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Price Bubbles and Their Persistence in the Art Market: Evidence from China

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Abstract

This study investigates price bubbles in the Chinese art market and their persistence from 2000 to spring 2022. We first use the hedonic pricing model to construct price indices and then apply sup ADF (SADF) and generalized sup ADF (GSADF) tests to examine bubbles during the study period. Furthermore, we use the quantile nonlinear unit root test (QKSS test) to identify mean-reverting behavior. The results indicate the presence of price bubbles in the Chinese art market. In terms of persistence, the Chinese art market is in general persistent in most quantiles, while contemporary artworks show evidence of mean-reverting behavior in lower quantiles, implying the existence of market inefficiency.

Keywords

Chinese Art Market; Price Bubbles; Right-tailed Tests; Quantile Nonlinear Unit Root Test.

1. Introduction

The Chinese art auction market celebrated its 32nd anniversary in 2024. Since 2010, China has been one of the three major forces in the global art market (the USA, China, and the UK). These remarkable achievements have been due to China's economic prosperity and attracted widespread public and academic interest.

Since Kräussl et al. (2016)[1] questioned whether the art market experienced a speculative bubble, researchers have increasingly used various methods to explore price bubbles worldwide. Applying a right-tailed unit root test with forward recursive regressions to detect explosive behaviors of six different art market segments for the period from 1970 to 2104, Kräussl et al. (2016)[1] identified two historical bubbles and found an explosive movement in "Impressionist and Modern," "Post-war and Contemporary," "American," and "Old Masters" fine art market segments. Lovo and Spaenjers (2018)[2] proposed a dynamic auction model in which rational agents trade art. They found that not only prices but also consignment volume increased during expansions because art owners would auction only when macroeconomic fundamentals were sufficiently good. Assaf (2018)[3] utilized several tests to detect explosive behaviors in art markets from 1998 to 2015 and argued that the market experienced some adjustment after the 2008 financial crisis and became more sensitive to economic and geopolitical events. Demir et al. (2018)[4] constructed a painting price index in Turkey using 32,391 sales transactions over the period 1990-2016. Their results did not reject the null hypothesis that there was no bubble in the Turkish painting price index. Penasse and Renneboog (2022)[5] argued that price increased in the post-war art market coincided with an increase in demand fundamentals but were followed by a predictable depression. High prices coincided with many attributes of speculative bubbles; trading volume, the share of short-term trade, the share of post-war art, and volatilities were all higher during booms. Bernales et al. (2022)[6] showed that an increase in speculative bubbles was associated with four elements: art supply constraints, a more negative correlation between collectors' wealth and the

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emotional value of an artwork, a more positive relationship between forgery and the emotional value of an artwork, and more heterogeneous beliefs.

When it comes to the Chinese art market, Li et al. (2020)[7] used the generalized supremum augmented Dickey-Fuller test to detect bubbles in the Chinese art market. The results indicated that two bubbles emerged in 2004–2005 and 2010–2011. The main reasons for this were the financialization of artwork, speculative behaviors of investment institutions, and macroeconomic fluctuations in China. Wang (2023)[8] analyzed the nonlinear and regime-switching properties of individual segments and concluded that occasional shocks would only temporarily alter their data-generating processes and had transitory effects.

There have been four main approaches to detecting bubbles. The first definition of bubbles is based on a comparison of the underlying asset's fundamental value and nominal value. The asset-pricing approach suggests that bubbles exist when the nominal value that coincides with market value is not equal to the fundamental value of the asset (Lucas, 1978)[9]. Foster and Wild (1999)[10] provided the second approach by using the sigmoid (or logistic) curve approach. This method is beneficial when trying to capture various phases in the evolution of a bubble, such as the expansion, the inflexion, and the saturation phase. These three phases are considered as typical ones during the price bubble formation. The main drawback of the sigmoid curve approach is its questionable effectiveness in measurement during multiple bubbles. The third methodology for testing bubbles is offered by the Markov-switching Augmented Dickey-Fuller (MSADF) unit root test that detects explosive autoregressive roots. This procedure is proposed by Hall et al. (1999)[11] to track alternations from non-bubble to bubble regimes. The primary disadvantage of this approach is the difficulty in determining whether high volatility or explosive behavior exists in regimes. Finally, Phillips et al. (2015a, b; 2017)[12,13,14] presented the most popular right-tailed tests for detecting price bubbles. These are about bubble tests based on the assumption that bubbles exhibit a mildly explosive behavior. These tests follow the theory that tendencies of prices during upward phases differ from those in downward periods.

As mentioned previously, wealth and other economic factors may cause art bubbles. Given that the behavior of most economic and financial variables may arise from nonlinear processes (Aye et al., 2018)[15], art prices are likely to exhibit nonlinear characteristics. In addition, many financial time series are heavy tailed (Falk & Wang, 2003)[16]. The quantile nonlinear unit root test is robust to non-normal innovation distribution and allows for different and potential asymmetric adjustment speeds at different quantiles (Koenker & Xiao, 2004)[17]. In this case, this approach allows us not only to analyze the persistence of the bubble prices as well as the mean-reverting behavior but also to examine possible asymmetry in the behavior of art indices (Tsong & Lee, 2011)[18].

This study examines the price performance of the Chinese art market. We first construct Chinese art market indices for different categories based on a hedonic pricing model. Next, we apply right-tailed tests for price bubbles in the Chinese art market from 2000 to spring 2022 and investigate the persistence of price spikes using a quantile nonlinear unit root test to identify mean-reverting behaviors. Our results indicate that price bubbles occurred in the Chinese art market during the study period. In terms of persistence, most of the Chinese art market shows no mean reversion, except for Contemporary artworks in the lower quantiles.

The contributions of our study are as follows: first, to the best of our knowledge, this is the first analysis of the Chinese art market's price bubbles' persistence. As the persistence helps to evaluate price risk in the future and reflects the market efficiency, market participants can make investment decisions or strategies in view of the price persistence. Second, we employ the quantile nonlinear unit root test for the persistence of price bubbles, which not only allows us to analyze the mean-reverting behavior of prices, but also considers possible asymmetries in the Chinese art market among quantiles. Finally, although Li et al. (2020)[7] and Wang

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(2023)[8] also investigated the phenomenon of price bubbles in the Chinese art market, our results differ from theirs due to different data and methods employed, thus providing a certain supplement to the study of the Chinese art market.

The remainder of this paper is organized as follows: Section 2 describes the methodologies employed in this study. Section 3 presents the data and the estimated market indices. Section 4 reports and discusses the empirical results, and Section 5 makes a conclusion.

2. Methodologies

2.1. Hedonic Pricing Model

We employ a hedonic pricing model to construct price indices for the Chinese art market. This method pools all available transaction data, and regresses prices on a set of value-determining attributes and time dummies, which allows us to determine the implicit price or contribution of each artwork's attributes within the total price, owing to their high heterogeneity and ease of differentiation (Garay, 2021)[19]. The standard approach is:

$$lnP_{it} = \alpha + \sum_{j=1}^{z} \beta_j X_{ijt} + \sum_{t=0}^{T} \gamma_t D_{it} + \varepsilon_{it}, \tag{1}$$

where lnP_{it} is the logarithm of the price of painting i at time t, α is the constant term, and X_{ijt} represents the jth characteristic of painting i. D_{it} is the time dummy variable, which equals one when painting i is sold at time t and zero otherwise. β_j is the coefficient of the jth characteristic. γ_t is the coefficient of time dummy variables, which is used to calculate the price index, and $\varepsilon_{it} \sim N(0, \sigma^2)$.

Using the estimated coefficients on the time dummies of Equation (1), the price index is then calculated as:

$$Index_{t+1} = \frac{\exp(\gamma_{t+1})}{\exp(\gamma_t)} * Index_t. \tag{2}$$

where γ_t is the coefficient on the time dummy D_{it} in Equation (1). In our study, we settle the spring of the year 2000 as the benchmark and normalize 100.

2.2. Right-tailed Tests

Phillips et al. (2015a, b; 2017)[12,13,14] proposed the right-tailed tests, including both SADF and GSADF tests. These tests are designed to implement the basic idea of repeated ADF tests on data subsamples recursively.

The SADF test refers to a repeated estimation of the ADF model on a forward-expanding sample sequence and is obtained as the supremum value of the corresponding ADF statistical sequence. For each time series y_t, we estimate the following autoregressive specification using least squares:

$$\Delta y_t = \hat{\alpha}_{r_1,r_2} + \hat{\beta}_{r_1,r_2} y_{t-1} + \sum_{i=1}^{k} \hat{\psi}_{r_1,r_2}^{i} \Delta y_{t-i} + \hat{u}_t, \tag{3}$$

where $\hat{\alpha}_{r_1,r_2}$ is the constant intercept, and r_1 and r_2 denote the start and end points of the regression sample (T), respectively. K is the lag order from minimizing the Bayesian information criterion (BIC), and $u_t \sim NID\left(0, \sigma_{r_1,r_2}^2\right)$. The null hypothesis is tested of being a unit root ($H_0: \beta = 1$) in contrast to the alternative of being an explosive process ($H_1: \beta > 1$).

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In practical applications, forward recursive calculations of ADF statistics are performed by applying a fixed starting point and an expanding window. The estimation procedure is as follows. The sample size is normalized to 1, which yields a sample interval of [0,1]. The window size r_w expands from r_0 to 1, where r_0 is the smallest sample window width fraction and 1 is the largest window width fraction in the recursion. The starting point r_1 of the sample sequence is fixed at 0, and the end r_2 of each sample is equal to r_w and varies from r_0 to 1. The regression is then estimated recursively by increasing the window size by one observation at a time. Thus, each estimation produces an ADF statistic, denoted as ADF_{r_2}. Finally, the estimation is based on the entire sample. The SADF test is then defined as the supremum value of the ADF_{r_2} sequence for $r_2 \in [r_0, 1]$:

$$SADF(r_0) = sup_{r_2 \in [r_0,1]}\{ADF_0^{r_2}\}, \tag{4}$$

The GSADF statistic is defined as the supremum of the ADF statistic sequence over all feasible ranges of r_1 and r_2, allowing for changes in not only the endpoint of the regression r_2 from r_0 to 1, but also the starting point r_1 from 0 to $r_2 - r_0$. That is,

$$GSADF(r_0) = \underset{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}}{sup} \{ADF_{r_1}^{r_2}\}, \tag{5}$$

Furthermore, Phillips et al. (2015a)[12] proposed a double recursive test procedure called the backward sup ADF test to perform a sup ADF test on a backward-expanding sample sequence, thus providing the date of the origin and termination of a bubble. That is,

$$BSADF_{r_2}(r_0) = sup_{r_1 \in [0, r_2 - r_0]}\{ADF_{r_1}^{r_2}\}, \tag{6}$$

Since the SADF test is based on repeated procedure of the ADF test for each $r_2 \in [r_0, 1]$ and the GSADF test is based on inferences of the sup value of the backward sup ADF statistic sequence, the date-stamping strategy refers to a procedure by comparison between $BSADF_{r_2}(r_0)$ and $scv^{\beta_T}(r_0)$, where $scv^{\beta_T}(r_0)$ is the $100 - (1 - \beta_T)\%$ right-side critical value of the sup ADF statistic based on $\lfloor Tr_2 \rfloor$ observations. In other words, a bubble emerges if $BSADF_{r_2}(r_0) > scv^{\alpha}(r_0)$, while a bubble collapses if $BSADF_{r_2}(r_0) < scv^{\alpha}(r_0)$. In this study, the critical values of both $SADF(r_0)$ and $GSADF(r_0)$ are obtained through Monte Carlo simulations using the random-walk process with an asymptotically negligible drift:

$$y_t = dT^{-\eta} + \theta y_{t-1} + e_t \quad e_t \sim N(0,1), \tag{7}$$

where d, η, and θ are constant, T is the sample size, and e_t is the error term. We set the significance level of the critical values at 95% and obtain the corresponding t-statistics after 2,000 replications.

2.3. Quantile Nonlinear Unit Root Test (QKSS)

To improve the power performance of tests in the absence of Gaussian conditions, Koenker and Xiao (2004)[17] proposed a unit root test based on the quantile autoregression approach. Furthermore, Li and Park (2018)[20] extended this approach by developing the QKSS test. In our study, we apply the QKSS test to investigate the potential of the art market to rebound after an initial shock. The QKSS test is robust against non-normal distributions and allows for

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different and potentially asymmetric adjustment speeds in different quantiles (Yang & Zhao, 2020)[21]. Following Galvao (2009)[22] and Yang and Zhao (2020)[21], the quantile nonlinear unit root test with covariates is defined as:

$$t(\tau) = \frac{f\left(\widehat{F^{-1}(\tau)}\right)}{\sqrt{\tau(1-\tau)}}(Y'_{-1}M_zY_{-1})^{\frac{1}{2}}\hat{\delta}(\tau), \tag{8}$$

where $f\left(\widehat{F^{-1}(\tau)}\right)$ is a consistent estimator of $f\left(F^{-1}(\tau)\right)$, with f and F representing the probability and cumulative density functions of ε_t, Y_{-1} is the vector of the values taken in the sample period by the lagged dependent variable y_{t-1} and M_z is the projection matrix onto the space orthogonal to $Z = \left(1, \Delta y_{t-1}, \dots, \Delta y_{t-p}, x'_{t-q_1}, \dots, x'_{t+q_2}\right)$. The test statistic $t(\tau)$ under the unit root null hypothesis is:

$$t(\tau) \Rightarrow \xi(\tau) = \lambda\frac{\int_0^1 \underline{W_1}dW_1}{\sqrt{\int_0^1 \underline{W_1^2}dr}} + \sqrt{1-\lambda^2}\frac{\int_0^1 \underline{W_1}dW_2}{\sqrt{\int_0^1 \underline{W_1^2}dr}}, \tag{9}$$

where $\underline{W_1} = W_1^3 - \int_0^1 W_1^3 dr$, W_1 and W_2 are standard Brownian motions and independent of one another, $\lambda = \lambda(\tau) = \frac{\sigma_{u\psi}(\tau)}{\sigma_u\sigma_\psi(\tau)} = \frac{\sigma_{u\psi}(\tau)}{\sigma_u\sqrt{\tau(1-\tau)}}$, $\psi_\tau(u) = \tau - I(u<0)$, $e_{t\tau} = \Delta y_t - z_t'\beta(\tau)$, and $E[\psi_\tau(e_{t\tau})|F_{t-1}] = 0$. We utilize the Ornstein-Uhlenbeck process as the near-integrated process for asymptotic theory.

The lag orders for the unit root test are selected using the BIC. For estimating long-run variance and covariance parameters (σ_u^2 and $\sigma_{u\psi}$), we use the Quadratic Spectral windows in the kernel estimators following Galvao (2009)[22] and Yang and Zhao (2020)[21]. The results are compared with pre-calculated critical values at several significance levels.

3. Data and Price Index Construction

As Prieto-Rodriguez and Vecco (2021)[23] pointed out, because of price dispersion, heterogeneity, limited information, and a lack of price transparency, the art market has different categories with various information requirements, rules, and prices. According to the definition of Artprice (www.artprice.com), the Chinese art market can be divided into two main categories. One is "Chinese Painting and Calligraphy" ("Traditional artworks" hereafter), which refers to traditional Chinese art such as works in ink on various substrates including Xuan paper, silk and fans. Specifically, Chinese calligraphy focuses on lettering, words, poems and wishes, whereas Chinese painting represents landscapes, people, birds and flowers. Iezzi (2013)[24] noted that it represented one of the most important art forms practiced in China. The other category is "Oil Painting and Contemporary Art" ("Contemporary artworks" hereafter), which refers to artworks created by Chinese artists who appropriated Western techniques and artistic media (oil painting, photography, sculpture, installation, drawing in pencil, gouache, watercolors, etc.) after an oil on canvas was presented in China for the first time in 1579. These two categories differ primarily in the nature of artworks and market participants. For example, investors and collectors of "Traditional artworks" are usually more interested in Chinese culture and art while younger investors and collectors who appreciate Western aesthetics and culture prefer "Contemporary artworks".

The dataset used in this study consists of 65,497 semiannual transactions of Chinese artwork from 2000 to spring 2022, including 59,131 traditional artworks and 6,366 contemporary artworks. All prices included buyers' premiums in the database and were collected from truly

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sold results of art auctions listed by Artron (https://amma.artron.net), the largest well-known Chinese art online database at present, expressed in Chinese Yuan (CNY). The average semiannual rate was used as the exchange rate.

Following Wang (2023)[8], the independent variables in the hedonic pricing model include attributes that constitute the artwork's characteristics. Descriptive statistics for these variables are presented in Table 1.

Medium. One factor that influences the price of an artwork is the medium and technique used. Because different art categories use various media, we classify them into seven categorical variables. Traditional artworks are color and ink, whereas Contemporary artworks are acrylic, board, canvas, mixed media, and paper. In the estimation, ink and mixed media serve as the reference categories for Traditional and Contemporary artworks, respectively.

Table 1. Descriptive statistics for hedonic variables

Variables	Traditional artworks						Contemporary artworks					
	Mean	S.D.	Min	Max	Skewness	Kurtosis	Mean	S.D.	Min	Max	Skewness	Kurtosis
ln(Price)	12.907	1.606	4.700	20.652	-0.012	0.210	14.421	1.438	8.657	19.914	`-0.017	-0.035
Medium												
Color	0.863	0.344	0	1	-2.114	2.470	/	/	/	/	/	/
Ink	0.137	0.344	0	1	2.114	2.470	/	/	/	/	/	/
Acrylic	/	/	/	/	/	/	0.079	0.269	0	1	3.133	7.824
Board	/	/	/	/	/	/	0.034	0.181	0	1	5.135	24.392
Canvas	/	/	/	/	/	/	0.834	0.372	0	1	-1.792	1.213
Mixed media	/	/	/	/	/	/	0.013	0.111	0	1	8.751	74.647
Paper	/	/	/	/	/	/	/	0.041	0	1	4.620	19.357
Sale auction houses												
Beijing Hanhai	0.105	0.307	0	1	2.574	4.626	0.058	0.233	0	1	3.789	12.371
China Guardian	0.256	0.437	0	1	1.116	-0.755	0.114	0.317	0	1	2.436	3.937
Christie's	0.070	0.254	0	1	3.383	9.445	0.221	0.415	0	1	1.346	-0.188
Council	0.065	0.246	0	1	3.545	10.569	0.040	0.196	0	1	4.681	19.926
Holly's	0.042	0.200	0	1	4.579	18.965	0.035	0.183	0	1	5.096	23.992
Poly	0.123	0.329	0	1	2.291	3.248	0.168	0.374	0	1	1.772	1..143
Rongbao	0.076	0.265	0	1	3.205	8.270	0.029	0.167	0	1	5.658	30.032
Sotheby's	0.064	0.245	0	1	3.561	10.683	0.182	0.386	0	1	1.652	0.730
Sungari	0.060	0.238	0	1	3.703	11.717	0.018	0.134	0	1	7.204	49.938
Xiling Yinshe	0.058	0.235	0	1	3.765	12.178	0.038	0.191	0	1	4.832	21.363
Others	0.081	0.272	0	1	3.077	7.469	0.098	0.298	0	1	2.701	5.300
Size												
Area	0.430	0.587	0.003	89.425	64.747	9,072.393	1.460	1.979	0.014	36.000	6.192	74.080
Topic												
Birds & Flowers	0.560	0.496	0	1	-0.240	-1.942	/	/	/	/	/	/
Calligraphy	0.012	0.107	0	1	9.156	81.847	/	/	/	/	/	/
Landscapes	0.329	0.470	0	1	0.727	-1.472	/	/	/	/	/	/
People	0.100	0.299	0	1	2.674	5.152	/	/	/	/	/	/
Abstract	/	/	/	/	/	/	0.240	0.427	0	1	1.218	-0.515
Figurative	/	/	/	/	/	/	0.760	0.427	0	1	-1.218	-0.515
Observations	59,131						6,366					

Table 1 reports the descriptive statistics of the hedonic variables of the Chinese art market segments from 2000 to spring 2022.

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Sale Auction Houses. Most studies confirm that auction house sales are a significant characteristic variable in the valuation of artworks (Renneboog & Spaenjers, 2013)[25]. In this study, we introduce 10 of the top 15 auction houses in China by auction turnover in the Artprice Report (2019): Beijing Hanhai, China Guardian, Christie's, Council, Holly's, Poly, Rongbao, Sotheby's, Sungari, and Xiling Yinshe. Other auction houses are specified as reference categories.

Size. An artwork's price is undoubtedly related to its size. We control for the size of the artwork using its surface area in square meters.

Topic. The topic of the artwork generally affects the aesthetic appreciation of art objects. Therefore, we categorize the artworks into different topic groups. We create the four categories of calligraphy, landscapes, people, and birds and flowers for Traditional artworks, and two categories of abstract and figurative for Contemporary artworks, where calligraphy and abstract are used as reference dummy variables for Traditional and Contemporary artworks, respectively, and given a value of zero.

Table 2 reports the results of the hedonic regression, which reveal that most variables are significant at the 1% level. For both art categories, Sotheby's sold artworks at a premium to other auction houses, making it the most profitable auction house in the Chinese art market. In terms of the medium, the average price of "Color" artwork in Traditional artworks and "Canvas" in Contemporary artworks is higher than that of other materials. Undoubtedly, the price of an artwork increases with its size. For the topic dummies, "Landscape" obtains the highest value among Traditional artworks while "Figurative" has a discount compared to "Abstract" in Contemporary artworks. Our results are consistent with those of Wang (2023)[8].

Table 2. Hedonic regression results

Variables	Traditional artworks		Contemporary artworks	
	Coefficient	S.E.	Coefficient	S.E.
Medium				
Color	0.2045***	0.0160	/	/
Acrylic	/	/	0.2633*	0.1542
Board	/	/	0.2668**	0.1619
Canvas	/	/	0.4878***	0.1413
Paper	/	/	-0.7606***	0.1593
Sale auction houses				
Beijing Hanhai	-0.5342***	0.0258	0.2714***	0.0840
China Guardian	-0.0295	0.0221	0.2808***	0.0702
Christie's	0.4956***	0.0283	0.3228***	0.0595
Council	0.2601***	0.0293	0.0138	0.0926
Holly's	0.0617*	0.0335	0.1656*	0.1002
Poly	0.1348****	0.0251	0.4900***	0.0637
Rongbao	-0.0881***	0.0278	-0.5113***	0.1068
Sotheby's	0.5123***	0.0290	0.3475***	0.0617
Sungari	-0.1755***	0.0294	-0.1850	0.1258
Xiling Yinshe	0.0208	0.0301	-0.3219***	0.0958
Size				
Area	0.6773***	0.0092	0.1757***	0.0079
Topic				
Birds & Flowers	0.4104***	0.0509	/	/
Landscapes	0.6657***	0.0513	/	/
People	0.4655***	0.0533	/	/
Figurative	/	/	-0.6456***	0.0411
Period				
2000A	-0.1208	0.0873	-0.4303	0.4769

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2001S	-0.0899	0.0884	0.5980	0.5150
2001A	0.0518	0.0916	0.3410	0.4318
2002S	-0.1895**	0.0829	0.5611	0.3974
2002A	-0.3562***	0.0876	0.4638	0.5160
2003S	-0.2010	0.1415	1.2961	0.9097
2003A	0.1956***	0.0751	1.2029***	0.3616
2004S	0.4659***	0.0731	0.7676**	0.3416
2004A	0.9137***	0.0739	1.2293***	0.3119
2005S	1.2281***	0.0744	1.5525***	0.3038
2005A	1.3862***	0.0719	1.6524***	0.2938
2006S	0.8733***	0.0751	1.8692***	0.2926
2006A	0.9614***	0.0764	1.8121***	0.2913
2007S	0.8004***	0.0768	2.1258***	0.2910
2007A	1.2630***	0.0752	2.3391***	0.2916
2008S	1.1335***	0.0754	2.1993***	0.2911
2008A	1.0317***	0.0788	1.8503***	0.2984
2009S	1.0442***	0.0760	1.7906***	0.3013
2009A	1.3866***	0.0723	2.1149***	0.2995
2010S	1.7627***	0.0731	2.1240***	0.2958
2010A	2.0404***	0.0718	2.2975***	0.2915
2011S	2.4424***	0.0715	2.5689***	0.2912
2011A	2.3291***	0.0723	2.4916***	0.2902
2012S	2.1768***	0.0752	2.2601***	0.2931
2012A	2.0535***	0.0749	2.3961***	0.2947
2013S	2.3575***	0.0742	2.5435***	0.2964
2013A	2.2859***	0.0748	2.8973***	0.2941
2014S	2.1351***	0.0747	2.7055***	0.2957
2014A	2.1587***	0.0743	2.4738***	0.3002
2015S	2.0975***	0.0775	2.8453***	0.3035
2015A	1.7252***	0.0764	2.5112***	0.3023
2016S	1.9827***	0.0778	2.7042***	0.3054
2016A	1.8669***	0.0768	2.8028***	0.3125
2017S	2.1434***	0.0776	2.7534***	0.3111
2017A	2.2990***	0.0762	2.5040***	0.2996
2018S	2.1147***	0.0805	3.0547***	0.3003
2018A	2.0155***	0.0798	2.9953***	0.2996
2019S	1.8419***	0.0821	3.0591***	0.3062
2019A	1.9832***	0.0775	2.6652***	0.3045
2020S	1.0011***	0.1897	2.3102***	0.2571
2020A	2.3054***	0.0775	2.7283***	0.3035
2021S	2.3444***	0.0815	2.4599***	0.3067
2021A	1.8442***	0.0778	2.0960***	0.3124
2022S	2.2863***	0.1441	2.6955***	0.3808
Intercept	10.3198***		11.9078***	
Adjusted R^2	0.3337		0.2797	
S.E. of regression	1.3111		1.2206	
F-statistics	502.8911		42.1924	
Observations	59,131		6,366	

Table 2 reports the hedonic regression results of the Chinese art market segments from 2000 to spring 2022. The abbreviations "S" and "A" refer to spring sales and autumn sales, respectively. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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Figure 1 illustrates the evolution of Chinese art market price indices from 2000 to spring 2022. Traditional artworks began to grow rapidly in 2002, peaked in 2011, fluctuated dramatically, and fell sharply in 2020 before rebounding. In contrast, the price of Contemporary artworks continued to rise from 2000, peaking in 2018, and fluctuated significantly thereafter.

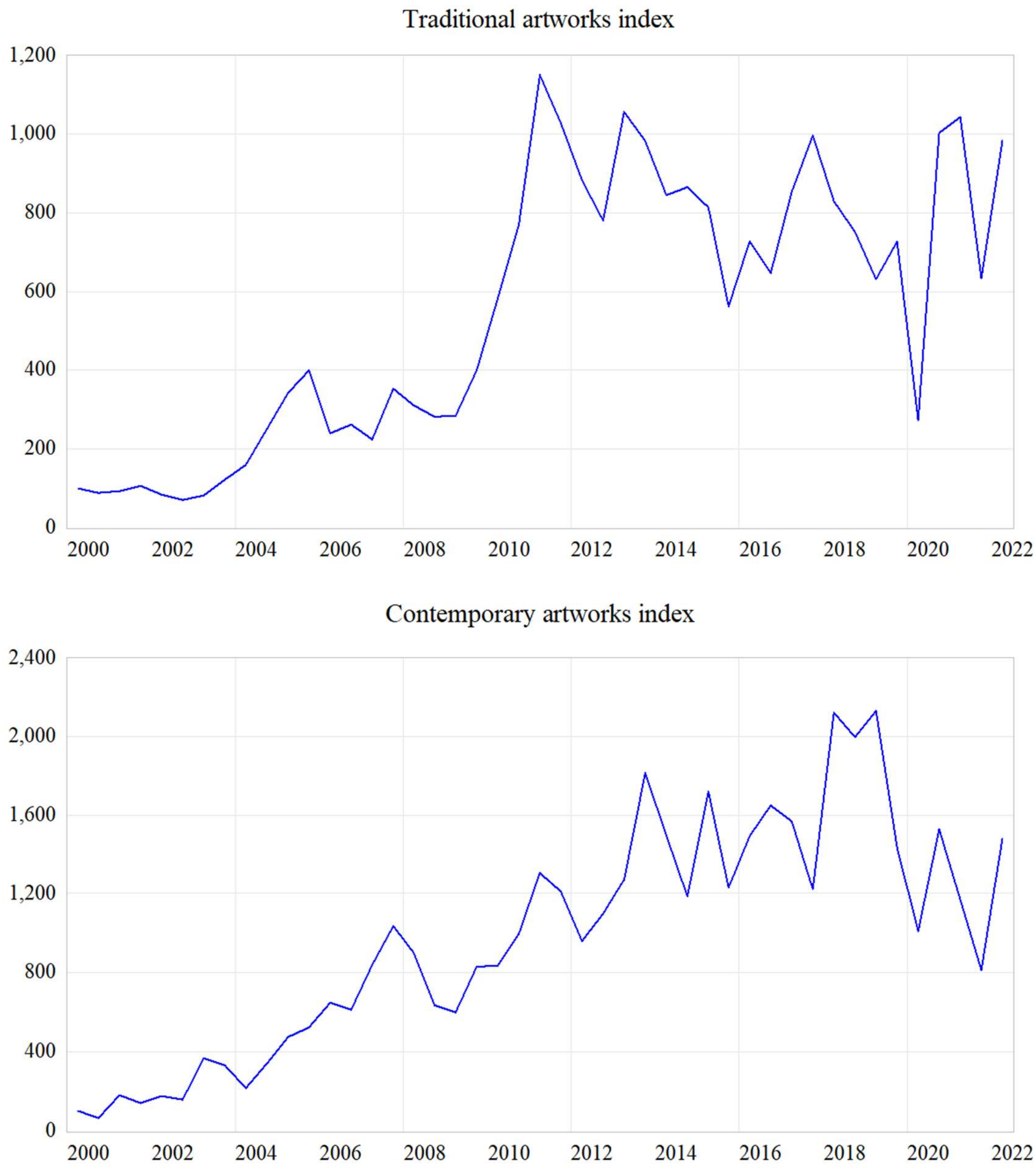

Figure 1. Price indices of the Chinese art market from 2000 to spring 2022.

This figure shows the price indices of the Chinese art market from 2000 to spring 2022. All series are semiannual data normalized to 100 in the spring of 2000.

4. Empirical Results and Discussion

To illustrate both the SADF and GSADF tests for bubble detection in our case, Table 3 reports the statistics of the null hypothesis of a unit root against the alternative of an explosive root for each category, where r_0= 0.10 (the initial start-up sample has 11 observations). Three cases are considered: with a constant, with both constant and trend, and with none. The sample period is

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2000 to spring 2022, with 45 semiannual observations. Various critical values are reported for each test, which are obtained using Monte Carlo simulations with 2,000 replications.

Table 3. The right-tailed ADF tests for the Chinese art market

	Traditional artworks				Contemporary artworks			
	T-statistics	Critical values			T-statistics	Critical values		
		90%	95%	99%		90%	95%	99%
Test for explosive behavior in the regression (constant)								
SADF	3.2966***	0.9124	1.2253	1.7820	1.0976*	0.9124	1.2253	1.7820
GSADF	3.5213***	1.6312	2.0155	3.0065	1.2355	1.6312	2.0155	3.0065
Test for explosive behavior in the regression (constant & trend)								
SADF	1.6135***	0.1196	0.3407	0.8779	0.9108*	0.8779	1.3407	1.8196
GSADF	1.7835**	0.9116	1.2063	1.8570	0.9514	0.9616	1.2063	1.8570
Test for explosive behavior in the regression (none)								
SADF	3.8503***	2.1302	2.5359	3.3362	2.5941**	3.3362	2.5359	2.1302
GSADF	3.9912**	3.0475	3.5473	4.9095	2.7608	3.0475	3.5473	4.9095

Table 3 reports the SADF and GSADF tests for the null hypothesis of a unit root against the alternative of an explosive root. The critical values for both tests are obtained through Monte-Carlo simulations with 2,000 replications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

For Traditional artworks, both SADF and GSADF tests exceed their respective 5% right-tailed significance level, indicating strong evidence of explosive bubbles during the sample period. In contrast, for Contemporary artworks, the test statistics of the SADF are greater than their 10% right-tailed significance level, while no evidence of explosive bubbles is found from the GSADF tests. Overall, the null hypothesis of no bubbles can be rejected, and explosive behaviors are found in both categories of the Chinese art market.

Figure 2 plots the bubbles detected in the Chinese art market. The blue line on the right axis, the red and the green lines on the left axis represent the price index, the 95% critical value sequence, and the backward SADF sequence, respectively. In Figure 2, the price bubbles in Traditional artworks occurred mainly in 2004–2005 and 2010–2011, which are marked in gray shading. Li et al. (2020)[7] also identified two price bubbles in the traditional Chinese art market during the same periods. For the first bubble, they concluded that the rapid growth of the Chinese economy might provide a powerful impetus for the art market. For the second bubble, the hugely increasing narrow money (M1) supply in 2010 was the main explanation for the pricing in the Chinese art market. In comparison, Contemporary artworks saw bubbles in 2007-2008. Thanks to increasing high prices of Contemporary artworks over the few years before 2007, this market received unprecedented attention, which attracted more investors and further boosted the overall price of Contemporary artworks. Hence, Contemporary artworks were considered to gather the most commercial speculation (Chinese Art Auction Market Research Report, 2008).

This figure shows the bubble periods in the Chinese art market from 2000 to spring 2022 using backward SADF tests. All series are semiannual data normalized to 100 in the spring of 2000.

Table 4 presents the QKSS test results. For Traditional artworks, most quantiles do not reject the null hypothesis, except for quantile 0.4. In other words, Traditional artworks do not show evidence of mean reversion, making them potentially risky for long-term investments. Especially, according to the efficient market hypothesis (EMH), current prices are unrelated to past prices. The absence of mean reversion complies with the EMH and implies that the market

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is efficient. In this way, Traditional artworks become an almost efficient market, and prices can fully reflect all available information in this market. In comparison, Contemporary artworks reject the null hypothesis in lower quantiles. As rejecting the null hypothesis implies that shocks do not accumulate over time and that prices would be mean-reverting, these lower quantiles may become more attractive for investors to gain excess returns.

Figure 2. GSADF tests for the Chinese art market.

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Table 4. Tests for quantile nonlinear unit root tests

Quantiles	Traditional artworks				Contemporary artworks			
	QKSS	Asymptotic critical values			QKSS	Asymptotic critical values		
		1%	5%	10%		1%	5%	10%
0.1	-2.003	-2.824	-2.301	-2.059	**-14.064*** **	**-2.784**	-2.116	-1.753
0.2	-1.771	-2.979	-2.332	-2.119	**-4.823*** **	**-3.111**	-.2469	-2.129
0.3	-1.773	-3.040	-2.381	-2.136	**-2.266***	-2.997	-2.346	**-1.995**
0.4	**-2.369***	-3.092	-2.442	**-2.151**	-1.582	-3.015	-2.361	-2.012
0.5	-1.860	-3.130	-2.496	-2.167	-0.619	-3.164	-2.544	-2.209
0.6	-1.154	-3.174	-2.559	-2.225	-0.542	-3.039	-2.380	-2.035
0.7	-0.658	-3.195	-2.588	-2.255	-0.364	-3.029	-2.372	-2.026
0.8	-0.448	-3.202	-2.595	-2.257	-0.123	-2.980	-2.332	-1.979
0.9	-0.310	-3.453	-2.786	-2.264	-0.043	-3.122	-2.485	-2.145

Table 4 shows the results of the quantile nonlinear unit root tests. The null hypothesis of the presence of a unit root is rejected if the calculated test statistic is lower in value than calculated asymptotic critical values at the 1% (***), 5% (**) and 10% (*) levels of significance. Statistically significant values and the respective asymptotic critical value that indicates a significance level are highlighted in bold.

Other scholars also have examined the efficiency market hypothesis for global art markets. For example, Aye et al. (2018)[15] found evidence of structural shifts and nonlinearity in the 15 art indices and suggested that the art market was inefficient. Assaf et al. (2021)[26] investigated the efficiency in the global art market and found that all markets were characterized by persistent behavior and overwhelming evidence of market inefficiency in almost all sectors. Kim and Park (2023)[27] used quarterly price index data to test the weak form of the efficient market hypothesis for 13 art market indices. They found strong asymmetrically efficient market hypothesis results between the lower and upper sub-intervals and suggested that art market inefficiency might originate from the lower quantile interval. In our case, the inefficiency in lower quantiles of Contemporary artworks aligns with the results of Kim and Park (2023)[27].

There are several possible reasons for these results. David et al. (2013)[28] argued that art market inefficiency was rooted in the design of trading systems, such as sellers' minimum transaction prices for artworks, the determination of hammer prices by bidding and no upper limits. Assaf et al. (2021)[26] supposed that the asymmetrical information, influential gallery power, and differentiated pieces and talents in the art markets could lead to the inefficiency in the art market. In terms of the inefficiency in lower quantiles, the asymmetric acquisition of information by market participants might explain why it occurred often when price levels were low (Ashenfelter & Graddy, 2003)[29]. In our case, the lower quantiles of Contemporary artworks account for a small share of the Chinese art market. investors and collectors view it more as access to artworks by famous artists. Hence, dealers, insiders, and experts have relatively more information than buyers, leading to the inefficiency in this market.

5. Conclusion

This study investigates price bubbles and their persistence in the Chinese art market from 2000 to spring 2022. We first use the hedonic pricing model to construct the price indices of different market categories and then apply the SADF and GSADF tests to identify bubbles' performance and investigate their persistence using quantile nonlinear unit root tests to identify mean-reverting behavior and market efficiency across quantiles.

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We document the presence of price bubbles in the Traditional artworks category during 2004–2005 and 2010–2011, and in the Contemporary artworks category from 2007 to 2008. In terms of persistence, Traditional artworks demonstrate almost no mean reversion, implying its market efficiency, while Contemporary artworks show mean reversion in lower quantiles.

Our findings have several important implications for future studies. The evidence of mean-reverting behavior in lower quantiles of the Contemporary artworks suggests that shocks to this market are short-lived with predictable returns. As art prices may not fully reflect all accessible information in the market, market participants can incorporate any concealed information into their investment and/or management strategies and, consequently, make excessive gains from participating in the market. In addition, although it is generally agreed that the role of policy is limited because shocks are temporary and other forces may bring the market to its equilibrium in the long run, policies can in turn improve participants' access to market information (Aye et al., 2018)[15]. Since information asymmetry is the fundamental source of inefficiency, increases in the number of participants in auction markets, access to information regarding art prices, and globalization may help to reduce the inefficiency in the Chinese art market.

Some extensions of this study are considered for future research. For example, research on the subject identifies mean-reverting behavior as a function of numerous factors such as bullish/bearish market conditions and market overreaction. Given the wide scope and complexity of the phenomenon coupled with the high heterogeneity of the Chinese art market, we acknowledge that more research is needed to investigate the phenomenon in detail to assess and identify the relationship among the factors.

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