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Nonlinearity and nonstationarity in international art market prices: evidence from Markov-switching ADF unit root tests

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Abstract This study investigates the presence (or lack thereof) of nonlinear dynamics and nonstationarity in international art market prices using quarterly data for the period 1990–2011. We first test whether art market price indices follow stochastic trends or whether they are stationary by means of linear unit root tests. Next, we estimate the Markov regime-switching ADF model and test whether the linear or the nonlinear regime-switching model provides a better characterization of the global art market price series. We find that all art market price indices (except for Drawings) exhibit nonlinearity. To our knowledge, our study is the first one in the literature to suggest that a nonlinear (Markov regime-switching) model provides a better characterization of the behavior of price dynamics in international art markets. In particular, our findings indicate that the market for the overall global art market, paintings, old

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masters, sculptures, photographs, prints, and contemporary art might indeed be stationary while exhibiting nonlinear regime-switching properties. On the other hand, the market for drawings and the Nineteenth century art are found to be nonstationary. Overall, despite the common ground of a regime-switching framework, we still find that the sub-segments of the art market have their own inner regime switching dynamics and hence they can evolve differently overtime.

Keywords Art market · Unit roots · Markov regime-switching model · Nonstationarity

JEL Classification Z11 · C20 · G11

1 Introduction

Empirical studies of price dynamics in markets for artworks have attracted wide public and academic interest. One of the main questions for both the academics and the practitioners in the finance profession is the returns to investing in art assets. While there is some evidence that art investments yield lower returns in comparison to conventional financial investments, this remains as an unresolved question due to the diversity of the results reported in the literature (Burton and Jacobsen 1999; Mei and Moses 2002; Ashenfelter and Graddy 2003; Hodgson and Vorkink 2004; Worthington and Higgs 2006; Campos and Barbosa 2009; Goetzmann et.al 2011; McCarthy 2010).

The efforts to calculate the returns to investing in artworks also led to the availability of time series data on prices in art markets. In addition, several art market businesses started to calculate their own indices not only for the general art market but also for its various sub-markets, such as old-master works, the Nineteenth century art, sculptures, prints, etc. Given the increased availability of data, a line of research on the financial economics of art markets examines the relationships between the prices in art markets and macroeconomic & financial indicators. One of the important findings is that there are wealth effects spillovers from stock markets to art markets (Goetzmann 1993; Goetzmann et.al 2011). In addition, the price inter-linkages between various sub-segments of the art market were also examined (Worthington and Higgs 2003, 2004). The general conclusion is that despite the presence of wealth effects and the influence of the general macroeconomic conditions on the art market, not only that the art market has its own inner dynamics but also various segments of the art market have their own idiosyncratic behavior. This is consistent with the nature and the peculiarities of the art market that distinguishes artworks from being a pure financial asset. For instance, Worthington and Higgs (2004, p. 217) put forth "... product heterogeneity, illiquidity, market segmentation, information asymmetries, behavioural abnormalities, and monopolistic price setting" as some of the characteristics of the art market that distinguish it from the financial markets. Furthermore, there also exist psychic returns to art market investments (see Atukeren and Seçkin 2007 for a review of the literature). In addition, changes in tastes, fashions and fads are also known to be important drivers in the art market. Interestingly, these idiosyncratic factors specific to the art market also make investing in art an attractive portfolio diversification venue.

An important research area in the financial economics literature is the testing for market efficiency, which is tightly linked to the predictability of the returns. The strong form of the efficiency hypothesis asserts that the returns to financial assets are not predictable even after using insider information. Semi-strong and weak forms of the market efficiency hypothesis allow for some form of predictability but maintain the point that the returns are in essence unpredictable by using publicly available information alone.

Extending the concept of market efficiency in financial markets to the art market is perhaps difficult due to the aforementioned distinct characteristics of the art market. Illiquidity, large transaction costs, lack of continuum of sales, and the difficulties in accounting for psychic returns would just be some possible obstacles to market efficiency in the conventional sense. But, posing the question in terms of predictability is possible. Chanel (1995), for example, asks exactly that question and finds that lagged financial variables help in predicting the prices in the art market, but systematic profits cannot be made due to the lags involved. As the first step in his analysis, Chanel (1995) tests for the time series properties of an art price index for the period 1963–1993. The unit root test results indicate that the art price index is integrated of order one or I(1). The finding of an I(1) property for art prices is interpreted as a weak form of market efficiency (Chanel 1995, p. 523).

Following Chanel (1995), a number of further studies tested for unit roots in art market price indices as part of their analyses. The conclusions are overwhelmingly in support of the unit root hypothesis. Nevertheless, all of the earlier studies employed linear unit root tests. The developments in time series analysis methods show that linear unit root tests lack power substantially if the underlying data generating process is nonlinear. This is an important consideration since art market prices may exhibit nonlinear behavior. For instance, transaction costs and illiquidity are recognized as a potential source of nonlinearity in asset prices. Furthermore, there is also evidence of nonlinearities and Markov regime-switching behavior in stock prices. Hence, it is possible that the nonlinear dynamics in the financial variables are passed-through via wealth effects into the art market prices.

Our study aims to contribute to the literature by shedding further light on the behavior of the prices in the global art markets by testing for the presence (or lack thereof) of nonlinearities and regime-switching properties. To the best of our knowledge, this is the first investigation of the nonlinearities and regime switching properties in art market prices in the literature. Our findings indicate that nonstationary Markov regime-switching properties are indeed prevalent in the global art market and in its segments. Nevertheless, the segments of the art market differ in their regime-switching properties and regime transition probabilities. Thus, they might evolve differently in response to common shocks.

The rest of the paper is organized as follows. In Sect. 2, we explain the general econometric framework for testing for nonlinear unit roots. We also review the literature on the nonlinear, regime-switching, properties found in the stock prices and other macroeconomic variables. In Sect. 3, we present the empirical results and discuss their implications. Section 4 concludes.

2 Econometric framework

Since Nelson and Plosser (1982) seminal article, the question of whether various economic time series have a unit root or are stationary has generated much research. Using standard tests, many researchers are unable to reject the unit root null hypothesis for macroeconomic and financial time series (Nelson et.al 2001). Because the conventional unit root tests have low power to reject null hypothesis of nonstationarity, many researchers have focused on developing more powerful unit root tests. One line of the literature investigated the effects of possible (structural) breaks in the series. For example, Perron (1989) argued that conventional unit root tests have low power to reject the null hypothesis of nonstationarity if there is a structural break in the series. To overcome this problem, Perron (1989) modified the augmented Dickey Fuller (ADF) test by adding dummy variables to account for structural breaks at known points in time. Zivot and Andrews (1992) suggested that structural breaks in the series may be endogenous and they extended Perron's methodology to allow for the endogenous estimation of the break date. Lumsdaine and Pappell (1997) and Lee and Strazicich (2003) developed tests for the case of two structural breaks in the series and they showed that conventional unit root tests suffer from size distortions in the presence of structural break in the series.

Although most of the literature focused on the effects of a fixed number of structural breaks on unit root tests, there is a growing consensus that the number of regime changes in economic and financial time series might be better modeled in a probabilistic process framework (Nelson et.al 2001). In this context, several studies have analysed the effects of regime-switching processes on linear unit root tests. An important contribution is made by Hall et.al (1999) who used a Markov-switching ADF (MS-ADF) model to detect periodically collapsing bubbles. Nelson et.al (2001) investigated the power and size performance of unit root tests when data generating process undergoes Markov regime-switching. Using Monte Carlo simulations, it was demonstrated that unit root tests had low power against a process with Markov-switching trend. Kanas and Genius (2005) and Kanas (2006, 2009) used the MS-ADF model to test for the stationarity of real exchange rates. Chen (2008) also employed the MS-ADF model to investigate the nonstationarity and nonlinearity of stock prices. The general finding of these studies is that if there is regime switching in the trend component of the series, conventional unit root tests lack power substantially and therefore the results obtained from them are not reliable.

Formally, the ADF test proposed by Dickey and Fuller (1979) is conducted as follows:

$$\Delta r_t = a + bt + \alpha r_{t-1} + \sum_{k=1}^{p} \rho_k \Delta r_{t-k} + \varepsilon_t \tag{1}$$

where, r_t is log of the art price indices, a is constant term, t is trend variable, and ε_t is an iid $N(0, \sigma^2)$. In Eq. (1), the null hypothesis of a unit root ($H_0 : \alpha = 0$) against the alternative of a stationary process ($H_1 : \alpha < 0$) can be tested using the conventional t-ratio for α. Nevertheless, the critical values are nonstandard (MacKinnon 1991). The ADF test is shown to lack power in some cases. Hence, other unit root tests, such as the

Phillips–Perron (PP) and the KPSS tests (where the null hypothesis is the stationarity of the series in question) are also employed in current practice.

The nonrejection of the unit root hypothesis in the context of this paper can be interpreted as evidence for the prices in art markets to follow nonmean-reverting process. An important implication of this is that there exists at least weak-form efficiency in art market prices as they cannot be predicted by their past alone. Furthermore, any shocks to the art market prices would not be considered as transitory. However, the linear nature of the ADF, PP, KPSS, or other similar unit tests necessitates that a series in question as a whole is either mean-reverting or not. That is, a (non) mean-reverting process is said to hold true for all time periods.

In the extensive literature, different MS-ADF model specifications are considered in testing for regime-switching unit root behavior. For instance, Hall et.al (1999) proposed a MS-ADF test in which only constant and autoregressive parameter are state-dependent. On the other hand, Kanas and Genius (2005) employed the MS-ADF test with state-dependent variance. Camacho (2011) considered trend and difference stationary model specifications of the MS-ADF to determine time series behavior of the US output.

In the context of this study, we consider the following model form:

$$\Delta r_t = a + \alpha r_{t-1} + bt + \sum_{k=1}^{p} \rho_k \Delta r_{t-1} + \varepsilon_t \quad \varepsilon_t \sim \text{NID}\left(0, \sum (s_t)\right) \qquad (2)$$

where r_t indicates the log of art price indices, s_t is the unobservable regime, a, α, b, and ρ are time-invariant parameters and ε_t is the innovation process.[1] In the context of this study, we assume that art price indices follow a two-regime Markov process where $s_t = 1$ can be named as the high volatility regime with $\sigma(s_t = 1) > \sigma(s_t = 2)$ and $s_t = 2$ can be named as the low volatility regime with $\sigma(s_t = 2) < \sigma(s_t = 1)$.[2,3] The unobserved state variable, s_t, evolves according to the first-order Markov-switching process described in Hamilton (1994):

1 We have implemented the MS-ADF model with time-varying deterministic trend and autoregressive variables and also estimated the model without deterministic trend. Nevertheless, these model specifications failed to clearly identify the regimes as low and high volatility regimes since the first moment parameters share the same transition regime variable with the variances. Hence, we allow only the variances of the regimes to be state-dependent in our model specifications. We thank an anonymous referee for suggesting alternative approaches to deal with the problem.

2 The identification of regimes is a key issue in the MS-ADF test. Studies in the literature generally named the regimes "low volatility" and "high volatility" according to estimated standard deviations being high or low (see for instance, Kanas and Genius 2005; Kanas 2006, 2009; Chen 2008.) On the other hand, it does not imply that the differences in the standard deviations are statistically significant. Thus, we first test for equal volatilities across the regimes and examine the transition probabilities of regimes and then we identify the regimes as low and high volatility.

3 As an anonymous referee points out, it is also possible to follow the McConnell and Perez-Quiros (2000) model where the first and the second moment parameters are governed by potentially different state variables. In this case, the degree of dependence between the state variables for the first and the second moments also needs to be taken into account.

$$
\begin{aligned}
&P\left[s_t = 1|s_{t-1} = 1\right] = p\\
&P\left[s_t = 1|s_{t-1} = 2\right] = 1 - p\\
&P\left[s_t = 2|s_{t-1} = 2\right] = q\\
&P\left[s_t = 2|s_{t-1} = 1\right] = 1 - q\\
&0 < p < 10 < q < 1
\end{aligned}
\tag{3}
$$

where p and q are the fixed transition probabilities of being in low- or high-volatility regime, respectively. Note that the mean duration of staying in a high or low volatility regime for the art market price indices in question can also be calculated by $d = 1/(1 - p_{ii})$.

In the MS-ADF model, the stationarity of an art price index can be tested as follows:

$$
\begin{aligned}
H_0 &: \alpha = 0\\
H_1 &: \alpha < 0
\end{aligned}
$$

At this point, there are a number of estimation issues to be addressed. Equation (2) can be estimated by using the maximum likelihood (ML) method based on the expectation–maximization (EM) algorithm discussed in Hamilton (1994) and Krolzig (1997). This iterative technique obtains the estimates of the parameters and the transition probabilities governing the Markov chain of the unobserved states. Let us denote this parameter vector by λ, so that for Eq. (2), $\lambda = \left[a, b, \alpha, \rho_k, \sum(s_t), p, q\right]$. λ is chosen to maximize the likelihood for given observations of r_t.

The EM algorithm consists of two steps. The expectation step involves a pass through the filtering and smoothing algorithms, using the estimated parameter vector $\lambda^{(j-1)}$ of the last maximization step in place of the unknown true parameter vector. This delivers an estimate of the smoothed probabilities $Pr\left(S|Y, \lambda^{(j-1)}\right)$ of the unobserved states s_t, where Y denotes the observed variables and S records the history of the Markov chain. In the maximization step, an estimate of the parameter vector λ is derived as a solution $\tilde{\lambda}$ of the first-order conditions associated with the likelihood function, where the conditional regime probabilities $Pr\,(S|Y, \lambda)$ are replaced with the smoothed probabilities $Pr\left(S|Y, \lambda^{(j-1)}\right)$ derived in the last expectation step. Equipped with the new parameter vector λ, the filtered and smoothed probabilities are updated in the next expectation step and so on, guaranteeing an increase in the value of likelihood function (Clements and Krolzig 1998).

Since the distribution under the null hypothesis is unknown in MS-ADF model, we conduct Monte Carlo simulations to obtain the critical values. The p values associated with the t tests of the null hypothesis α=0 against the respective one-sided alternative α <0 is obtained by estimating Eq. (2) under the null α=0 and then generating 10,000 samples of size T that follow this estimated DGP. To this end, the estimation transition probabilities are used to simulate a single series s_t. Then, 10,000 series for ε_t are drawn from a $N\left(0, \sum(s_t)\right)$ and the aforementioned estimates of the parameters under the null are used to generate data for r_t. We next fit the Eq. (2) to each realization of r_t, thus obtaining two series of t-statistics for the parameter α, one for the high volatility regime and the other for the low volatility regime. The resulting p values are then the percentage of generated t ratios that are below the t values from the estimated model (Kanas and Genius 2005).

We then employ an LR test to determine which testing method is more appropriate.[4] In the LR test, the null hypothesis is no regime-switching in the series and the alternate hypothesis is the presence of regime-switching. In other words, the LR test at this stage enables us to determine whether the MS-ADF test or the linear ADF test is more appropriate for testing the stationarity of the art market prices indices. The LR test statistic can be expressed as $\mathrm{LR} = 2\left[\ln L(\lambda) - \ln L(\lambda_r)\right]$, where $L(\lambda)$ is the log-likelihood value for the MS-ADF model and $L(\lambda_r)$ is the log-likelihood value for ADF model. The LR test has a χ^2 distribution with r degrees of freedom, where r is the number of restrictions. Nevertheless, a problem arises in testing the regime-switching models against the linear models. This is because the transition probabilities in regime-switching models are not identified in the linear model, and thus the LR test does not follow the standard χ^2 distribution. To overcome this problem, Davies (1987) suggests the calculation of the upper bound p values which are given by:

$$M : Pr\left[\sup \mathrm{LR}(\gamma) > K\right] \leq Pr\left[\chi_r^2 > M\right] + VM^{\frac{1}{2}(r-1)} e^{-\frac{1}{2}M} \frac{2^{-\frac{1}{2}r}}{\Gamma\left(\frac{1}{2}r\right)} \tag{4}$$

where $M = 2\left[\ln L(\lambda) - \ln L(\lambda_r)\right]$, $\Gamma(.)$ is the gamma distribution function, r is the number of restrictions, and $V = 2K^{1/2}$.

In addition, we employ a bootstrap resampling procedure proposed by Di Sanzo (2009) to determine the approximate distribution of the LR test. The most important feature of Di Sanzo (2009) bootstrap resampling procedure is its ease of implementation and less intensive computational requirements. Furthermore, Di Sanzo (2009) finds that bootstrap resampling procedure outperforms the linearity test that is suggested by Hansen (1992) and Carrasco et.al (2009). It is indicated that the testing procedure yields superior results even if the sample size is small.

Di Sanzo (2009) bootstrap algorithm consists of five steps. In the first step, a linear model is estimated. Next, the standardized residuals from the linear model are obtained. The LR test that is described above is calculated in the third step. The fourth step involves the generation of the bootstrap errors by using the standardized residuals of the linear model. The bootstrap sample is then constructed by means of these bootstrap errors. In the final step, the LR test statistic (LR*) is calculated by using the bootstrap sample and the steps four and five are repeated 499 times.[5] This provides a distribution of LR* which is the bootstrap distribution of LR. Then, the bootstrap p value can be calculated as $p_B = \mathrm{card}(\mathrm{LR}^* \geq \mathrm{LR})/499$, that is the fraction of LR* values which is greater than the observed value LR. (The procedure "card" indicates the number of cases where $\mathrm{LR}^* \geq \mathrm{LR}$ holds.)

[4] Although large number of studies examines linearity testing in the literature, these studies involve computational difficulties in practice (Hansen 1992; Garcia 1998; Cho and White 2007; Carrasco et.al 2009). Therefore, several studies in the literature used the LR test to compare the ADF and MS-ADF test results. See Kanas and Genius (2005), Kanas (2006, 2009), and Chen (2008, 2010).

[5] We follow Di Sanzo (2009) and choose the number of repetitions as 499 times.

Table 1 Descriptive statistics for the art price indices: quarter-over-quarter returns

Indices	n	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis
Global art market index	82	−0.002	0.115	−0.250	0.061	−1.097	5.841
Paintings	82	−0.003	0.081	−0.162	0.048	−1.247	4.770
Prints	82	−0.005	0.093	−0.178	0.054	−1.001	4.360
Sculptures	82	0.001	0.117	−0.165	0.047	−0.667	4.506
Photographs	82	0.006	0.249	−0.234	0.091	−0.109	3.180
Drawings	82	−0.001	0.076	−0.160	0.047	−0.787	3.651
Old masters	82	−0.005	0.168	−0.270	0.090	−0.423	2.834
Nineteenth century	82	−0.002	0.108	−0.190	0.057	−0.630	3.642
Contemporary	82	−0.001	0.225	−0.333	0.082	−0.723	5.841

Source Authors' own calculations based on data obtained from Artprice™

3 Data and the estimation results

In our study, we use the art market price series calculated by the Artprice™ (http://www.artprice.com). Artprice™ is company specializing in art market information and data services.[6] Using world-wide auction information, Artprice™ calculates price indices for the global art market, broad art sub-market groups (such as paintings, old masters, prints, photographs, etc.) as well as for the works of individual artists. The indices are calculated by means of a repeat-sales model drawn from a database of over 27 million auction records from over 3,600 auction houses around the world. The number of artists included in the database is over 405,000. Due to the nature of art auction markets (e.g., infrequent sales, uniqueness of each item sold), there are, of course, inherent difficulties with the calculation overall price indices for art markets. As a result, there may exist a number of indices (e.g., Mei and Moses 2002) with a different value for the same period. Nevertheless, despite the differences in methodology and the data used, major art market indices follow a similar trend and capture the mood of the art market developments. Our choice of the index calculated by the Artprice™ is motivated by the fact that it is based on a comprehensive data set, that it is available as quarterly data going back to 1990, and it has been used in academic research previously (Atukeren and Seçkin 2009).

The estimation period in our study runs from the second quarter of 1990 to the first quarter of 2011. In particular, we use data on the Global art market index and several other art market segments including the market for "Paintings", "Prints", "Sculptures", "Photographs", "Drawings", "Old Masters", "nineteenth century art", and "Contemporary art". All indices are measured in US dollars.

The descriptive statistics for all art market indices are presented in Tables 1 and 2. According to results in Table 1, the mean of both return series is found to be negative except for Sculptures, and Photographs. In addition, return series of photographs and

[6] The authors are not affiliated with Artprice™. Our use of the price indices calculated by Artprice is for academic research purposes only and should not be taken as a recommendation on the company.

Table 2 Descriptive statistics for the art price indices in levels (1990:2 = 100), $N = 83$

Indices	2011Q1	Mean	Max.	Period	Min.	Period	Std. Dev.
Global art market index	90.7	65.0	114.7	2008Q1	44.5	1993Q4	18.5
Paintings	81.6	62.5	109.5	2008Q2	42.9	1994Q1	18.4
Prints	66.4	58.8	100.0	1990Q2	43.7	2001Q4	13.0
Sculptures	109.3	89.9	146.1	2008Q2	64.3	1994Q4	21.4
Photographs	169.3	119.9	217.5	2008Q2	54.6	1994Q2	46.8
Drawings	93.7	65.5	103.8	2008Q2	45.2	1997Q2	18.7
Old masters	67.1	74.6	104.8	2008Q4	47.6	1993Q4	12.5
Nineteenth century	81.9	82.0	120.9	2008Q3	56.6	1993Q4	14.9
Contemporary	95.2	64.5	133.6	2008Q1	40.1	1994Q3	24.9

Source Authors' own calculations based on data obtained from Artprice™

old masters indices exhibit evidence of higher volatility according to the greater value of its standard deviation. Table 2 displays the descriptive statistics for the level of the series with 1990Q2=100. It is seen that price index for art photographs have the highest and the most volatile values. The effects of the great recession are felt in the art markets in 2008. Nevertheless, the art market prices started picking up again since then as of 2011.

3.1 Linear ADF unit root test results

We test for the stationarity of the above described art market prices first by means of the conventional ADF, PP, and KPSS unit root tests. We include a constant term and trend in all unit root tests and select the lag specification according to the Modified Akaike Bayesian information criterion (MAIC) proposed by Ng and Perron (2001).[7] The unit root test results are presented in Table 3.

Table 3 shows mixed results on whether the art market indices are stationary or not. For instance, according to ADF test results, the null hypothesis of nonstationarity could not be rejected for all art market price indices at the 5 % significance level except for the global art market index. The Phillips–Perron test, however, finds all series except the nineteenth century art as stationary in levels. The KPSS test, where the null hypothesis is the stationarity of the series in question, indicates that sculptures, photographs, old masters, and the nineteenth century art as stationary in levels, while all other art markets display nonstationarity in levels. The mixed evidence on the unit root properties in art market indices is in some contrast to the earlier studies in the literature which generally reported unit roots in art price indices. See, for instance, Chanel (1995), Wieand et.al (1998), Worthington and Higgs (2003), Worthington and Higgs (2004), Atukeren and Seçkin (2009), Melnik and Plaut (2009), and Hodgson and Seçkin (2012). As well-known in the literature, linear unit root tests lack power

[7] We employ the ADF test without a constant term and trend for the first differences of the series.

Table 3 ADF unit root test results

Indices	ADF		PP		KPSS	
	Level	First differences	Level	First differences	Level	First differences
	Test statistics	Test statistics	Test statistics	Test statistics	Test statistics	Test Statistics
Global art market index	−4.224*** (0)	−3.268*** (5)	−4.048**	−7.519***	0.242	0.159***
	[0.006]	[0.000]	[0.010]	[0.000]		
Paintings	−2.297 (9)	−2.986*** (4)	−4.044**	−2.811 ***	0.239	0.166***
	[0.429]	[0.003]	[0.010]	[0.005]		
Prints	−1.998 (8)	−4.113*** (0)	−3.639**	−4.016***	0.225	0.119***
	[0.592]	[0.000]	[0.032]	[0.000]		
Sculptures	−2.234 (8)	−2.866*** (4)	−3.186*	−4.636***	0.202***	0.289***
	[0.463]	[0.004]	[0.094]	[0.000]		
Photographs	−2.536 (6)	−6.568*** (0)	−3.482**	−6.278***	0.118***	0.119***
	[0.398]	[0.000]	[0.048]	[0.000]		
Drawings	−2.413 (7)	−4.735*** (0)	−3.978**	−4.467***	0.269	0.190***
	[0.369]	[0.000]	[0.013]	[0.000]		
Old masters	−2.220 (4)	−6.174*** (0)	−3.739**	−5.773***	0.110***	0.093***
	[0.471]	[0.000]	[0.025]	[0.000]		
Nineteenth century	−2.184 (4)	−4.668*** (0)	−2.646	−3.775***	.126***	0.172***
	[0.491]	[0.000]	[0.261]	[0.000]		
Contemporary	−2.087 (11)	−2.709*** (10)	−4.404***	−2.965***	0.239	0.184***
	[0.543]	[0.007]	[0.003]	[0.003]		

The figures in *parentheses* show the optimal number of lags selected according to the modified AIC. The figures in *square brackets* show the probability (p values) of rejecting the null hypothesis nonstationarity. ***, **, and * indicate that the series in question is stationary at the 1, 5, and 10 % significance level, respectively when the underlying process is nonlinear in nature. Therefore, we now turn to the examination of nonlinear regime-switching properties in art market indices.

3.2 Estimation results from the MS-ADF model

There is now a large body of literature documenting evidence in favour of regime-switching properties in stock returns and economic variables. For instance, Schaller and Van Norden (1997) find regime-switching behavior in the US stock markets via Markov regime-switching model. Li and Lin (2004) also suggest that Markov-switching autoregressive conditional heteroskedasticity (ARCH) model provides better estimates of the Value-at-Risk (VaR) on returns of stock market indexes including Dow Jones, Nikkei, Frankfurt, and FTSE. Furthermore, Wang and Theobald (2008) detect regime-switching behavior in the returns of the six East Asian emerging stock markets. Chen (2008) finds that stock prices in 11 OECD countries are characterized by a two-regime Markov-switching unit root process. Li (2007) also indicate that Markov-switching moving average model outperforms to better understand and to predict Dow Jones stock returns. A number of studies also provide evidence in favor of nonlinearities in macroeconomic processes. For instance, Camacho (2005) examines the short and long run asymmetric relationship among output, consumption and investment by means of a Markov regime-switching vector error correction model. Binner et.al (2006) provide evidence in favor of nonlinearities in the US inflation using a Markov regime-switching autoregressive model. In addition, Tillmann (2007) detects regime shifts in the interest rate in the U.S. via a Markov regime-switching vector error correction model.

Given the widespread evidence in favor of nonlinearities in the economic environment surrounding the art markets, it is likely that there might be possible spillovers of these nonlinear dynamics into the behavior or art market prices as well. In addition, own market idiosyncrasies of the art market, such as large transaction costs, infrequency of sales, and illiquidity, might also lead to the presence of nonlinear dynamics in art prices. Then, in empirical terms, the use of linear unit root tests to determine the nature of the art market prices becomes questionable. As discussed earlier, the conventional unit root tests, such as the ADF, may have low power if the data generating process behind the series in question has regime-switching properties. Hence, as the next step in our analysis, we employ the MS-ADF test to examine if the art market price series have nonlinear, regime-switching, properties.

The lag order selection in the test equation is an important issue in the MS-ADF as well. Accordingly, we use the AIC, with the maximum lag length being 13, in the first stage. The "lags" column in Table 4 indicates the number of lags chosen by the AIC for the respective art market indices. According to results in Table 4, two (quarter) lags for the contemporary art, three lags for the overall global art market index, the sculptures, and the drawings, the four lags for the nineteenth century art, six lags for the photographs, eight lags for the prints, ten lags for the paintings and twelve lags for the old master art index are found to sufficient to render residuals white noise.

Next, we employ a likelihood ratio (LR) test to determine whether a nonlinear model (MS-ADF) or the linear ADF model better characterizes the behavior of the

Table 4 LR test results

Indices	Lags	Log likelihood (H_0)	Log likelihood (H_A)	χ^2 p value	Davies p value	Di Sanzo Bootstrap p value
Global art market index	3	124.157	134.046	0.000	0.000	0.045
Paintings	10	193.711	200.739	0.007	0.013	0.068
Prints	8	167.072	172.389	0.031	0.057	0.082
Sculptures	3	161.836	167.523	0.022	0.041	0.074
Photographs	6	105.750	116.578	0.000	0.000	0.030
Drawings	3	166.396	170.940	0.099	0.178	0.286
Old masters	12	119.620	131.045	0.000	0.000	0.021
Nineteenth century	4	150.966	167.302	0.000	0.000	0.030
Contemporary	2	109.991	114.644	0.053	0.073	0.095

price developments in various global art market segments. In Table 4, the H_0 column indicates the value of the log likelihood under the linear ADF specification; H_A column shows the log likelihood of the MS-ADF specification; χ^2 column displays the p value of the LR test under the standard χ^2 distribution; the "Davies" column presents the results obtained from Davies (1987) upper-bound p value calculation; and Bootstrap p value column indicates the calculated p value based on Di Sanzo (2009) bootstrap procedure.

The results presented in Table 4 strikingly indicate the rejection of the null hypothesis of no regime-switching (i.e., linearity) for all art market indices at the 10 % significance level except for the drawings art index. Note that the global art market, photographs, old masters, and the nineteenth century art price series are found to exhibit nonlinearly at the 5 % statistical significance level according to Di Sanzo (2009) bootstrapped p values test. A comparison of the results from the Davies upper bound p values, and the Di Sanzo bootstrapped p values also show that the former might lack power. Still, our findings provide evidence in favor of nonlinear (regime-switching) properties in the behavior of art market prices. Thus, it is necessary to consider the possibility of nonlinear dynamics in the study of the art market prices.[8]

The estimation results from the MS-ADF models are presented in Table 5. The following observations can be made.

(1) We first test for the equality of variances across the regimes in the MS-ADF test and find that the standard deviations of the first regimes are found to be lower than the second regimes for all art segments at 10 % level. Therefore, we identify the first regime as the low-volatility regime.
(2) The price index for the overall global art market (in USD) is found to be stationary processes at 1 % level. The price indices for the sculptures, photographs,

[8] We also examine whether the LR test results are affected by the nonstationarity of art price indices. We estimate the Markov regime-switching autoregressive model with the first difference of art price index considered as the dependent variable. Then a LR test is conducted and test results are found to be in favor of the MS-AR model.

Table 5 MS-ADF Results

Indices	α_1 [p value]	Constant	Trend	σ_{low}	σ_{high}	$\Sigma\rho_k$	p_{11}	p_{22}	Mean duration		χ_1^2
									Regime 1: low volatility	Regime 2: high volatility	
Global art market index	−0.082***	0.291	0.100	0.035	0.096	0.235	0.984	1.000	66.00	13.00	7.236
	[0.000]	[0.017]	[0.002]								[0.007]
Paintings	−0.046*	0.158	0.060	0.008	0.023	0.739	0.901	0.879	11.00	9.33	17.190
	[0.082]	[0.003]	[0.003]								[0.000]
Prints	−0.045*	0.160	0.054	0.015	0.041	0.619	0.973	0.905	26.00	11.00	9.568
	[0.054]	[0.082]	[0.045]								[0.002]
Sculptures	−0.069**	0.283	0.066	0.017	0.041	0.746	0.969	0.967	39.00	20.00	16.784
	[0.042]	[0.021]	[0.022]								[0.000]
Photographs	−0.062**	0.238	0.151	0.019	0.087	0.245	0.785	0.794	6.00	5.67	33.173
	[0.043]	[0.056]	[0.009]								[0.000]
Drawings	−0.070	0.242	0.118	0.021	0.057	0.442	0.873	0.300	14.80	1.25	3.481
	[0.400]	[0.000]	[0.000]								[0.062]
Old masters	−0.168**	0.713	0.003	0.005	0.063	0.614	0.726	0.870	4.50	7.17	63.133
	[0.039]	[0.000]	[0.820]								[0.000]
Nineteenth century	−0.067	0.276	0.062	0.001	0.042	0.263	0.614	0.910	2.43	10.17	4.656
	[0.500]	[0.503]	[0.508]								[0.030]
Contemporary	−0.046**	0.146	0.107	0.032	0.086	0.036	0.821	0.780	9.00	4.33	14.328
	[0.043]	[0.196]	[0.012]								[0.000]

The figures in *square brackets* show the probability (p values) of rejecting the null hypothesis nonstationarity. σ_{low} shows the standard error of regression for the low volatility period, σ_{high} shows the standard error of regression for the high volatility period. $\sum \rho_k$ indicates sum of autoregressive parameters. p_{ii} indicate regime transition probabilities. χ_1^2 indicates test statistics for equal standard errors ($\sigma_1 = \sigma_2$).***, **, and * indicate that the series in question is stationary at the 1, 5, and 10 % significance level, respectively

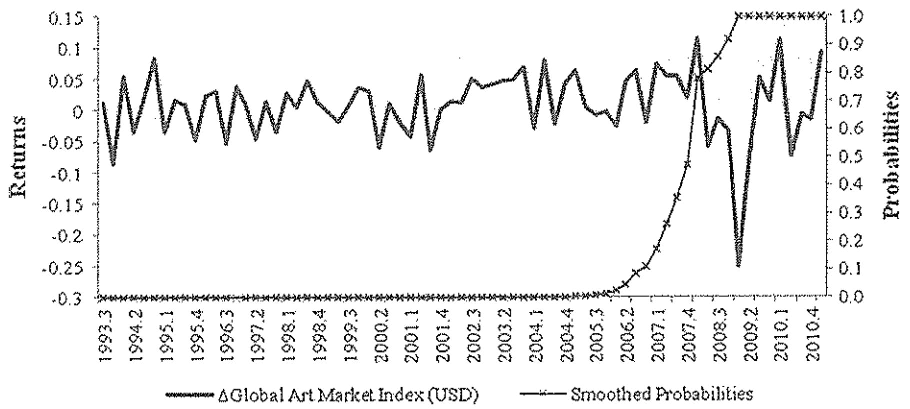

Fig. 1 Quarterly returns for the global art market index (smoothed probabilities indicate high volatility regime)

old master and contemporary are stationary at 5 % level and the price index for paintings and prints are determined as stationary at 10 % level. That is, there is evidence of mean-reversion in prices, but the process is a nonlinear one.

(3) The MS-ADF model estimation results indicate the nonstationarity of the price indices for Drawings and nineteenth century. In the financial economics sense, they are closest to exhibiting at least weak-form efficiency.

(4) The probability of remaining in a high volatility regime at time t when the series is also in a high volatility regime at time $t-1$ is above 80 % for all art price indices except for photographs, drawings, and contemporary. On the other hand, the probability of remaining in a low volatility regime at time t when the series is also in a low volatility regime at time $t-1$ is above 80 % for all indices except for Photographs, old masters, and nineteenth century.

(5) The mean duration of a low volatility regime is longer than two quarters for all art markets. The high volatility regime duration is generally longer than four quarters (except for Drawings, 1.2 quarters) with a range between 4.33 and 20. This is in line with the long side-way movements observed in art market prices.

We now examine the smoothed regime probabilities of being in the high volatility regime at each point of the sample period. Figures 1, 2, 3, 4, 5, 6, 7, and 8 show the high volatility regime transition probabilities along with the plots of the first differenced (log) art market price indices. It should be noted that the initial visual inspection can be misleading.[9] The issue is complicated by the transitions from a nonlinear but stationary regime with low (high) volatility to a nonstationary but nonlinear regime with high (low) volatility. Especially if the regime durations are short, it might be hardly possible to make a sensible visual inference about the nature and the volatility levels of the regime. The nonlinear nature of the series makes the visual inspection

[9] The smoothed regime transition probabilities are not illustrated for the drawings segment of the art market since the linearity hypothesis could not be rejected (See Table 4).

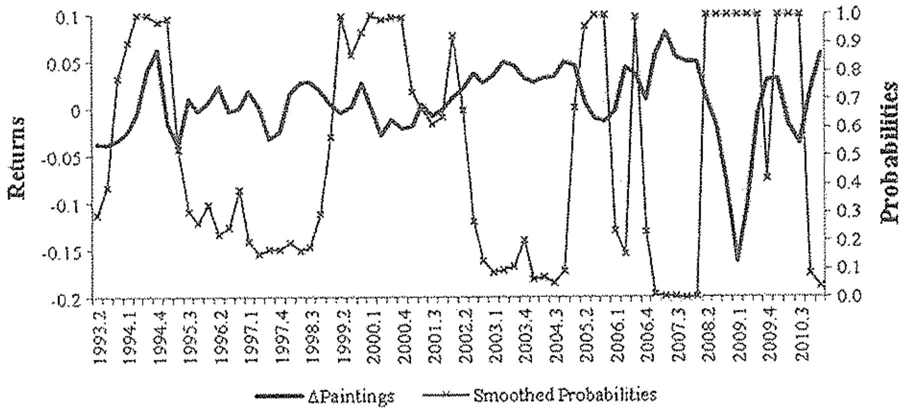

Fig. 2 Quarterly returns for the paintings index (smoothed probabilities indicate high volatility regime)

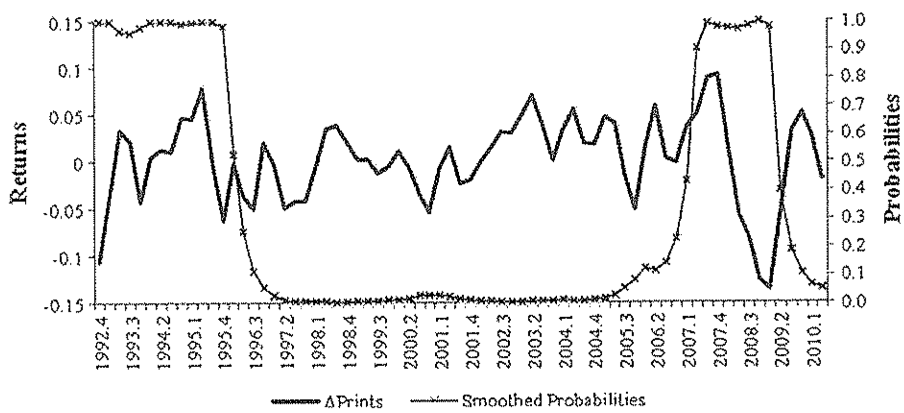

Fig. 3 Quarterly returns for the prints index (smoothed probabilities indicate high volatility regime)

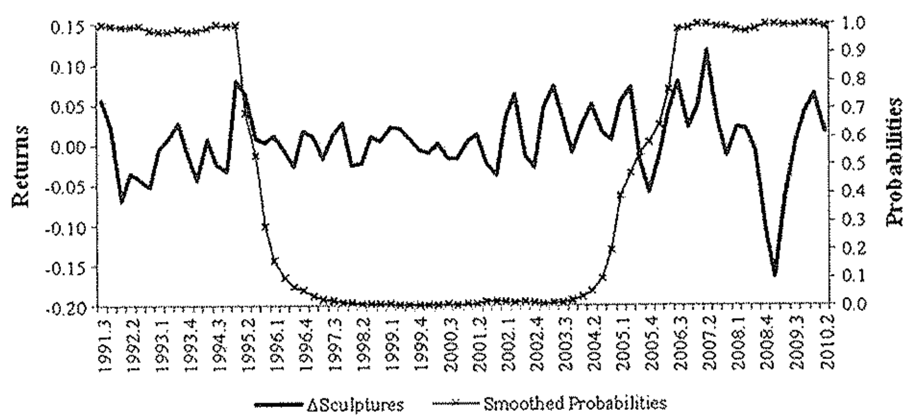

Fig. 4 Quarterly returns for the sculptures index (smoothed probabilities indicate high volatility regime)

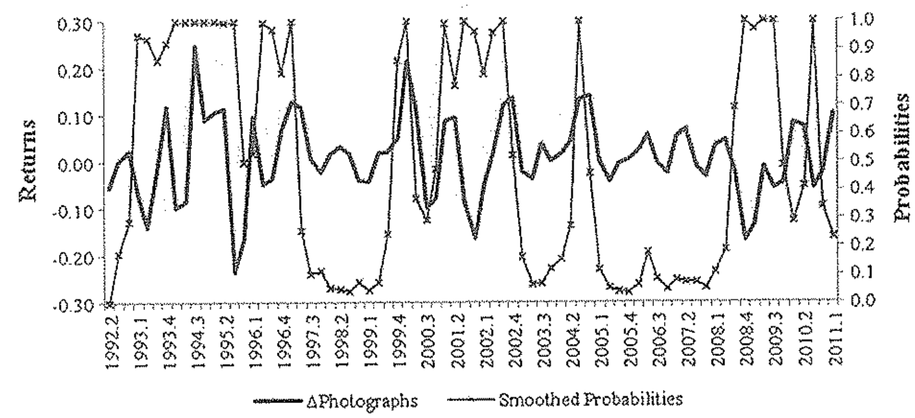

Fig. 5 Quarterly returns for the photographs index (smoothed probabilities indicate high volatility regime)

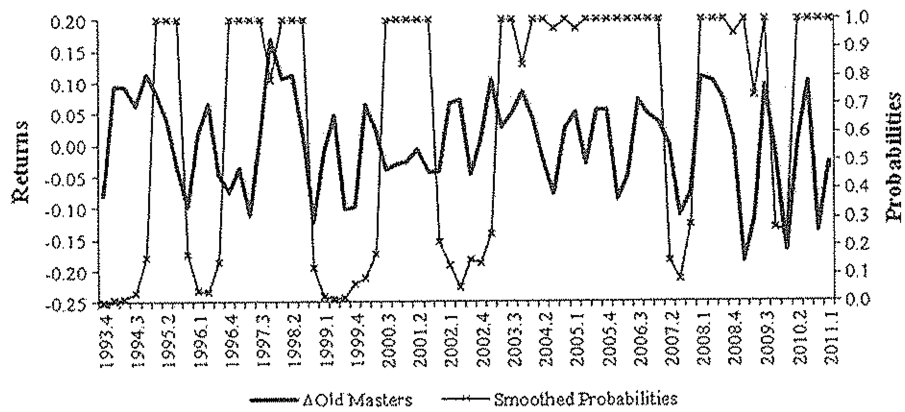

Fig. 6 Quarterly returns for the old masters index (smoothed probabilities indicate high volatility regime)

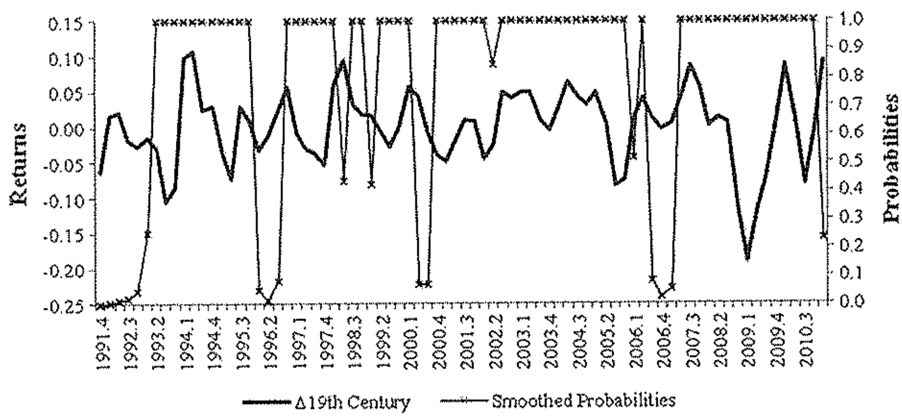

Fig. 7 Quarterly returns for the nineteenth century art index (smoothed probabilities indicate high volatility regime)

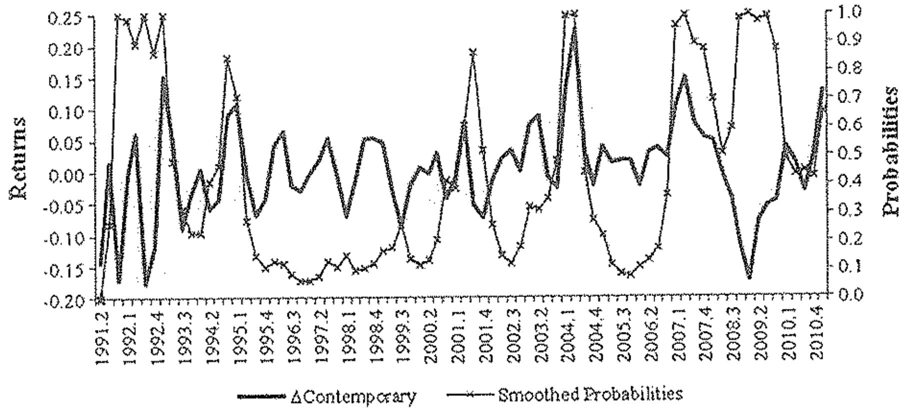

Fig. 8 Quarterly returns for the contemporary art index (smoothed probabilities indicate high volatility regime)

even harder. This might explain some of the possible ambiguities that might arise in the visual inspection of the smoothed probabilities and the actual index developments.

The global financial crisis which started in the U.S. in late-2007 has generally led to increased price volatility in various segments of the art market. This is seen for all art market categories in differing intensities in Figures 1, 2, 3, 4, 5, 6, 7, and 8. According to the Art Market Report 2009 (Artprice 2009), the drop in the art market prices between the end of 2007 and the first quarter of 2009 was about 37 %. This figure is closely comparable to the 44 % drop during the 1990–1992 period. In terms of volumes, the size of the world art auction market was about 3 billion USD in 2000. This figured reached its peak with 10 billion USD at the end of 2007 but then decreased by half to 5 billion USD in 2009 as a result of the global financial crisis. The percentage of unsold lots (or bought-in) was about 43 % in 2009 against a long-term average of 30–35 %. Despite this downturn in global art market performance, Thierry Ehrmann, the CEO of Artprice, observes that:

> "...the art market reached a stage of maturity that allows it to fluctuate at the same speed as economic indicators and financial assets...the key point to remember about 2009 is this historical and sociological change in the art market...We are lightyears away from the 1991 crisis when the art market was incapable of implementing crisis strategies." (Artprice, Art Market Trends 2009, p. 3)

The change in the response of the global art market and its segments to a financial crisis episode cannot be adequately addressed in a linear model framework. The Markov regime-switching framework employed in this paper provides more insights into this phenomenon in a setting with differing regime transition probabilities and the possibility of stationarity or nonstationarity in different volatility regimes. A further investigation of the factors that mediate regime switches (or affect regime-switching probabilities) is left as a topic for future research.

4 Conclusions

There is widespread evidence in the recent literature that the behavior of various macroeconomic and financial variables might arise from nonlinear processes. The earlier literature on the nature of the economic and financial variables focused on testing whether they are stationary or nonstationary processes mostly by means of linear unit root tests. Advances in time series econometrics, however, demonstrated that linear unit root tests suffer from low power if the underlying data generating process arises from a nonlinear model, such as a Markov regime-switching process. Obtaining higher power in determining the nature of a financial series correctly has implications in terms of the predictability of the series and the market efficiency hypothesis in general.

In this paper, we examine the time series properties of the prices in the global art market and in its various segments. The availability of time series data on prices and returns in international art markets led to many empirical analyses of the dynamics of art market prices. It should be noted that art markets have their own characteristics and they operate in a different manner than the conventional financial markets. Still, as in the financial markets, one of the main questions is the predictability of art market prices. Applying linear unit root tests, many researchers find that art market prices follow unit root processes. Nevertheless, to the best of our knowledge, price dynamics in the art markets have hitherto not been investigated for the possibility of nonlinearities and regime-switching properties. The possibility that prices in the art markets might have nonlinear properties is supported by many studies in the literature that the economic and financial environment surrounding the art markets are better captured by regime-switching models.

As the first step in our analysis, we first test for the unit roots in art market price indices by using the conventional linear ADF test. We find that while the global art market index is stationary at 5 % statistical significance level, there is mixed evidence of nonstationarity in the sub-segments of the art market. As the second step, we estimate the Markov regime-switching ADF model (MS-ADF) and compare the likelihoods of the linear model and the MS-ADF model via likelihood ratio tests. As a robustness check of our results, we employ Di Sanzo (2009) bootstrapped p values in addition to Davies's upper bound p values test. We reject the null hypothesis of the linear ADF model for the global art price index at the 5 % level. To the best of our knowledge, this is the first finding in the literature on the nonlinearity of art prices. In addition, the null hypothesis of linearity is rejected for all art markets price indices except for drawings segment. Hence, the MS-ADF captures the behavior of the art market price indices better than the linear ADF model.

Then, we examine the estimation results from the MS-ADF model. Our findings show that despite the common ground of a regime-switching framework, the sub-segments of the art market have their own inner regime-switching dynamics and thus they can evolve differently. This is in line with the arguments made in the literature that individual art market segments are rather isolated markets (Worthington and Higgs 2003, 2004).

Overall, there is strong evidence of nonlinearity in the prices in the overall global art market and its various diverse segments. The behavior of the prices in global art market and its segments can be best examined in a nonlinear regime-switching framework. In the literature, the behavior of art market prices were generally found to be unit root processes upon testing by linear unit root tests. The Markov-switching ADF test employed in our study weakens this evidence and suggests that there is nonlinearity in the behavior of the global art market prices. Still, individual sub-segments of the art market may still exhibit nonstationarity in one regime and might behave differently in high and low volatility regimes. There are also differences in the magnitude of the regime-switching probabilities and mean duration of the regimes. Hence, different segments of the global art market might evolve differently in response to common and idiosyncratic shocks. This is in line with the generally accepted views in the literature that art markets segments have their own dynamics. Nevertheless, our study is the first one to shed light on the internal dynamics of individual art market segments by expressing them in terms of nonlinear regime-switching properties. The identification of such properties for the behavior of art market segments might help the players in art markets in their market timing and art portfolio diversification decisions.

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References

Artprice (2009) Art market trends 2009 Artprice.com S.A, Saint-Roman-au-Mont-d'Or, France. http://imgpublic.artprice.com/pdf/trends2009_en.pdf. Accessed 1 June 2012

Ashenfelter O, Graddy K (2003) Auctions and the price of art. J Econ Lit 41:763–786

Atukeren E, Seçkin A (2007) On the valuation of psychic returns to art market investments. Econ Bull 26(5):1–12

Atukeren E, Seçkin A (2009) An analysis of the price dynamics between the Turkish and the international paintings markets. Appl Financ Econ 19:1705–1714

Binner JMC, Elger T, Nilsson B, Tepper JA (2006) Predictable non-linearities in U.S. inflation. Econ Lett 93:323–328

Burton BJ, Jacobsen JP (1999) Measuring returns on investment in collectibles. J Econ Perspect 13:193–212

Camacho M (2005) Markov-switching stochastic trends and economic fluctuations. J Econ Dyn Control 29:135–158

Camacho M (2011) Markov-switching models and the unit root hypothesis in real US GDP. Econ Lett 112:161–164

Campos NF, Barbosa RL (2009) Paintings and numbers: an econometric investigation of sales rates, prices, and returns in Latin American art auctions. Oxf Econ Pap 61:28–61

Chanel O (1995) Is art market behaviour predictable. Eur Econ Rev 39:519–527

Chen S-W (2008) Non-stationarity and non-linearity in the stock prices: evidence from the OECD countries. Econ Bull 3:1–11

Chen S-W (2010) Regime non-stationarity and non-linearity in inflation rates: evidence from OECD countries International Research. J Fin Econ 463:47–57

Carrasco M, Hu L, Ploberger W (2009) Optimal test for Markov switching. Mimeo, Economics Department, Rochester University, Rochester

Cho J, White H (2007) Testing for regime switching. Econometrica 75:1671–1720

Clements MP, Krolzig HM (1998) A comparison of the forecast performance of Markov-switching and threshold autoregressive models of US GNP. Econ J 1:47–75

Davies RB (1987) Hypothesis testing when the nuisance parameter is present only under the alternative. Biometrika 74:33–43

Dickey DA, Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 74:427–431
Di Sanzo S (2009) Testing for linearity in Markov switching models: a bootstrap approach. Stat Method Appl 18:153–168
Garcia R (1998) Asymptotic null distribution of the likelihood ratio test in Markov switching models. Int Econ Rev 39:763–788
Goetzmann WN (1993) Accounting for taste: art and the financial markets over three centuries. Am Econ Rev 83:370–1376
Goetzmann WN, Renneboog L, Spaenjers C (2011) Art and Money. Am Econ Rev 101(3):222–226
Hall SG, Psaradakis Z, Sola M (1999) Detecting periodically collapsing bubbles: A Markov-switching unit root test. J Appl Econ 14:143–154
Hamilton JD (1994) Time series analysis. Princeton University Press, Princeton
Hansen B (1992) The likelihood ratio test under non-standard conditions: testing the Markov switching model of GNP. J Appl Econ 7:61–82
Hodgson DJ, Vorkink KP (2004) Asset pricing theory and the valuation of Canadian paintings. Can J Econ 37:629–655
Hodgson DJ, Seçkin A (2012) Dynamic price dependence of Canadian and international art markets: an empirical analysis. Empirical Economics. doi:10.1007/s00181-011-0502-z (in press)
Kanas A (2006) Purchasing power parity and Markov regime switching. J Money, Credit, Bank 38: 1669–1687
Kanas A (2009) Real exchange rate, stationarity, and economic fundamentals. J Econ Financ 33:393–409
Kanas A, Genius M (2005) Regime (non)stationarity in the US/UK real exchange rate. Econ Lett 87: 407–413
Krolzig H (1997) Markov-switching vector autoregressions modeling, statistical inference, and application to business cycle analysis. Springer, Berlin
Lee J, Strazicich MC (2003) Minimum lagrange multiplier unit root test with two structural breaks. Rev Econ Stat 85:1082–1089
Li M-YL (2007) Volatility states and international diversification of international stock markets. Appl Econ 39:1867–1876
Li M-YL, Lin H-WW (2004) Estimating Value-at-Risk via Markov switching ARCH models—an empirical study on stock index returns. Appl Econ Lett 11:679–691
Lumsdaine RL, Pappell DH (1997) Multiple trend breaks and the unit root hypothesis. Rev Econ Stat 79:212–218
MacKinnon JG (1991) Critical values for cointegration tests. In: Engle RF, Granger CWJ (eds) Long-run econometric relationships: readings in cointegration. Oxford University Press, Oxford
McCarthy E (2010) The fine art of investing: is art a good way to diversify a client's portfolio. CFA Magazine May/June issue: 29–32
McConnell M, Perez-Quiros G (2000) Output fluctuations in the United States: what has changed since the early 80s. Am Econ Rev 90:1464–1476
Mei J, Moses M (2002) Art as an investment and the underperformance of masterpieces. Am Econ Rev 92:1656–1668
Melnik AL, Plaut SE (2009) Art as a component in investment portfolios. Mimeo. Paper presented at the European Financial Management Association Annual Meetings, Madrid
Nelson CR, Plosser CI (1982) Trends and random walks in macroeconomic time series: some evidence and implications. J Monet Econ 10:139–162
Nelson CR, Piger J, Zivot E (2001) Markov regime switching and unit-root tests. J Bus Econ Stat 19: 404–415
Ng S, Perron P (2001) Lag length selection and the construction of unit root tests with good size and power. Econometrica 69:1519–1554
Perron P (1989) The great crash, the oil price shock, and the unit root hypothesis. Econometrica 57: 1361–1401
Schaller H, Van Norden S (1997) Regime switching in stock markets returns. Appl Financ Econ 7:177–191
Tillmann P (2007) Inflation regimes in the US term structure of interest rates. Econ Model 24:203–223
Wang P, Theobald M (2008) Regime-switching volatility of six East Asian emerging markets. Res Int Bus Financ 22:267–283
Wieand K, Donaldson J, Quintero S (1998) Are real assets priced internationally? evidence from the art market. Multinatl Financ J 2:167–187

Worthington AC, Higgs H (2003) Art as an investment: short and long-term comovements in major painting markets. Empir Econ 28:649–668
Worthington AC, Higgs H (2004) Art as an investment: risk, return and portfolio diversification in major painting markets. Account Financ 44:257–271
Worthington AC, Higgs H (2006) A note on financial risk, return and asset pricing in Australian modern and contemporary art. J Cult Econ 30:73–84
Zivot E, Andrews DWK (1992) Further evidence on the great crash, the oil-price shock and the unit root hypothesis. J Bus Econ Stat 10:251–270