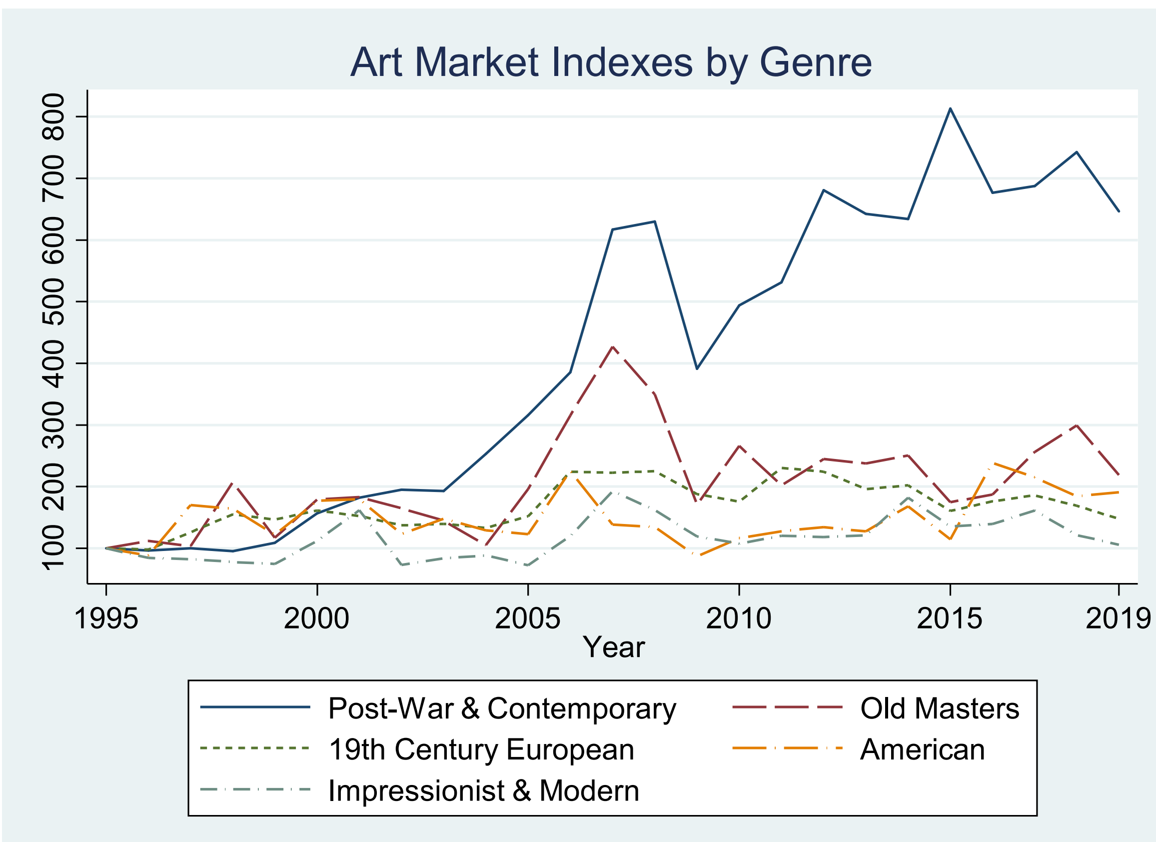
Difference in returns on indexes that include bought-ins and indexes that exclude bought-ins

	Mean	Std. Dev	Min	Max
Aggregate	0.37%	0.11%	-0.53%	2.58%
19th Century European	0.24%	-0.61%	4.27%	-5.54%
American	-0.12%	-0.58%	1.54%	6.26%
Post-War & Contemporary	0.83%	-0.17%	-2.46%	4.18%
Impressionist & Modern	-0.44%	3.50%	-23.97%	0.42%
Old Masters	0.62%	6.32%	-17.45%	10.74%

Original Index:

Figure 1

Price indexes for "Post-War & Contemporary," "19th Century European," "Impressionist & Modern," "Old Masters," and "American" markets from 1995 to 2019 before including bought-ins in index creation. All series are annual data and normalized to 100 in 1995.



SADF-Based Bubble Detection

Table 3

SADF Critical values for identifying the existence of a bubble episode (found in Philips et al., 2014), and critical values for dating the start and finish of an episode after the existence of a bubble has been established (found through 5000 Monte Carlo simulations)

	Identifying Existence of Bubble	Identifying Start and End Dates
90% Level	0.86	-0.448
95% Level	1.17	-0.092
99% Level	1.77	0.602

Table 4

Shows SADF values by genre before and after including bought-ins. SADF values are the highest of the ADF scores across all years for each genre. Post-War & Contemporary SADF scores are statistically significant at a 99% confidence level, as per the critical t-values in Table 3.

	Excluding Bought-Ins	Including Bought-Ins
Aggregate	-0.17	-0.29
19th Century European	-0.80	-0.60
American	-2.64	-2.95
Post-War & Contemporary	2.17***	1.95***
Impressionist & Modern	-1.78	-1.35
Old Masters	-1.02	-0.80

Table 5

Shows SADF-test based bubbles, identified by genre at different confidence levels before and after including bought-ins. Bubbles identified and dated using the critical t-stats in table 3.

90% Confidence

	Excluding Bought-Ins		Including Bought-Ins	
	1st Episode	**2nd Episode**	**1st Episode**	**2nd Episode**
Aggregate	-	-	-	-
19th Century European	-	-	-	-
American	-	-	-	-
Post-War & Contemporary	2004-2008	-	2004-2008	-
Impressionist & Modern	-	-	-	-
Old Masters	-	-	-	-

95% Confidence

	Excluding Bought-Ins		Including Bought-Ins	
	1st Episode	**2nd Episode**	**1st Episode**	**2nd Episode**
Aggregate	-	-	-	-
19th Century European	-	-	-	-
American	-	-	-	-
Post-War & Contemporary	2004-2008	-	2004-2008	-
Impressionist & Modern	-	-	-	-
Old Masters	-	-	-	-

99% Confidence

	Excluding Bought-Ins		Including Bought-Ins	
	1st Episode	**2nd Episode**	**1st Episode**	**2nd Episode**
Aggregate	-	-	-	-
19th Century European	-	-	-	-
American	-	-	-	-
Post-War & Contemporary	2005-2008	-	2005-2008	-
Impressionist & Modern	-	-	-	-
Old Masters	-	-	-	-

Figure 2

Shows the aggregate market index, which is based on a hedonic regression with data from all five genres, before and after including bought-ins in index creation. Series are annual data and normalized to 100 in 1995.

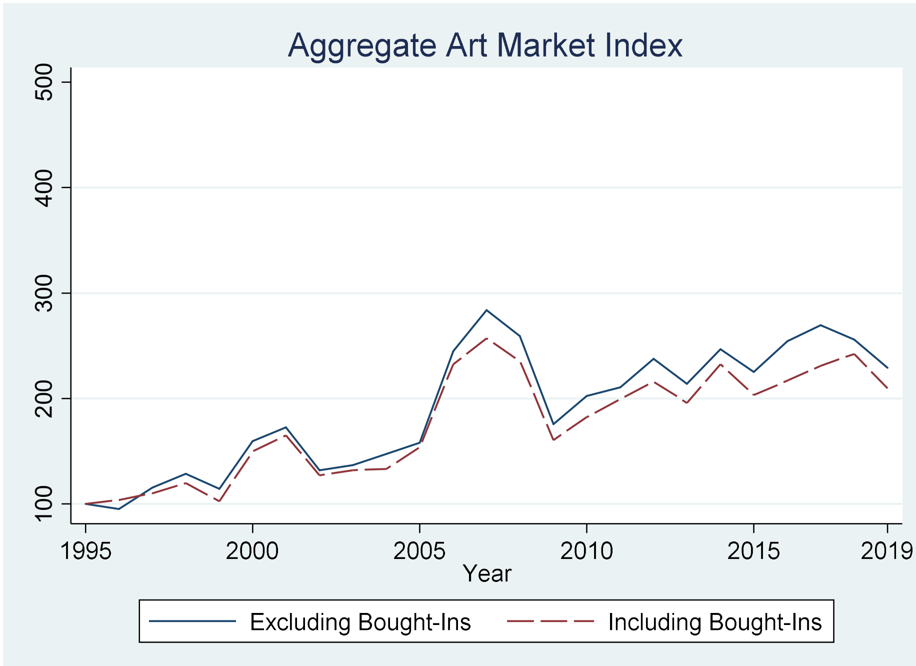


Figure 3

Shows the "Aggregate Index" ADF t-statistic sequence before and after including bought-ins. T-statistics are found using forward recursive calculations with an expanding window and initial window size of 10 years. T-stats are tested against corresponding critical values for bubble identification at the 90%, 95% and 99% level, which are the same critical values as the "Identifying Existence of Bubble" critical values in Table 3

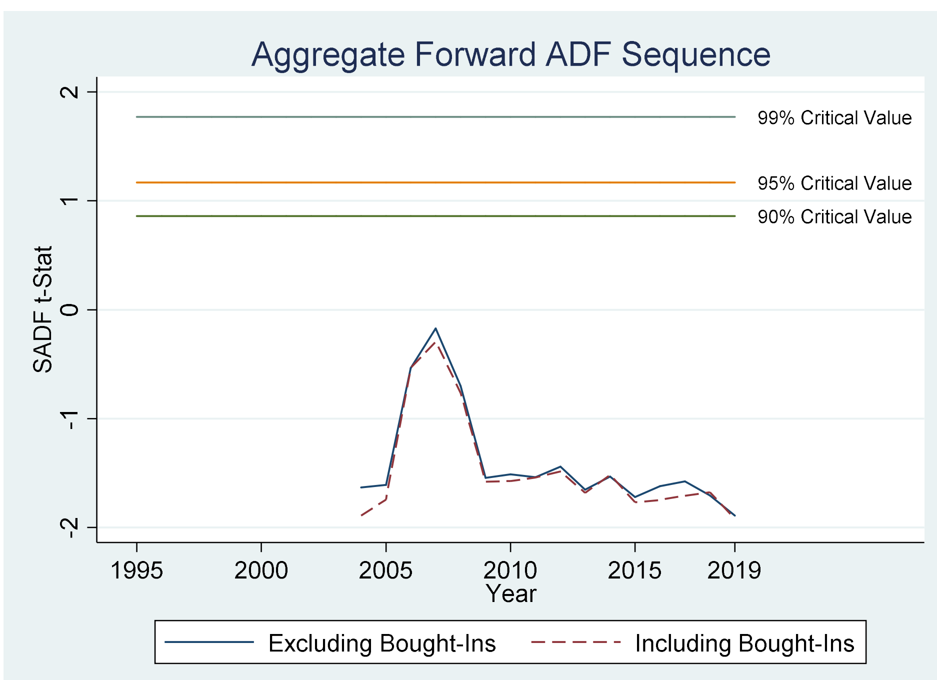


Figure 4

Shows the 19th Century European art market index from 1995 to 2019 before and after including bought-ins in index creation. Series are annual data and normalized to 100 in 1995

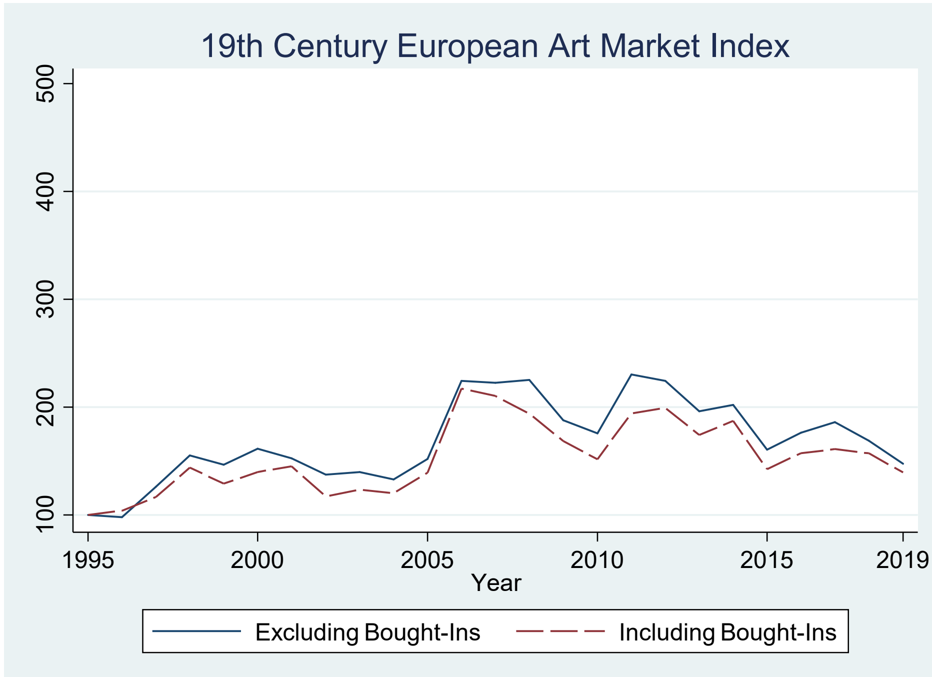


Figure 5

Shows the 19th Century European ADF t-statistic sequence before and after including bought-ins. T-statistics are found using forward recursive calculations with an expanding window and initial window size of 10 years. T-stats are tested against corresponding critical values for bubble identification at the 90%, 95% and 99% level, which are the same critical values as the "Identifying Existence of Bubble" critical values in Table 3

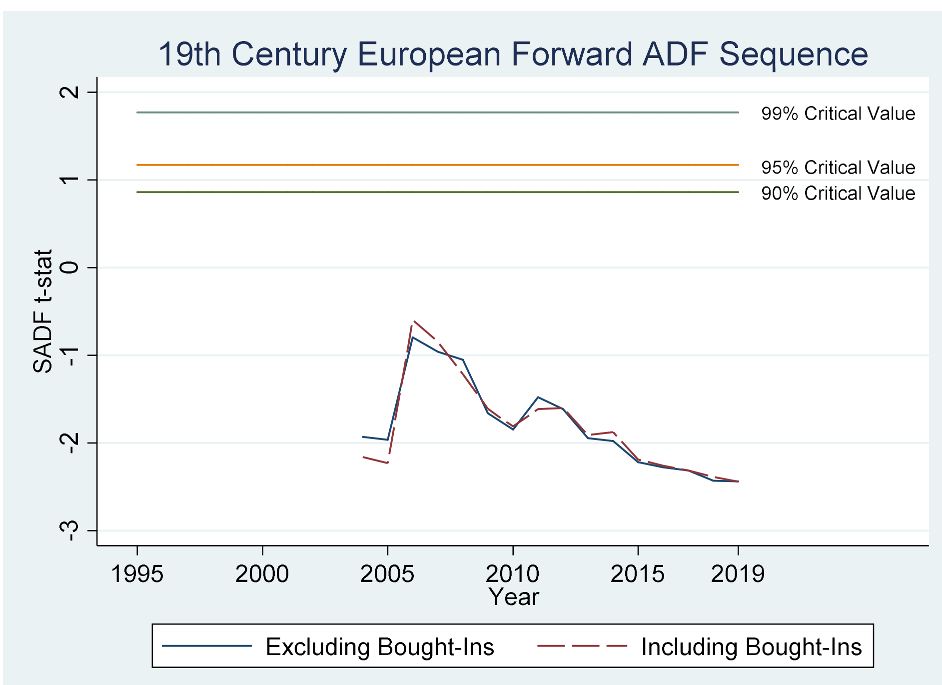


Figure 6

Shows the American art market index from 1995 to 2019 before and after including bought-ins in index creation. Series are annual data and normalized to 100 in 1995

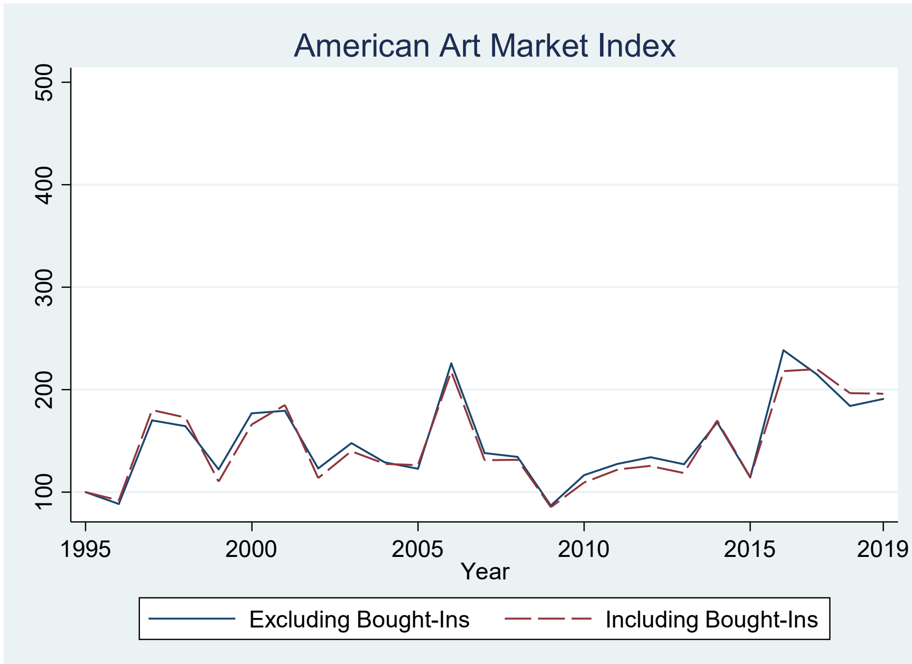


Figure 7:

Shows the American ADF t-statistic sequence before and after including bought-ins. T-statistics are found using forward recursive calculations with an expanding window and initial window size of 10 years. T-stats are tested against corresponding critical values for bubble identification at the 90%, 95% and 99% level, which are the same critical values as the "Identifying Existence of Bubble" critical values in Table 3

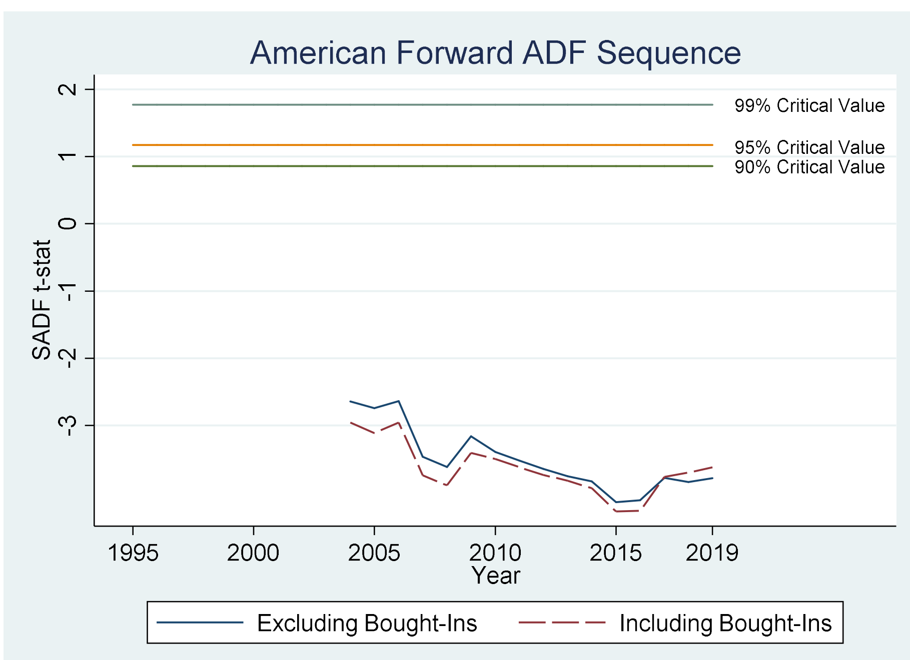


Figure 8

Shows the Post-War & Contemporary art market index from 1995 to 2019 before and after including bought-ins in index creation. Series are annual data and normalized to 100 in 1995

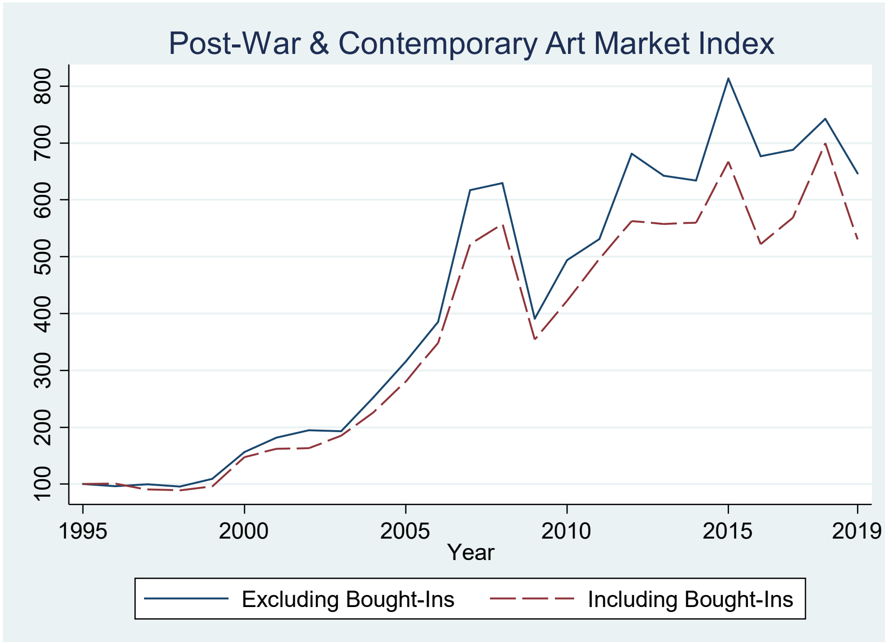


Figure 9

Shows the PW&C ADF t-statistic sequence before and after including bought-ins. T-statistics are found using forward recursive calculations with an expanding window and initial window size of 10 years. T-stats are tested against corresponding critical values for bubble identification at the 90%, 95% and 99% level, which are the same critical values as the "Identifying Existence of Bubble" critical values in Table 3

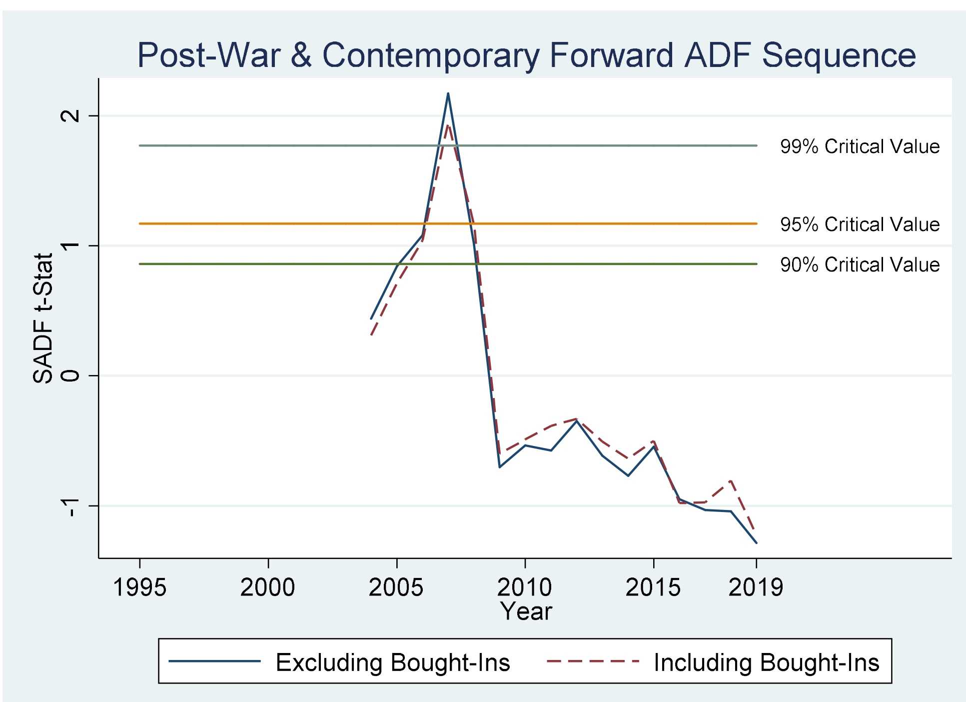


Figure 10

Shows the Impressionist & Modern art market index from 1995 to 2019 before and after including bought-ins in index creation. Series are annual data and normalized to 100 in 1995

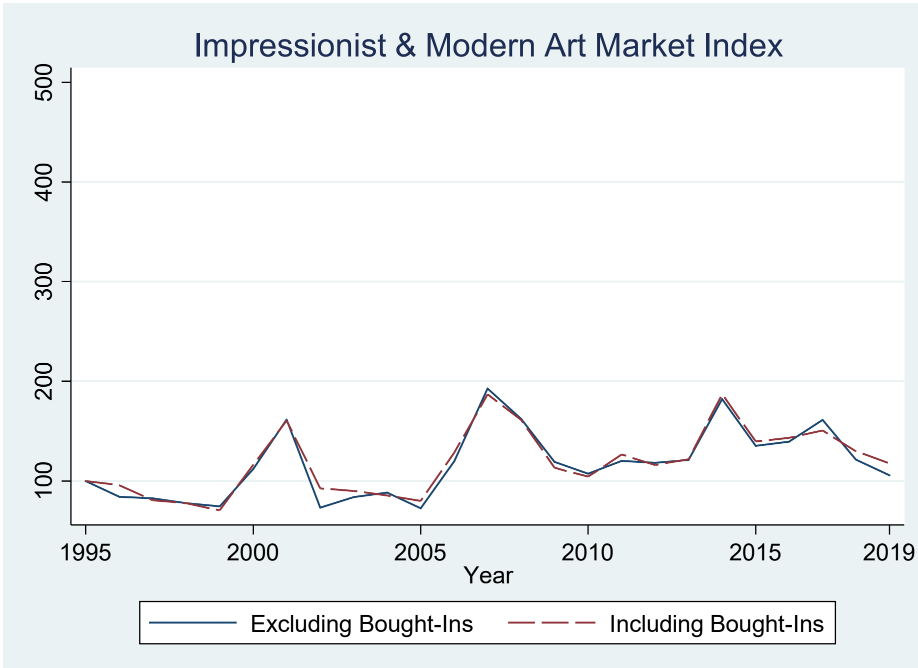


Figure 11

Shows the Impressionist & Modern ADF t-statistic sequence before and after including bought-ins. T-stats are found using forward recursive calculations with an expanding window and initial window size of 10 years. T-stats are tested against corresponding critical values for bubble identification at the 90%, 95% and 99% level, which are the same critical values as the "Identifying Existence of Bubble" critical values in Table 3

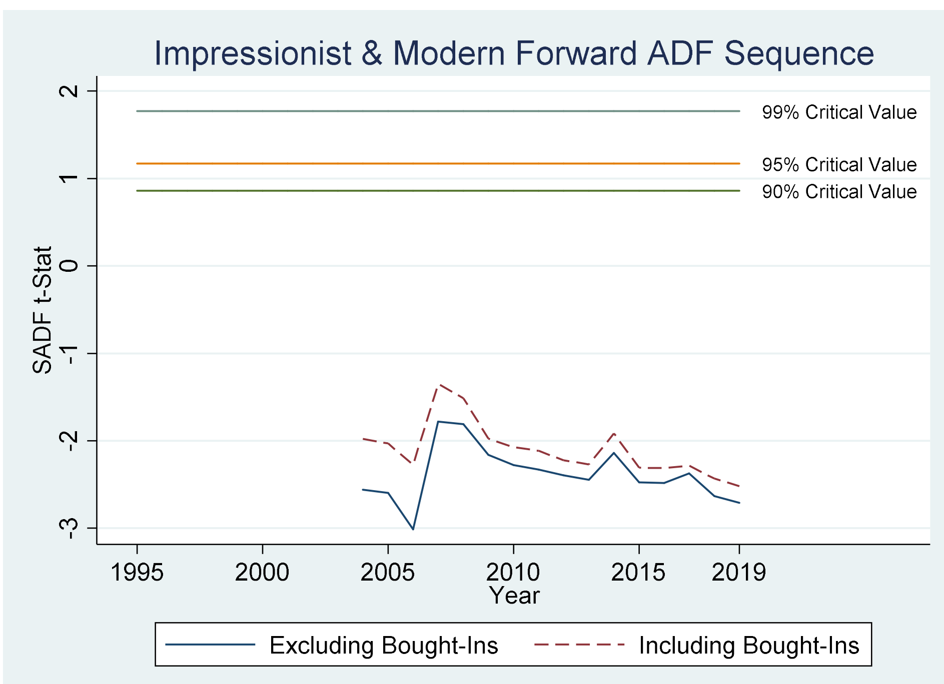


Figure 12

Shows the Old Masters art market index from 1995 to 2019 before and after including bought-ins in index creation. Series are annual data and normalized to 100 in 1995

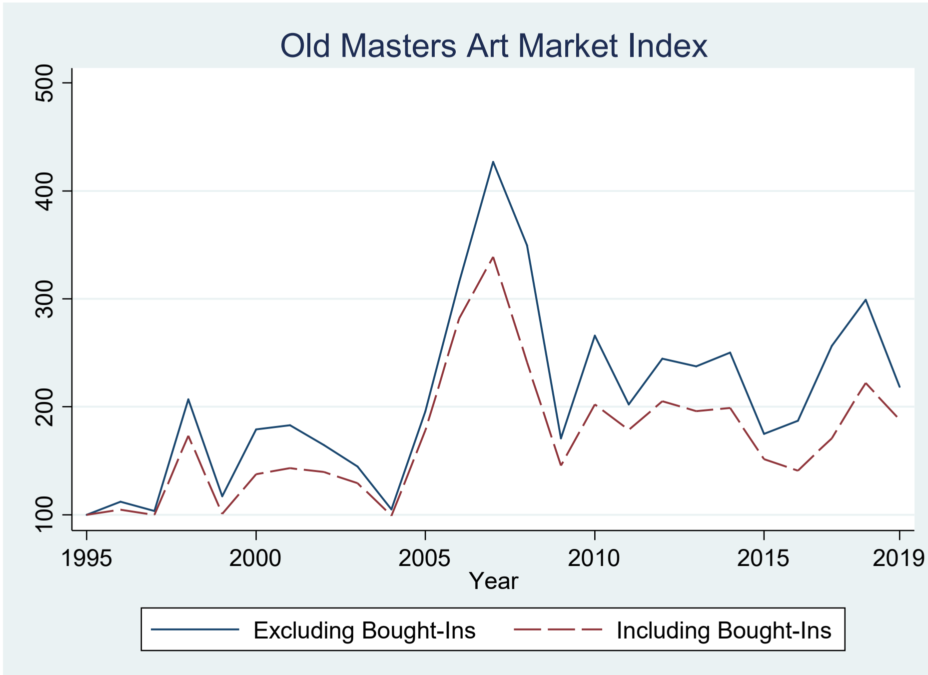
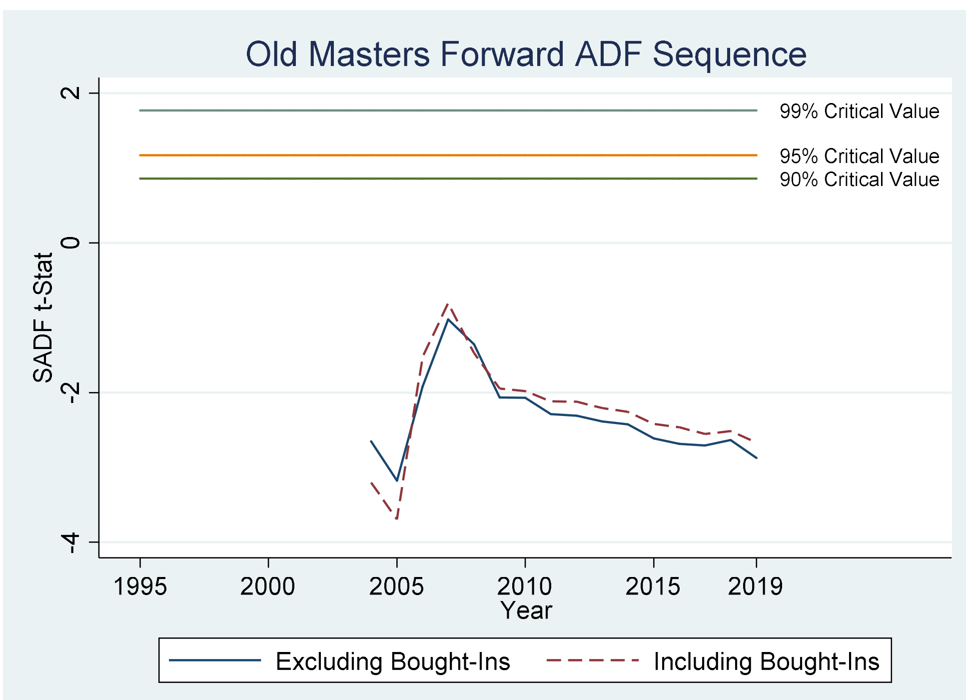


Figure 13

Shows the Old Masters ADF t-statistic sequence before and after including bought-ins. T-stats are found using forward recursive calculations with an expanding window and initial window size of 10 years. T-stats are tested against corresponding critical values for bubble identification at the 90%, 95% and 99% level, which are the same critical values as the "Identifying Existence of Bubble" critical values in Table 3



“Significant Year” Bubble Detection

Table 6

Bubbles identified by genre at different confidence levels using the “Significant Year” approach. Years with statistically significant annual dummy variables after controlling for hedonic characteristics of art and stock index performance are classified as bubble years. NOTE: Genres that are not bold have a statistically insignificant relationship between the stock performance control variable and painting prices before and after including bought-ins (see Appendix tables 4 and 5). This invalidates the purpose and results of the test for these genres (see paper section 4Aiii.).

90% Confidence

	Excluding Bought-Ins				Including Bought-Ins		
	1st Episode	**2nd Episode**	**3rd Episode**	**4th Episode**	**1st Episode**	**2nd Episode**	**3rd Episode**
Aggregate	**2001**	**2006-2010**	**2014**	-	**2006-2008**	-	-
19th Euro*	1997-2019	-	-	-	2006-2009	-	-
American	-	-	-	-	-	-	-
PW & C	**2003-2019**	-	-	-	**2005-2015**	-	-
I&M*	2003	2005	-	-	2001	2007-2008	2014
OM*	1998	2000-2003	2005-2014	2017	2006-2007	-	-

95% Confidence

	Excluding Bought-Ins				Including Bought-Ins		
	1st Episode	**2nd Episode**	**3rd Episode**	**4th Episode**	**1st Episode**	**2nd Episode**	**3rd Episode**
Aggregate	**2001**	**2006-2010**	-	-	**2006-2008**	-	-
19th Euro*	1997-2019	-	-	-	2006	-	-
American	-	-	-	-	-	-	-
PW&C	**2005-2018**	-	-	-	**2006-2013**	-	-
I&M*	-	-	-	-	2001	2007-2008	2014
OM*	1998	2006-2010	2012-2013	-	2006-2007	-	-

99% Confidence

	Excluding Bought-Ins				Including Bought-Ins		
	1st Episode	**2nd Episode**	**3rd Episode**	**4th Episode**	**1st Episode**	**2nd Episode**	**3rd Episode**
Aggregate	**2006-2008**	-	-	-	**2006-2007**	-	-
19th Euro*	1997-2018	-	-	-	-	-	-
American	-	-	-	-	-	-	-
PW & C	**2007-2012**	-	-	-	**2008-2009**	**2012**	-
I&M*	-	-	-	-	-	-	-
OM*	1998	2006-2008	-	-	-	-	-

Figure 14

Shows the "original" Aggregate art market index from 1995 to 2019 before controlling for stock performance or including bought-ins, and then the index after controlling for stock market performance since 1995 (called "income" here), both before and after including bought-ins. Yellow dots correspond with 99% significant coefficients for the "bubble identification" test.

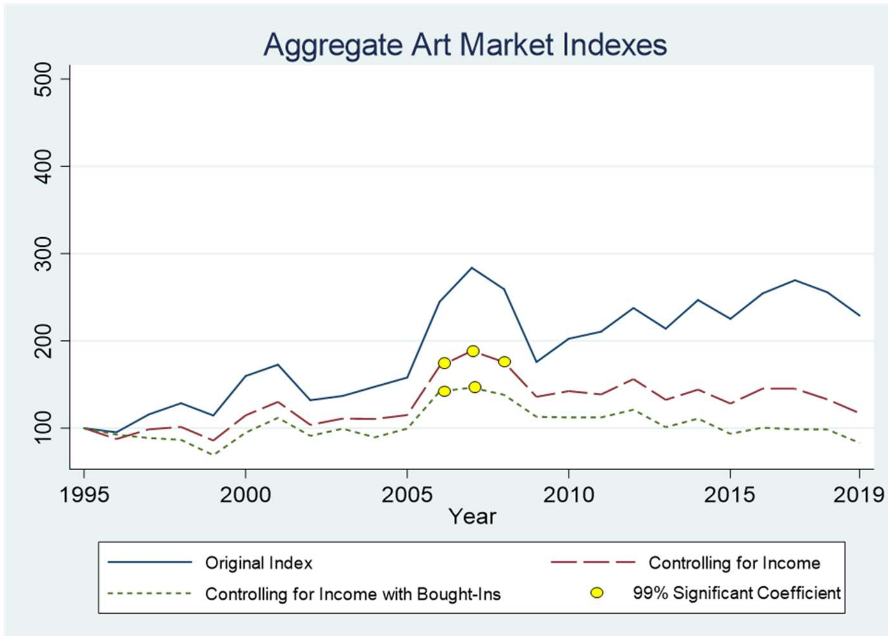


Figure 15

Shows the "original" 19th Century European art market index from 1995 to 2019 before controlling for stock performance or including bought-ins, and then the index after controlling for stock market performance since 1995, here called "income," both before and after including bought-ins. Yellow dots correspond with 99% significant coefficients for the "bubble identification" test. NOTE: These "bubble identifications" are invalid (see note on Table 6 and paper section 4Aiii.).

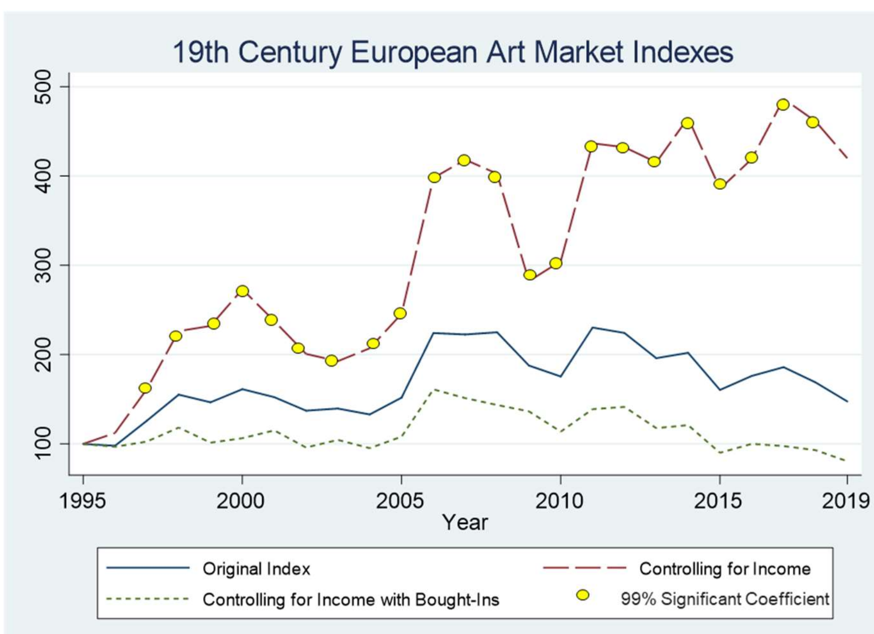


Figure 16

Shows the "original" American art market index from 1995 to 2019 before controlling for stock performance or including bought-ins, and then the index after controlling for stock market performance since 1995(called "income" here) both before and after including bought-ins. Yellow dots correspond with 99% significant coefficients for the "bubble identification." These results are valid, but controlling for stock market performance deflates the American index and leaves no statistically significant coefficients.

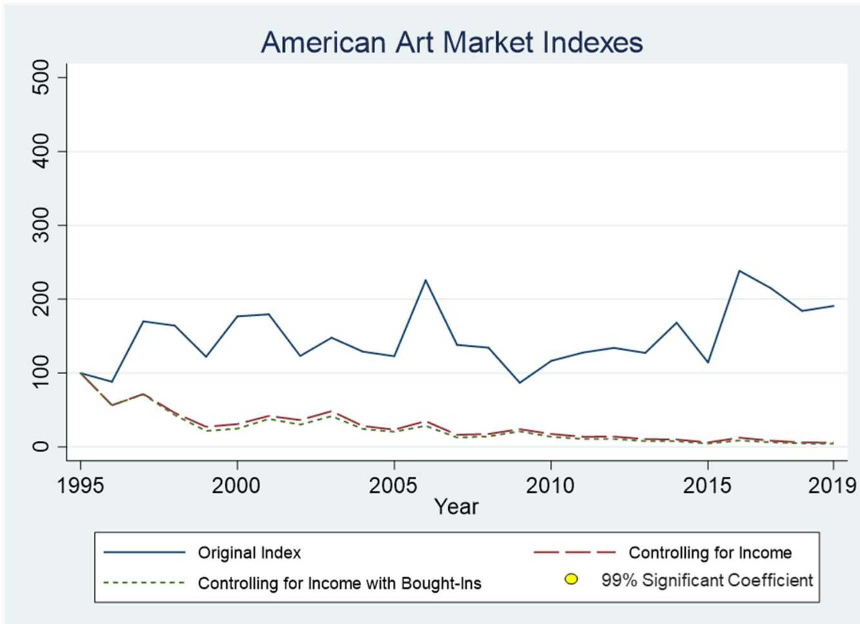


Figure 17

Shows the "original" PW&C art market index from 1995 to 2019 before controlling for stock performance or including bought-ins, and then the index after controlling for stock market performance since 1995, here called "income," both before and after including bought-ins. Yellow dots correspond with 99% significant coefficients for the "bubble identification" test. These results are valid, due to the statistically significant relationship between stock market performance and PW&C market prices.

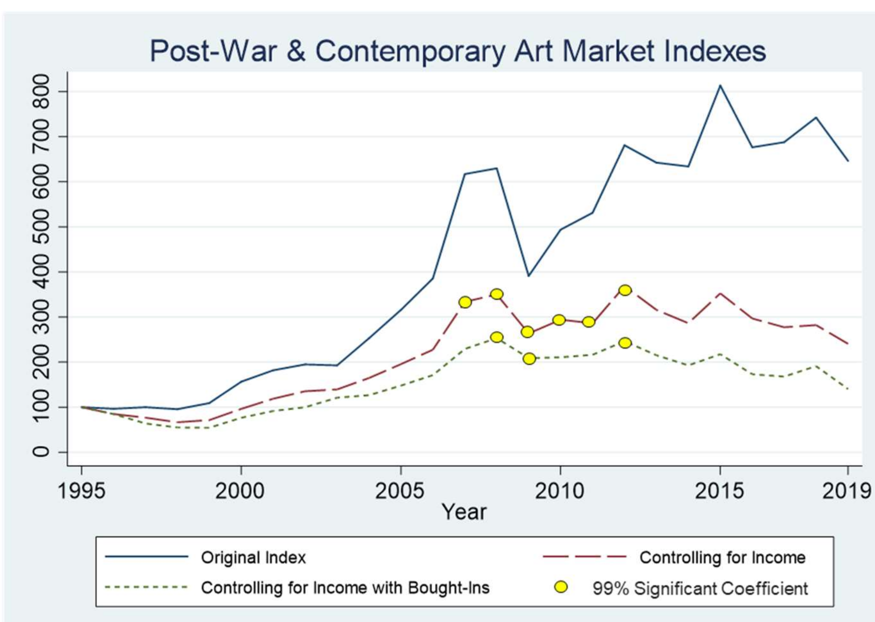


Figure 18

Shows the "original" Impressionist & Modern art market index from 1995 to 2019 before controlling for stock performance or including bought-ins, and then the index after controlling for stock market performance since 1995, here called "income," both before and after including bought-ins. Yellow dots correspond with 99% significant coefficients for the "bubble identification" test. No bubbles are identified at the 99% level, but "bubble identifications" in this market are invalid anyway (see note on Table 6 and paper section 4Aiii.).

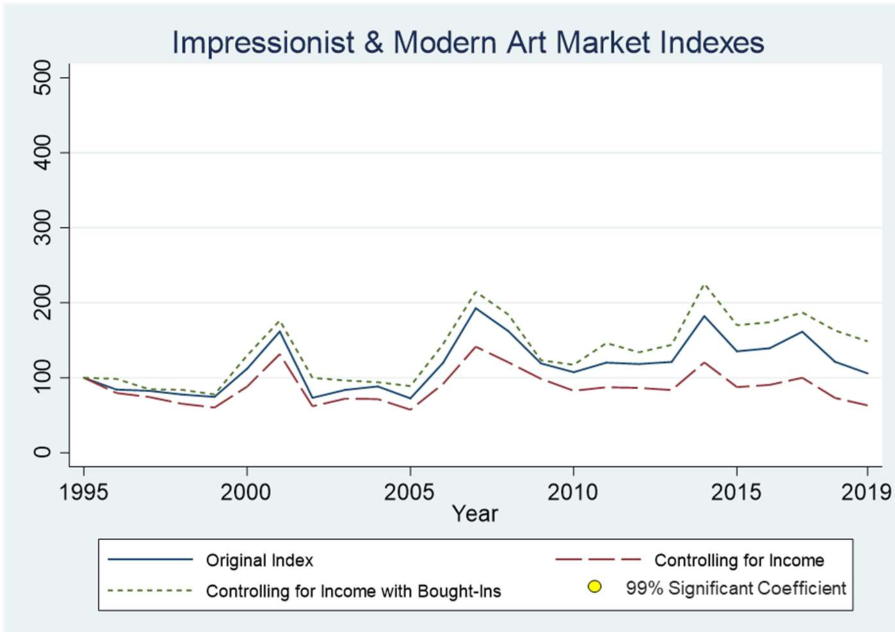
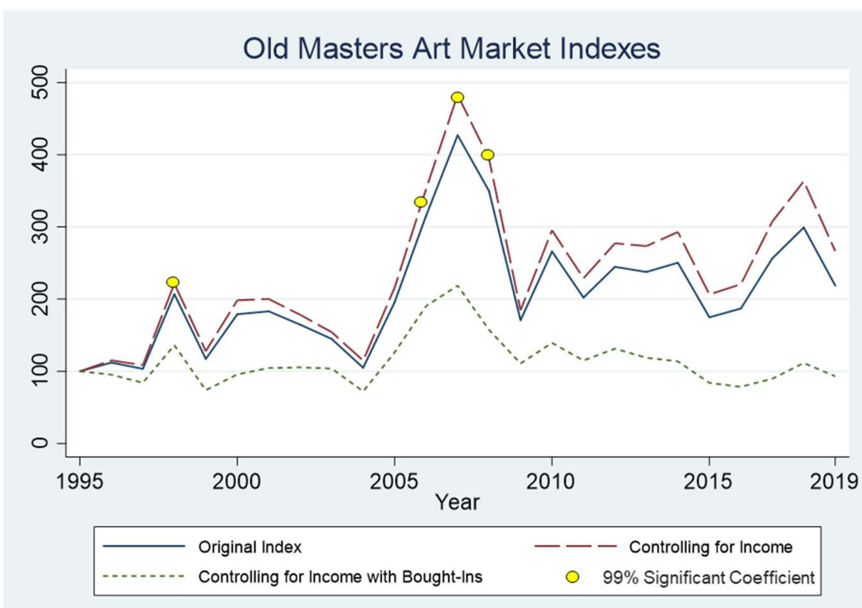


Figure 19

Shows the "original" Old Masters art market index from 1995 to 2019 before controlling for stock performance or including bought-ins, and then the index after controlling for stock market performance since 1995, here called "income," both before and after including bought-ins. Yellow dots correspond with 99% significant coefficients for the "bubble identification" test. NOTE: These "bubble identifications" are invalid (see note on Table 6 and paper section 4Aiii.).



Robustness Checks

Pricing Bought-Ins Differently

Figure 20

Helps visualize the effect of pricing bought-ins differently on the Aggregate Art Index. Regardless of what fraction of the low estimate bought-ins are priced, including bought-ins deflates the aggregate art index.

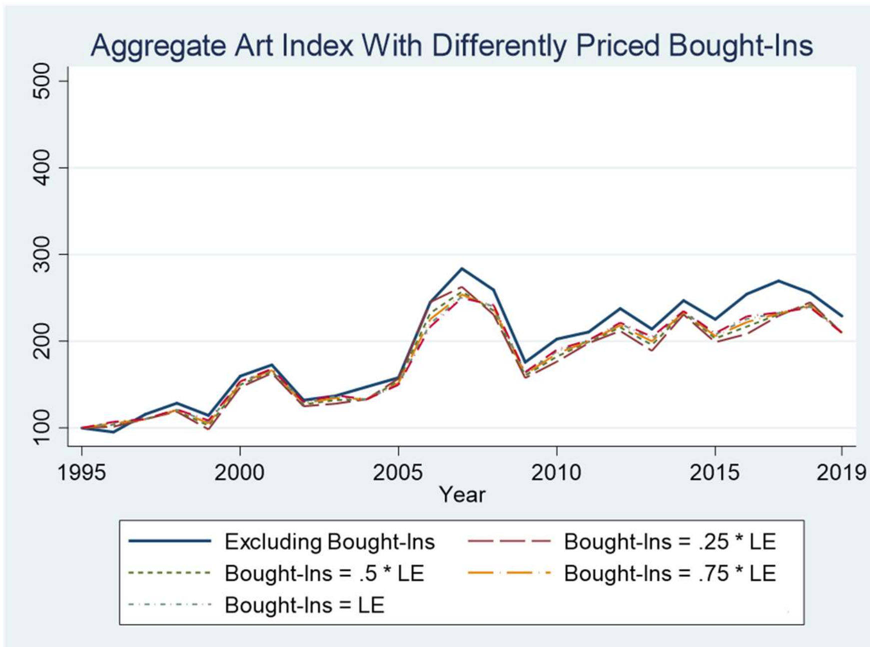


Figure 21

Shows the difference between the aggregate index that excludes bought-ins, and an aggregate index of bought-ins only. Pricing bought-ins at different multiples of the low estimate does not change the performance of a bought-in only index. As a whole, bought-ins underperform sold paintings.

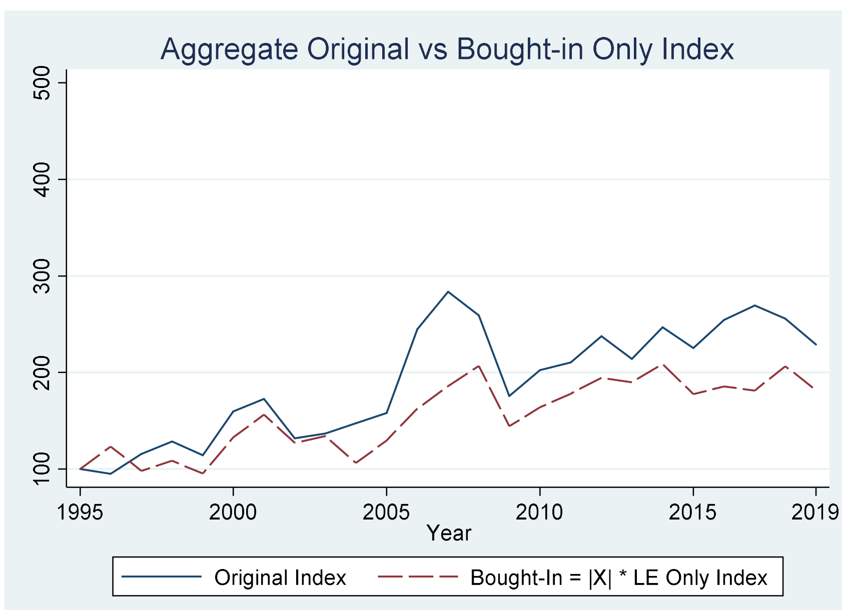


Table 7

Shows SADF t-stats by genre before including bought-ins and then including bought-ins at different multiples of each painting's low estimate. The default bought-in this paper is le*.5. Here, deviating away from le*5 does alter which genres have statistically significant SADF scores. Pricing bought-ins at .25 * le does reduce the confidence level of the PW&C's t-stat from >99% to >95%.

	Excluding Bought-Ins	le*.25	le*.5	le*75	le*100
Aggregate	-0.17	-0.31	-0.29	-0.29	-0.30
19th Century European	-0.80	-0.42	-0.60	-0.77	-0.91
American	-2.64	-3.04	-2.95	-2.88	-2.83
Post-War & Contemporary	2.17***	1.65**	1.95***	2.11***	2.21***
Impressionist & Modern	-1.78	-1.16	-1.35	-1.47	-1.55
Old Masters	-1.02	-0.74	-0.80	-0.90	-1.01

Defining Genres Differently

Table 8

Shows SADF t-stats by genre using original genre classifications, and then alternate genre classifications (based on the year each painting was painted – see paper section 4Bii.) Alternate genre classifications do not change which genres have statistically significant SADF scores

	Original Genre Classification		Alt Genre Classification	
	Excluding Bought-Ins	**Including Bought-Ins**	**Excluding Bought-Ins**	**Including Bought-Ins**
19th Century European	-0.80	-0.60	-0.84	-0.78
American	-2.64	-2.95	-2.62	-2.87
Post-War & Contemporary	2.17***	1.95***	2.29***	1.78***
Impressionist & Modern	-1.78	-1.35	-1.41	-1.30
Old Masters	-1.02	-0.80	-1.10	-.80

Excluding Paintings with Adjusted "Hammer Prices"

Table 9

Shows SADF t-stats by genre using original indexes, and then alternate indexes that are built only using paintings originally priced at their "premium price." "Premium-based" indexes generally have lower SADF scores, but PW&C SADF t-stat are still statistically significant at a >95% confidence level.

	Original Indexes		**Premium-based Indexes**	
	Excluding Bought-Ins	**Including Bought-Ins**	**Excluding Bought-Ins**	**Including Bought-Ins**
Aggregate	-0.17	-0.29	-0.330	-0.332
19th Century European	-0.80	-0.60	-1.63	-1.13
American	-2.64	-2.95	-2.68	-2.94
Post-War & Contemporary	2.17***	1.95***	1.57**	1.29**
Impressionist & Modern	-1.78	-1.35	-1.99	-1.68
Old Masters	-1.02	-0.80	-0.67	-0.51

Trimester-Based Indexes

Table 10

Shows SADF t-stats by genre using original "annual" indexes, and then "trimester" indexes, which estimate index changes using sales from only one trimester a year. This has mixed effects and reduces the significance of PW&C SADF t-stats from a >99% confidence level to a >95% confidence level

	Annual Indexes		**Trimester-based Indexes**	
	Excluding Bought-Ins	**Including Bought-Ins**	**Excluding Bought-Ins**	**Including Bought-Ins**
Aggregate	-0.17	-0.29	-0.23	0.059
19th Century European	-0.80	-0.60	-0.16	-0.57
American	-2.64	-2.95	-2.16	-2.39
Post-War & Contemporary	2.17***	1.95***	1.37**	1.38**
Impressionist & Modern	-1.78	-1.35	-1.89	-1.21
Old Masters	-1.02	-0.80	-0.69	-0.41

**** Appendix ****

Regression Result References

Table 1A

Lists all hedonic regression variables and the motivation for using them.

Variable	Variable Definition
i.Year	Dummy variable for each year in the sample. Reference/base/omitted year is 1995, so that coefficients on each annual dummy variable shows changes in prices relative to 1995.
i.Artist	Dummy variable for each artist in the sample who has painting sales across more than one year. Intended to capture the heterogenous effect of the reputation of artists on the prices of their paintings. Artists with only one painting or multiple paintings in a single year are grouped as a single dummy variable to avoid perfect collinearity between annual dummy variables and dummy variables for these artists. Due to the high number of artists, coefficients for each artist are not included in the regression results in tables 2A-6A.
i.Auctionhouse	Dummy variable for each auction house in the sample. Intended to capture the heterogenous effect of the reputation of each auction house on the price of the paintings it sells. Auction houses with sales concentrated in a single year are grouped as a single dummy variable to avoid high collinearity between annual dummy variables and dummy variables for each auction house. Due to the high number of different auction houses, coefficients for each house are not included in the regression results in tables 2A-6A, but coefficients for each auction house in the "Original Aggregate" regression are listed in tables 18A, 19A, and 20A
Signed	Dummy variable for whether the painting is signed or not. Anderson (1974) explains that attribution to the painter can be a significant feature of the sales price, so one should expect a "signed" painting to sell for more.
Stamped	Dummy variable for whether the painting is stamped or not. Stamps are generally on the back of paintings were often placed by old suppliers of the paintings with the names and addresses of their businesses. It is unclear whether "stamped" paintings should sell for more.
Inscribed	Dummy variable for whether the painting is inscribed or not. Inscriptions are usually on the back of the painting, and are often the inscribed initials of previous owners of the paintings or old handwritten notes about the painting. It is unclear whether "inscribed" paintings should sell for more.
Size (inches)	Continuous variable that measures the size of paintings (height x width). At first, bigger paintings are expected to sell for more because all else equal a larger painting requires more work on the part of the artist. However, owning a huge painting might be impratical, and thereby after painting sizes are too big to fit in ordinary interior spaces, demand might diminish for paintings. If this were true, there would be a quadratic relationship between prices and painting size and this variable would be positive.
Size Squared	Continuous variable that measures the squared size of paintings (height x width). If the presumed quadratic relationship between painting size and painting prices exists, this size-squared should have a negative relationship with price.
Other Medium	Dummy variable for "other" types of paint. Oil paintings are the omitted/reference group. "Other medium" encompasses unconventional types of "paint." For example, one painting in the database was done using "chewing gum on canvas." Chewing gum is classified as a type of "other medium." Given the unusual nature of "other" types of paint, it is unclear how this dummy variable should affect prices.
Pastel	Dummy variable for pastel paints. Oil painting are the omitted/reference group. Generally of all painting mediums, oil has the highest sales price (Kräussl et al., 2016), so I expect this coefficient to be negative. However, pastel paints produce similar colors to oil paints and should have a more positive effect on painting prices than other non-oil paints.
Graphite/ Chalk	Dummy variable for whether graphite/chalk is used as paint. Oil paintings are the omitted/reference group. Generally of all painting mediums, oil has the highest sales price (Kräussl et al., 2016), so I expect this coefficient to be negative. Graphite/chalk is generally used to draw, not paint, and it produces pictures that are less rich in color than oil or other paints. Graphite/Chalk should thereby have a more negative effect on prices than other non-oil paints.
Fresco	Dummy variable for whether a painting is a fresco. Oil paintings are the omitted/reference group. Generally of all painting mediums, oil has the highest sales price (Kräussl et al., 2016), but the fresco technique to painting is now uncommon, and buyers might value the novelty that comes with buying an older "fresco" painting, the effect of fresco's on prices relative to oil paintings is unclear.
Watercolor	Dummy variable for watercolor paints. Oil paintings are the omitted/reference group. Generally of all painting mediums, oil has the highest sales price (Kräussl et al., 2016), so I expect this coefficient to be negative. Unlike pastels, watercolor paints are very distinct from oil paints are often regarded as inferior. I thereby expect watercolors to have more of a negative effect on prices than pastels but less than graphite/chalk.
Acrylic	Dummy variable for acrylic paints. Oil paintings are the omitted/reference group. Generally of all painting mediums, oil has the highest sales price (Kräussl et al., 2016), so I expect this coefficient to be negative. Acrylic paints are bright, very distinct from oil paints, and more commonly used in the present than in the past. It is unclear how these charachteristics will affect their prices relative to other non-oil paints.

Other Material	Dummy variable for when a painting is painted on "other" types of material. Canvas is the omitted/reference group for material. "Other material" encompasses unconventional materials used to paint on, for example, "colorized salt." Given the unusual nature of most "other" materials, it is unclear how this dummy variable should affect prices.
Panel	Dummy variable for when a painting is painted on a panel. Canvas is the omitted/reference group for material. Many Old Masters painted on panels, but canvas is more popular today. This suggests that panels might have a positive impact on prices in the Old Masters genre because its connote authenticity, but less of an impact in more recent genres.
Paper/ Cardboard	Dummy variable for when a painting is painted on paper or cardboard. Canvas is the omitted/reference group. Paper and cardboard are much cheaper than canvas, so I expect this coefficient to be negative.
Metal	Dummy variable for when a painting is painted on metal. Canvas is the omitted/reference group. Metal generally is more expensive than canvas, so I expect this coefficient to be positive.
In the manner of	Dummy variable for whether a painting is "in the manner of" the artist listed as opposed to actually painted by the artist. I expect this coefficient to be negative, because if an artist is having paintings done in their manner, they are likely influence/ well-known, and buyers would prefer paintings from a well-known artist over paintings from someone imitating the well-known artist
Circle/Follower	Dummy variable for whether a work is painted by someone in the circle of or directly following the artist listed, as opposed to actually painted by the artist. I expect this coefficient to be negative, because buyers would prefer paintings from the original well-known artist themselves, but I expect this coefficient to be less negative than the "in the manner" coefficient, because the label "in the circle of / follower of" implies that there was contact/proximity between the painting's actual artist and the well-known artist that is listed.
Attributed to	Dummy variable for whether a work is "attributed" to the artist listed, as opposed to certainly painted by the artist listed. I expect this coefficient to be negative, because buyers prefer painting that are unambiguously attributed to the artist listed (Anderson, 1974)
"Untitled"	Dummy variable for whether a work is titled "untitled" (or translations of "untitled"). I expect this coefficient to be negative, because "untitled" is generic, and signals less care was put into characterizing the content of a work.
"Composition"	Dummy variable for whether a work is titled "composition" (or translations of "composition"). I expect this coefficient to be negative, because "composition" is generic, and signals less care was put into characterizing the content of a work.
Title Length	Continuous variable that measures the number of letters in the title of a painting. Longer painting titles could suggest that more effort has been put into characterizing the content in a work. Shorter titles may also be more likely to be generic. For example, all else equal, buyers might perceive a painting titled "Landscape" less favorably than a painting titled "An Italian landscape with a traveler on a path by a waterfall" (this is the title of a painting in the paper's sample).
ln(stock market index)	Continuous variable used for the "significant year" tests. Proxies for appreciation of the wealth of the wealthy since 1995, and is then used to control for changes in art demand due to changes in income since 1995. It is the natural log of an index of all returns (including dividends) on all stocks in the CRSP database of American stocks. This is expected to vary positively with art prices (see paper section 2Cii.)

Table 2A

Shows hedonic regression results done on data that excludes bought-ins. Exponentiated coefficients on the annual dummy variables correspond to the genre-based indexes in Figure 2. Controls for all artists and auction houses are included in this regression but are not listed due to the high number of dummy artist and auction house variables.

***p<0.01, ** p<0.05, *p<0.1

	Aggregate	19th Euro	American	PW &C	I&M	OM
1996	-0.05	-0.02	-0.12	-0.04	-0.17	0.11
1997	0.15***	0.23**	0.53***	0.00	-0.19	0.03
1998	0.25***	0.44***	0.50***	-0.05	-0.25**	0.73***
1999	0.13**	0.38***	0.20*	0.09	-0.29**	0.16
2000	0.47***	0.48***	0.57***	0.45***	0.11	0.58***
2001	0.55***	0.42***	0.59***	0.60***	0.48***	0.60***
2002	0.28***	0.32**	0.21**	0.67***	-0.31**	0.50***
2003	0.31***	0.33**	0.39***	0.66***	-0.18	0.37
2004	0.39***	0.29***	0.26**	0.93***	-0.12	0.05
2005	0.46***	0.42***	0.21**	1.15***	-0.32***	0.67***
2006	0.90***	0.81***	0.81***	1.35***	0.18	1.15***
2007	1.04***	0.80***	0.32***	1.82***	0.66***	1.45***
2008	0.95***	0.81***	0.30***	1.84***	0.48***	1.25***
2009	0.56***	0.63***	-0.14	1.36***	0.18	0.54***
2010	0.71***	0.56***	0.15	1.60***	0.07	0.98***
2011	0.74***	0.83***	0.24	1.67***	0.18	0.70***
2012	0.87***	0.81***	0.29*	1.92***	0.17	0.89***
2013	0.76***	0.67***	0.24	1.86***	0.19	0.87***
2014	0.90***	0.70***	0.52***	1.85***	0.60	0.92***
2015	0.81***	0.47***	0.14***	2.10***	0.30**	0.56***
2016	0.93***	0.57***	0.87***	1.91***	0.33***	0.63***
2017	0.99***	0.62***	0.77***	1.93***	0.48***	0.94***
2018	0.94***	0.52***	0.61***	2.00***	0.19	1.10***
2019	0.83***	0.39***	0.65***	1.87***	0.06	0.78***
Signed	-0.06***	0.31***	0.13***	0.07*	0.29***	0.12***
Stamped	-0.34***	0.00	-0.26	-0.18*	0.03	-0.58**
Inscribed	-0.04*	0.01	0.02	-0.04	-0.02	0.05
Size (inches)	.000034***	.00016***	.000046***	.00013***	.00044***	0.00042***
Size Squared	-1.04e-11 ***	-6.40e-10***	-1.41e-11***	-1.39e-10***	-2.13e-08***	-2.74e-08***
Other Medium	-0.18***	-0.23	-0.14	-0.26***	-0.42***	0.44***
Pastel	0.05	-0.48**	0.01	-0.59***	0.35*	-0.23
Graphite/Chalk	-0.79***	-0.63**	-1.64***	-0.35**	-1.22***	-0.53*
Fresco	0.49	(omitted)	(omitted)	0.19	-0.01	-0.05
Watercolor	-0.34***	-0.26*	-0.36***	-0.43***	-0.54***	-0.96***
Acrylic	0.06	(omitted)	-0.11	0.06	0.04	(omitted)
Other Material	-0.45***	-0.15	-0.05	-0.35***	-0.37***	-0.32**
Panel	-0.19***	-0.27***	-0.32***	-0.25***	-0.19***	0.28***
Paper/Cardboard	-0.81***	-0.57***	-0.73***	-0.79***	-0.38***	-0.15
Metal	0.12	-0.20	0.52	0.09	5.95***	0.31***
In the manner of	-1.38***	-0.79**	-0.32	(omitted)	-1.23	-1.47***
Circle/Follower	-1.12***	-0.86***	-1.14*	0.33	-1.57	-1.29***
Attributed to	-0.38***	0.23	0.24	2.82***	-0.64	-0.68***
“Untitled”	-0.35***	0.32	-0.08	-0.28***	-0.37	(omitted)
“Composition”	-0.34***	0.99	-.06	-0.38***	-0.05	0.43
Title Length	0.01***	0.004***	.004***	0.001	0.002*	0.004***
Constant	10.37***	9.73***	9.19***	10.09***	10.80***	10.10***
Observations	34,302	5,876	6,580	8,531	7,478	5,837
R-Squared	0.7487	0.7746	0.6971	0.8528	0.7591	0.7061

Table 3A

Shows hedonic regression results done on data that includes bought-ins. Exponentiated coefficients on the annual dummy variables correspond to the bought-in inclusive genre-based indexes in Figure 2, 4, 6, 8, 10, and 12. Controls for all artists and auction houses are included in this regression but are not listed due to the high number of dummy artist and auction house variables.

***p<0.01, ** p<0.05, *p<0.1

	Aggregate	19th Euro	American	PW &C	I&M	OM
1996	0.04	0.04	-0.08	0.01	-0.04	0.04
1997	0.10**	0.15*	0.59***	-0.10	-0.21**	0.00
1998	0.18***	0.36***	0.55***	-0.12	-0.25***	0.55***
1999	0.03	0.25***	0.10	-0.04	-0.35***	0.01
2000	0.40***	0.34***	0.51***	0.39***	0.15	0.32***
2001	0.50***	0.37***	0.62***	0.48***	0.47***	0.36***
2002	0.24***	0.16*	0.13	0.49***	-0.08	0.33***
2003	0.28***	0.21**	0.34***	0.62***	-0.10	0.26***
2004	0.29***	0.18**	0.24**	0.82***	-0.16	-0.01
2005	0.43***	0.33***	0.23***	1.03***	-0.22**	0.58***
2006	0.84***	0.77***	0.78***	1.25***	0.25**	1.04***
2007	0.94***	0.74***	0.27***	1.65***	0.62***	1.22***
2008	0.86***	0.66***	0.27***	1.72***	0.48***	0.88***
2009	0.47***	0.52***	-0.16	1.27***	0.12	0.38***
2010	0.60***	0.42***	0.09	1.44***	0.04	0.70***
2011	0.69***	0.66***	0.20**	1.60***	0.24***	0.58***
2012	0.77***	0.69***	0.23**	1.73***	0.15	0.72***
2013	0.67***	0.55***	0.17*	1.72***	0.20**	0.67***
2014	0.84***	0.63***	0.53***	1.72***	0.63***	0.69***
2015	0.71***	0.35***	0.14	1.90***	0.34***	0.42***
2016	0.77***	0.45***	0.78***	1.65***	0.36***	0.34***
2017	0.84***	0.48***	0.79***	1.74***	0.41***	0.54***
2018	0.88***	0.45***	0.68***	1.95***	0.26***	0.80***
2019	0.74***	0.33***	0.67***	1.67***	0.16	0.63***
Signed	-0.07***	0.25***	0.18***	0.08**	0.21***	0.10***
Stamped	-0.35***	-0.10	-0.24	-0.11	-0.10	-0.34*
Inscribed	-0.03	-0.02	0.02	-0.01	0.01	0.07
Size (inches)	.000042***	.00021***	.000049***	.00012***	.00047***	.00029***
Size Squared	-1.32e-11***	--8.37e-10***	-1.50e-11***	-1.32e-10***	-2.32e-08***	-7.88e-09***
Other Medium	-0.21***	-0.02	-0.14	-0.31***	-0.37***	0.44***
Pastel	-0.04	-0.40**	-0.11	-0.61***	0.10	0.01
Graphite/Chalk	-0.81***	-0.63***	-1.37***	-0.60***	-1.21***	-0.63**
Fresco	0.53	(omitted)	(omitted)	0.38	0.35	0.30
Watercolor	-0.33***	-0.05*	-0.33***	-0.49***	-0.46***	-1.07***
Acrylic	0.04	(omitted)	-0.02	0.09**	-0.27	-2.30
Other Material	-0.45***	-0.31	-0.10	-0.29***	-0.40***	-0.48***
Panel	-0.16***	-0.26***	-0.26***	-0.20***	-0.15***	0.23***
Paper/Cardboard	-0.75***	-0.51***	-0.73***	-0.73***	-0.36***	-0.16
Metal	0.09	-0.10	-0.11	0.11	6.19***	0.25***
In the manner of	-1.46***	-1.02**	0.05	(omitted)	-2.43***	-1.62***
Circle/Follower	-1.15***	-0.89***	-0.87	0.84	-0.90*	-1.33***
Attributed to	-0.40***	-0.11	0.18	1.18	-0.33	-0.72***
"Untitled"	-0.34***	0.92	-0.09	-0.28***	-0.08	-1.56
"Composition"	-0.30***	-0.07	0.01	-0.25***	0.00	0.15
Title Length	0.01***	0.01***	0.0045***	.0028**	0.00***	.0038***
Constant	10.10***	9.44***	8.92***	9.92***	10.43***	10.03***
Observations	50,055	9,348	8,606	11,497	11,022	9,582
R-Squared	0.7266	0.7746	0.6608	0.8432	0.7542	0.6683

Table 4A

Shows hedonic regression results after controlling for stock market returns on data that excludes bought-ins. These are the results used for the "significant coefficient" test. The statistically insignificant relationship between ln(stock market index) and prices in the 19th Euro, I&M and OM markets suggests that the "significant coefficient" test is invalid for these genres (see 2Bii.). Hedonic controls not listed.

***p<0.01, ** p<0.05, *p<0.1

	Aggregate	19th Euro	American	PW &C	I&M	OM
1996	-0.13	0.12	-0.57	-0.16	-0.23	0.14
1997	-0.01	0.48***	-0.33	-0.26	-0.30	0.08
1998	0.01	0.82***	-0.77	-0.41	-0.43	0.80***
1999	-0.15	0.84***	-1.30	-0.34	-0.51	0.25
2000	0.14	1.00***	-1.17	-0.04	-0.13	0.69*
2001	0.26**	0.87***	-0.87	0.17	0.27	0.69**
2002	0.04	0.70***	-1.01	0.30	-0.48	0.58*
2003	0.10	0.66***	-0.72	0.33*	-0.33*	0.43*
2004	0.10	0.73***	-1.26	0.50*	-0.33	0.14
2005	0.14	0.90***	-1.45	0.67**	-0.56*	0.77**
2006	0.54***	1.38***	-1.05	0.82**	-0.09	1.26***
2007	0.63***	1.43***	-1.80	1.21***	0.35	1.57***
2008	0.56***	1.39***	-1.73	1.25***	0.19	1.37***
2009	0.31***	1.04***	-1.42	0.97***	-0.01	0.61**
2010	0.35**	1.11***	-1.73	1.08***	-0.19	1.08***
2011	0.33	1.47***	-1.97	1.05***	-0.14	0.83**
2012	0.45	1.46***	-1.96	1.30***	-0.15	1.02**
2013	0.28	1.42***	-2.23	1.15***	-0.18	1.01**
2014	0.37*	1.54***	-2.29	1.05**	0.19	1.07*
2015	0.25	1.35***	-2.79	1.26**	-0.13	0.72
2016	0.37	1.43***	-2.07	1.09**	-0.10	0.79
2017	0.37	1.58***	-2.46	1.02***	0.00	1.12*
2018	0.28	1.53***	-2.78	1.04***	-0.31	1.29
2019	0.16	1.43**	-2.83	0.88*	-0.46	0.98
Hedonic Controls	Yes	Yes	Yes	Yes	Yes	Yes
ln(stock market index)	0.32***	-0.49	1.64***	0.46***	0.25	-.092
Observations	34,302	9,348	5,876	8,531	7,478	5,837
R-Squared	0.7487	0.7747	0.6984	0.8529	0.7591	0.7061

Table 5A

Shows hedonic regression results after controlling for stock market returns (ln(Stock Market Index)) on data that excludes bought-ins. These are the results used for the "significant coefficient" test. The statistically insignificant relationship between ln(stock market index) and prices in the 19th Euro, I&M and OM markets suggests that the "significant coefficient" test is invalid for these genres (see 2Bii.). Hedonic controls not listed.

***p<0.01, ** p<0.05, *p<0.1

	Aggregate	**19th Euro**	**American**	**PW &C**	**I&M**	**OM**
1996	-0.08	-0.03	-0.57	-0.17	-0.02	-0.05
1997	-0.12	0.03	-0.34	-0.45	-0.17	-0.17
1998	-0.14	0.17	-0.84	-0.60	-0.18	0.31
1999	-0.37	0.01	-1.52	-0.61	-0.25	-0.30
2000	-0.05	0.06	-1.39	-0.27	0.26	-0.04
2001	0.11	0.14	-0.97	-0.09	0.57***	0.05
2002	-0.09	-0.04	-1.19	0.00	0.00	0.05
2003	-0.01	0.04	-0.87	0.19	-0.04	0.04
2004	-0.11	-0.05	-1.41	0.24	-0.06	-0.33
2005	0.00	0.08	-1.57	0.39*	-0.12	0.23
2006	0.35***	0.48**	-1.25	0.54**	0.37	0.64**
2007	0.38***	0.41*	-2.05	0.83**	0.76**	0.78**
2008	0.32**	0.36*	-1.94	0.93***	0.61**	0.45
2009	0.12	0.31**	-1.55	0.74***	0.21	0.10
2010	0.12	0.13	-1.97	0.74***	0.16	0.33
2011	0.12	0.33	-2.21	0.77**	0.38	0.14
2012	0.19	0.35	-2.22	0.90***	0.29	0.27
2013	0.01	0.16	-2.52	0.77**	0.36	0.17
2014	0.10	0.19	-2.54	0.66*	0.81**	0.13
2015	-0.07	-0.10	-3.06	0.78*	0.53	-0.17
2016	0.01	0.00	-2.42	0.55	0.55	-0.24
2017	-0.01	-0.03	-2.72	0.52	0.63	-0.11
2018	-0.02	-0.07	-3.02	0.65	0.49	0.11
2019	-0.18	-0.22	-3.12	0.34	0.40	-0.07
Hedonic Controls	Yes	Yes	Yes	Yes	Yes	Yes
ln(stock market index)	0.438***	0.256	1.786***	0.62**	-0.11	0.329***
Observations	50,055	9,348	8,606	11,497	11,022	9,582
R-Squared	0.7267	0.7285	0.6624	0.8433	0.7542	0.6684

Table 6A

Shows hedonic regression results for the "Aggregate Index" done on data that either excludes bought-ins or prices them at different multiples of each painting's low estimate. Exponentiated coefficients on the annual dummy variables correspond to indexes in figure 20. Hedonic controls are included in each of these regressions.

***p<0.01, ** p<0.05, *p<0.1

	No Bought-Ins	**BI = .25 * LE**	**BI = .5 * LE**	**BI = .75 * LE**	**BI = LE**
1996	-0.05	0.02	0.04	0.05	0.06
1997	0.15***	0.10**	0.10**	0.10**	0.10**
1998	0.25***	0.17***	0.18***	0.19***	0.19***
1999	0.13**	-0.02	0.03	0.05	0.07*
2000	0.47***	0.38***	0.40***	0.42***	0.42***
2001	0.55***	0.49***	0.50***	0.51***	0.52***
2002	0.28***	0.22***	0.24***	0.25***	0.26***
2003	0.31***	0.25***	0.28***	0.30***	0.31***
2004	0.39***	0.29***	0.29***	0.29***	0.29***
2005	0.46***	0.45***	0.43***	0.42***	0.41***
2006	0.90***	0.90***	0.84***	0.81***	0.79***
2007	1.04***	0.97***	0.94***	0.93***	0.92***
2008	0.95***	0.84***	0.86***	0.87***	0.88***
2009	0.56***	0.46***	0.47***	0.48***	0.49***
2010	0.71***	0.57***	0.60***	0.62***	0.63***
2011	0.74***	0.68***	0.69***	0.69***	0.70***
2012	0.87***	0.75***	0.77***	0.78***	0.79***
2013	0.76***	0.64***	0.67***	0.69***	0.71***
2014	0.90***	0.84***	0.84***	0.85***	0.85***
2015	0.81***	0.69***	0.71***	0.72***	0.73***
2016	0.93***	0.73***	0.77***	0.80***	0.81***
2017	0.99***	0.83***	0.84***	0.84***	0.84***
2018	0.94***	0.90***	0.88***	0.88***	0.87***
2019	0.83***	0.74***	0.74***	0.74***	0.74***
Hedonic Controls	Yes	Yes	Yes	Yes	Yes
Observations	34,302	50,055	50,055	50,055	50,055
R-Squared	0.7487	0.6948	0.7266	0.7369	0.7396

ADF Result References

Table 7A

For indexes excluding bought-ins: ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 5.

	Aggregate	19th Euro	American	PW & C	I &M	OM
2004	-1.631	-1.930	-2.642	0.439	-2.559	-2.650
2005	-1.608	-1.962	-2.739	0.842	-2.596	-3.178
2006	-0.536	-0.797	-2.636	1.081	-3.011	-1.921
2007	-0.170	-0.961	-3.465	2.171	-1.781	-1.024
2008	-0.699	-1.051	-3.614	1.008	-1.808	-1.357
2009	-1.542	-1.660	-3.160	-0.704	-2.159	-2.066
2010	-1.512	-1.848	-3.392	-0.535	-2.277	-2.072
2011	-1.537	-1.480	-3.520	-0.574	-2.327	-2.290
2012	-1.440	-1.616	-3.646	-0.348	-2.396	-2.311
2013	-1.652	-1.945	-3.756	-0.614	-2.446	-2.388
2014	-1.533	-1.979	-3.831	-0.770	-2.138	-2.425
2015	-1.719	-2.221	-4.138	-0.545	-2.473	-2.613
2016	-1.619	-2.279	-4.110	-0.949	-2.483	-2.687
2017	-1.576	-2.316	-3.779	-1.033	-2.374	-2.705
2018	-1.706	-2.430	-3.839	-1.042	-2.631	-2.636
2019	-1.890	-2.439	-3.781	-1.286	-2.709	-2.872

Table 8A

For indexes including bought-ins (priced at .5 *LE): ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 5.

	Aggregate	19th Euro	American	PW & C	I &M	OM
2004	-1.890	-2.162	-2.954	0.312	-1.980	-3.201
2005	-1.743	-2.229	-3.112	0.710	-2.030	-3.695
2006	-0.534	-0.598	-2.954	1.042	-2.273	-1.525
2007	-0.291	-0.844	-3.738	1.949	-1.350	-0.806
2008	-0.766	-1.215	-3.888	1.166	-1.513	-1.474
2009	-1.579	-1.612	-3.409	-0.599	-1.976	-1.946
2010	-1.573	-1.812	-3.495	-0.489	-2.073	-1.980
2011	-1.540	-1.616	-3.620	-0.385	-2.115	-2.117
2012	-1.484	-1.601	-3.735	-0.332	-2.223	-2.123
2013	-1.681	-1.910	-3.818	-0.506	-2.269	-2.207
2014	-1.516	-1.877	-3.932	-0.637	-1.917	-2.258
2015	-1.768	-2.190	-4.277	-0.501	-2.307	-2.419
2016	-1.746	-2.260	-4.267	-0.979	-2.313	-2.463
2017	-1.708	-2.315	-3.762	-0.973	-2.286	-2.554
2018	-1.677	-2.387	-3.700	-0.807	-2.432	-2.513
2019	-1.919	-2.441	-3.621	-1.228	-2.518	-2.666

Table 9A

For indexes including bought-ins (priced at .25 *LE): ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 7.

	Aggregate	19th Euro	American	PW & C	I &M	OM
2004	-1.933	-2.492	-3.038	0.206	-1.915	-3.300
2005	-1.706	-2.562	-3.220	0.531	-2.010	-3.756
2006	-0.391	-0.420	-3.039	0.908	-2.096	-1.280
2007	-0.311	-0.893	-3.843	1.648	-1.164	-0.742
2008	-0.860	-1.404	-3.994	0.970	-1.451	-1.529
2009	-1.559	-1.649	-3.419	-0.573	-1.874	-1.888
2010	-1.575	-1.814	-3.461	-0.473	-1.983	-1.957
2011	-1.534	-1.742	-3.594	-0.401	-2.037	-2.067
2012	-1.501	-1.679	-3.710	-0.366	-2.162	-2.099
2013	-1.700	-1.955	-3.765	-0.565	-2.207	-2.178
2014	-1.534	-1.893	-3.946	-0.650	-1.859	-2.233
2015	-1.787	-2.219	-4.241	-0.517	-2.263	-2.367
2016	-1.792	-2.297	-4.263	-1.015	-2.289	-2.397
2017	-1.725	-2.346	-3.775	-0.948	-2.264	-2.504
2018	-1.667	-2.419	-3.706	-0.737	-2.409	-2.485
2019	-1.915	-2.479	-3.619	-1.224	-2.496	-2.589

Table 10A

For indexes including bought-ins (priced at .75 *LE): ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 7.

	Aggregate	19th Euro	American	PW & C	I &M	OM
2004	-1.876	-2.115	-2.884	0.365	-2.014	-3.198
2005	-1.775	-2.189	-3.031	0.814	-2.029	-3.692
2006	-0.634	-0.774	-2.893	1.108	-2.360	-1.742
2007	-0.291	-0.860	-3.657	2.114	-1.465	-0.905
2008	-0.709	-1.099	-3.807	1.273	-1.554	-1.463
2009	-1.594	-1.625	-3.393	-0.619	-2.038	-2.007
2010	-1.574	-1.850	-3.508	-0.504	-2.129	-2.018
2011	-1.550	-1.556	-3.628	-0.380	-2.169	-2.174
2012	-1.478	-1.595	-3.743	-0.317	-2.268	-2.162
2013	-1.671	-1.919	-3.842	-0.473	-2.314	-2.250
2014	-1.511	-1.919	-3.909	-0.633	-1.963	-2.298
2015	-1.761	-2.213	-4.286	-0.495	-2.341	-2.471
2016	-1.720	-2.280	-4.258	-0.957	-2.334	-2.526
2017	-1.705	-2.340	-3.757	-0.991	-2.307	-2.607
2018	-1.691	-2.412	-3.701	-0.854	-2.453	-2.558
2019	-1.927	-2.461	-3.628	-1.231	-2.538	-2.738

Table 11A

For indexes including bought-ins (priced at 1.0 *LE): ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 7.

	Aggregate	19th Euro	American	PW & C	I &M	OM
2004	-1.870	-2.143	-2.826	0.395	-2.035	-2.143
2005	-1.801	-2.230	-2.966	0.883	-2.023	-2.230
2006	-0.714	-0.938	-2.846	1.143	-2.412	-0.938
2007	-0.298	-0.906	-3.591	2.215	-1.548	-0.906
2008	-0.668	-1.020	-3.741	1.340	-1.585	-1.020
2009	-1.608	-1.657	-3.378	-0.636	-2.083	-1.657
2010	-1.575	-1.898	-3.513	-0.517	-2.170	-1.898
2011	-1.559	-1.526	-3.630	-0.380	-2.211	-1.526
2012	-1.476	-1.615	-3.743	-0.309	-2.304	-1.615
2013	-1.665	-1.945	-3.853	-0.450	-2.351	-1.945
2014	-1.511	-1.976	-3.884	-0.631	-2.001	-1.976
2015	-1.758	-2.252	-4.286	-0.494	-2.368	-2.252
2016	-1.703	-2.315	-4.245	-0.941	-2.353	-2.315
2017	-1.705	-2.381	-3.754	-1.005	-2.327	-2.381
2018	-1.704	-2.453	-3.704	-0.889	-2.471	-2.453
2019	-1.936	-2.498	-3.637	-1.234	-2.556	-2.498

Table 12A

For indexes of markets with alternate genre classifications excluding bought-ins: ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 8.

	19th Euro	American	PW & C	I &M	OM
2004	-1.079	-1.522	-2.212	0.014	-2.919
2005	-1.519	-1.453	-2.165	-0.177	-3.211
2006	-0.518	-0.164	-2.389	0.456	-3.255
2007	-0.227	-0.719	-3.020	1.366	-2.238
2008	-0.696	-1.387	-3.166	0.890	-1.894
2009	-1.406	-1.234	-2.775	-0.661	-2.278
2010	-1.405	-1.665	-2.926	-0.435	-2.444
2011	-1.402	-1.318	-3.068	-0.485	-2.533
2012	-1.264	-1.703	-3.178	-0.209	-2.592
2013	-1.140	-1.873	-3.271	-0.331	-2.349
2014	-1.303	-1.865	-3.407	-0.577	-2.166
2015	-1.375	-2.127	-3.434	-0.319	-2.434
2016	-1.206	-2.137	-3.575	-0.638	-2.447
2017	-1.349	-2.154	-3.385	-0.884	-2.460
2018	-1.320	-2.344	-3.466	-0.514	-2.587
2019	-1.606	-2.224	-3.418	-1.074	-2.668

Table 13A

For indexes of markets with alternate genre classifications including bought-ins: ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 8.

	19th Euro	American	PW & C	I &M	OM
2004	-1.938	-2.622	-0.078	-2.349	-2.758
2005	-1.997	-2.823	0.244	-2.508	-3.259
2006	-0.841	-2.902	0.823	-2.434	-1.963
2007	-0.970	-3.542	1.783	-1.408	-1.099
2008	-0.990	-3.667	1.244	-1.766	-1.425
2009	-1.673	-3.170	-0.605	-2.120	-2.086
2010	-1.861	-3.419	-0.527	-2.213	-2.084
2011	-1.521	-3.555	-0.439	-2.272	-2.293
2012	-1.702	-3.664	-0.334	-2.368	-2.268
2013	-1.968	-3.672	-0.478	-2.447	-2.406
2014	-1.985	-3.816	-0.587	-2.187	-2.482
2015	-2.245	-3.797	-0.480	-2.639	-2.613
2016	-2.304	-4.053	-0.864	-2.509	-2.686
2017	-2.351	-4.098	-0.929	-2.290	-2.660
2018	-2.453	-4.223	-0.662	-2.733	-2.612
2019	-2.464	-4.328	-1.107	-2.802	-2.862

Table 14A

For indexes built on data that excludes paintings originally priced at their "hammer price," and excludes bought-ins: ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 9.

	Aggregate	19th Euro	American	PW & C	I &M	OM
2004	-1.627	-2.094	-2.680	-0.270	-2.055	-1.974
2005	-1.597	-2.210	-2.787	0.019	-2.169	-3.877
2006	-0.635	-1.629	-2.709	0.465	-2.614	-1.853
2007	-0.330	-1.767	-3.665	1.571	-1.989	-0.672
2008	-0.878	-1.867	-3.860	0.307	-2.337	-0.867
2009	-1.676	-2.260	-3.569	-0.800	-2.566	-1.958
2010	-1.650	-2.395	-3.743	-0.564	-2.671	-2.009
2011	-1.679	-2.072	-3.885	-0.629	-2.768	-2.218
2012	-1.630	-2.163	-4.005	-0.732	-2.863	-2.216
2013	-1.759	-2.374	-4.110	-0.622	-2.952	-2.377
2014	-1.706	-2.477	-4.227	-0.714	-2.749	-2.409
2015	-1.843	-2.688	-4.490	-0.628	-2.985	-2.575
2016	-1.786	-2.762	-4.275	-1.093	-3.085	-2.658
2017	-1.568	-2.751	-3.509	-0.961	-3.002	-2.719
2018	-1.799	-2.915	-3.614	-0.953	-3.287	-2.678
2019	-1.935	-3.003	-3.495	-1.215	-3.363	-2.851

Table 15A

For indexes built on data that excludes paintings originally priced at their "hammer price," and includes bought-ins: ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 9.

	Aggregate	19th Euro	American	PW & C	I &M	OM
2004	-1.910	-1.938	-3.056	-0.372	-1.888	-2.229
2005	-1.889	-2.058	-3.237	0.028	-1.905	-4.458
2006	-0.878	-1.133	-2.940	0.388	-2.210	-1.619
2007	-0.332	-1.240	-3.819	1.292	-1.681	-0.512
2008	-0.986	-1.429	-4.004	0.391	-2.186	-0.844
2009	-1.675	-1.919	-3.804	-0.918	-2.350	-1.805
2010	-1.636	-1.968	-4.008	-0.653	-2.455	-1.831
2011	-1.651	-1.532	-4.159	-0.784	-2.536	-2.019
2012	-1.625	-1.722	-4.282	-0.789	-2.625	-2.022
2013	-1.749	-1.932	-4.392	-0.681	-2.660	-2.174
2014	-1.668	-2.014	-4.518	-0.847	-2.354	-2.182
2015	-1.832	-2.238	-4.776	-0.745	-2.662	-2.381
2016	-1.836	-2.263	-4.488	-1.133	-2.699	-2.436
2017	-1.650	-2.235	-3.678	-1.080	-2.668	-2.531
2018	-1.738	-2.450	-3.622	-1.187	-2.879	-2.460
2019	-1.924	-2.518	-3.503	-1.341	-2.948	-2.630

Table 16A

For trimester-based indexes that exclude bought-ins: ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 10.

	Aggregate	19th Euro	American	PW & C	I &M	OM
2004	-1.08	-1.52	-2.21	0.01	-2.92	-2.58
2005	-1.52	-1.45	-2.16	-0.18	-3.21	-3.13
2006	-0.52	-0.16	-2.39	0.46	-3.25	-1.77
2007	-0.23	-0.72	-3.02	1.37	-2.24	-0.69
2008	-0.70	-1.39	-3.17	0.89	-1.89	-1.33
2009	-1.41	-1.23	-2.77	-0.66	-2.28	-1.94
2010	-1.41	-1.66	-2.93	-0.43	-2.44	-1.83
2011	-1.40	-1.32	-3.07	-0.49	-2.53	-2.20
2012	-1.26	-1.70	-3.18	-0.21	-2.59	-2.18
2013	-1.14	-1.87	-3.27	-0.33	-2.35	-2.37
2014	-1.30	-1.86	-3.41	-0.58	-2.17	-2.42
2015	-1.38	-2.13	-3.43	-0.32	-2.43	-2.55
2016	-1.21	-2.14	-3.57	-0.64	-2.45	-2.63
2017	-1.35	-2.15	-3.38	-0.88	-2.46	-2.65
2018	-1.32	-2.34	-3.47	-0.51	-2.59	-2.65
2019	-1.61	-2.22	-3.42	-1.07	-2.67	-2.78

Table 17A

For trimester-based indexes that exclude bought-ins: ADF t-stats for each year of the forward recursive ADF regressions that begins with a window size of 10. The highest t-stat in each market is the SADF t-stat for that market, which corresponds to the SADF t-stats in Table 10.

	Aggregate	19th Euro	American	PW & C	I &M	OM
2004	-1.53	-2.33	-2.39	-0.10	-1.96	-3.12
2005	-1.64	-1.88	-2.41	-0.16	-2.11	-3.60
2006	-0.48	-0.64	-2.54	0.41	-2.06	-1.38
2007	0.06	-0.57	-2.98	1.38	-1.31	-0.41
2008	-0.84	-1.53	-3.18	0.88	-1.47	-1.47
2009	-1.44	-1.44	-2.63	-0.62	-1.84	-1.82
2010	-1.48	-1.78	-2.68	-0.41	-1.99	-1.78
2011	-1.40	-1.38	-2.84	-0.35	-2.10	-2.00
2012	-1.33	-1.88	-2.92	-0.20	-2.19	-1.96
2013	-1.28	-2.03	-3.04	-0.23	-2.07	-2.17
2014	-1.30	-1.94	-3.16	-0.49	-1.71	-2.22
2015	-1.43	-2.29	-3.20	-0.25	-2.16	-2.34
2016	-1.30	-2.35	-3.34	-0.62	-2.11	-2.38
2017	-1.48	-2.44	-3.13	-0.85	-2.25	-2.48
2018	-1.34	-2.52	-3.08	-0.39	-2.31	-2.47
2019	-1.65	-2.46	-3.04	-1.05	-2.41	-2.50

Additional Summary Statistics

Figure 1A

Shows density of 19th Century European Sales by Year of Work. NOTE: Not all paintings are dated. These are missing data points in these density distributions. Paintings painted more recently are more likely to be dated, so this distribution is biased towards the present.

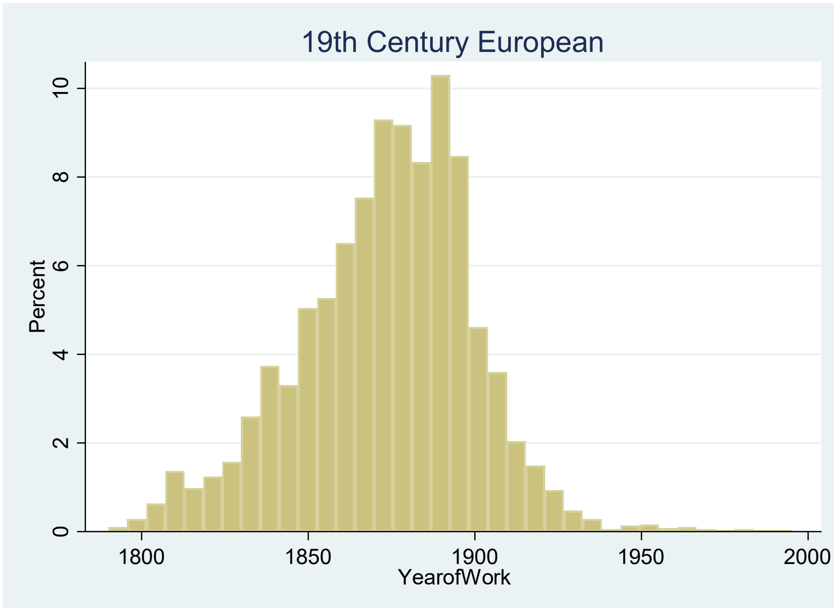


Figure 2A

Shows density of American Sales by Year of Work. NOTE: Not all paintings are dated. These are missing data points in these density distributions. Paintings painted more recently are more likely to be dated, so this distribution is biased towards the present.

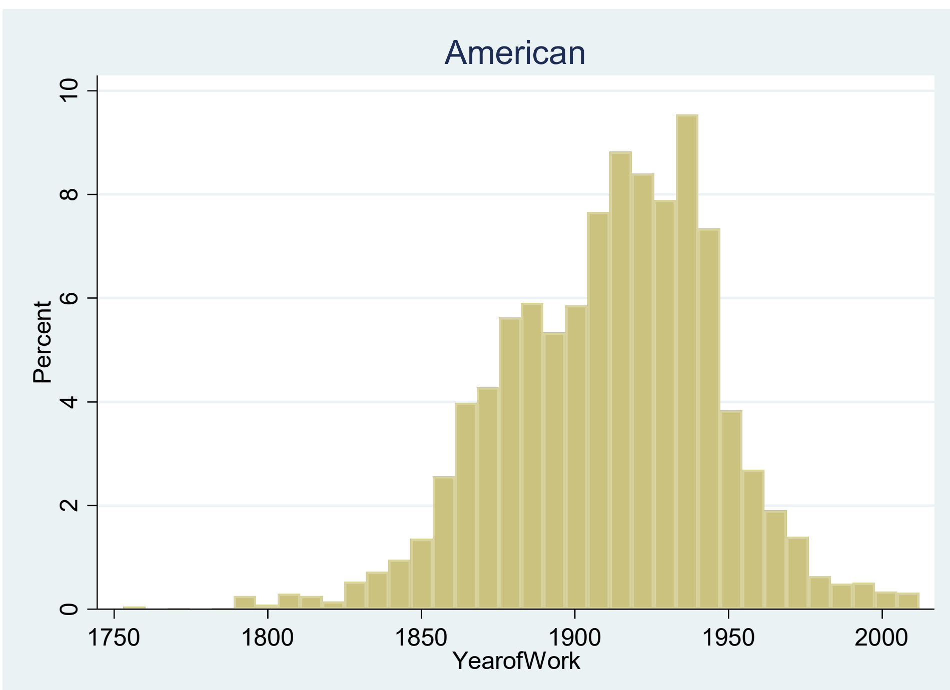


Figure 3A

Shows density of Post-War & Contemporary Sales by Year of Work. NOTE: Not all paintings are dated. These are missing data points in these density distributions. Paintings painted more recently are more likely to be dated, so this distribution is biased towards the present.

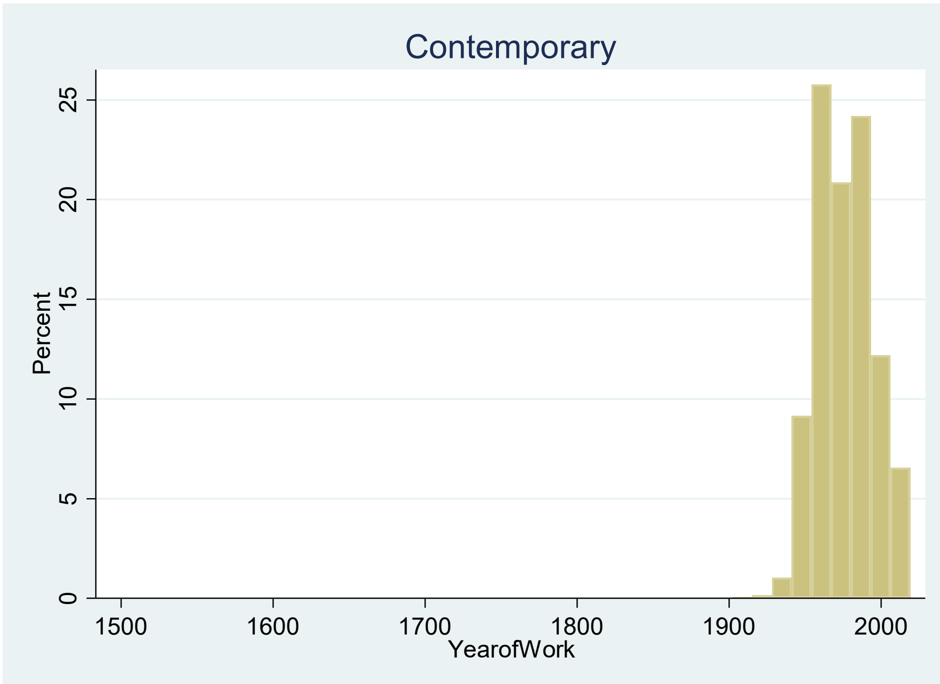


Figure 4A

Shows density of Impressionist & Modern Sales by Year of Work. NOTE: Not all paintings are dated. These are missing data points in these density distributions. Paintings painted more recently are more likely to be dated, so this distribution is biased towards the present.

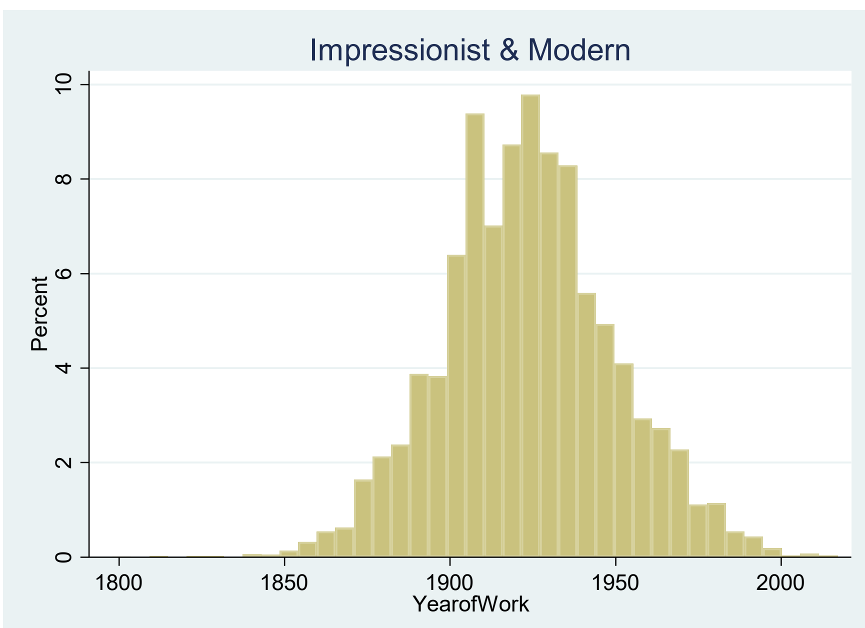


Figure 5A

Shows density of Impressionist & Modern Sales by Year of Work. NOTE: Not all paintings are dated. These are missing data points in these density distributions. Paintings painted more recently are more likely to be dated, so this distribution is biased towards the present.

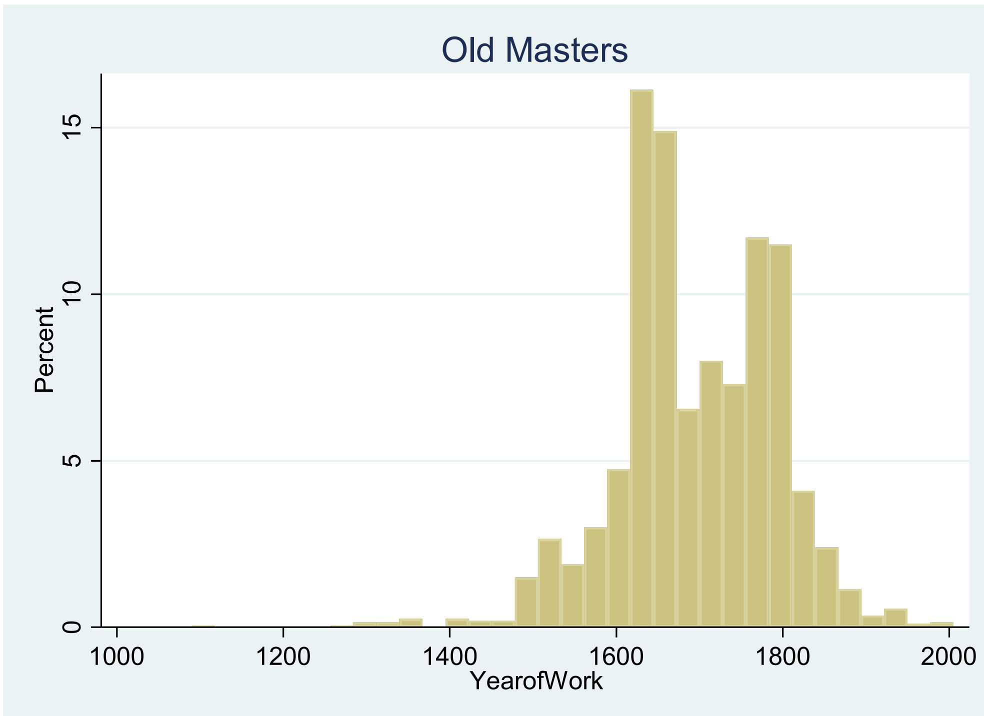


Figure 6A

Shows the frequency of painting prices as % of Low Estimate. This frequency distribution is built using "premium prices" only – i.e, the hammer price that someone actual bids at, plus some auction fee. The right tail of the distribution is cut off, because the data is skewed far to the right.

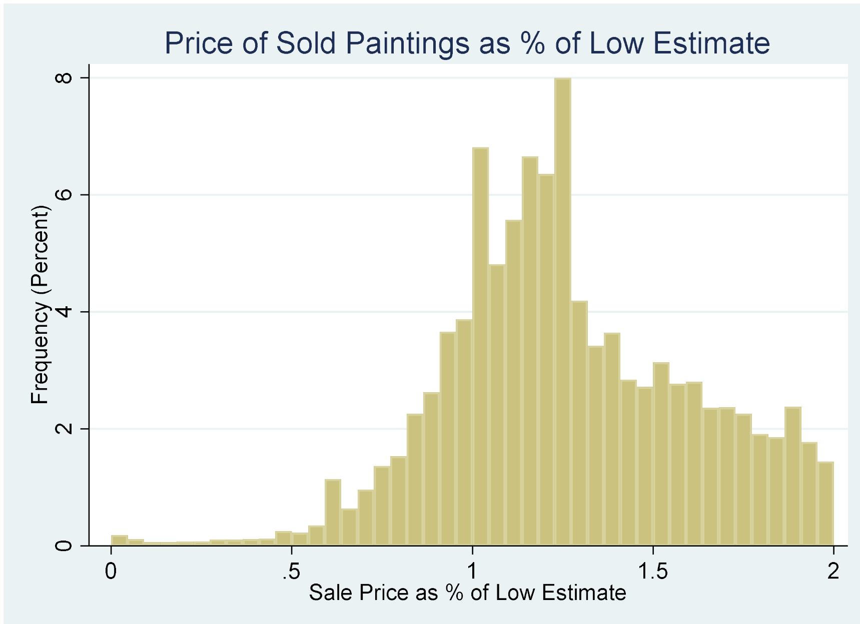


Figure 6A

Shows the frequency of painting prices as % of Low Estimate. This frequency distribution is built using "hammer prices" only – i.e, the hammer price that someone actual bids at. The right tail of the distribution is cut off, because the data is skewed far to the right. Hammer prices are concentrated around exactly the low estimate, suggesting buyers use that as a metric to place their bids.

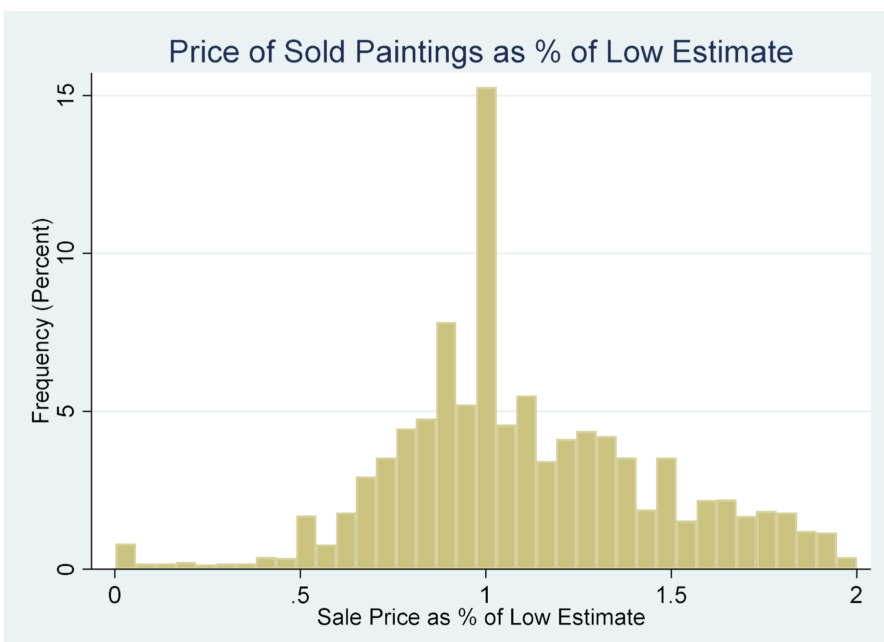


Table 18A: Christies/Sothebys Summary Statistics

Where "nationality" is the country from which a given auction house's sales were sampled. Christie's and Sothey's have auction houses around the world, but most of their sales in the genres this paper examines were done at their London and New York locations. Because of this, this paper samples from these locations. "Hedonic Coefficient" is the coefficient on the auction-house dummy variable in the five-market hedonic regression that excludes bought-ins, and serves as a metric for each auction house's effect on prices. Sotheby's is the omitted/reference dummy variable. Numbers under each genre represent the number of sales in that genre sampled for each auction house.

Auction House	Nationality	Hedonic Coefficient	Aggregate Transactions	19th Euro	American	PW&C	I&M	OM	Unclassified
Christie's	American/British	0.14	12,848	2,702	2,541	2,532	2,403	2,544	126
Sotheby's	American/British	(omitted)	12,673	2,460	2,488	2,495	2,599	2,601	30

Table 19A: Large Auction House Summary Statistics

Summary stats for the "large" auction houses. Where "nationality" is the country from which a given auction house's sales were sampled. "Hedonic Coefficient" is the coefficient on the auction-house dummy variable in the five-market hedonic regression that excludes bought-in and serves as a metric for each auction house's effect on prices. Sotheby's is the omitted/reference dummy variable. Numbers under each genre represent the number of sales in that genre sampled for each auction house. Auction houses marked *** are grouped together as a single dummy variable in the hedonic regression to avoid collinearity between year and auction house dummy variables.

Auction House	Nationality	Hedonic Coefficient	Aggregate Transactions	19th Euro	American	PW&C	I&M	OM	Unclassified
Artcurial	French	-1.37	1,150	142	1	0	716	261	30
Audap & Mirabaud	French	-2.10	226	50	3	23	16	131	3
Bonhams	British	-1.06	1,833	1,043	352	2	5	405	26
Claude Aguttes	French	-1.57	874	66	3	166	562	44	33
Cornette de Saint Cyr	French	-1.62	1,433	23	3	1,124	256	3	24
Charlton Hall	American	-2.81	377	67	150	55	59	21	25
CottoneAuctions* **	American	-1.43	84	13	48	15	4	2	2
Coutau-Bégarie	French	-2.04	415	122	4	68	132	79	10
Dorotheum	Austrian	-0.21	724	0	0	0	0	714	10
Freeman's	American	-2.04	575	77	377	62	40	9	10
Grisebach	German	-0.63	266	0	0	260	1	0	5
Hampel* **	German	-1.43	125	0	0	0	0	119	6
Freeman's	American	-2.04	575	77	377	62	40	9	10
Ketterer Kunst	German	-0.93	311	0	0	296	7	0	8
Koller	Swiss	-0.83	1,734	591	5	37	512	568	21
Lempertz	German	-0.21	375	136	0	1	0	227	11
Mats Art* **	Israeli	-1.43	75	5	0	0	69	0	1
Nagel* **	German	-1.43	25	0	0	0	1	24	0
Neal Auction Company	American	-1.99	522	88	315	74	29	8	8
New Orleans Auctions	American	-2.32	500	136	209	74	62	8	11
Shannon's	American	-0.80	599	12	518	22	39	5	3
Tajan	French	-1.51	1,191	76	0	106	551	431	21
Van Ham	German	-1.43	75	0	0	0	0	73	2
Versailles Enchères	French	-1.75	438	7	0	396	21	13	1

Table 20A: Medium/Small Auction House Summary Statistics

Summary stats for the "small" auction houses. Where "nationality" is the country from which a given auction house's sales were sampled. "Hedonic Coefficient" is the coefficient on the auction-house dummy variable in the five-market hedonic regression that excludes bought-in and serves as a metric for each auction house's effect on prices. Sotheby's is the omitted/reference dummy variable. Numbers under each genre represent the number of sales in that genre sampled for each auction house. Note that Phillips is classified as a "small" auction house, despite being very large. This is due to the methodology under which auction houses were sampled/classified (see Other Methodology: Sampling). Auction houses marked *** are grouped together as a single dummy variable in the hedonic regression to avoid collinearity between years and auction house dummy variables.

Auction House	Nationality	Hedonic Coefficient	Aggregate Transactions	19th Euro	American	PW&C	I&M	OM	Unclassified
Baron Ribeyre	French	-1.45	172	24	1	80	40	26	1
Barridoff	American	-2.07	418	21	267	87	26	11	6
Beaussant & Lefèvre	French	-1.79	1,126	294	19	71	412	317	13
Bernaerts	Belgian	-2.56	512	235	1	85	164	16	11
Bloomsbury Rome* **	Italian	-1.43	47	4	0	8	3	32	0
Brunk Auctions	American	-2.45	294	67	86	82	25	24	10
Charlton Hall	American	-2.81	377	67	150	55	59	21	25
CottoneAuctions* **	American	-1.43	84	13	48	15	4	2	2
Coutau-Bégarie	French	-2.04	415	122	4	68	132	79	10
Dumousset & Deburaux	French	-1.53	241	71	0	37	110	22	1
Est-OuestAuctionsCo	Chinese	-1.41	196	7	0	142	41	3	3
European Arts	Czech	-1.98	623	111	3	152	348	5	4
Finarte	Italian	-0.72	355	12	3	166	38	133	3
Fernando Durán Subastas	Spanish	-1.61	195	45	3	63	57	17	10
Galerie Kornfeld Bern	Swiss	-0.99	281	26	3	61	181	8	2
Germann Auktionshaus	Swiss	-1.42	840	22	3	566	242	2	5
Hauswedell & Nolte	German	-1.66	459	55	2	177	173	47	5
Heritage Auctions* **	American	-1.43	97	0	47	47	1	0	2
Illustration House	American	-1.53	655	2	476	160	15	1	1
Marc-Arthur Kohn	French	-0.87	957	118	7	109	223	489	11
Martinot, Savignat	French	-1.63	374	170	6	20	165	7	6
Massol	French	-1.61	581	137	10	105	181	135	13
Nadeau's* **	American	-1.43	42	5	34	1	2	0	0
Phillips New York	American	-0.44	1,057	16	41	815	183	1	1
Pierre Berge & Associés	French	-1.79	457	29	2	294	87	39	6
Pook & Pook, Inc.	American	-2.39	630	78	452	34	29	25	12
Rachel Davis	American	-2.95	208	12	120	57	18	0	1
Shinwa	Japanese	-0.89	577	1	0	314	222	0	40

Additional Tests

Estimating η

Table 21A

The critical values in Table 5 are contingent on population parameter, η being > .5 (Philips et al., 2014). The appendix of Phillips et al. demonstrates how to estimate η: first, regress the annual index on a time trend t ∈ {1, …, T) , and obtain the slope coefficient (α). Then estimate η a $\eta = -\frac{\log|\alpha|}{\log|T|}$. This table shows log(α), log(T), and the estimate of η for each market. These estimates are found on indexes that exclude bought-ins, but incorporating bought-ins does not significantly alter α.

	Aggregate	19th Century Euro	American	Contemporary	Impressionist & Modern	Old Masters
log(α)	-3.21	-3.94	-4.33	-2.31	-3.81	-3.45
log(T)	3.22	3.22	3.22	3.22	3.22	3.22
Estimate of η	1.00	1.22	1.35	0.72	1.18	1.07

Choosing the number of autoregressive lags to include in ADF tests

I chose the number of autoregressive lags by minimizing the Bayesian Information Criterion (BIC). After running an ADF test for the maximum number of period (i.e., through 2019) at a given number of lags, k, I use the estat ic command in Stata to generate a BIC value. I change the number of lags and repeat. Using 0 lags minimizes the BIC value in the aggregate market, and so I use ADF tests with 0 lags to generate this paper's ADF values.

Testing for Serial Correlation in Returns

Table 22A

Shows autoregressive slope coefficients for hedonic regression index returns using different numbers of TS DVs annually. There is no evidence of positive serial correlation in returns using full year indexes, and there is little evidence that using different numbers of TS DVs annually changes this.

	Aggregate	19th Century Euro	American	Contemporary	Impressionist & Modern	Old Masters
Full Year	-0.036	0.059	-0.501**	-0.022	-0.126	-0.297
Half-Year	-0.060	-0.039	-0.279	-0.191	-0.198	-0.348
Trimester	-0.134	-0.152	-0.275	-0.248	-0.282	-0.315
Month	-0.182	-0.699***	-0.570***	-0.241	-0.335	-0.307

Table 23A

Shows standard deviations in returns for indexes using different numbers of TS DVs annually. There is little evidence that using annual DVs "smooths" returns relative to indexes using half-year or trimester DVs. SDs rise when using month DVs, but this is likely do to the small sample size.

	Aggregate	19th Century Euro	American	Contemporary	Impressionist & Modern	Old Masters
Full Year	0.177	0.151	0.333	0.197	0.297	0.364
Half-Year	0.178	0.158	0.319	0.204	0.293	0.364
Trimester	0.168	0.156	0.319	0.256	0.279	0.366
Month	0.189	0.656	0.491	0.268	0.345	0.550

Other Methodology

Sampling**

** Paper section 3B. describes the overarching procedure for sampling. Additional details follow:

Databases and motivation for sampling procedure: I sample from two databases: Artnet (64% of sampled sales), and Askart (36% of sampled sales). The Artnet database has records on over 12 million auction sales dating back to 1985. Askart's website is less specific about their records, but contains "millions of auction results" from 1987 onward. Both databases have limits on auction record searches/views, and Askart has scarce data from before 2007. "Searches" entail the first 100 results that come after searching for sales from a particular artist, or sales from a set of auction houses. Because of these limiting factors, I had to derive a way to sample art records that, 1. Maximized the effectiveness of each search, and 2. Provided a sample that was as representative as possible of each market. This led me to sample within groups of auction houses. Sampling by auction house allows sampling from sales within each genre – for example – many auction houses hold "American Art" sales. Sampling annual "American Art" sales within a sample of auction houses 1. Guarantee that a search is drawing "American Art" (i.e., no wasted searches on irrelevant genres) and 2. Ensures that data samples from a variety of artists within genres. This second point is particularly important: my sampling procedure results in sampling over 2000 unique artists in each genre – presumably capturing a broad cross-section of different quality paintings within genres.

Auction house selection and sizes: Paper section 3B describe the "cluster sampling" that the paper does between groups of auction houses. I do this in hopes of capturing how the entire market is doing – not just Sotheby's and Christie's – and sample ~50% of sales from auction houses other than Christie's and Sotheby's. I measure size of "auction houses" based on the number of sales each auction house has since 1995 in the Artnet database. "Large" auction houses are houses with more than 8,000 sales listed since 1995 (i.e., auction houses that have averaged more than 320 sales a year over 25 years), and auction houses with fewer than 8,000 sales are classified as "small/medium." I use a random sample of sales since 1995 on Artprice.com to select 30 big auction houses, and 30 small auction houses for each genre. I then calculate "genre specialization scores" for each auction house. For large auction houses, I take the five auction houses with the highest "specialization score" in each genre to be the designated group of auction houses to sample from for that genre. For small auction houses, I take auction houses in the order of their "specialization score" until the total sales since 1995 for all the small chosen auction houses add up to 20,000. Many small auction houses have few than 1000 sales since 1995, so just taking the five with the highest specialization scores often results in a group of auction houses with not enough sales to sample 100 sales a year for 25 years.

The specialization metric: A group of "specialized" auction-houses are chosen for each genre, because it increases the chances that paintings are classified under the genre with which their group of auction houses corresponds (if they have to be classified), and thereby, that there are a similar number of auction results for each genre. To find "specialized" auction houses, I develop a genre specialization score. The score is simple: I find 10 "genre-defining" artists for each genre using sale results from Christie's and Sotheby's, and then calculate which of the sampled auction houses have the highest ratio of sales of paintings done by genre defining artists for a given genre to total sales. The 10 "genre-defining" artists are the ten artists with the most sales in a given genre since 1995. They follow:

- **19th Century European:** Edouard Léon Cortès, Eugen von Blaas, Giovanni Boldini, Gustave Courbet, Jean Béraud, Jean-Baptiste-Camille Corot, Jean-Léon Gérôme, John William Godward, Jules Breton, William-Adolphe Bouguereau
- **American:** Albert Bierstadt, William Aiken Walker, Norman Rockwell, John George Brown, Jasper Francis Cropsey, Guy Carleton Wiggins, Grandma Moses, George Inness, Ernest Lawson, Eric Sloane
- **Post-War & Contemporary:** Willem de Kooning, Tom Wesselmann, Sam Francis, Roy Lichtenstein, Robert Motherwell, Jean-Michel Basquiat, Jean Dubuffet, Gerhard Richter, Frank Stella, Andy Warhol
- **Impressionist & Modern:** Camille Pissarro, Claude Monet, Fernand Léger, Louis Valtat, Pierre-Auguste Renoir, Pierre Bonnard, Pablo Picasso, Maurice Utrillo, Maurice de Vlaminck, Marc Chagall
- **Old Masters:** Jan Brueghel the Younger, Anthony van Dyck, Hubert Robert, Luca Giordano, Lucas Cranach the Elder, Nicolaes Maes, Peter Paul Rubens, Pieter Brueghel the Younger, Salomon van Ruysdael, Claude Joseph Vernet

I use Artnet's search function to find the number of sales by "genre-defining" artists each randomly selected auction house has had since 1995, and then divide this by their total sales since 1995. While some of the "genre-defining" artists are recognizable, these are not necessarily the most prestigious artists in each genre. For example, our sampling captures the sale of the "Salvator Mundi," the most expensive painting ever. The painting was done by Da Vinci and is partly so expensive because there are so few Da Vinci paintings one can buy.

Selected Auction Houses:

Random sampling and then selection based on specialization leads to these auction houses for each genre:

- **Large 19th Century European:** Koller, Bonhams, Lempertz, Artcurial, Claude Aguttes
- **Small/Medium 19th Century European:** Martinot-Savignat-Antoine, Dumousset-Deburaux, Coutau-Bégarie, Kaminski & Co*, European Arts Investments Ltd, Massol
- **Large American:** Freemans, Neal Auction Co., New Orleans Auction Co., Shannon's, Bonhams
- **Small/Medium American**: Morphy Auctions*, Nadeau's Auction Gallery, Cottone , Brunk Auctions, Illustration House, Charlton Hall Galleries, Barridoff Galleries, Pook & Pook
- **Large PW&C:** Versailles Enchères, Grisebach, Cornette de Saint Cyr, Ketterer, Lempertz
- **Small/Medium PW&C:** Phillips New York, Galerie Kornfeld and Cie, Rachel Davis Fine Arts, Germann, Hauswedell & Nolte
- **Large Impressionist & Modern:** Mats Art, Claude Aguttes, Artcurial, Koller, Tajan
- **Small/Medium Impressionist & Modern:** Mathias-Le Roux-Morel*, Marc-Arthur Kohn S.A.S, Laurin-Guilloux-Buffetaud-Tailleur*, Shinwa Art Auction, Est-Ouest Auctions Co, Briest , Audap-Mirabaud
- **Large Old Masters:** Hampel, Koller, Dorotheum, Lempertz, Van Ham
- **Small/Medium Old Masters:** Semenzato*, Baron Ribeyre & Associes, Pierre Berge, Bernaerts, Bloomsbury Auctions Rome, Beaussant Lefevre

There are four things to note here. 1. Not all of the Small/Medium auction houses have results in the final sample. This is because they have a low number of sales and weren't caught by the paper's sampling procedure of sales within genre/size-based auction house clusters. 2. Many of auction houses intended to catch sales in certain genres ended up capturing sales across many genres (Tables 19A and 20A). 3. Some of the "Large" auction houses are repeated between genre clusters. For example, this paper uses Koller Auction House to sample for both Old Masters and 19th Century European art. This is because large auction houses have a broader scope and enough data points to sample for multiple genres. 4. Phillips Auction house – one of the biggest auction houses in the world – is classified as "small." This is because its New York location has fewer than 8,000 sales listed on Artnet. Generally though, bigger art houses have more sales listed on Artnet. This is confirmed by Artprice's listing of Top 15 houses by auction turnover in 2019. This paper's sampling procedure captures 5 of the 13 biggest auction houses after Christie's and Sotheby's and all of these are classified as "Large" houses besides Phillips.

Classifying Unidentified Paintings and Genre Definitions

The three genre classification waves:

1. If possible, I sampled results from auction sales named after a given genre. For example, "American Art Sale." However, small/medium auction houses rarely named their sales. Large auction houses and Christie's and Sotheby's consistently labeled their sales, but often had joint-genre sales, for example "Old Masters & 19th Century European." The first wave of genre classification used single-genre sale titles to classify the paintings in those sales. For example, all paintings in a "American Art" sale were classified as "American." Paintings in sales "Old Masters & 19th Century European" were left unclassified.
    - ➔ 55.3% of paintings (28,118) are classified based on auction sale title
2. If any of the remaining unclassified paintings were made by an artist who had other paintings consistently classified as a specific genre, I classify them under the same genre as the rest of their paintings. I use 80% to measure consistency. For example, William Aiker Walker had many paintings sold at auctions without sale titles. These paintings went unclassified in the first wave. However, 100% of his paintings that had been classified in the first wave of classification were classified as "American." Because of this, his paintings that went unclassified in the first wave were classified as "American" in the second wave.
    - ➔ 30.2% of paintings (15,395) are classified based how other paintings by their artist were classified
3. For the remaining paintings, I found the nationality of the artist, and the year each painting was painted. If I could not find a year the painting was painting, I estimated a year using an average of the artist's birth and death date (if the artist was still living, I automatically classified their work as "Post-War & Contemporary"). Using nationality and a year of work, I manually classified each painting, based on "genre definition" (see next section). However, some paintings did not fit into any of the paper's five genres and went unclassified.
    - ➔ 13.2% of paintings (6,734) are manually classified as a genre
    - ➔ 1.1% of paintings (595) go unclassified.

Genre Descriptions/Classifications:

19th Century European Art

- Description: 19th Century European art that preceded the impressionist and modern movements. Movements within 19th European Art include Symbolism, Orientalism, Realism, and Academic schools.
- Classification: If artist is European and their work is made between 1800 and 1900, I "manually classify" their paintings as 19th Century European in the third wave of genre classification.

American Art

- Description: Art made by American artists from the 18th through early 20th century. Movements include the Hudson River School, American Impressionism, American Romanticism, and American Modernism.
- Classification: If artist is American, and their work is made between 1700 and 1945, I "manually classify" their paintings as American in the third wave of genre classification.

Post-War & Contemporary Art

- Description: Art made between the end of the Second World War (1945) and the present
- Classification: Any work made since 1945 (regardless of artist nationality) is classified as Post-War & Contemporary in the third wave of genre classification.

Impressionist & Modern Art

- Late 19th and early 20th century movements that include Impressionism, Fauvism, Cubism and Surrealism. Impressionism started in Europe, but "Modern" movements existed in Asia, Latin American, and the United States
- Classification: If paintings are made between 1900 and 1945 by non-American artists, I classify them as "Impressionist & Modern" in the third wave of genre classification.

Old Masters Art

- European art made before the 19th century.
- Classification: If paintings are done by a European artist before 1800, I classify them as "Old Masters."

Repricing Hammer Prices

Table 24A

Roughly 30% of paintings in the sample had prices listed as the "hammer price." I reprice the paintings with "hammer prices" using estimated auction fees for each relevant auction house below. This is similar to what other papers like McAndrew et al. (2012) done, but instead of using Christie's auction fees as an estimate for the rest of the market, I find each auction house's auction fee. While some auction houses have a flat fee across all prices for paintings, some have multiple premiums that decrease as prices rise.

	First Price-Range	First Premium	Second Price-Range	Second Premium	Third Price-Range	Third Premium	Fourth Price-Range	Fourth Premium
Audap & Mirabaud	All Prices	22.6%						
Baron Ribeyre	All Prices	28.0%						
Barridoff	< $500,000	22.0%	> $500,000	17.0%				
Beaussant & Lefèvre	All Prices	27.0%						
Bernaerts* **	All Prices	24.3%						
Bloomsbury Rome	< $500000	25.0%	$500000-$1000000	20.0%	>1000000	12.0%		
Bonhams	< $3000	27.5%	3000-400000	25.0%	$400000-$4000000	20.0%	4,000,000	13.9%
Brunk Auctions	All Prices	23.0%						
Charlton Hall	All Prices	23.0%						
Christie's	< $300000	25.0%	$300000-$4000000	20.0%	>$4000000			
Claude Aguttes	< $150000	27.0%	> 150,000	25.0%				
Cornette de Saint Cyr	< $20000	24.0%	$20,000-$600,000	20.0%	>$600,000	12.0%		
CottoneAuctions	All Prices	18.0%						
Coutau-Bégarie	All Prices	24.0%						
Dorotheum	< $10000	28.0%	$10000-$100000	25.0%	$100000-$600000	22.0%	>$600000	15.0%
Dumousset & Deburaux* **	All Prices	24.3%						
Est-OuestAuctionsCo	All Prices	21.0%						
European Arts	All Prices	24.3%						
Freeman's	< $300,000	25.0%	$300,000-3,000,000	20.0%	>$300,000	12.0%		
Galerie Kornfeld Bern	< $500,000	20.0%	$500,000 -$2,000,000	15.0%	>$2,000,000	10.0%		
Germann Auktionshaus	<$10,000	25.0%	$10,000-$400,000	20.0%	> $400,000	15.0%		
Hampel	All Prices	29.5%						
Hauswedell & Nolte	All Prices	24.3%						
Ketterer Kunst	< $500,000	32.0%	>$500,000	27.0%				
Koller	<$10,000	25.0%	$10,000-$400000	22.0%	>$400,000	15.0%		
Lempertz	<$400,000	24.0%	>$400,000	20.0%				
Marc-Arthur Kohn	<$500,000	25.0%	>$500,000	21.0%				
Martinot,Savignat	All Prices	24.3%						
Massol	All Prices	24.3%						
Nadeau's	All Prices	22.0%						
Nagel	All Prices	27.0%						
Neal Auction Company	<$200,000	22.0%	>$200,000	10.0%				
New Orleans Auctions	All Prices	25.0%						
Pierre Berge & Associés	<$200,000	22.0%	>$200,000	17.0%				

Pook&Pook,Inc.	All Prices	22.0%							
Rachel Davis	All Prices	26.0%							
Shinwa	<$18,600	16.2%	$18,600 - $495,000	13.0%	>$495,000	10.8%			
Shannon's	All Prices	24.3%							
Tajan	<$150,000	25.0%	$150,000-$2,000,000	20.0%	> $2,000,000	12.0%			
Van Ham	<$400,000	29.0%	> $400,000	25.0%					
Versailles Enchères	All Prices	24.3%							