Bubbles and Trading Frenzies: Evidence from the Art Market*

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Abstract

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Abstract

We use the art market as a laboratory to test speculative bubble models based on investor disagreement. Several aspects distinguish the art market from other markets: it features unlevered and wealthy investors, financial and technological innovations are absent, and transaction costs are substantial. We find that prices not only positively correlate with volume but also with very short-term transactions. Large volumes are followed by negative returns. Finally, short-term transactions underperform and are riskier than long-term transactions. The evidence is consistent with a resale option model of speculative trading where the impossibility to sell short embeds a bubble component in prices.

As a collector, I trade all the time, it's the capitalist in me.[1]

The history of financial markets is replete with episodes of booms and busts in asset prices that are difficult to reconcile with underlying economic fundamentals. Such episodes are commonly described as financial *bubbles*, although the term remains controversial. The asset pricing literature has highlighted various aspects of asset bubbles: first, bubbles tend to coincide with large trading volume; second, they are often associated with technological or financial innovations; third, they tend to coincide with low interest rates and high leverage (see e.g. Brunnermeier and Oehmke 2012; Xiong 2013). Of these three aspects, only the first — large volume — can be present in the market that this paper studies, namely the art market. While similar in many dimensions to other asset markets, the art market is an interesting laboratory to test theories of asset bubbles. It features unlevered and wealthy investors who are less likely to be subject to financial shocks; financial or technological innovation is absent; short-selling is impossible, and transaction costs are minimally 20% of hammer prices.[2]

Yet this market is characterized by frequent booms and busts, which are accompanied by parallel swings in trading volume. Figure 1 shows that trading volume — defined as

[1] Quoted in the *Wall Street Journal* (Peers, 2008).

[2] Auction houses typically charge commissions of around 10% to both buyers and sellers (Pesando (1993), Ashenfelter and Graddy (2003)). Art buyers also have to take into account storage and insurance costs. Also note that transactions costs up to 50% are common in art galleries.

the total number of transactions — rose 45% from 1985 until its peak in 1989, while many segments of the market reached even higher levels. For example, during the same period we find that the prices and volume of Pop artists respectively rose 354% and 167%; more works by Andy Warhol were sold in 1989 than in the four previous years combined. The positive correlation between art prices and volume has also been observed for many historical bubbles, such as the South Sea Bubble, or more recently the Internet bubble in the late 1990s.[3] Interestingly, the relation between prices and volume is not confined to a few episodes or markets. Price increases generally coincide with rises in volume: we find a 0.39 correlation between changes in art prices and changes in art volume over the 1957-2006 period.

Speaking of "bubbles" requires a definition of fundamental value, which is challenging when applied to art. As art prices soar, art dealers, auctioneers, and art gallery sales people often emphasize the resell value, while after a bust, they tend to comfort collectors by stating that pleasure is the best dividend when investing in art. For economists, works of art differ from traditional assets or durable goods in that they yield a non-pecuniary aesthetic or utility dividend. This utility dividend can be seen as the rent one would be willing to pay to own this work of art over a given time frame. It can reflect aesthetic pleasure but also has the ability to signal its owner's wealth. The value of this dividend is of course unobservable and is likely to vary tremendously across art collectors. However, the auction market introduces a common-value element into prices (e.g. Bukhchandani and Huang (1989)). The price of a work of art should therefore equal the present value of future (private) utility dividends over one's expected holding period, plus the expected (market) resell value, i.e. the discount rate model could be used to price art. We can then readily propose a definition of a bubble. A "bubble" corresponds to a market where agents are willing to pay more than the present value of their future utility dividends, because they expect to resell later at a higher price.

[3] See e.g. Cochrane (2003); Ofek and Richardson (2003). Xiong (2013) notes that classical economists such as Adam Smith, John Stuart Mill, Knut Wicksell, and Irving Fischer proposed the concept of "overtrading", the process whereby euphoric investors buy assets solely in anticipation of future capital gains (Kindleberger, 1978). The first historical bubbles where readily characterized by trading frenzies. For example, Carlos et al. (2006) show that turnover in the shares of the Bank of England, the East India Company, and the Royal African Company increased dramatically during the South Sea Bubble of 1720.

Viewing art as an asset helps understand the possible sources of art price fluctuations. The price of an asset can vary over time because expected future cash flows change, or because discount rates — expected returns — vary over time. For a piece of art, the cash flow channel requires utility dividends to fluctuate over time. Such intangible dividends, in turn, depend on buyers' willingness to pay for art, and therefore on collectors' preferences and wealth. It is unlikely that preferences move enough to explain the substantial volatility of art prices. While fads can temporarily emerge for some specific artists or schools of art (Pénasse et al., 2014), the previous literature has shown that tastes tend to be very stable, even in the long run (Ginsburgh and Weyers, 2008; Vermeylen et al., 2013; Graddy, 2013). Alternatively, the utility dividend can vary over time with collectors' wealth, or with the population of collectors. The literature has provided evidence supporting this idea, which we denote as luxury consumption (Mandel, 2009; Hiraki et al., 2009; Goetzmann et al., 2011). Yet it is not clear how fundamental factors can explain the dramatic booms and busts that we observe in the art market. In fact, the art market is not so different from traditional asset markets, where changes in expected cash flows only account for a small fraction of asset prices fluctuations (see, e.g., Cochrane (2011)).[4]

Our empirical analysis is guided by a simple model of speculative trading, in the spirit of Scheinkman and Xiong (2003). The model features 'collectors', with a constant utility dividend, and 'speculators' who are sometimes willing to pay more for art than collectors. The model requires that speculators' willingness to pay is volatile. We interpret this as volatile beliefs (e.g. speculators are overconfident), although in principle speculators may also be subject to wealth or preferences shocks, as suggested above. Because selling short is impossible, prices always correspond to the valuation of the most optimistic agent. It follows that both collectors and speculators are willing to pay a price higher than their own valuation, because they expect to resell to even more optimistic investors in the future (Harrison and Kreps, 1978).[5] The difference between their willingness to pay

[4] Lovo and Spaenjers (2014) propose a dynamic auction model where agents trade to consume a unique durable good that can be interpreted as a work of art. Agents' wealth and tastes are subject to random shocks which generate endogenous trading. In line with traditional asset pricing models, their model requires very large shocks to move prices and trading volume.

[5] A rather extreme example of such investment scheme is the rise of art-storage companies. A rising share of new bought artworks are immediately stored in high-security warehouses, specially designed for the purpose of their subsequent resale (Alden, 2015).

and their own valuation is the price of the option to resell the asset in the future. This corresponds to our definition of a bubble.

As in prior models emphasizing resale options, bubbles build on the fluctuations of investors' heterogeneous beliefs. When the probability to disagree increases, agents trade more (volume increases) and more speculators enter the market, which pushes prices and volatility up. Changes in disagreement therefore predict a correlation between prices, volume, the variance of prices, and the share of speculators. Also because disagreement is stationary, high volume (or a large share of speculators) signals that prices are above their fundamental value. While our model is highly stylized, it sheds light on a number of characteristics of the art market: trading volume and, in particular, short-term speculative trading rises with prices; and high trading volume is followed by negative returns. The prior literature has shown that even when investors' beliefs are unbiased, changes in disagreement can lead to significant price bubbles through frenzied trading (e.g. Scheinkman and Xiong 2003). Such features are difficult to rationalize in conventional models, where agents trade for liquidity and portfolio rebalancing motives (Hong and Stein, 2007).

We test the predictions of our model using a comprehensive data set of nearly 1.1 million auction sales. We begin by examining what drives trading volume. The previous literature, which has extensively studied the demand for works of art, has remained silent on the informational content of trading volume.[6] We find that the share of very short-term transactions and art-specific volatility are positively correlated with prices and volume, as predicted by our model.

We then ask whether high volume coincides with overpricing. Although the fundamental value of art is unobservable, a clear test of overpricing is that volume negatively predicts returns. Crucially, our dataset contains more than 30,000 pairs of transactions where identical items have been identified at the time of purchase and subsequent resale. This enables us to test directly the overpricing prediction of our model. We find that a one standard deviation increase in volume (15.5%) lowers future returns by -6.4%. Fur-

[6] Ashenfelter and Graddy (2011) study sales rates at art auctions, but not volume per se. Bai et al. (2013) examine volume through the lens of international trade. Korteweg et al. (2016) examine how changes in market values correlate with the likelihood of trading for individual artworks and provide a selection-corrected estimator.

ther, about 43% of art excess returns forecasts are negative, which lines up well with the idea of a bubble.

In addition to these known properties of resale option models, our model yields additional predictions for holding periods. We assume that the asset is indivisible, which entails that it can only be owned by a collector or a speculator at any point in time. Collectors enjoy the asset more on average, and only sell to a speculator in states of the world where speculators like the asset more. Therefore collectors on average buy low and sell high, and symmetrically speculators on average buy high and sell low. In addition, speculators have shorter holding periods. This is consistent with anecdotal evidence of speculators buying and selling works of art over very short periods of time ("flips" in the art market jargon). This property, together with our assumption that speculators tend to sell at a loss, implies that short-term transactions earn lower return on average. Our model also predicts that short-term transactions are more volatile. We validate these predictions empirically.

The previous literature has provided empirical evidence of overpricing during events that are limited in time, such as the Chinese warrant bubble (Xiong and Yu, 2011) and the Chinese A-B share premia (Mei et al., 2009). Our findings are novel in that they are not limited to a single event. The predictive relation between volume and returns is not limited in time; rather, it describes the normal behavior of the art market. While our data stops in the mid-2000s, further developments in art prices suggest that the relation persisted ever since (e.g. Maneker 2015). When the two major auction houses (Christie's and Sotheby's) colluded to increase transaction costs, the volume-returns relation briefly disappeared, as we demonstrate in Section IV.C. Several characteristics specific to the art market make this market an interesting study object in the light of speculative trading: while financial innovations and ample credit and leverage have shown to be typical ingredients of asset price bubbles, the art market in contrast is characterized by no (or few) innovations, little impact of credit or leverage, and in addition by high transaction costs.[7]

The remainder of this paper is structured as follows. Section I sets up a simple trading model motivating the empirical analysis. We present our dataset in Section II. Section III discusses the information content of volume. Our core results are presented in Section IV, where we show that volume predicts returns. Section V documents that short-term transactions — our proxy for speculative transactions — are less profitable and more volatile. Section VI concludes. The Appendix provides all proofs. An Online Appendix studies variants of the model, describes some of the econometric procedures that are not provided in the text and contains additional robustness checks.

I. A Model of Speculative Trading

This section develops a simple model in the flavor of Scheinkman and Xiong (2003) and Scheinkman (2014) and derives key empirical predictions. The next sections test these predictions empirically.

Consider the market for a risky asset. The asset is indivisible and for simplicity only one unit of the asset is available. The asset cannot be sold short. There is also a riskless asset in perfectly elastic supply, and fiat money. Investing $\delta < 1$ units of money in the riskless asset at t yields one unit in $t+1$. There is an infinite horizon, and at each date t, the following sequence of events occurs: (i) the risky asset pays a random dividend θ; (ii) investors observe a public signal about next-period dividend; (iii) trading may occur. Two types of risk-neutral agents compete for the asset, speculators $\mathcal{S}$ and collectors $\mathcal{C}$. The latter tend to value the asset on average more than speculators, which we model by assuming that collectors receive an additional private dividend d at the beginning of each period.

Once the dividend has been paid, agents observe a public signal, denoted $\sigma_t \in \{-s, 0, s\}$. Before the signal is observed, agents hold identical beliefs that $E\theta = \bar{\theta}$. Conditional on the signal, speculators' expected value of holding the asset becomes $\bar{\theta} + \sigma$.

[7] Auction houses may sometimes lend part of the purchase to buyers, but this practice is uncommon and confined to major purchases (Thompson, 2009). Auction houses can also provide guarantees to sellers who are concerned that not enough bidders will enter the auctions for their items (although such guarantees can also be provided by third parties). Graddy and Hamilton (2014) study the effect of guarantees (both in-house and third party) and find that they have no significant impact on final prices.

We assume that the probability that $\sigma_t = -s$ equals the probability that $\sigma_t = s$, so that speculators' forecasts of next-period dividend are on average the same as collectors'. Both types of agents know this probability that we write as $\pi \leq 1/2$. Note that, after having observed the signal, speculators and collectors have different forecasts with probability 2π, (and agree with probability $1-2\pi \geq 0$). In Scheinkman and Xiong (2003) and Scheinkman (2014), signals are independent of future dividends. Speculators believe the signals are informative: they display overconfidence about their ability to forecast future asset prices. We may thus think of the parameter π as a measure of differences in beliefs (Scheinkman, 2014). In the context of art, we do not need to assume that speculators are overconfident. σ_t may reflect expected utility services derived by speculators, but not by collectors. The model only requires that agents may have different expectations regarding θ.

Suppose first that the asset cannot be resold. We denote $\bar{b}_t^{\mathcal{C}}$ and $\bar{b}_t^{\mathcal{S}}$ as the willingness to pay of collectors (respectively, speculators) for such an asset. In the absence of a resale opportunity, the willingness to pay is the present value of expected future dividends:

$$\bar{b}_t^{\mathcal{C}} = \frac{\delta}{1-\delta}\left(\bar{\theta} + d\right) \tag{1}$$

$$\bar{b}_t^{\mathcal{S}} = \frac{\delta}{1-\delta}\left(\bar{\theta} + (1-\delta)\sigma_t\right). \tag{2}$$

We assume that even if the signal is high, collectors still value the asset more than speculators, so that $\bar{b}_t^{\mathcal{C}} > \bar{b}_{t|\sigma_t=s}^{\mathcal{S}}$. This amounts to assuming that $s < d/(1-\delta)$.

We now turn to the case where the asset can be resold. At each date, after the public signal is observed, the owner of the asset (either a collector or a speculator) can choose to pay a fixed cost $c > 0$ to put the asset for sale.[8] In that case, a large number of agents of the other type compete for the asset *à la* Bertrand. Because the asset cannot be sold short, competition pushes the agents' bids up to their reservation value.

Suppose that a collector holds the asset at time t. Let $b_t^{\mathcal{C}}$ denote the willingness to pay of the collector. He will choose to resell the asset if the price $p_t > b_t^{\mathcal{C}} + c$. Since speculators do not receive a private dividend, they may only want to buy the asset when

[8]We assume that only the seller pays a transaction cost. Including buyer commissions slightly complicates computations and does not yield any additional insights.

they believe the next-period dividend will be large, that is when $\sigma_t = s$. We assume that s is large enough, so that speculators are indeed willing to buy the asset in that case.[9] Thus when $\sigma_t = s$, speculators will compete for the asset. Because competition pushes prices up to the bidders' willingness to pay, the market clears at the price $p_t = b^{\mathcal{S}}_{t|\sigma_t=s}$. If $\sigma_t \in \{0, -s\}$, no one trades and the collector keeps the asset.

Alternatively, if a speculator holds the asset at time t, he will choose to resell it if $p_t > b^{\mathcal{S}}_t + c$. Thus if the signal is high, the speculator keeps the asset. Otherwise if $\sigma_t \in \{0, -s\}$, he resells it to a collector and the market clears at the price $p_t = b^{\mathcal{C}}_t$.

For simplicity, we assume that when agents do not trade the price of the asset equals its owner's willingness to pay. Hence prices can only take two values. When $\sigma_t = s$, a speculator buys (or keeps) the asset and $p_t = b^{\mathcal{S}}_{t|\sigma_t=s}$. This occurs with probability π. Otherwise, with probability $1 - \pi$, a collector buys (or keeps) the asset and $p_t = b^{\mathcal{C}}_t$.

We can now solve the model by writing the willingness to pay for the asset by collectors and (optimistic) speculators at time t:

$$b^{\mathcal{C}}_t = \delta\left(\bar{\theta} + d + \pi(b^{\mathcal{S}}_{t+1|\sigma_{t+1}=s} - c) + (1-\pi)b^{\mathcal{C}}_{t+1}\right) \quad (3)$$

$$b^{\mathcal{S}}_{t|\sigma_t=s} = \delta\left(\bar{\theta} + s + \pi b^{\mathcal{S}}_{t+1|\sigma_{t+1}=s} + (1-\pi)(b^{\mathcal{C}}_{t+1} - c)\right) \quad (4)$$

If a collector buys the asset in t, he will resell it in $t+1$ to a speculator if the signal is high, paying a trading cost c. Otherwise, he will enjoy the asset for an additional period. Collectors' willingness to pay $b^{\mathcal{C}}_t$ therefore equals next-period expected dividend $\bar{\theta} + d$, a term reflecting the resale value to a speculator (times π) and a term corresponding to his willingness to pay in $t+1$ (times $1-\pi$). The same logic applies to the speculator's willingness to pay.

Observe that the difference between the willingness to pay of both agents is constant: $b^{\mathcal{S}}_{t|\sigma_t=s} - b^{\mathcal{C}}_t = \delta\left(s - d - c(1-2\pi)\right)$. Let Δ denote the premium that an optimistic speculator is willing to pay in excess of a collector's willingness to pay:

$$\Delta \equiv \delta\left(s - d - c(1-2\pi)\right). \quad (5)$$

[9] This amounts to assuming that $b^{\mathcal{S}}_{t|\sigma_t=s} > b^{\mathcal{C}}_t + c$. Note that we do not index collectors' willingness to pay with σ_t, since the latter ignore the signal.

Substituting $b^{\mathcal{S}}_{t|\sigma_t=s} = b^{\mathcal{C}}_t + \Delta$ in (3) yields $b^{\mathcal{C}}_t = \delta b^{\mathcal{C}}_{t+1} + \delta\left(\bar{\theta} + d + \pi(\Delta - c)\right)$. Assuming that $\lim_{T\to+\infty} \delta^T b^{\mathcal{C}}_{t+T} = 0$, we obtain

$$b^{\mathcal{C}}_t = p_{t|\sigma_t\in\{-s,0\}} = \frac{\delta}{1-\delta}\left(\bar{\theta} + d + \pi(\Delta - c)\right) \tag{6}$$

$$b^{\mathcal{S}}_{t|\sigma_t=s} = p_{t|\sigma_t=s} = \frac{\delta}{1-\delta}\left(\bar{\theta} + d + \pi(\Delta - c)\right) + \Delta. \tag{7}$$

We next derive predictions regarding expected prices, trading volume, and price variance are correlated (All proofs are in the Appendix).

Proposition 1. *Expected prices, price variance, and volume rise with the difference of opinions parameter* π.

As in Scheinkman and Xiong (2003), fluctuations in disagreement, modeled here by the parameter π, will generate comovements between prices and trading volume. The next proposition makes explicit our assumption that short-term transactions stem from speculators:

Proposition 2. *On average, a collector holds the asset for a longer period than a speculator. The average holding periods for agents of each group are*

$$E(h|\mathcal{C}) = \frac{1}{\pi} \tag{8}$$

$$E(h|\mathcal{S}) = \frac{1}{1-\pi}. \tag{9}$$

Comparing Equations (1)-(6) and (2)-(7) reveals the existence of a speculative component in the price of the risky asset. This speculative component reflects the price of the *resale option* (as in Harrison and Kreps (1978)) that the buyer is willing to pay, knowing that he will be able to resell the asset in the future.

Proposition 3. *There is a bubble in the price of the asset. Buyers always pay a higher price than their own estimates of the value of future dividends.*

$$b^{\mathcal{C}}_t - \bar{b}^{\mathcal{C}}_t = \frac{\delta}{1-\delta}\pi(\Delta - c) \tag{10}$$

$$b^{\mathcal{S}}_{t|\sigma_t=s} - \bar{b}^{\mathcal{S}}_{t|\sigma_t=s} = \frac{\delta}{1-\delta}\Big(\pi(\Delta - c) + d - (1-\delta)s\Big) + \Delta. \tag{11}$$

The size of the bubble increases with the difference of opinion parameter π, and decreases with the transaction cost c.

Therefore, a large π is symptomatic of a large bubble. This property of the model does not depend on whether the signal σ reflects irrational beliefs or actual differences in willingness to pay for holding the asset. Both collectors and speculators are willing to pay more for the asset than their private value.

Since the econometrician cannot distinguish speculators from collectors, it is useful to derive predictions in terms of the length of the holding period, which is observable. We denote h as the length of the holding period and k as the number of time periods (e.g. months) between two trades. Let R denote the round-trip return of a given transaction, defined as the difference between the resale and purchase log-prices. The following proposition describes the term structure of conditional returns and volatilities.

Proposition 4. *Expected returns increase with the holding period. Long-term transactions are less volatile than short-term transactions. Expected returns and variances conditional on the holding period are given by:*

$$E(R|h=k) = \Delta \frac{(1-\pi)^{k-1} - \pi^{k-1}}{(1-\pi)^{k-1} + \pi^{k-1}} \quad (12)$$

$$V(R|h=k) = \Delta^2 - (E(R|h=k))^2. \quad (13)$$

In our model, collectors always resell artworks at a profit to speculators, who therefore always underperform. Both speculators and collectors know the future resale price and thus face a zero variance. When the holding period increases, Proposition 4 implies that the econometrician observes more transactions from collectors and fewer transactions from speculators. Therefore, conditional expected returns increase, because collectors outperform speculators. In this simple setup, since the only source of variance comes from the distribution of sales across agents, the conditional variance of returns decreases with the holding period and converges to zero when only transactions from collectors are observed.

Empirical predictions Our model yields four testable predictions:

1. Art prices, art volume, the variance of art prices, and the proportion of short-term transactions are positively correlated.

2. Periods of large volume are followed by low or negative long-term returns.

3. An increase in transaction costs reduces asset prices, and reduces price- and return-volume correlations.

4. Average returns increase with the holding period. The variance of round-trip returns decreases with the holding period.

In a world where many assets are traded, where signals are uncorrelated across assets, Proposition 1 establishes that the average price and the average number of transactions increases with π. Price variance also increases with π. By definition, π also gives us the proportion of speculators. Changes in π therefore correspond to changes in the probability of disagreement, changes in the proportion of speculators, and changes in volume. This corresponds to Prediction 1. Broadly defined, as in the previous literature, volume can thus be seen as an indicator of investor sentiment (Baker and Stein, 2004; Hong and Stein, 2007).

Proposition 3 implies that the size of the bubble is an increasing function of π. An unusually large trading volume (or a large share of short-term transactions) will come with an unusually high price. Because π cannot be larger than $\frac{1}{2}$, large values for π are eventually followed by lower values. Hence a large volume will forecast low returns. This proposition gives us the central prediction of resale option theory (Prediction 2).

The existence of the bubble rests on our assumption that the difference between speculators' and collectors' willingness to pay is large enough to compensate for transaction costs, i.e. $\Delta > c$. A modest increase in c reduces the size of the bubble as long as this assumption holds. A large increase in c may destroy the incentive to resell later. This gives us Prediction 3. Finally, Prediction 4 follows from Proposition 4.

In the Online Appendix, we ask whether alternative mechanisms may generate a similar set of predictions. We first show that our model generates trading volume and changes in prices even when π is constant. When the signal becomes high, a collector sells to a speculator; the price of the asset increases and volume equals one. Symmetrically, when a speculator sells to a collector, the price decreases and volume equals one. When the signals are correlated across assets, we observe high volume whenever aggregate prices increase or decrease. This is different from the effect of changes in π (as in our main model above), where decreases in prices coincide with fewer, not more, transactions. In addition, since the signals are unpredictable, changes in prices and volume are also unpredictable. We also consider a variant of the model where collectors hold the asset in good times and are hit by liquidity shock (which we label as "bad times") when they are forced to sell to "arbitrageurs". We show that this model predicts that volume and the share of short-term transaction are negatively correlated with prices, while our model predicts a positive correlation. So, while liquidity shocks to collectors are present in the art market, liquidity shocks still do not explain some of the main features of the art market. Of course, this does not rule out the possibility of alternative mechanisms which could generate a positive price-volume correlation without bubbles. What we are unaware of is a strictly rational model where volume predicts negative returns, as we document in this paper.

II. Data

This paper uses the historical data set constructed by Renneboog and Spaenjers (2013), which comprises information on more than one million transactions of art at auction over the period from 1957 until 2007. The dataset initially overweighs the London sales, but as of the middle of the 1970s, the coverage consists of all major, medium-sized, and even smaller auction houses around the world. The sales concern oil/acrylic paintings and works on paper (water colors, gouaches, etchings, prints) by more than 10,000 artists.

Each auction record contains information on the artist, artwork, and sale. We observe the name of the artist, his nationality, and whether he is alive. Almost half of the artists are classified into one or more of the following movements: Medieval & Renaissance; Baroque; Rococo; Neoclassicism; Romanticism; Realism; Impressionism & Symbolism; Fauvism & Expressionism; Cubism, Futurism & Constructivism; Dada & Surrealism; Abstract Expressionism; Pop; Minimalism & Contemporary.[10] Artwork information in-

[10] See Renneboog and Spaenjers (2013) for details on the compilation of the list of artists, the classification of artists into movements, and the collection of sales information.

cludes its title, year of creation (for about a third of observations), medium, size, whether the piece is signed, and how precisely it can be attributed to the artist. Sale information includes the auction house, date of the auction, lot number, and hammer price. The hammer price is the price for which the artwork was sold, before transaction costs, converted to 2007 U.S. dollars.

Repeat-sales. Most of our analysis relies on a subset of the dataset for which pairs of identical objects of art can be identified. We don't observe the identity of the buyer and therefore the repeat-sales are matched on observed characteristic, as in the prior literature. Matching is based on the name of the artist (excluding pupils and followers), size, title (excluding vague titles such as "Untitled" and "Composition"), medium, and the presence of signature and date. Each resale pair is considered as a unique point in our dataset. For each pair of transactions, we observe the purchase and sale prices, P_i^b and P_i^s, expressed in logarithm. The log-return for holding a work of art i between the date of purchase b_i and the date of sale s_i is thus given by $P_i^s - P_i^b$.

Potential Bias. We make use of this dataset to test the predictive relation between volume and returns, and between holding periods and returns. We are concerned that selection bias may affect the interpretation of our results. For example, Goetzmann (1993) argues that both the upper and lower tails of art return distribution may not be observed, because works of art that fall out of fashion or are acquired by museums and major private collections are unlikely to reappear on the market. A potential concern, therefore, is that the distribution of returns conditional on a resale differs from the unconditional distribution of returns.[11] If more works of art are offered for sale when prices appear high, we may observe a correlation between prices and volume. We would also observe a correlation between round-trip returns and volume at resale. However, selection bias cannot explain why volume at purchase forecasts future returns. Such a bias is in any case likely to be small. To see that, we compare statistics from the full dataset and the presumably biased repeat-sale dataset. The correlation between returns computed using

[11] Korteweg et al. (2016) propose a procedure to address the selection bias that arises when artworks with higher returns are more likely to be resold. By design, their approach conditions on information available at resale to address the possible selection bias. This is not suitable to test our main hypotheses, which is that information available upon purchase forecasts returns.

a repeat-sale estimator on this latter subsample and the art returns using the hedonic estimator is 0.98. Both indices also show very similar long-term trends, which implies that survivorship bias is likely to be very small. Finally, the distribution of sale-to-sale returns (not shown) is quite symmetric (with a skewness of 0.38) and no particular discontinuity can be observed in the tails of the distribution.[12] The scope of our data — in terms of number of art objects, artists, movements, auction houses, geographical spread, and time window — explains why the bias is negligible. The fact that our data also comprises art objects auctioned in small auctions houses (around the world) guarantees that we are picking up new, rising artists and that more important artists who may gradually fall out of vogue with the large auction houses are still traded in medium-sized or smaller auction houses. Also, some auction houses tend to specialize in specific art movements, which entails that they are quicker in detecting (and creating) new trends.

We complete the dataset by constructing measures of volume at the transaction level. We first collect the total number of objects sold by Sotheby's or Christie's in London or New York on the last twelve months preceding t. We focus on the sales by the two leading auction houses to mitigate the influence of changes in sample coverage over time. Sotheby's and Christie's account for 49.2% of total transactions in our dataset.[13] Following Baker and Stein (2004), we then normalize our series by the average volume over the last five years. Taking logs, our monthly measure of volume is given by

$$\text{VOLUME}_t = \log\left(\sum_{i=t-12}^{t-1} v_i\right) - \log\left(\frac{1}{5}\sum_{i=t-60}^{t-1} v_i\right) \tag{14}$$

where v_t is the number of transactions observed in a given month t. Detrending the series brings about several benefits. First, as can be seen in Figure 2, Equation (14) generates a persistent series. Such a property is desirable for a variable that is expected to predict

[12] In the Online Appendix, we compare the return distribution of the repeat-sale data with the return distribution of a pseudo dataset constructed by matching randomized pairs after controlling for observable characteristics. The volatility of the pseudo returns is an order of magnitude larger (unsurprisingly), but the scaled distributions are very similar.

[13] Our results remain if we use the full sample of transactions instead of sales from Sotheby's and Christie's, but this requires to exclude the first years of observations where the coverage gradually extends to the smaller auction houses.

long-term returns. Second, volume supposedly proxies for the price of the resale option — the overpricing component in prices — and this component must be stationary. Third, Equation (14) gives us a relatively high frequency series, which is not affected by art market seasonality. Finally, the series is constructed recursively, which ensures that only information that is truly available to the investor when making his forecast appears in his information set.

We merge these series with our repeat-sale dataset: for each resale pair, we record the value of VOLUME_t at the month preceding the purchase and at the month preceding the sale. Our final dataset spans 1962 to 2007 (we lose the first five years in the construction of our trading volume measure).

We also add controls for potential changes in fundamental value between the two transactions dates. As we have already emphasized the prominent role of stock market wealth effects on art prices (Hiraki et al., 2009; Goetzmann et al., 2011), we use the Global Financial Data (GFD) world index to proxy for worldwide equity wealth and equity systematic risk. In line with Mei and Moses (2005), we also include controls for other risk factors, namely the Fama-French factors (Fama and French, 1993) and the Pastor and Stambaugh (2003) liquidity factor. Finally, we use the one-month Treasury bill rate as the risk-free rate.

Although tastes are relatively slow-moving (Graddy, 2013; Vermeylen et al., 2013), we proxy for potential changes in tastes by measuring temporal variation in artist fame. To do so, we collect the percentage of mentions of each artist name in the English-language books digitized by Google Books (Michel et al., 2011; Google, 2012). We find annual series for 2,528 artists (out of 3,257), which yields 30,060 resale pairs with information about artists' fame. Many artists emerged over the sample period, and it is not uncommon that the share of mentions in Google Books is exactly zero at some point. We therefore winsorize the log changes in "Fame" at the 1% level. Finally, we use a dummy variable indicating whether the artist died between the purchase and resale of the artwork.

Table I gives the descriptive statistics for the repeat-sale database, expressed in log difference between the time of first and second transaction. For art, we see an average excess return of 2.1% over an average holding period of 6.2 years within the period 1962-2007, with a standard deviation of 79%. Equities are undoubtedly financially dominating art, with an excess return of nearly 8.3% measured over the same average repeat-sales time window and a standard deviation of almost 31.0%. Volume barely changes on average (-3.0%), and was much less volatile (18.9% standard deviation), which reflects the smoothing of the volume series. We see that for about 3.7% of transactions, the artist died between the purchase and the resale. Finally, the percentage of mentions of each artist (fame) fell -6.0% on average and has a dispersed distribution (the standard deviation is 38.6%).

Interestingly, this large volatility at the artist level averages out at movement level, as depicted by Figure 3. Over our sample period, we observe the increasing popularity of Andy Warhol, whose share of mentions of his name in Google Books increased dramatically. Roy Lichtenstein, another famous Pop artist, also gained increasing attention over our sample period. By contrast, Figure 3 shows that the exposure of the average Pop artist increased smoothly over the five decades of our sample. We observe similar patterns for the other art movements: artist trajectories can be erratic, but the degree of exposure is very smooth at the aggregate level. This illustrates the fact that tastes move slowly, as pointed out by Graddy (2013). Hence changes in tastes are unlikely to explain the dramatic fluctuations that characterized art prices during that period.

III. The Information Content of Volume

This section tests Prediction 1 of our model. We construct annual time series of prices, trading volume, the share of short-term transactions, and art volatility, which we expect to be positively correlated with one another. We also construct additional series which, we argue, proxy for the level of "sentiment" in the market, and for collectors' wealth. Because these data series are typically nonstationary, all results in this section are based on first-differenced series.

Aggregate prices and trading volume We build our aggregate real price index by applying a hedonic regression model to the full dataset (see Section II in the Online Appendix for a description of the hedonic regression model). To construct the index in real terms, we deflate hammer prices with the US consumer price index. To create our measure of trading volume, we record the number of observed transactions for each year. Our database does not include buy-ins (i.e., items that do not reach the reserve price set by the seller), and we therefore work with the lot numbers that actually sold. We construct a proxy for the average sales rate (the percentage of objects actually sold in an auction relative to all objects offered for sale), as discussed later in this section. The data coverage is very limited in 1963, where only some of the highest priced sales are included. This leads to artificially low volume and high prices for 1963, which affects the years 1963-64 in percentage changes. Our dataset also ends before the end of 2007, so that we cannot measure reliably volume for that year. We therefore drop these three years for the purpose of testing Prediction 1.

Share of short-term transactions Our model hypothesizes that short-term transactions reflect speculation. In the introduction of this paper, we have shown that the share of short-term transactions peaked during the 1990 bubble. Given the huge transaction costs that characterize the art market, it is very unlikely that these works of art were bought for the pure "retinal" pleasure. We construct the variable 'share of short-term transactions' by means of the repeat-sale sample, and define it as the share of purchases that were resold within a year. More precisely, for all transactions that were resold in t, we divide the number of transactions with a holding period below one year on the total number of transactions. Working with resales only ensures that there is no look-ahead bias in the series.

This definition implies a mechanical downward trend in the series (e.g., by construction, the ratio has a value of one for the first year). We indeed observe a strong downward trend until the mid-eighties. In the following years, the ratio is more stable and short-term transactions account for 10% to 30% of trading volume. This is still a surprisingly high level, given the large transaction costs that characterize this market.

We are concerned that some transactions may be falsely classified as resale pairs due to measurement error. To mitigate this risk, we also reconstruct the series of short-term transactions by dropping about 10,000 artworks with duplicate titles, and find a similar level and pattern. Also, even if the level is affected by measurement error, there is little reason that these errors persist in differences.

Hedonic Volatility Prediction 1 also implies that art price volatility is positively correlated with prices, volume, and more generally with market sentiment. To obtain a proxy for yearly art volatility, we take the standard deviation of the residuals in a regression of art prices on hedonic characteristics (Section II in the Online Appendix), measured each year. We denote this series as Hedonic Volatility.

In addition to the share of short-term transactions and art volatility, we construct two art-specific proxies for market sentiment.

Sales rate Our first proxy for sentiment is the sales rate, the percentage of the lots sold in an auction. Sellers of individual artworks usually set a secret reserve price and if the highest bid does not reach this level, the items are "bought in" and go unsold. The convention in the art market is that the reserve price is set at or below the auctioneer's low estimate. There is anecdotal evidence that the sales rate tends to be lower in depressed markets where prices are lower and are therefore less likely to meet sellers' reserve prices (Thorncroft, 1990). Ashenfelter and Graddy (2011) find that the sales rate is not related to art prices, but is strongly positively related to unexpected price changes, defined as the difference between the hammer price and the presale estimate produced by auction house experts. A higher sales rate may therefore indicate that the market is dominated by optimists, who are willing to pay more than sellers' reserve prices, which are themselves related to expert estimates. Ashenfelter and Graddy (2011) indeed report that sales rates crashed in the bust of the 1990 bubble. Since our dataset does not include items that were bought in, we construct a proxy for the sales rate. For each auction, we divide the number of observed transactions by the maximum lot number. We then take, for each year, the average sales rate across auctions as our proxy for the aggregate sales rate.

Share of Postwar Art Newspaper articles also suggest that the share of Modern and Contemporary Art is higher in "hot" markets. For example, (Thorncroft, 1990) reports a flight to quality (i.e. to Old Masters paintings) after the 1990 bubble burst: "the auction world has returned to its traditional ways, where connoisseurs rule and established works of art hold pride of place." This can be related to sentiment, as overconfident collectors are more likely to hunt for relatively young artists with larger upside potential, just as overconfident investors scrutinize the stock market hoping to find the next Google.[14] When speculators do no participate the market, trading should decrease and be confined to the less speculative art movements. A high share of Postwar Art in the aggregate trading volume thus signals that speculators dominate the market. We therefore construct a second proxy for sentiment consisting of the annual share of Postwar Art.[15] There are, by definition, few Postwar Art sales in the beginning of our sample period. The share of Modern and Contemporary Art rises from zero to about 25% over time. We report correlations for the 1974-2007 period, where Postwar Art always accounts to at least 5% of yearly trading volume.

Art objects offered for sale It is also of interest to understand whether volume increases mostly because of an increase of demand, or because a higher number of items are offered for sale. In our model, all items offered are sold, since we do not model the possibility for the seller to set a reserve price. Since auction houses are more likely to solicit potential sellers in "hot" markets (Pesando and Shum, 2008), the number of artworks offered may also be positively correlated with market sentiment. We use the number of transactions divided by our sales rate to proxy for the number of art objects offered for sale.

Top income Finally, we would like to know to what extent prices and volume correlate with fundamentals. The previous literature has emphasized the role of wealth, and in particular the wealth of the most privileged members of society, as drivers of art prices. In line with Goetzmann et al. (2011), we use the data from Piketty and Saez (2006) to build a consistent series of the share of total income received by the top 0.1 percent of all income earners in the US.

Table II presents the correlation matrix of the percentage changes in art prices, art

[14] Tobias Meyer, who in 2006 was the director of Sotheby's Contemporary Art department worldwide, said to the New York Times (Vogel, 2006): "Collectors want to beat the galleries at their own game [...]. This insatiable need for stardom has made buying student work the art-world version of 'American Idol.'"

[15] This corresponds to Abstract Expressionism, Pop, Minimalism & Contemporary Art.

volume, and the percentage changes in the six variables discussed above (the share of short-term transactions, the sales rate, the number of art objects offered for sale, the share of transactions in Postwar Art, hedonic volatility, and the top income). The correlation between prices and volume is 0.39. We see that when prices and volume increase, the share of short-term transactions tends to increase. The correlation between volume change and the change in short-term transactions is a highly significant 0.42.

In line with the Prediction 1 of our model, we also see that hedonic volatility is positively correlated with prices and volume. The share of Postwar Art also increase with both prices and volume (the correlations are 0.48 and 0.33, respectively). We also learn from Table II that the sales rate is positively correlated with prices, but is uncorrelated with volume.

Finally, Table II shows that art returns are positively correlated with changes in top incomes, although the correlation is insignificant. Top incomes are uncorrelated with all measures of trading volume.

IV. Volume and Overpricing

A. Baseline Results

The most important prediction of resale option theory is overpricing (Hong and Stein, 2007). When disagreement increases, both the value of the resale option and trading volume increase. A high volume should therefore predict low, or even negative, returns (Prediction 2). We test this prediction on our repeat-sale dataset, where each transaction is identified by its purchase and subsequent resale date. For each resale pair, we record trading volume at the time of the purchase.

We start by comparing the performance of strategies based on trading volume at the time of purchase. Each month we compute five-year rolling deciles of our market volume measure. Our Low (High) Volume strategies record all purchases that occurred when volume was in the lowest (highest) decile. We emphasize that our strategies are constructed "out of sample", and thus could have been implemented in real time. The High-Volume strategy realizes an average excess return of -17.2% (or -2.8% per year, the average holding period being 6.2 years). The Low-Volume strategy achieves an average excess return of 8.0%. We assess statistical significance by regressing round-trip returns on dummies corresponding to Low-Volume and High-Volume. We are concerned about cross-sectional correlation of the residuals, and consequently we estimate standard errors that cluster in the time dimension throughout. The underperformance of the High-Volume strategy is statistically significant, with a t-stat of -3.8. The Low-Volume strategy does not achieve an average return that is statistically different from the average excess return.

More generally, we find that volume at the time of purchase forecasts art returns. To see this, we regress art excess returns on volume measured at the time of purchase:

$$r_i - \sum_{t=b_i+1}^{s_i} r_{ft} \quad = \quad \alpha + \nu_0 \text{VOLUME}_{b_i} + \epsilon_i \tag{15}$$

where $r_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. The top panel of Table III shows the estimated slopes for the full sample as well as for two subsamples: Postwar Art and Old Masters. The first subsample corresponds to Modern and Contemporary Art, as in Section III. The second one consists of artists who worked in Europe before 1800, and hence comprises late Medieval and Renaissance Art, Baroque, and Rococo. The estimated slopes are significantly negative in all samples. The slopes are larger for Postwar Art and lower for Old Masters. The effect of volume is economically large. In the full sample, a one standard deviation increase in volume (15.5%) lowers future returns by -6.4%.

The evidence that a variable forecasts asset returns is not enough to establish the existence of a bubble. Volume may forecast art returns because art investors require a risk premium to hold art, and because this risk premium varies over time. More convincing is to show that volume forecasts *negative* returns (see, e.g., Eugene Fama's Nobel lecture (2014)). In fact, in the full sample, 43% of art excess returns forecasts are negative. This should not come as a surprise because average art returns in excess of the risk-free rate are about 2.1%, as noted in Section II. A small increase in volume above its long-term average is thus enough to generate negative forecasts. We emphasize that these are excess returns before transaction costs and that net excess returns forecasts are likely to be much lower.

One could object that that we may overestimate the forecasting power of volume, because the art market was characterized by a large boom and bust in both prices and volumes in the middle of our sample. To address this concern, the bottom panel of Table III estimates Equation (3) excluding repeat-sales that occurred during the 1985-1995 years. More specifically we exclude pairs that were purchased or resold during the 1985-1995 sample period. Table III indicates that the predictive slopes actually increase (in absolute value) when we exclude that time period.

We present additional robustness checks in the Online Appendix. Namely, we verify that the results are not affected by outliers by winsorizing excess returns (Table A.I). We also show that the results hold for relatively cheap and expensive items (Table A.II). Our model also implies that the share of speculators (proxied by the share of short-term transactions) predicts returns. We therefore repeat our analysis replacing Volume by the share short-term transactions, constructed again from Equation (14). Short-term transactions are mechanically high in the beginning of the sample period and trend downward. This is a minor concern in Section III, because we work on first-differenced series. In contrast, the share of short-term transactions remains high when detrended with a moving average. We therefore drop the first years of the sample and work with data from the 1982-2007 period. We find comparable results, which are reported in Tables A.III.

We obtain symmetric results when we measure volume at the time of resale. Selling when volume is in the lowest decile corresponds to an average loss of -12.9% (t-stat of -3.9), whereas selling when it is high is much more profitable, with an average return of 23.0% (t-stat of 6.6).[16] Table A.IV in the Online Appendix presents estimates for regressions of round-trip excess returns on resale volume. We find a positive and large effect of volume at the time of resale, again in line with the idea of bubble formation. The results again persist (albeit somewhat weaker) when we exclude the 1985-1995 years.

[16]Estimates that condition on resales (rather than purchases) exhibit stronger statistical significance. As noted in Section II, if investors are more likely to sell when prices are high, we may indeed find a positive relation between round-trip returns and volume at resale. Although this could bias our resale-estimates upward, we find that this is not likely to be the case because it is the increased precision that explains the stronger significance. We also note that magnitudes of the estimates conditioning on resales and purchases are relatively similar.

B. Returns and cumulative changes in volume

Roundtrip returns are likely to be affected by changes in economic conditions between the purchase and resale dates. For example, tastes and aggregate wealth may change over time. Relatedly, volume may capture shocks that affect individual art collectors: some collectors who bought when volume was high may be hit by liquidity shocks, and be hence forced to sell when volume was low. In this section, we study the relation between returns and volume by explicitly controlling for potential changes in fundamental value, captured by wealth shocks and changes in tastes. In the spirit of Mei and Moses (2005), we use the classic CAPM model to estimate the systematic risk of artworks, and employ our worldwide equity index as the market index. We expand the CAPM model by our artist fame and death variables, and volume. After dropping the observations from 750 artists who do not appear in Google's books database, we estimate the following equation:

$$
\begin{aligned}
r_i - \sum_{t=b_i+1}^{s_i} r_{ft} &= \alpha + \beta \sum_{t=b_i+1}^{s_i} \mathrm{MKT}_t + \gamma_1 \sum_{t=b_i+1}^{s_i} \mathrm{FAME}_{a,t} + \gamma_2 \sum_{t=b_i+1}^{s_i} \mathrm{DEATH}_{a,i} \\
&\quad + \nu \sum_{t=b_i+1}^{s_i} \mathrm{VOLUME}_t + \epsilon_i \qquad (16)
\end{aligned}
$$

where $r_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. On the right-hand side, we include the cumulative changes in volume, the sum of world equity excess returns between purchase and sale times, measured by MKT_t. We also add the change in artist's fundamental value, measured by $\mathrm{FAME}_{a,t}$ and our DEATH dummy. All variables are observed with monthly frequency, except $\mathrm{FAME}_{a,t}$, which is only updated annually.

Equation (16) states that the percentage change in the price of an artwork in excess of the risk-free rate is a function of four factors. The three fundamental factors are changes in wealth, measured by the percentage increase in the GFD equity index between the purchase and sale time, changes in tastes measured by the increase in mentions in the Google corpus, and the death of the artist during the holding period of an art object. Our test variable is ν, which measures the correlation with cumulative changes in volume.

This corresponds the the log difference between volume measured at resale and volume measured at purchase. Volume at purchase forecasts returns negatively and volume at resale is positively correlated with returns. We therefore expect ν, which measures the effect of the difference between the two quantities, to be positive.

In order to control for art exposure to additional risk factors, we also extend our estimation to Fama and French (1993) factors and the Pastor and Stambaugh (2003) liquidity factor:

$$\begin{aligned} r_i - \sum_{t=b_i+1}^{s_i} r_{ft} &= \alpha + \beta_1 \sum_{t=b_i+1}^{s_i} \text{MKT}_t + \beta_2 \sum_{t=b_i+1}^{s_i} \text{SMB}_t + \beta_3 \sum_{t=b_i+1}^{s_i} \text{HML}_t \\ &+ \beta_4 \sum_{t=b_i+1}^{s_i} \text{LIQ}_t + \gamma_1 \sum_{t=b_i+1}^{s_i} \text{FAME}_{a,t} + \gamma_2 \sum_{t=b_i+1}^{s_i} \text{DEATH}_{a,i} \\ &+ \nu \sum_{t=b_i+1}^{s_i} \text{VOLUME}_t + \epsilon_i \end{aligned} \tag{17}$$

Table IV presents our empirical findings: controlling for changes in fundamental value, volume has a large positive correlation with returns. The results are consistent across the samples and models and are also economically significant: for the full sample (model 1), a one-standard deviation increase in volume (18.7%) increases excess returns by 13.7% over the holding period (or 2.2% per year on average). This long-term effect of volume on art returns is much larger than the effect of a one standard deviation increase in stock returns (that is 6.6% or 1.1% per year on average) and the effect of taste (which is 5.7% or 0.9% per year on average), and of the same order of magnitude as the death of the artist (13.4%).

Table IV also reports estimates for Postwar Art and Old Masters. We observe that Postwar Art loads more on trading volume than more traditional art. A one standard deviation increase in volume corresponds to an increase in returns of 20.6% for Postwar Art and 7.9% for the Old Masters. This pattern is reminiscent of Lee and Swaminathan (2000), who find that high (low) volume stocks exhibit many glamour (value) characteristics.

C. A Natural Experiment: the "Price Fixing Conspiracy"

The previous results indicate that changes in volume have a sizeable correlation with ex-post returns, and that this relation is sustained across periods of time. Yet our model also predicts that a large increase in transactions costs may destroy the buyer's incentive to resell later, so that the value of the resale option would collapse (Prediction 3). This suggests that we could exploit an exogenous variation in transaction costs to provide further evidence for our theory. Transaction costs were roughly constant during our sample period. After the art market collapse of 1990, however, Sotheby's and Christie's engaged in collusive behavior. In the spring 1995, the two auction houses announced they would charge a fixed and non-negotiable commission on sales, which would be effective from September 1995. The new policies were effective until the beginning of 1997 (Ashenfelter and Graddy, 2005). It is difficult to evaluate the exact increase in transactions costs, but it was arguably large.[17] In addition, by drawing media attention on auction houses' commissions, we believe this episode made transaction costs more salient to collectors.

We use this episode to test Prediction 3 of an increase in transaction costs: we expect returns to be lower and the return-volume relation to be considerably weaker for resales that occurred between September 1995 and January 1997. We estimate the following variant of the model on the sample of sales that occurred at Sotheby's or Christie's:

$$\begin{aligned} r_i - \sum_{t=b_i+1}^{s_i} r_{ft} &= \alpha + \beta \sum_{t=b_i+1}^{s_i} \mathrm{MKT}_t + \gamma_1 \sum_{t=b_i+1}^{s_i} \mathrm{FAME}_{a,t} + \gamma_2 \sum_{t=b_i+1}^{s_i} \mathrm{DEATH}_{a,i} \\ &+ \phi D_{i,c} + (\nu_1 D_{i,c} + \nu_2 D_{i,pc}) \sum_{t=b_i+1}^{s_i} \mathrm{VOLUME}_t + \epsilon_i \end{aligned} \quad (18)$$

where $D_{i,c}$ and $D_{i,pc}$ indicate artworks that were sold during and after the collusion period and where VOLUME_t is computed from the sales by the two auction houses. We expect ϕ to be negative and ν_1 to be smaller than ν_2.

Table V shows that the 1995-1997 period is characterized by a negative performance of at least -27.3% (in the four-factor model), that cannot be explained by any of the stock or art market factors, nor by volume. This is particularly impressive, because art prices

[17] In the civil suit that followed in 2001, Sotheby's and Christie's agreed to each pay 256 million dollars to the plaintiffs.

have remained relatively stable after 1995, and suggests that, given the performance of the various factors, art prices should have rebounded substantially. We also learn from Table V that the return-volume relation completely disappeared during the collusion period: the coefficient associated to cumulative volume changes is indistinguishable from zero, validating our conjecture that an increase in transaction costs had an adverse impact on the resale option.

Figure 4 supplements Table V by plotting returns and cumulative volume changes against the resale date for all sales that took place at Sotheby's and Christie's. Median returns and volume are represented as solid lines, and the dashed lines correspond to the 10th and 90th percentiles. Although there is a huge dispersion in realized returns, we see a remarkable relation between returns and volume, in particular during the market collapse of 1990, but also during the early eighties and in the last decade. The main exception corresponds to the collusion period (delimited by vertical lines), where there is no correlation between the two series, contrasting with a significant 0.29 for the full period. Remarkably, we see that volume grew steadily after the 1990 market collapse and fell exactly in September 1995, when auction houses decided to increase sellers' commission.

V. The Underperformance of Short-term Transactions

In this section we test the prediction of our model relative to the term structure of returns (Prediction 4). Our model suggests that speculators hold works of art for shorter periods and realize lower returns, so that transactions with shorter holding periods should underperform. We test this hypothesis by estimating the following regression:

$$r_i/h_i = \mu_b D_{b,i} + \eta h_i + \epsilon_i \tag{19}$$

where μ_b is a vector of purchase year fixed effects and $h_i = (s_i - b_i)$ is the holding period (in years) for the sale i. The dependent variable r_i/h_i is annualized returns. If speculators underperform collectors, we expect them to earn lower annualized returns, so that $\eta > 0$.

Whereas elsewhere in the paper we follow the literature by analyzing raw returns, an analysis on holding period returns requires taking into account transaction costs which weigh heavily on return over the short run but less so for longer holding periods. We thus estimate Equation (19) assuming 20% transactions costs but also test the impact of transaction costs in the range [0%-30%] with multiples of 5%. As mentioned earlier, a 20% transaction cost is probably a lower bound, as one also needs to account for the costs related to insurance, transportation, framing and (country-specific) taxes.

Other economic forces may also affect η. In particular, η will be biased downward if agents are more likely to resell winning round-trips. Further, some speculators may gamble on future fame, and therefore be willing to accept longer holding periods for new artists. In short, a positive η may suggest that the underperformance channel is strong enough to dominate other factors.

The estimation results are displayed in Table VI. The η-estimate is significantly positive for transaction costs above 10%. For a 20% transaction cost, a one standard deviation decrease in holding period (about 6 years) decreases ex post returns by 17.6%, in line with our assumption that speculators underperform on average.[18]

Prediction 4 also claims that short-term transactions are more volatile. In our model, both collectors and speculators know the future resale price, so that they face a zero round-trip variance. From the point of view of the econometrician, the only source of round-trip variance comes from the distribution of sales across agents. Thus the conditional variance of returns decreases with the holding period, until it converges to zero when only transactions from collectors are observed. Hence round-trip variance should decrease with holding periods. Short-term transactions will also appear riskier if returns are positively autocorrelated (Lo and MacKinlay, 1988), which would occur if changes in disagreement are persistent. A number of studies have provided evidence that past art returns can help predict future returns (Cutler et al., 1991; Pesando, 1993; Goetzmann, 1995). More recently, Erdos and Ormos (2010) and David et al. (2013) have provided mixed evidence based on variance ratio (VR) tests. The central idea

[18] A potential concern is that the underperformance is driven mostly by very short round-trips. Our results are robust if we exclude transactions with holding periods below one year. Lovo and Spaenjers (2014) find a negative relation between annualized returns and holding periods in auction markets, but they ignore transaction costs.

of variance ratio tests is that when returns are uncorrelated over time, the variance of the h-period log-returns should equal h times the variance of one-period returns, i.e. $\text{Var}(r_t + \cdots + r_{t-h+1}) = h\text{Var}(r_t)$. Under this null hypothesis the variance ratio statistics

$$\text{VR}^{index}(h) = \frac{\text{Var}(r_t + \cdots + r_{t-h+1})}{h\text{Var}(r_t)}$$

will be close to one. We test our hypothesis by constructing a variance ratio test that is directly applied to transaction data. We partition pairs of transactions in one-year groups (i.e. 0-1 years holding period, 1-2 years, etc.) and compute the variance of returns for each group. The variance ratio is then written as:[19]

$$\text{VR}(h) = \frac{\text{Var}(\{\text{r}_{i,t}\}_{h-1<y<h})}{h\text{Var}(\{\text{r}_{i,t}\}_{y<1})} \tag{20}$$

where $\{\text{r}_{i,t}\}_{h-1<y<h}$ is the set of resale pairs with a holding period between $h-1$ and h years. Under the null of a random walk, the VR should remain approximately equal to one across holding periods.

Table VII presents the variance ratios calculated over holding periods of one to ten years. We see that the variance ratio decreases with the holding period. The volatility of round-trip returns in the one-year group is 52%, whereas the volatility in the 10-year group is 95%. In order to test for mean reversion, we construct a bootstrap procedure in the spirit of Kim (2006) and Chow and Denning (1993). We describe this procedure in Online Appendix IV. The resulting p-values, which are presented on the last line of Table VII, indicate that less than five percent of simulated statistics fall below the real ones for all holding periods.[20]

[19] We do not include the small sample adjustment proposed by Cochrane (1988), since we focus on simulated results for the purpose of our statistical test (see Online Appendix IV). The variance ratio is calculated in the same way in both data and simulations, any adjustment is thus unnecessary.

[20] A potential concern is selection bias due to plausible loss aversion. To address this concern, we repeated our simulations assuming that various fractions of the reselling losses were not resold. Doing so had materially no effect on our results (see Online Appendix IV).

VI. Conclusion

This paper argues that limits to arbitrage, namely the impossibility to sell art short, induce a speculative component into art prices. As pessimists cannot short-sell, their opinions are not incorporated into art prices, which hence only reflect the opinion of the most optimistic investors. As a result, an optimist is willing to pay more than her own private value because she knows that, in the future, there may be other collectors that value the work of art more than she does. The difference between her willingness to pay and her own private value reflects a speculative motive, the value of the right to sell the work of art in the future.

This paper investigates this resale option theory by studying the behavior of art prices and volume and by directly measuring returns over a comprehensive data set of worldwide art auctions. The empirical discussion is guided by a simple model of trading between collectors and speculators that predicts that prices, volume and the share of short-term transactions are correlated, that a high volume predicts negative returns, and that short-term transactions underperform and are riskier than long-term transactions. The empirical evidence supports the model's predictions. Rising prices tend to be accompanied by more short-term transactions, which we interpret as trading frenzies given the huge trading costs that characterize the art market. Trading frenzies tend to concentrate on the works of Postwar artists, which are more likely to appear at auctions when prices and volume are high. When trading volume is high, we find that buyers tend to overpay, in that a high volume strongly predicts negative returns in the subsequent years. We also study the impact of an increase in transaction costs, exploiting an episode of price collusion between the leading auction houses, and find further support for the predictions of the resale option model.

Appendix

Proof of Proposition 1. Expected prices increase with π :

$$\begin{aligned} Ep_t &= \frac{\delta}{1-\delta}\Big(\bar{\theta}+d+\pi(\Delta-c)\Big)+\pi\Delta \\ \frac{\partial Ep_t}{\partial \pi} &= \frac{1}{1-\delta}\Big(\Delta-\delta c(1-2\pi)\Big) > 0. \end{aligned}$$

Price variance increases with π :

$$\begin{aligned} Vp_t &= \Delta^2\pi(1-\pi) \\ \frac{\partial Vp_t}{\partial \pi} &= \Delta\left(\Delta(1-2\pi)+4\delta c\pi(1-\pi)\right) > 0. \end{aligned}$$

We now show that expected trading volume increases with π. Observe that expected trading volume depends on who owns the asset. The probabilities that a collector or a speculator owns the asset at a given time are respectively $1-\pi$ and π. If a collector owns it, he will end up reselling it with a probability π. Trading volume thus equals 1 with probability π and 0 with probability $1-\pi$. If instead a speculator owns the asset, he will resell it with a probability $1-\pi$. Expected volume is therefore π if the owner is a collector, $1-\pi$ if the owner is a speculator, so that unconditional expected volume writes:

$$Ev_t = (1-\pi)\pi + \pi(1-\pi) = 2\pi(1-\pi),$$

thus

$$\frac{\partial Ev_t}{\partial \pi} = 2(1-2\pi) > 0.$$

□

Proof of Proposition 2. Let h denote the holding period between two trades. We denote $E(h|\mathcal{C})$ and $E(h|\mathcal{S})$ as the expected holding period, given that the buyer is a collector or a speculator, respectively. The holding period for a collector (speculator) follows a geometric distribution with success probability π (respectively $1-\pi$). We have:

$$Pr(h = k|\mathcal{C}) = (1-\pi)^{k-1}\pi \quad (1)$$
$$Pr(h = k|\mathcal{S}) = \pi^{k-1}(1-\pi). \quad (2)$$

For example, a collector sells when speculators have high valuations ($\sigma_t = s$). If a collector keeps the asset for k periods, the signal must have remained low for $k-1$ periods. The first moments of the geometric distribution give us Equation (8). Thus $Eh^{\mathcal{C}} > Eh^{\mathcal{S}}$ since $\pi < 1/2$. □

Proof of Proposition 3. First observe that the value of the resale option is positive for both collectors and optimistic speculators. This follows from our assumption that $\Delta > c$ and also, for Equation (11), from the assumption that $s < d/(1-\delta)$.

Second, we check that the option value increases with π and decreases with c (recall that $1-2\pi > 0$ and that Δ depends on π and c):

$$\begin{aligned}
\frac{\partial(b_t^{\mathcal{C}} - \bar{b}_t^{\mathcal{C}})}{\partial\pi} &= \frac{\delta}{1-\delta}\Big(\Delta - c + 2c\pi\delta\Big) > 0 \\
\frac{\partial(b_{t|\sigma_t=s}^{\mathcal{S}} - \bar{b}_{t|\sigma_t=s}^{\mathcal{S}})}{\partial\pi} &= \frac{\delta}{1-\delta}\Big(\Delta - c + 2c(1-\delta(1-\pi))\Big) > 0 \\
\frac{\partial(b_t^{\mathcal{C}} - \bar{b}_t^{\mathcal{C}})}{\partial c} &= \frac{-\delta\pi}{1-\delta}\Big(\delta(1-2\pi) + 1\Big) < 0 \\
\frac{\partial(b_{t|\sigma_t=s}^{\mathcal{S}} - \bar{b}_{t|\sigma_t=s}^{\mathcal{S}})}{\partial c} &= \frac{-\delta}{1-\delta}\Big((1-2\pi)(1-\delta(1-\pi)) + \pi\Big) < 0.
\end{aligned}$$

□

Proof of Proposition 4. In our model, collectors always resell artworks at a profit Δ to speculators, who realize a symmetric loss (ignoring the transaction cost). Thus the round-trip return R is either Δ or $-\Delta$.

Expected returns conditional on the holding period are given by:

$$\begin{aligned}
E(R|h = k) &= Pr(\mathcal{C}|h = k) \times \Delta + Pr(\mathcal{S}|h = k) \times (-\Delta) \\
&= \frac{Pr(h = k|\mathcal{C})Pr(\mathcal{C})}{Pr(h = k)} \times \Delta + \frac{Pr(h = k|\mathcal{S})Pr(\mathcal{S})}{Pr(h = k)} \times (-\Delta),
\end{aligned}$$

which gives us Equation (12). We used the fact that the unconditional distribution for the holding period h is $Pr(h = k) = Pr(h = k|\mathcal{C})Pr(\mathcal{C}) + Pr(h = k|\mathcal{S})Pr(\mathcal{S})$, and that $Pr(\mathcal{C}) = 1-\pi$ and $Pr(\mathcal{S}) = \pi$. It is easy to see that the conditional expectation increases with k for $k > 1$.

Likewise, the variance of returns conditional on the holding period is given by:

$$\begin{aligned} V(R|h = k) &= E(R^2|h = k) - (E(R|h = k))^2 \\ &= \Delta^2 - (E(R|h = k))^2, \end{aligned}$$

which is Equation (13) and is a decreasing function of k for $k > 1$. □

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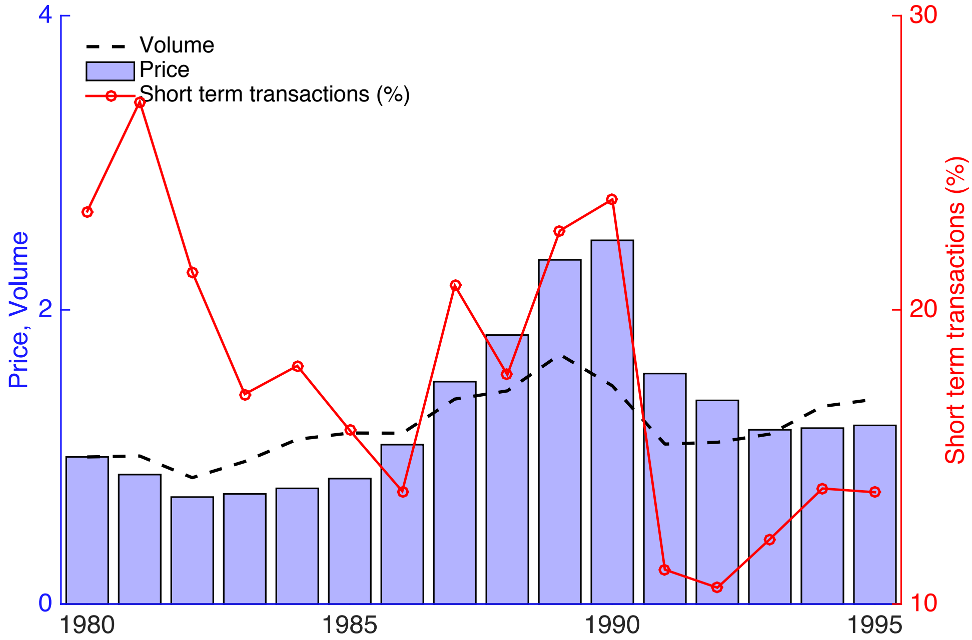

Figure 1: Price, Volume, and Short Term Transactions around the 1990s Bubble
This figure shows the aggregate (hedonic) price index, the total volume of transactions, and the share of short-term transactions around the 1990s bubble (1980-1995). Prices and volume are expressed in function of their 1980 level (left scale). The share of short-term transactions is defined as the share of purchases that were resold within the next year, and is computed from the repeat-sale data set (right scale).

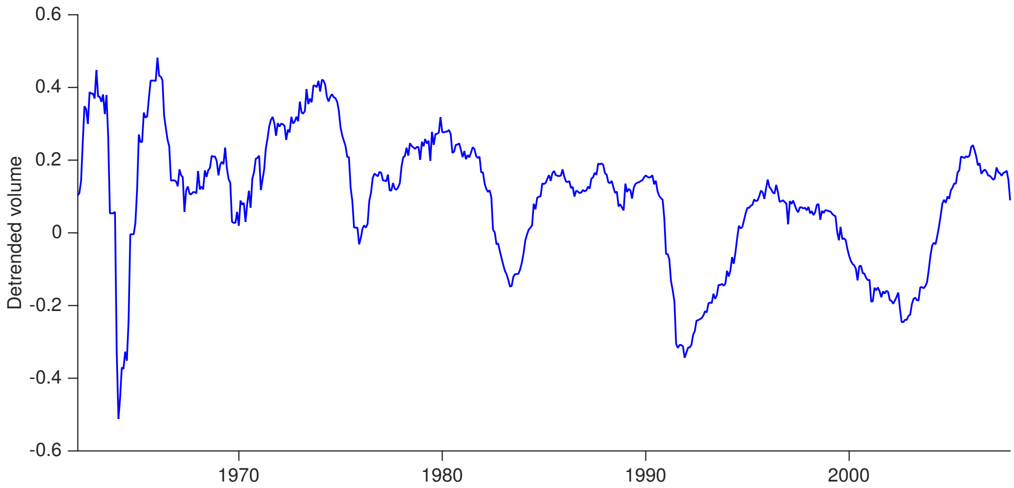

Figure 2: Detrended Market Volume
This figure plots the monthly measure of volume constructed by means of Equation (14). Each month t we take the log of the number of sales by Sotheby's and Christie's on the last twelve months preceding t. We then normalize our series by subtracting the log of the average number of sales by Sotheby's and Christie's over the last five years.

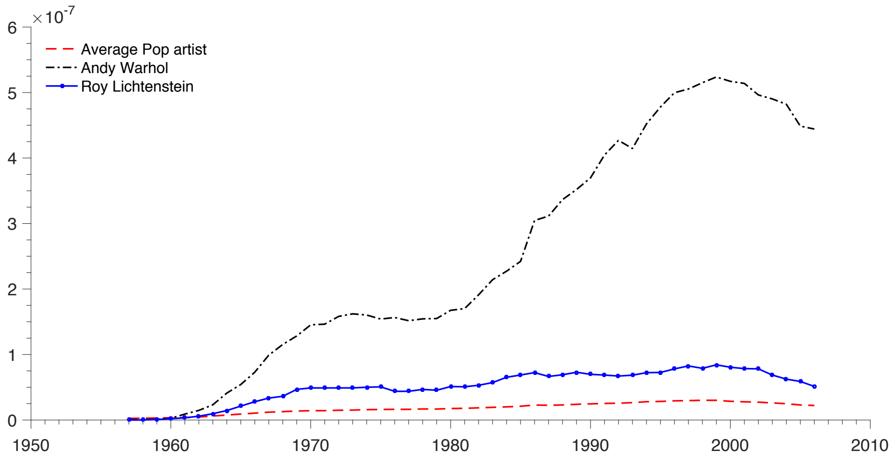

Figure 3: Artist Fame: Andy Warhol and Pop Art
This figure depicts the share of mentions of Andy Warhol's and Roy Lichtenstein's names in the Google Books database, and of the average share of the 111 Pop artists in our data set.

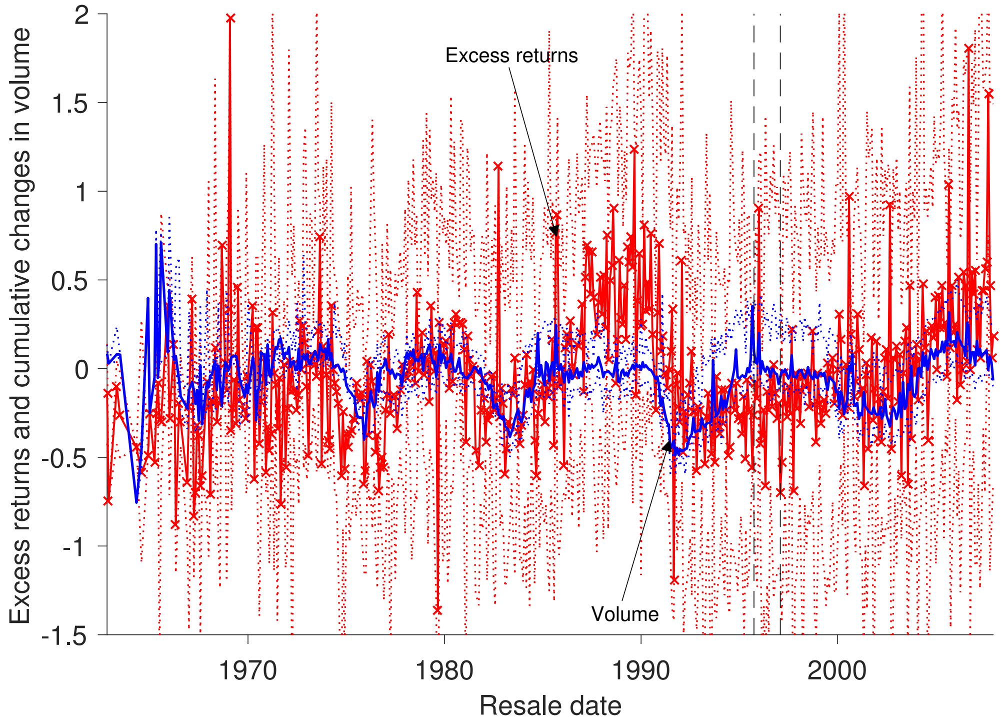

Figure 4: Excess Returns, Volume, and the "Price Fixing Conspiracy"
This figure shows art returns in excess of the risk-free rate and cumulative changes in volume from a subset of repeat sales auctioned in Sotheby's or Christie's. Both returns and volume are measured at the time of resale. For each month, the plain lines correspond to the median value of returns (respectively change in volume) and the dashed lines correspond to the 10th and 90th percentiles. The vertical lines delimit the period during which Sotheby's and Christie's colluded over commission rate paid by sellers.

Table I: Repeat-sale Data: Sample Statistics

	Mean	S.D.	Min	Max
Art excess returns	2.13	79.10	-458.20	554.05
Volume (purchase)	8.08	15.47	-51.16	48.15
Volume (cum. change)	-3.00	18.88	-76.39	85.22
Holding period	6.26	6.56	0.08	45.03
Equity excess returns	8.31	30.95	-121.37	128.06
SMB	9.72	26.68	-61.43	138.83
HML	28.93	35.73	-57.08	252.64
Liquidity[a]	33.98	41.95	-28.20	225.76
Fame[b]	-5.96	38.64	-141.82	124.14
Death	3.66	18.78	0.00	100.00
N	33,180			

This table presents the descriptive statistics (mean, standard deviation (S.D.), minimum and maximum) of the variables used in our repeat-sale analysis. These observations span the 1962-2007 period. All variables are expressed in percentage changes between each resale pair. Art excess return is the return on artworks between the purchase and sale times in excess of the risk-free rate: $r_i = \sum_{t=b_i+1}^{s_i} r_{it} - \sum_{t=b_i+1}^{s_i} r_{ft}$. Equity excess returns measures the equity index returns minus the risk-free rate, obtained from Global Financial Data. SML and HML are the Fama and French (1993) risk factors and Liquidity is the Pastor and Stambaugh (2003) liquidity risk factor. Death is a dummy indicating the death of the artist within a round-trip transaction. Fame is the share of mentions in Google Books for each artist and Volume is the volume measure defined in Equation (14). [a]Liquidity is available for 32,721 observations (from 1967). [b]Fame is available for 30,060 observations.

Table II: Information Content of Trading Volume

	Art price	Number of trans.	Short-term trans.	Sales rate	Art obj. for sale	Postwar	Volatility	Top
Art price								
Number of transactions	**0.39**							
Short-term transactions	0.24	**0.42**						
Sales rate	**0.35**	-0.04	-0.05					
Art objects offered for sale	0.20	**0.89**	**0.37**	**-0.49**				
Postwar art	**0.48**	**0.33**	**0.47**	-0.09	**0.44**			
Hedonic Volatility	**0.48**	0.19	0.09	**0.29**	0.06	**0.40**		
Top income	0.17	-0.10	-0.00	0.01	-0.08	**0.30**	0.02	

This table presents pairwise correlations between price, volume, the share of short-term transactions, the sales rate, the number of art objects offered for sale, the share of Postwar items, and the top income. The variables are observed annually over the period 1957-2006 (with two exceptions: the years 1963-1964 are omitted and the share of Postwar Art is observed from 1974 onwards). All variables are expressed in log-differences. Art price is the hedonic price index. Short-term transactions is the share of round-trip transactions with holding periods less than one year, and come from the repeat-sale data set. Sales rate is the average percentage of items sold at auctions by year. The number of art objects offered for sale is the proxy for the number of items offered at auctions, obtained by dividing the number of transactions by the sales rate. Postwar Art indicates the share of Abstract Expressionism, Pop Art, and other Modern and Contemporary Art paradigms within the global art market. Hedonic Volatility is the standard deviation of the residuals in a regression of individual artwork prices on hedonic characteristics. Top income is the share of total income received by the top 0.1 percent of all income earners in the US, constructed by Piketty and Saez (2006). Coefficients statistically significant at (at least) the 10% level are in bold.

Table III: Past Volume Forecasts Excess Returns

	Full sample	Postwar Art	Old Masters
		Full sample period	
Volume at purchase	-0.414	-0.479	-0.373
t-stat	(-4.74)	(-2.56)	(-3.20)
R^2	0.007	0.007	0.008
N	33,180	3,873	1,519
		Excluding 1985-1995	
Volume at purchase	-0.769	-0.716	-0.495
t-stat	(-9.02)	(-3.50)	(-3.74)
R^2	0.026	0.018	0.013
N	20,117	2,071	1,193

This table presents the estimates of the following regression:

$$r_i - \sum_{t=b_i+1}^{s_i} r_{ft} \quad = \quad \alpha + \nu_0 \text{VOLUME}_{b_i} + \epsilon_i, \tag{3}$$

where $r_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. The variable VOLUME_{b_i} is market volume defined in Equation (14) and measured at the date of purchase. Descriptive statistics for all variables are provided in Table I. Postwar Art consists of Abstract Expressionism, Pop Art, and Modern and Contemporary Art. Old Masters comprises late Medieval and Renaissance Art, Baroque, and Rococo. Standard errors are clustered at year level.
(t-Statistics are in parentheses.)

Table IV: Excess Returns and Volume

	Full sample		Postwar Art		Old Masters	
	(1)	(2)	(3)	(4)	(5)	(6)
MARKET	0.216	0.263	0.337	0.292	0.343	0.439
t-stat	(4.43)	(4.08)	(3.35)	(2.38)	(4.09)	(4.97)
FAME	0.150	0.185	0.111	0.211	-0.012	-0.040
t-stat	(8.02)	(10.94)	(1.71)	(3.53)	(-0.21)	(-0.69)
DEATH	0.181	0.115	0.518	0.376		
t-stat	(5.30)	(3.44)	(6.55)	(4.84)		
VOLUME	0.733	0.725	1.100	1.031	0.423	0.328
t-stat	(9.35)	(9.41)	(7.28)	(7.44)	(3.26)	(2.31)
SMB		0.146		0.051		-0.126
t-stat		(2.13)		(0.34)		(-1.13)
HML		-0.169		-0.221		0.107
t-stat		(-2.54)		(-1.78)		(0.84)
LIQ		0.210		0.567		-0.036
t-stat		(2.74)		(4.59)		(-0.30)
R^2	0.049	0.060	0.102	0.141	0.043	0.061
N	30,060	29,630	3,759	3,754	1,182	1,090

This table presents the estimates of the following regression:

$$
\begin{aligned}
r_i - \sum_{t=b_i+1}^{s_i} r_{ft} &= \alpha + \beta_1 \sum_{t=b_i+1}^{s_i} \text{MKT}_t + \beta_2 \sum_{t=b_i+1}^{s_i} \text{SMB}_t + \beta_3 \sum_{t=b_i+1}^{s_i} \text{HML}_t \\
&+ \beta_4 \sum_{t=b_i+1}^{s_i} \text{LIQ}_t + \gamma_1 \sum_{t=b_i+1}^{s_i} \text{FAME}_{a,t} + \gamma_2 \sum_{t=b_i+1}^{s_i} \text{DEATH}_{a,i} \\
&+ \nu \sum_{t=b_i+1}^{s_i} \text{VOLUME}_t + \epsilon_i \qquad (4)
\end{aligned}
$$

where $r_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. The variable MKT_t is the world equity excess returns between purchase and sale times, SMB_t and HML_t are the Fama and French (1993) factors and LIQ_t is the Pastor and Stambaugh (2003) liquidity factor. $\text{FAME}_{a,t}$ is the log of the share of mentions in Google Books for artist a at time t. VOLUME_t is the market volume measure defined in Equation (14). Descriptive statistics for all variables are provided in Table I. Postwar Art consists of Abstract Expressionism, Pop Art, and Modern and Contemporary Art. Old Masters comprises late Medieval and Renaissance Art, Baroque, and Rococo. Standard errors are clustered at year level.
(*t*-Statistics are in parentheses.)

Table V: Excess Returns and Volume During the "Price Fixing Conspiracy"

	Collusion dummy	Volume Coll. period	Post-coll. period	Diff.
CAPM	-0.352	0.076	0.819	0.744
	(-3.18)	(0.21)	(6.09)	(5.53)
Fama-French	-0.290	0.147	0.744	0.597
	(-2.63)	(0.42)	(5.85)	(4.70)

Between 1995 and 1997, Christie's and Sotheby's agreed to increase seller's commission. This table presents the estimates for the collusion dummy ϕ and for the volume coefficients ν_1 and ν_2 of the following regression:

$$\begin{aligned} r_i - \sum_{t=b_i+1}^{s_i} r_{ft} &= \alpha + \beta \sum_{t=b_i+1}^{s_i} \text{MKT}_t + \gamma_1 \sum_{t=b_i+1}^{s_i} \text{FAME}_{a,t} + \gamma_2 \sum_{t=b_i+1}^{s_i} \text{DEATH}_{a,i} \\ &+ \phi D_{i,c} + (\nu_1 D_{i,c} + \nu_2 D_{i,pc}) \sum_{t=b_i+1}^{s_i} \text{VOLUME}_t + \epsilon_i \end{aligned}$$

where $r_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. The variable MKT_t is the world equity excess returns between purchase and sale times, SMB_t and HML_t are the Fama and French (1993) factors and LIQ_t is the Pastor and Stambaugh (2003) liquidity factor. $\text{FAME}_{a,t}$ is the log of the share of mentions in Google Books for artist a at time t. VOLUME_t is the market volume measure defined in Equation (14). $D_{i,c}$ and $D_{i,pc}$ are dummy variables indicating that the item was sold during and after the collusion period. The variables ν_1 and ν_2 measure the correlation between volume and excess returns for each period. The Difference column reports the result of a t-test that ν_2 is larger than ν_1. Standard errors are clustered at year level.
(t-Statistics are in parentheses.)

Table VI: Test of Relative Performance: Holding Period

Transaction costs	0%	5%	10%	15%	20%	25%	30%
Holding period	-0.025	-0.011	0.002	0.016	0.029	0.043	0.056
	(-11.42)	(-5.22)	(1.04)	(7.27)	(13.40)	(19.33)	(25.00)
R^2	0.011	0.011	0.014	0.018	0.021	0.026	0.033
N	33,361	33,361	33,361	33,361	33,361	33,361	33,361

This table presents the η estimates in the following regression:

$$r_i/h_i = \mu_b D_{b,i} + \eta h_i + \epsilon_i$$

where r_i/h_i is the annualized return on item i between b_i and s_i (after transaction costs) and where μ_b is a vector of purchase year fixed effects and $h_i = (s_i - b_i)$ is the holding period (in years) for the sale i. The three-stage-generalized-least square RSR estimation of Case and Shiller (1987) is used to estimate the regressions.
(t-Statistics are in parentheses.)

Table VII: Variance Ratio Test

h	1	2	3	4	5	6	7	8	9	10
Volatility	0.519	0.561	0.664	0.704	0.765	0.793	0.818	0.869	0.940	0.949
Ratio	1.00	0.58	0.55	0.46	0.43	0.39	0.35	0.35	0.36	0.33
p-value		0.012	0.011	0.011	0.011	0.011	0.010	0.010	0.010	0.010

This table presents the volatilities and the results of variance ratio tests for transactions with an holding period (h) between 1 to 10 years. The ratio is defined in Equation (20). The last line shows the p-values of the multiple variance ratio tests. The null hypothesis is that art prices follow a random walk. The variance ratio statistics are computed from the transaction dataset and the tests are performed by simulation (see Section IV of the Online Appendix).

Online Appendix for "Bubbles and Trading Frenzies: Evidence from the Art Market"

I. Alternative models

A. Constant π, perfectly correlated signals

A key parameter is our model is π, the probability that collectors and speculators disagree about the value of the asset. Our main prediction requires π to vary over time. This allows us to model periods of "high sentiment", where agents are more likely to disagree, and therefore trade. This generates times where volume is high, and where art prices are also high, because the presence of speculators pushes prices up with binding short-sale constraints. The model can nevertheless generate changes in prices and trading volume even when π is constant. In that case, agents trade depending on the realization of the signal (i.e. when their willingness to pay changes). However, because the probability to disagree is constant, we cannot produce a positive correlation between prices and volume.

For simplicity, assume again that there is a large number of assets traded but that speculators and collectors all observe the same signal for all goods (i.e. signals are perfectly correlated). Since π is constant, we are interested in prices and volume conditional on σ_t, rather than expected prices and expected volumes conditional on π.

When $\sigma_t = s$, speculators buy all assets and all prices are high. Otherwise, collectors own the assets and prices are low. Prices increase when the signal becomes high and collectors sell to speculators. Symmetrically, we see a decrease in prices when speculators sell back to collectors. Trading occurs only when prices change. Therefore, we get a correlation between volume and *absolute changes* in prices.[1] This is different from our empirical findings, and from the resale option theory more generally, when differences in

[1]This prediction is not uncommon in the literature. See e.g. (Copeland, 1976; Tauchen and Pitts, 1983; Harris and Raviv, 1993; Shalen, 1993; Wang, 1994; Kandel and Pearson, 1995) and Banerjee and Kremer (2010).

opinion (π) move over time. In this latter case, we find a correlation between volume and prices, or equivalently a correlation between changes in volume and changes in prices.

Equally important, since σ_t is not forecastable, returns are not forecastable if π is constant. A high volume does not signal high prices. In contrast, in the paper, strong differences of opinion eventually revert to the mean, inducing predictable returns.

B. *Liquidity shocks*

We next explore a variant of the model. Instead of collectors and speculators, the model features collectors and "arbitrageurs". In the main model, speculators buy or hold the asset in good times (when they receive a positive signal) and collectors hold the asset in bad times (when speculators do not receive a positive signal). In this alternative model, "arbitrageurs" have a constant willingness to buy. There is no signal, but liquidity shock may emerge, which can hit collectors, but not arbitrageurs. A collector holds the asset in good times and his expected dividend is $\bar{\theta}+d$. In bad times, which occur with probability π, he is hit by a liquidity shock so that his expected value of holding the asset become 0. Arbitrageurs always expect $E\theta = \bar{\theta}$ and do not receive a private dividend. When a bad shock occurs and a collector owns the asset, he is forced to sell to an arbitrageur at a low price. In contrast to the main model where speculators pay too much for the asset and earn negative returns, arbitrageurs earn positive returns.

Let the high state H denote good times (when there are no liquidity shocks to collectors; in the main text, this corresponds with high realizations of the signal), and let L denote bad times, when collectors are hit by liquidity shocks. Under conditions similar to the main model, the willingness to pay for the asset by collectors (in high states H) and arbitrageurs at time t are:

$$b^{\mathcal{C}}_{t|H} = \delta\left(\bar{\theta} + d + \pi(b^{\mathcal{A}}_{t+1} - c) + (1-\pi)b^{\mathcal{C}}_{t+1|H}\right) \quad (1)$$

$$b^{\mathcal{A}}_{t} = \delta\left(\bar{\theta} + \pi b^{\mathcal{A}}_{t+1} + (1-\pi)(b^{\mathcal{C}}_{t+1|H} - c)\right). \quad (2)$$

The premium that a high-state collector is willing to pay in excess of an arbitrageur's willingness to pay is thus $\Delta \equiv \delta \left(d + c(1-2\pi) \right)$.

Assuming that $\lim_{T \to +\infty} \delta^T b^{\mathcal{C}}_{t+T} = 0$, we find

$$b^{\mathcal{C}}_{t|H} = \quad p_{t|H} \quad = \frac{\delta}{1-\delta} \left(\bar{\theta} + d + \pi(c - \Delta) \right) \tag{3}$$

$$b^{\mathcal{A}}_{t} = \quad p_{t|L} \quad = \frac{\delta}{1-\delta} \left(\bar{\theta} + d + \pi(c - \Delta) \right) - \Delta. \tag{4}$$

We assume $\Delta > c$, so that $p_{t|H} > p_{t|L} + c$ and arbitrageurs are willing to sell the asset in good times.

We have $Ep_t = \frac{\delta}{1-\delta} \left(\bar{\theta} + d + \pi(c - \Delta) \right) - \pi\Delta$, which implies that $\frac{\partial Ep_t}{\partial \pi} < 0$. Expected volume is identical to the main model: $Ev_t = (1-\pi)\pi + \pi(1-\pi) = 2\pi(1-\pi)$ and increases with π. Also as in the model, the proportion of arbitrageurs, who have short holding periods, is equal to π.

This model therefore predicts that volume and the share of short-term transaction are positively correlated, as in the main model. However, prices are negatively correlated with both volume and the share of short-term transactions, which is contradicted by our empirical findings. So, while liquidity shocks to collectors are present in the art market, liquidity shocks still do not explain some of the main features of the art market.

II. Hedonic regression

Hedonic regressions are a popular methodology for constructing constant-quality price indexes for infrequently traded goods like houses or collectibles. Hedonic models control for temporal variation in the quality of the transacted goods by attributing implicit prices to their "utility-bearing characteristics" (Rosen, 1974). Our model relates the natural logs of USD hammer prices to year dummies, while controlling for a wide range of hedonic characteristics. More formally, our regression can be expressed as follows:

$$p_{it} = \alpha + \sum_{m=1}^{M} \beta_m X_{mit} + \sum_{t=1}^{T} \gamma_t D_{it} + \epsilon_{it}. \tag{5}$$

where p_{it} represents the real log USD price of an art object i at time t, X_{mit} is the value of characteristic m of item i at time t, and D_{it} is a dummy variable that equals one if object i is sold in time period t. The coefficients β_m reflect the attribution of a relative shadow price to each of the m characteristics. The estimates of γ_t can be used to construct an art price index.[2] Apart from the variables related to the timing of the sale, the hedonic variables X used follow Renneboog and Spaenjers (2013), and capture characteristics of the artist (through the inclusion of artist dummies and an art history textbook dummy), the work (through the inclusion of variables capturing attribution, authenticity, medium, size, and topic), and the sale (through the inclusion of auction house dummies).

III. Potential Bias: Simulation Results

In this section we investigate further how the return distribution from the repeat-sale data differs from the unobserved return distribution from the hedonic data. To do so we create a pseudo dataset from the hedonic dataset, which mimics the properties of the repeat-sale data. We start from the estimates of the hedonic regression (5). Prices of pseudo constant-quality items can be obtained as:

$$\tilde{p}_{it} = p_{it} - \sum_{m=1}^{M} \beta_m X_{mkt}. \tag{6}$$

We can use Equation (6) to construct a pseudo repeat-sale dataset using the same purchase and resale dates as in the true data, but using randomly drawn pseudo prices instead of the true purchase and resale prices. Round-trip returns can then be computed as the difference between log resale and purchase prices.

Figure A.I shows the true hedonic index (which uses the full dataset), the repeat-sale index (which uses the repeated sales only and is thus possibly biased) and the repeat-sale index using the pseudo data. We see that the indices based on the true data are highly correlated (the return correlation is 0.98) and are approximately as volatile. The pseudo

[2] A subtle point is that the resulting index tracks the geometric means — not the arithmetic means — means of prices over time, due to the log transformation prior to estimation.

index is noisier but still capture the large movements of the aggregate market.

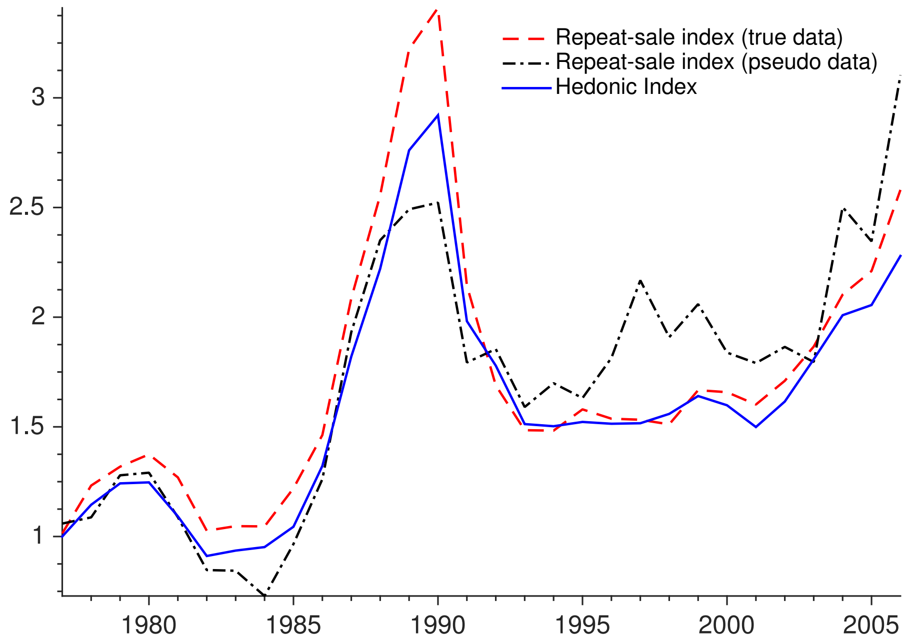

Figure A.I: True and Pseudo Price Indices
This figure plots price indices for the whole dataset using a hedonic estimator (Hedonic Index) and two repeat sales indices constructed from the true dataset and a simulated pseudo dataset.

We now turn to the properties of the return distributions. Both true and pseudo repeat sale datasets exhibit almost the same round-trip return on average, but pseudo returns are about twice more volatile (140% volatility vs. 78% for the true dataset). This reflects the fact that the hedonic methodology captures only imperfectly unobserved quality. Low quality items are artificially matched with high quality items (and vice versa), inflating the volatility of round-trip returns in the pseudo dataset. To facilitate comparison, Figure A.II plots the standardized return distributions of the two datasets. We see that the distributions are roughly identical. Recall that the pseudo distribution is constructed from the hedonic dataset. If the distribution of returns conditional on a resale differs from the unconditional distribution of returns, we would expect the distributions to differ. In particular, if sellers were more likely to sell winning transactions than losing transactions, the true distribution should be skewed to the right, or at least more skewed than the pseudo dataset. The true distribution is indeed slightly skewed (the skewness is 0.26 vs. 0.05 for the pseudo distribution), which suggest that the bias is in fact very modest.

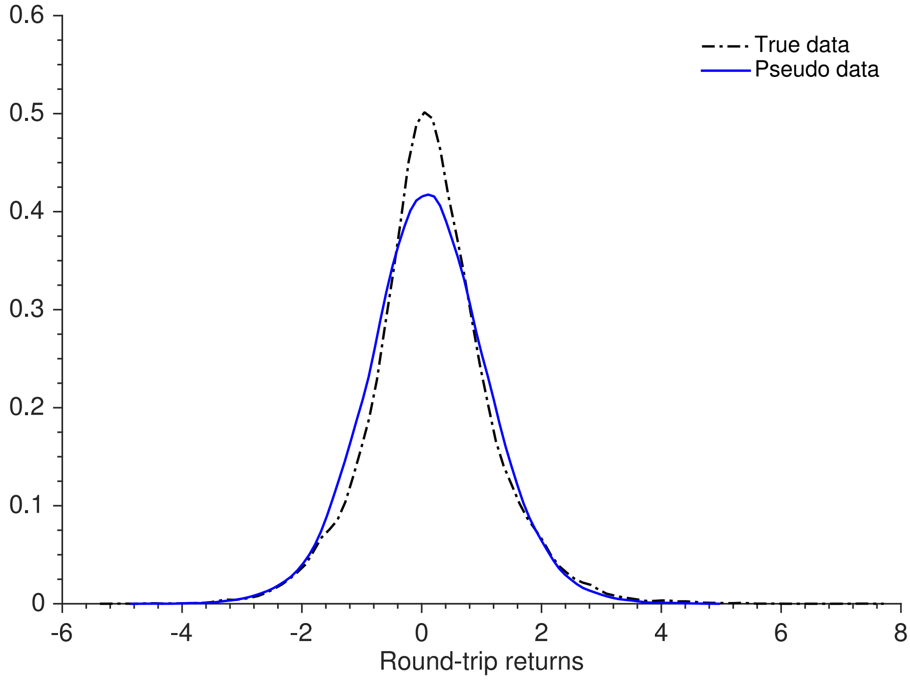

Figure A.II: Round-trip Returns: True vs. Pseudo Datasets
This figure shows the kernel densities of round-trip returns in the true and pseudo datasets. Both distributions are standardized to have a unit variance.

IV. Variance Ratio Test

In order to assess mean reversion of returns, we develop a residual resampling strategy based on wild bootstrap. Our variance ratio statistic writes as:

$$\mathrm{VR}(h) = \frac{\mathrm{Var}(\{\mathrm{r}_{i,t}\}_{h-1<y<h})}{h\mathrm{Var}(\{\mathrm{r}_{i,t}\}_{y<1})} \tag{7}$$

where $\{\mathrm{r}_{i,t}\}_{h-1<y<h}$ is the set of resale pairs with a holding period y between $h-1$ and h years. Under the null of a random walk, the variance ratio should remain approximately equal to one across the horizon.

Equation (7) corresponds to a test where the null hypothesis is tested for an individual value of k. Such a test ignores the joint nature of testing for the random walk hypothesis and is therefore likely to have low statistical power. To address this concern, we construct a multiple test in the spirit of Chow and Denning (1993), which is based on the idea that the decision regarding the null hypothesis can be obtained from the maximum value of the individual VR statistics:

$$\mathrm{VRM}(h) = \max_{2\leq i\leq h} (\mathrm{VR}(i)) \tag{8}$$

To implement the bootstrap to resale data with unknown forms of heteroscedasticity, we adopt the wild bootstrap of Mammen (1993). Under the null that art prices follow a random walk, the continuously compounded return of a price index of art, μ_t is equal to:

$$\mu_t = \mu + \eta_t \tag{9}$$

Where η_t is a serially uncorrelated but potentially heteroscedastic. We assume that the continuously compounded return for a given artwork i in period t, $r_{i,t}$, may be represented by μ_t and an error term:

$$\mathrm{r}_{i,t} = \mu_t + \epsilon_{i,t} \tag{10}$$

where the item-specific return $\epsilon_{i,t}$ is assumed to be uncorrelated over time and across paintings. The bootstrap can be conducted as follows:

1. Estimate $\hat{\mu}_t$, using the three-stage estimator based on Case and Shiller (1987) and obtain estimates of the art price changes under the null $\hat{\eta}_t$.

2. Form a bootstrap of $t = 1, \ldots, T$ observations $\mu_t^* = \hat{\mu} + v_t\hat{\eta}_t$, where v_t is a random sequence with $E(v_t) = 0$ and $E(v_t^2) = 1$. As for the form of the distribution for v_t

we choose the Rademacher distribution:

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

Conditionally on $\hat{\mu}_t$, μ_t^* is a serially uncorrelated sequence of which the innovations have the same distribution as $\hat{\mu}_t$.

3. Form a bootstrap of $i = 1, \ldots, N$ observations for art returns $\mathrm{r}_{i,t}^* = \mu_t^* + w_{i,t}\hat{\epsilon}_{i,t}$, where $w_{i,t}$ is again simulated from the Rademacher distribution.

4. Compute VR* and VRM*, which are the VR and VRM statistics defined in Equation (7) and (8), and obtained from the bootstrap sample generated in stage 3.

5. Repeat (2)-(4) $m = 1000$ times to form a bootstrap distribution of the test statistics $\{\mathrm{VRM(j)}^*\}_{j=1}^m$.

The bootstrap distributions are used to approximate the sampling distribution of the VR and VRM statistics. The p-value of the test is estimated as the proportion of $\{\mathrm{VRM(j)}^*\}_{j=1}^m$ greater than the VRM statistics calculated from the original data.

A potential concern is that a fraction of transactions fails to meet the reserve price or is never resold. For example, loss adverse collectors may choose not to put on sale items that are susceptible to selling at a loss. We address selection bias in the data by randomly removing individual returns $\mathrm{r}_{i,t}^*$ that end up with losses. While removing fractions of losses clearly affect art price trends, the impact on VR test is fairly limited.

Table A.I: Past Volume Forecasts Excess Returns (Winsorized Returns)

	Full sample	Postwar Art	Old Masters
		Full sample period	
Volume at purchase	-0.335	-0.424	-0.246
t-stat	(-4.66)	(-2.83)	(-2.96)
R^2	0.008	0.009	0.007
N	33,180	3,873	1,519
		Excluding 1985-1995	
Volume at purchase	-0.615	-0.638	-0.335
t-stat	(-9.37)	(-4.12)	(-3.62)
R^2	0.031	0.027	0.012
N	20,117	2,071	1,193

This table presents the estimates of the following regression:

$$r_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha + \nu_0 \text{VOLUME}_{b_i} + \epsilon_i, \quad (11)$$

where $r_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. Returns are winsorized at the 10% level. The variable VOLUME_{b_i} is market volume defined in Equation (14) and measured at the date of purchase. Descriptive statistics for all variables are provided in Table I. Postwar Art consists of Abstract Expressionism, Pop Art, and Modern and Contemporary Art. Old Masters comprises late Medieval and Renaissance Art, Baroque, and Rococo. Standard errors are clustered at year level.
(t-Statistics are in parentheses.)

Table A.II: Past Volume Forecasts Excess Returns (Subsamples)

	Major Auction Houses	Expensive	Inexpensive
		Full sample period	
Volume at purchase	-0.411	-0.392	-0.273
t-stat	(-4.23)	(-2.71)	(-2.54)
R^2	0.006	0.006	0.003
N	15,569	3,303	3,310
		Excluding 1985-1995	
Volume at purchase	-0.785	-0.681	-0.613
t-stat	(-7.12)	(-4.65)	(-4.92)
R^2	0.024	0.021	0.017
N	9,391	2,002	2,004

This table presents the estimates of the following regression:

$$r_i - \sum_{t=b_i+1}^{s_i} r_{ft} \quad = \quad \alpha + \nu_0 \text{VOLUME}_{b_i} + \epsilon_i, \tag{12}$$

where $r_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. The variable VOLUME_{b_i} is market volume defined in Equation (14) and measured at the date of purchase. Descriptive statistics for all variables are provided in Table I. Major Auction Houses stands for the subsample of the works auctioned at Sotheby's and Christies' London and New York branches. Expensive (respectively Inexpensive) corresponds to transactions within the top (bottom) 10% prices at purchase as compared with other items sold the same year. Standard errors are clustered at year level.
(t-Statistics are in parentheses.)

Table A.III: Short-term Transactions Forecasts Excess Returns

	Full sample	Postwar Art	Old Masters
		Full sample period	
Short-term % at purchase	-0.610	-0.600	-0.620
t-stat	(-5.07)	(-3.42)	(-3.24)
R^2	0.021	0.016	0.028
N	23,953	3,321	586
		Excluding 1985-1995	
Short-term % at purchase	-0.334	-0.505	-0.762
t-stat	(-2.53)	(-2.03)	(-2.45)
R^2	0.006	0.010	0.027
N	10,890	1,519	260

This table presents the estimates of the following regression:

$$r_i - \sum_{t=b_i+1}^{s_i} r_{ft} \quad = \quad \alpha + \nu_0 \text{SHORT-TERM}_{b_i} + \epsilon_i, \tag{13}$$

where $r_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. The variable SHORT-TERM$_{s_i}$ is the share of short-term transactions defined as our Volume measure (see (14)) and measured at the date of purchase. Postwar Art consists of Abstract Expressionism, Pop Art, and Modern and Contemporary Art. Old Masters comprises late Medieval and Renaissance Art, Baroque, and Rococo. Standard errors are clustered at year level. The sample period is 1982-2007.
(t-Statistics are in parentheses.)

Table A.IV: Excess Returns and Volume at Resale

	Full sample	Postwar Art	Old Masters
		Full sample period	
Volume at resale	0.788	1.453	0.142
t-stat	(7.75)	(7.38)	(1.12)
R^2	0.023	0.058	0.001
N	33,180	3,873	1,519
		Excluding 1985-1995	
Volume at resale	0.286	0.694	0.126
t-stat	(3.39)	(3.61)	(0.82)
R^2	0.003	0.016	0.001
N	20,117	2,071	1,193

This table presents the estimates of the following regression:

$$r_i - \sum_{t=b_i+1}^{s_i} r_{ft} \quad = \quad \alpha + \nu_0 \text{VOLUME}_{s_i} + \epsilon_i, \qquad (14)$$

where $r_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. The variable VOLUME_{s_i} is market volume defined in Equation (14) and measured at the date of resale. Postwar Art consists of Abstract Expressionism, Pop Art, and Modern and Contemporary Art. Old Masters comprises late Medieval and Renaissance Art, Baroque, and Rococo. Standard errors are clustered at year level.
(t-Statistics are in parentheses.)

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