Speculative Trading and Bubbles: Evidence from the Art Market*

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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 largely absent, and transaction costs are substantial. We find that high prices coincide with large volume and are followed by negative returns. Short-term transactions, which are an important driver of trading volume, underperform and are riskier than long-term transactions. We rationalize these findings in a stylized model of speculative trading where the impossibility to sell short embeds a non-fundamental component in prices.

JEL: G12, P34, Z11, D44.

Keywords: Speculative Bubbles; Trading volume; Art Market.

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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 periods of radical 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 and technological innovation are largely absent; short-selling is impossible, and transaction costs are minimally 20% of hammer prices.

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 the total number of transactions — rose 50% from the early 1980s until its peak in 1989, while many segments of the market reached even higher levels. Over a five-year period (1985-1989), the prices of Postwar artists were multiplied by four and their volume more than doubled; more works by Andy Warhol were sold in 1989 than in the four previous years combined. Positive correlations between art prices and volume have also been observed during many historical bubbles, such as the South Sea Bubble, or more recently the Internet bubble in the late 1990s.² In the art market, interestingly, the relation

¹Quoted in the Wall Street Journal (Peers, 2008).
²See 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.
between prices and volume is not confined to a few episodes or markets. Price increases generally coincide with rises in volume: we find a 0.45 correlation between changes in art prices and changes in art volume over the 1957-2006 period.

Are these large swings in prices and volume the result of “animal spirits”? Works of art differ from other assets, such as stocks, in that they provide utility services to their owner, which are private and unobserved. With few exceptions, it is impossible to rent works of art, so that art dividends cannot be expressed in monetary units. It is therefore common to use the term utility dividend, to describe the utility services associated to owning a work of art. Utility services, such as aesthetic pleasure or the ability to signal one’s wealth, are likely to vary considerably across individuals, and may also change over time for a given individual. In principle, shocks to the utility dividend may explain why prices move and why people trade. Quantitatively, however, these effects are small, so that art prices seem to display excessive volatility in the sense of Shiller (1981). Obviously, we don’t observe changes in utility dividends, but we do observe changes in the likely determinants of utility dividends, namely preferences and wealth. Artistic tastes tend to be very stable, even in the long run (Ginsburgh and Weyers, 2008; Vermeylen et al., 2013; Graddy, 2013). Furthermore, we find that shocks to wealth are small relative to changes in prices. These differences of magnitudes should not come as a surprise: it is well documented that cash flows shocks only account for a small fraction of asset prices fluctuations (see, e.g., Cochrane (2011)).³

This paper suggests that an amplifying mechanism — speculative trading — can explain the excessive volatility of art prices, as well as other puzzling features of the market such as the strong comovements between prices and volume. Our empirical analysis is guided by a simple model 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 pref-

³Lovo 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.
ferences shocks, as suggested above. Because selling short is impossible, prices always correspond to the valuation of the most optimistic agent (Miller, 1977). 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). The difference between their willingness to pay and their own valuation is the price of the option to resell the asset in the future.

As in prior models emphasizing differences of opinions, bubbles build on the fluctuations of investors’ heterogeneous beliefs. When the probability to disagree increases, investors trade more (volume increases) and more speculators enter the market, which pushes prices and volatility up. Changes in disagreement create a correlation between prices, volume, the variance of prices, and the share of speculators. We assume that changes in disagreement are stationary, a detail that investors ignore. Relatively high disagreement is therefore associated to relatively high volumes, but also to high prices, which eventually decrease as disagreement reverts to the mean. Investors ignore that disagreement fluctuates, and therefore experience losses on average if they bought when disagreement was relatively high. This corresponds to our definition of an asset price bubble, which we borrow from Fama (2014). 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, Barberis et al. (2016)).

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.4 We find that short-term transactions and art-specific volatility are positively correlated with prices and volume, as predicted by our model.

4 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.
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 (Fama, 2014). 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 lowers future returns by 6.7%. Further, about 47% of art excess returns forecasts are negative, which lines up well with the idea of a bubble.

In addition to these known properties of disagreement-based 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. In our model, speculators do on average worse than collectors and in addition have shorter holding periods. This is consistent with anecdotal evidence of speculators buying and selling works of art over short periods of time (“flips” in the art market jargon), and more generally with prior findings that stock market investors’ performance is negatively related to trading activity (Barber and Odean, 2000). Speculators’ short-sightedness, together with our assumption that speculators underperform on average, implies that short-term transactions earn lower returns. Our model also predicts that short-term transactions are more volatile, which renders them even less attractive. We validate these predictions empirically.

While in our model changes in disagreement are exogenous, we connect our empirical findings to two recent papers featuring endogenous disagreement through extrapolative beliefs. Barberis et al. (2016)’s model features extrapolators and fundamental investors who trade with each other at various phases of a bubble. In Defusco et al. (2016), price increases attract fewer long-term investors than short-term investors, so that the latter amplify volume by selling more frequently, as we also find in the art market. A new prediction of Barberis et al. (2016)’s model is that volume increases with past returns.

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5 Extensive research suggests that many investors hold extrapolative expectations, relying on past returns to make guesses about future returns. For instance, Greenwood and Shleifer (2014) use data from multiple investor surveys to show that investors’ expectations about future returns are predicted by past returns, but also negatively related to future returns. Case et al. (2012) also find that U.S. homebuyers’ expectations are positively predicted by lagged price appreciations.
We provide corroborating evidence around the late 1980s bubble in Section III.B.

The previous literature has shown 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 different in that they describe the regular behavior of the art market, rather than events limited in time. 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 III.D. In addition, 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.6

The remainder of this paper is structured as follows. The next section sets up a stylized trading model motivating the empirical analysis. Section II provides background information, presents our dataset, and documents new findings regarding the behavior of prices and volume. Our core results are presented in Section III, where we show that volume negatively predicts future returns. Section IV documents that short-term transactions — our proxy for speculative transactions — are less profitable and more volatile. Section V 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

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6Auction 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.
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 $\theta$; (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 $S$ and collectors $C$. The latter tend to value the asset on average more than speculators, which we model by assuming that collectors receive an additional private utility 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 $\bar{\theta} + \sigma$. 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 $\pi < 1/2$. Note that, after having observed the signal, speculators and collectors have different forecasts with probability $2\pi$, (and agree with probability $1 - 2\pi > 0$). 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 $\pi$ as a measure of differences in beliefs (Scheinkman, 2014). In the context of art, we do not need to assume that speculators are overconfident. The signal $\sigma_t$ may reflect expected utility services derived by speculators, but not by collectors. The model only requires that agents sometimes have different expectations regarding $\theta$.

Suppose first that the asset cannot be resold. We denote $\bar{b}_C^t$ and $\bar{b}_S^t$ 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:

\[ \bar{b}_C^t = \frac{\delta}{1-\delta} (\bar{\theta} + d) \] (1)

\[ \bar{b}_S^t = \frac{\delta}{1-\delta} (\bar{\theta} + (1-\delta)\sigma_t) \] (2)

We assume that even if the signal is high, collectors still value the asset more than speculators, so that \( \bar{b}_C^t > \bar{b}_S^{t|\sigma_t=s} \). 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.\(^7\) 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 \( b_C^t \) denote the willingness to pay of the collector. He will choose to resell the asset if the price \( p_t > b_C^t + c \). Since speculators do not receive a private dividend, they may only want to buy the asset when 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.\(^8\) 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 \( p_t = b_S^{t|\sigma_t=s} \). 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 \( p_t > b_S^t + c \). 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 \( p_t = b_C^t \).

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 \( p_t = b_S^{t|\sigma_t=s} \). This occurs with probability \( \pi \). Otherwise, with probability \( 1-\pi \), a collector buys (or keeps) the asset and \( p_t = b_C^t \).

We can now solve the model by writing the willingness to pay for the asset by collectors

\(^7\)We assume that only the seller pays a transaction cost. Including buyer commissions slightly complicates computations and does not yield any additional insights.

\(^8\)This amounts to assuming that \( b_S^{t|\sigma_t=s} > b_C^t + c \). Note that we do not index collectors’ willingness to pay with \( \sigma_t \), since the latter ignore the signal.
and (optimistic) speculators at time $t$:

\begin{align*}
    b^C_t &= \delta (\bar{\theta} + d + \pi (b^S_{t+1|\sigma_{t+1}=s} - c) + (1 - \pi)b^C_{t+1}) \quad (3) \\
    b^S_{t|\sigma_{t}=s} &= \delta (\bar{\theta} + s + \pi b^S_{t+1|\sigma_{t+1}=s} + (1 - \pi)(b^C_{t+1} - c)) \quad (4)
\end{align*}

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 $b^C_t$ therefore equals next-period expected dividend $\bar{\theta} + d$, a term reflecting the resale value to a speculator (times $\pi$) 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: $b^S_{t|\sigma_{t}=s} - b^C_t = \delta (s - d - c(1 - 2\pi))$. Let $\Delta$ denote the premium that an optimistic speculator is willing to pay in excess of a collector’s willingness to pay:

$$\Delta \equiv \delta (s - d - c(1 - 2\pi)).$$  

Substituting $b^S_{t|\sigma_{t}=s} = b^C_t + \Delta$ in (3) yields $b^C_t = \delta b^C_{t+1} + \delta (\bar{\theta} + d + \pi(\Delta - c))$. Assuming that $\lim_{T \to +\infty} \delta^T b^C_{t+T} = 0$, we obtain

\begin{align*}
    b^C_t &= p_t|_{\sigma_t \in \{-s, 0\}} = \frac{\delta}{1 - \delta} (\bar{\theta} + d + \pi(\Delta - c)) \quad (6) \\
    b^S_{t|\sigma_{t}=s} &= p_t|_{\sigma_t = s} = \frac{\delta}{1 - \delta} (\bar{\theta} + d + \pi(\Delta - c)) + \Delta. \quad (7)
\end{align*}

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 $\pi$.

As in Scheinkman and Xiong (2003), fluctuations in disagreement, modeled here by the parameter $\pi$, 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

\[ E(h|C) = \frac{1}{\pi} \]  
\[ E(h|S) = \frac{1}{1 - \pi}. \]

Comparing Equations (1) to (6) and (2) to (7) reveals the existence of an extra component in the price of the risky asset. This 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. Buyers always pay a higher price than their own estimates of the value of future dividends.

\[ b^C_t - \bar{b}^C_t = \frac{\delta}{1 - \delta} \pi (\Delta - c) \]  
\[ b^S_{t|\sigma_1=s} - \bar{b}^S_{t|\sigma_1=s} = \frac{\delta}{1 - \delta} \left( \pi (\Delta - c) + d - (1 - \delta)s \right) + \Delta. \]

The size of the resale option increases with the difference of opinion parameter \( \pi \), and decreases with the transaction cost \( c \).

Therefore, a relatively large \( \pi \) signifies that the price of the asset exceed the value of the asset in the absence of reselling opportunities. This property of the model does not depend on whether the signal \( \sigma \) 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:

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

$$V(R|h = k) = \Delta^2 - (E(R|h = k))^2.$$  \hspace{1cm} (13)$$

In our model, collectors always resell artworks at a profit to speculators, who therefore always underperform. In fact, both speculators and collectors face a zero return variance. When the holding period increases, Proposition 4 implies that the econometrician observes more transactions initiated by collectors and fewer transactions initiated by speculators. Therefore, conditional expected returns increase, because collectors outperform speculators. In this simple setup, since the only source of return variance comes from the distribution of sales across agents, the conditional variance of returns decreases with the holding period as fewer transactions initiated by speculators 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 $\pi$. Price variance also increases with $\pi$. By definition, $\pi$ also gives us the proportion of speculators. Changes in $\pi$ therefore correspond to changes in the probability of disagreement, changes in the proportion of active 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).

Prediction 2 follows from our assumption that $\pi$ varies over time, a fact that both collectors and speculators neglect. This is in fact our only departure from strict rationality. Proposition 3 implies that the size of the resale option is an increasing function of $\pi$. An unusually large trading volume (or a large share of short-term transactions) will come with an unusually high price. We assume that $\pi$ is bounded (it is strictly smaller than $\frac{1}{2}$), so that large values for $\pi$ are eventually followed by lower values. Hence a large volume forecasts low future returns.

The positive price of the resale option 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 price of the option as long as this assumption holds. A large increase in $c$ may destroy the incentive to resell later. This gives us Prediction 3. Finally, the fourth prediction follows from Proposition 4, which says that expected returns (return volatility) are negatively (positively) correlated with holding periods, respectively.

In the Online Appendix, we study alternative mechanisms and find that they generate counterfactual predictions. We first show that our model generates trading volume and changes in prices even when $\pi$ 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 $\pi$ (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 short-term transactions are negatively correlated with prices, while our model predicts a positive correlation, which we confirm empirically. 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. Art Prices and Trading Volume

A. Background

Works of art are usually sold through two types of intermediaries, dealers and auction
houses. Dealers mostly serve the primary market, mostly for living artists, and this
market is largely opaque. Auction houses effectively act as brokers and operate most of
the secondary market for art and other luxury goods. The market is quite concentrated,
Sotheby’s and Christie’s accounting for 42% of the world’s art auction sales in 2015.
Auction data is reliable and publicly available, and has been used to study a broad
number of finance and economics questions (e.g. Galenson and Weinberg (2000), Beggs
and Graddy (2009), Mei and Moses (2005)).

Transaction costs are substantial in the art market. Auction houses typically charge
commissions of around 10% to both buyers and sellers (Pesando (1993), Ashenfelter and
Graddy (2003)). When a work of art goes unsold (i.e., it is “bought-in”), some charges,
such as shipping and handling costs may still apply. Art buyers also have to take into
account storage and insurance costs, which can be substantial. Although transactions
costs remained relatively constant during our sample period, we are aware of at least one
episode of collusion between the major auction houses. We make use of this episode in
Section III.D.

In spite of these large transaction costs, art-as-investment is increasingly popular. The
first formal art fund was one launched by the British Rail Pension Fund in 1974, investing
some $70 million worth of art and luxury furniture (Trucco, 1989). According to Kräussl
(2015), 50 or so similar investment funds were launched in the seventies and eighties.
Kräussl (2015) documents that among the few funds that survived, performance has
been tepid, much weaker than traditional asset classes. According to the Art & Finance Report 2014, a joint report by Deloitte Luxembourg and ArtTactic, there were about 72 art funds in operation in 2014, among which 55 invest only in Chinese Art, arguably one of the most speculative segments of the market (Picinati di Torcello and Petterson, 2014). Art funds are of course only the tip of the art investment iceberg. 76 percent of art buyers still view their acquisitions as investments, intending to at least avoid negative returns (Picinati di Torcello and Petterson, 2014). There are about 300,000 art advisors in the world today (Reyburn, 2014). Equally interesting is the practice of flipping art. Art flippers purchase art with the intent of offering the piece at a drastically higher price shortly after purchase (Kazakina, 2015). Flipping is increasingly popular, and facilitated by specialized firms, which business consists in storing new bought artworks in high-security warehouses, specially designed for the purpose of their subsequent resale.9

We document that while flipping contributes to a sizable fraction of art trading volume, short-term transactions are in fact poor investments after transaction costs (see Section IV). This is consistent with prior evidence that stock investors who trade more have lower returns because they have to pay large fees for their trades (Barber and Odean, 2000). Although we do not observe the identity of the individuals participating in the auction market, we suspect that a large portion of poor returns are driven by new and potentially inexperienced art investors.10 Evidence suggests that investors overlook transaction costs in the art market, especially first buyers (Loader-Wilkinson, 2010), and that art advisors tend to inflate the potential return to art investing (Grant, 2014). Considering the role of advisors, Hong et al. (2008) propose a model in which bubbles arise because some advisors inflate their recommendations to attract clients. Mei and Moses (2005) also present evidence that auction houses manipulate their presale estimates to increase their revenues.

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9For example, the New York Times Magazine (Alden, 2015) covers a new storage company, Uovo: “Everything about the facility seems designed to remove friction from the art market — to turn physical objects into liquid assets. Apart from its private viewing rooms for deal making, which are now common in the storage business, what really sets Uovo apart is its vast database. [...] [G]iving clients and prospective buyers remote access to so much data, while making the business more efficient, also helps make the art more like a tradable unit, able to change hands without even leaving a warehouse.”

10Greenwood and Nagel (2009) show that young mutual fund managers exhibited trend-chasing behavior during the technology bubble.
B. Auction Data

Our primary data source is the historical auction 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 1970, 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. Artwork information includes 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.

Figure 1 documents the strong connection between art prices, volatility and the volatility of art prices, in line with Prediction 1. Our price index is based on the hedonic regression approach, which consists in regressing log prices on time dummies, while controlling for a host of hedonic characteristic (see Section II in the Online Appendix for a description of our hedonic regression model). To construct the index in real terms, hammer prices are deflated by means of the US consumer price index. We measure yearly art volatility as the cross-sectional standard deviation of the residuals of the hedonic regression. Trading volume is defined as the number of observed transactions sold by Sotheby’s or Christie’s in London or New York each year. Sotheby’s and Christie’s account for 49.2% of total transactions in our dataset. We focus on the sales by the two leading auction houses to mitigate the influence of changes in sample coverage over our sample period, namely 1957-2006.\textsuperscript{11} Panel (a) plots our price index and trading volume. High prices tend to coincide with high volume, not only during the strong boom-bust of the late 1980s bubble, but also in normal times. The correlation between percentage changes in prices and

\textsuperscript{11}The data coverage is very small in 1963, when only some of the highest priced sales are included. This leads to artificially low volume and high prices for 1963. We therefore ignore the years 1963-64 when computing correlations. Our dataset also ends before the end of 2007, so that we cannot reliably measure volume for that year.
volume is 0.45. Panel (b) shows that art volatility also exhibits substantial variation over the period, and is strongly correlated with art prices, as predicted by our model.

It is also interesting to get a sense of how much do prices comove with “fundamentals”. Since the supply of art is inelastic (at least for deceased artists), long run prices are determined by demand. Goetzmann et al. (2011) show that the time series of top incomes and aggregate art prices are cointegrated. Economically, this means that prices cannot deviate forever from top incomes, which is a good proxy for the demand for art. It is instructive to ask how much do prices deviate from top incomes series, or put differently, what fraction of art return variance can be “explained” by changes in top incomes. In line with Goetzmann et al. (2011), we use the share of total income received by the top 0.1 percent of all income earners in the US, constructed in Piketty and Saez (2006). We find that the correlation between percentage changes in prices and percentage changes in top incomes is 0.17. This implies that $0.17^2 \approx 3\%$ of the variance of art prices can be related to changes in top incomes. While other covariates (e.g. stock returns) may produce higher numbers, as we discuss in Section III.C, this low correlation is not surprising in light of the asset pricing literature (e.g. Cochrane (2011)).

C. Repeat-sales

A subset of the dataset matches pairs of identical objects, which is useful to study returns to investing in objects of art. 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, $P^b_i$ and $P^s_i$, 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 $P^s_i - P^b_i$.

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.\textsuperscript{12} 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. In any case, such a bias is 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 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 slightly positive skewness of 0.38) and no particular discontinuity can be observed in the tails of the distribution.\textsuperscript{13} 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 (Renneboog and Spaenjers, 2014).

\textbf{Covariates. } We complete the repeat-sale dataset by measuring volume at the transaction level. We first collect the total number of objects sold by Sotheby’s or Christie’s in

\textsuperscript{12}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.

\textsuperscript{13}In the Online Appendix, we compare the return distribution of the repeat-sale data with the return distribution of a pseudo dataset constructed from the full dataset, 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.
London or New York over the last twelve months preceding \( t \). We focus on objects sold by the major auction houses and start our analysis in 1964. We do so to mitigate the potential effect of a change in coverage over the sample period and because of an artificial drop in coverage in 1963, but working with the full sample of transactions produces very similar results. Following Baker and Stein (2004), we normalize our series by the average volume over the last five years. Taking logs, our monthly measure of volume is given by

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

(14)

where \( v_i \) is the number of transactions observed in a given month \( t \). Note that we use capital letters to distinguish our transaction-level and detrended measure of volume from our annual measure of trading volume. Detrending the series brings about several benefits. First, as can be seen in Figure 2, VOLUME is highly persistent. Such a property is desirable for a variable that is expected to predict 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 this series with our repeat-sale dataset: for each resale pair, we record the value of \( \text{VOLUME}_t \) at the month preceding the purchase and at the month preceding the sale. Our final dataset spans 1969 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.
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 29,460 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 transactions. For art, we see an average excess return of 1.8% — before transaction costs — over an average holding period of 6.1 years within the period 1969-2007, with a standard deviation of 79%. Equities are undoubtedly financially dominating art, with an excess return of nearly 9.1% measured over the same average repeat-sales time window and a standard deviation of almost 30.3%. Volume barely changes on average (-3.0%), and was much less volatile (18.7% standard deviation), which reflects the smoothing of the volume series. We see that for about 3.6% of transactions, the artist died between the purchase and the resale. Finally, the percentage of mentions of each artist (fame) fell -6.2% on average and has a dispersed distribution (the standard deviation is 38.5%).

Interestingly, this large volatility at the artist level averages out at movement level, as depicted by Figure A.III (in the Online appendix). 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 A.III 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 aggregate art prices during that period.
D. Decompositions of Trading Volume

We have shown in Section II.B that prices, volume, and art price volatility are correlated, in line with Prediction 1. This section tests the second part of Prediction 1, namely we document that short-term transactions account for a significant fraction of changes in trading volume. We also show that periods of high trading volume are associated with more trades of Postwar Art and more consignments to auction houses.

Short-term transactions Figure 3 shows that a substantial share of variation in trading volume is due to very short-term transactions, defined has transactions with holding periods of one year or less. Given the huge transaction costs that characterize the art market, it is very unlikely that these works of art were bought for the pure aesthetic pleasure. To show this, we focus on the repeat-sale dataset and each year we look at transactions that were resold. We compare the total number of transactions to transactions that were initiated within this year. By construction, the share of short-term transactions trends downward (e.g., the ratio has a value of one for the first year). In the last twenty years of the sample, where the trend is visually small, we still find that short-term transactions account for 10% to 30% of trading volume. This is a surprisingly high level, given the large transaction costs. 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. We nevertheless work in percentage changes to cancel the effect of the mechanical trend. We also focus on the last thirty years (1976-2006) because the number of repeat-sale transactions is very small in the beginning of our sample.

Panel (a) of Figure 3 compares changes in volume to changes in the number of short-term transactions. The number of short-term transaction correlates strongly with total volume (the correlation coefficient is 0.83) and is about twice more volatile. We also find that short-term transactions are strongly correlated with prices (the correlation coefficient is 0.56). Panel (b) further shows that short-term transactions strongly contribute to fluctuations in total volume. On the x-axis, we again show the change in total volume. On the y-axis, we now report the variation of total volume due to short-term transactions.
(i.e. the change in the number of short-term trades between $t$ and $t+1$, divided by time-$t$ total volume.) We also plot the least-square line. The slope of this line indicates that the elasticity of total trading volume to short-term transaction is 0.33. Interestingly, this result is very similar, both economically and quantitatively, to the findings in Defusco et al. (2016) that short-term transactions explain a large part of changes in trading volume during the U.S. real estate bubble. The art market seems special, however, in that our findings span 30 years of data, while Defusco et al. (2016) describe the behavior of the real estate market during exceptional times.

**Postwar Art** Newspaper articles also suggest that the Postwar Art is more likely to be traded in “hot” markets. A Financial Times article describes in colorful terms the flight to quality (i.e. to Old Masters paintings) that occurred after the 1990 market crash: “[T]he auction world has returned to its traditional ways, where connoisseurs rule and established works of art hold pride of place” (Thorncroft, 1990). Just as short-term transactions, Postwar Art transactions are more likely to be speculative. In our sample period, most of these artists are alive and relatively new to the art scene, and offer large prospective upside potential.\(^ {14}\) 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 may therefore hint that speculators dominate the market. There are, by definition, few Postwar Art (i.e. Abstract Expressionism, Pop Art, and Modern and Contemporary Art) sales in the beginning of our sample period. The share of Postwar Art rises from zero to about 25% over time. We again focus on the 1976-2006 period, where Postwar Art always amounts to at least 5% of yearly trading volume.

Figure 4 shows that a significant fraction of total volume growth is due to Postwar Art volume. We perform a similar exercise as in Figure 3. In Panel (a), we compare changes in total volume to changes in Postwar Art volume. In Panel (b), we quantify the fraction of the changes in total volume that is due to Postwar Art. We find that about 17% of volume growth is due to Postwar Art. The correlation between the two volume

\(^ {14}\) 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.’”
Collectors usually set a secret reserve price when offering an item for sale. If the highest bid does not reach this level, the items are “bought in” and go unsold. Volume therefore equals to the number of consignments to auction houses times the sales rate. It is interesting to know what fraction of changes in volume is due to changes in consignments, and what fractions is due to changes in the sales rate. 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 when 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. There is also evidence that auction houses are more likely to solicit potential sellers in “hot” markets (Pesando and Shum, 2008).

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 next take, for each year, the average sales rate across auctions as our proxy for the aggregate sales rate. Because Volume = Consignments × Sales rate, we can decompose volume growth as

\[
\frac{\Delta \text{Volume}}{\text{Volume}} \approx \frac{\Delta \text{Consignments} \times \text{Sales rate}}{\text{Volume}} + \frac{\text{Consignments} \times \Delta \text{Sales rate}}{\text{Volume}}.
\]

Figure 5 compares the respective contributions of intensive and extensive margins to volume growth. We find that about 88% of changes in trading volume comes from additional works of art being offered for sale, the remaining being due to changes in the sales rate.
III. Volume and Overpricing

A. Baseline Results

The most important prediction of disagreement-based models is overpricing (e.g. 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.

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 -21.1% (or -3.4% per year, the average holding period being 6.1 years). The Low-Volume strategy achieves an average excess return of 8.3%. 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 -4.0. 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:

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

(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 II shows the estimated slopes for the full sample as well as for two subsamples: Postwar Art and Old Masters. The first subsample corresponds to Abstract Expressionism, Pop Art, and Modern and Contemporary Art, as in Section
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 (15.3%) lowers future returns by 6.7%.

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, 47% 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 1.8%, as noted in Section II.B. 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 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 II estimates Equation (15) 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 II indicates that the predictive slopes actually increase (in absolute value) when we exclude that time period. We return to that point in the next section.

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 of short-term transactions, constructed again by means of Equation (14). We find comparable results, which are reported in Table 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 23.6% ($t$-stat of 6.8). 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.

B. The Late 1980s Bubble

Although we emphasize that our predictability results hold throughout our sample period, it is interesting to zoom in to the 1985-1995 years, as these years correspond to the largest boom-bust in the art market over the postwar period. Many commentators at the time stressed the role of Japanese collectors in the development of the art bubble, and indeed the timing of the art market boom-bust coincides with the timing of the Japanese asset price bubble. Hiraki et al. (2009) document that art imports into Japan was strongly positively correlated with both art prices and Japanese stock prices during the Japanese “bubble period”. Although this narrative is interesting and credible, it is unlikely that the influence of Japanese markets alone was sufficient to explain the dramatic market fluctuations over the period. Hiraki et al. (2009) show that the Japanese buying spree was mostly concentrated on French Impressionist and Post-Impressionist art, which is particularly attractive to Japanese culture, notably due to the influence of Japanese woodblock prints technique and themes on Impressionist art. As noted earlier, however, the boom and bust were not limited to Impressionist Art. Pénasse et al. (2014) show that prices increased, in different magnitudes, across all segments of the market. The price increases over 1985-1990 almost perfectly predicted the subsequent declines over 1990-1995.

Figure 6 summarizes and complements these prior results. Panel (a) shows price in-

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15Estimates that condition on resales (rather than purchases) exhibit stronger statistical significance. As noted in Section II.B, 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.
Panel (b) plots VOLUME, our detrended measure of trading volume based on Equation (14), against average future round-trip returns above the risk-free rate. Panel (c) compares VOLUME against average past round-trip returns above the risk-free rate. We see that over the 1985-1990 period, Impressionist Art prices increased by about 500%, while volume doubled. The Postwar segment of the market experienced a similar price increase, with even stronger increases in volume, in line with our results in Section II.D. The remaining segments of the market experienced strong price increases, but only modest increases in volume. This pattern is reminiscent of the explosion of high tech stock prices and volume during the Internet bubble of 1998-2000 (see Hong and Stein (2007), Figure 1).

Also remarkable is the strong mean reversion in art prices during the bubble period. The red bars in Panel (c) show the average return of collectors who decided to sell, while the blue bars in Panel (b) show the average future returns on different items, which where purchased at the same time. The first picture is almost the symmetric of the second, the correlation between the two series is -0.55. For example, collectors who sold on average during any month in 1989 experienced large gains on average, while collectors who bought art in the same months experienced an average loss.

Historical accounts of financial bubbles suggest that bubbles develop in context of radical innovation or fundamental uncertainty. Our findings suggest the entry of Japanese investors is likely to have acted as a precipitating event, to borrow the terminology of e.g., Shiller (2000). This event attracted speculators who pushed prices and volume further up (the share of short-term transactions rose 43% over the 1985-1989 period). In our model, changes in disagreement are exogenous, but this chain of events could arise if speculators extrapolate past returns. Barberis et al. (2016), in particular, propose a model where endogenous disagreement arises because some investors have extrapolative beliefs. A series of positive cash flow news increases prices, which attracts extrapolators who trade with fundamental traders. Extrapolation exacerbates disagreement that grows endogenously over the course of the bubble. Barberis et al. (2016) suggest comparing the correlation between past return and volume as a diagnostic of their model. Using data from several historical bubbles, they show that this correlation is systematically larger.
during the bubble period than in the aftermath of the bubble. As can be seen from Panel (c) of Figure 6, there is a strong relationship between VOLUME and the average past round-trip return. The correlation between the two series is 0.40 between January 1985 and December 1991. This is indeed larger than the correlation in the three-year post-bubble period from January 1992 to December 1995, which is 0.11. Hence the late 1980s bubble does not seem different from other historical episodes. This confirms that extrapolative beliefs are a plausible driver of disagreement and volume.

Also noteworthy is that volume was persistently high during the run up of the bubble (panel (b) of Figure 6) and reached its maximum a year before the peak in aggregate prices (Panel (a) of Figure 1). Hong and Stein (2007) and Defusco et al. (2016) document similar facts, in the Internet and US real estate bubble, respectively. This asynchronicity between prices and volume during the 1980s bubble helps understanding why our predictability results are stronger when we exclude the bubble period in Table II. Panel (b) of Figure 6 indicates that VOLUME is high during the run up of the bubble and thus correctly forecasts negative returns between 1988 and 1991. It drops about a year before the burst of the market, yielding counterfactual positive return forecasts about a year too early. Hence dropping the bubble years paradoxically improves the forecasting performance of VOLUME.

C. Returns and Cumulative Changes in VOLUME

Round-trip 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:

\[
\begin{align*}
    r_i - \sum_{t=b_i+1}^{s_i} r_{ft} &= \alpha + \beta \sum_{t=b_i+1}^{s_i} \text{MKT}_t + \gamma_1 \sum_{t=b_i+1}^{s_i} \text{FAME}_{a,t} + \gamma_2 \sum_{t=b_i+1}^{s_i} \text{DEATH}_{a,i} \\
    &+ \nu \sum_{t=b_i+1}^{s_i} \Delta \text{VOLUME}_t + \epsilon_i \\
\end{align*}
\]

(16)

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 FAME\( _{a,t} \) and our DEATH dummy. All variables are observed with monthly frequency, except 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 \( \nu \), which measures the correlation with cumulative changes in volume. This corresponds to 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 \( \nu \), 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:

\[ r_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha + \beta_1 \sum_{t=b_i+1}^{s_i} \text{MKT}_t + \beta_2 \sum_{t=b_i+1}^{s_i} \text{SMB}_t + \beta_3 \sum_{t=b_i+1}^{s_i} \text{HML}_t + \beta_4 \sum_{t=b_i+1}^{s_i} \text{LIQ}_t + \gamma_1 \sum_{t=b_i+1}^{s_i} \text{FAME}_{a,t} + \gamma_2 \sum_{t=b_i+1}^{s_i} \text{DEATH}_{a,i} + \nu \sum_{t=b_i+1}^{s_i} \Delta \text{VOLUME}_t + \epsilon_i. \] (17)

Table III 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 13.9% over the holding period (or 2.3% 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 7.5% or 1.2% per year on average) and the effect of taste (which is 5.5% or 0.9% per year on average), and of the same order of magnitude as the death of the artist (13.4%).

Table III 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 6.5% for the Old Masters.

D. 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. This relation may nevertheless change with transaction costs. In the context of our model, we show that if an increase in transactions costs is large enough, then buyers stop buying in anticipation of a further resell. In that case the relation between volume and returns may disappear (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. In the mid-nineties, however, evidence sug-
gests 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. In addition, by drawing media
attention on auction houses’ commissions, we believe this episode made transaction costs
more salient to collectors. Figure 2 illustrates the fluctuations in VOLUME around the
collusion period. VOLUME, which is steadily recovering since the end of 1991, stops
growing in the months following the onset of the collusion period, and drops remarkably
during the whole 1996. The drop occurred with a few months lag, which is natural given
the lengthy delays between the decision to put an item for sale and the actual auction.
Volume suddenly recovers at the turn of 1997, when the collusion ended.

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:

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

where \(D_{i,c}\) and \(D_{i,pc}\) indicate artworks that were sold during and after the collusion period
and where \(\text{VOLUME}_t\) is computed from the sales by the two auction houses. We expect \(\phi\) to be negative and \(\nu_1\) to be smaller than \(\nu_2\).

Table IV shows that the 1995-1997 period is characterized by a negative performance
of at least 29% (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
have remained relatively stable after 1995, and suggests that, given the performance of

\footnote{In the civil suit that followed in 2001, Sotheby’s and Christie’s agreed to each pay 256 million dollars
to the plaintiffs.}
the various factors, art prices should have rebounded substantially. We also learn from Table IV 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 value of the resale option.

IV. The Underperformance of Short-term Transactions

In this section we test whether short-term transactions perform differently than long-term transactions (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 are expected to underperform. We test this hypothesis by estimating the following regression:

\[ \frac{r_i}{h_i} = \mu_b D_{b,i} + \eta h_i + \epsilon_i \]  

where \( \mu_b \) 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 \( \frac{r_i}{h_i} \) 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 \( \eta \). In particular, \( \eta \) 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 \( \eta \) may suggest that the underperformance channel is strong
enough to dominate other factors.

The estimation results are displayed in Table V. The $\eta$-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.¹⁷

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 decline with holding periods.

Beyond the prediction of our model, short-term transactions will also appear riskier if art prices tend to revert to the mean, so that positive returns tend to be followed by negative returns (Lo and MacKinlay, 1988). 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 evidence based on variance ratio (VR) tests. The central idea 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

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

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

---

¹⁷A 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.
for each group. The variance ratio is then written as:

\[
VR(h) = \frac{\text{Var}(\{r_{i,t}\}_{h-1<y<h})}{h \text{Var}(\{r_{i,t}\}_{y<1})}
\]  

(21)

where \(\{r_{i,t}\}_{h-1<y<h}\) 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 VI 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 VI, indicate that about one percent of simulated statistics fall below the real ones for all holding periods. This confirms the prediction of our model.\(^{19}\)

V. 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 or speculators 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 the predictions of disagreement-based models by studying the

\(^{18}\)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.

\(^{19}\)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 observed. Doing so had no material effect on our results (see Online Appendix IV).
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. This high trading intensity tends 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 our model.

**Appendix**

*Proof of Proposition 1.* Expected prices increase with $\pi$ :

\[
E_{p_t} = \frac{\delta}{1 - \delta} \left( \theta + d + \pi(\Delta - c) \right) + \pi \Delta \\
\frac{\partial E_{p_t}}{\partial \pi} = \frac{1}{1 - \delta} \left( \Delta - \delta c(1 - 2\pi) \right) > 0.
\]

Price variance increases with $\pi$ :

\[
V_{p_t} = \Delta^2 \pi (1 - \pi) \\
\frac{\partial V_{p_t}}{\partial \pi} = \Delta \left( \Delta (1 - 2\pi) + 4\delta c \pi (1 - \pi) \right) > 0.
\]

We now show that expected trading volume increases with $\pi$. 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 $\pi$. If a collector owns it, he will end up reselling it with a probability $\pi$. Trading volume thus equals 1
with probability $\pi$ 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 $\pi$ 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

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

\[\Box\]

**Proof of Proposition 2.** Let $h$ denote the holding period between two trades. We denote $E(h|C)$ and $E(h|S)$ 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 $\pi$ (respectively $1 - \pi$). We have:

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

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 $Eh^C > Eh^S$ since $\pi < 1/2$.

\[\Box\]

**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 $\pi$ and decreases with $c$ (recall that $1 - 2\pi > 0$ and that $\Delta$ depends on $\pi$ and $c$):
\[
\frac{\partial (b_C^t - \bar{b}_C^t)}{\partial \pi} = \frac{\delta}{1 - \delta} \left( \Delta - c + 2c\pi \delta \right) > 0
\]
\[
\frac{\partial (b_S^t|\sigma_t^s = s - \bar{b}_S^t|\sigma_t^s = s)}{\partial \pi} = \frac{\delta}{1 - \delta} \left( \Delta - c + 2c(1 - \delta(1 - \pi)) \right) > 0
\]
\[
\frac{\partial (b_C^t - \bar{b}_C^t)}{\partial c} = -\frac{\delta}{1 - \delta} \left( \delta(1 - 2\pi) + 1 \right) < 0
\]
\[
\frac{\partial (b_S^t|\sigma_t^s = s - \bar{b}_S^t|\sigma_t^s = s)}{\partial c} = -\frac{\delta}{1 - \delta} \left( (1 - 2\pi)(1 - \delta(1 - \pi)) + \pi \right) < 0.
\]

\[ \Box \]

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

Expected returns conditional on the holding period are given by:

\[
E(R|h = k) = Pr(C|h = k) \times \Delta + Pr(S|h = k) \times (-\Delta)
\]
\[
= \frac{Pr(h = k|C)Pr(C)}{Pr(h = k)} \times \Delta + \frac{Pr(h = k|S)Pr(S)}{Pr(h = k)} \times (-\Delta),
\]

which gives us Equation (12). We used the fact that the unconditional distribution for the holding period \( h \) is \( Pr(h = k) = Pr(h = k|C)Pr(C) + Pr(h = k|S)Pr(S) \), and that \( Pr(C) = 1 - \pi \) and \( Pr(S) = \pi \). 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:

\[
V(R|h = k) = E(R^2|h = k) - (E(R|h = k))^2
\]
\[
= \Delta^2 - (E(R|h = k))^2,
\]

which is Equation (13) and is a decreasing function of \( k \) for \( k > 1 \). \[ \Box \]
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Figure 1: Prices, Volume, and Price Volatility

(a) Prices, Volume

This figure quantifies the strong connection between art prices, volume, and the volatility of art prices. The price series is the aggregate market index, constructed from a hedonic regression. Volume is defined as the number of transactions. Hedonic Volatility is the cross-sectional standard deviation of the residuals in the hedonic regression that is used to construct the price index. All series are observed annually over the period 1957-2006. The years 1963-1964 are omitted (see Section II.B).
Figure 2: Detrended Market Volume

This figure plots VOLUME, 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 over 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. The vertical lines delimit the period during which Sotheby’s and Christie’s colluded over commission rates paid by sellers (see Section III.D).
Figure 3: Volume Decomposition: The Role of Short-Term Transactions

(a) Change in Volume and Change in Short-Term Transactions

(b) Contribution of Short-Term Volume to Volume Growth

This figure quantifies the relation between volume and short-term transactions. Both panels are scatter plots with volume growth on the x-axis. Volume is defined as the yearly number of transactions. Panel (a) shows the yearly percentage growth in short-term transactions on the y-axis. Panel (b) quantifies the importance of short-term transactions as a component of volume, by showing volume growth against volume growth due to short-term transactions.
Figure 4: Volume Decomposition: The Role of Postwar Art Transactions

(a) Change in Volume and Change in Postwar Art Transactions

(b) Contribution of Postwar Art Volume to Volume Growth

This figure quantifies the relation between volume and Postwar Art transactions. Both panels are scatter plots with volume growth on the x-axis. Volume is defined as the yearly number of transactions. Panel (a) shows the yearly percentage growth in Postwar Art transactions on the y-axis. Panel (b) quantifies the importance of Postwar Art transactions as a component of volume, by showing volume growth against volume growth due to Postwar Art transactions.
Volume equals the number of artworks offered for sales (consignments) times the sales rate. This figure decomposes volume growth in terms of changes in the number of consignments while keeping the sales rates constant in Panel (a), and changes in the sales rates while keeping the number of consignments constant in Panel (b). In both panels, the x-axis is volume growth, where volume is defined as the yearly number of transactions. The y-axes are respectively the contribution of consignment (sales rate) growth to volume growth.
Panel (a) shows price and volume indices for Impressionists, Postwar Art, and other segment of the art market. For a given market segment, price indices are constructed from hedonic regressions and volume is defined as the number of transactions, as in Figure 1, Panel (a). Impressionist Art corresponds to the works of August Renoir, Edgar Degas, and Claude Monet, following Hiraki et al. (2009). Panel (b) and (c) plot average future (past) round-trip returns in excess of the risk-free rate against VOLUME (Equation (14)) at purchase (resale), respectively.
<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Art log excess returns</td>
<td>1.85</td>
<td>78.71</td>
<td>-458.20</td>
<td>554.05</td>
</tr>
<tr>
<td>VOLUME (purchase)</td>
<td>7.88</td>
<td>15.33</td>
<td>-34.36</td>
<td>42.12</td>
</tr>
<tr>
<td>∆VOLUME (cum. change)</td>
<td>-2.99</td>
<td>18.75</td>
<td>-73.69</td>
<td>56.60</td>
</tr>
<tr>
<td>Holding period</td>
<td>6.13</td>
<td>6.35</td>
<td>0.08</td>
<td>37.86</td>
</tr>
<tr>
<td>Equity log excess returns</td>
<td>9.14</td>
<td>30.34</td>
<td>-121.37</td>
<td>128.06</td>
</tr>
<tr>
<td>SMB</td>
<td>9.08</td>
<td>25.86</td>
<td>-61.43</td>
<td>120.24</td>
</tr>
<tr>
<td>HML</td>
<td>28.04</td>
<td>34.26</td>
<td>-57.08</td>
<td>218.31</td>
</tr>
<tr>
<td>Liquidity\textsuperscript{a}</td>
<td>33.91</td>
<td>41.91</td>
<td>-28.20</td>
<td>225.76</td>
</tr>
<tr>
<td>Fame\textsuperscript{b}</td>
<td>-6.19</td>
<td>38.45</td>
<td>-142.41</td>
<td>122.23</td>
</tr>
<tr>
<td>Death</td>
<td>3.57</td>
<td>18.56</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>N</td>
<td>32,534</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 1969-2007 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 series defined in Equation (14) and measured at the month preceding the transaction. \textsuperscript{a}Liquidity is available for 32,534 observations (from 1967). \textsuperscript{b}Fame is available for 29,460 observations.
Table II: Past Volume Forecasts Excess Returns

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>Postwar Art</th>
<th>Old Masters</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full sample period</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volume at purchase</td>
<td>-0.437</td>
<td>-0.498</td>
<td>-0.330</td>
</tr>
<tr>
<td>(t)-stat</td>
<td>(-4.81)</td>
<td>(-2.66)</td>
<td>(-2.79)</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.007</td>
<td>0.007</td>
<td>0.006</td>
</tr>
<tr>
<td>(N)</td>
<td>32,534</td>
<td>3,865</td>
<td>1,382</td>
</tr>
<tr>
<td><strong>Excluding 1985-1995</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volume at purchase</td>
<td>-0.808</td>
<td>-0.747</td>
<td>-0.479</td>
</tr>
<tr>
<td>(t)-stat</td>
<td>(-9.14)</td>
<td>(-3.66)</td>
<td>(-3.45)</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.029</td>
<td>0.020</td>
<td>0.012</td>
</tr>
<tr>
<td>(N)</td>
<td>19,471</td>
<td>2,063</td>
<td>1,056</td>
</tr>
</tbody>
</table>

This table presents the estimates of the following regression:

\[
 r_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha + \nu_0 VOLUME_{b_i} + \epsilon_i, \tag{1}
\]

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 trading volume, as defined in Equation (14) and measured at the month preceding the purchase date. 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 III: Excess Returns and Volume

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>Postwar Art</th>
<th>Old Masters</th>
</tr>
</thead>
<tbody>
<tr>
<td>MARKET</td>
<td>0.248</td>
<td>0.272</td>
<td>0.349</td>
</tr>
<tr>
<td>t-stat</td>
<td>(4.84)</td>
<td>(4.07)</td>
<td>(3.42)</td>
</tr>
<tr>
<td>FAME</td>
<td>0.144</td>
<td>0.182</td>
<td>0.108</td>
</tr>
<tr>
<td>t-stat</td>
<td>(7.57)</td>
<td>(10.77)</td>
<td>(1.67)</td>
</tr>
<tr>
<td>DEATH</td>
<td>0.142</td>
<td>0.110</td>
<td>0.497</td>
</tr>
<tr>
<td>t-stat</td>
<td>(4.21)</td>
<td>(3.29)</td>
<td>(6.32)</td>
</tr>
<tr>
<td>VOLUME</td>
<td>0.744</td>
<td>0.723</td>
<td>1.101</td>
</tr>
<tr>
<td>t-stat</td>
<td>(9.26)</td>
<td>(9.28)</td>
<td>(7.28)</td>
</tr>
<tr>
<td>SMB</td>
<td>0.150</td>
<td>0.062</td>
<td>-0.136</td>
</tr>
<tr>
<td>t-stat</td>
<td>(2.11)</td>
<td>(0.41)</td>
<td>(-1.18)</td>
</tr>
<tr>
<td>HML</td>
<td>-0.180</td>
<td>-0.232</td>
<td></td>
</tr>
<tr>
<td>t-stat</td>
<td>(-2.68)</td>
<td>(-1.86)</td>
<td></td>
</tr>
<tr>
<td>LIQ</td>
<td>0.211</td>
<td>0.568</td>
<td>-0.043</td>
</tr>
<tr>
<td>t-stat</td>
<td>(2.75)</td>
<td>(4.60)</td>
<td>(-0.36)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.052</td>
<td>0.060</td>
<td>0.101</td>
</tr>
<tr>
<td>N</td>
<td>29,460</td>
<td>29,460</td>
<td>3,751</td>
</tr>
</tbody>
</table>

This table presents the estimates of the following regression:

$$r_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha + \beta_1 \sum_{t=b_i+1}^{s_i} \text{MKT}_t + \beta_2 \sum_{t=b_i+1}^{s_i} \text{SMB}_t + \beta_3 \sum_{t=b_i+1}^{s_i} \text{HML}_t + \beta_4 \sum_{t=b_i+1}^{s_i} \text{LIQ}_t + \gamma_1 \sum_{t=b_i+1}^{s_i} \text{FAME}_{a,t} + \gamma_2 \sum_{t=b_i+1}^{s_i} \text{DEATH}_{a,i} + \nu \sum_{t=b_i+1}^{s_i} \Delta \text{VOLUME}_t + \epsilon_i \tag{2}$$

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 $\text{MKT}_t$ is the world equity excess returns between purchase and sale times, $\text{SMB}_t$ and $\text{HML}_t$ are the Fama and French (1993) factors and $\text{LIQ}_t$ 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 $t$. $\text{VOLUME}_t$ 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 IV: Excess Returns and Volume During the “Price Fixing Conspiracy”

<table>
<thead>
<tr>
<th></th>
<th>Collusion dummy</th>
<th>Coll. period</th>
<th>Post-coll. period</th>
<th>Diff.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAPM</td>
<td>-0.358</td>
<td>0.083</td>
<td>0.847</td>
<td>0.764</td>
</tr>
<tr>
<td></td>
<td>(-3.25)</td>
<td>(0.23)</td>
<td>(6.19)</td>
<td>(5.58)</td>
</tr>
<tr>
<td>Fama-French</td>
<td>-0.290</td>
<td>0.132</td>
<td>0.736</td>
<td>0.603</td>
</tr>
<tr>
<td></td>
<td>(-2.63)</td>
<td>(0.38)</td>
<td>(5.74)</td>
<td>(4.71)</td>
</tr>
</tbody>
</table>

Between 1995 and 1997, Christie’s and Sotheby’s agreed to increase seller’s commission. This table presents the estimates for the collusion dummy $\phi$ and for the volume coefficients $\nu_1$ and $\nu_2$ of the following regression:

$$r_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha + \beta \sum_{t=b_i+1}^{s_i} \text{MKT}_t + \gamma_1 \sum_{t=b_i+1}^{s_i} \text{FAME}_{a,t} + \gamma_2 \sum_{t=b_i+1}^{s_i} \text{DEATH}_{a,t}$$

$$+ \phi D_{i,c} + (\nu_1 D_{i,c} + \nu_2 D_{i,pc}) \sum_{t=b_i+1}^{s_i} \Delta \text{VOLUME}_{t} + \epsilon_i$$

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 $\text{MKT}_t$ is the world equity excess returns between purchase and sale times, $\text{SMB}_t$ and $\text{HML}_t$ are the Fama and French (1993) factors and $\text{LIQ}_t$ 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 $t$. $\text{VOLUME}_{t}$ 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 $\nu_1$ and $\nu_2$ measure the correlation between volume and excess returns for each period. The Difference column reports the result of a $t$-test that $\nu_2$ is larger than $\nu_1$. Standard errors are clustered at year level.

($t$-Statistics are in parentheses.)
Table V: Test of Relative Performance: Holding Period

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

This table presents the $\eta$ 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 $\mu_b$ 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 VI: Variance Ratio Test

<table>
<thead>
<tr>
<th>h</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volatility</td>
<td>0.519</td>
<td>0.561</td>
<td>0.664</td>
<td>0.704</td>
<td>0.765</td>
<td>0.793</td>
<td>0.818</td>
<td>0.869</td>
<td>0.940</td>
<td>0.949</td>
</tr>
<tr>
<td>Ratio</td>
<td>1.00</td>
<td>0.58</td>
<td>0.55</td>
<td>0.46</td>
<td>0.43</td>
<td>0.39</td>
<td>0.35</td>
<td>0.36</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.012</td>
<td>0.011</td>
<td>0.011</td>
<td>0.011</td>
<td>0.010</td>
<td>0.010</td>
<td>0.010</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 (21). The last line shows the $p$-values of the multiple variance ratio tests. The null hypothesis is that annualized volatility does not depend on the holding period. The variance ratio statistics are computed from the transaction dataset and the tests are performed by simulation (see Section IV of the Online Appendix).