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# Monthly art market returns*

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**Abstract**

We provide an innovative methodological contribution to the measurement of returns on infrequently traded assets using a novel approach to repeat-sales regression estimation. The model for price indices we propose allows for correlation with other markets, typically with higher liquidity and high frequency trading. Using the new econometric approach, we propose a monthly art market index, as well as sub-indices for Impressionist, Modern, Post-War, and Contemporary paintings based on repeated sales at a monthly frequency. The correlations enable us to update the art index via observed transactions in other markets that have a link with the art market.

*Keywords*: art index, repeated sales, correlation
*JEL classification*: **C14, C43, Z11**

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# 1 Introduction

The recent financial crises caused by the Lehman bankruptcy and the European sovereign debt problems have increased the interest of safe haven investments. Standard safe haven investments having either no protection against inflation (in the case of bonds) or high volatility (such as gold), investors may have been attracted by alternative assets such as real estate, fine art, or wine. The development of the fine art funds confirms that investors view artworks as just another asset class of investment. This growth was fueled by many factors, including a search by investors for higher yields, entrance into the market of Chinese and emerging markets collectors who are diversifying their acquisitions and investing in art. Practitioners in the field of art-finance require tools to track evolution of prices in the art market. For instance, regulated funds must be able to refresh regularly their Net Asset Value for regulatory purposes, as well as to serve redemptions at fair value to their investors. Insurers equally face challenges to regularly re-assess the insured value of art. According to Deloitte (Picinati di Torcello 2012), the outstanding value of artworks exceeds three trillion dollars globally. The Observer (Grant 2018) reports that hurricane Sandy cost approximately half a billion dollars in damage to artworks in private home and commercial galleries. Regularly tracking movements in the art market is essential for insurers and brokers to properly manage their market risks and re-evaluate insurance premia to their clients. The evaluation of these markets on a higher frequency time scale such as monthly is hampered by the heterogeneity of goods and illiquidity caused by periods of few if any transactions. Nonetheless, a reliable high frequency evaluation is important for optimal investment allocation, risk management, and the understanding of correlation and spill-overs from and to other markets. The purpose of this paper is to introduce a new approach to the construction of monthly art indices. So far, the literature addressed mostly the heterogeneity issue. Two estimation methods are commonly used to construct indices: (1) repeat-sales regression (RSR) and (2) the hedonic regression (HR).

RSR uses prices of individual objects traded at two distinct moments in time. If the characteristics of an object do not change (which is usually the case for collectibles), the heterogeneity issue is bypassed. Goetzmann (1993) constructs a decennial repeated sales index, using 2,809 artworks re-sold at auction from Gerald Reitlinger and Enrique Mayer databases over a period covering 1715 to 1986. Mei and Moses (2002) construct a repeated-sales data set based on auction art price records at the New York Public

Library as well as the Watson Library at the Metropolitan Museum of Art with a total of 4,896 price pairs covering the period 1875-2000. They construct an annual art index to study the risk-return characteristics of paintings which they find compare favorably to those of traditional financial assets, such as stocks and bonds. Korteweg, Kräussl, and Verwijmeren (2016) consider repeat-sales as endogenous by including a hazard model for the probability of a sale. They construct an annual index using 32,928 transactions over the period 1960 to 2013.

The basic idea of the HR method is to regress prices on various attributes of objects (dimensions, artist, subject matter, etc.) and to use time dummies in the regression to obtain "characteristic-free" prices to compute a price index. See e.g. Ginsburgh, Mei, and Moses (2006) for an extensive description of hedonic regressions and their application to the art market.

The main advantage of RSR, compared to HR, is that the estimation of the returns does not require the inclusion of explanatory variables in the model. The main disadvantage of the repeated-sales methodology is the low frequency of available resales pairs, whereas the HR typically allows for more frequent observations thanks to the better availability of data.

We provide an innovative methodological contribution to the measurement of returns on infrequently traded assets using a novel approach to repeat-sales regression estimation. Using the new econometric approach, we propose a monthly art market index, as well as sub-indices for Impressionist, Modern, Post-War, and Contemporary paintings based on repeated sales at a monthly frequency. Our starting point is a model proposed by Bocart and Hafner (2015). We address the question by extending a recently proposed dynamic state space model - inspired by Aruoba, Diebold, and Scotti (2009) - for price indices of heterogeneous goods to allow for correlation with other markets, typically with higher liquidity and high frequency trading. Ignoring correlation would lead to flat indices in times of no transactions, as is common in the art markets due to strong biannual cycle of auctions. A precise estimation of correlation enables us to update the art index via observed transactions in other markets that have a link with the art market. In statistical terms, this improves the efficiency of estimated price indices.

In particular, the construction of the monthly index exploits links of art with other assets available at higher frequencies such as liquid Exchange Traded Funds focusing on consumer goods or real estate, baskets of art-related companies (Sotheby's, artnet, artprice, etc.) or furniture companies, and safe haven assets like gold or U.S. Treasuries.

The paper is organized as follows. In section 2 we present the econometric model specification and estimation. Empirical findings for the five price indices: Impressionist art, Modern art, Post-War art and Contemporary art and finally a Global art market index are reported in section 3. In section 4 we study art as an asset class and report standard asset pricing model estimates for the various art market indices. A final section concludes the paper.

# 2 Model Specification and Estimation

Our objective is to construct a monthly art index from repeated sales which are observed on an irregular time scale. Let $Y_{it}$ denote the log price of an artwork $i$ sold at time $t$, with $N$ denoting the total number of artworks in the sample. The repeated sales methodology requires that each artwork $i$ has been traded at least twice over the sample period, otherwise it is excluded from the sample. At date $t$, let $n_t$ be the total number of transactions, which may be zero, so that $0 \leq n_t \leq N$. The transactions are collected in the vector $Y_t = (Y_{1t}, \ldots, Y_{Nt})'$, where missing observations are skipped, so that $Y_t$ is of dimension $(n_t \times 1)$. Additional to these prices we observe $G_t$, a $K$-vector of observed prices of traded assets that are related to the art market, or other quantitative information that is presumed to be related. For example, $G_t$ could contain the price of a basket of stocks listed on a stock exchange whose constituents have business in the art market (e.g. Sotheby's, artnet, artprice, etc.), or say the price of gold or other precious metal. In general, $G_t$ will be non-stationary, e.g. a random walk in the case of stock prices. For our purposes we transform $G_t$ to obtain a stationary sequence $g_t$, e.g. taking log-returns.

## 2.1 Model specification

The model consists of the following system of equations:

$$Y_{it} = \alpha_i + \beta_t + u_{it}, \quad t = 1, \ldots, T; \quad i = 1, \ldots N \tag{1}$$

$$\beta_t = \beta_{t-1} + \nu + \xi_t \tag{2}$$

$$g_t = \mu_t + \varepsilon_t \tag{3}$$

$$\begin{pmatrix} u_t \\ \xi_t \\ \varepsilon_t \end{pmatrix} \sim N(0, \Sigma), \quad \Sigma = \begin{pmatrix} \sigma_u^2 I_{n_t} & 0 & 0 \\ 0 & \sigma_\xi^2 & \sigma_{\xi\varepsilon}' \\ 0 & \sigma_{\xi\varepsilon} & \sigma_{\varepsilon\varepsilon} \end{pmatrix} \tag{4}$$

Equation (1) is similar to the models of Bailey, Muth, and Nourse (1963) or Goetzmann (1992) used to estimate real estate returns from repeated sales. Both are special cases of Case and Shiller (1987).[1] The coefficients $\alpha_i$ are fixed effects, specific for each artwork, and invariant over time. The evolution of the market index is determined by the latent process $\beta_t$ which, as specified in equation (2), evolves as a random walk with drift. The system of equations (1)-(2) is essentially a dynamic panel model with random nonstationary time effects and fixed painting-specific effects $\alpha_i$. The panel is unbalanced because missing observations are discarded from equation (1).

Without equation (3), or equivalently with $\sigma_{\xi\varepsilon} = 0$, this model would be a classical repeated sales model. A non-zero covariance $\sigma_{\xi\varepsilon}$ links the price equation (1) for artworks to that of observed asset returns $g_t$ in (3). These observed returns $g_t$ have conditional expectation $\mathrm{E}[g_t|\mathcal{F}_{t-1}] = \mu_t(\phi)$, parameterized by a $p$-vector $\phi$, where $\mathcal{F}_{t-1}$ denotes the information set generated by lagged $Y_{it}$ and $g_t$ up to time $t-1$. That is, $g_t$ could follow e.g. an ARMA-type process, perhaps including lags of observed art returns, or simply follow a random walk.

The error covariance structure imposes zero correlation between the idiosyncratic errors of the repeated sales regression and the remaining error terms. The novelty is the assumption of a potential correlation between the error term of the art market, $\xi_t$, and the error terms of the observed assets, $\varepsilon_t$. This will allow the filter to update the index $\beta_t$ taking into account the observations $g_t$.

While the complete covariance matrix $\Sigma$ has dimension $(n_t + K + 1 \times n_t + K + 1)$ it

[1]The way of writing the repeated sales model in log prices rather than returns facilitates comparison with hedonic regressions and has also been used e.g. by Francke (2010).

should be noted that the matrix features many zero restrictions. In particular, the upper left $n_t \times n_t$ sub-matrix is diagonal with a single parameter governing the homoskedastic errors. In addition the lack of correlation between those innovations and respectively $\xi_t$ and $\varepsilon_t$ imposes another $2((K+1) \times n_t)$ zero restrictions. Hence, we are left with a $(K+1) \times (K+1)$-dimensional sub-matrix of parameters to estimate, with $K$ relatively small.

## 2.2 Estimation

To estimate the model we propose a maximum likelihood estimator combined with the Kalman filter to recover the underlying state variables. Without further constraints, the parameters in the term $\alpha_i + \beta_t + u_{it}$ are not jointly identified. A common practice in repeated sales is to take "first differences", i.e. returns, that eliminate the asset specific effects $\alpha_i$. An equivalent approach is to impose that $\beta_t + u_{it}$ has a mean of zero and to estimate $\alpha_i$ as the average of transaction prices of asset $i$. We follow the second approach, obtain estimates of $\alpha_i$, and of the composite error term $u_{it} + \beta_t$. Then, the model (1) permits the following linear Gaussian state space representation:

$$\begin{aligned} Z_t &= a_{0t}\beta_t + m_t + \eta_t, \quad \eta_t = (\varepsilon_t', u_t')' \\ \beta_t &= \beta_{t-1} + \nu + \xi_t \\ m_t &= (\mu_t', \underbrace{0, \ldots, 0}_{n_t})' \quad a_{0t} = (\underbrace{0, 0 \ldots, 0}_{K}, \underbrace{1, 1, \ldots, 1}_{n_t})' \end{aligned}$$

for $Z_t = (g_t, Y_{1t} - \alpha_1, \ldots, Y_{Nt} - \alpha_N)'$, where $m_t$, $Z_t$ and $a_{0t}$ are vectors of length $n_t + K$.[2] Also, let $a_t = (1, \ldots, 1)'$, a vector of length $n_t$. We denote the following conditional distributions,

$$\begin{aligned} (\beta_t | Z_1, \ldots, Z_{t-1}) &\sim N(\beta_{t|t-1}, \sigma_\beta(t|t-1)) &(5)\\ (\beta_t | Z_1, \ldots, Z_t) &\sim N(\beta_{t|t}, \sigma_\beta(t|t)) &(6)\\ (Z_t | Z_1, \ldots, Z_{t-1}) &\sim N(Z_{t|t-1}, \Sigma_z(t|t-1)). &(7) \end{aligned}$$

For a given set of parameters, the conditional means and variances can be obtained using the following Kalman recursions:

[2] In the vector $Z_t$, missing observations $Y_{it} - \alpha_i$ are discarded, so that this vector is of length $n_t + K$.

1. Prediction step ($t = 1, \ldots, T$)

$$\begin{aligned}
\beta_{t|t-1} &= \nu + \beta_{t-1|t-1} && (8)\\
\sigma^2_\beta(t|t-1) &= \sigma^2_\beta(t-1|t-1) + \sigma^2_\xi && (9)\\
Z_{t|t-1} &= a_{0t}\beta_{t|t-1} + m_t && (10)\\
\Sigma_z(t|t-1) &= \begin{pmatrix} \sigma_{\varepsilon\varepsilon} & \sigma_{\xi\varepsilon} a'_t \\ a_t\sigma'_{\xi\varepsilon} & a_t\sigma^2_\beta(t|t-1)a'_t + \sigma^2_u I_{n_t} \end{pmatrix} && (11)
\end{aligned}$$

2. Correction step ($t = 1, \ldots, T$)

$$\begin{aligned}
\beta_{t|t} &= \beta_{t|t-1} + \sigma^2_\beta(t|t-1)a'_{0t}\Sigma_z^{-1}(t|t-1)(Z_t - Z_{t|t-1}) && (12)\\
\sigma^2_\beta(t|t) &= \sigma^2_\beta(t|t-1) - \sigma^4_\beta(t|t-1)a'_{0t}\Sigma_z^{-1}(t|t-1)a_{0t} && (13)
\end{aligned}$$

3. Smoothing step ($t = T-1, T-2, \ldots, 1$)

   To estimate the underlying state $\beta_t$, one uses the full sample information ($t = 1, \ldots, T$).

$$\begin{aligned}
\beta_{t|T} &= \beta_{t|t} + \frac{\sigma^2_\beta(t|t)}{\sigma^2_\beta(t+1|t)}\left\{\beta_{t+1|T} - \beta_{t+1|t}\right\} && (14)\\
\sigma^2_\beta(t|T) &= \sigma^2_\beta(t|t) + \frac{\sigma^4_\beta(t|t)}{\sigma^4_\beta(t+1|t)}\left\{\sigma^2_\beta(t+1|T) - \sigma^2_\beta(t+1|t)\right\} && (15)
\end{aligned}$$

The second term on the right hand side of the updating equation for $\beta_t$ in (12) would be zero if $\sigma_{\xi\varepsilon}$ were zero, because then $\Sigma_z(t|t-1)$ and its inverse would be block-diagonal. With $\sigma_{\xi\varepsilon} \neq 0$, however, the updating of $\beta_t$ will depend on this correlation, and on the prediction error of returns $g_t$. The above steps assume that $n_t \geq 1$, so that at each time $t$ we have at least one transaction in the art market. For the case where $n_t = 0$, we use a fictitious art transaction whose log price corresponds exactly to its prediction $\beta_{t|t-1}$[3]. This

[3]In our empirical example, this occurs in only five months of a total 189 months covered by the sample.

ensures that, in times of no activity in the art market, the market index is still updated via the second term in (12).

Parameter estimation can be achieved in an efficient and straightforward way by maximum likelihood. Denote the parameter vector by $\theta = (\nu, \phi, \sigma_\xi^2, \sigma_u^2, \sigma_{\xi\varepsilon}, \sigma_{\varepsilon\varepsilon})$ and corresponding parameter space $\Theta$, which is $K(K+1)+p+3$-dimensional. Let $e_t(\theta) = Z_t - Z_{t|t-1}$ and $\Sigma_t(\theta) = \Sigma_z(t|t-1)$. Then, the log-likelihood, up to an additive constant, can be written as

$$L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left\{\ln(|\Sigma_t(\theta)|) + e_t(\theta)'\Sigma_t(\theta)^{-1}e_t(\theta)\right\} \tag{16}$$

and the maximum likelihood estimator is defined as

$$\hat{\theta} = \arg\max_{\theta\in\Theta} L(\theta).$$

The maximization problem has no analytical solution, but numerical methods can be used conveniently.

Simplifications are possible by assuming that $\mathcal{F}_t = \sigma(g_t, g_{t-1}, \ldots)$, so that the conditional mean of $g_t$ only depends on its own history. In that case, one can estimate $\phi$ and $\sigma_{\varepsilon\varepsilon}$ separately in a first step. In the second step, the dimension of $\theta$ reduces to $K + p + 2$. One has to impose restrictions on $\sigma_{\xi\varepsilon}$ that keep $\Sigma$ positive definite, but this is easier to achieve than a simultaneous estimation of $\theta$ if $K$ is large.

# 3 Empirical Findings

Our goal is to compute five price indices. Four of them correspond to the most important periods of recent art history: Impressionist art, Modern art, Post-War art and Contemporary art. A fifth index is built, merging all movements into a global art market index. For each category, we select the 50 artists that exhibited the largest monetary volumes of paintings sold at auction between January 2002 and September 2017. Art data and categorization of artists by movements are provided by artnet A.G. These 200 artists represent 49,641 lots sold at auction for a total amount of \$43.9 billion. However, only 3059 artworks by these artists were sold at multiple intervals between January 2002 and September 2017, for a total of \$6.9 billion in repeated sales. Prices include the buyer's premium, i.e. transaction costs.

To help estimating the evolution of prices of each art category, several liquid assets are selected: the S&P 500 index, the iShares U.S. consumer goods ETF, the iShares U.S. real estate ETF, the iShares $20^+$ years treasury ETF, the spot price of the gold bullion, the West Texas Intermediate spot price, an equally-weighted basket of art-related companies consisting of Sotheby's, artnet A.G., artprice S.A. and Collector Universe Inc., an equally-weighted basket of furniture-related companies.[4] Finally, we also construct equally-weighted basket of the following luxury companies: Dior S.A., Moët Hennessy Louis Vuitton SE and Kering. All data are provided by Yahoo! Finance, except the Gold Fixing Price in London Bullion Market in USD and the West Texas Intermediate spot price that are provided by the Federal Reserve Bank of St. Louis.

As discussed in the previous section, the index is computed in two steps. First, the conditional means $\mu_t(\phi)$ of financial asset returns are separately estimated as the six months moving average of log price returns for each of the listed assets. This also gives an estimator of $\sigma_{\varepsilon\varepsilon}$, the variance-covariance matrix of the error term $\varepsilon_t$. The painting-specific effects $\alpha_i$ are estimated as the average log transaction prices of each painting. In a second step, parameters of the Kalman filter are estimated via maximum likelihood.

Figure 1 illustrates the five price indices: Impressionist art, Modern art, Post-War art and Contemporary art and the solid line representing the Global art market index. Overall, we observe a rise of the indices up until the recent financial crisis. Starting roughly 2009 we also observe for the Global art index as well as some of the sub-indices an upward trend. A notable exceptions are the Impressionist art index and to a certain degree Modern art as well, which are mostly flat since the financial crisis. In contrast, we note a strong performance of both the Contemporary and Post War indices.

Since the inclusion of financial market information is relevant only in case of non-zero correlation, we proceed to maintain candidates that exhibit a correlation of at least 10% in absolute value between their monthly log-returns and the art index's monthly log-returns. The empirical results appear in the middle panel of Table 1.

Out of the different assets selected, only a few exhibit correlation with art: S&P500, art companies, real estate ETF and luxury companies exhibit a positive correlation in their returns with those of the global art index, ranging from 12% for luxury companies to 25% for the basket of art-related companies. Gold returns on the other hand are

[4]These companies are Bassett Furniture Industries Inc., Stanley Furniture Co., Leggett & Platt Inc., Lazboy Inc., Haverty Furniture Companies Inc., and American Woodmark Corp

negatively correlated with returns of the global art index. As expected, all art movements positively correlate with the monthly stock returns of art companies.

Monthly returns of the contemporary art index seem to correlate negatively with those of luxury companies (-14%), a result a priori counter-intuitive since one would expect luxury contemporary art to correlate positively with performance of luxury companies. A possible explanation would be substitution effect between different types of luxury goods, highlighting a switch in demand for luxury goods sold in shops and galleries to the ones sold at second hand auctions.

Monthly returns of Post-War art correlate with those of the S&P 500 but also with furniture companies, a sign that prices of artworks by artists like Andy Warhol and Roy Lichtenstein may benefit from increased spendings in interior decoration. Modern Art returns present a positive correlation with real estate ETF returns, indicating a co-movement between blue chip Modern artists such as Pablo Picasso or Joan Miro and the real estate sector. A few asset classes do not exhibit any form of correlation with any of the art movements: returns of the iShares U.S. consumer goods ETF, the West Texas Intermediate (oil price) and US treasury bonds do not comove with those of artworks. Impressionist art, that correlates positively with art companies, has the lowest Sharpe ratio (0.02) given an annualized return close to zero for a volatility (12%) similar to Contemporary Art (11%) or the S&P 500 (14%).

The lower panel of Table 1 displays the correlations among the different art indices. The Global index correlates most with Post War and Modern. Correlations among the sub-indices is at most 27 %, namely between Post War and Modern.

In Table 2 we report the correlation of the Global art index with the 49 industry portfolios retrieved from the Ken French webpage. We report results for three samples. Besides the full sample, we report a pre-crisis sample which ends in August 2008, and a post-crisis sample starting in September 2008 and ending in September 2017. The industries are ranked from high correlations to low, using the full sample results. We observe that the top of the list is the beer and liquor industry with a correlation of roughly 27 %. The other toppers are quite heterogeneous. It includes banking and trading, but also "other" which stands for anything not listed in the 48 other industries, rubber and plastic, candy and soda and retail, personal services, business supplies and services. The pre-crisis sample features smaller correlations, whereas the opposite is the case for the post-crisis sample. In fact, the highest correlation for the latter is again beer and liquor and reaches 35 %. The tail end of the list is the precious metals industry with a large negative correlation of 25 % in the pre-crisis sample. This finding relates to the earlier reported correlation of the art indices with gold. In the Appendix we also provide results pertaining to the 49 industry correlations and the sub-indices - see Tables A.1 through A.4. Overall the findings are similar for all but the Contemporary art index, except that typically the correlations are lower that those for the Global art index. The Comtemporary art index appearing in Table A.4 shows a correlation ranking that is quite different. Top industry in the full sample is Fabricated products for example - although that correlation is only 13 %. Finally, almost a third of the industries feature negative correlations with the Contemporary art index.

# 4 Art as an Asset Class

Having art market indices at the monthly frequency brings us in line with the more traditional asset pricing literature. A number of studies have analyzed the infrequently observed auction-based price series. Initial studies include Stein (1977), Baumol (1986), Goetzmann (1993), Buelens and Ginsburgh (1993), Pesando (1993), Chanel (1995), Mei and Moses (2002) and (2005), among others.

Anderson (1974) concluded, using data for the period 1643–1970, that paintings had offered a return that was about fifty percent lower than the return offered by common stocks. Using U.S. and U.K. auction prices for paintings sold between 1946 and 1968, Stein (1977) finds a nominal return of 10.5 % compared to an annual nominal return on stocks of 14.3 % for the same period whereas Baumol (1986), based on records from 640 painting transactions between 1652 and 1961, finds that paintings had a lower return when compared to that of risk-free assets. More recently, Renneboog and Spaenjers (2013), using data covering the period 1957–2007, built an art index that exhibited a modest 3.97 % real annual return expressed in U.S. dollars; that is, a performance similar to that of corporate bonds but with much higher risk. Mandel (2009) also found similar results for the period 1950–1999, namely, that art exhibited returns lower than both the S&P 500 and the Dow Jones industrial index, but with higher volatility.

A traditional explanation for lower returns of art compared to other assets is the “aesthetic dividend”, described by Baumol (1986) and Mandel (2009). The aesthetic dividend theory states that lower returns are compensated by higher utility of holding the work: art collectors enjoy the piece and benefit from the social status associated with art ownership. However, the implied aesthetic dividend differs greatly between Contemporary Art (+6% average annualized return) and Modern Art (+2% average annualized return) or Impressionist Art (0% average annualized return). It appears that older art movements lead to lower short term returns. Arguably, artworks distributing the highest aesthetic dividend should also be the ones in higher demand for their aesthetic characteristics. It is expected that these works in high demand would also exhibit higher liquidity at auction. As a consequence, one should observe lower bought-in rates [5] for these older artworks. However, the opposite is observed: it seems that not only Contemporary Art outperforms its peers in terms of returns, but it has also been more successful at auction in the period 2003-2017, with only 20% of lots failing to sell compared to 25% for Modern artists or 26% for Impressionist masters. This contradiction cannot be easily reconciled with the notion of aesthetic dividend that suggests artworks have low returns when they are highly desirable. One could conjecture that another mechanism is behind these lower returns for older artists: these more established artists, like Renoir, Manet or Gauguin, though less fashionable[6] have a proven track record of surviving trends and fashion cycles throughout history. Established masters may offer more guarantees of a future resale, on time horizons untested by the scope of our data set. In a nutshell, it can be conjectured that a basket of contemporary artists in the 21st century may be more risky to hold over long periods of time than a basket of established Impressionist or Modern artists. In other words, even though volatility of short term returns may be similar between Impressionism and Contemporary Art, liquidity risks borne by art investors on much lower time frequencies (typically, decades or even centuries) could justify lower short term returns. This hypothesis is supported by Vermeylen, van Dijck, and de Laet (2013) who track canon formation for Flemish and Dutch painters from the 17th century. The authors highlight the high volatility in market preferences through time. They observe that many artists believed to be contemporary canons at different periods "fell through the cracks of history".

Buelens and Ginsburgh (1993) use a hedonic regression approach and find the conclusions of Baumol overly pessimistic. In a similar vein, Goetzmann (1993) finds that

[5] the bought-in rate is defined as the proportion of works that do not meet the reserve price at auction and are left unsold

[6] according to their higher bought-in rate

paintings investment had an annual appreciation of 17.5 % between 1900 and 1986, while the London Stock Exchange index had a return of merely 4.9 % over the same period. Likewise, Mei and Moses (2002) report that the returns on art works is higher than returns on fixed-income assets and equivalent to returns on equities – while featuring higher volatility. Renneboog and Spaenjers (2013) provide a comprehensive literature review regarding art returns. Using a hedonic price index based on 1.1 million auction transactions, they find that art has a lower Sharpe ratio than equities. Oosterlinck (2016) finds that art outperformed all other asset classes in occupied Paris in 1940-1944, suggesting that art may be a good hedge against low probability disasters.

The above discussion highlights the fact that there are a wide range of results, many contradictory, regarding the performance of art as an asset class. Although a somewhat uniform verdict emerges from the literature: art returns associated with paintings do not appear attractive when compared with stocks and bonds.

Our new indices allow us to shed new light on the asset pricing implications of art holdings. We start with the top panel of Table 1. We note that the annualized returns of the art indices are all below the 8 % for the S&P 500 over the full sample. The best returns are obtained with Contemporary and Post War art. The most dismal performance is Impressionist art. In terms of volatility and Sharpe ratio we note Contemporary art appears to perform almost as well as the S&P 500. Nevertheless, Art and Luxury goods companies show better performance numbers that any of the art indices. Interestingly, real estate is not as attractive as Contemporary and Post War art when one compares their Sharpe ratios.

Next we turn our attention to Table 3 in which CAPM parameter estimates are reported for the full sample as well as the pre- and post-crisis subsamples. The results show that the beta estimates are low, most between .10 and .15. The Impressionist art index features a negative beta, except post-crisis. The most remarkable results is the Contemporary art index. In the full sample it has a zero beta and an alpha of .38 - implying about a 4.5 % annual return. However, in the pre-crisis sample the alpha increases to almost one - or a 12 % annual return, with a slightly negative beta. This looks more like the performance of a respectable hedge fund. In the post-crisis sample, this stellar performance totally disappeared however. Tables 4 and 5 paint a similar picture. They report time-series regressions of the monthly returns associated with each art index on respectively the Fama and French (1993) three factors (Table 4) and the same three factors augmented with the momentum factor (UMD) of Carhart (1997) and the liquidity factor (PS) of Pástor and Stambaugh (2003). Note that these results imply that the art market index returns cannot be explained by standard equity momentum or liquidity risk factors.

# 5 Conclusions

We provide an innovative methodological contribution to the measurement of returns on infrequently traded assets using a novel approach to repeat-sales regression estimation. Our starting point is a model proposed by Bocart and Hafner (2015). We address the question by extending a recently proposed dynamic state space model - inspired by Aruoba, Diebold, and Scotti (2009) - for price indices of heterogeneous goods to allow for correlation with other markets, typically with higher liquidity and high frequency trading.

Leaving the artistic and aesthetic value of paintings aside, there is a growing interest in the investment value of art. The new econometric methodology allows us to estimate a monthly art market index, as well as sub-indices for Impressionist, Modern, Post-War, and Contemporary paintings based on repeated sales at a monthly frequency.

In terms of volatility and Sharpe ratio we find that Contemporary art appears to perform almost as well as the S&P 500. Nevertheless, Art and Luxury goods companies show better performance numbers that any of the art indices. Interestingly, real estate is not as attractive as Contemporary and Post War art when one looks at their Sharpe ratios. The most remarkable result is the Contemporary art market index. In a sample up to the financial crisis the alpha and beta of the index feature the performance of a respectable hedge fund. None of the art index returns load significantly on momentum or liquidty factors, let alone the Fama-French factors.

The methodology proposed in the current paper has many other applications in markets with features similar to those of the art market. In particular, markets where trading occurs infrequently during periodically scheduled auctions and one observes frequently traded related assets. Examples include wine, rare coins, stamps and other collectibles.

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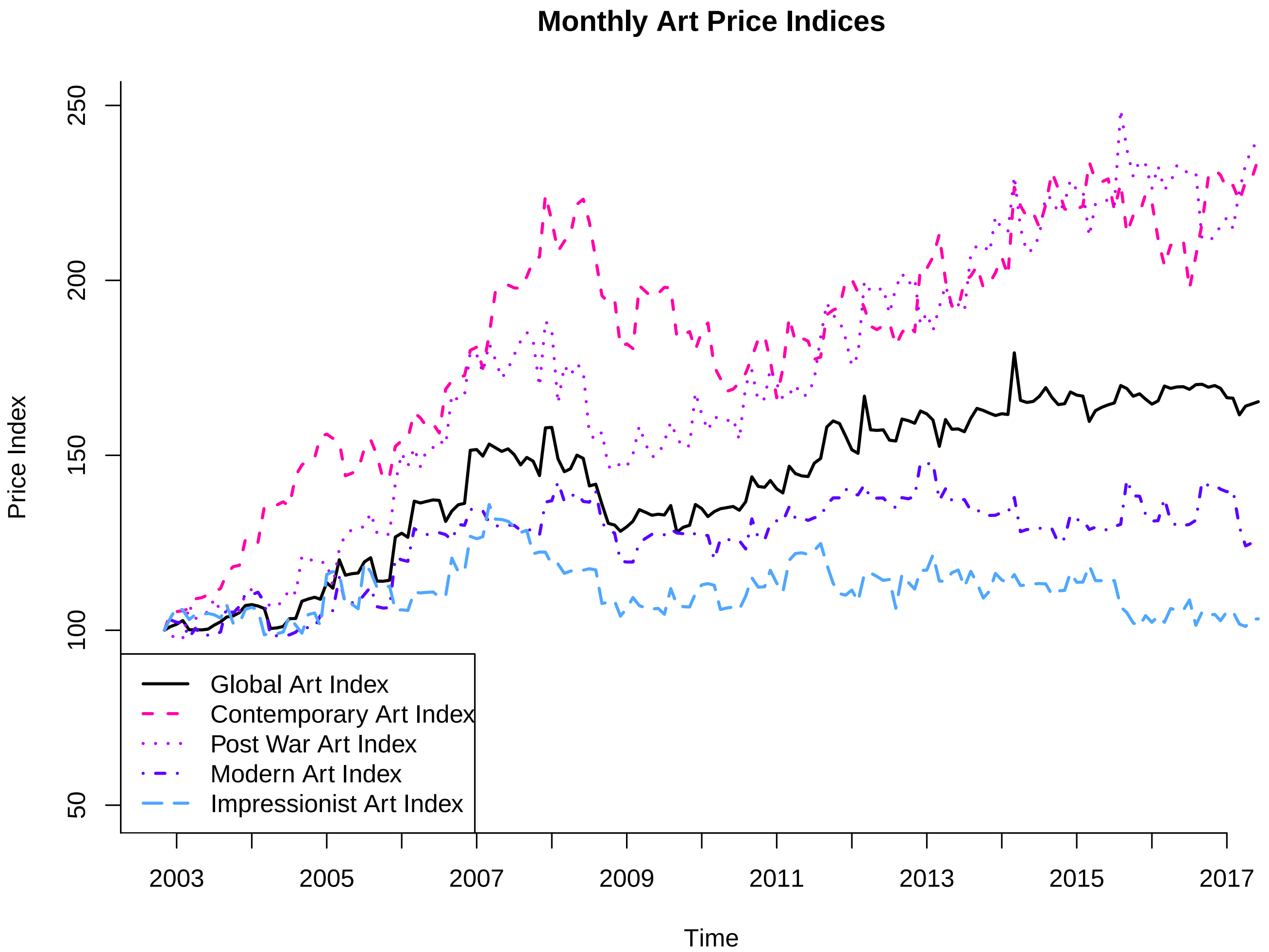


Figure 1: Art Indices

| | S&P500 | Gold | Art Co | Real Estate ETF | Luxury Co | Furniture Co | Global Art Index | Contemporary Art Index | Post War Art Index | Modern Art Index | Impressionist Art Index |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Annualized returns | 0.08 | 0.10 | 0.20 | 0.10 | 0.17 | 0.09 | 0.04 | 0.06 | 0.06 | 0.02 | 0.00 |
| Annualized volatility | 0.14 | 0.18 | 0.33 | 0.23 | 0.24 | 0.26 | 0.10 | 0.11 | 0.14 | 0.10 | 0.12 |
| Sharpe ratio | 0.56 | 0.53 | 0.62 | 0.43 | 0.71 | 0.36 | 0.37 | 0.52 | 0.46 | 0.16 | 0.02 |
| Bought-in rate | | | | | | | 0.23 | 0.19 | 0.20 | 0.25 | 0.26 |
| Correlations | | | | | | | | | | | |
| S&P500 | 1.00 | -0.14 | 0.46 | 0.74 | 0.63 | 0.63 | **0.22** | 0.00 | **0.18** | **0.12** | -0.00 |
| Gold | | 1.00 | 0.01 | -0.14 | -0.02 | -0.03 | **-0.22** | 0.02 | 0.07 | **-0.24** | -0.03 |
| Art Co | | | 1.00 | 0.39 | 0.38 | 0.27 | **0.25** | **0.12** | **0.15** | **0.19** | **0.14** |
| Real Estate | | | | 1.00 | 0.51 | 0.56 | **0.15** | -0.03 | 0.07 | **0.10** | -0.07 |
| Luxury Co | | | | | 1.00 | 0.44 | **0.12** | **-0.14** | 0.08 | 0.07 | 0.01 |
| Furniture Co | | | | | | 1.00 | 0.08 | 0.07 | **0.15** | 0.07 | **-0.11** |
| Art Indices | | | | | | | | | | | |
| Global | | | | | | | 1.00 | **0.34** | **0.62** | **0.61** | **0.34** |
| Contemporary | | | | | | | | 1.00 | **0.13** | **0.27** | **0.15** |
| Post War | | | | | | | | | 1.00 | 0.09 | 0.07 |
| Modern | | | | | | | | | | 1.00 | **0.21** |

Table 1: Returns, volatility and correlation of the price indices

Table 2: The table reports the Pearson correlation between the Global Art Index and each of the Fama and French 49 industry groups over three time periods. Full sample refers to correlations computed using monthly data ranging from 2002:04 to 2017:09, Pre-crisis correlations are computed using data ranging from 2002:04 to 2008:08, and Post-crisis correlations are computed using data ranging from 2008:09 to 2017:09.

| **Industry** | **Full sample** | **Pre-crisis** | **Post-crisis** | **Industry** | **Full sample** | **Pre-crisis** | **Post-crisis** |
|---|---|---|---|---|---|---|---|
| Beer & Liquor | 0.27 | 0.19 | 0.35 | Electronic Equipment | 0.15 | 0.13 | 0.19 |
| Other | 0.25 | 0.22 | 0.29 | Computer Software | 0.15 | 0.11 | 0.21 |
| Banking | 0.23 | 0.18 | 0.27 | Construction | 0.15 | -0.01 | 0.27 |
| Rubber & Plastic Products | 0.22 | 0.17 | 0.27 | Medical Equipment | 0.15 | 0.01 | 0.24 |
| Trading | 0.21 | 0.18 | 0.24 | Utilities | 0.15 | 0.00 | 0.28 |
| Personal Services | 0.21 | 0.09 | 0.29 | Electrical Equipment | 0.15 | 0.02 | 0.23 |
| Candy & Soda | 0.21 | 0.28 | 0.16 | Restaurants, Hotels, Motels | 0.14 | 0.08 | 0.21 |
| Retail | 0.20 | 0.21 | 0.22 | Shipbuilding, Railroad Equipment | 0.14 | -0.01 | 0.23 |
| Business Supplies | 0.20 | 0.08 | 0.30 | Chemicals | 0.14 | 0.00 | 0.22 |
| Business Services | 0.20 | 0.09 | 0.29 | Agriculture | 0.14 | -0.01 | 0.22 |
| Insurance | 0.19 | 0.11 | 0.26 | Shipping Containers | 0.13 | 0.06 | 0.19 |
| Communication | 0.19 | 0.15 | 0.24 | Steel Works, etc. | 0.13 | 0.02 | 0.21 |
| Real Estate | 0.19 | 0.23 | 0.19 | Petroleum & Natural Gas | 0.13 | -0.03 | 0.25 |
| Construction Materials | 0.19 | 0.08 | 0.26 | Pharmaceutical Products | 0.13 | 0.02 | 0.22 |
| Transportation | 0.19 | 0.09 | 0.26 | Recreation | 0.12 | 0.14 | 0.12 |
| Food Products | 0.19 | 0.13 | 0.24 | Non-Metallic & Industrial Metal Mining | 0.12 | -0.05 | 0.22 |
| Wholesale | 0.18 | 0.13 | 0.22 | Apparel | 0.11 | 0.20 | 0.07 |
| Automobiles & Trucks | 0.18 | 0.13 | 0.22 | Computers | 0.11 | 0.06 | 0.16 |
| Entertainment | 0.17 | 0.18 | 0.19 | Aircraft | 0.11 | -0.01 | 0.20 |
| Printing & Publishing | 0.17 | 0.06 | 0.25 | Textiles | 0.09 | 0.04 | 0.12 |
| Measuring & Control Equipment | 0.17 | 0.09 | 0.25 | Defense | 0.06 | -0.13 | 0.22 |
| Machinery | 0.16 | 0.04 | 0.25 | Coal | 0.06 | -0.19 | 0.21 |
| Fabricated Products | 0.16 | 0.06 | 0.23 | Tobacco Products | 0.03 | -0.03 | 0.10 |
| Consumer Goods | 0.16 | 0.08 | 0.21 | Precious Metals | -0.01 | -0.25 | 0.14 |
| Healthcare | 0.16 | 0.10 | 0.20 | | | | |

Table 3: The table reports the results of time-series regressions of the monthly returns associated with each art index on the excess returns of the value-weighted market portfolio (MKTRF). $\alpha$ is expressed as a percentage per month and Newey-West $t$-statistics are reported in parentheses. Note that returns for the Contemporary Art Index begin in 2002:07.

| **Art index** | $\alpha$ | *MKTRF* | $R^2$ |
|---|---|---|---|
| Full sample: 2002:04 to 2017:09 | | | |
| Global | 0.064 | 0.145 | 0.048 |
| | (0.322) | (3.042) | |
| Impressionist | 0.034 | -0.034 | 0.002 |
| | (0.135) | (-0.580) | |
| Modern | -0.102 | 0.105 | 0.022 |
| | (-0.469) | (2.034) | |
| Post War | 0.199 | 0.158 | 0.029 |
| | (0.702) | (2.339) | |
| Contemporary | 0.377 | 0.003 | 0.000 |
| | (1.545) | (0.058) | |
| Pre-crisis: 2002:04 to 2008:08 | | | |
| Global | 0.243 | 0.103 | 0.016 |
| | (0.716) | (1.090) | |
| Impressionist | 0.246 | -0.160 | 0.025 |
| | (0.594) | (-1.387) | |
| Modern | 0.030 | 0.172 | 0.038 |
| | (0.084) | (1.716) | |
| Post War | 0.326 | 0.043 | 0.002 |
| | (0.708) | (0.340) | |
| Contemporary | 0.914 | -0.088 | 0.012 |
| | (2.783) | (-0.939) | |
| Post-crisis: 2008:09 to 2017:09 | | | |
| Global | -0.076 | 0.168 | 0.085 |
| | (-0.312) | (3.147) | |
| Impressionist | -0.152 | 0.027 | 0.002 |
| | (-0.499) | (0.402) | |
| Modern | -0.182 | 0.079 | 0.016 |
| | (-0.668) | (1.328) | |
| Post War | 0.078 | 0.211 | 0.064 |
| | (0.217) | (2.699) | |
| Contemporary | -0.004 | 0.049 | 0.004 |
| | (-0.012) | (0.659) | |

Table 4: The table reports the results of time-series regressions of the monthly returns associated with each art index on the Fama and French (1993) three factors. $\alpha$ is expressed as a percentage per month and Newey-West $t$-statistics are reported in parentheses. Note that returns for the Contemporary Art Index begin in 2002:07.

| **Art index** | $\alpha$ | *MKTRF* | *SMB* | *HML* | $R^2$ |
|---|---|---|---|---|---|
| | | Full sample: 2002:04 to 2017:09 | | | |
| Global | 0.059 | 0.131 | 0.056 | 0.029 | 0.051 |
| | (0.293) | (2.563) | (0.633) | (0.352) | |
| Impressionist | 0.052 | -0.011 | -0.162 | 0.043 | 0.014 |
| | (0.210) | (-0.175) | (-1.473) | (0.427) | |
| Modern | -0.109 | 0.099 | 0.054 | -0.029 | 0.024 |
| | (-0.497) | (1.788) | (0.563) | (-0.329) | |
| Post War | 0.179 | 0.127 | 0.177 | -0.006 | 0.040 |
| | (0.633) | (1.758) | (1.418) | (-0.053) | |
| Contemporary | 0.382 | -0.051 | 0.155 | 0.161 | 0.027 |
| | (1.578) | (-0.810) | (1.399) | (1.629) | |
| | | Pre-crisis: 2002:04 to 2008:08 | | | |
| Global | 0.202 | 0.101 | 0.053 | 0.078 | 0.020 |
| | (0.576) | (1.018) | (0.358) | (0.423) | |
| Impressionist | 0.385 | -0.116 | -0.350 | -0.083 | 0.081 |
| | (0.925) | (-0.989) | (-1.997) | (-0.378) | |
| Modern | 0.001 | 0.155 | 0.111 | -0.022 | 0.044 |
| | (0.004) | (1.480) | (0.709) | (-0.112) | |
| Post War | 0.228 | 0.038 | 0.124 | 0.185 | 0.016 |
| | (0.483) | (0.285) | (0.623) | (0.747) | |
| Contemporary | 0.892 | -0.103 | 0.076 | 0.033 | 0.016 |
| | (2.654) | (-1.018) | (0.494) | (0.183) | |
| | | Post-crisis: 2008:09 to 2017:09 | | | |
| Global | -0.077 | 0.161 | 0.045 | -0.009 | 0.086 |
| | (-0.309) | (2.622) | (0.405) | (-0.099) | |
| Impressionist | -0.143 | 0.022 | -0.017 | 0.034 | 0.002 |
| | (-0.460) | (0.293) | (-0.121) | (0.298) | |
| Modern | -0.187 | 0.082 | 0.005 | -0.017 | 0.017 |
| | (-0.676) | (1.198) | (0.039) | (-0.171) | |
| Post War | 0.052 | 0.198 | 0.197 | -0.117 | 0.082 |
| | (0.145) | (2.222) | (1.204) | (-0.877) | |
| Contemporary | 0.059 | -0.029 | 0.202 | 0.166 | 0.038 |
| | (0.174) | (-0.345) | (1.315) | (1.320) | |

Table 5: The table reports the results of time-series regressions of the monthly returns associated with each art index on the Fama and French (1993) three factors augmented with the momentum factor (UMD) of Carhart (1997) and the liquidity factor (PS) of Pástor and Stambaugh (2003). $\alpha$ is expressed as a percentage per month and Newey-West $t$-statistics are reported in parentheses. Note that returns for the Contemporary Art Index begin in 2002:07.

| **Art index** | $\alpha$ | *MKTRF* | *SMB* | *HML* | *UMD* | *PS* | $R^2$ |
|---|---|---|---|---|---|---|---|
| | | | Full sample: 2002:04 to 2017:09 | | | | |
| Global | 0.116 | 0.152 | 0.079 | 0.026 | 0.039 | -0.053 | 0.062 |
| | (0.511) | (2.534) | (0.769) | (0.252) | (0.749) | (-0.837) | |
| Impressionist | 0.073 | -0.043 | -0.135 | 0.103 | -0.021 | 0.015 | 0.016 |
| | (0.267) | (-0.590) | (-1.091) | (0.823) | (-0.328) | (0.195) | |
| Modern | -0.051 | 0.147 | 0.060 | -0.025 | 0.081 | -0.017 | 0.048 |
| | (-0.222) | (2.418) | (0.579) | (-0.238) | (1.540) | (-0.270) | |
| Post War | 0.193 | 0.189 | 0.153 | 0.088 | 0.142 | -0.036 | 0.066 |
| | (0.620) | (2.302) | (1.100) | (0.622) | (2.006) | (-0.416) | |
| Contemporary | 0.383 | -0.050 | 0.128 | 0.204 | 0.047 | 0.002 | 0.031 |
| | (1.462) | (-0.708) | (1.049) | (1.683) | (0.788) | (0.026) | |
| | | | Pre-crisis: 2002:04 to 2008:08 | | | | |
| Global | 0.301 | 0.121 | 0.057 | 0.081 | 0.007 | -0.096 | 0.028 |
| | (0.791) | (0.991) | (0.372) | (0.430) | (0.073) | (-0.753) | |
| Impressionist | 0.571 | -0.123 | -0.319 | -0.095 | -0.047 | -0.148 | 0.098 |
| | (1.274) | (-0.854) | (-1.750) | (-0.428) | (-0.417) | (-0.984) | |
| Modern | 0.041 | 0.170 | 0.109 | -0.018 | 0.013 | -0.044 | 0.046 |
| | (0.101) | (1.316) | (0.665) | (-0.088) | (0.124) | (-0.324) | |
| Post War | 0.204 | 0.144 | 0.068 | 0.229 | 0.146 | -0.059 | 0.034 |
| | (0.402) | (0.879) | (0.327) | (0.909) | (1.135) | (-0.346) | |
| Contemporary | 0.984 | -0.107 | 0.093 | 0.018 | -0.028 | -0.077 | 0.024 |
| | (2.717) | (-0.877) | (0.581) | (0.096) | (-0.307) | (-0.624) | |
| | | | Post-crisis: 2008:09 to 2017:09 | | | | |
| Global | -0.024 | 0.180 | 0.100 | -0.022 | 0.051 | -0.056 | 0.106 |
| | (-0.078) | (2.448) | (0.698) | (-0.156) | (0.798) | (-0.708) | |
| Impressionist | -0.062 | -0.031 | 0.038 | 0.226 | 0.008 | 0.089 | 0.028 |
| | (-0.172) | (-0.360) | (0.223) | (1.357) | (0.106) | (0.944) | |
| Modern | -0.063 | 0.130 | 0.032 | 0.026 | 0.127 | -0.007 | 0.079 |
| | (-0.216) | (1.854) | (0.232) | (0.196) | (2.085) | (-0.094) | |
| Post War | 0.132 | 0.231 | 0.234 | -0.038 | 0.130 | -0.060 | 0.111 |
| | (0.311) | (2.266) | (1.168) | (-0.191) | (1.469) | (-0.539) | |
| Contemporary | 0.039 | -0.037 | 0.169 | 0.282 | 0.088 | 0.025 | 0.050 |
| | (0.100) | (-0.388) | (0.908) | (1.549) | (1.077) | (0.246) | |

# APPENDIX

Table A.1: The table reports the Pearson correlation between the Impressionist Art Index and each of the Fama and French 49 industry groups over three time periods. Full sample refers to correlations computed using monthly data ranging from 2002:04 to 2017:09, Pre-crisis correlations are computed using data ranging from 2002:04 to 2008:08, and Post-crisis correlations are computed using data ranging from 2008:09 to 2017:09.

| **Industry** | **Full sample** | **Pre-crisis** | **Post-crisis** | **Industry** | **Full sample** | **Pre-crisis** | **Post-crisis** |
|---|---|---|---|---|---|---|---|
| Beer & Liquor | 0.07 | 0.06 | 0.10 | Trading | -0.05 | -0.10 | -0.01 |
| Banking | 0.05 | 0.02 | 0.08 | Electronic Equipment | -0.06 | -0.13 | 0.04 |
| Fabricated Products | 0.05 | -0.17 | 0.18 | Business Services | -0.06 | -0.16 | 0.03 |
| Other | 0.05 | 0.05 | 0.05 | Candy & Soda | -0.06 | 0.02 | -0.12 |
| Agriculture | 0.04 | -0.07 | 0.09 | Computers | -0.06 | -0.11 | -0.02 |
| Healthcare | 0.01 | -0.09 | 0.09 | Pharmaceutical Products | -0.06 | -0.09 | -0.02 |
| Printing & Publishing | 0.01 | -0.05 | 0.06 | Tobacco Products | -0.06 | -0.07 | -0.06 |
| Entertainment | 0.00 | -0.10 | 0.06 | Computer Software | -0.06 | -0.13 | 0.01 |
| Insurance | -0.01 | 0.00 | 0.00 | Transportation | -0.07 | -0.24 | 0.05 |
| Precious Metals | -0.01 | -0.24 | 0.13 | Coal | -0.07 | -0.34 | 0.09 |
| Business Supplies | -0.02 | -0.16 | 0.08 | Machinery | -0.07 | -0.25 | 0.03 |
| Chemicals | -0.02 | -0.15 | 0.05 | Aircraft | -0.08 | -0.21 | 0.03 |
| Consumer Goods | -0.02 | -0.15 | 0.06 | Textiles | -0.08 | -0.19 | -0.02 |
| Food Products | -0.02 | -0.08 | 0.03 | Retail | -0.08 | -0.16 | 0.00 |
| Real Estate | -0.02 | -0.16 | 0.04 | Measuring & Control Equipment | -0.08 | -0.21 | 0.04 |
| Automobiles & Trucks | -0.03 | -0.15 | 0.06 | Restaurants, Hotels, Motels | -0.08 | -0.15 | -0.01 |
| Personal Services | -0.03 | -0.13 | 0.03 | Non-Metallic & Industrial Metal Mining | -0.09 | -0.27 | 0.01 |
| Defense | -0.03 | -0.12 | 0.04 | Construction | -0.09 | -0.24 | 0.03 |
| Utilities | -0.04 | -0.14 | 0.05 | Electrical Equipment | -0.09 | -0.23 | -0.01 |
| Medical Equipment | -0.04 | -0.15 | 0.02 | Wholesale | -0.10 | -0.22 | -0.02 |
| Construction Materials | -0.04 | -0.18 | 0.03 | Apparel | -0.10 | -0.17 | -0.06 |
| Shipbuilding, Railroad Equipment | -0.04 | -0.29 | 0.08 | Steel Works, etc. | -0.11 | -0.30 | 0.01 |
| Petroleum & Natural Gas | -0.04 | -0.21 | 0.07 | Shipping Containers | -0.12 | -0.20 | -0.07 |
| Rubber & Plastic Products | -0.05 | -0.21 | 0.06 | Recreation | -0.12 | -0.26 | -0.02 |
| Communication | -0.05 | -0.05 | -0.03 | | | | |

Table A.2: The table reports the Pearson correlation between the Modern Art Index and each of the Fama and French 49 industry groups over three time periods. Full sample refers to correlations computed using monthly data ranging from 2002:04 to 2017:09, Pre-crisis correlations are computed using data ranging from 2002:04 to 2008:08, and Post-crisis correlations are computed using data ranging from 2008:09 to 2017:09.

| **Industry** | **Full sample** | **Pre-crisis** | **Post-crisis** | **Industry** | **Full sample** | **Pre-crisis** | **Post-crisis** |
|---|---|---|---|---|---|---|---|
| Beer & Liquor | 0.22 | 0.23 | 0.23 | Computer Software | 0.11 | 0.16 | 0.06 |
| Food Products | 0.22 | 0.10 | 0.32 | Banking | 0.10 | 0.14 | 0.09 |
| Personal Services | 0.21 | 0.17 | 0.23 | Shipping Containers | 0.10 | 0.17 | 0.06 |
| Rubber & Plastic Products | 0.20 | 0.18 | 0.23 | Trading | 0.10 | 0.19 | 0.04 |
| Business Supplies | 0.18 | 0.20 | 0.18 | Candy & Soda | 0.10 | 0.23 | 0.00 |
| Consumer Goods | 0.17 | 0.16 | 0.19 | Computers | 0.09 | 0.14 | 0.05 |
| Wholesale | 0.16 | 0.25 | 0.11 | Chemicals | 0.09 | 0.11 | 0.08 |
| Communication | 0.16 | 0.18 | 0.15 | Construction | 0.09 | 0.07 | 0.10 |
| Agriculture | 0.15 | 0.11 | 0.18 | Restaurants, Hotels, Motels | 0.08 | 0.10 | 0.08 |
| Retail | 0.15 | 0.21 | 0.12 | Machinery | 0.08 | 0.11 | 0.07 |
| Other | 0.15 | 0.18 | 0.14 | Steel Works, etc. | 0.08 | 0.12 | 0.05 |
| Electrical Equipment | 0.14 | 0.20 | 0.11 | Printing & Publishing | 0.08 | 0.09 | 0.10 |
| Transportation | 0.14 | 0.18 | 0.13 | Entertainment | 0.07 | 0.20 | 0.01 |
| Measuring & Control Equipment | 0.13 | 0.12 | 0.15 | Recreation | 0.07 | 0.24 | -0.03 |
| Utilities | 0.13 | 0.02 | 0.23 | Petroleum & Natural Gas | 0.07 | 0.03 | 0.09 |
| Business Services | 0.13 | 0.19 | 0.10 | Medical Equipment | 0.07 | 0.02 | 0.09 |
| Construction Materials | 0.13 | 0.19 | 0.12 | Aircraft | 0.06 | 0.04 | 0.08 |
| Real Estate | 0.12 | 0.27 | 0.08 | Tobacco Products | 0.06 | -0.02 | 0.15 |
| Automobiles & Trucks | 0.12 | 0.16 | 0.11 | Non-Metallic & Industrial Metal Mining | 0.05 | 0.05 | 0.05 |
| Electronic Equipment | 0.11 | 0.20 | 0.03 | Apparel | 0.05 | 0.27 | -0.07 |
| Healthcare | 0.11 | 0.21 | 0.06 | Defense | 0.02 | 0.03 | 0.01 |
| Fabricated Products | 0.11 | 0.09 | 0.12 | Textiles | 0.02 | 0.09 | -0.01 |
| Shipbuilding, Railroad Equipment | 0.11 | 0.07 | 0.14 | Coal | 0.01 | -0.02 | 0.02 |
| Pharmaceutical Products | 0.11 | 0.14 | 0.10 | Precious Metals | -0.08 | -0.11 | -0.06 |
| Insurance | 0.11 | 0.17 | 0.08 | | | | |

Table A.3: The table reports the Pearson correlation between the Post War Art Index and each of the Fama and French 49 industry groups over three time periods. Full sample refers to correlations computed using monthly data ranging from 2002:04 to 2017:09, Pre-crisis correlations are computed using data ranging from 2002:04 to 2008:08, and Post-crisis correlations are computed using data ranging from 2008:09 to 2017:09.

| **Industry** | **Full sample** | **Pre-crisis** | **Post-crisis** | **Industry** | **Full sample** | **Pre-crisis** | **Post-crisis** |
|---|---|---|---|---|---|---|---|
| Retail | 0.22 | 0.18 | 0.25 | Steel Works, etc. | 0.12 | -0.01 | 0.21 |
| Beer & Liquor | 0.21 | 0.11 | 0.30 | Automobiles & Trucks | 0.12 | 0.03 | 0.18 |
| Business Services | 0.19 | 0.05 | 0.29 | Communication | 0.12 | 0.04 | 0.19 |
| Trading | 0.19 | 0.10 | 0.25 | Shipping Containers | 0.12 | 0.00 | 0.20 |
| Candy & Soda | 0.17 | 0.15 | 0.19 | Measuring & Control Equipment | 0.12 | 0.02 | 0.21 |
| Construction | 0.17 | 0.06 | 0.24 | Computer Software | 0.12 | 0.03 | 0.21 |
| Transportation | 0.17 | 0.05 | 0.24 | Printing & Publishing | 0.12 | 0.05 | 0.16 |
| Insurance | 0.16 | 0.01 | 0.25 | Electrical Equipment | 0.10 | -0.09 | 0.22 |
| Other | 0.16 | 0.09 | 0.21 | Utilities | 0.10 | 0.06 | 0.13 |
| Banking | 0.16 | 0.05 | 0.23 | Consumer Goods | 0.10 | 0.03 | 0.14 |
| Restaurants, Hotels, Motels | 0.16 | 0.09 | 0.22 | Pharmaceutical Products | 0.10 | -0.07 | 0.21 |
| Real Estate | 0.16 | 0.14 | 0.18 | Agriculture | 0.09 | -0.01 | 0.15 |
| Construction Materials | 0.15 | 0.02 | 0.22 | Chemicals | 0.09 | -0.05 | 0.17 |
| Machinery | 0.15 | 0.02 | 0.22 | Petroleum & Natural Gas | 0.09 | 0.00 | 0.15 |
| Medical Equipment | 0.15 | -0.01 | 0.23 | Electronic Equipment | 0.09 | -0.01 | 0.20 |
| Rubber & Plastic Products | 0.15 | 0.15 | 0.16 | Non-Metallic & Industrial Metal Mining | 0.09 | -0.05 | 0.16 |
| Apparel | 0.15 | 0.11 | 0.17 | Aircraft | 0.07 | -0.06 | 0.17 |
| Business Supplies | 0.15 | 0.05 | 0.21 | Textiles | 0.07 | -0.03 | 0.13 |
| Wholesale | 0.15 | 0.09 | 0.19 | Coal | 0.07 | -0.04 | 0.14 |
| Shipbuilding, Railroad Equipment | 0.15 | 0.06 | 0.19 | Defense | 0.06 | -0.14 | 0.22 |
| Personal Services | 0.14 | 0.06 | 0.19 | Food Products | 0.06 | 0.05 | 0.07 |
| Recreation | 0.13 | 0.02 | 0.21 | Computers | 0.05 | -0.08 | 0.17 |
| Entertainment | 0.13 | 0.14 | 0.13 | Tobacco Products | 0.03 | 0.00 | 0.07 |
| Healthcare | 0.13 | 0.00 | 0.21 | Precious Metals | 0.00 | -0.04 | 0.01 |
| Fabricated Products | 0.13 | 0.03 | 0.18 | | | | |

Table A.4: The table reports the Pearson correlation between the Contemporary Art Index and each of the Fama and French 49 industry groups over three time periods. Full sample refers to correlations computed using monthly data ranging from 2002:07 to 2017:09, Pre-crisis correlations are computed using data ranging from 2002:07 to 2008:08, and Post-crisis correlations are computed using data ranging from 2008:09 to 2017:09.

| **Industry** | **Full sample** | **Pre-crisis** | **Post-crisis** | **Industry** | **Full sample** | **Pre-crisis** | **Post-crisis** |
|---|---|---|---|---|---|---|---|
| Fabricated Products | 0.13 | -0.08 | 0.20 | Retail | 0.01 | -0.06 | 0.06 |
| Personal Services | 0.10 | -0.04 | 0.16 | Business Services | 0.00 | -0.10 | 0.06 |
| Other | 0.10 | 0.26 | 0.05 | Computers | 0.00 | -0.04 | 0.02 |
| Healthcare | 0.10 | 0.05 | 0.13 | Candy & Soda | 0.00 | 0.04 | 0.00 |
| Business Supplies | 0.08 | 0.09 | 0.10 | Communication | 0.00 | -0.09 | 0.06 |
| Consumer Goods | 0.07 | 0.04 | 0.09 | Shipbuilding, Railroad Equipment | 0.00 | -0.05 | 0.02 |
| Rubber & Plastic Products | 0.07 | 0.01 | 0.11 | Electrical Equipment | -0.01 | -0.10 | 0.03 |
| Real Estate | 0.07 | 0.02 | 0.09 | Insurance | -0.01 | -0.07 | 0.04 |
| Banking | 0.06 | -0.06 | 0.12 | Chemicals | -0.01 | -0.02 | -0.01 |
| Printing & Publishing | 0.05 | -0.25 | 0.17 | Textiles | -0.01 | -0.03 | 0.01 |
| Transportation | 0.05 | -0.01 | 0.08 | Non-Metallic & Industrial Metal Mining | -0.01 | -0.13 | 0.01 |
| Measuring & Control Equipment | 0.05 | -0.11 | 0.15 | Aircraft | -0.01 | -0.01 | -0.01 |
| Apparel | 0.04 | 0.03 | 0.05 | Coal | -0.02 | -0.24 | 0.04 |
| Shipping Containers | 0.04 | 0.05 | 0.03 | Construction | -0.02 | -0.23 | 0.08 |
| Automobiles & Trucks | 0.04 | -0.06 | 0.10 | Agriculture | -0.02 | -0.07 | -0.02 |
| Restaurants, Hotels, Motels | 0.03 | -0.03 | 0.08 | Beer & Liquor | -0.02 | -0.01 | 0.00 |
| Trading | 0.03 | -0.15 | 0.11 | Computer Software | -0.02 | -0.05 | 0.00 |
| Medical Equipment | 0.03 | -0.15 | 0.08 | Electronic Equipment | -0.03 | -0.10 | 0.04 |
| Wholesale | 0.02 | -0.11 | 0.09 | Utilities | -0.03 | -0.20 | 0.06 |
| Machinery | 0.02 | -0.09 | 0.07 | Recreation | -0.03 | -0.11 | 0.01 |
| Defense | 0.02 | 0.04 | 0.03 | Food Products | -0.03 | -0.07 | 0.00 |
| Steel Works, etc. | 0.02 | -0.10 | 0.06 | Tobacco Products | -0.10 | -0.05 | -0.16 |
| Entertainment | 0.02 | 0.07 | 0.02 | Pharmaceutical Products | -0.10 | -0.23 | -0.03 |
| Petroleum & Natural Gas | 0.02 | -0.12 | 0.06 | Precious Metals | -0.12 | -0.20 | -0.10 |
| Construction Materials | 0.01 | -0.10 | 0.06 | | | | |