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Bubbles and Trading Frenzies:
Evidence from the Art Market*

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Abstract

The art market is subject to frequent booms and busts in both prices and volume, which are difficult to reconcile with models where agents are rational and hold homogenous beliefs. This paper shows that (i) volume is mainly driven by speculative transactions; (ii) positive price-volume correlation is pervasive across art movements, and is larger for the most volatile segments of the art market; (iii) volume predicts negative long-term returns, a relation that is statistically and economically large. Overall, our evidence supports the bubble model of Scheinkman and Xiong (2003), which predicts that speculative trading can generate significant price bubbles, even if trading costs are huge and leverage is impossible.

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Keywords: Art Market; Bubbles; Return Predictability; Auction; Trading Volume.

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Evidence from the Art Market

Abstract

The art market is subject to frequent booms and busts in both prices and volume, which are difficult to reconcile with models where agents are rational and hold homogenous beliefs. This paper shows that (i) volume is mainly driven by speculative transactions; (ii) positive price-volume correlation is pervasive across art movements, and is larger for the most volatile segments of the art market; (iii) volume predicts negative long-term returns, a relation that is statistically and economically large. Overall, our evidence supports the bubble model of Scheinkman and Xiong (2003), which predicts that speculative trading can generate significant price bubbles, even if trading costs are huge and leverage is impossible.

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

In January 1989, Financial Times journalist Robin Duthy (1989) wrote: "The art market today is in a sound state, but the danger is that the long run of sparkling results for paintings by Monet, Van Gogh, and other household names will create an illusion that all art is safely strapped in on some kind of magic escalator." In the five-year period from 1985 to 1989, art prices had grown by 164%, in a context of record sales and apparent overoptimism. In the subsequent two years, real prices bounced back to their 1986 levels. A similar run up in prices, and subsequent collapse, was to a lesser extent reproduced in 2002-2008, and many are those who see another "bubble" in current prices.

Speaking of "bubbles" requires a definition of fundamental value, which is challenging when applied to art. As art prices soar, art dealers, auctioneers, and art gallery sales people often emphasize the resell value, while after a bust, they tend to comfort collectors by stating that pleasure is the best dividend when investing in art. For economists, works of art differ from traditional assets or durable goods in that they yield a non-pecuniary aesthetic or utility dividend. This utility dividend can be seen as the rent one would be willing to pay to own this work of art over a given time frame. It can reflect aesthetic pleasure but also has the ability to signal its owner's wealth. The value of this dividend is

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

of course unobservable and is likely to vary tremendously across art collectors. As pointed by Lovo and Spaenjers (2014), however, the auction market introduces a common-value element into prices. The price of a work of art should therefore equal the present value of future (private) utility dividends over one's expected holding period, plus the expected (market) resell value, i.e. the discount rate model could be use to price art. We can readily propose a definition of fundamental value. Assuming the last bidder on a work of art is the one who values it the most, the fundamental value of an artwork is his own private value. Hence, a "bubble" corresponds to a market where agents are willing to pay more than their private value, because they expect to resell later at a larger price.[2]

Viewing art as an asset helps understand the possible sources of art price fluctuations. The most straightforward explanation is that the utility dividends fluctuate over time as they depend on buyers' willingness to pay for art, which in turn depends on their preferences and wealth[3] (Mandel, 2009). In order to explain art prices volatility, preferences regarding art and culture as a whole would have to fluctuate dramatically. Even if fads can temporarily emerge for some specific artists or school of art (Penasse et al., 2014), the previous literature has shown that tastes tend to be very stable, even in the long run (Ginsburgh and Weyers, 2008; Graddy, 2014).[4] Alternatively, the utility dividend can oscillate because people's wealth fluctuates over time. The literature has provided evidence supporting this idea, which we denote as the *luxury consumption* hypothesis. For example Goetzmann et al. (2011) find cointegrating relationships between top incomes and art prices. Finally, art's fundamental value can fluctuate because the discount rate, i.e. the risk premium associated to holding works of art changes over time.[5]

A salient feature of art price booms is that they are accompanied, and sometimes preceded, by large volumes. Figure 1 shows that the total number of transactions rose 45% from 1985 until its peak in 1989, and many segments of the market reached much

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[2]Two years before the 1990 bust, the following quote appeared in the *New York Times*: "Paintings that used to sell for $400,000 are now going for $4 million to $5 million. [. . .] And when you pay those prices, you're an investor. You'll see the paintings bought at these sales come up for auction again in several years" (Glueck, 1988).

[3]Assuming that art consumption increases with wealth, i.e. that works of art are luxury goods.

[4]Citing Stigler and Becker (1977), LeRoy (2004) further argues "against relying on assumed preference shifts to explain price fluctuations, especially when there exist alternative explanations that do not appeal to preference shifts."

[5]Fluctuations in the discount rate is the most straightforward explanation of asset prices fluctuation within efficient markets (Cochrane, 2011).

higher levels. For example, during the same period, the prices and volume of Pop artists respectively rose 354% and 167%; more works by Andy Warhol where sold in 1989 than in the four previous years combined. The positive correlation between the art prices and volume corroborates a similar observation about many historical bubbles, such as the South Sea Bubble, or more recently the Internet bubble in the late 1990s.[6] Moreover, the share of short-term transactions, identified as purchases that were resold within the next year, rose from 10% to almost 20%. This is a remarkable increase, knowing that the transaction costs in auction markets are minimally 25% of the hammer price. Interestingly, the relation between prices and volume is not confined to a few episodes or markets. Price increases generally coincide with rises in volume: between 1976 and 2006, the correlation between changes in art prices and changes in art volume was as high as 54%.

[Insert Figure 1 about here]

What can explain such trading frenzies? In traditional asset pricing models agents cannot trade when they share identical prior beliefs (Tirole, 1982; Milgrom and Stokey, 1982), they rather trade to consume, i.e. because their preferences, or wealth, differ. The rationality assumption rules out any form of speculative trading, because in such models agents agree on economic fundamentals and therefore cannot expect to make a profit by reselling later. Several seminal papers, in contrast, emphasize the role of speculation on price formation when agents hold heterogeneous beliefs or priors (Miller, 1977; Harris and Raviv, 1993). For example, agents can trade because they are overconfident about their own trading abilities (Scheinkman and Xiong, 2003), because they suffer from confirmatory bias (Pouget et al., 2014), or because they are trying to infer what others are thinking (Biais and Bossaerts, 1998). These models suggest that "market sentiment" or differences of opinion can push prices above fundamentals. Their arguments hinge on the assumption that short-sale constraints prevent arbitrageurs from pulling back prices to fundamentals (Miller, 1977; Baker and Stein, 2004). When prices are high, pessimists

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[6]See e.g. Cochrane (2003); Ofek and Richardson (2003). Xiong (2013) notes that classical economists such as Adam Smith, John Stuart Mill, Knut Wicksell, and Irving Fischer readily 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.

would like to short sell, but instead simply stay out of the market or sell to optimists at inflated prices. Moreover, optimists may be willing to pay higher prices than their own valuations, because they expect to resell to even more optimistic investors in the future (Harrison and Kreps, 1978; Scheinkman and Xiong, 2003). The difference between their willingness to pay and their own optimistic valuation is the price of the option to resell the asset in the future. The price of the resale option imparts a stationary bubble component in asset prices, and can explain price fluctuations unrelated to macroeconomic fundamentals. This mechanism is particularly appealing in explaining art price fluctuations, because in art markets short selling is not possible and, absent a rental market, the only possibility to make a profit is by reselling at a higher price.

It is important to stress that speculative trading is not the only cause of price-volume correlation.[7] Price-volume correlation can also arise when the market is subject to supply or demand shocks, and if supply is less elastic than demand (or reciprocally). A prominent example of demand shock is the Japanese stock and real estate "bubble" of the late 1980s. Hiraki et al. (2009) document how Japanese collectors entered the market chasing French Impressionist art, pushing both prices and volumes up. They argue that their findings reflect luxury consumption, consistent with predictions of consumption capital asset pricing models (Aït-Sahalia et al., 2004). Lovo and Spaenjers (2014) present a dynamic auction model where transaction prices and voluntary trading volume increase when the economy enters an expansion, and decrease when a recession commences. A crucial difference between the two former explanations of trading volume is that the latter is silent about who trades and about the kind of goods that are traded. Further, resale option theory states that a high volume should be associated to prices above fundamental value, so that a high trading volume should predict negative returns.

In this paper, we use a comprehensive data set of nearly 1.1 million auction sales to study asset price fluctuations and trading in the fine art auction market. First, we intend to analyze 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. We have presented two competing theories — the speculative trading

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[7]To avoid making this paper too cumbersome, we will liberally speak of price-volume correlation. What we mean is correlation between log-differences.

theory and the luxury consumption theory — that can explain a correlation between prices and volume. Consonant with the *speculative trading* hypothesis, we find that the share of very short-term transactions, the sales rate, and the share of the riskier art movements increase when volume increases. While prices increase with top incomes, as predicted by the *luxury consumption* hypothesis, the contemporaneous relation of top income augmentation with volume is positive but insignificant.

Second, we find that the positive contemporaneous price-volume correlation is robust and pervasive across art movements and that the riskier (respectively, safer) artists tend to exhibit higher (lower) price-volume correlation. Perhaps unsurprisingly, riskier art (Pop, Abstract Expressionism, Minimalism and Contemporary art) belongs to the second half of twentieth century, while safer art (Romanticism, Baroque, Rococo) ended no later than the first half of the nineteenth century.

While supportive of the *speculative trading* hypothesis, these findings are not yet conclusive. Our third objective is thus to study whether a high volume coincides with overpricing, which is the most important prediction of the resale option theory (Hong and Stein, 2007). Although the fundamental value of art is unobservable, a clear test of overpricing is that volume negatively predicts returns, while controlling for potential changes in fundamental value. Crucially, our dataset contains more than 20,000 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 the resale option theory. In order to control for changes in fundamental value, we then turn to the classic capital asset pricing model (CAPM) to express art excess returns in terms of systematic risk, and additionally control for changes in artist fame and changes in volume. A one standard deviation increase in volume will on average increase future excess returns by 15.1% over the holding period, or 2.6% per year. This long-term effect of volume on art returns is much larger than the effect of stock returns (5.5% on average) and the effect of taste (6% on average). Importantly, this relation is robust across time, which means our results are not driven by the 1990s boom.

Our paper contributes to a number of strands of the literature.

First, we provide evidence supporting a resale option theory and, in particular, the bubble model of Scheinkman and Xiong (2003). The previous literature has provided

empirical evidence related to events limited in time, such as the Chinese warrant bubble (Xiong and Yu, 2011) and the Chinese A-B share premia (Mei et al., 2009). Palfrey and Wang (2012) also find evidence of speculative overpricing in laboratory-controlled asset markets. Our finding is novel, in that overpricing is not driven by a single event. Speculation occurs in spite of huge transaction costs, as conjectured by Scheinkman and Xiong (2003). We directly relate the large fluctuations in art prices to a stationary overpricing component. We argue that this overpricing component, which is proxied by trading volume, induces predictability in art returns.[8] Bubbles in the art market are unique in that they can start in the absence of large uncertainty or innovation[9] and are not driven by excess credit or leverage (Stein, 1995; Geanakoplos, 2010).

Second, our data enables us to examine the empirical relation between prices and volume. While this relation has been extensively examined in other asset markets, including the housing market,[10] virtually no research exists on markets of collectibles. 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. Our set-up is complementary to that of Korteweg et al. (2013) and Lovo and Spaenjers (2014), who examine how changes in market values correlate with the likelihood of trading for individual artworks.

Third, our paper extends the understanding of the drivers of "emotional asset" prices. Previous research has insisted on the role of wealth, proxied by equity returns and changes in the income distribution (Goetzmann et al., 2011; Hiraki et al., 2009). Interestingly, Hiraki et al. (2009) explains the 1990 art price bubble in fundamental terms: luxury consumption by Japanese art collectors pushed international art prices up until the art bubble burst as a direct consequence of the collapse of the Japanese real estate market. We provide an alternative interpretation emphasizing speculative dynamics, which has been largely overlooked by the literature. Penasse et al. (2014) use survey data to show that optimism about individual contemporary artists has predictive power of short-run

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[8]This stands in marked contrast to the purely rational view that argues that changes in the discount factor induces return predictability (see Cochrane (2011) for an overview of this literature). A recent paper by Cujean and Hasler (2014) also argues that disagreement generates predictability over the business cycle.

[9]Innovation and uncertainty is an inherent element of asset prices bubbles (see e.g. Xiong (2013)), which complicates the identification of bubbles even ex post. See, e.g. Pastor and Veronesi (2006) for a rational explanation of the 1990 internet bubble.

[10]See Genesove and Mayer (2001), Clayton et al. (2008); see also Piazzesi and Schneider (2009) and Favara and Song (2013) for arguments in terms of overpricing.

art returns, in line with the idea that fads affect the prices of individual artists. In a similar vein, Renneboog and Spaenjers (2013) construct an aggregate art market sentiment indicator, based on sales volume, buy-in rates, and the tone of press reports on the art market, which covaries with art prices. Still, that study does not address a price-volume correlation nor provides evidence of return predictability.[11]

Fourth, we shed more light on the behavioral anomalies that characterize the auction market. Mei and Moses (2005) show that high estimates at the time of purchase are associated with adverse subsequent abnormal returns, which suggests that credulous collectors are likely to be influenced by biased presale estimates. Beggs and Graddy (2009) and Graddy et al. (2014) provide evidence of anchoring and loss aversion in art auctions. De Silva et al. (2012) show that investors' emotional state (in their paper influenced by the weather at the time of the auction) can affect price formation of paintings with a relative high private value. Pesando and Shum (2007) present anecdotal evidence of "irrational exuberance" in the prices realized at the 1997 sale of the collection of Victor and Sally Ganz at Christie's in New York. They argue that the buyers of five Picasso prints probably overpaid, as evidenced by the dramatically lower prices realized by these prints in their subsequent appearances at auction. Our results suggest that this tendency of collectors to overpay is significant and pervasive.

The remainder of this paper is structured as follows. We present our dataset in Section I. Section II provides evidence on what drives volume. Our core results are presented in Sections III and IV, where we study price-volume correlation across art movements and show that volume has long-term predictive power. Section V discusses the interpretation of our empirical findings and Section VI concludes.

I.   Data

This paper uses the historical data set constructed by Renneboog and Spaenjers (2013), which comprises information on more than one million transactions of art at auction

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[11]Two recent papers also investigate the short-term dynamics of art prices. Pownall et al. (2013) employ a regime switching model to describe the dynamics of art prices using a threshold variable that drives prices into possibly locally explosive regimes. Kräussl et al. (2014) use a right-tailed unit root test with forward recursive regressions to detect explosive behaviors in the prices of four different art market segments.

over the period from 1957 until 2007. The dataset initially overweighs the London sales, but as of the middle of the 1970s, the coverage consists of all major auction houses around the world. We thus concentrate our analysis of price and volume on the 1976-2006 period.[12] The sales concern oil/acrylic paintings and works on paper (water colors, gouaches, etchings, prints) by more than 10,000 artists. Almost half of the artists are classified into one or more of the following movements: Medieval & Renaissance; Baroque; Rococo; Neoclassicism; Romanticism; Realism; Impressionism & Symbolism; Fauvism & Expressionism; Cubism, Futurism & Constructivism; Dada & Surrealism; Abstract Expressionism; Pop; Minimalism & Contemporary.[13] For the purposes of the current study, we create a separate subsample of transactions for each of these movements. If an artist is categorized under more than one movement, we assign all the sales of his or her work to the art movement the artist has most contributed to.[14] As a result, there is no overlap between the different subsamples, and correlations between the return estimates and volume changes across movements cannot be driven by the repeated use of the same data. The number of sales in the movement subsamples ranges from 10,485 for Neoclassicism to 102,234 for Baroque.

We make use of this dataset in two ways. First, we construct a panel data set of art returns and transaction volumes for 13 art movements. Second, we use identical resale pairs to test long-term predictions on actual transactions.

A.   Times Series Data

We build aggregate and movement-specific real price indexes by applying a hedonic regression model to the full dataset and to each subsample (see Appendix VI for a description of our hedonic regression model). To construct our measure of trading volume, we record the number of observed transactions for each year in the period 1976 to 2006. Our database does not include buy-ins (i.e., items that do not reach the reserve price set by the seller), and we thus work with the numbers of lots that actually sold. We construct a proxy for

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[12]We do do not include 2007 because our data set doesn't span the full year.

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

[14]For example, Edgar Degas is classified both under Realism and under Impressionism & Symbolism. We will use the sales of his work only to estimate the price and volume changes in the market for Realism.

the average sales rate in Section II.

Figure 2 presents the evolution of price and volume over our time frame. There is a strong cross-sectional correlation in prices, as previously documented by, e.g., Ginsburgh and Philippe (1995); Worthington and Higgs (2003). Interestingly, the volume series are also significantly cross-sectionally correlated. A regression of movement-level series on market-level series yields an R-squared of 0.63 for returns and 0.44 for changes in volume. Some art movements are clearly riskier than others: for example, Pop art prices culminated in 1990 to levels more than 5 times their 1984 level, *in real terms*. Our index suggests that Pop art prices subsequently fell by 83%.

[Insert Figure 2 about here]

The riskiest art movements are shown to also be the most profitable bets. Table I presents the summary statistics on price and volume series. There is a clear risk-return relationship: the correlation between return and volatility is as high as 81.6%, as is exhibited by Panel (a) of Figure 3. Price and volume volatility are of the same order of magnitude; the riskier (safer) movements also exhibit more (less) volatile volume. Unsurprisingly, the riskier movements (Pop, Abstract Expressionism, Minimalism and Contemporary art) belong to the second half of twentieth century, i.e. Modern and Contemporary Art, while the safer (Romanticism, Baroque, Rococo) are Old Masters, i.e. ended no later than the first half of the nineteenth century.

We also report correlations between price and volume. The correlations are extremely high, 54% for the aggregate indices, as they are also induced by the impressive boom and bust that characterized both prices and volume during the 1990 bubble. As can be seen in Panel (b) of Figure 3, the riskiest schools of art are characterized by the highest correlation between prices and volumes. This pattern is reminiscent of Lee and Swaminathan (2000), who find that high (low) volume stocks exhibit many glamour (value) characteristics.[15] In our analysis, we will therefore consider subsamples using "High Volatility" (Pop, Abstract Expressionism, Minimalism and Contemporary art) and "Low Volatility" (Romanticism, Baroque, Rococo) artists.

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[15]In the absence of a significant rental market for art, we cannot compute valuation ratios such as rent to price ratios. Any definition of glamour and value is necessarily informal and based on the "test of time".

B. Repeat-sale Data

We also use a subset of the dataset for which pairs of identical, or at least very similar objects of art can be identified. Each resale pair is considered as a unique point in our dataset, and the resales comprise 22,716 observations, spanning 1976 to 2006. For each pair of transactions, we observe the purchase and sale prices, P_i^b and P_i^s, expressed in logarithm. The log-return for holding a work of art i between the date of purchase b_i and the date of sale s_i is thus given by $P_i^s - P_i^b$. The average holding period in our sample is 5.7 years.

We make use of this dataset to test the predictive relation between volume and returns, as well as price mean reversion. A potential concern is that selection bias may affect the interpretation of our results. For example, **?** 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. If present, such censoring is likely to be fairly small. The correlation between returns computed using a repeat-sale estimator on this subsample and the art returns using the hedonic estimator is 0.98. Both indices also show very similar long-term trends, which implies that survivorship bias is likely to be very small. Finally, the distribution of sale-to-sale returns (not shown) is quite symmetric (with a skewness of 0.27) and no particular discontinuity can be observed in the tails of the distribution.

We complete the dataset by constructing a measure of volume at the transaction level. We first collect the total number of sales on the last twelve months preceding t. Following Baker and Stein (2004), we then normalize our series by the average volume over the last five years. Taking logs, our monthly measure of volume is given by

$$\text{VOLUME}_{m,t} = \log\left(\sum_{i=t-12}^{t-1} v_{m,i}\right) - \log\left(\frac{1}{5}\sum_{j=t-60}^{t-1} v_{m,j}\right) \tag{1}$$

where $v_{m,t}$ is the number of transactions for movement m observed in a given month t. In order to use the largest number of observations, we assign the aggregate measure

of volume to artists who are not matched to a specific movement. Aggregate volume is defined as above, but using the entire data set instead of summing the sales of a specific movement. Detrending the series brings about several benefits. First, as can be seen in Figure 4 for market volume, Equation (1) generates a persistent series. 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 (1) gives us a relatively high frequency series, which is not affected by art market seasonality. Finally, the series is constructed recursively, which ensures that only information that is truly available to the investor when making his forecast appears in his information set.

We merge these series with our repeat-sale dataset: for each resale pair, we record the value of $\text{VOLUME}_{m,t}$ at the month preceding the purchase and at the month preceding the sale.

[Insert Figure 4 about here]

Finally, we 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 (1996) and the Pastor and Stambaugh (2003) liquidity factor. Finally, we use the one-month Treasury bill rate as the risk-free rate.

Although tastes are relatively slow-moving (Graddy, 2014), 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 2190 artists (out of 2769), which leave us with 20,604 resale pairs with taste information.

Table II gives the descriptive statistics for the repeat-sale database, expressed in log difference between the time of first and second transaction. For art, we see an average excess return of 1.2% over an average holding period of 5.7 years, with a standard deviation

of 78%. Equities are undoubtedly financially dominating art, with an excess return of nearly 12% and a standard deviation of almost 29% over the period 1976-2006. Volume barely changes on average (-3%), and was much less volatile (19% standard deviation), which reflects our choice of smoothing the volume series. Finally, the percentage of mentions of each artist (fame) fell 7% on average and has a dispersed distribution (the standard deviation is 44%).

[**Insert Table II about here**]

Interestingly, this large volatility at the artist level averages out at movement level, as depicted by Figure 5. Over our sample period, we observe the increasing popularity of Andy Warhol, while the share of mentions of his name in Google Books increased by 88%. Roy Lichtenstein, another famous Pop artist, also gained increasing attention over our sample period. By contrast, Figure 5 shows that the exposure of the average Pop artist remained largely stable for three decades. We observe similar patterns for the other art movements: artist trajectories can be erratic, but the degree of exposure is very stable at the aggregate level. This illustrates the fact that tastes move very slowly, as pointed out by Graddy (2014), and that changes in tastes cannot explain the dramatic fluctuations that characterized art prices during that period.

[**Insert Figure 5 about here**]

II. The Information Content of Volume

In a recent survey on art collecting, only a tenth of the respondents said they bought art purely as an investment, whereas 75% cited enjoyment as the key motivation (Barclays, 2012). Such a financially disinterested behavior stands in contrast with the steady growth of the art-as-an-investment industry. The specialized press regularly reports the creation of art funds, or the launch of services targeted at private investors who want to build up an art collection for investment purposes.[16] Besides surveys and anecdotal evidence,

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[16]For example, the Fine Art Fund Group, started by Philip Hoffman, a former finance director at Christie's, launched a managed art portfolio service targeted at high-net-worth individuals. The minimum investment for this type of fund is $1m over three years (Powley, 2013).

little is known about what drives volume in the fine art auction market. Since the seminal study of Baumol (1986), the literature has extensively considered what drives the demand for art, but overlooked supply and therefore volume. This makes perfect sense, as far as the supply side is thought as the *production* of works of art. Unless one discovers a forgotten masterpiece in a local flea market, the supply of works of art is inelastic — to the very least for dead artists. However, the traditional view overlooks the existence of a secondary market where collectors can sell. In a rational model such as Mandel (2009), such a secondary market doesn't exist.

In fact, the purely rational view predicts that collectors should not trade at all. This is due to the "no-trade theorem": if one agent considers trading with another agent, each of them needs to consider why the other agent might be willing to trade at a particular price, which results in no trade (Tirole, 1982; Milgrom and Stokey, 1982). In order to generate trade in a rational model, one needs to assume that people are different. According to this view, people trade in the art market for idiosyncratic liquidity reasons or because their wealth or tastes differ. A change in the population of bidders can thus affect art's fundamental value and generate volume. Any increase in demand, if deemed permanent, logically leads to higher fundamental prices. Lovo and Spaenjers (2014) show that it can also lead to a contemporaneous increase in volume, even in a rational model where prices follow macroeconomic fundamentals. It is not clear, however, to what extent changes in the population of bidders can explain the sizeable price-volume correlation documented in this paper. In particular, since art yields conspicuous utility (Mandel, 2009), the utility of owning art should increase with prices, thus reducing the incentive to sell when the entry of new buyers pushes prices up.

In contrast to the purely rational view on trading, resale option models argue that speculation is an important driver of trading volume. Speculative trading arises whenever someone buys an item above its own private valuation, in order to resell it later at a higher price. A prominent example of such investment scheme is the purchase of Van Gogh's Portrait of Doctor Gachet in 1990 at the then record price of $82.5 million. The Portrait was sold within three minutes to Ryoei Saito, Japan's second-largest paper manufacturer. Immediately after taking possession of the painting, he secured it in a climate-controlled warehouse where it remained unexhibited for seven years (Taylor, 2012).

In order to distinguish consumption-driven trading from speculative trading, we look at the composition of aggregate volume. In the introduction of this paper, we showed that the share of short-term transactions peaked during the 1990 bubble. Given the huge transaction costs that characterize the art market, it is very unlikely that these works of art were bought for the pure "retinal" pleasure. These transactions thus credibly proxy for the frenzied trading predicted by Scheinkman and Xiong (2003). We construct this variable by means of the repeat-sale sample, and define it as the share of purchases that were resold within the next year. These resale pairs account for 10% to 30% of trading volume within our sample.

A common thread in the disagreement literature is that trading volume appears to act as an indicator of investor sentiment (Baker and Stein, 2004; Hong and Stein, 2007). A high volume is supposed to be symptomatic of overvaluation, signifying that the market is dominated by optimists. The following two variables therefore proxy for market sentiment.

Our first proxy for sentiment is the sales rate, the percentage of the lots sold in an auction. Sellers of individual artworks usually set a secret reserve price and if the highest bid does not reach this level, the items are "bought in" and go unsold. The convention in the art market is that the reserve price is set at or below the auctioneer's low estimate. There is anecdotal evidence that the sales rate tends to be lower in depressed markets where prices are lower and are therefore less likely to meet sellers' reserve prices (Thorncroft, 1990). Ashenfelter and Graddy (2011) find that the sales rate is not related to art prices, but is strongly positively related to unexpected price changes, defined as the difference between the hammer price and the presale estimate produced by auction house experts. A higher sales rate may therefore indicate that the market is dominated by optimists, who are willing to pay more than sellers' reserve price, which are themselves related to expert estimates. Ashenfelter and Graddy (2011) indeed report that sales rates crashed in the bust of the 1990 bubble. Since our dataset does not include items that were bought in, we construct a proxy for the sales rate. For each auction, we divide the number of observed transactions by the maximum lot number. We then take, for each year, the average sales rate across auctions as our proxy for the aggregate sales rate, from 1976 to 2006.

Newspaper articles also suggest that the share of Modern and Contemporary art is

higher in "hot" markets. For example, Thorncroft (1992) reports a flight to quality (i.e. to Old Masters paintings) after the 1990 bubble burst: "the auction world has returned to its traditional ways, where connoisseurs rule and established works of art hold pride of place." This can be related to sentiment for two reasons. First, overconfident collectors are more likely to hunt for relatively young artists with larger upside potential, just as overconfident investors scrutinize the stock market hoping to find the next Google.[17] When sentiment is low, trading should decrease and be confined to the less speculative art movements. Second, we expect collectors who engage in speculative trading to turn to the most liquid items available. Modern and contemporary items are arguably more liquid than items from older schools of art, which are to a larger extent locked up in museums or private collections.[18] A high share of modern and contemporary art in the aggregate trading volume thus signals that the market is dominated by optimistic speculators. We therefore construct a second proxy for sentiment consisting of the annual share of Modern and Contemporary art, which corresponds to our "High Volatility" group (Pop Art, Abstract Expressionism, Minimalism, and Contemporary art).

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

Finally, it is of independent interest to understand whether volume increases mostly because of an increase of demand, or because a higher number of items are offered for sale. Both theories predict that higher prices should be associated with a larger number of works of art offered for sale. If sentiment is high and art prices are above their fundamental values, pessimists will react and put more items for sale. Moreover, auction houses are more likely to solicit potential sellers in "hot" markets (Pesando and Shum, 2008). On the

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[17]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.'"

[18]Modern and contemporary art should thus enjoy a higher level of liquidity, *ex ante*. A simple coordination argument suggests that they should be even more liquid *ex post*, because liquidity is self-reinforcing.

other hand, higher prices can attract sellers whose present value of future utility dividends is below the expected auction price.[19] As a proxy for the number of art objects offered for sale, we use the number of transactions divided by our sales rate.

Table III presents the correlation matrix of the percentage changes in price, volume, and the percentage changes in the five variables discussed above (the share of short-term transactions, the sales rate, the number of art objects offered for sale, the share of transactions in modern and contemporary art within the global art market, and the top income). We see that when price and volume increase, the share of short-term transactions tends to increase. The correlation between volume change and the change in short-term transactions is a highly significant 0.42.

We also learn from Table III that the sales rate tends to increase with volume. The correlation is statistically and economically large: 0.36. Volume is, by definition, given by the number of art objects offered for sale multiplied by the sales rate. If the sales rate comoves with volume, one may wonder whether volume changes *because* of changes in the sales rate. Hiraki et al. (2009) argues that the 1990 bubble was mainly driven by the influx of Japanese buyers in the art market. Anecdotal evidence also supports the idea of inexperienced and wealthy collectors competing in auction and buying at unreasonable prices. More generally, since higher bids are more likely to reach sellers' reserve prices, the entry of new buyers alone could push the sales rate up, which, in turn, would mechanically increase volume. We find, instead, that the number of art objects offered for sale increases in concert with volume. Said otherwise, people trade more, and not only because of the influx of new buyers. To see that, first consider the correlation between the sales rate and prices. Table III exhibits a 0.22 correlation, which is less than half of the price-volume correlation. Also, the former correlation is not statistically significant, in line with Ashenfelter and Graddy (2011). Moreover, if changes in volume were only due to demand shocks, the number of art objects offered for sale should not be correlated to prices. We find a highly significant 0.47 correlation between the offered art

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[19]A prominent example of such an increase in supply was described in the press during the 1990 bubble. At the peak of the bubble, several major museums, including the Guggenheim in New York, announced that they were disposing of important works of arts — works by Chagall, Modigliani and Kandinsky. Although this practice of de-accession is not uncommon, and serves the purpose of financing new acquisitions, it was unusual enough to be qualified a "selling spree" by the *Financial Times* (Thorncroft, 1990). The timing of the selling indeed suggests museums were trying to benefit from the very high prices reached by a few star artists (Glueck, 1990).

objects and prices.

<center>[**Insert Table III about here**]</center>

In line with the speculative trading hypothesis, we also expect new buyers to be primarily attracted by Modern and Contemporary art, which offer the most speculative, glamorous artists. Table III shows that the share of Modern and Contemporary art does indeed increase with both price and volume (the correlations are 0.59 and 0.52, respectively). We saw in Section I that the Modern and Contemporary Art movements are more volatile and exhibit the highest price-volume correlation. These positive correlations strengthen our argument that, when sentiment is high, buyers and sellers agree to disagree and turn to the most speculative items.

Finally, Table III provides limited support for the consumption trading hypothesis. In line with Goetzmann et al. (2011), art returns are significantly correlated with changes in inequality, with a significant 0.35 correlation, but only modestly and insignificantly with all measures of trading volume.

III. Price-Volume Correlation

A. Contemporaneous Relation

We now turn to the analysis of price-volume correlation across art movements, using the time series data described in Section I.A. The central relation between price and volume is presented in Table IV. Each panel reports fixed effect regression results for the 13 art movements, as well as for the 3 most volatile and 3 least volatile movements. We first look at the contemporaneous relation between prices and volumes, and then turn to regressions including equity returns, which traditionally proxy for changes in wealth.[20]

<center>[**Insert Table IV about here**]</center>

Panel A of Table IV documents a significant and pervasive price-volume correlation. Model 1 reports that a one percent change in volume is associated with an average 0.59% change in return. Price-volume correlation explains on average 25% of return variance.

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[20]Controlling for changes in top incomes instead of equity returns does not materially affect our results.

<center>18</center>

The relation is much stronger for high-risk movements (with an R-squared of nearly 0.40 in model 3) and much lower for Low Volatility artists (the R-squared is around 0.05, in model 5). Interestingly, the price-volume correlation remains largely intact when controlling for contemporaneous and lagged stock returns. Moreover, the R-squared increases only marginally when including stock returns, suggesting that volume is more informative than stocks in the short run.[21]

This result is consistent with both consumption and speculative trading, and is therefore of little help to distinguish between the theories. As argued in Section II, both hypotheses predict a causal relation from prices to the number of works of art offered for sale, and plausibly to the number of transactions. Resale option theory can also predict a lead-lag relation between lagged volume and prices, if information diffuses slowly. This is arguably the case for art where, absent a centralized market, information has to diffuse through the media and by word of mouth. Further, auctions around specific themes occur infrequently and hence the trading frequency in the art market makes information spread slowly. Empirical evidence shows that art market returns lag stock returns by a year (see e.g. Chanel (1995), Renneboog and Spaenjers (2013)), and take at least six months to reflect information contained in Sotheby's stock price (Penasse, 2014). It is therefore likely that sentiment would diffuse slowly into art prices. In the United States housing bubble, Soo (2013) similarly finds that house prices followed volume with a substantial lag and shows that both volume and prices were predicted by market sentiment.

In order to disentangle our two main hypotheses, we thus turn to an analysis of lead-lag relations between prices and volume.

B.   Lead-lag Relations

Before turning to the estimation of lead-lag relations, some words of caution must be spoken regarding the econometric model and the time series used. First, it is well known that fixed effects regressions with lagged dependent variables generate biased estimates. The bias is of order $1/T$ and, given the relatively large time-dimension of our panel (30 years), we do not attempt to remove it. Second, both price and volume indices are by

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[21]Penasse (2014) presents evidence that volume is indeed more informative than stock prices for the purpose of short-term forecasting.

construction moving averages over each year and may thus be artificially smooth. Time aggregation of data can lead to variances that are underestimated and autocorrelations that are overestimated relative to the true underlying process (Working, 1960). Moreover, the art auction market is very seasonal, with the second and the fourth quarters of the year generally witnessing the highest trading intensity and most important sales. In order to avoid identifying spurious lead-lag relations between price and volume, we construct distinct price and volume indices from the observations in the fourth quarter (October-December) of each year.

Panel B of Table IV shows that volume tends to lead prices. The elasticity of current returns to lagged changes in volume is 0.258 (model 1), a little less than half the elasticity to current volume, but it remains significant at the 5% level. Again, the contribution of additional predictors seems marginal: neither lagged stock returns nor lagged price remain significant when controlling for lagged volume.

Panel C tests the alternative relations where prices lead volume: we regress volume changes on lagged price changes and control in a second regression for lagged equity returns and possible volume autocorrelation. Panel C provides limited support for a causal relation from returns to volume. We only find a borderline significant relation in the High Volatility group, where a 10% price change forecasts a 2.1% change in volume on the following year (model 4). All specifications in Panel C show a negative autocorrelation of volume. A plausible explanation is market timing. Someone with a limited number of items to sell will put more items at auctions when he sees a selling opportunity, which will leave him with fewer items to dispose of the year after. A similar argument holds for a buyer with limited resources and this argument generalizes to auction houses trying to maximize revenue by soliciting more artworks when they expect higher prices.

IV. Volume and Overpricing

A. *Volume Deciles*

The most important prediction of asset pricing theories incorporating disagreement is overpricing (Hong and Stein, 2007). In the absence of short selling, a high trading volume signals that prices are above the fundamental values of the art objects. A high volume at

the time of a purchase should predict lower returns while controlling for potential changes in fundamental value. We test this prediction on our repeat-sale dataset, where each transaction is identified by its purchase and subsequent resale date. For each resale pair, we record the sales volume at the time of the purchase and at the time of the sale. As our analysis concentrates on overpricing, we calculate abnormal real returns, which we define as the returns in excess of the sample mean of the whole repeat-sale dataset. We construct "portfolios" based on volume deciles; the largest decile corresponds to the largest volume relative to five-year average volume. We calculate the annualized abnormal returns of resale pairs that occurred when volume was within a given decile. For example, market volume fell within the first decile from September 1982 to June 1983. We collect all pairs of transactions where the artwork was bought or sold for each decile and record the average abnormal return as a function of volume decile. Figure 6 exhibits the annualized abnormal returns as a function of volume; the dashed lines indicate the 5% confidence bands around the null of absence of abnormal returns.

Buying art when volume was in the highest decile yielded an average abnormal return of -3.5% per annum. This effect is economically large, compared to the average real return in our sample, which is 0.8% per annum. In contrast, a high volume of trading at the time of the sale is associated to abnormal gains of 9.3% per annum, on average. Symmetrically, low volumes at the selling date tend to be associated with low returns. For example, selling when volume is at its lowest decile generates an average abnormal loss of 8.6%. The pattern at the time of resale is stronger than the one at the time of purchase. We interpret this as evidence of overpricing, although we cannot claim that this overpricing is predictable, because the "resale" portfolios are constructed based on volume at the time of sale. Perhaps surprisingly, purchases in the lowest volume decile did not earn a significant abnormal return in the following years. The reason is that sales tended to plunge prior to the price crash when the 1990 bubble burst. Hence, a large fraction of purchases related to the first volume decile took place before prices collapsed, weighting down the average returns in that particular decile.

Ignoring the purchases in the lowest volume decile, Figure 6 depicts a remarkably regular pattern across deciles. Buying when volume is low and selling when volume is high seems a quite profitable strategy (but we ignore transaction costs), and is in line

with the idea of bubble formation. We repeat this exercise for all subsamples and report the results in Table V. We find similar or even stronger abnormal returns for the High Volatility group, but not for the Low Volatility group, which is consistent with our previous findings on price-volume correlation.

[Insert Figure 6 and Table V about here]

B.   Asset Pricing Models

Changes in fundamental value may be responsible for the correlations between price and volume. We therefore evaluate the impact of volume on future returns by explicitly controlling for 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 characteristic and volume. After dropping the observations from 601 artists who do not appear in Google's books database, we estimate the following equation:

$$\mathrm{r}_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha + \beta \sum_{t=b_i+1}^{s_i} \mathrm{MKT}_t + \gamma \sum_{t=b_i+1}^{s_i} \mathrm{FAME}_{a,t} + \nu \sum_{t=b_i+1}^{s_i} \mathrm{VOLUME}_{m,t} + \epsilon_i \quad (2)$$

where $\mathrm{r}_i = \sum_{t=b_i+1}^{s_i} r_{it}$ 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 sum of world equity excess returns between purchase and sale times, measured by MKT_t. We also add the change in artist fame, measured by $\mathrm{FAME}_{a,t}$. We capture the change in the volume measure $\mathrm{VOLUME}_{m,t}$ as defined in Equation (1) for movement m. All variables are observed with monthly frequency, except $\mathrm{FAME}_{a,t}$, which is only updated annually.

Equation (2) states that the percentage change in the price of an artwork in excess of the risk-free rate is a function of three factors. The two fundamental factors are changes in wealth, measured by the percentage increase in the GFD equity index between the purchase and sale time, and changes in tastes measured by the increase in mentions in the Google corpus. Our test variable is ν, which measures the impact of changes in

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volume. If the degree of overpricing is proportional to the volume of transactions, we expect ν to be positive.

In order to control for art exposure to additional risk factors, we also extend our estimation to Fama and French (1996) factors and the Pastor and Stambaugh (2003) liquidity factor:

$$
\begin{aligned}
\mathrm{r}_i - \sum_{t=b_i+1}^{s_i} r_{ft} &= \alpha + \beta \sum_{t=b_i+1}^{s_i} \mathrm{MKT}_t + \theta \sum_{t=b_i+1}^{s_i} \mathrm{SMB}_t + \phi \sum_{t=b_i+1}^{s_i} \mathrm{HML}_t \\
&+ \lambda \sum_{t=b_i+1}^{s_i} \mathrm{LIQ}_t + \gamma \sum_{t=b_i+1}^{s_i} \mathrm{FAME}_{a,t} + \nu \sum_{t=b_i+1}^{s_i} \mathrm{VOLUME}_{m,t} + \epsilon_i
\end{aligned} \quad (3)
$$

Following, e.g., Mei and Moses (2005), we estimate Equations (2) and (3) using a three-stage estimation procedure on our sample of repeat sales, based on Case and Shiller (1987). In a first step, we regress returns on the matrix of regressors using OLS. In a second stage, we regress the squared residuals from the first step on an intercept and the time between sales. In a third step, we redo the repeat sales regression (RSR) with weighted least squares, using the fitted squared residuals as weights.

Table VI presents our empirical findings: controlling for changes in fundamental value, volume has a large positive impact on 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 (19%) will increase future excess returns by 15.1% over the holding period, or by 2.6% per year. This long-term effect of volume on art returns is much larger than the effect of stock returns (that is 5.5% on average) and the effect of taste (which is 6% on average). The impact of volume is however smaller in magnitude in the subsamples, where a larger fraction of returns is captured by the market risk factor, while the models are estimated on a much smaller number of observations.

In order to ensure that these findings are not driven by a single event, namely the 1990 "bubble", we reestimate Equations (2) and (3) by allowing the effect of volume to

change for each decade of our sample. For example, we estimate the CAPM as:

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

$$+ \nu_1 \sum_{t=b_i+1}^{1986} \text{VOLUME}_{m,t} + \nu_2 \sum_{1987}^{1996} \text{VOLUME}_{m,t} + \nu_3 \sum_{1997}^{s_i} \text{VOLUME}_{m,t} + \epsilon_i$$

Table VII presents the estimated values for each decade: the coefficients associated with volume are again significant in each specification. Perhaps unsurprisingly, the impact of volume is much larger during the 1987-1996 period, which coincides with the Japanese bubble. In the last decade of our sample period, the impact of volume is less than half the coefficient estimated on the full sample, but we must keep in mind that we only observe transactions that occurred over a limited time span (purchases that took place in the beginning of that decade given that the holding period averages more than 6 years). Moreover, prices soared after 2001 and our dataset do not include transactions from the 2008-2009 price collapse.

[Insert Tables VI and VII about here]

V. Discussion

This paper documents evidence supporting theories where agents engage in speculative trading that pushes art price above fundamentals, which are defined, for a given work of art, as the private valuation of the most optimistic agent. A key feature of these models is that pessimists cannot sell short, which implies that their own valuations are not incorporated into prices. Our main findings can be summarized as follows: (i) a high trading volume coincides with more speculative trades and higher market sentiment, (ii) prices and volume are significantly correlated, and this correlation is higher in the most volatile segments of the art market, and (iii) a high volume predicts negative returns. We readily argued that these findings are difficult to reconcile with a model where agents hold identical beliefs and trade on the basis of taste or wealth. In this section, we examine alternative mechanisms that can generate some of these findings and discuss alternative interpretations.

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A. Time-varying Risk Premia

The most straightforward explanation of return predictability is that risk premia or discount rates vary over time (Cochrane, 2011). To the extent that our volume measure correlates with discount rates, the predictability we observe is consistent with a rational model. For example, volume may vary with business cycles fluctuations, such that when volume is low, art collectors demand higher risk premia for holding works of art. It seems however fairly unlikely that art volume would capture business cycle fluctuations or risk premia, which are not readily captured by the four risk factors we include in our pricing model. Moreover, we readily argued that such a model would be unable to explain the composition of volume, for example that the share of short-term transactions is significantly related to volume and prices. Finally, we showed that when volume is very high, collectors on average earned negative returns, which is incompatible with the assumption that predictability reflects a risk premium.

B. Alternative Bubble Models

In a seminal article, Blanchard and Watson (1983) provide a bubble model that is fully consistent with rational expectations and constant expected returns. The overpricing component in asset prices is independent of the asset's fundamental and bursts on any period with a constant probability. If the bubble does not burst, it grows at a faster rate than the discount rate. It may therefore be rational to ride a bubble, if it grows on average at the same rate as the discount rate. Although rational bubbles can occur in infinite horizon models, the theoretical conditions needed to support them are quite stringent and generally require that the asset price bubble not emerge over time. If, for instance, new works of art are created when prices increase, and if these new works are viewed as appropriate substitutes for existing works of art, no bubble can emerge.[22] An important difference between rational bubble models and the resale option theory is that rational bubbles must grow explosively, while the bubble component generated by the resale option is stationary over time. It is this stationary component that fuels return predictability, while rational bubble models generally assume that expected returns are

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[22]See e.g. Brunnermeier and Oehmke (2013) for further discussion on the theoretical conditions required to support rational bubbles.

constant over time.

An important strand of the behavioral finance literature suggests that investors are likely to form expectations by extrapolating past price changes, which may generate bubbles. This idea features prominently in many classical accounts of asset bubbles (e.g. Kindleberger (1978), Minsky (1986), Shiller (2000)). Investors extrapolate past prices because they suffer from behavioral biases such as the representativeness bias, a tendency to view events as typical of some specific class (Barberis et al., 1998), or the self-attribution bias, a tendency to attribute success to one's own ability but failure to external factors (Daniel et al., 1998). A central prediction of these models is time series momentum: returns should be positively autocorrelated. Table III provides little support for this prediction, where returns are not found to be significantly autocorrelated when controlling for lagged volume. Furthermore, returns are only positively autocorrelated for the High Volatility art movements (model 4).

C.   Credit and Leverage Cycles

A frequent explanation of asset prices bubbles emphasizes the role of credit and leverage. This is particularly true for the real estate market, most people borrow to buy houses. Stein (1995) argues that, because the ability to borrow is directly tied to the value of houses, a positive income shock that increases housing demand and real estate prices relaxes the borrowing constraint, which further increases the demand for houses. In a heterogeneous-beliefs model, Geanakoplos (2010) introduces a mechanism where pessimistic agents are willing to finance investments made by optimistic agents. In contrast to resale option models, beliefs do not change over time, and therefore there is no resell premium. Large price fluctuations are attributed to fluctuations in endogenous leverage, which is too high in booming periods and too low in declining periods.

These credit and leverage models predict that changes in wealth may have more-than-proportional effects on asset prices, while resale option models emphasize the role of fluctuations in beliefs. A distinct feature of the art market is that credit and leverage play almost no role. Auction houses may sometimes lend part of the purchase to buyers, but this practice is uncommon and confined to major purchases (Thompson, 2009).[23] It

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[23]Auction houses can also provide guarantees to sellers who are concerned that not enough bidders will

is therefore quite unlikely that art price fluctuations are driven by credit cycles.

D.   Loss Aversion

The disposition effect (Shefrin and Statman, 1985) can also explain a positive price-volume relation. If loss averse collectors decide to delay losses and choose not to sell in falling markets, then price declines could predict a decrease in trading volume. In a framework close to ours, Clayton et al. (2008) provide strong support for this hypothesis in the US real estate market, where real-estate prices are shown to Granger-cause trading volume. Statman et al. (2006) argue that Granger causality of prices towards volume can also be generated by overconfidence about one's trading skills and they provide evidence for both the disposition effect and overconfidence in the stock market.

If loss aversion is driving the price-volume correlation in the art market, we expect lagged returns to have some forecasting power and negative returns to predict drops in volume. This is precisely what we find in Table VIII, which reports that art market losses forecast low volumes. For the full sample (model 1), a 10% drop in art prices is related to an average decline of 1.8% in volume, an effect significant at the 5% level. We find that this relation is strongest for the most risky art movements (model 2).

These findings are in line with Graddy et al. (2014) who provide evidence of loss aversion in repeat-sale art data. The disposition effect is therefore likely to amplify the fall in volume following market crashes, but is by definition unable to drive the contemporaneous booms in both prices and volumes.

[Insert Table VIII about here]

E.   Volume and the Cross Section of Art Returns

It is important to emphasize that our results pertain to the time series dimension of art returns. We find little evidence of a cross-sectional relation between trading volume and returns. Although some art movements are more speculative than others, we do not

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enter the auctions for their items. 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 economic effect on final prices.

find that, within a given year, high volume artists tend to earn lower returns. Fads can temporarily affect the prices of some artists, as shown by Penasse et al. (2014), but they are not systematically characterized by large volumes. To put it differently, our findings suggest that changes in volume reflect shocks that affect the market *as a whole*, where "fads" pertain to the cross section of art returns.

To illustrate this, we use the repeat-sale dataset and construct three portfolios based on trading volume. For each year of a purchase, we sort transactions based on the volume variable defined in section I and we allocate to the first portfolio all purchases falling in the lowest volume tercile, to the second portfolio the transactions from the second tercile and to the third portfolio the transactions with the highest volume. In each case, we apply the RSR methodology to estimate returns; in other words, we "buy" and "sell" whenever the owner bought and sold in reality. We show the evolution of each price index in Figure 7. If high volume artists where overpriced with respect to low volume artists, we would expect the "high volume" strategy to underperform in the long run.[24] Although the "high volume" strategy appears to be more volatile than the two others, especially during the peak of 1990, we find no evidence of underperformance. For example, the p-value of a t-test on the difference between "high volume" and "low volume" returns is 0.14. In contrast to the results of Section IV, where we allocated sales based on the time series dimension, the strategies based on the cross-sectional dimension show little heterogeneity. This suggests that volume contains little information about whether a given art movement is subject to a temporary fad. Indeed, we readily argued that volume across art movements is mostly affected by common shocks, which we attributed to changes in market sentiment. This result also rules out the interpretation of the predictive results of Section IV in terms of liquidity premia. If art collectors were willing to pay a premium for the most liquid (and volatile) art movements, we would plausibility obtain a cross-sectional relation between trading volume and returns.

[**Insert Figure 7 about here**]

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[24]The underperformance of high-volume stocks is pervasive in the literature (see e.g. Brennan et al. (1998), Datar et al. (1998)) and is generally interpreted as evidence for a liquidity premium and differences of opinion.

VI. Conclusion

The art market is subject to large fluctuations that characterize prices and trading volume, and that are difficult to reconcile with a rational model which captures how people trade to consume. This paper argues that limits to arbitrage, namely the impossibility to sell art short, induce a speculative component to 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 collectors. As a result, an optimist is willing to pay more than her own private value because she knows that, in the future, there may be other collectors that value the work of art more than she does. The difference between her willingness to pay and her own private value reflects a speculative motive, the value of the right to sell the work of art in the future.

This paper investigates this theory by looking at the behavior of art prices and volumes and by directly measuring returns over a comprehensive data set of worldwide art auctions. Rising prices tend to be accompanied by more short-term transactions, which we interpret as trading frenzies, given the huge trading costs that characterize the art market. Trading frenzies tend to concentrate on the works of Modern and Contemporary artists, for which prices and volume are on average more volatile and more correlated. 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. Art returns are therefore predictable, not because risk premia change over time as in traditional models, but instead because prices fluctuate above the fundamental value that would prevail in the absence of short-selling constraints.

Appendix: Hedonic Regression

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

$$\ln P_{kt} = \alpha + \sum_{m=1}^{M} \beta_m X_{mkt} + \sum_{t=1}^{T} \gamma_t D_{kt} + \epsilon_{kt} \tag{4}$$

where P_{kt} represents the real USD price of an art object k at time t, X_{mkt} is the value of characteristic m of item k at time t, and D_{kt} is a dummy variable that equals one if object k is sold in time period t. The coefficients β_m reflect the attribution of a relative shadow price to each of the m characteristics. The estimates of γ_t can be used to construct an art price index.[25] Apart from the variables related to the timing of the sale, the hedonic variables X used are the same as in Renneboog and Spaenjers (2013), and capture characteristics of the artist (through the inclusion of artist dummies and an art history textbook dummy), the work (through the inclusion of variables capturing attribution, authenticity, medium, size, and topic), and the sale (through the inclusion of auction house dummies). The R-squareds of the different hedonic regressions lie between 56% and 76% (detailed results available on request).

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

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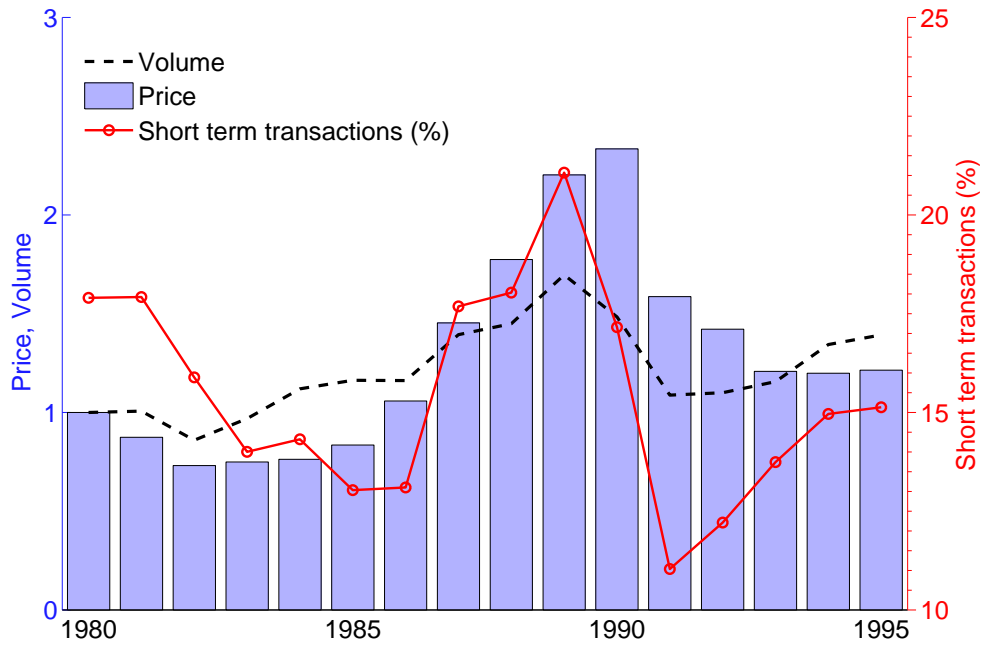
Figure 1: Price, Volume and Short Term Transactions During the 1990 Bubble
This figure shows aggregate art prices, the total volume of transactions, and the share of short-term transactions during the 1990 bubble (1980-1995). Prices and volume are expressed in function of their 1980 level (left scale). The share of short-term transactions is defined as the share of purchases that were resold within the next year, and is computed from the repeat-sale data set (right scale).
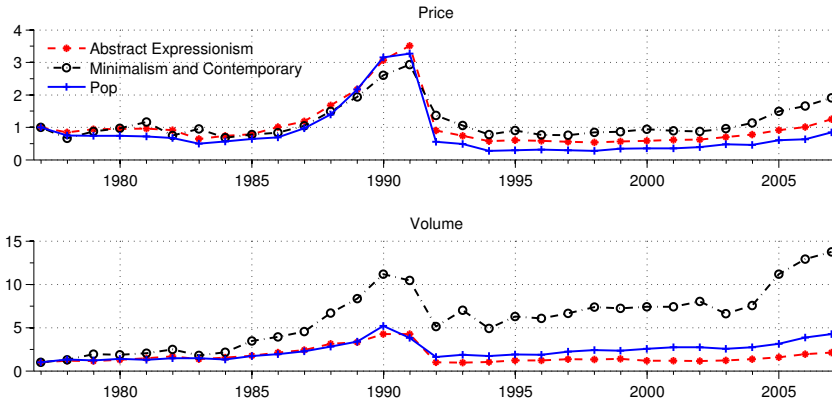
(a) High Volatility movements
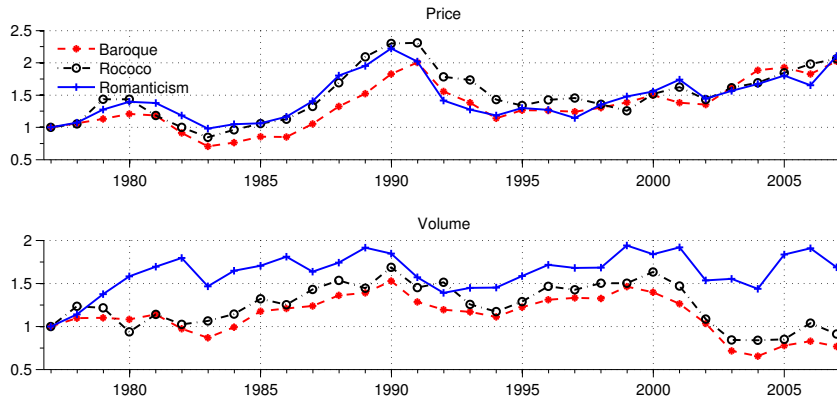
(b) Low Volatility movements
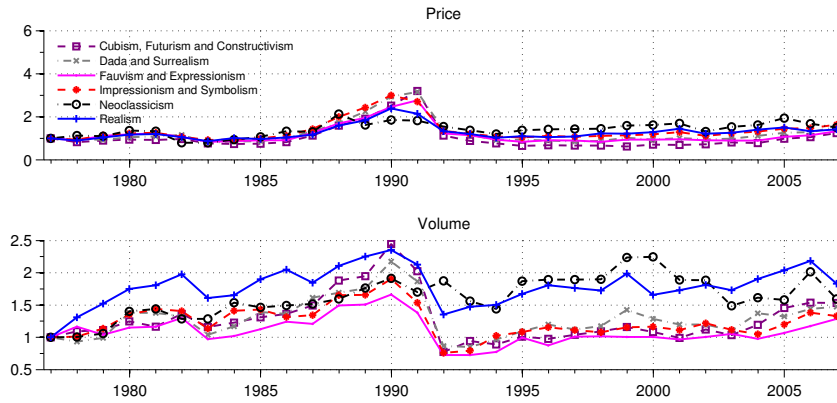
(c) Remaining movements

Figure 2: Prices and Volumes of 13 Art Movements (1976-2006)
This figure plots prices and volume for each of the thirteen art movements, with 1976 as their standardized benchmark level.
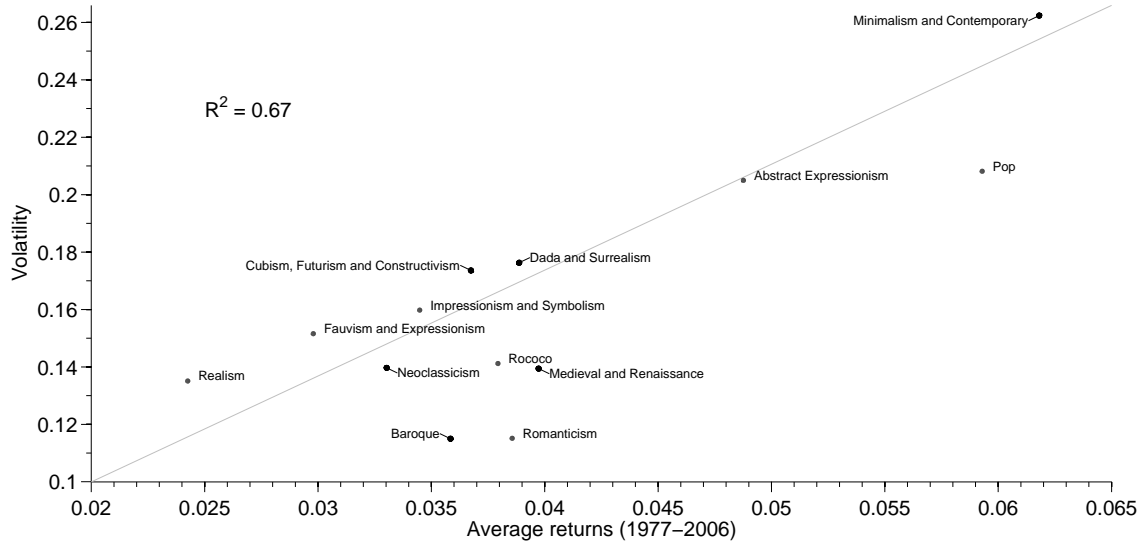
(a) Returns and Volatility
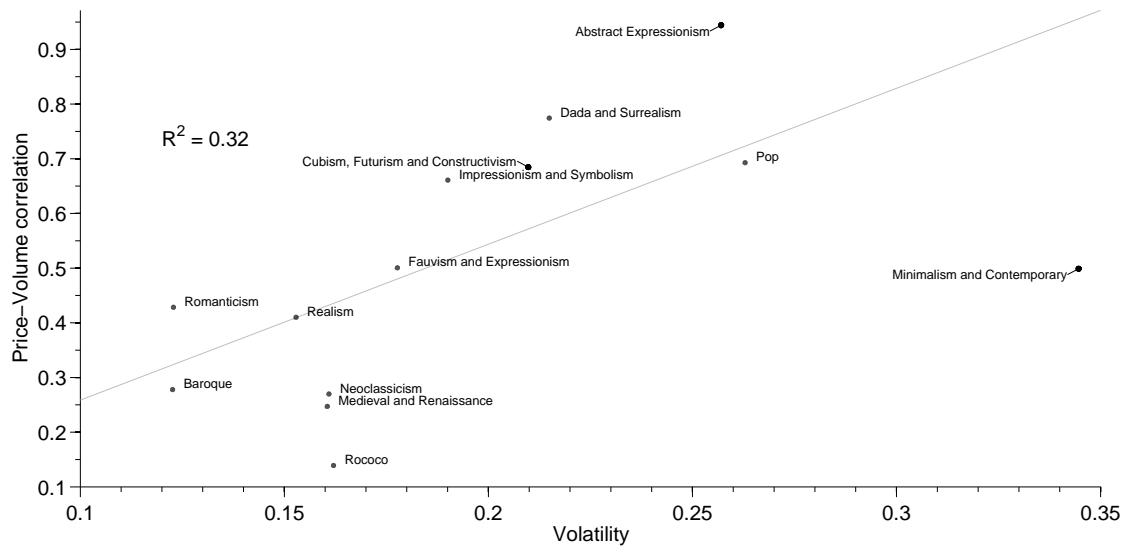
(b) Volatility and Price-Volume Correlation

Figure 3: Returns, Volatility and Price-Volume Correlation
These figures are scatter-plots of the first and second moments of the return series (the values of which are provided in Table I). Panel (a) plots the average return of each of the thirteen art movements of our sample against their volatility. Panel (b) plots the volatility of each movement against their price-volume correlation.
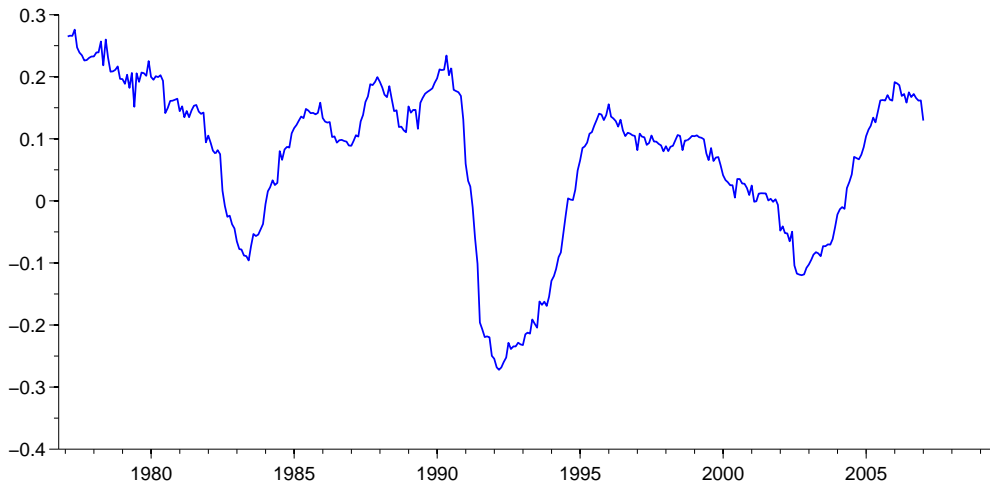
Figure 4: Detrended market volume
This figure plots the monthly measure of volume constructed by means of Equation (1) and the whole sample of 1.1 million of auction transactions. Each month t we take the log of the total number of sales on the last twelve months preceding t. We then normalize our series by subtracting the log of the average number of sales over the last five years.
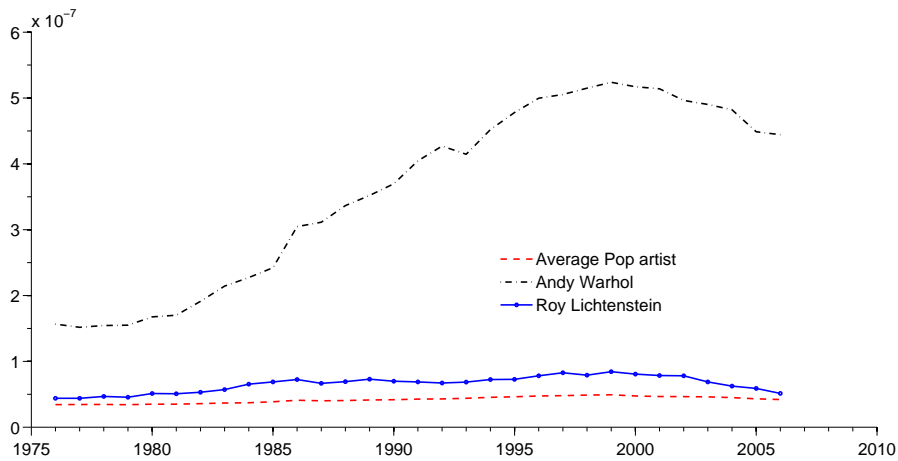
Figure 5: Artist Fame: Andy Warhol and Pop Art
This figure depicts the share of mentions of Andy Warhol's and Roy Lichtenstein's names in the Google Books database, and of the average share of the 111 Pop artists in our data set.

39
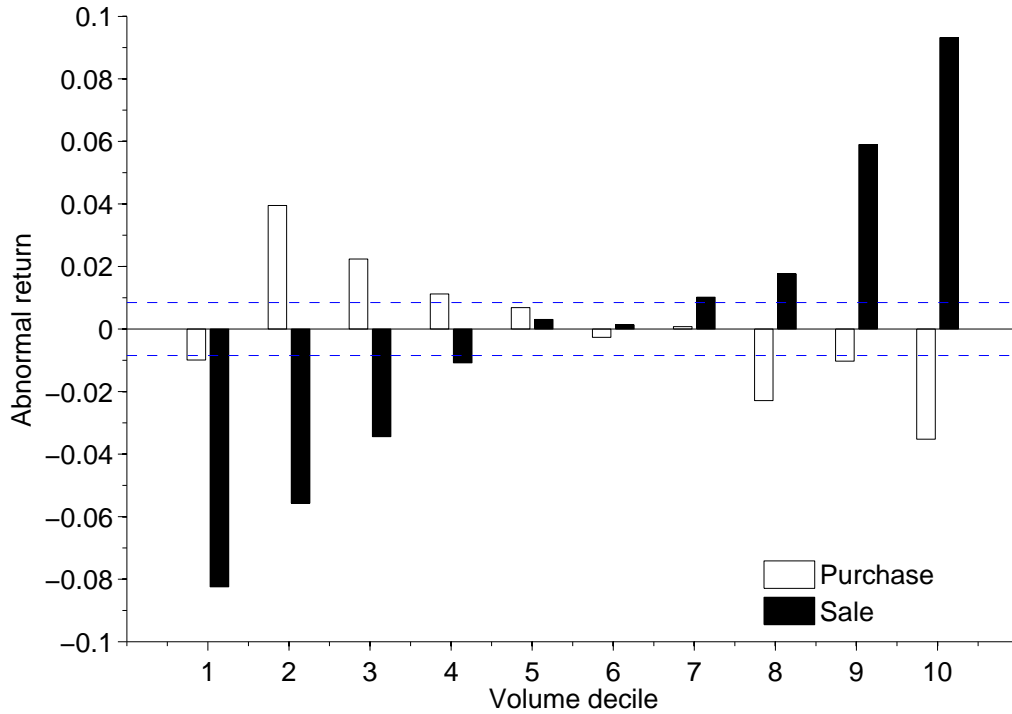
Figure 6: Volume and Abnormal Returns

This figure shows abnormal returns expressed by volume deciles (whereby decile 10 corresponds to the largest volume). Each repeat-sale transaction is identified by purchase and sale date. We construct "portfolios" of paintings based on volume at the time of purchase or sale. Volume is constructed according to Equation (1) (see also Figure 4). We compute the average abnormal return of each "portfolio" and rank them from the lowest volume (first decile) to highest (tenth decile) for the full sample and specific subgroups. Abnormal returns are defined as annualized returns in excess of the sample average. The dashed lines indicate the 5% confidence bands around the null of absence of abnormal returns.
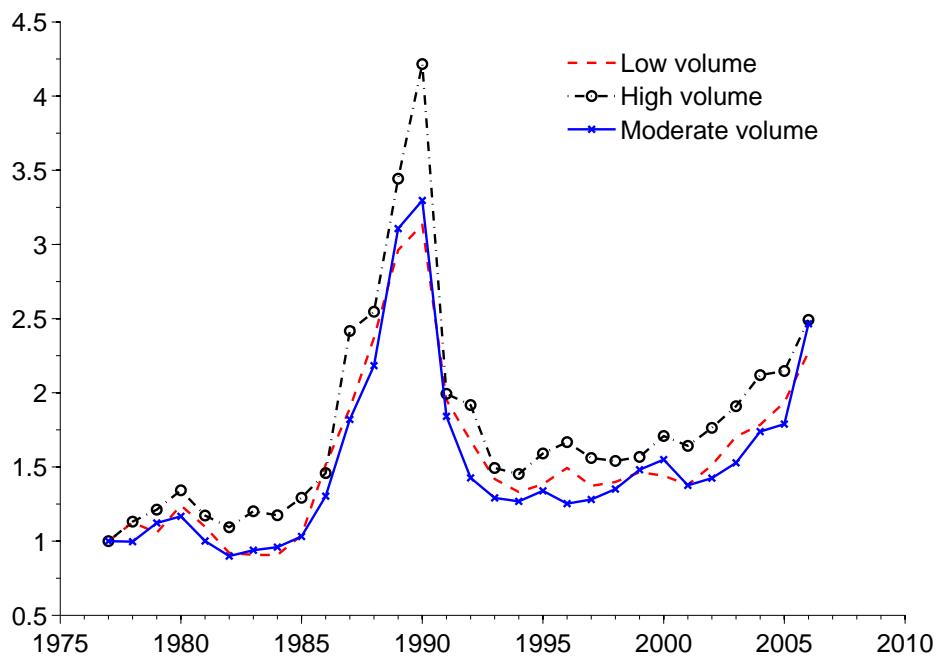
Figure 7: Repeat-Sales Price Indices
This figure presents the prices indices constructed from the "Low Volume", "Moderate Volume" and "High Volume" strategies (described in Section V.E). The indices are obtained by applying a repeat-sale regression to resale pairs allocated to each volume tercile.

Table I: Time Series Data: Sample statistics

	Price changes				Volume changes				Price-volume correlation
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	
Abstract Expressionism	4.2	22.3	-74.1	41.7	5.7	19.5	-76.4	30.8	78.0
Baroque	3.2	13.2	-22.9	26.0	-0.2	11.3	-30.7	18.8	24.1
Cubism, Futurism, and Constructivism	3.3	20.7	-64.9	40.6	3.3	16.6	-61.7	26.0	56.5
Dada and Surrealism	3.5	18.7	-55.8	30.8	2.9	16.9	-53.7	39.1	64.0
Fauvism and Expressionism	2.8	17.9	-55.6	38.5	2.1	14.6	-47.6	28.2	42.0
Impressionism and Symbolism	3.1	16.4	-50.4	39.5	2.3	15.4	-50.6	29.3	54.9
Minimalism and Contemporary	5.3	23.7	-53.4	42.6	12.1	24.7	-50.9	59.8	41.8
Medieval and Renaissance	3.5	17.7	-34.8	50.3	0.4	13.6	-38.5	27.9	21.6
Neoclassicism	3.0	18.8	-40.0	62.7	2.4	13.6	-21.0	32.2	23.5
Pop	5.0	27.7	-83.1	55.9	7.2	19.7	-58.1	53.2	57.4
Realism	2.3	15.2	-38.2	35.6	2.9	13.1	-36.4	30.9	34.7
Rococo	3.4	14.2	-22.8	36.0	0.6	13.7	-26.1	23.5	13.0
Romanticism	3.4	13.7	-29.8	28.2	2.4	11.3	-19.9	27.7	36.2
Art market	3.6	13.8	-32.0	37.4	3.8	10.3	-26.7	20.0	54.3

This table presents the descriptive statistics (mean, standard deviation (S.D.), minimum, maximum, and price-volume correlation) of the log-differences of prices and volumes, for each of the thirteen movements and for the whole art market, expressed in percentage terms.

Table II: Repeat-sale Data: Sample Statistics

	Mean	S.D.	Min	Max
ART	1.20	78.43	−458.20	554.05
EQ MKT	11.97	28.85	−77.86	128.06
SMB	4.87	21.64	−61.43	89.12
HML	24.12	29.60	−57.08	164.11
LIQ	31.13	38.55	−28.20	198.95
FAME	−6.03	40.49	−367.89	401.86
VOLUME	−2.80	19.46	−107.82	74.91
N	24889			

This table presents the descriptive statistics (mean, standard deviation (S.D.), minimum and maximum) of the variables used in our repeat-sale analysis. All variables are expressed in percentage changes between each resale pair. ART is the return on artworks between the purchase and sale times in excess of the risk-free rate: $\text{ART}_i = \sum_{t=b_i+1}^{s_i} r_{it} - \sum_{t=b_i+1}^{s_i} r_{ft}$. EQ MKT measures equity excess returns, and SML, HML and LIQ are the Fama and French (1996) and Pastor and Stambaugh (2003) risk factors. FAME is the share of mentions in Google Books for each artist and VOLUME is the volume measure, defined in Equation (1).

Table III: Information Content of Trading Volume

	Price	Volume	Short term trans.	Sales rate	Art obj. off. for sale	Mod. and Contemp.	Top inc.
Price	1.00						
Volume	**0.54**	1.00					
Short-term transactions	**0.35**	**0.58**	1.00				
Sales rate	0.22	**0.36**	0.19	1.00			
Art objects offered for sale	**0.47**	**0.86**	**0.52**	-0.15	1.00		
Modern and Contemporary	**0.59**	**0.52**	**0.50**	0.02	**0.57**	1.00	
Top income	**0.35**	0.23	0.29	0.22	0.14	0.26	1.00

This table presents pairwise correlations between price, volume, the share of short-term transactions, the sales rate, the number of art objects offered for sale, the share of Modern and Contemporary items, and the top income. The variables are observed annually over the period 1976-2006. Each independent variable is expressed in log-difference. The price is the hedonic price index. Volume is the number of transactions observed each year based on data from Renneboog and Spaenjers (2013). Short-term transactions is the number of purchases that were resold within the next year, and come from the repeat-sale data set. Sales rate is the average percentage of items sold at auctions for each year. The number of art objects offered for sale is the proxy for the number of items offered at auctions, obtained by dividing the number of transactions by the sales rate. Modern and Contemporary indicates the share of Abstract Expressionism, Pop Art, and other Modern and Contemporary Art within the global art market (the aggregate of the thirteen art movements). Top income is the share of total income received by the top 0.1 percent of all income earners in the US, constructed by Piketty and Saez (2006). Coefficients significant at the 10% level are in bold.

Table IV: Price-Volume Correlation

	All Movements		High Volatility		Low Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)

Panel A: Contemporaneous Correlation

	Δ Price	Δ Price	Δ Price	Δ Price	Δ Price	Δ Price
Δ Volume	0.590***	0.544***	0.716***	0.704***	0.271**	0.247**
	(3.32)	(3.55)	(3.36)	(3.63)	(2.16)	(2.14)
Δ Stock		-0.133		0.036		-0.148
		(-0.67)		(0.15)		(-0.79)
Δ_{-1} Stock		0.284		0.075		0.241
		(1.41)		(0.32)		(1.29)
R^2	0.251	0.279	0.395	0.396	0.054	0.099
N	377	377	87	87	87	87

Panel B: Price Changes

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Price	Δ Price	Δ Price	Δ Price	Δ Price	Δ Price
Δ_{-1} Price		-0.036		0.156		-0.056
		(-0.27)		(1.29)		(-0.42)
Δ_{-1} Volume	0.258**	0.235**	0.315**	0.216*	0.338*	0.312*
	(2.01)	(2.58)	(2.06)	(1.96)	(1.96)	(1.77)
Δ_{-1} Stock		0.318		0.321		0.210
		(1.20)		(0.86)		(0.59)
R^2	0.052	0.073	0.096	0.133	0.080	0.092
N	377	377	87	87	87	87

Panel C: Volume Changes

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Volume	Δ Volume	Δ Volume	Δ Volume	Δ Volume	Δ Volume
Δ_{-1} Price	0.078	0.112	0.146	0.214*	-0.010	0.002
	(0.69)	(1.14)	(1.01)	(1.68)	(-0.09)	(0.02)
Δ_{-1} Volume		-0.160*		-0.162*		-0.179*
		(-1.82)		(-1.83)		(-1.85)
Δ_{-1} Stock		0.213		0.370		0.234
		(0.82)		(1.27)		(0.94)
R^2	0.007	0.037	0.021	0.062	0.000	0.036
N	377	377	87	87	87	87

Panel A and B report the estimation results for price changes on (lagged) volume changes, with and without controlling for lagged price changes and equity returns. Panel C comprises the estimation results for volume changes on lagged price changes, while controlling for lagged volume changes and equity returns. The annual series in Panel A are constructed from the full sample, while those in Panel B and C are constructed from fourth-quarter observations (see Section III). We report the results for the aggregated art prices and volume (comprising 13 art movements), and for the aggregated three most volatile movements (Pop, Abstract Expressionism, Minimalism and Contemporary art) and the aggregated three least volatile art schools of art (Romanticism, Baroque, Rococo). Standard errors are clustered at year and movement level.
(t-Statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.)

Table V: Volume and Abnormal Returns

Decile	Purchase	Sale	Purchase	Sale	Purchase	Sale
	Full sample		High Volatility		Low Volatility	
Low	−0.99*	−8.25***	0.34	−3.75**	−0.52	−1.49
2	3.95***	−5.57***	5.51***	−12.92***	3.18	−4.21
3	2.24***	−3.44***	−1.62	−6.19***	0.50	−3.60
4	1.12**	−1.08***	4.30***	−4.40***	0.33	0.52
5	0.69	0.30	1.24	0.80	0.36	0.30
6	−0.27	0.13	0.60	−1.19	−1.93	0.72
7	0.07	1.02**	−4.23***	8.62***	−0.66	1.32
8	−2.29***	1.76***	0.84	5.92***	−0.09	3.34
9	−1.03**	5.90***	−4.38***	2.51*	−1.34	3.22
High	−3.52***	9.32***	−2.68**	10.82***	0.06	−0.12

This table presents the annualized returns in excess of the average (abnormal return) by volume decile (decile 10 corresponds to the largest volume). Each repeat-sale transaction is identified by purchase and sale date. We construct "portfolios" of paintings based on volume at the time of purchase or sale. Volume is constructed according to Equation (1). We compute the average abnormal return of each "portfolio" and rank them from the lowest volume (first decile) to highest (tenth decile) for the full sample and specific subgroups. Abnormal returns are defined as annualized returns in excess of the sample average. The "Full sample" corresponds to Figure 6. "High Volatility" are sales of Pop, Abstract Expressionist, and Modern and Contemporary art ($N = 2822$), and "Low Volatility" are sales of Romantic, Baroque and Rococo art ($N = 1107$). (***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.)

Table VI: Volume and Overpricing

	Full sample		High Volatility		Low Volatility	
	(1)	(2)	(3)	(4)	(5)	(6)
α	-0.001	-0.026***	0.013	-0.163***	-0.135***	-0.086**
	(-0.11)	(-3.55)	(0.69)	(-7.03)	(-4.76)	(-2.44)
MARKET	0.192***	0.332***	0.550***	0.569***	0.400***	0.433***
	(10.97)	(14.40)	(9.45)	(7.62)	(5.21)	(4.23)
SMB		0.353***		0.416***		-0.153
		(10.61)		(3.85)		(-1.02)
HML		-0.268***		-0.083		-0.727***
		(-9.07)		(-0.90)		(-5.18)
LIQ		0.169***		0.444***		0.475***
		(6.76)		(5.80)		(3.89)
FAME	0.147***	0.176***	0.129***	0.261***	0.008	0.001
	(13.05)	(15.17)	(2.91)	(5.95)	(0.16)	(0.02)
VOLUME	0.777***	0.751***	0.240**	0.432***	0.213*	0.183
	(29.10)	(27.97)	(2.43)	(4.38)	(1.73)	(1.51)
R^2	0.055	0.064	0.033	0.083	0.038	0.058
N	24889	24889	3361	3361	1052	1052

This table presents the estimates of the following regression:

$$\mathrm{r}_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha + \beta \sum_{t=b_i+1}^{s_i} \mathrm{MKT}_t + \theta \sum_{t=b_i+1}^{s_i} \mathrm{SMB}_t + \phi \sum_{t=b_i+1}^{s_i} \mathrm{HML}_t$$

$$+ \lambda \sum_{t=b_i+1}^{s_i} \mathrm{LIQ}_t + \gamma \sum_{t=b_i+1}^{s_i} \mathrm{FAME}_{a,t} + \nu \sum_{t=b_i+1}^{s_i} \mathrm{VOLUME}_{m,t} + \epsilon_i$$

where $\mathrm{r}_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. The variable MKT_t is the world equity excess returns between purchase and sale times, SMB_t and HML_t are the Fama and French (1996) factors and LIQ_t is the Pastor and Stambaugh (2003) liquidity factor. $\mathrm{FAME}_{a,t}$ is the log of the share of mentions in Google Books for artist a at time t. $\mathrm{VOLUME}_{m,t}$ is the volume measure defined in Equation (1) for movement m. The three-stage-generalized-least square RSR estimation of Case and Shiller (1987) is used to estimate the regression for the three samples.
(t-Statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.)

Table VII: The "Pricing" of Volume by Subperiod

	1977-1986	1987-1996	1997-2006
CAPM	0.491***	1.070***	0.393***
	(11.89)	(29.58)	(4.91)
Fama-French	0.556***	0.981***	0.311***
	(13.26)	(26.92)	(3.87)

This table presents the estimates of the following regression:

$$
\mathrm{r}_i - \sum_{t=b_i+1}^{s_i} r_{ft} = \alpha + \beta \sum_{t=b_i+1}^{s_i} \mathrm{MKT}_t + \theta \sum_{t=b_i+1}^{s_i} \mathrm{SMB}_t + \phi \sum_{t=b_i+1}^{s_i} \mathrm{HML}_t
$$

$$
+ \quad \lambda \sum_{t=b_i+1}^{s_i} \mathrm{LIQ}_t + \gamma \sum_{t=b_i+1}^{s_i} \mathrm{FAME}_{a,t}
$$

$$
+ \quad \nu_1 \sum_{t=b_i+1}^{1986} \mathrm{VOLUME}_{m,t} + \nu_2 \sum_{1987}^{1996} \mathrm{VOLUME}_{m,t} + \nu_3 \sum_{1997}^{s_i} \mathrm{VOLUME}_{m,t} + \epsilon_i
$$

where $\mathrm{r}_i = \sum_{t=b_i+1}^{s_i} r_{it}$ is the return on item i between b_i and s_i, computed as the difference between the log of sale price and the log of purchase price and where r_{ft} is the risk free rate. The variable MKT_t is the world equity excess returns between purchase and sale times, SMB_t and HML_t are the Fama and French (1996) factors and LIQ_t is the Pastor and Stambaugh (2003) liquidity factor. $\mathrm{FAME}_{a,t}$ is the log of the share of mentions in Google Books for artist a at time t. $\mathrm{VOLUME}_{m,t}$ is the volume measure defined in Equation 1 for movement m. The variables ν_i, $i = 1 \ldots 3$ measure the impact of volume on excess returns for each sub-period: 1977-1986, 1987-1996 and 1997-2006. The three-stage-generalized-least square RSR estimation of Case and Shiller (1987) is used to estimate the regression for the three samples.
(t-Statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.)

Table VIII: Asymmetric Effects Of Lagged Returns On Volume

	All Movements (1)	High Volatility (2)	Low volatility (3)
	Δ Volume	Δ Volume	Δ Volume
Gains$_{-1}$	0.029	0.072	-0.133
	(0.14)	(0.25)	(-0.55)
Losses$_{-1}$	-0.184**	-0.329***	-0.098
	(-2.37)	(-3.57)	(-0.81)
Δ_{-1} Volume	-0.169**	-0.162*	-0.197**
	(-1.98)	(-1.90)	(-2.32)
Δ_{-1} Stock	0.272	0.466	0.325
	(1.04)	(1.58)	(1.09)
R^2	0.043	0.077	0.053
N	377	87	87

This table reports the estimated coefficients of a regression of volume on lagged returns, which separates positive from negative values of lagged log differences of art prices (gains and losses). The series are constructed from fourth-quarter observations (see Section III.B and Table IV). The "Gains" (respectively "Losses") series correspond to change in price when the latter is positive (respectively negative) and zero otherwise. We report the results for the aggregated art prices and volume (comprising 13 art movements), and for the aggregated three most volatile movements (Pop, Abstract Expressionism, Minimalism and Contemporary art) and the three least volatile art paradigms (Romanticism, Baroque, Rococo). Standard errors are clustered at year and movement level.

(***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.)