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Abstract

The record-breaking prices observed in the art market over the last three years raise the question of whether we are experiencing a speculative bubble. Given the difficulty to determine the fundamental value of artworks, we apply a right-tailed unit root test with forward recursive regressions (SADF test) to detect explosive behaviors directly in the time series of four different art market segments ("Impressionist and Modern", "Post-war and Contemporary", "American", and "Latin American") for the period from 1970 to 2013. We identify two historical speculative bubbles and find an explosive movement in today's "Post-war and Contemporary" and "American" fine art market segments.

Keywords: Art market; Alternative investments; Speculative bubbles; Explosive behavior
JEL Codes: G12, G14, Z11

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1. Introduction

Is there a bubble in the art market? This question was raised on November 15, 2013, by CNN journalist Ben Rooney, after a record-setting week for the art market: that broke the highest price ever paid for an auctioned painting (Francis Bacon's 1969 "Three Studies of Lucian Freud" fetched $142.4 million on November 12, 2013, at Christie's New York), set the highest price for a living artist ($58.4 million for Jeff Koon's 1994 "Balloon Dog (Orange)" – auctioned the same night at Christie's), and provided the auction house Christie's with the largest sale to date in the art market (more than $691 million). Earlier that year, hedge fund manager Steven Cohen had purchased Pablo Picasso's 1932 "Le Rêve" for about $155 million, on a private deal; a price only topped by one of the five versions of Paul Cezanne's 1892-93 "The Card Players", which was privately acquired by the State of Qatar in May of 2011 for a reported price of more than $250 million. New York Times journalist Conrad de Aenlle recently argued that "[...] wealthy investors have bid up prices of works by a handful of Contemporary artists so high that it's turning the heads of collectors of more modest means". He continues by speculating that "[…] such a concentration of interest and money in one segment of a market leads to instability down the road [...]", and "[…] authorities on art investment worry that the budding romance could end quickly and badly".

But such an important rise in prices of artworks does not necessarily mean that there is an actual speculative bubble in the art market. Bubbles are generally defined as high-volume trading of a given category of assets at prices that are far above their intrinsic values (King et al., 1993). Given this definition, one can isolate the following constraints to the detection of bubbles: (i) high volumes must be traded, and (ii) prices must be above their fundamental values. When it comes to the art market, those constraints raise two questions. First, does the recent dramatic increase in art prices concern the entire art market? Or is it a "top one percent" phenomenon that benefits only to a few "brand-name" artists (high volumes constraint)? The second and most puzzling issue is the determination of the intrinsic value of an artwork? If we cannot determine the intrinsic value, it is impossible to detect a speculative bubble.

Stein (1977) notes that artworks and more particularly paintings are peculiar financial assets; they are actually both consumable goods and financial assets. Their market has existed for over five centuries when collectors, in the 16th century, had started acquiring works of art for aesthetic reasons, social status, and also as a mean of investment (Getty Museum, 2013). However, as Campbell (2008) notes, art markets still remain somehow opaque and rather illiquid. The art market is further characterized by significant transaction costs and high barriers to entry (Kräussl and Wiehenkamp, 2012). Moreover, the value of artworks depends on a set of numerous variables, which are sometimes difficult to apprehend such as individual tastes, fashion effects (Chanel 1995), and the actual location of the sale.

In spite of all those specificities, economists like William Baumol started considering art as a financial asset as early as in the 1960s, and the interest for art as a financial asset has kept on growing along the growth of the art market itself. Beyond scholars and economists, the art market has attracted large financial institutions (e.g. UBS, Credit Suisse, Deutsche Bank, BNP Paribas, Société Générale) in the sense of providing art advisory services to their wealthiest clients (Kräussl and Wiehenkamp, 2012).

As of 2012, the auction market for art represents a total of $12.3 billion worldwide (Artprice, 2013). In a broader perspective, McAndrew (2008) estimates the global art market (auction and private deals) to be over $3 trillion with a $50 billion annual turnover. Artprice (2013) reports that in 2013, 80% of the transactions on the global auction market involved artworks priced at or under $5,000. Only 1% of all auctioned paintings over the period 1970 to 2013 had fetched prices higher than $1 million. Therefore, the high-end, record-level pieces discussed in the media represent only a tiny part of the global market. Taking into consideration this global art markets numbers and the first question raised, we run tests on different art market segments, namely "Impressionist and Modern", "Post-war and Contemporary", "American", and "Latin American", grasping a broad spectrum of the art market.

Answering the second question is not that straightforward but key. Even though Frey and Pommerehne (1989), Gérard-Varet (1995), and Chanel et al. (1996) list a few variables that are supposed to explain the formation of artwork prices (e.g. production cost, size and type of work, buyer income, measure of aesthetic quality, measures of artists' attributes, etc.), determining the fundamental value of an artwork is almost an impossible feat in itself. Under rational expectations, the fundamental value of an asset equals its discounted expected stream of cash flows (present value theory). It is relatively easy to obtain the expected cash flow earned by owning a share of stock (dividend) or a piece of real estate (rent). The ownership of an artwork, on the other hand, provides no claim for monetary return but some kind of convenience yield, which is also described as a "dividend of enjoyment" by Campbell (2008) and as "aesthetic pleasure" by Gérard-Varet (1995). Thus, reasons closely dependent on the motivations and characteristics of owner make it impossible to clearly quantify the return on art. To overcome this 'fundamental value' issue, we use a new and direct method of bubble detection developed by Phillips et al. (2011). This approach is based on a right-tailed ADF (augmented Dickey-Fuller) test, which can detect explosive behaviors directly in a time series.

Our empirical findings suggest that there is strong evidence of a speculative bubble - in the mania phase of its formation, which started in late 2011 – in both the "Post-war and Contemporary" and "American" art market segments. We observe that these two markets were already in the stage of a speculative movement around 2006 - 2008. The absence of such phenomena in the other segments of our study makes "Post-war and Contemporary" and "American" the most likely to develop bubble-type behaviors. The finding of the well-known bubble of 1990, which was observed in all market segments, shows how reliable the methodology is and, therefore, gives further robustness to the results. Future research needs to concentrate on higher-frequency time series and more market segments, as larger data sets become available.

The remaining part of the paper is structured as follows: Section 2 motivates the theory behind bubble detection and reviews the different testing methods. Section 3 presents the data and the corresponding art market indices. Section 4 discusses our empirical findings and Section 5 concludes.

2. Framework

The detection of bubble has captured the attention of scholars and researchers over the last four decades. From the seminal work of Kindleberger (1978) to the recent modeling approach of Phillips et al. (2011), numerous statistical tests have been developed to identify the presence of bubbles in time series. The basis for all approaches on the matter relies on the definition that a bubble consists of a sharp rise in a given asset price, i.e., above a level sustainable by some fundamental values, followed by a sudden collapse. Under rational expectations, the price of an asset is equal to its discounted expected fundamental value (present value theory), we obtain the following relation:

$$P_t = \frac{1}{1+R} E_t(P_{t+1} + \psi_{t+1}), \tag{1}$$

where R is the constant discount rate (R > 0), P_t is the observed asset price at time t, and $\psi_t$is its discounted expected fundamental value, which takes the form of the real dividend/convenience yield received for owning the asset between t-1 and t.

When $t+n$ is far in the future, $\left[\frac{1}{(1+R)^n} E_t(P_{t+n})\right]$ does not affect P_t as:

$$\lim_{t+n\to\infty} \frac{1}{1+R} E_t(P_{t+n}) = 0. \tag{2}$$

This implies that n periods forward, Equation (1) can be rewritten as follows:

$$P_t^* \equiv E_t\left[\sum_{i=1}^{n} \frac{1}{1+R} (\psi_{t+n})\right] \tag{3}$$

The right-hand side of Equation (3) is also called the market fundamental solution. But if a gap between the market fundamental solution and the actual price exists and, therefore, the terminal condition (3) does not hold, an additional "bubble component", B_t, has to be added to the solution of equation (1):

$$P_t = P_t^* + B_t\ . \tag{4}$$

In this case, the market fundamental solution, P_t^*, is only the "fundamental component" of the price, and B_t is any random variable that satisfies the following condition:

$$B_t = \frac{1}{1+R} E_t(B_{t+n}). \tag{5}$$

Hence, the bubble component is included in the price process, and anticipated to be present in the next period with an expected value of (*1 + R*) multiplied by its current value. Being then fully in line with the rational expectation framework, the bubble component can take the name of "rational bubble".

We apply a series of indirect tests that evaluates the validity of the market fundamental solution. The variance bound test proposed by Shiller (1981), where the variance of the observed asset price should exceed the bound imposed by the variance of the fundamental value in case of a rational bubble, is one of the earliest method ever elaborated. Though it was not originally designed to test for the presence of bubbles, it can be used for this reason with the limitation that emphasis is put on the volatility, an element which can also be caused by variations in expected returns or by fads, as pointed out by West (1987, 1988).

Campbell and Shiller (1987) leverage on the bubble literature and introduce another indirect method of bubble detection based on unit root testing. They anchor their approach on the idea that if a gap between the asset price and its fundamental value exists, it will exhibit an explosive behavior during the process of bubble formation. They identify two scenarios that can strongly suggest the presence of a rational bubble: (i) when the asset price is non-stationary in level but the fundamental value is, or (ii) when both the asset price and the fundamental value are non-stationary. In that second case, however, a co-integration test is needed; if the asset price and its fundamental value are co-integrated, and hence have co-movement in the long run, their non-stationary behavior is not a sign of a bubble presence. Diba and Grossman (1988) demonstrate that the idea of Campbell and Shiller (1987) is sufficient to prove the existence of a bubble.

In spite of their limitations, pointed out by Evans (1991), left-tailed unit-roots tests and co-integration tests have been the go-to approach in bubble detection. Evans (1991) finds that these tests fail to detect explosive bubbles when there are periodically collapsing bubbles in the time series because they are not able to differentiate a periodically collapsing bubble trend from a stationary process, i.e., the collapsing bubbles present in the data "break" the non-stationary characteristics of the sample. Therefore, a time series that contains several bubbles can be interpreted by the standard left-tailed unit-root test as a stationary series, leading to the wrong conclusion that the data contains no bubble.

The limitations of the left-tailed unit root tests[1] have been taken into account in a recent - and direct – bubble testing approach developed by Phillips et al. (2011).[2] The authors arrange a right-tailed

[1] Left-tailed unit-root tests are generally standard Augmented Dickey-Fuller (ADF) tests (see Dickey and Fuller, 1979).

ADF test instead of the standard left-tailed test. While both the left-tailed and the right-tailed ADF tests used by Philips et al. (2011) test the null hypothesis of a unit root behavior, their alternative hypothesizes diverge: "stationary behavior" for the former and "mildly explosive" for the latter. Therefore, by looking directly for evidence of non-linear explosive behavior in the data, Phillips et al. (2011) avoid the risk of misinterpreting a rejection of the null hypothesis due to stationary behavior and, hence, overcome the issue of periodically collapsing bubble recognition.

In the following we will apply the approach developed by Phillips et al. (2011) in identifying price bubbles to test whether the recent increase in the price of artworks can be characterized as a bubble (i.e., non-linear explosive behavior in our dataset). As Equation (4) indicates, the price of the assets tested here (P_t) contains two components: a fundamental component (P_t^*) and a bubble component (B_t), so that $P_t = P_t^* + B_t$, where $P_t^* \equiv E_t\left[\sum_{i=1}^{n} \frac{1}{1+R}(\psi_{t+n})\right]$ and $B_t = \frac{1}{1+R} E_t(B_{t+n})$.

The statistical properties of P_t^* and B_t determine those of P_t so that if ψ_t is an integrated process of order 1, i.e., I(1) - P_t^* is also an I(1) process. If no bubble exists, i.e., B_t= 0, the properties of P_t are determined only by those of P_t^*. However, if $B_t \neq 0$, current prices will exhibit an explosive behavior, as B_t reflects a stochastic process in which the expected value of next period's value is greater than or equal to the current period's value (Areal et al., 2013). Therefore, we implement a right-tailed version of the standard ADF test for a unit root (which means B_t= 0) against the alternative of an explosive root ($B_t \neq$ 0, right tail):

$$H_0 : \delta = 1$$

$$H_1 : \delta > 1$$

where δ is the estimated first order regression coefficient of the following equation:

$$y_t = \mu + \delta y_{t-1} + \sum_{j=1}^{J} \phi_{r_w}^{j} \Delta y_{t-j} + \varepsilon_t \qquad , \qquad (6)$$

with μ being an intercept, J the lag order, r_w the sample window size, and ε_t the error term.

[2] Though first empirically implemented by Phillips et al. (2011) for bubbles detection in stock prices, their methodology has also been used in the real estate literature (Yiu et al., 2012), food commodities (Etienne et al., 2013), and other agricultural commodities (Areal et al., 2013).

Instead of estimating the model (6) as a whole (like in a standard ADF test) or by using rolling windows of a fixed, pre-determined size, we use forward recursive calculations of the ADF statistics with an expanding window, which do not only provide more accuracy in case of multiple bubbles, but also allow us to date-stamp the origination and collapse of the bubble. This method, which is based on forward recursive regressions, is called 'sup ADF test' (referred to hereafter as SADF test).

In forward recursive regressions, model (6) is estimated repeatedly by least squares, using subsets of the sample data incremented by one observation at a time. The sample size is normalized to 1 (R = 1), which yields a sample interval of $[0,1]$. The first observation in our sample is set as the starting point of the estimation window: $r_1 = 0$; and the end point of our initial estimation window, r_2, is set according to our choice of minimal window size such that the initial window size is $r_w = r_2$. Therefore, the first regression produces an ADF statistic denoted ADF_{r_1}. The model is estimated while incrementing the window size by one observation at each pass, and the last estimation is based on the whole sample (i.e. r_w= 1), and the corresponding statistic is ADF_1.

Even though the SADF is very similar in nature to an ADF test, the critical values for testing the null hypothesis differ since the right tail of the statistic's distribution is needed. Following the latest update of Philips et al. (2013), we derive the critical values using Monte-Carlo simulations, through the following random walk process with an asymptotically negligible drift:

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

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 90, 95, and 99% and obtain the corresponding *t*-statistics after 2,000 replications.

In order to date-stamp the origination and termination of a bubble - in the case where the null hypothesis is rejected - we match the time series of the recursive *t*-statistic ADF_r against the right-tailed critical values of the asymptotic distribution of the standard ADF *t*-statistic. Let r_e be the origination date and r_f the collapse of some explosive behavior in the data, the estimates of these dates are given by:

$$\hat{r}_e = inf_{r \geq r_2} \left\{ r : ADF_r > cv_{\beta_n}^{adf}(r) \right\}, \tag{8}$$

$$\hat{r}_f = inf_{r \geq \hat{r}_e} \left\{ r : ADF_r < cv_{\beta_n}^{adf}(r) \right\}, \quad (9)$$

where $cv_{\beta_n}^{adf}(s)$ is the right side critical value of ADF_s that corresponds to a significant level of β_n, which we set at the 1% level. When plotted in a graph, the estimated starting point of a bubble is the first chronological observation for which ADF_s crosses upwardly the corresponding critical value. Conversely, the estimated termination point of a bubble is the first chronological observation for which ADF_s crosses downwardly the corresponding critical value.

3. Data and Art Price Index Construction

Our sample is constructed from the Blouin Art Sales Index (BASI), which is an online database that provides data on artworks sold at over 350 auction houses worldwide.[3] The BASI database is presently the largest known database of artworks, containing roughly 4.6 million artworks by more than 225,000 individual artists over the period 1922 to 2013. We solely focus on paintings, which are represented by 2.7 million entries in the database.

For each auction record, the database contains information on the artist, artwork, and sale. We observe the artist's name, nationality, year of birth, and year of death (if applicable). For the artwork, we know its title, year of creation, medium, size, and style, and whether it is signed or stamped. For the sale, we have data on the auction house, date of the auction, lot number, hammer price (the price for which the artwork was sold, excluding any premiums paid by the buyer to the auction house, and converted to U.S. dollars at the prevailing spot price), and whether the artwork was "bought in" or withdrawn.[4]

Art markets differ substantially from financial markets, and this potentially limits the applicability of standard financial techniques. Investing in art typically requires an extensive knowledge of art and the art market, and a large amount of capital to acquire works of well-known artists. The market is highly segmented and dominated by a few large auction houses, and only a small number of works are

[3] Art is not only sold in auction but also privately, for example through dealers. Renneboog and Spaenjers (2013) note that it is generally accepted that auction prices set a benchmark that is also used in the private market.
[4] An artwork is "bought in" when the highest bid does not reach the reserve price, and the artwork goes unsold.

presented for sale throughout the year. Art comes with risk, deriving from both physical risks such as fire and theft to the possibility of reattribution to a different artist. As a result, insurance costs can be prohibitive. While auction prices represent the value of artworks, it comes with a complex and subjective set of beliefs that is based on past, present and future prices, individual taste and fashion.

Paintings are heterogeneous assets and a variety of physical and non-physical characteristics provide the uniqueness of a painting. To construct our four individual art indices, being "Impressionist and Modern", "Post-war and Contemporary", "American", and "Latin American", we follow standard hedonic modeling to separate those characteristics that determine the price of a painting. The dependent variable in our hedonic model is the natural logarithm of the sales price in USD. The independent variables used in our model represent the following characteristics: medium, auction house, surface, signature, estimate price, living status, artist reputation, and sale date. A major disadvantage of the hedonic pricing model is multicollinearity. A high correlation between the considered variables increases the number of standard errors of the regression coefficient. In order to overcome this problem, each dummy variable contains a reference variable, which is deleted from the sample.

Sales date: These dummy variables are based on the sales date of the paintings. Each dummy variable represents one year starting from 1970 to 2013. A value of one indicates the painting is created in period *t* using the respective art index.

Auction house: According to de la Barre et al. (1994) the more renowned auction houses have a positive significant effect on the price of an individual painting. They reason this conclusion by assuming that the more established and famous auction houses will offer the 'best' work, while the less familiar and smaller ones will have less quality paintings (see also, Renneboog and Spaenjers, 2013). We assign those auction houses a separate dummy variable, i.e., a value of one indicates that the painting was auctioned by one of the leading auction houses: Christie's London or New York and Sotheby's London or New York. Assuming that the better and more expensive artists (paintings) will be auctioned by these auction houses, we can expect that the coefficient estimates will have a positive sign.

Medium: We know from the seminal art market literature that oil on canvas is the most used material by painters, and has the highest sales prices. Therefore, we will specify oil on canvas as the reference variable in our hedonic regression model; we assign other mediums a separate dummy variable. The dummy D_{it} will have a value of one when one of the dummies has the appointed medium. We expect negative coefficient estimates since the reference variable oil on canvas is assumed to fetch the highest prices.

Surface: The variable surface explains the impact of a painting's size and is calculated as the width multiplied by the height. These continuous surface values are logged in the hedonic regression model.

Signature: Anderson (1974) explains that the strength of the attribution towards the painter is a significant feature of the sales price. Paintings that are signed by the artist are generally more expensive. A dummy value of one indicates that the artist did not sign the painting. We expect that signed paintings are more valuable than unsigned painters, and will thereby have positive coefficients.

Living status: Production of paintings will halt when the respective artist dies. Since the artist is no longer able to create artworks, one might assume that the value of the considered artist's paintings will increase. However, when the deceased artist is not famous at the time she dies, there is also a chance of a decrease in the value of her paintings, since she is no longer able to promote her work. We specify this dummy variable as follows: a value of one indicates that an artist is alive. Due to the contrarian explanations regarding the living status of an artist we just made, it is expected that the coefficient will not be significant.

To make use of our time dummy variables and perform an OLS regression on the pooled data from all available sales, we construct the following hedonic regression model:

$$\ln P_{\mathrm{it}} = \alpha + \sum_{\mathrm{j}=1}^{\mathrm{z}} \beta_{\mathrm{j}} \, \mathrm{X}_{\mathrm{ij}} + \sum_{\mathrm{t}=0}^{\tau} \gamma_{\mathrm{t}} \, \mathrm{D}_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \qquad \varepsilon \sim N(0, \sigma^2), \tag{7}$$

where P_{it} represents the price of painting i at time t, α is the regression intercept, β_j is the coefficient value of quality characteristic X, Xij is the quality characteristic value of the painting i, the antilog of λ_{t}

reflects the coefficient value for the time dummy, and D_{it} represents the time dummy variable, which has the value of one when the paintings was sold in the considered time period *t*.

The estimated coefficients of the time dummies, i.e., the outcome from the hedonic regression model, are used to create the 4 different art price indices over the period 1970 to 2013. The “Impressionist and Modern”, “Post-war and Contemporary”, “American”, and “Latin American” art prices indices are computed using the following equation:

$$Index_{t+1} = \frac{\mathrm{Exp}\ (\mathrm{Y_{t+1}})}{\mathrm{Exp}(\mathrm{Y_t})} \qquad (2)$$

The antilog (or exponential) of the time dummies sequence is taken. We set the first year, i.e., the base year to 100 and compute the relative changes to this base year for the next years. The art price indices are presented in Figure 1, and summary statistics in Table I.

Figure 1 and Table I show that all four indices have dramatically risen over the last four decades, reaching levels that range from 1,200 to 3,300 points in 2013. We can see that the “Post-war and Contemporary” market has been the most profitable segment, but each and every segment have followed the same trend too, with two identifiable jumps between 1985 and 1990 and between 2005 and 2009.

Figure 2 displays the volumes, i.e., the number of trades over the period 1970 to 2013 for our distinct four art price indices and shows that the number of trades has grown 80-fold over the period. A closer look also indicates that the “popularity” of segments has changed over time: while the “Impressionist and Modern” market had dominated the art market as a whole until the early 2000s, it is now the second segment in terms of volume, behind the “Post-war and Contemporary market”, which had already passed the “American” segment in the late 1980s.

4. Bubble Detection

We run the test described in Section 2 for each of our 4 art market segments (“Impressionist and Modern”, “Post-war and Contemporary”, “American”, and “Latin American”). The summary output of the SADF test is displayed in Table II, and shows that the critical values always appear below the *t*-stats of every segment. Therefore, we reject the null hypothesis of a unit root for each of them.

Figures III, IV, V, and VI present the date stamp procedure for the SADF test. They include the time series of the index, the ADF statistics sequence and its corresponding 1% critical values. In each case, the graphs confirm the results found in Table II since there is always at least one point in time between 1970 and 2013 where the sequence of ADF statistics juts out over its corresponding critical value. This clearly shows an explosive root and, therefore, the existence of at least one bubble in every subsample.

More specifically, the results presented in Figure III indicate, at the 1% critical level, the presence of only one bubble in the "Impressionist and Modern" art price index, which we date back to 1986 using the date-stamping procedure explained in Section 2, until its burst in 1991 with a highest point displayed in 1989. This finding is in line with the historical facts of the market when the 1986-1991 economic bubble in Japan, after fueling the art market with overconfidence and speculation, came to an end. Japanese investors, through a "wealth effect" that gave them access to loans backed by the collateral value of lands and skyrocketing real estate prices in an overheated economy, had invested massively in international art markets in the late 1980s. When the uncontrolled credit expansion was stopped and the economy no longer sustained by an excessive monetary easing policy, prices of real estate and land started to declining, forcing Japanese investors to sell their holdings in art even at considerable bargains (Hiraki et al., 2009).

Looking at Figure IV, which displays the "Post-war and Contemporary" subsample and its corresponding art price index, we identify the same bubble between 1986 and 1991 with the peak in 1990, but two other bubbles appear to be also present in the data. The first is identified between 2006 and 2008 with the maximum reached in 2007 (which corresponds to the pre-financial crisis period), and the second has started after 2012 (the recursions of 2009, 2010 and 2011 give upward moving *t*-stats that approach the critical values but the *t*-stats only get passed the critical values in 2012).

For the “American” art price index, shown in Figure V, the test detects a similar explosive behavior from 2011 onwards to the one observed in the “Post-war and Contemporary” market segment. The previous bubble, which we identified in the period 2006 to 2008 for the “Post-war and Contemporary” market segment, seems to have started even earlier in the “American” segment, i.e., 2005 to 2008 with the peak in 2007. However, the earlier bubble period appears much shorter in length, i.e., 1988 to 1991 with the peak in 1989, than for both the “Impressionist and Modern” market and “Post-war and Contemporary” market segments, where we observed the bubble period from 1986 to 1991.

Figure VI plots the test on the Latin American data and only shows the presence of the earlier 1990 bubble; the bubble period lasted from 1986 to 1991, reaching the highest point in 1990.

In other words, all market segments exhibit the same 1990 bubble but only the “Post-war and Contemporary” and the “American” market segments seem to have been affected by the 2008 bubble and the recent one, which started at the end of 2011. This 2011 one is according to our findings still in the mania phase of its formation (see the definition by Kindleberger and Aliber, 2005), i.e., it has not yet reached its peak and might very likely continue for another couple of years.

We observe that even though there exist some discrepancies amongst the origination dates of bubbles in the four studied subsamples, the termination dates coincide always perfectly. All bubble termination dates in all art market segments are in exact lockstep, which eliminates the possibility of arbitrages amongst different segments. Moreover, the particularities of artworks prevent investors from “riding” a bubble by rapidly trading a particular artwork, because such leads to a noticeable reduction in value (see Kräussl, 2013).

5. Conclusion

Our study examines the question of the existence of explosive behaviors in four different segments of the art market: “Impressionist and Modern”, “Post-war and Contemporary”, “American”, and “Latin American”. The empirical findings suggest that there is strong evidence of a speculative bubble that has started in late 2011 and is still in the mania phase of its formation for both the “Post-war and

Contemporary” and “American” art market segments. We find that these two segments were already in the stage of a speculative movement during the period 2006 to 2008. The absence of such phenomena in the other markets of our study makes the “Post-war and Contemporary” and “American” segments the most likely to develop bubble-type behaviors. The finding of the well-known bubble of 1990, which is present in every market, shows how accurate the methodology developed by Phillips et al. (2011) is, and gives, therefore, further robustness to the results stated above. Future research needs to concentrate on higher-frequency time series and more market segments, as more data become available.

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Table I: Summary Statistics.

This table provides the summary statistics of the four distinct art market indices in the Blouin Art Sales Index (BASI) data set over our sample period from 1970 to 2013: "Impressionist and Modern", "Post-war and Contemporary", "American", and "Latin American". Based on 2.7 million artworks, the indices are constructed by using standard hedonic modeling with the following variables: medium, auction house, surface, signature, estimate price, living status, artist reputation, and sale date. All annual series are normalized to 100 in 1970.

Variables	Observations	Mean	Standard Deviation	Min	Max
"Impressionist and Modern"	44	675.82	499.25	100	2,011
"Post-war and Contemporary"	44	889.14	796.47	100	3,311
"American"	44	399.45	284.50	99	1,197
"Latin American"	44	533.20	369.55	96	1,282

Table II: Test for explosive behavior in the art market from 1970 to 2013.

This table reports the SADF tests of the null hypothesis of a unit root against the alternative of an explosive root, where the initial time-window is set to 10 observations and the significant level set to 99 percent. The series are the "Impressionist and Modern", "Post-War and Contemporary", "American", and "Latin American" art markets. The sample period is 1970 to 2013 with 44 annual observations. The critical values for the SADF test are obtained through Monte-Carlo simulations with 2,000 replications.

	Time Series	*t*-Statistics
	"Impressionist and Modern"	9.818
	"Post-war and Contemporary"	6.371
	"American"	3.176
	"Latin American"	7.942
Test critical values for the explosive alternative	99% level	1.959
	95% level	1.268
	90% level	0.983

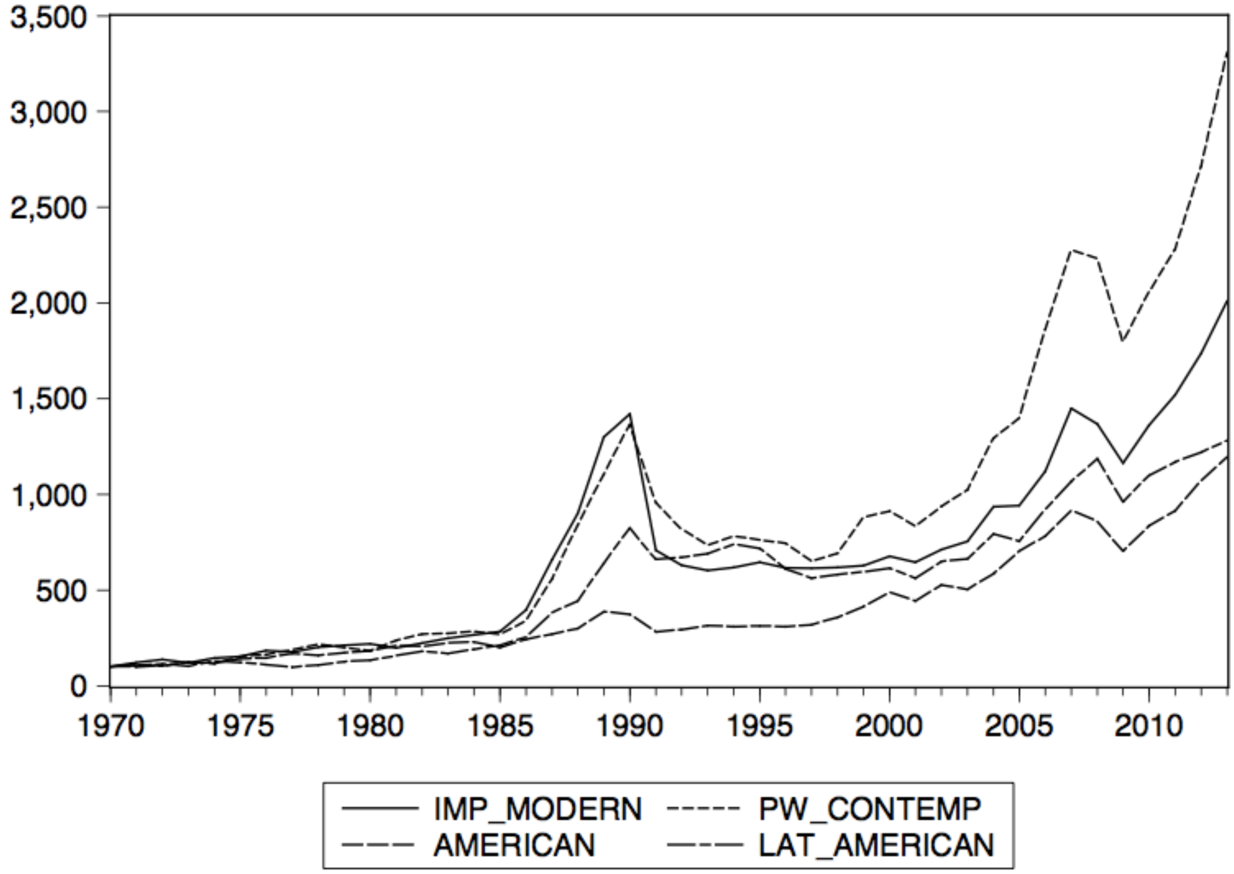

Figure 1: Art Market Indices.

This figure shows the price indices for the "Impressionist and Modern", "Post-War and Contemporary", "American", and "Latin American" art market segments from 1970 to 2013. All series are annual data and are normalized to 100 in 1970.

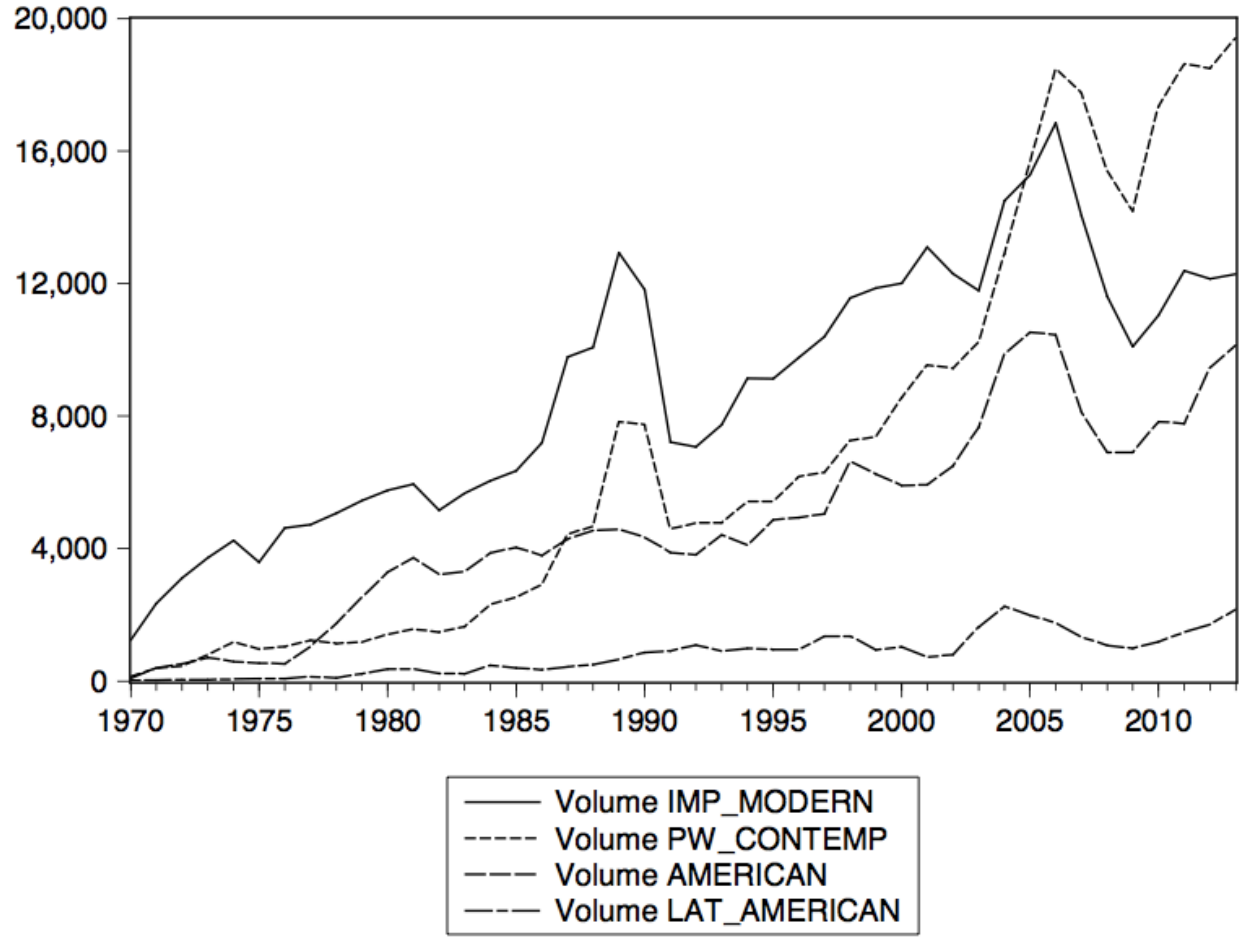

Figure 2: Art Market Volumes.

This figure shows from 1970 to 2013 the total number of sales for each art price segment: "Impressionist and Modern", "Post-war and Contemporary", "American", and "Latin American".

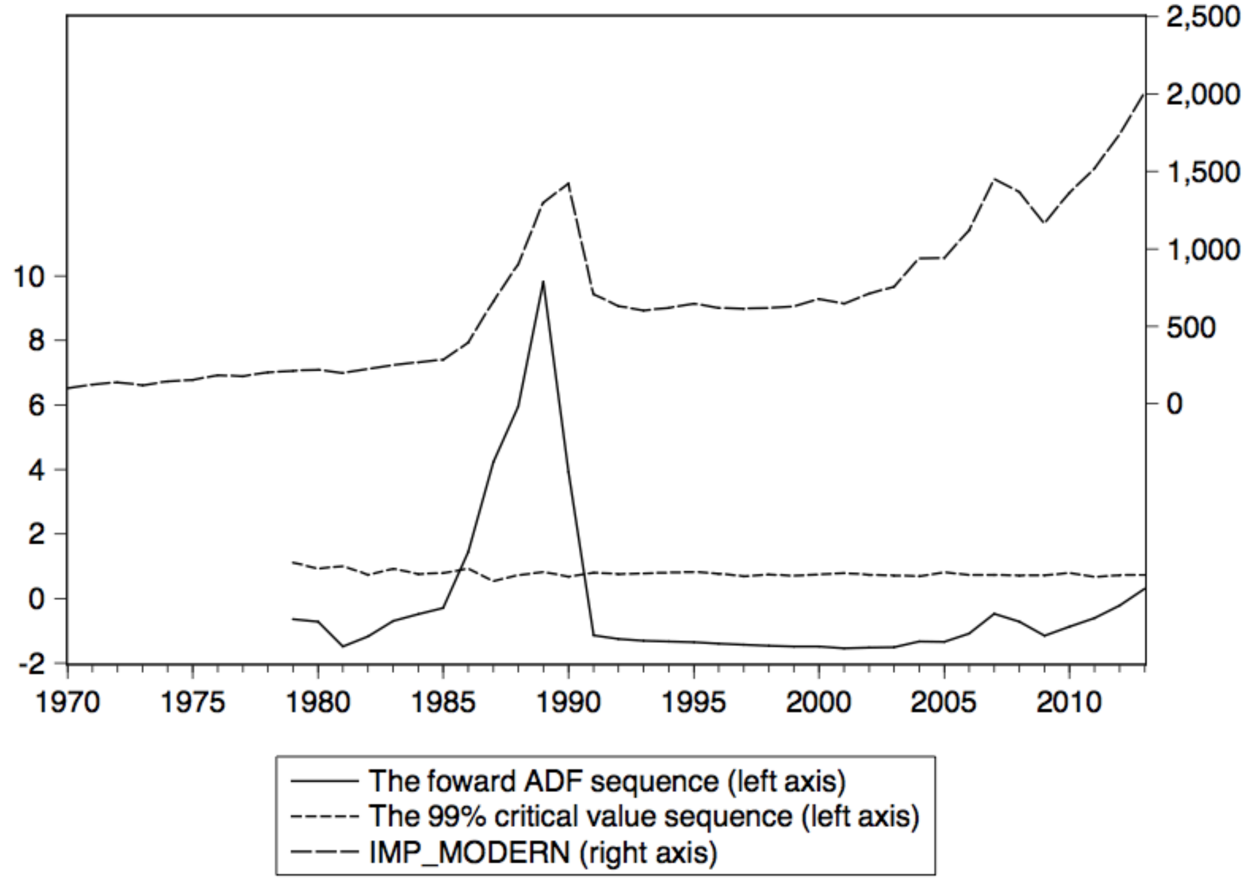

Figure 3: SADF Test and Date-Stamp, "Impressionist and Modern" Art Market.

This figure graphically represents the SADF tests of the null hypothesis of a unit root against the alternative of an explosive and shows the times series of the SADF *t*-Statistic sequence for the "Impressionist and Modern" index on the left-hand (solid line), its corresponding sequence of critical values at the 99% level on the left-hand (small striped line), and the price index on the right-hand (large striped line) from 1970 to 2013. SADF *t*-Statistics are obtained from forward recursive calculations with an expanding window (initial size: 10 observations).

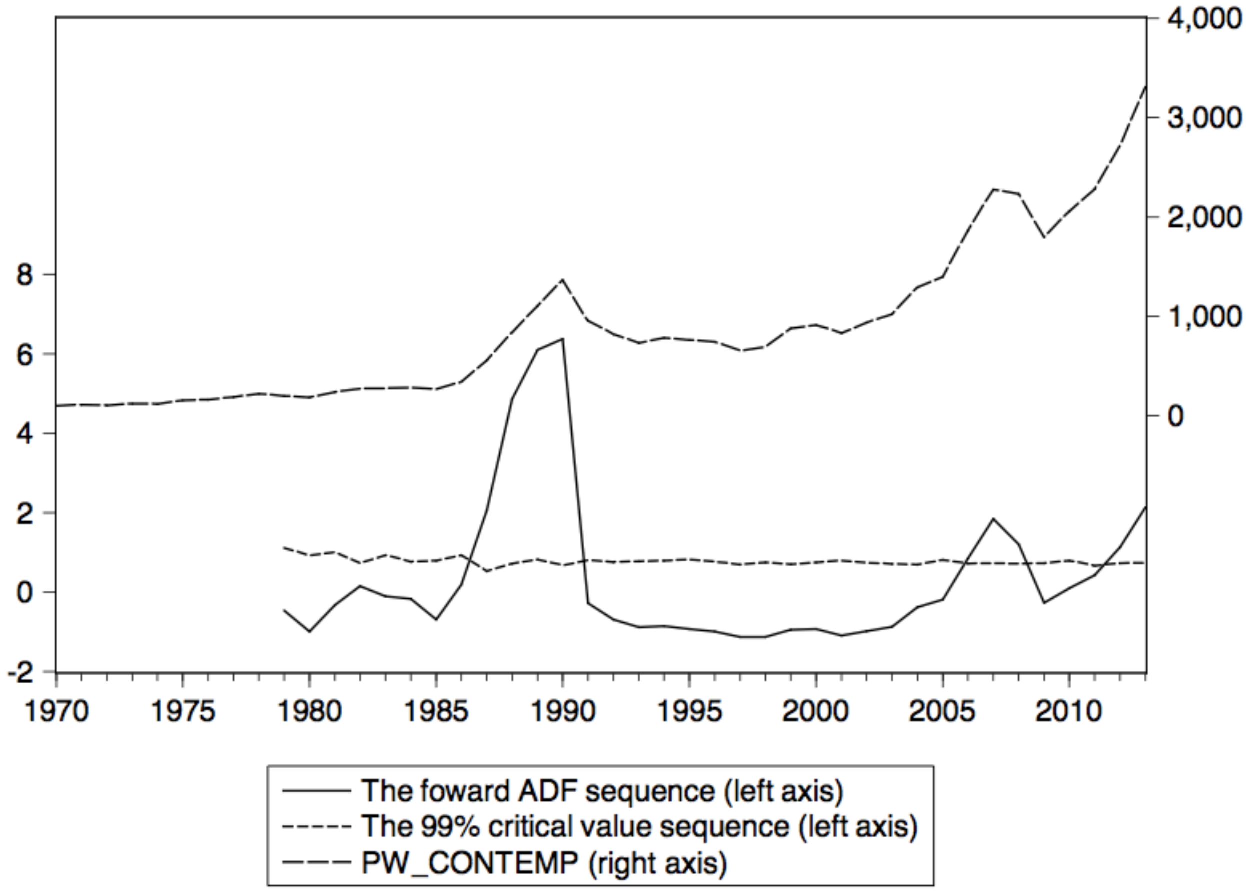

Figure 4: SADF Test and Date-Stamp, "Post-war and Contemporary" Art Market.
This figure graphically represents the SADF tests of the null hypothesis of a unit root against the alternative of an explosive and shows the times series of the SADF *t*-Statistic sequence for the "Post-war and Contemporary" index on the left-hand (solid line), its corresponding sequence of critical values at the 99% level on the left-hand (small striped line), and the price index on the right-hand (large striped line) from 1970 to 2013. SADF *t*-Statistics are obtained from forward recursive calculations with an expanding window (initial size: 10 observations).

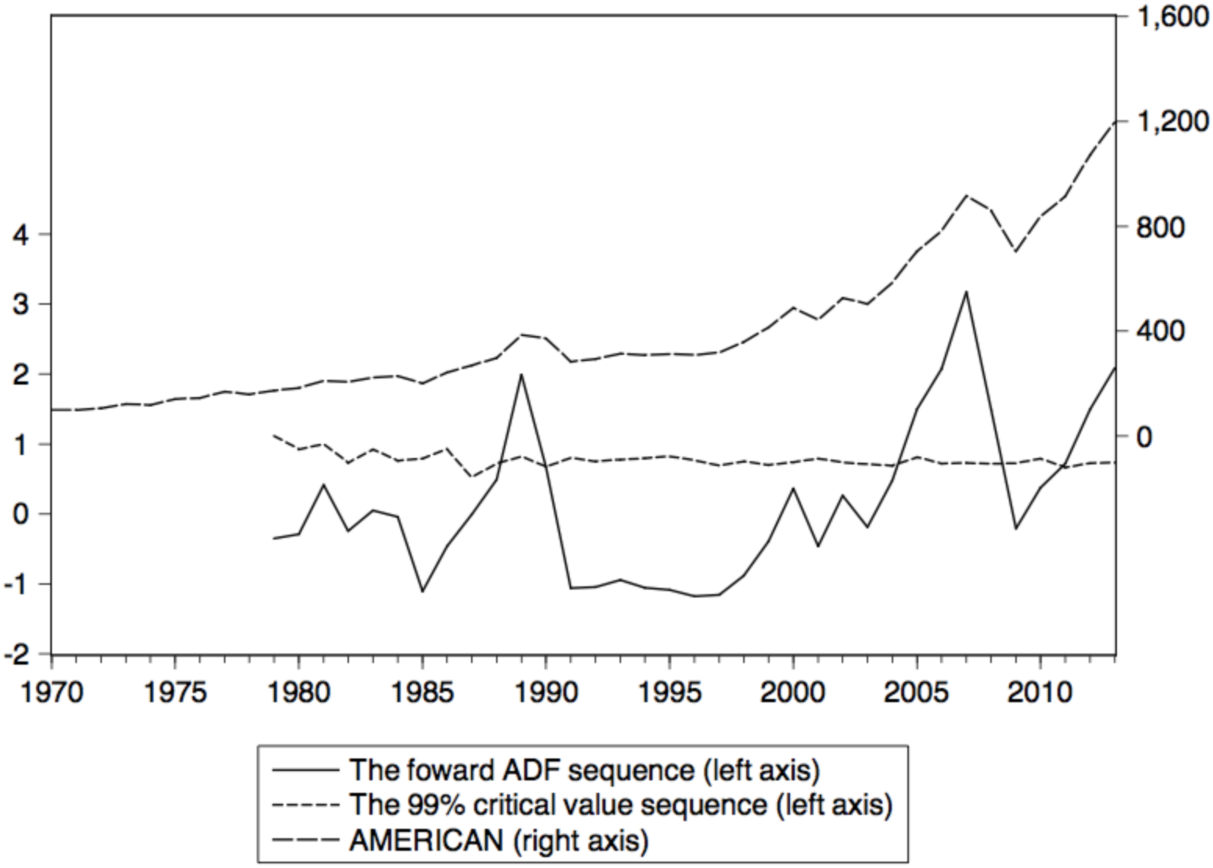

Figure 5: SADF Test and Date-Stamp, "American" Art Market.

This figure graphically represents the SADF tests of the null hypothesis of a unit root against the alternative of an explosive and shows the times series of the SADF *t*-Statistic sequence for the "American" index on the left-hand (solid line), its corresponding sequence of critical values at the 99% level on the left-hand (small striped line), and the price index on the right-hand (large striped line) from 1970 to 2013. SADF *t*-Statistics are obtained from forward recursive calculations with an expanding window (initial size: 10 observations).

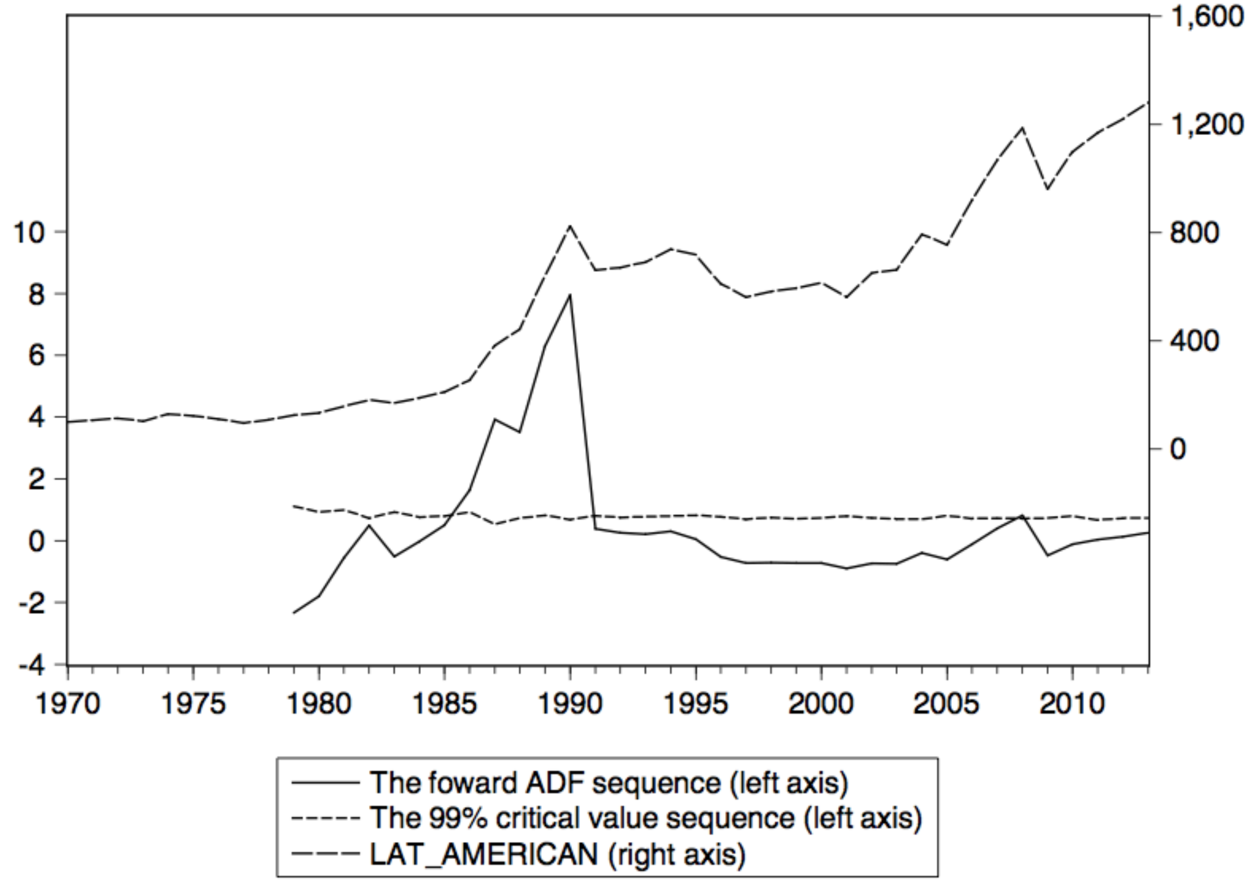

Figure 6: SADF Test and Date-Stamp, "Latin American" Art Market.

This figure graphically represents the SADF tests of the null hypothesis of a unit root against the alternative of an explosive and shows the times series of the SADF *t*-Statistic sequence for the "Latin American" index on the left-hand (solid line), its corresponding sequence of critical values at the 99% level on the left-hand (small striped line), and the price index on the right-hand (large striped line) from 1970 to 2013. SADF *t*-Statistics are obtained from forward recursive calculations with an expanding window (initial size: 10 observations).