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Market efficiency in the art markets using a combination of long memory, fractal dimension, and approximate entropy measures

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ABSTRACT

In this paper, we investigate the efficiency in the art markets, using a generalized spectral test (GST) in a rolling window approach to detect departure from the martingale difference hypothesis (MDH) and trace the periods of market efficiency over time. Then we complement our results using the approximate entropy, the rescaled range analysis, and fractal dimension. We combine the three measures in an Efficiency Index for each market. Applying these methods, we find that the Modern Art, Paintings, Post-war, Prints, the USA market, and the global market in Euro show the largest values for the Approximate Entropy. Using the rescaled range estimates, we find that all markets are characterized by persistent behavior and, then using the Efficiency Index, our results indicate overwhelming evidence of market inefficiency in almost all sectors. Finally, we support our findings with some explanation of the reasons behind market inefficiency, related to asymmetrical information, influential galleries power, and differentiated pieces and talents in the art markets.

1. Introduction

Empirical studies on price dynamics in the art markets have attracted a lot of attention in the last decade. The concerns have been mainly in determining the returns to investing in the art assets and comparing that to traditional financial instruments. Some progress has been made by interpreting the artistic goods and paintings as particular assets that provide investors with an aesthetic dividend and a capital appreciation; a feature that is consistent with the alternative forms of financial investment (see, for example, Baumol, 1986; Mandel, 2009; Munteanu and Pece, 2015). However, the studies are still incon-

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clusive as there are divergent views and/or empirical findings on the comparison of art investment with traditional assets (Aye et al. 2018; Demir et al. 2018)

An investor's ability to make a consistently above average (excess) return over time will mainly depend on the efficiency of the market (Aye et al. 2018). The issue of testing for market efficiency in the financial markets and the predictability of the asset returns has been widely investigated in the finance literature. According to Fama (1970), in an efficient art market, the price changes should reflect new information that is publicly available. In addition, those prices should not depend systematically on current price levels or past prices or past returns. Otherwise, there might be some arbitrage opportunities that could be rapidly exploited. Therefore, extending the concept of market efficiency to the art markets would be fruitful. Although this was a challenging task for the case of art market due to data limitations (Frey and Eichenberger, 1995) based on infrequent sales and illiquidity of the artworks (Pesando, 1993), the literature witnesses more interest in studying the market efficiency in the art markets with the rising data availability (Aye et al. 2018). While the earlier studies mostly rely on linear and relatively more simple approaches (Louargand and McDaniel, 1991 Chanel, 1995), recent studies tend to use non-parametric and non-linear (Erdös and Ormos, 2010; Çevik et al. 2013) methods. The evidence from these studies is mixed and inconclusive with some of them supporting art market efficiency and others rejecting it. That motivates further investigation of the test of art market efficiency.

In this study, we extend the previous works by examining the efficiency of art markets by using the proposed Generalized spectral test of Escanciano and Velasco (2006). Then to provide further evidence, we complement our results with the use of approximate entropy, forecastable component analysis, and rescaled range analysis. The Generalized spectral test (GST) does not depend on the distributional assumptions of the time series returns and is a non-parametric test. It has an ability to detect linear and non-linear dependencies in the conditional mean. Hence, it has more power than other competing tests such as the wild-bootstrapped automatic variance ratio test and the automatic portmanteau Box-Pierce test (Charles *et al*., 2010). In the case when the market is predictable, arbitrageurs can take advantage of that and can study past prices and predict future prices. We also contribute to the existing literature by employing the rolling window approach of using the GST method which will detect the evolution of the market efficiency of art market segments through time.

To further study the market efficiency in the art markets, we use other measures including the Hurst Exponent, the fractal dimension, and Entropy measure. Then, we combine those measures in order to rank markets with respect to their efficiency by using an Efficiency Index introduced by Kristoufek and Vosvrda (2013). The index has been further developed in subsequent works by Kristoufek and Vosvrda (2014a, 2014b, 2016) and Kristoufek (2018).

In order to conduct our analysis, we use data from 1998 to 2018 on a quarterly basis. We obtain data for the following indices: the 19th Century, Contemporary, Drawings, Modern Art, Old Masters, Paintings, Photography, Post-War, Prints, Sculptures, France Index/Euro, Global Index/Euro, Global Index/USA, UK index/BP and USA index/USA. We find that all indices except the French index and the Prints and Paintings show evidence of structural change in their mean return with the test statistics suggesting more than four breaks during the sample period. The majority of the breaks happening during the 2007–2008 period.

Then applying the Efficiency Index to our series, we find that the majority of markets are found to be statistically significantly inefficient. Then, we try to rank the analyzed sectors with respect to market efficiency and find that the Global Index denominated in Euro is clearly the least efficient of the indices (the Global Index denominated in USD is also significantly inefficient but currency clearly plays a role as well) and Modern Art is the least efficient. Overall, given that the artworks are different from traditional securities in terms of the frequency of transactions, uniqueness, illiquidity, ownership structure, and the availability of price information (Baumol, 1986), we are able to show that most markets can be considered inefficient and thus unpredictable. Uniqueness has to do with the physical nature of artworks since they are imperfect substitutes, even if they are related to the same artist. Also, according to Baumol's view, with unique artworks, an owner has a monopoly over his work. Another feature is that the art sales are not frequent and have high transaction costs. Moreover, the price of artwork can be difficult to determine, since the details of many private sales are not necessarily disclosed to outside parties. Finally, Baumol (1986) suggested that the theory of efficient markets does not necessarily apply to works of art, because while the equilibrium price of a traditional securities like stock or bond is known, the existence of private art sales means we may not make the same assumption for artworks (see Chong, 2005).

Market inefficiency in the art markets can be also related the way the auction markets operate, its functioning and the absence of transaction that is quite common in these markets. It is estimated that close to 30% of the artworks remaining unsold according to Ashenfelter (1989) and Ashenfelter and Graddy (2011). In practice, in the auction markets, the seller fixes a confidential reserve price below which no transaction takes place. If the trade is not realized, no price will be observed and the art market index will fail to incorporate price information. The reserve-price dynamics skewed the observed price distribution and make them upwardly biased, which may explain the positive return autocorrelation in the art returns[1]. Put it differently, Sellers, having a monopoly over certain artworks, set a minimum transaction price. Since hammer prices are determined only be bidding, there would be an upper limit on the prices. As a result, relying on realized prices is insufficient to build unbiased predictions of future prices. Market inefficiency in this case is related to the design of the trading system taking place in the art markets. In fact, the operation of the auction mechanism does not distort prices, but the mispricing comes from the

[1] For example, Frey and Eichenberger (1995) relate the high positive auto-correlation in the art market indices to some microstructural and psychological factors such as a large number of collectors, irrational financial valuations, impossible sort selling, art supply inelasticity and asymmetric information.

unreported missing sales and undisclosed reserve prices. That will give informational superiority to market insiders, specifically auction houses and their managers.

The paper is organized along the following sections. In Section 2, we present the literature review. Section 3 explains the methodology used in the paper while Section 4 describes the data and its features. Section 5 presents the empirical results. Finally, the last section provides our conclusions.

2. Literature review

Due to the increased availability of data on the art markets, efforts have been put to construct price indices. These indices have been used to examine the dynamic relationships between financial and macroeconomics indicators and the art markets. Some studies focus on the transmission of wealth effects and spillovers from the equity markets to the art markets (Goetzmann 1993; Goetzmann et al. 2011) while others focus on the connectedness and price inter-linkages between various sub-segments (Worthington and Higgs 2003, 2004). The major evidence is that the art markets have their specifications in terms of market segmentation, asymmetry, abnormalities, monopolistic price setting, and the existence of some psychic returns. As a result, these idiosyncratic factors make investing in the art markets a new attractive portfolio diversification tool.

A vast amount of research focuses on calculating the performance of the art investments and comparing that to traditional financial assets. In one of the earliest studies, Stein (1977) studies both the U.S. and U.K. auction prices for paintings and shows that paintings are no more or less attractive than other assets. Baumol (1986) compares the rate of return on paintings and risk-free assets and finds that paintings had a lower return. Buelens and Ginsburgh (1993) argue that Baumol's (1986)'s findings are too pessimistic and conclude that market returns of paintings are higher than returns on stocks and bonds in a longer period. Following those pioneer works, several studies examine and compare the performance of art investment in a different country setting, for example, Higgs and Worthington (2005) and Higgs (2012) for Australia; Kraeussl and Logher (2010) for emerging markets; Renneboog and Spaenjers (2013) for Europe and the U.S.; Demir et al. (2018) and Atukeren and Seçkin (2009) for Turkey; Agnello and Pierce (1996), Agnello (2002) and Mei and Moses (2002) for the U.S.; Shi et al. (2018) for China; Hodgson and Seckin (2012) for Canada; Renneboog and Spaenjers (2010) for Russia; and Garay (2020) for Venezuela. Despite the increasing number of studies, the question of whether the artworks yield lower or higher returns in comparison to other alternative available financial assets is still unresolved especially once the risks and the unique characteristics of the art markets are taken into account.

A strand of the art economics literature tests for the existence of bubbles in the art markets. Kraeussl et al. (2016) find that there is a speculative bubble starting in late 2010 in some specific art segments. Assaf (2018) documents the existence of two regimes and the bubble is documented in some specific art segments before the financial crisis of 2008. After 2008, it was observed that these markets are going through an adjustment process and tend to behave like financial markets. Li et al. (2020) detect two bubbles in the periods from 2004 to 2005 and 2010 to 2011 in the Chinese art market. Recently, Bernales et al. (2020) show that there are speculative bubbles in artworks that tend to increase with art supply constraints, heterogeneous beliefs, and emotional value. On the contrary, Demir et al. (2018) show that no bubble is present in the Turkish art market.

There is a mature literature on testing efficiency mostly on the stock, debt, FX, commodity, and recently cryptocurrency markets (Erdös and Ormos, 2010). Despite the earlier view which argues that market efficiency test is impossible in art markets due to data limitations (Frey and Eichenberger, 1995) based on infrequent sales and illiquidity of the artworks (Pesando, 1993), the literature witnesses more interest in studying the market efficiency in the art markets with the rising data availability (Aye et al. 2018). In one of the earliest studies, by performing two-sample t-tests, Louargand and McDaniel (1991) find that there is pricing efficiency in 13 categories of Americana. Pesando (1993) uses repeat sales data to develop a semiannual index of art prices for the period 1977–1992 and show that there is short-term persistence in returns. Chanel (1995) constructs the art market index based on 25,300 transactions for the period of 1963–1993 and the unit root test results imply the weak efficiency of the market. Goetzmann (1995) shows that there is a serial correlation in the market for paintings, which implies a persistent trend. However, there is an increase in informational efficiency as the price risk has been declining. Erdös and Ormos (2010) implement variance test ratios based on non-parametric methods to determine the size of the random walk in the US art market. The random walk hypothesis does not hold over the whole sample period of 1875–2008. However, they detect several structural breaks after 1935, and the random walk hypothesis and the weak-form efficiency cannot be rejected in the 1935 to 2008 period. Taylor and Coleman (2011) construct the art price index for 4000 paintings by Australian Aboriginal artists. The index is found to be stationary suggesting that that art prices may mean revert. If this is the case, makes art prices would be predictable. However, the authors find little evidence of this market inefficiency. David et al. (2013) use the hedonic index built by Renneboog and Spaenjers (2013) which includes 1,088,709 sales of paintings and works on papers over the 1957–2007 period to test the market efficiency. The Ljung–Box test documents significant autocorrelation of order one in art market returns. Likewise, the variance-ratio test rejects the random walk hypothesis. Finally, runs test and the Bartels test reject the independence of art price returns. Those results document that the art market is not weakly efficient as price formation is not transparent to outsiders who don't have information on unsold artworks. Çevik et al. (2013) explore the time-series features of international art price indices for the period 1990–2011. Conventional linear ADF tests document mixed results of nonstationary in the segments of the art market and the global art market is found to be stationary. However, the Markov regime-switching ADF model can capture the art market behavior better compared to the linear ADF model. It is found that there is non-linearity in the art market prices therefore the market can be nonstationary in one regime while exhibiting a different behavior in another regime. Drawings and nineteenth-century art market prices are in the weak-form efficiency. Aye et al. (2017) explore the weak-form efficiency in 15 art price indices. Using standard and non-parametric single and joint variance ratio tests, they find the majority of the art markets are inefficient. By using a similar data set, Aye et al. (2018) implement the nonlinear quantile-based unit root test by taking into account the sharp shifts and smooth breaks to test for the efficient market hypothesis. The conventional unit root tests cannot reject the null of stationarity in the data. However, once the same tests are performed again by accounting for sharp shifts and smooth breaks, the authors reject the unit root null for unit root and/or stationary in each art price index. It is concluded that the art market is inefficient.

Etro and Stepanova (2019) study the art market behavior based on repeated sales data from two global auction houses in the 2000–2018 period. By regressing art returns on their past returns, they show that the art market is in a weak form. It is also found that investors are not able to make higher returns based on the value of their investment. Moreover, there are no significant differences in returns for artworks sold at different auction houses. These findings imply that the efficiency hypothesis cannot be rejected. Recently, Le Fur (2020) analyzes the short- and long-run linkages between art market indexes between 1998 and 2016. The Granger noncausality test shows that there exist causal links among some of the 15 art market index. This implies a violation of weak-form efficiency as past prices of one market index can be used to predict another index.

3. Empirical methodology

3.1. The generalized spectral test

Let us consider $\{Y_t\}_{t=1}^{n}$ to be a stationary time series returns. To test the null hypothesis of the martingale difference sequence of the series, we use the pairwise method as follows:

H_0: $m_j(y) = 0$, $j >= 1$ almost surely where $m_j(y) = E[Y_t - \mu | Y_t - j = y]$

$H_1 : P(m_j(Y_{t-j})) \neq 0 > 0$ for same $j \geqslant 1$

Given $y_j(x) = E[Y_t - \mu)e^{ixT_{t-j}}]$ a nonlinear dependence measure, then we can use the exponential weighting function to quantify the conditional mean dependence. In this case, the above null hypothesis is in line with $y_j(x) = 0$ for all $j \geqslant 1$. Escanciano and Velasco (2006) proposed the use of the generalized spectral distribution function:

$$H(\lambda, x) = y_0(x)\lambda + 2\sum_{j=1}^{\infty} \gamma_j(x)\left[\frac{\sin(j\pi\lambda)}{j\pi}\right] \tag{1}$$

where $\lambda \in [0, 1]$. Then the sample estimate of H equals to;

$$\hat{H}(\lambda, x) = y_0(x)\lambda + 2\sum_{j=1}^{\infty} (1 - j/n)^{1/2} \hat{y}_j(x) \frac{\sin(j\pi\lambda)}{j\pi} \tag{2}$$

where $(1 - j/n)^{1/2}$is a sample finite correction factor, $\hat{y}_j(x) = (n-j)^{-1}\sum_{t=t+j}^{n}(Y_t - Y_{n-j}^{-})e^{ixY_{t-j}}$and $(n-j)^{-1}\sum_{t=1+k}^{n} Y_t$is the generalized spectral distribution function. Then under the null of the martingale difference hypothesis, that results in $H(\lambda, X) = y_0(x)\lambda$. In this case, the test statistic is the difference between $\hat{H}(\lambda, X)$and $\hat{H}_0(\lambda, X) = y_0(x)\lambda$ defined as follows:

$$S_n(\lambda, X) = (\frac{n}{2})^{1/2}[\hat{H}(\lambda, x) - \hat{H}_0(\lambda, X = \sum_{j=1}^{\infty} (1 - j/n)^{1/2} \hat{y}_j(x) \frac{\sqrt{2}\sin(j\pi\lambda)}{j\pi} \tag{3}$$

Then based on the Cramer-von Mises norm in Eq. (4), we are able to calculate the distance of $S_n(\lambda, X)$ to zero given all possible values of λ and x.

$$D_n^2 = \int_R \int_0^1 |S_n(\lambda, X)|^2 W(dx)d\lambda = \sum_{j=1}^{n-1}(n-j)\frac{1}{(j\pi)^2}\int_R |\hat{y}(x)|^2 W(dx) \tag{4}$$

with the weighting function $W(.)$ satisfying some mild conditions. If this function settles to the standard normal cumulative distribution functions, then we obtain the following statistics results:

$$D_n^2 = \sum_{j=1}^{n-1} \frac{(n-j)}{(j\pi)^2} \sum_{t=j+1}^{n} \sum_{s=j+1}^{n} (Y_t - Y_{n-j}^{-})(Y_s - Y_{n-j}^{-})\exp[0.5(Y_{t-j} - Y_{s-j})^2] \tag{5}$$

when D_n^2large, H_0 is rejected. Escanciano and Velasco (2006) suggest the use of the wild bootstrap procedure and the p-values forD_n^2 are obtained as follows. First, calculate D_n^2 for $\{Y_t\}_{t=1}^{n}$ then simulate the sequence $\{W_t\}_{t=1}^{n}$ based on zero mean, and unit variance independent random variables. Then we compute:

$\hat{\gamma}_0^*(x) = (n-j)^{-1}\sum_{t=1+j}^{n}(Y_t - Y_{n-j}^{-}\hat{\Phi}_{t-j}(\chi)w_t$ then $S_n^*$and D_n^2*

$$\text{where } \hat{\Phi}_{t-j}(x) = e^{-ixY_{t-j}} - (n-j)\sum_{t=j+1}^{n} e^{ixT_{t-j}} \tag{6}$$

We repeat the above procedure several times in order to obtain a bootstrap distribution of D_n^2. The corresponding p-value is thus calculated as the proportion of D_n^2* greater than D_n^2. We compute the p-value first for the first 5 years of data (20 observations), then, we drop the first observation and roll the sample one quarter forward to re-calculate the next p-value. Finally, we make use of a relative efficiency indicator of Lim (2007) that considers the share of time windows where a p-value is less than 0.05.

3.2. The approximate entropy

The approximate entropy (*ApEn*) was introduced by Pincus (1991) and based on the work of Grassberger and Procaccia (1983). It is used as a measure of regularity and predictability in relatively noisy and short time-series data. Smaller *ApEn*-values is an indication of a higher regularity in the data. While high entropy values suggest little information in the series and thus low predictability and high efficiency contrary to low entropy which characterizes deterministic and thus predictable series. Briefly, we describe how the *ApEn* can be calculated.

For any data sequence $u(i)$ from i = 1 to N, define the vector sequences $x(i)$ made up of consecutive $u(i)$ and including length m, as follows:

$$x(i) = (u[i], u[i+1], ..., u[i+m-1] \tag{7}$$

We estimate the frequency of $x(i)$ vectors repeating themselves in the dataset given a tolerance r. (see, for example, Pincus (1991) Pincus and Kalman (2004), and Kristoufek and Vosvrda (2012)). Then, a correlation sum of vector $x(i)$ can be calculated as:

$$C_i^m = \frac{[\text{number of j suchthatd}(x[i], x[j]) \leqslant r]}{(N-m+1} \tag{8}$$

where $j \leq (N - m + 1)$.

Given a tolerance r, the $C_i^m(r)$ measures the regularity of patterns and represents the sum of the correlation of vector $x(i)$ with other vectors. Then, the mean logarithmic correlation sum can be estimated as:

$$\Phi^m(r) = \sum_i \ln C_i^m(r)/(N-m+1) \tag{9}$$

where $\sum_i$is a sum from i = 1 to (N – m + 1). $\Phi^m(r)$measures the prevalence of repetitive patterns of length m. Then $\Phi^m(r)$shows the average frequency of all the m-point patterns. Then approximated entropy can be measured as:

$$ApEn(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r) \tag{10}$$

For the estimation of approximate entropy, we utilize the bounded version of entropy as suggested by Pincus (1991) and Pincus and Kalman (2004).

3.3. The rescaled range analysis

Long-range dependence is related to the auto-correlation structure of the series and processes are considered long-range dependent if the auto-correlation structure decays slowly, usually in a hyperbolic manner (as opposed to short-range dependence characteristic by an exponential vanishing). The Hurst exponent H is a measure of long-range dependence and varies between 0 and 1 for stationary processes, while 0.5 is the midpoint for processes with no long-range dependence (Beran, 1994). When $0 < H < 1$ a time series is represented as a fractional Brownian motion. When $0.5 < H < 1$ the series is persistent, while H = 0.5 indicates an uncorrelated time series. The presence of persistence in a time series means that if fluctuations increases are happening at a time period, they are expected to continue increasing at future dates. For the case when $0 < H < 0.5$, we have anti-persistence.

Hurst (1951) provided a way to estimate the Hurst exponent using the ratio R/S described by the following relation: $R/S = (c\tau)^H$where τ is the time span, and H is the Hurst exponent, with c equal to 0.5 by Hurst (1951). The range R is defined as:

$$R(\tau) = \max(X(t,\tau)) - \min(X(t,\tau)) \tag{11}$$

where t takes values from [1 τ] and S is given by:

$$S = \left\{\frac{1}{\tau}\sum_{t=1}^{\tau}[\xi(t) - \langle\xi\rangle_\tau]^2\right\}^{1/2} \tag{12}$$

where $\langle\xi\rangle_\tau = \sum_{t-1}^{\tau}\xi(t)/\tau\langle\xi\rangle_\tau$and $X(t,\tau) = \sum_{u=1}^{t}[\xi(u) - \langle\xi\rangle_\tau]$.

3.4. The fractal dimension

Fractal dimension measures the local correlation structure of a time series and graphically can be connected to the roughness of the analyzed series (Kristoufek and Vosvrda, 2013). Given a univariate series, the fractal dimension can range between 1 and 2 with the central point of 1.5 which characterizes a serially uncorrelated process. The fractal dimension D is related to the long memory so that $D + H = 2$. A series that has $D = 1.5$, it is an indication of a random series with no local trending, and when $D < 1.5$, the series shows less roughness and resembles a local persistence. However, for $D > 1.5$, the series is locally anti-persistent. Overall, a low fractal dimension suggests lower roughness of the series and thus local positive auto-correlation structure whereas a high fractal dimension describes rough series with negative auto-correlation structure. For our purpose and given a short time series, we utilize two methods of fractal dimension estimation that are well suited for such – the Hall-Wood and Genton estimators (Gneiting and Schlather, 2004, Gneiting et al., 2010).

3.5. The efficiency index

Testing for the capital market efficiency is usually restricted to a single test or a family of tests that use the random walk or martingale definition of the efficient market hypothesis as the null hypothesis for testing. It is well illustrated in the literature of the previous section that the results of the tests lead to different results and, importantly, these tests only test the hypothesis in a binary framework – the tested market either is efficient or it is inefficient. However, we might be interested in comparing two or more different markets and distinguish between them or even rank them with respect to their efficiency. The idea of combining more measures and statistics of market efficiency into a single measure that would be comparable across different markets or assets lead to an introduction of the Efficiency Index by Kristoufek and Vosvrda (2013), which has been further developed in subsequent works by Kristoufek and Vosvrda (2014a, 2014b, 2016) and Kristoufek (2018). The idea of the Efficiency Index is quite simple as it can be seen as a distance of the analyzed market's characteristics from the efficient market state. This can be written as

$$EI = \sqrt{\sum_{i=1}^{n}\left(\frac{M_i - M_i^*}{R_i}\right)^2} \tag{13}$$

where M_i represents the *ith* measure of market efficiency. M_i^* represents the expected value of the *ith* measure and R_i represents its range. Then the ranges are standardized in order to have the range equal to one. For a market to be characterized as efficient, the efficiency index will be equal to zero, and for the least efficient market, $EI = \frac{\sqrt{n}}{2}$, where n is a number of measures used in estimating the index. Therefore, the efficiency index is defined on a unit n-dimensional cube with an efficient market in the center, i.e. $EI = 0$ for the efficient market (see Kristoufek and Vosvrda (2014a, 2014b, 2016) and Kristoufek (2018) (for more details). Such specification of the index allows us to include more ways of testing market efficiency into one final measure. However, this limits the set of possible included measures to the ones that are restricted, i.e. they have a specific finite range, and have a clear value for the efficient market behavior. In our application, we utilize three measures – long-range dependence, fractal dimension, and approximate entropy[2].

Efficiency Index based on Eq. (13) is thus based on five estimates where four of them have a range of one (two Hurst exponent estimators and two fractal dimension estimators) and one has to be rescaled as it can be twice as far from the efficient market situation (approximate entropy). As the Efficiency Index is quite general and can comprise various measures that meet the criteria, its limiting distribution needs to be studied for each specification. To control both for serial uncorrelatedness (in fact, independence) of the efficient market time series as well as the distributional properties of the studied series, we utilize a bootstrapping procedure to obtain confidence intervals for the Efficiency Index of an efficient market. Specifically, we take the following steps:

1. Estimate the efficiency index using the original series.
2. Then, construct a bootstrapped series of the returns original series (with replacement and the same time series length).
3. Then, estimate the efficiency index for the bootstrapped series.
4. Repeat Steps 2 and 3 (in our case 333 times).
5. Then, take the 95th quantile of the EIs based on the bootstrapped series. That will represent the critical value of a one-sided test for the null hypothesis of an efficient market.
6. Finally, compare the original efficiency index obtained from Step 1 with the critical value from Step 5. In case the original value is above the critical value, then we reject the null hypothesis of market efficiency.

[2] The estimation is run using two methods – the Whittle estimator (Robinson, 1995) and the GPH estimator (Geweke and Porter-Hudak, 1983), while for the approximate entropy, the suggested method by Pincus (1991) and Pincus and Kalman (2004) will be used.

4. Data

Most art indices are constructed for prices that are the function of characteristics like quality and elements that vary over time. Traditionally, there are three approaches to develop the art price indices. The *repeat-sales approach* controls for the heterogeneity of works that have been sold more than once during a time period and the quality is held constant. Then, the *hedonic modeling method* controls for differences in the characteristics of assets in various samples. For this approach, hedonic prices are related to attributes of the artist, the painting, and the characteristics of the sale. Then, the third approach, the *hybrid modeling* combines information related to repeated sales and on single sales in one single model.

For our paper, we obtain the art series from the database of Artprice and use their constructed indices for the different sectors. Artprice database is commonly used in the literature (Aye et al. 2017; Demir et al. 2018). The Artprice database has been in operation since 1987 and covers a wide range of art auctions and artists. The Artprice also publishes annual reports and articles concerning the art market developments through their annual summary *Trends*. In this paper, we obtain the quarterly data from 1998 to 2018 with 84 quarterly observations for 15 segments of the art market in line with the previous studies (Assaf, 2018; Aye et al. 2017, 2018). The list is available in Table 1[3].

5. Findings

In this section, we present the empirical results for testing the efficiency in the art markets. Before doing that, we provide some statistical analysis of the indices and their characteristics over time. Fig. 1 presents a plot of the quarterly observations of the art market indices, with the indices showing a noticeable strong growth after 2007. The graph also shows that all series behave in a similar fashion and exhibit some large deviations from their sample means over the sample period. Overall, the movements in the art indices have a stochastic trend and do not seem to vary regularly around a fixed value. We also observe that the majority of indices go through some shifts in their trend, as it is evident in the 2006–2008 and 2011–2014 periods. Table 1 provides statistical measures of the returns. The majority of series are normally distributed except the 19th Century, Modern Art Prints, and those of the UK index since the Jarque-Bera statistics are significant at the 5% level. The majority of indices have negative skewness and kurtosis that is less than 3.

We also subject the series to stationarity tests, using the Augmented Dickey and Fuller (1979) ADF tests for each individual series, with the results included in Table 2. In running the tests, we set the lag length at 4 and conduct the tests with and without a trend. The results indicate that the null hypothesis is rejected for all series at the conventional significance levels. That concludes that all return series are stationary and shocks have only temporary effects.

Since structural breaks might be of importance in these markets, we test for structural breaks in their mean returns using the statistics of Bai and Perron (1998, 2003a, 2003b). Table 2 includes the results and the possible estimated breaks are reported in Table 3. For all series, except the French index and the Prints and Paintings, both double maximum statistics are not significant and provide evidence of structural break for the majority of markets. The $F(l+1|l)$ statistics are insignificant at the 5% level or higher, for the majority of markets except again for that of the French index and the Prints and Paintings. That suggests the presence of more than four breaks (5 regimes) in the series. Table 3 provides the possible breaks for each series with overwhelming evidence of the third break happening in the period 2007–2008. Overall, the results indicate the presence of multiple regimes in the art market returns and require more analysis using tests that accommodate those shifts.

To support further our empirical analysis, Table 4 includes the results of Saikkonen and Lütkepohl (2002) and Lanne et al. (2002) stationary tests, incorporating shifts in their methods. Three shift functions can be included in the tests: a dummy shift variable function, an exponential function, and a rational function, respectively. Then, we consider two forms of the tests, one without a time trend and one with a time trend. For the case without a time trend, the null hypothesis of nonstationarity is rejected only for the 19th Century sector, the Prints sector, and the Global index in the USA dollar, at the 5% significance level. That shows that most of the art market returns are integrated of order one and fall in the line of the random walk behavior. However, when considering a time trend in the regression, the null hypothesis of nonstationarity is rejected for the majority of art price returns at the 5% significance level. Table 4 also provides the estimated breaks during our sample period. Surprisingly, all are sectors show the break to occur in the 2008 financial crisis period, except for the 19th Century sector and Drawings that show a break in 2011, and those of Photographies and Prints that show a break in 2004 and 2006, respectively. The breakpoints in the art sectors coincide mainly with the economic and financial crisis that took place during the 2008–2009 crisis.

The results are not surprising given the impact of the global financial crisis on financial markets, including the art markets. For example, before the GFC of 2008, the Contemporary art sector had strong growth, but then after, it had the heaviest decline. The prices of Contemporary art pieces were strongly affected when the largest two auction houses, Christie and Sotheby, did not continue to provide price guarantees to sellers.

Table 5 provides the results from the Approximate Entropy (*ApEn*) estimation, the rescaled range analysis, and the fractal dimension estimates. Accordingly, the Modern Art, Paintings, Post-war, Prints, the USA market, and the global market in Euro show the largest values for the Approximate Entropy indicating market inefficiency in these sectors. For the rest of the sec-

[3] We obtained the data from ARTPRICE at: http://www.artprice.com.

Table 1
Descriptive statistics for the art markets returns.

	Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque Bera
19th Century	−0.007	0.128	−0.279	0.062	−1.236	6.949	64.24* (0.000)
Contemporary	0.0009	0.162	−0.179	0.066	0.000	3.217	0.140 (0.932)
Drawings	0.011	0.192	−0.183	0.076	−0.341	3.668	2.701 (0.259)
France Index/Euro	0.000	0.047	−0.100	−0.498	−0.498	2.986	2.945 (0.229)
Global Index/Euro	0.005	0.281	−0.206	0.102	0.146	3.113	0.293 (0.863)
Global Index/USA	0.005	0.329	−0.245	0.111	0.338	3.560	2.283 (0.319)
Modern Art	0.006	0.253	−0.129	0.052	1.437	9.407	145.9* (0.000)
Old Masters	−0.008	0.128	−0.175	0.068	−0.297	2.319	2.420 (0.298)
Paintings	0.003	0.092	−0.129	0.039	−0.577	4.145	7.826* (0.019)
Photographies	0.011	0.169	−0.167	0.072	−0.071	2.614	0.501 (0.562)
Post-War	0.016	0.172	−0.106	0.054	0.279	3.278	1.152 (0.562)
Prints	0.004	0.076	−0.126	0.039	−0.879	4.643	17.14* (0.000)
Sculptures	0.003	0.102	−0.153	0.047	−0.285	3.526	1.782 (0.410)
UK Index /BP	0.005	0.117	−0.168	0.052	−0.602	4.044	7.519* (0.023)
USA Index/USA	0.007	0.095	−0.127	0.041	−0.359	3.843	3.633 (0.162)

Notes: The table presents the descriptive statistics of the art market returns. J.B. is the normality test statistic and follows a chi-square distribution with 2 degrees of freedom. *p*-values are in parentheses. * indicates significance at 5%.

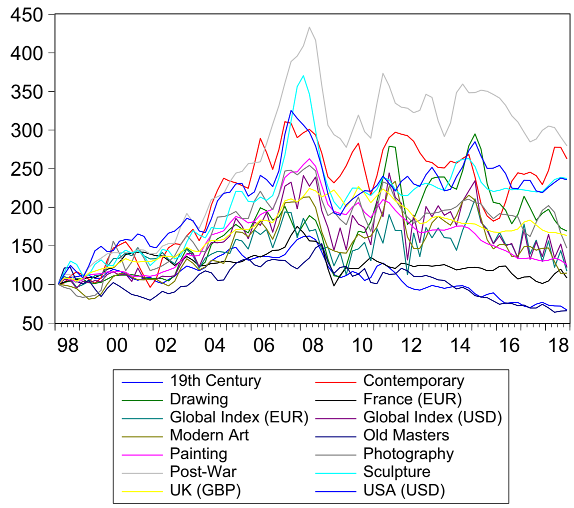

Fig. 1. The time series of art indices between Q1-1998-Q4-2018.

Table 2
Unit root and multiple breaks test statistics in the art markets returns.

Commodity	ADF-with trend	ADF-without trend	UDmax[a]	WDmax(5%)[b]	F(1|0)[c]	F(2|1)[c]	F(3|2)[c]	F(4|3)[c]	F(5|4)
19th Century	−4.067	−3.281	8.99	8.99	8.99	5.47	3.99	3.39	2.92
Contemporary	−3.765	−3.430	7.129	7.129	7.129	5.685	4.734	3.770	3.003
Drawings	−3.797	−3.840	6.300	7.513	2.616	6.300	4.882	4.255	3.423
France Index/Euro	−4.545	−3.842	11.90*	14.22*	11.90*	7.890*	9.055*	7.795*	6.482
Global Index/Euro	−3.713	−3.616	1.583	2.346	0.744	1.539	1.583	1.240	1.069
Global Index/USA	−6.281	−6.113	2.061	2.061	2.061	1.198	1.261	1.084	0.895
Modern Art	−3.689	−3.863	5.291	7.029	3.718	5.291	4.882	3.728	2.966
Old Masters	−4.391	−2.410	6.725	6.881	6.725	5.473	4.780	3.897	3.040
Paintings	−3.805	−3.653	23.01*	23.01*	23.01*	16.53*	12.311*	9.260	7.425
Photographies	−5.716	−5.388	3.604	4.527	3.604	3.587	2.720	2.546	2.063
Post-War	−2.176	−2.290	7.856	9.657	7.856	7.073	6.708	5.331	5.304
Prints	−4.527	−4.432	11.28*	14.54*	11.28*	10.46*	10.10	7.897	6.341
Sculptures	−3.591	−3.169	8.454	8.454	8.454	6.223	5.030	3.828	3.088
UK Index /BP	−4.636	−4.063	5.170	5.170	5.170	3.452	2.937	2.516	2.342
USA Index/USA	−3.887	−3.936	8.609	9.305	8.609	7.830	6.452	5.023	3.974

Notes: The table presents the ADF (Dickey and Fuller, 1979) and the Bai and Perron (1998, 2003a) test statistics. *indicates significance at the 5%. [a] UDmax is an upper-tail test of the null hypothesis of 5 breaks with critical values of 7.46, 8.88, 12.37 at 10%, 5% and 1% levels, respectively. [b] WDmax is an upper-tail test of 0 breaks against an unknown number of breaks with an upper bound of 5 with a critical value equal to 9.91. [c] Represents the upper-tail tests of *l* breaks against *l + 1* breaks. The 10%, 5% and 1% critical values are: F(1|0),7.04,8.58, and 12.29; F(2|1),8.51,10.13, and 13.89; F(3|2),9.41,11.14, and 14.80; F(4|3),10.04,11.83, and 15.28;F(5|4),10.58, 12.25, and 15.76. Critical values for ADF tests are −4.100, −3.478, and −3.166 at 1%, 5%, and 10% respectively.

Table 3
Estimated breaks in the art markets returns.

19th Century	Contemporary	Drawings	France Index/Euro	Global Index/Euro
2002Q2	2002Q1	2001Q4	2001Q2	2001Q3
2005Q1	2004Q3	2004Q2	2004Q4	2004Q2
2008Q1	2008Q1	2006Q6	2007Q4	2007Q3
2010Q3	2010Q3	2009Q2	2010Q2	2010Q1
2013Q2	2013Q2	2011Q4	2013Q3	2013Q2
Global Index/USA	Modern Art	Old Masters	Paintings	Photographies
2002Q1	2001Q4	2001Q4	2002Q1	2002Q2
2004Q3	2005Q4	2004Q2	2006Q1	2004Q4
2007Q3	2008Q2	2007Q2	2008Q3	2008Q2
2010Q1	2010Q4	2010Q1	2011Q1	2010Q4
2013Q2	2013Q3	2013Q1	2013Q3	2013Q2
Post-War	Prints	Sculptures	UK Index /BP	USA Index/USA
2001Q4	2002Q2	2003Q1	2001Q2	2000Q4
2004Q2	2005Q3	2006Q1	2005Q3	2004Q4
2008Q1	2008Q2	2008Q3	2008Q2	2007Q3
2010Q3	2010Q4	2011Q1	2010Q4	2010Q1
2013Q1	2013Q3	2013Q3	2013Q2	2013Q2

Notes: The table includes the estimated break-points based on Bai and Perron (1998, 2003a, 2003b) statistics.

Table 4
Unit root tests with shifts for the art markets returns.

	Test without time trend				Test with time trend		
	Shift function			Shift date	Shift function		
	$f_t^{(1)}$	$f_t^{(2)}$	$f_t^{(3)}$	$f_t^{(1)}$	$f_t^{(1)}$	$f_t^{(2)}$	$f_t^{(3)}$
19th Century	−3.202*	−3.179*	−2.647*	2011 Q4	−2.841	−2.797	−2.609
Contemporary	−2.012	−1.350	−1.309	2008 Q1	−3.450*	−3.454*	−3.436*
Drawings	−2.558	−2.606	−2.695	2011 Q1	−4.587*	−4.637*	−3.568*
France Index/Euro	−0.917	−0.839	−1.770	2009 Q4	−3.041*	−3.041*	−2.968
Global Index/Euro	−2.112	−2.167	−2.546	2007 Q3	−4.197*	−4.298*	−6.026*
Global Index/USA	−2.461	−2.573	−3.582*	2007 Q3	−3.566*	−3.629*	−6.421*
Modern Art	−1.594	−1.796	−2.299	2008 Q4	−2.046	−2.663	−2.265
Old Masters	−1.937	−1.973	−3.783	2008 Q4	−3.700*	−3.635*	−3.631*
Paintings	−2.865	−1.239	−1.074	2008 Q2	−3.288*	−2.087	−1.654
Photographies	−2.526	−2.155	−1.955	2004 Q4	−3.866*	−4.193*	−3.206*
Post-War	−1.246	−0.381	−0.227	2008 Q1	−2.793	−3.493*	−3.488*
Prints	−3.418*	−3.478*	−2.885*	2006 Q3	−3.699*	−3.354*	−2.146
Sculptures	−2.459	−1.543	−1.518	2008 Q2	−3.902*	−2.950	−2.815
UK Index /BP	−2.355	−2.263	−1.767	2008 Q2	−2.161	−2.159	−2.321
USA Index/USA	−2.064	−0.971	−0.894	2007 Q3	−3.538*	−3.784*	−3.078*

Notes: The table includes the tests proposed by Saikkonen and Lütkepohl (2002) and Lanne et al. (2002). Critical values are as follows: −3.48, −2.88, and −2.58 for 1, 5, and 10%, levels, respectively. * indicates significance at the 5% level.

Table 5
Approximate Entropy, Hurst Exponent and Fractal Dimension for the art markets returns.

	ApEn	Simple R/S	Corrected R/S	Empirical R/S	Fractal Dimension
19th Century	0.497	0.612	0.674	0.538	1.95
Contemporary	0.374	0.611	0.695	0.586	1.98
Drawings	0.399	0.551	0.587	0.549	1.96
France Index/Euro	0.409	0.623	0.721	0.588	1.91
Global Index/Euro	0.540	0.384	0.375	0.399	1.89
Global Index/USA	0.474	0.427	0.510	0.438	1.88
Modern Art	0.643	0.685	0.836	0.601	1.90
Old Masters	0.439	0.544	0.588	0.514	1.94
Paintings	0.609	0.682	0.803	0.611	1.88
Photographies	0.438	0.587	0.602	0.540	1.90
Post-War	0.503	0.664	0.803	0.622	1.89
Prints	0.519	0.644	0.729	0.639	1.85
Sculptures	0.493	0.595	0.615	0.512	1.95
UK Index /BP	0.488	0.483	0.487	0.491	1.93
USA Index/USA	0.593	0.603	0.655	0.598	1.94

Notes: The table includes the results of the Approximate Entropy, the rescaled range analysis (R/S), and fractal dimension measures. The fractal dimension is estimated by the Hall-Wood estimator (Gneiting and Schlather, 2004, Gneiting et al., 2010).

Table 6
Efficiency Market Index Measures applied to the art markets returns.

	Efficient Index Results					p-value of GST Test
	EI	EI_Null	SD	$Q_{0.95}$	p-val	
19th Century	0.7790	0.5228	0.1540	0.8070	0.0599	0.33%*
Contemporary	0.6342	0.5366	0.1317	0.8252	0.1737	14.33%
Drawings	0.8331	0.5355	0.1658	0.8428	0.0599	4.67%*
France Index/Euro	0.7337	0.5806	0.1569	0.8766	0.1258	0.00%*
Global Index/Euro	1.0989	0.5319	0.1677	0.8612	0.0180	0.00%*
Global Index/USA	0.8562	0.5243	0.1728	0.8553	0.0509	0.00%*
Modern Art	0.9022	0.5364	0.1813	0.8660	0.0389	0.33%*
Old Masters	0.6373	0.5215	0.1890	0.7985	0.1617	36.67%
Paintings	0.7755	0.4896	0.1591	0.7788	0.0539	0.33%*
Photographies	0.7875	0.5399	0.1483	0.8296	0.0749	5.33%
Post-War	0.7676	0.5253	0.1604	0.8093	0.0659	0.33%*
Prints	0.7695	0.5168	0.1690	0.8204	0.0719	1.33%*
Sculptures	0.7641	0.5138	0.1421	0.7918	0.0569	4.00%*
UK Index /BP	0.6999	0.5256	0.1480	0.8035	0.1138	31.33%
USA Index/USA	0.7149	0.5095	0.1583	0.8110	0.0958	7.00%

Notes: The table provides the results of the market efficiency measure applied to the Art Market indices set over the sample period of Q1-1998 to Q2018. * indicates significance at the 5% level.

tors, the average value of the ApEn is around 0.4. The results from the Approximate Entropy match those obtained from the rescaled range analysis and fractal dimension measures. The Modern Art, Paintings, Post-War, Prints, the USA market show the largest persistence since all the rescaled range statistics are higher than 0.5, indicating again market inefficiency in these sectors. While the estimates from the fractal dimension show the anti-persistence behavior, the rescaled range estimates of the H values are all above 0.5, indicating a persistent behavior in the art markets. That implies if the trend in these series has been positive in the last observed period, it is likely to be positive in the next period. In addition, it is observed that the strength of the persistence is greater for the majority of the series since all the H coefficients are above 0.5 and by large amounts. For example, Modern Art, Post-war, and Prints reach values of 0.7 and 0.8 values. Overall, the H exponent indicates further evidence of the rejection of the random walk hypothesis in the majority of the Art sectors.

In Table 6, we summarize the results for the Efficiency Index for each analyzed sector and index. The table includes the Efficiency Index ("EI"), the bootstrapped Efficiency Index for the null hypothesis of an efficient market based on 333 bootstrapped repetitions ("EI_Null"), the standard deviation of EI under this null hypothesis ("SD"), the 95th quantile of the bootstrapped values serving as a 95% critical value ("$Q_{0.95}$") and the p-value for the null hypothesis of an efficient market based on the bootstrapping procedure ("p-value"). Note that the 95th quantile is an arbitrarily set significance level and indeed more information is provided by the p-value.

Several interesting findings can be drawn from the results of Table 6. First, the Efficiency Index for the null hypothesis of an efficient market is rather stable across different categories and indices around 0.5. The same is true for the standard deviation of around 0.15 and the 95% critical value around 0.8. This shows that the proposed Efficiency Index and mainly the proposed bootstrapping procedure gives reasonable statistical validity to the results. Second, all studied sectors and indices have the Efficiency Index well above the mean value of the bootstrapped series under the null. This suggests that all analyzed series can be seen as inefficient with respect to the efficient market hypothesis. However, and third, this inefficiency is not statistically significant for all cases. Still, for 11 out of 15 analyzed series, we find statistically significant inefficiency at least at the 90% confidence level. Moreover, even for the four cases which have not been found significantly inefficient (Contemporary, France Index/Euro, Old Masters, and UK Index/BP), the p-values are rather close to 0.1 (none crosses over 0.2). And fourth, if we want to rank the analyzed sectors and indices with respect to market efficiency, the Global Index denominated in Euro is clearly the least efficient of the indices (the Global Index denominated in USD is also significantly inefficient but currency clearly plays a role as well) and Modern Art is the least efficient across the sectors, even though the differences across sectors are not as wide. Overall, the picture is quite clear that even for a rather short time series with very specific dynamics as the art markets surely are, we are able to show that most of the markets can be considered inefficient and thus predictable.

Finally, we complement our findings by using the generalized spectral test (GST) to detect departure from the random walk hypothesis. A higher p-value indicates non-rejection of hypothesis and implies that the financial series are efficient (at weak form) and it is not possible to generate abnormal profit trading in such periods. When the MDH test is conducted for the entire period (April 1998 to April 2018), the majority of the tested series have shown significant departure from market efficiency. The p-values of the various series are given also in Table 6. The test measures given in the table show that the null hypothesis of market efficiency for 10 series out of 15 series can be rejected at the 5% level. Only 5 series (Contemporary, Old-Masters, Photographs, UKGBP, USAUSD) were efficient according to the test, and the remaining series were inefficient.

To obtain a better picture of the changing nature of market efficiency, we measured the p-value of the test on a rolling window. We consider the first observations for the period April 1998 to January 2003 covering a period of 5 years (20 quarterly observations). Thereafter the window was moved by one quarter each time and accordingly, the second window was from July 1998 to April 2003. Fig. 2 shows the changing p-values of the test, and it is found that the p-value of all the series fell below the 5% level in several instances, indicating a departure from market efficiency. For example, the p-value of the Global USD series was less than 10% from January 07 to October 2011 and came down to 3% from April 2008 to October 2013. Market efficiency, in general, was lowest from July 2008 to April 2013, when the p-value of 13 series out of 15 series was less than 10% (refer to Fig. 3). Therefore, the results of the GST test are also in line with those obtained from the Hurst exponent, the approximate entropy, and efficiency index measures.

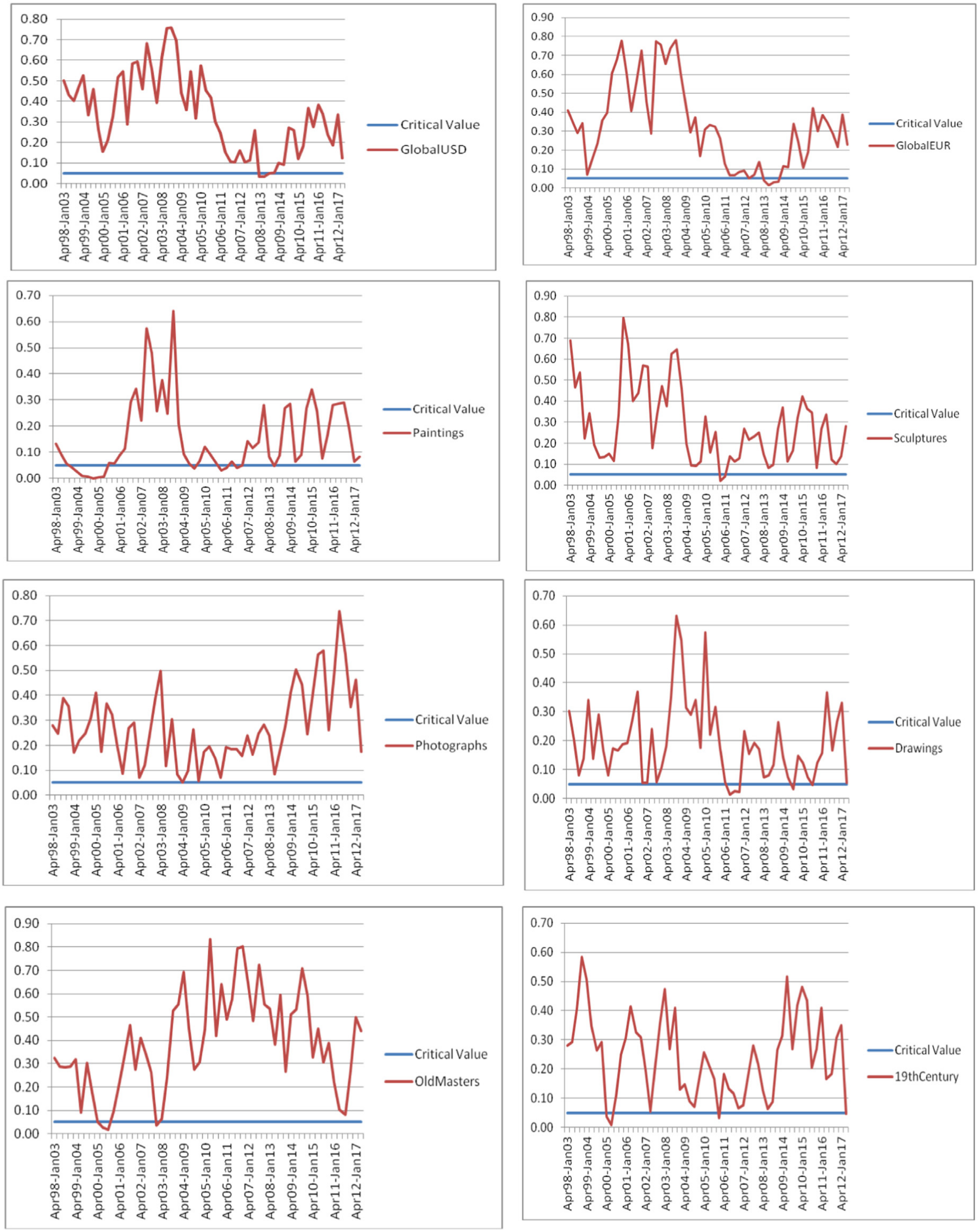

Fig. 2. Plots of the p-values using a rolling window of 5 years.

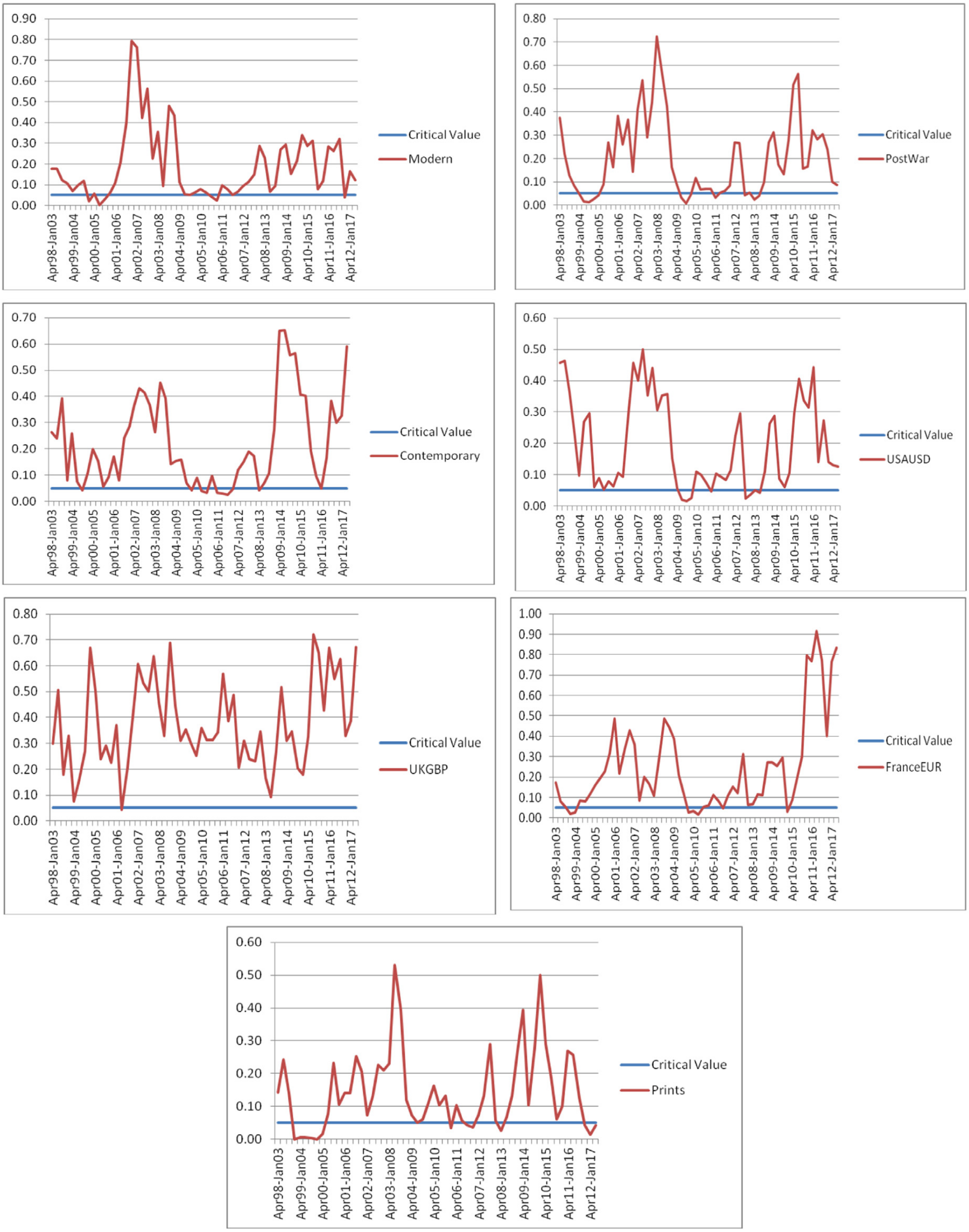

Fig. 2 (*continued*)

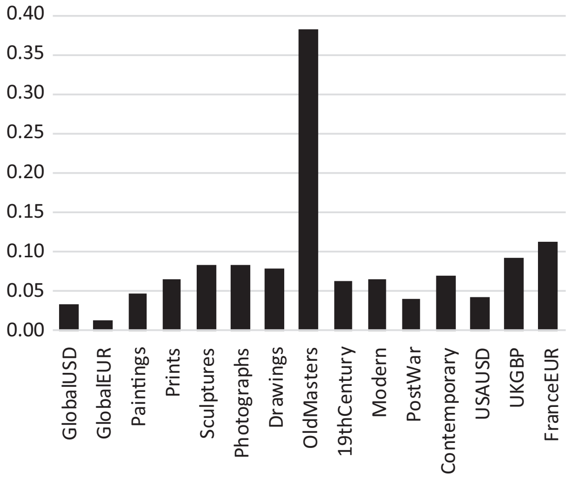

Fig. 3. *p*-value of GST test results during July 2008 to April 2013.

6. Conclusion and implications

The characterization of the art market returns as random has been challenged recently by many studies due to the importance of the art markets in the investment process. In this paper, we provide new evidence on the stochastic properties of the art markets, using a battery of different tests. We test for the presence of market efficiency in these markets for the time period from Q1-1998 to Q4-2018. Before conducting our analysis, we subject the series to different unit root tests that account for structural breaks. Our results indicate that regardless of the sector considered, the returns are stationary, even when incorporating structural breaks. Then, by applying the approximate entropy, the Hurst exponent, fractal dimension measures, and a graphical representation of the General spectral test, we find that the evidence from the majority of markets is inefficient.

The presence of market inefficiency in the art markets can be associated with many different factors., such as the influential role played by galleries, asymmetrical information distribution, and the differentiated characteristics of these markets in terms of quality and artists' earnings. The art markets are one of the most well-known markets where auctions take place. In this market, artists or art owners come along with some potential buyers for the purpose of reaching each other in a potential transaction. This happens through the roles played by galleries and auction houses who play a major role in matching sellers with buyers. Despite their transparency and openness, auction houses can be complex and result in market failures. The utility maximization of players in these markets might not be achieved and may lead to inefficiency. Campbell (2008) for example, discusses the impact of dealers share on the valuation of art market and the rate of return reflected by the indices. He points that art private dealers adopt a very similar strategy to those of auctions houses to take advantage of the inefficiencies through their insider knowledge and expertise. These features are likely to produce art market returns which could be greater than what is implied by the efficient market hypothesis.

Related to that is the role of information and its asymmetrical distribution as the cause of market inefficiency. As observed by Ashenfelter and Graddy (2003) due to the asymmetry of information, it is problematic to values different pieces in terms of economic and aesthetic sense. The auctioneers and valuers, galleries, and experts contribute to this unequal distribution of information. Usually, the less informed players in the art markets will either pay high unrealistic prices or be left to the mercy of galleries and auctioneers. Given that these markets are mainly dominated by the two largest auction houses, namely Christie's and Sotheby's, it is expected that some imperfections will arise. The two houses gained enormous market power in making them the two most important players forming a near duopoly. The entrance barriers imposed by the two houses on the entrance of new artists kept the roles played by the very influential and resulted further in market failures and inefficiency. For example, before the global financial crisis of 2008, the Contemporary art sector witnessed a strong growth relative to other sectors. But then due to the impact of the GFC (Global Financial Crisis), auctions in this sector fell dramatically and had a heavy decline. The reason behind this drop was the abundance of price guarantees to sellers by Christie and Sotheby auctions houses.

Frey and Eichenberger (1995) also suggest that the art markets are not efficient, since actors in these markets are not generally pursuing profits but often have some emotional attachment to the art objects. This may contradict the assumption of rationality under which agents and market players make informed and rational decisions. The lack of rationality and surplus of emotions will lead to the inefficiency inherent in the art markets. Another possible explanation according to Frey and Eichenberger (1995) is the impossible arbitrage in the art markets due to the limited accessibility to certain traders and the delay for certain purchases. These factors may lead to an inelastic supply due to the efforts and time taken to offer new pieces to the market. Further, art pieces must be carried with care and may be subjected to high transportation costs and security efforts. As a result, prices in these markets are not settled at equilibrium levels and will be higher than they should be, resulting in market inefficiency and anomalies.

Recent justification for the presence of market inefficiency can be related to the art market prices and their relation to the creation of bubbles. For example, Ahn et al. (2011). Ahn et al. (2011) derive an equilibrium model between rational agents who look at art as worthless and uninformed investors who attribute value to it. This led to a two state model with the presence of bubbles as corresponding to non-stationary behavior in the deviation from fair value in at least one regime, and therefore defeating the martingale difference hypothesis.

A final reason can be associated with the differentiated pieces traded and the different talents of artists. Given that the artworks are unique and some artists may earn more than others, the distribution of their earnings will be skewed to the right. That may result in some market failures and inefficiency, since independent of the quality, art prices are not objectively established and will depend on different variables other than those related to the intrinsic value of the artwork. Artworks can be owned as a commodity in inventory- a benefit represented by the convenience yield- allowing owners to take advantage of tight supply conditions (Keynes 1930). In the case of art markets, this benefit is derived from an *aesthetic dividend*, mentioned repeatedly by Anderson (1974), Baumol (1986) and Campbell (2008)- benefits very similar in nature to those contained in the convenience yield of Kaldor (1939). Further, the convenience yield in the art market can be also associated with the concept of *ownership yield* as the total benefit attached to art possession. It can be argued that the *ownership yield* is the driving force behind very high prices being paid for artworks, and therefore supporting a large rarity premia in recent years.

CRediT authorship contribution statement

Ata Assaf: Conceptualization, Methodology, Software, Writing - original draft. **Ladislav Kristoufek:** Data curation, Software, Writing - review & editing. **Ender Demir:** Supervision, Writing - review & editing. **Subrata Kumar Mitra:** Investigation, Software, Validation, Writing - review & editing.

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