

ESTIMATING A SOUTH AFRICAN ART PRICE INDEX

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The South African art market has grown markedly over the last two decades, and yet there is currently very little research on this market. The aim of this paper is two-fold. The first to construct measures of the overall price movements in South African art prices over time. Three broad methodologies are used to estimate quality-adjusted price indices for South African art since the turn of the millennium: central tendency, hedonic and hybrid repeat sales. The regression-based indices point to similar trends over the period, which demonstrates the importance of regression-based methods to produce quality-corrected price indices. According to these measures, the South African art market experienced a huge price increase in the run-up to the Great Recession. The second aim of the paper is to use the art price indices to look for evidence of a bubble in the South African art market over the period. The regression-based indices seem to point to consistent evidence of mildly explosive price behaviour in the run-up to the Great Recession.

Keywords: South African Art, Hedonic Price Index, Pseudo Repeat Sales, Explosive Prices

1 Introduction

Contemporary African art has experienced a surge in popularity over the last few decades. The South African art market in particular has received a lot of attention, and has grown markedly over the last two decades, both in terms of the number of transactions and total turnover (Fedderke and Li, 2014). Artworks by South African artists have reached record prices at international and local auctions, both for the country's "masters" - including Irma Stern, Walter Battiss, and JH Pierneef - and contemporary artists like William Kentridge (Naidoo, 2013). In 2011 Bonhams in London sold Irma Stern's "*Arab Priest*" for a hammer price of £2.7 million, a world record for a South African artwork at auction. Also in 2011, Stern's "*Two Arabs*" was sold by Strauss & Co. for a hammer price of R19 million, a record for a South African auction. The increase in interest in South African art, both locally and abroad, has sparked a vibrant market for collectors and investors.

In his book *The Value of Art*, Findlay (2012) argues that collectors have three main motives for collecting art: a genuine love of art, social promise and investment possibilities. The first motive relates to the essential (or intrinsic) value of art and is often called aesthetic pleasure. The second relates to the social value or status consumption of art. To the extent that art is a luxury good, collectors may derive utility from the signal of wealth that it conveys (Mandel, 2009). The third motive involves the commercial value of art and relates to its role as an alternative asset. In addition to the potential for appreciation in value, artworks may be

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used to aid portfolio diversification, as collateral for loans, or to take advantage of slacker regulatory and tax rules. Thus, unlike pure financial investments, artworks are durable goods with consumption and investment good characteristics (Renneboog and Spaenjers, 2014).

The increase in the popularity of South Africa art, at least partly as an investment vehicle, is commensurate with international trends, where fine art has become an important asset class in its own right. In 2010 around 6% of total wealth was held in so-called passion investments, which include art, wine, antiques and jewellery (Renneboog and Spaenjers, 2014). In 2013, art made up around 17% of high net worth individuals' allocations to passion investments (Capgemini, 2013). Of all these passion investments, art is the most likely to be acquired for its potential appreciation in value (Capgemini, 2010).

To date there has been little research on the South African art market and particularly trends in art prices. It is important to analyse price movements over time in order to understand the dynamics of the market and to be able to answer questions about the development of the market. Estimating accurate indicators of unique assets like art can be challenging. Artworks are less liquid than traditional assets and have a low transaction frequency, which means that only a small part of the overall market is traded at any given time. They are also typically unique or heterogeneous, which makes it difficult to compare different artworks over time. These features make it challenging to measure the state of the overall market over time.

This paper attempts to make two contributions to the literature. The first is to construct measures of the overall movements in South African art prices over time. Three broad methodologies are used to develop price indices for South African art: central tendency methods, hedonic methods and hybrid repeat sales methods. The paper argues that central tendency measures do not adequately control for quality-mix or compositional changes over time. Various indices are estimated with the hedonic regression method, which is able to control more adequately for quality-mix changes by attributing implicit prices to a set of asset characteristics. The hedonic indices seem to paint a relatively consistent picture of the trend in South African art prices over time.

The main shortcoming of the hedonic method is that it has potential omitted variable bias, which might bias the coefficients and therefore the indices. The repeat sales method can control for quality-mix changes by tracking the same asset over time. However, the repeat sales method utilises only artworks that have sold more than once. The limited number of repeat sales observations in the database limits the usefulness of the classical repeated sales approach in this case. The paper uses a simple hybrid repeat sales method to estimate alternative price indices for South African art. The repeat sales indices suffer less from potential omitted variable bias, but have the shortcoming of potential sample selection bias.

The paper compares and contrasts the various art price indices estimated with these methodologies. While each method has strengths and weaknesses, the indices estimated with the regression-based methods seem to point to the same general trend in South African art prices. The regression-based indices differ markedly from the central tendency indices, which demonstrates the importance of adjusting for quality-mix changes when producing price indices for unique assets. The similarities between the hedonic and repeat sales indices provide some confidence that potential omitted variable bias and sample selection bias are not pervasive in this case or dictating the results (Calomiris and Pritchett, 2016).

According to these measures, the South African art market experienced a huge price increase in the run-up to the Great Recession. Many commentators claimed that the market was overheating and suggested the possibility of a bubble in the market (see for example Rabe (2011); Hundt (2010); Curnow (2010)). The second contribution of the paper is to look for evidence of a bubble in South African art prices over the period, by looking for mildly explosive behaviour in the estimated price indices. The regression-based indices seem to point to consistent evidence of explosive prices in the run-up to the Great Recession.

2 Methodologies for Constructing Price Indices

The construction of price indices for unique assets is challenging for at least two reasons (Jiang, Phillips and Yu, 2014). Firstly, the low frequency of trading means that only a subset of the market is traded at a given time, while the prices of non-transacted items are unobservable. Secondly, the heterogeneity of these items means that the quality of assets sold is not constant over time. Thus, the composition of items sold will generally differ between periods, making it difficult to compare prices over time (Hansen, 2009). Constructing an index for unique items, like artworks, therefore requires a different approach than is used for indices of stocks, bonds and commodities. Four broad measurement techniques have been used to construct these indices (Eurostat, 2013):

- a) Central tendency methods
- b) Hedonic methods
- c) Repeat sales methods
- d) Hybrid methods

The following sections provide a brief introduction to these methodologies. The literature does not provide an *a priori* indication of the most appropriate method and, in practice, the data dictates the choice.

2.1 Central Tendency Methods

The simplest way to construct a price index is to calculate a measure of central tendency from the distribution of prices. The median is often preferred to the mean as a measure of central tendency, because price distributions are generally positively skewed. This may be due to the zero lower bound on transaction prices, positively skewed income distributions, and the unique nature of these assets (Hansen, 2009). These average measures have the advantage of being simple to construct and do not require detailed data.

However, an index based on average prices does not account for the difficulties mentioned above. For assets like artworks, central tendency indices may be more dependent on the mix of objects that come to market than changes in the underlying market. For instance, if there is an increase in the share of higher quality assets, an average measure will show an increase in price, even if the prices in the market did not change. Hence, such a measure may not be

representative of the price movements of all the assets in the market. If there is a correlation between turning points in asset price cycles and compositional and quality changes, then an average could be especially inaccurate (Hansen, 2009).

Stratified central tendency measures can control for compositional changes in assets sold over time to some extent. Stratified measures control for compositional changes by separating the sample into subgroups according to individual characteristics such as artist and medium. After constructing a measure of the central tendency for each subgroup, the aggregate mix-adjusted index is typically calculated as a weighted average of the indices for the subgroups. The Fisher index, which is the geometric mean of the Laspeyres and Paasche indices², is often recommended (Eurostat, 2013).

Stratified measures are currently used by ABSA, FNB and Standard Bank to construct property price indices for South Africa. The ABSA House Price Index is based on the mean sales price of properties categorised by house size and price segment, based on the finance applications received (Aye *et al.*, 2013).

However, scholarly work rarely employs stratified central tendency indices, as these mix-adjusted measures adjust only for the variation in the quality of assets across the subgroups. The ABSA House Price Index, for instance, does not control for changes in the mix of properties unrelated to size and price segment. The number of subgroups may be increased to reduce the quality-mix problem, if the data permits, although some quality-mix changes will likely remain (Hansen, 2009). However, this will reduce the average number of observations per subgroup and raise the standard error of the overall index (Eurostat, 2013). If the subgroups become very small, small changes can have a large impact on the index. As a consequence of these difficulties the repeat sales and hedonic methods have dominated the international literature.

2.2 Hedonic Methods

The hedonic method is based on hedonic prices theory, which is useful for differentiated goods. Griliches (1961) first applied the hedonic method for the valuation of automobiles. Anderson (1974) was the first to apply the method to the art market. In a seminal paper, Rosen (1974) proposed a model of market behaviour describing markets for differentiated goods, applying the theory to analyse housing markets.

The hedonic method is derived from the microeconomic theory of implicit prices, which supposes that utility is derived from the characteristics or attributes of goods (Lancaster, 1966). Each good i is described by a vector x of J quantifiable and inseparable attributes that determines its price: $x_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{iJ})$. In the context of art, attributes may include physical (e.g. medium) and non-physical attributes (e.g. artist reputation). According to this theory, goods offer buyers distinct packages of attributes. When a consumer chooses a particular good i , they have chosen a particular vector x of attributes to purchase (Rosen, 1974).

²The Laspeyres index holds the quantity weights fixed in the base period, while the Paasche index holds the quantity weights fixed at the comparison period.

The price of the good will be determined by the particular combination of attributes: $p_i = p(x_i) = p(x_{i1}, x_{i2}, x_{i3}, \dots, x_{iJ})$. One can thus interpret the price of good i as a function of its vector of attributes x . The hedonic price function $p(x)$ specifies how the market price of the commodity varies as the attributes vary (Epple, 1987).

Rosen (1974) provides a theoretical framework in which $p(x)$ emerges from the interaction between buyers and sellers. Buyers and sellers base their locational and quantity decisions on maximising behaviour and will be in equilibrium along the hedonic price function. The solution to the maximisation problem produces a set of implicit (or shadow) prices for the attributes (Anderson, 1974).

The implicit prices for each attribute j of good i may be represented as: $p_j(x_i) = \frac{\Delta p}{\Delta x_j}$. This p_j is considered an implicit price, as there is no direct market for the attributes and their prices are not independently observed. One could infer that this price represents the value added to a good for a unit increase of a given attribute. The demand and supply for the goods implicitly determine the marginal contributions of the attributes to the prices of the goods (Eurostat, 2013). Implicit prices are revealed to agents from observed prices of differentiated goods and the specific amounts of attributes associated with them. Thus, the approach is based on the revealed preferences of buyers and sellers in actual market conditions (Els and Von Fintel, 2014).

The hedonic approach estimates the value attached (i.e. the implicit prices) to each of these attributes. The approach entails regressing the logarithm of the sales price on the relevant attributes. The standard hedonic model usually takes the following form:

$$\ln P_{it} = \sum_{t=1}^T \delta_t D_{it} + \sum_{j=1}^J \beta_{jt} X_{jit} + \sum_{k=1}^K \gamma_{kt} Z_{kit} + \epsilon_{it}$$

where P_{it} represents the price of item i at time t ($t = 1, \dots, T$); D_{it} is a time dummy variable taking the value of 1 if item i is sold in period t and 0 otherwise, $X_{ jit}$ is a set of j ($j = 1, \dots, J$) observed attributes of item i at time t ; Z_{kit} is a set of k ($k = 1, \dots, K$) unobserved attributes that also influence the price; and ϵ_{it} is a random (white noise) error term.

The coefficients on the time dummies provide an estimate of the average increase in prices between periods, holding the change in any of the measured quality dimensions constant (Griliches, 1961). In other words, they capture the “pure price effect” (Kräussl and Lee, 2010). The price index is then simply the series of estimated coefficients: $\hat{\delta}_1, \dots, \hat{\delta}_T$.

The most common form of the hedonic equation assumes that the implicit prices (i.e. the coefficients β_t and γ_t) are constrained to be constant over time. However, when demand and supply conditions (e.g. tastes) change, the implicit prices of the attributes may change (Renneboog and Spaenjers, 2012). One way to allow for shifts in parameters is to employ an adjacent-periods or chained regression (Triplett, 2004). Separate regressions are estimated for adjacent time periods and the estimates are then chain-linked together to form the overall index (McMillen, 2012).

The hedonic method therefore controls for quality-mix changes by attributing implicit prices to a set of value-adding characteristics of the individual item. Hedonic regressions control for

the observable attributes of an asset to obtain an index reflecting the price of a “standard asset” (Renneboog and Van Houtte, 2002). Thus, the hedonic approach can circumvent the problems of changes in composition or quality over time (Hansen, 2009).

The choice of the attributes in a hedonic regression is limited by data availability and involves subjective judgement. If the functional form is misspecified or the omitted variables are correlated with sales timing, it will result in misspecification or omitted variable bias, which will bias the parameter estimates and therefore the indices (Jiang, Phillips and Yu, 2014). The primary difficulty with hedonic price indices is this potential omitted variable bias. However, the bias is often small in practice (Triplett, 2004; Renneboog and Spaenjers, 2012).³ Relatively detailed data is available for art, which should capture a large part of the variation in sales prices. Omitted variable bias should therefore be less of a problem than for other unique assets like real estate.⁴

2.3 Repeat Sales Method

The repeat sales method provides an alternative estimation method for quality-adjusted price indices, based on price changes of items sold more than once. It was initially proposed by Bailey, Muth and Nourse (1963) to calculate house price changes. It was subsequently extended by Case and Shiller (1987) and is currently used to produce the S&P/Case-Shiller Home Price Indices in the US. Mei and Moses (2002) constructed the most influential repeat sales art price index.

The repeat sales method tracks the sale of the same item over time. It aggregates sales pairs and estimates the average return on the set of items in each period (Kräussl and Lee, 2010). As a result, it does not require the measurement of quality, only that the quality of each item be constant over time (Case and Shiller, 1987). Advocates of the repeat sales approach argue that it controls more accurately for the attributes of goods, as well as potential omitted variables (Jiang, Phillips and Yu, 2014).

The repeat sales model can be derived from the hedonic model,⁵ if the hedonic model is

³According to Triplett (2004), even if the hedonic coefficients are biased it is not necessarily the case that the hedonic index will be biased. It will depend on whether the correlations among included and omitted characteristics in the cross section imply the same correlations in the time series. If cross section correlations and time series correlations are the same, the hedonic index may be unbiased, even though the hedonic coefficients are biased. It is possible that changes in (unobserved) characteristics between two periods move to offset the error in estimating the implicit prices of included variables. The bias therefore becomes an empirical matter, because it is the effect on the price index that matters, not just the effect on the hedonic coefficients.

⁴According to Hansen (2009), there are various weighting approaches. If one is interested in the change in the value of the art stock (or a representative portfolio), then a higher weight should be given to price changes in higher-value artworks because of their greater share in the total value of the art stock. On the other hand, if one wishes to measure price changes in the representative artwork, then an equal weighting of observed art price inflation rates would be appropriate. This paper focuses on the pure price changes for a representative artwork, assuming an equal weighting.

⁵While the repeat sales model can be derived as the differenced hedonic model, it can also stand on its own as a primal specification (Guo et al 2014). Baily et al (1963) saw their procedure as a generalisation of the chained matched model methodology applied previously in the construction of real estate price indices.

differenced with respect to consecutive sales of items that have sold more than once in the sample period (McMillen, 2012). The standard model may be formulated as the change in the log of the sales price of item i that sold at time t and an earlier time s :

$$\ln P_{it} - \ln P_{is} = (\sum_{t=1}^T \delta_t D_{it} - \sum_{s=1}^T \delta_s D_{is}) + (\sum_{j=1}^J \beta_{jt} X_{jit} - \sum_{j=1}^J \beta_{js} X_{jis}) + (\sum_{k=1}^K \gamma_{kt} Z_{kit} - \sum_{k=1}^K \gamma_{ks} Z_{kis}) + (\epsilon_{it} - \epsilon_{is})$$

If the attributes (X and Z) of item i and the implicit prices (β and γ) are constant between sales, the equation reduces to the standard estimating equation:

$$\ln \frac{P_{it}}{P_{is}} = \sum_{t=1}^T \delta_t G_{it} + u_{it}$$

where P_{it} is the purchase price for item i in time t ; δ_t is the parameter to be estimated for time t ; G_{it} represents a time dummy equal to 1 in period t when the resale occurs, -1 in period s when the previous sale occurs, and 0 otherwise; and u_{it} is a white noise residual.

Thus, in the standard repeat sales model the dependent variable is regressed on a set of dummy variables corresponding to time periods. The coefficients are estimated only on the basis of changes in asset prices over time. Again, the price index is simply the series of estimated coefficients: $\hat{\delta}_1, \dots, \hat{\delta}_T$.

This estimating equation provides unbiased estimates of pure time effects without having to correctly specify the item attributes X or the functional form of the hedonic equation (Deng, McMillen and Sing, 2012). By differencing the hedonic equation it also potentially controls omitted variables Z . It also has the advantage of not being data intensive, as the only information required to estimate the index is the price, the sales date and a unique identifier (e.g. the address of the property). The repeat sales method has often been applied in the construction of real estate indices (e.g. Bailey, Muth and Nourse (1963), Case and Shiller (1987), Hansen (2009), Shimizu, Nishimura and Watanabe (2010)), where there is a lack of detailed information on each sale.

A disadvantage of the repeat sales method is the possibility of sample selection bias. Items that have traded more than once may not be representative of the entire population of items. For example, if cheaper artworks sell more frequently than expensive artworks, but high-quality artworks appreciate faster, a repeat sales index will tend to have a downward bias (Eurostat, 2013). The size and direction of the bias will vary by the sample under investigation. The biggest problem with the repeat sales method in the current context is that single-sale data is discarded. This is problematic because the resale of a specific artwork may only occur infrequently, which reduces the total number of available observations substantially.

2.4 Hybrid Models

The major problem with the hedonic method is the potential for omitted variable bias, while the biggest difficulties with the repeat sales method is that it suffers from potential

sample selection bias and that it discards single-sale observations. A number of hybrid methods, which involve a combination of the two methods, have been proposed to address these problems. A combination of the two methods might lead to a quality-adjusted index that exploits all the sales data and reduces both sample selection and omitted variable bias (Jiang, Phillips and Yu, 2014).

In the context of real estate, for instance, Case and Quigley (1991) used single-sale and repeat sale properties to jointly estimate price indices using generalised least squares regressions. More recently, Nagaraja, Brown and Zhao (2011) suggested a model composed of a fixed time effect, a random ZIP (postal) code effect, combined with an autoregressive component. The index can be viewed as a weighted average of estimates from single and repeat sales homes, with the repeat sales prices having a substantially higher weight.

An interesting perspective, which is relevant to this paper, is to view the repeat sales specification as an extreme solution to a matching problem. The repeat sales approach requires an exact match to estimate the index. For example, the same Van Gogh “*Wheat Field with Crows*” is tracked over time to control for all the observable and unobservable attributes. The idea behind the imperfect matching method proposed by McMillen (2012) is that some items may be similar enough to control for many of the differences in (observable and unobservable) attributes. For example, Van Gogh’s well-known *Sunflowers* series, of which there are five versions, might be similar enough to be treated as repeat sales. The objective is to match sales observations over time, according to some criterion, so as to cancel out as many as possible of the differences in attributes, making the model more parsimonious and robust (Guo *et al.*, 2014).

McMillen (2012) used a matching criterion based on propensity score matching. Each property sold in the base period was matched with one property sold in each subsequent period, based on propensity scores from a logit model. The procedure is essentially a data pre-processing procedure for building an estimation sample.

Guo *et al.* (2014) proposed a pseudo-repeat sales (ps-RS) method to construct price indices for newly constructed homes in China. The ps-RS procedure was developed to deal with two features in the Chinese urban residential market. Firstly, new home sales accounted for a large share of total sales (87% in 2010). As a consequence there was a limited number of repeat sales, similar to the South African art market. Secondly, new housing developments occurred with a high degree of homogeneity in the units built within the typical residential complex. The idea was then to match similar homes within each complex or building in order to construct a large pseudo repeat sales sample.

As a matching criterion they used a distance metric to identify similar transactions across adjacent periods. The distance metric between two sales was defined as the absolute value of the difference between the two predicted prices from a hedonic equation, excluding time dummies (i.e. the non-temporal component). Pairs with their distance metric smaller than a certain threshold were selected as pseudo-pairs. The threshold for the distance metric is a trade-off between the within-pair homogeneity and sample size and was set flexibly.

This ps-RS model was then regressed on all the pseudo-pairs. The ps-RS model is similar to the differential hedonic regression above. For a given building b , home i in quarter t and

home h in quarter s are adjacent transactions ($t > s$), and make a matched pair:

$$\ln P_{itb} - \ln P_{hsb} = \sum_{j=1}^J \beta_j (X_{itbj} - X_{hsbj}) + \sum_{t=0}^T \delta_t G_{it} + \epsilon_{ithsb}$$

where G_{it} is again a time dummy equal to 1 if the later sale in the pair occurred in quarter t , -1 if the former sale in the pair occurred in quarter s , and 0 otherwise; and ϵ_{ithsb} again represents a white noise residual.

Within-pair first differencing will cancel out any variables for which the attributes are the same between the two units, including both observable (e.g. number of bedrooms) and unobservable attributes (e.g. locational or neighbourhood effects). Only attributes that differ between the two units within a pair will be left on the right-hand side of the equation as independent variables, differenced between the second minus the first sale, reflecting the hybrid specification. The ps-RS indices were then calculated based on the coefficients of the time dummies. Guo *et al.* (2014) found that the ps-RS method provided greater control for quality-mix differences over time and a smoother index indicating less random estimation error.

The approach is a hybrid model of the type that has been demonstrated to have desirable features in the literature. It mitigates the problem of potential omitted variable bias with the hedonic method by taking first differences between similar items. It mitigates the problems of small sample sizes and sample selection bias with repeat sales methods by using more of the transaction data (McMillen, 2012).

Calomiris and Pritchett (2016) used a similar procedure, based on the differential hedonic equation, in analysing slave price indices. They argued that while their hedonic pricing model controlled for observable slave transaction characteristics, it may be sensitive to the presence of unobservable characteristics. They created a matched sample that enabled the estimation of a repeat sales model for the changes in slave prices. Because they observed repeat sales for the same slave, the unobserved characteristics would be similar for both transactions. In addition, they allowed for the possibility that the observable attributes may have changed between the date of initial purchase and the subsequent sale. They then used the following regression to estimate the hybrid repeat sales model, which eliminated the time-invariant and unobserved effects:

$$\ln P_{it} - \ln P_{is} = (X_{it} - X_{is})\beta + (\delta_t - \delta_s) + (u_{it} - u_{is})$$

Calomiris and Pritchett (2016) found that their hybrid repeat sales index was similar to the hedonic price index, but with greater volatility. They argued that the similarities between the indices provided confidence that temporal variation in unobservable characteristics were not dictating the results.

As previously mentioned, there is no consensus regarding the preferred approach of constructing quality-adjusted price indices, either theoretically or empirically. However, there is reason to believe that constructing more advanced measures may provide a better guide to pure price changes than a simple median (Hansen, 2009). The specific methodology adopted is dependent on the data available. Art price indices tend to employ some variant of the hedonic

method, due to the availability of more detailed data on characteristics and a lack of repeat sales of artworks. The following section provides a brief literature review of the estimation of art price indices. The empirical sections then consider the alternative approaches to gauge their performance and to see if they point to the similar aggregate trends.

3 Brief Literature Review

A relatively large number of academic studies have constructed art price indices for various art markets around the world. These studies have typically been interested in evaluating the risk-adjusted returns to art, in order to investigate whether it provides potential diversification benefits for an investment portfolio. The recent increase in the availability of data on art prices has increased the interest in art as an asset class (Campbell, 2009).

These studies have typically relied on publically available auction prices.⁶ Art is also sold privately, either directly by artists or through dealers. However, dealers' sales records are generally not available, as releasing such information may be damaging to the dealer's business and dealers have an incentive to give the impression that there is high demand for their artworks. Nevertheless, it is generally accepted that auction prices set a benchmark that is also used in the private market (Renneboog and Spaenjers, 2012). For instance, if an artwork sells for a lower price at auction than the prices offered by a dealer, buyers would likely move to another dealer or simply purchase at auction. Thus, prices for private sales are likely anchored by auction prices and are likely to be highly correlated for the same works (Olckers, Kannemeyer and Stevenson, 2015).

The majority of studies have used hedonic models to construct indices, due to the lack of repeat sales of artworks and the availability of information on many of their important attributes. Anderson (1974) was the first to apply a hedonic regression to art prices. More recent examples include: Renneboog and Van Houtte (2002), who estimated an index of Belgian paintings; Kräussl and Lee (2010), who studied the prices of the top 500 artists in the world; Kräussl and Logher (2010), who analysed the performance of art in Russia, China and India; and Kräussl (2014) who analysed art from the Middle East and Northern Africa region.

In estimating art price indices, studies typically to set up some form of selection criteria for which artists to include in the index calculation. The number of artists is constrained by the number of artist dummies that can be included in the model (i.e. the degrees of freedom). A common criterion has been historical importance, measured as the frequency with which an artist was mentioned in a collection of art literature. Kräussl and Van Elsland (2008) argued that availability and liquidity are better criteria from an investor's point of view, as the index would reflect artworks actually traded in the market. This implies that selection could be based on the number of sales, rather than historic relevance. Kräussl and Van Elsland (2008) developed a two-step hedonic approach, which allows the use of every auction record, instead

⁶Auctions account for around half of the art market according to The European Fine Art Fair Art Market Report 2014.

of only those auction records that belong to a sub-sample of selected artists. This approach is discussed in more detail below.

Hedonic models typically include characteristics that are relatively easily observable and quantifiable. The attributes include the artist, the auction house, the size, the medium, the theme, whether the artwork is signed, and the artist's living status (Kräussl and Logher, 2010). Although omitted variables are a problem in every model, hedonic pricing is particularly suitable for luxury consumption goods, where a limited number of key characteristics often determine the willingness to pay for an item. In any event, the omitted variable bias is often small in practice (Triplett, 2004; Renneboog and Spaenjers, 2012).

Multi-period pooled hedonic regressions have been criticised for holding the hedonic coefficients fixed over the entire sample. Another problem with the multi-period pooled model is that the coefficients are not stable when data from additional periods are added to the sample. The adjacent-period method can deal with this by estimating separate overlapping hedonic models and then chaining the sequence of shorter indices together to form a continuous time series. Thus, it allows the coefficients, and therefore the implicit prices assigned to the characteristics, to vary in each regression (Triplett, 2004).

A few studies have utilised the repeat sales method to estimate art price indices. These studies have typically relied on very large sales databases, due to the infrequency of repeat sales of individual artworks. Indeed, for artworks the resale of a specific item may occur only rarely, which might be related to the high transaction costs involved. Mei and Moses (2002) constructed the seminal repeat sales index of art prices for the period 1875-2000. The resulting index returns were compared to a range of assets. Their methodology is currently used to produce the Mei Moses Art Index for Beautiful Asset Advisors. Goetzmann, Renneboog and Spaenjers (2011) used a long-term repeat sales art market index to investigate the impact of equity markets and top incomes on art prices. The analysis was based on over a million sales dating back to the 18th century.

Korteweg (2013) constructed a repeat sales index based on a large database of repeat sales between 1972 and 2010. They argued that standard repeat sale indices suffer from a sample selection problem, as sales are endogenously related to asset performance. If artworks with higher price increases were more likely to trade, the index would be biased and not representative of the entire market. In periods with few sales it would be possible to observe large positive returns, even if overall values were declining. A Heckman selection model, predicting whether an artwork actually sold, was used to correct for this bias. The correction decreased the returns to an investment in art significantly.

Bought-in lots (i.e. items that do not reach the reserve price and remain unsold) are always a problem when constructing these indices. Most studies lack data on buy-ins and are forced to ignore the problem. Collins, Scorcu and Zanola (2009) developed a hedonic index that corrected for sample selection bias from buy-ins. They argued that because auctions have high proportions of unsold lots (typically 30%-40%), price indices suffer from non-randomness in the data. A sample based only on sold lots systematically excludes "less fashionable" artworks, potentially introducing a bias in the sample of prices. A Heckman selection model

was used to address this issue.⁷ The results confirmed a statistically significant sample selection problem, in line with similar studies in the property market.

3.1 South African art price literature

In the South African context, Olckers, Kannemeyer and Stevenson (2015) created a proxy for the cultural value of art by constructing an Art Critic Index based on a survey of the South African art literature. The auction results (1996-2012) were obtained from AuctionVault's online database. Using a hedonic model they found that cultural value was positively correlated with auction prices, i.e. the economic value of art. Interestingly, they singled out and analysed some specific artists that were outliers in this relation.

Fedderke and Li (2014) studied the relationship between South Africa's two major fine art auction houses: Strauss & Co and Stephan Welz & Co. The analysis was based on a hand-coded dataset of auction prices. They developed a theoretical framework to consider the interaction between the market leader (Strauss) and the market follower (Stephan Welz). The model predicted that the market follower would be forced to issue excessive price estimates to attract sellers, at the cost of higher buy-in rates. The predictions were tested by employing a hedonic model to construct a counterfactual for auction prices. Both direct and indirect tests confirmed the predictions of the theoretical model.

Citadel, a wealth manager, has been publishing the Citadel Art Price Index (CAPI) since 2011. The CAPI is intended to outline general trends in the South African art market. It uses an adjacent-period hedonic regression model, based on the top 100 artists in terms of sales volumes, and a 5-year rolling window estimation period (Econex, 2012). The estimation below builds on the CAPI in order to contribute to the research on the South African art market.⁸

4 South African Art Auction Data

Auction prices are the only consistently available price data on the South African art market. This paper will therefore rely on publicly available auction prices, similar to almost all other studies estimating art price indices. As explained above, there should be a strong correlation between auction prices and private prices (Olckers, Kannemeyer and Stevenson, 2015).

Strauss & Co and Stephan Welz & Co are the two local auction houses that have handled the bulk of sales in recent years, with auctions in Cape Town and Johannesburg. Other local auction houses include Bernardi in Pretoria and Russell Kaplan in Johannesburg. Bonhams in London is the only major international auction house with a dedicated South African art department, though some competition is emerging from Sotheby's and Christie's. Bonhams

⁷The nature of sample selection bias is different in the approaches. The repeat sales method ignores all information on single sales, so that it may not represent the population. The hedonic method only uses sold items, so that bias may arise from unsold items.

⁸The CAPI is estimated by the author on behalf of Citadel.

has two major South African art sales annually. The auction houses follow an open ascending auction, where the winner pays the highest bid. A sale is only made if the hammer price is above the secret reserve price. Otherwise the artwork is unsold and is said to be bought in (Fedderke and Li, 2014).

The indices are based on data recorded by AuctionVault. This data cover sales of South African art at 8 auction houses⁹ between 2000 and 2015. The database includes 52,059 sales by 4,123 different artists. The following characteristics are available for each auction record: hammer price, artist name, title of work, medium, size, whether or not the artwork is signed, dated and titled, auction house, date of auction, and the number of distinct works in the lot. Like most studies, the database lacks information on buy-ins and the analysis is forced to disregard the potential sample selection problem.¹⁰

Figure 1 illustrates the number of auction lots sold in the sample over the period (2000-2015) by auction house. The number of sales in the sample increased markedly over the period, especially in 2007 and 2011. This increase was due to an improvement in data collection from existing auction houses and the entry of auction houses such as Strauss & Co and Bonhams. These two auction houses now account for the bulk of turnover in the market.

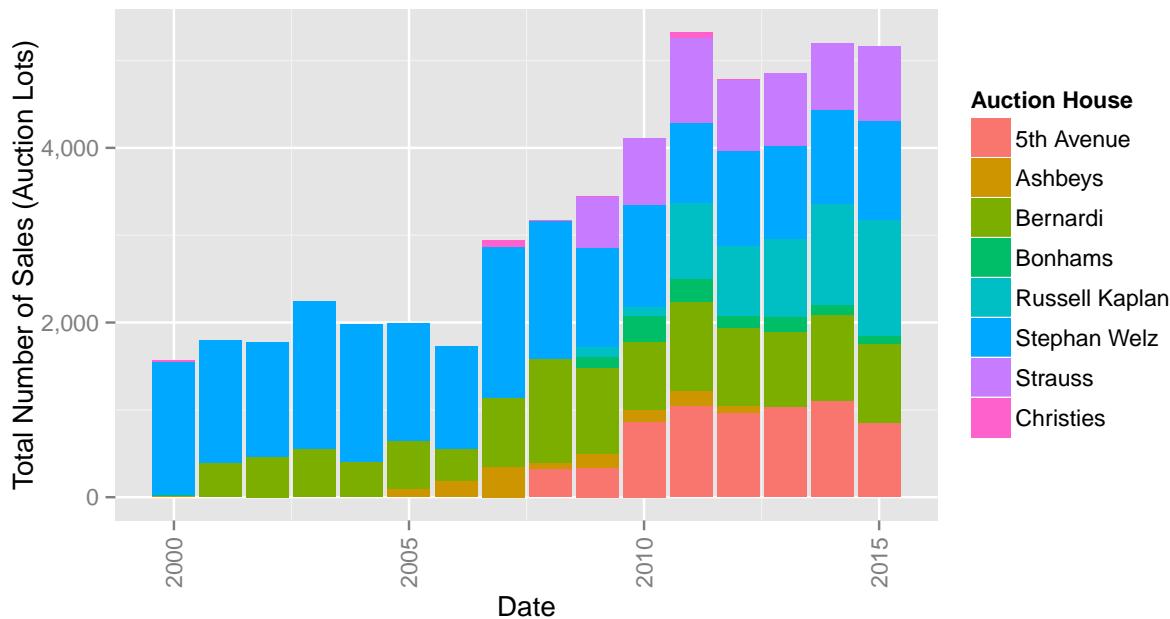


Figure 1: Total Number of Auction Lots Sold by auction house (2000-2015)

Figure 2 illustrates the total sales turnover in the sample, as well as the annual median sales price. Total auction turnover echoed the increase in the number of lots over the period. At its peak in 2011, turnover in the sample had reached almost R400 million. The increase in

⁹These are: 5th Avenue, Ashbeys, Bernardi, Bonhams, Christies, Russell Kaplan, Stephan Welz & Co and Strauss & Co.

¹⁰Truncated regression techniques cannot be performed, as the cut-off points (i.e. the secret reserve prices) are different for each artwork and unknown.

annual median sales prices was especially large, from R3,200 in 2003 to R10,000 at its peak in 2010. This confirms anecdotal evidence on the rise in popularity of the South African art market.

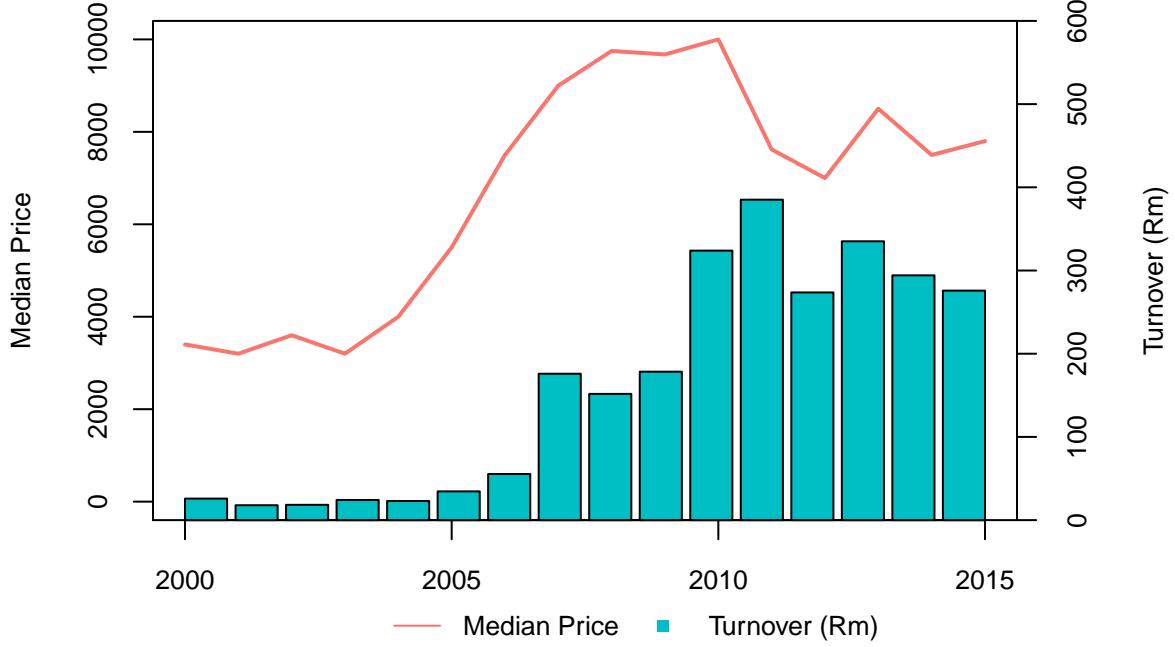


Figure 2: Median hammer prices and total turnover at auction (2000-2015)

Table 1 reports descriptive statistics for the hammer prices over the sample period. The mean price of R49,824 was much higher than the median of R7,000. This indicates that the sample is positively skewed by very high prices for certain artworks, including the hammer price of over R30 million for Irma Stern's "*Arab Priest*".

Table 1: Descriptive statistics of auction hammer prices

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
20.00	2600.00	7000.00	49824.76	24000.00	30147660.00

4.1 Artwork characteristics

Hedonic art price models typically include characteristics that are relatively easily observable and quantifiable. This section briefly discusses the variables typically included in hedonic models of art prices.

Artist reputation: Hedonic models typically include dummy variables to control for the artists. However, some artists often have to be excluded from estimation, due to a lack of degrees

of freedom. Alternatively, a reputation variable can be constructed, either from the art literature, or from the auction data itself with a procedure like the 2-step hedonic approach suggested by Kräussl and Van Elsland (2008). The models in this paper are estimated using a continuous reputation variable, as explained below.

Size: The most common variable used to describe the physical characteristics of an artwork is its size or surface area. The models use the natural logarithm of the surface area of the artwork in cm^2 . The models also include an interaction term for sculpture size, as the size of a sculpture is usually only recorded in terms of its height (in cm). Figure 3 illustrates the positive relationship between artwork sizes and prices, by medium. Squared values are occasionally included to take potential non-linearities into account (Fedderke and Li, 2014). In this sample, however, the relationship does not seem to exhibit an inverted U-shape and the squared term is positive and economically insignificant in the regression models.

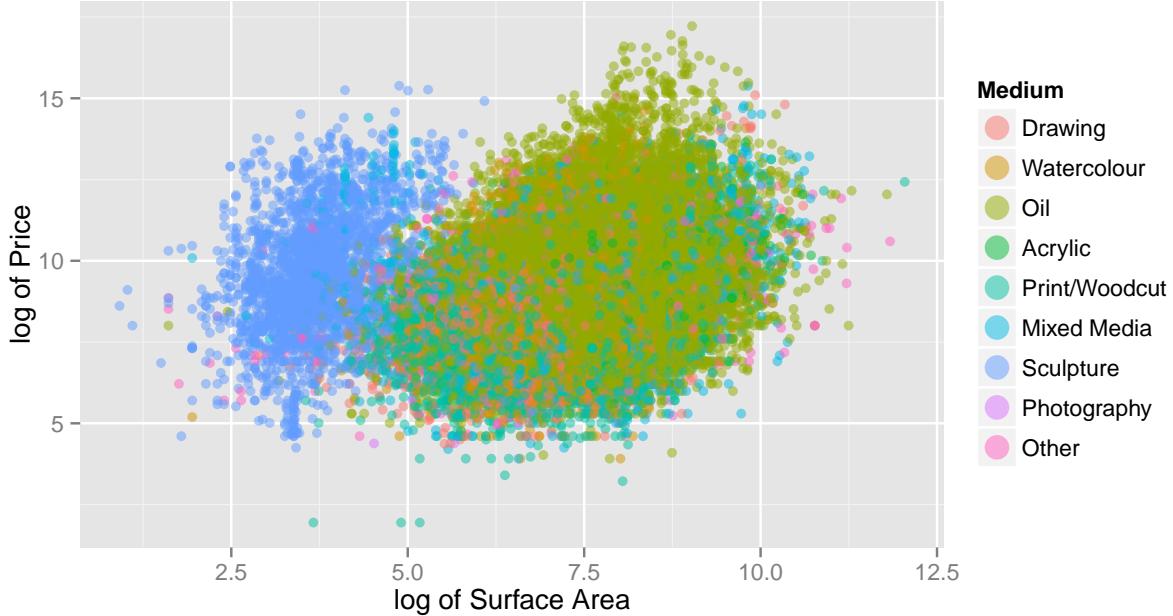


Figure 3: Relationship between prices and artwork sizes, by medium

Auction house: Dummy variables for the auction houses are also typically included. The more prominent auction houses usually have a positive effect on prices. One reason might be that the more renowned auction houses will offer higher quality work (Kräussl and Logher, 2010). Thus, the variables might be picking up otherwise unobservable quality differences and do not necessarily reflect auction house certification (Renneboog and Spaenjers, 2012). Moreover, different auction houses charge different commissions to both buyers and sellers. For example, Strauss & Co reported a buyer's premium of 10%-15%, while Bonhams charged premiums of up to 25% (Olckers, Kannemeyer and Stevenson, 2015). The hammer prices exclude these premiums and are therefore not a perfect measure of the cost to the buyer and revenue to the seller. For the purposes of a price index the auction house dummies should capture the different premiums charged by the auction houses.

Mediums: Average prices vary across mediums. This might be due to the durability of the medium, the stage of production the medium is associated with (e.g. preparatory drawings) and in some case the replacement value of the materials used (e.g. sculptures cast in bronze). Oil paintings traditionally earn the highest prices. The availability of copies may decrease the prices of prints and photographs relative to other mediums. Studies typically include dummy variables for the different mediums as defined in their data (Kräussl and Logher, 2010). The models in this section use the 9 mediums defined in the dataset; the same mediums used by Olckers, Kannemeyer and Stevenson (2015).¹¹

Authenticity dummies: Models often include dummies for whether the artwork is signed and dated. There might be a premium for these attributes, as there is less uncertainty about authenticity (Renneboog and Spaenjers, 2014). These dummies are included in the models below and are expected to have positive coefficients.

Number of works in the lot: The models below also control for cases in which more than one artwork was sold in the same auction lot. This is because the recorded size corresponded to each artwork separately and not the group. Moreover, it is possible that lots including more than one artwork fetch a lower price per artwork than if they sold separately.

Date dummies: The models below include time dummies at a quarterly frequency, which are used to estimate the indices. The exponentials of the time dummy coefficients represent the appreciation in the value of art in that specific period, relative to the common base period.¹²

4.1.1 Continuous artist reputation variable: two-step hedonic approach

The number of artist dummy variables that can be included in the hedonic regression is limited by the degrees of freedom, which means that some artists usually get excluded from the sample. Kräussl and Van Elsland (2008) developed a two-step hedonic approach, which allows the use of every auction record, instead of only those auction records that belong to a sub-sample of selected artists. The approach involves the estimation of a continuous artist reputation variable, which is included in the regression instead of the artist dummy variables. In this way the approach increases the sample size of artworks that can be included in the regression models and reduces selection bias.

¹¹The data do not include enough detail to differentiate between medium (e.g. oil) and material (e.g. canvas), or to identify the subject matter or theme of an artwork (e.g. portraits, landscapes, abstract works). A few studies have included dummies to indicate whether an artist was alive. Artworks of artists who are no longer alive are generally thought to be more valuable, as the production has ceased. However, artists who are no longer alive are not able to build on their reputation, which might result in lower sale prices in the long run (Kräussl & Lee 2010). Hence, it is not clear if the variable will be significant. Fedderke & Li (2014) found that the date of death and age of the artist were statistically insignificant for their South African sample.

¹²Such an index will track the geometric mean, rather than the arithmetic mean, of prices over time, because of the log transformation prior to estimation. This is important for the estimation of returns if there is time variation in the (heterogeneity-controlled) dispersion of prices. If it is assumed that the regression residuals are normally distributed in each period, a correction can be made by defining corrected index values as: $I_t = \exp [\gamma_t + 1/2(\sigma_t^2 - \sigma_0^2)] * 100$, where σ_t^2 is the estimated variance of the residuals in period t (Renneboog & Spaenjers 2012). In practice this adjustment is often negligible (Hansen 2009), which is also the case in this sample.

Triplett (2004) showed that a hedonic function with a logarithmic dependent variable would yield an index equal to the ratio of the unweighted geometric means of prices in periods t and $t + 1$, divided by a hedonic quality adjustment. The superscripts n and m indicate the generally unequal number of artworks sold per period. The hedonic quality adjustment is a quantity measure of the mean change in the j characteristics of items sold in period t and $t + 1$, valued by their implicit prices (β_j):

$$\text{Index} = \frac{\prod_{i=1}^n (P_{i,t+1})^{\frac{1}{n}}}{\prod_{i=1}^m (P_{i,t})^{\frac{1}{m}}} / \text{hedonic adjustment}$$

$$\text{hedonic adjustment} = \exp \left[\sum_{j=1}^J \beta_j \left(\sum_{i=0}^n \frac{X_{ji,t+1}}{n} - \sum_{i=1}^m \frac{X_{ji,t}}{m} \right) \right]$$

Kräussl and Van Elsland (2008) argued that the same method could be used to adjust the average price of an artist's work for differences in quality. The resulting index yields the value of artworks by artist y , relative to the base artist 0:

$$\text{Artist reputation index} = \frac{\prod_{i=1}^n (P_{i,y})^{\frac{1}{n}} / \prod_{i=1}^m (P_{i,0})^{\frac{1}{m}}}{\exp \left[\sum_{j=1}^z \beta_j \left(\sum_{i=0}^n \frac{X_{ji,y}}{n} - \sum_{i=1}^m \frac{X_{ji,0}}{m} \right) \right]}$$

where $P_{i,y}$ is the value of painting i ($i = 0, \dots, n$), created by artist y ; X_{ji} are the characteristics of the artworks, excluding the artist dummy variables.

The first step is to estimate the full hedonic model on a sub-sample of artists to obtain the characteristic prices (β_j). Following Kräussl and Van Elsland (2008), the sub-sample includes the top 100 artists in terms of volume, representing 53% of records and 92% of the value in the sample. The coefficients are similar to those for the full pooled model and it is assumed that the characteristic prices are representative. In the second step, the artist reputation index is calculated for each artist relative to the base artist (Walter Battiss), i.e. the relative quality-corrected prices for the works of artist y relative to artist 0. The reputation index is then used as a continuous proxy variable for artistic value in the hedonic models, instead of the artist dummies.

Figure 4 illustrates the positive relationship between artwork prices and the reputation index. As a robustness check, the models are also estimated including all of the artist dummies, except for those artists that only sold one artwork over the sample period. The results were very similar, in line with the findings in Kräussl and Van Elsland (2008).

5 Central Tendency Indices

Two central tendency price indices are estimated at a quarterly frequency to act as a baseline for the index comparisons. The median index is simply the median price for each quarter. The Fisher index is a mix-adjusted central tendency index, which is stratified by artist and medium. The base periods are allowed to vary for each index point and the index points are then chained together to form the overall chain-link index.

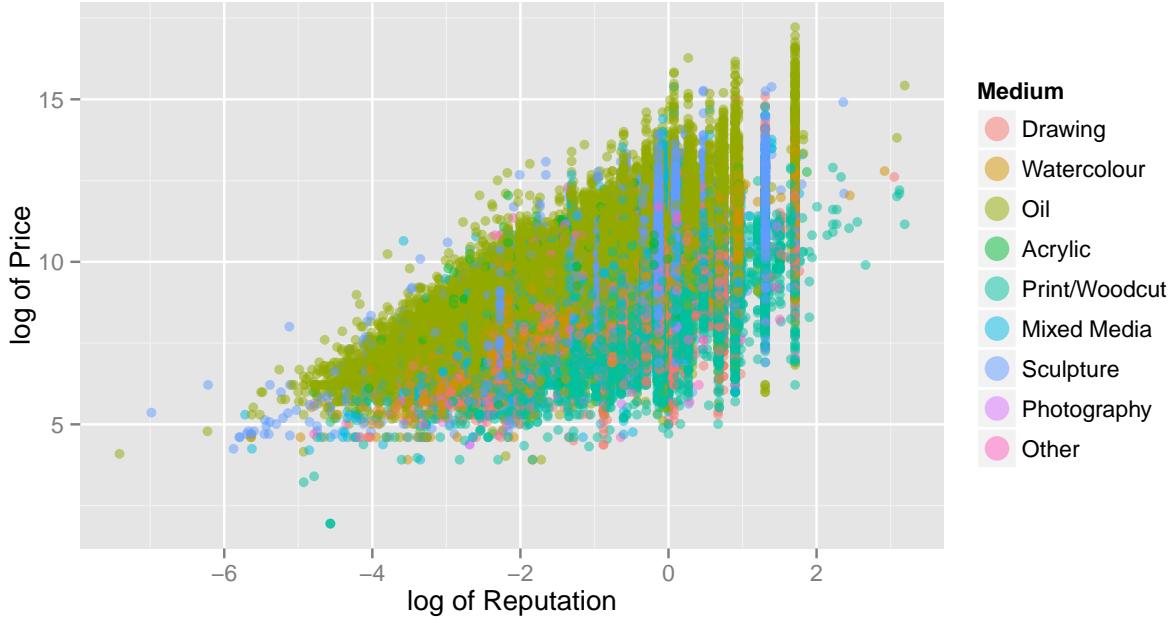


Figure 4: Relationship between prices and reputation index

Figure 5 illustrates the two central tendency indices. The simple median index provides a noisy estimate of price changes and no consistent picture emerges. The large variation is likely due to the large differences in quality-mix or composition of the artworks sold between different periods.

The Fisher index also exhibits a large variation and implausibly large increases over the sample period. In this case the stratification does not seem to be very effective. This is probably because the artist and medium categories only capture a small portion of the differences in the quality of artworks that come to market between periods. The mix-adjusted measure will not account for any changes in the mix of artworks sold that are unrelated to artist and medium type. The stratified index also does not account for changes in the mix of artworks sold within each subgroup, in this case changes in the mix of artworks by a certain artist in a specific medium (Eurostat, 2013). Moreover, the subgroups become small when separated in this way, which means that small changes can have a large effect on the index.

The results illustrate that central tendency measures are deficient in this case and should be used with caution, confirming the findings in Els and Von Fintel (2014). As a consequence, regression-based measures are generally preferred in the academic literature. The hedonic indices in the following section control for quality changes by taking many more of the artwork attributes into account.

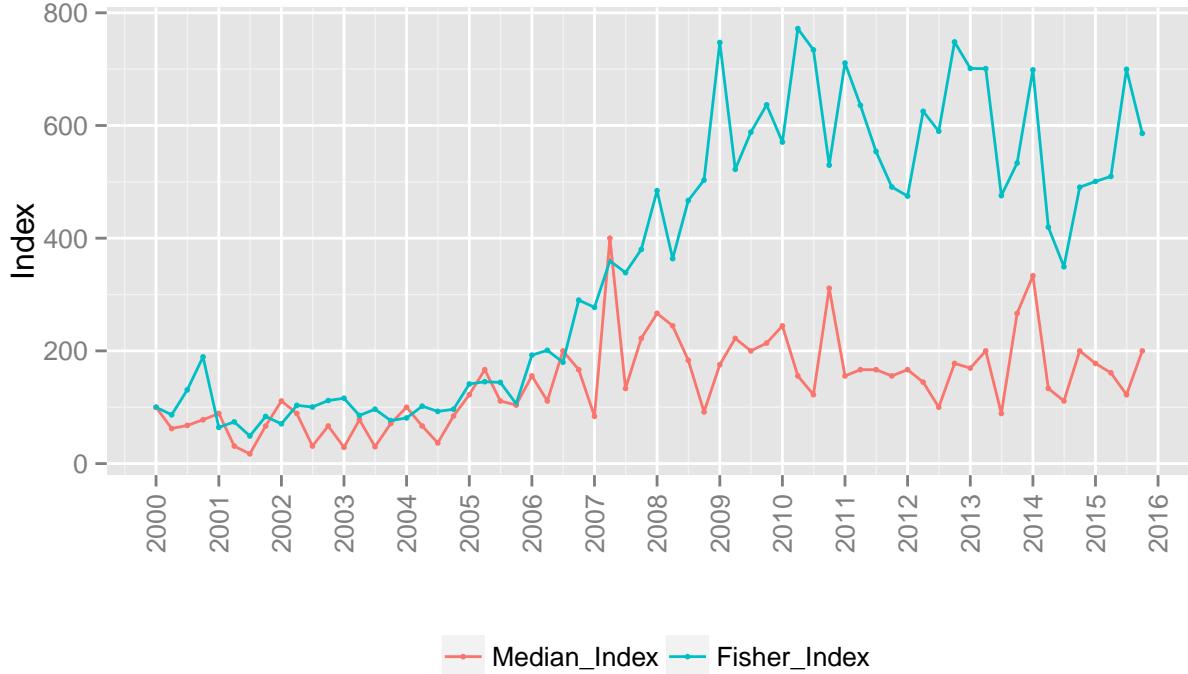


Figure 5: Central tendency South African art price indices (2000Q1=100)

6 Hedonic Indices

The full pooled sample estimation results are reported in Table 2. The coefficients are all significant and have the expected signs. The size of the artwork is highly significant and positive, as is the sculpture interaction term. Bonhams and Strauss & Co are the auction houses with the highest average prices, after controlling for other factors, probably reflecting higher quality work and higher commission structures. Oil is the most expensive medium category. The authentication dummies are both positive and significant, as is the artist reputation variable. The number of works dummy indicates that more than one artwork in a lot leads to slightly lower prices per artwork. The adjusted R^2 is relatively high, suggesting that these variables capture a relatively large part of the variation in sales prices. The time dummy variable are then used to calculate the full period pooled hedonic index.

To allow for shifts the implicit prices, two adjacent-period or chain-linked indices are calculated by estimating separate models for adjacent sub-samples. There is a trade-off in selecting the length of the estimation window. Shorter estimation windows decrease the likelihood of large breaks but also decrease the number of observations used to estimate the parameters (Dorsey *et al.*, 2010). 1-year and 2-year estimation windows are selected, similar to Dorsey *et al.* (2010) in the context of real estate and Renneboog and Spaenjers (2012) in the context of art. This seems to be reasonable for the South African art market, where large auctions are held relatively infrequently. The indices are then calculated by chain-linking the estimates together, as Figure 6 illustrates for the 2-year version of the index.

Table 2: Hedonic Regression results

	<i>Dependent variable:</i>
	lnprice
lnarea	0.405*** (0.004)
ah_codeAshbeys	0.114*** (0.028)
ah_codeBernardi	0.122*** (0.013)
ah_codeBonhams	1.198*** (0.026)
ah_codeChristies	1.152*** (0.065)
ah_codeRussell Kaplan	0.129*** (0.015)
ah_codeStephan Welz	0.590*** (0.013)
ah_codeStrauss	1.126*** (0.016)
med_codeWatercolour	0.553*** (0.017)
med_codeOil	1.435*** (0.014)
med_codeAcrylic	1.039*** (0.033)
med_codePrint/Woodcut	-0.759*** (0.015)
med_codeMixed Media	0.554*** (0.017)
med_codeSculpture	1.767*** (0.084)
med_codePhotography	-0.618*** (0.085)
med_codeOther	0.703*** (0.035)
lnsculpt_area	0.236*** (0.021)
dum_signed	0.208*** (0.016)
dum_dated	0.045*** (0.007)
nr_works	-0.096*** (0.003)
lnrep	0.949*** (0.003)
Constant	5.101*** (0.065)
Quarterly dummies	Yes
Observations	51,454
R ²	0.782
Adjusted R ²	0.782
Residual Std. Error	0.780 (df = 51369)
F Statistic	2,196.018*** (df = 84; 51369)

Note: *p<0.1; **p<0.05; ***p<0.01

In the context of real estate, Shimizu, Nishimura and Watanabe (2010) suggested a so-called overlapping-periods hedonic regression method using multiple “neighbourhood periods”, allowing gradual shifts in the parameters. Parameters are estimated by taking a certain length as the estimation window and shifting the period forward in rolling regressions. They argued that this method should be able to handle seasonal changes in parameters better than adjacent-periods regressions, although it may suffer more from the disadvantages associated with pooling. To apply this method, 5-year rolling regressions were run, which corresponds to the rolling 5-year regressions used to estimate the Citadel Art Price Index. The estimation

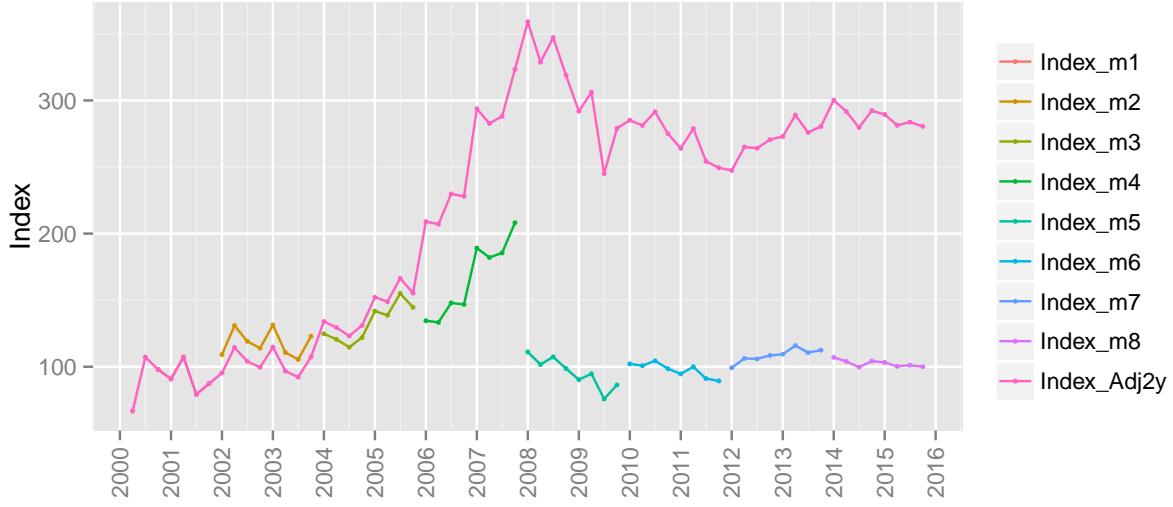


Figure 6: Chain-linked two-year adjacent period art price index

window is then shifted forward one year, allowing for gradual shifts in the parameters.

The coefficients from these models are similar in magnitude to the full pooled sample model and significant in virtually all cases. For example, the coefficient associated with the size of the artwork is 0.426 using the standard hedonic regression, while the average coefficients from the other regressions are 0.44, 0.43 and 0.42. However, there are a few cases in which the estimated parameters fluctuate quite substantially. For example, the coefficient of the Strauss auction house dummy varies between 1.04 in the pooled model and 0.77 in one of the sub-samples, indicating that non-negligible structural changes might have occurred during the sample period.

Figure 7 illustrates the resulting quarterly art price indices from these four models. The hedonic indices follow a similar cyclical pattern over the period, although the levels are slightly different, and appreciated rapidly in the run-up to the Great Recession. The indices seem more plausible than the central tendency measures, supporting the case for regression-based measures.¹³ All four of the indices peak in 2008Q1, which is before the peak in sales and annual median prices in the sample. All four of the indices displayed dramatic increases in auction prices of more than 200% between 2003 and 2008. This conforms to the idea that there was a surge in the popularity of South African art over the period, as well as the idea of the formation of a so-called bubble, with a dramatic rise and subsequent decrease in prices.

The hedonic price indices display similar trends over the period, with large price increases in the run-up to the Great Recession. However, the hedonic indices may suffer from omitted variable or misspecification bias. Ramsey RESET tests indicate that the models might be misspecified. The omitted variables might include unobservable (or difficult to measure) nuances that make a given artwork unique and influence its price. The omitted variables

¹³Two additional hedonic model extensions were performed as a robustness test: stratified hedonic indices by medium and quantile hedonic indices. The results are very similar to the results reported above.

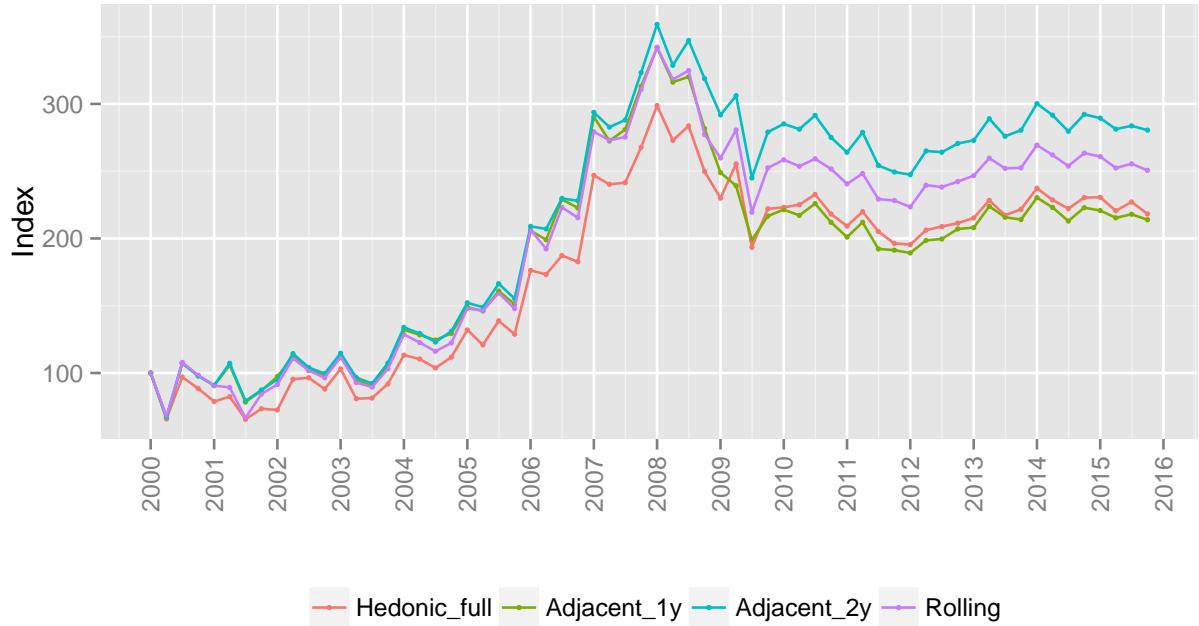


Figure 7: Hedonic South African art price indices (2000Q1=100)

might include, for instance, interaction terms (e.g. artist and medium combinations), squared terms, finer medium classifications (e.g. a specific artist's Print/Woodcuts might typically be linocuts), or attributes such material, theme and style (e.g. a specific artist's oil paintings might typically use the same material such as canvas, or have the same theme such as a portrait). These omitted variables potentially bias the coefficients if they are correlated with sales timing, which in turn may bias the indices, although the bias is often small in practice (Triplett, 2004; Renneboog and Spaenjers, 2012).

The following section estimates alternative art price indices using a hybrid repeat sales methodology, which should be less prone to omitted variable bias. If the alternative indices displays the same kind of trend and the same marked increase in prices as the hedonic indices, this should provide more confidence that the results are robust to changes in methodology and that omitted variable bias is not driving the results.

7 Hybrid Indices: Pseudo-Repeat Sales

The repeat sales method is less prone to potential omitted variable bias than the hedonic method, as it tracks the sales of the same item over time. Because the dataset does not uniquely identify each artwork, repeat sales of the same artwork were identified by matching sales records using the following hedonic attributes: artist name, artwork title, size, and medium, the presence of a signature and a date, and the number of artworks in the lot. Only 515 true repeat sales pairs could be identified in the sample. Figure 8 illustrates the

index generated using the classical repeated sales approach. The index is volatile, with many missing values, and exhibits a large appreciation in prices over the period. The limited number of repeat sales observations therefore limits the usefulness of the classical repeated sales approach in this case.

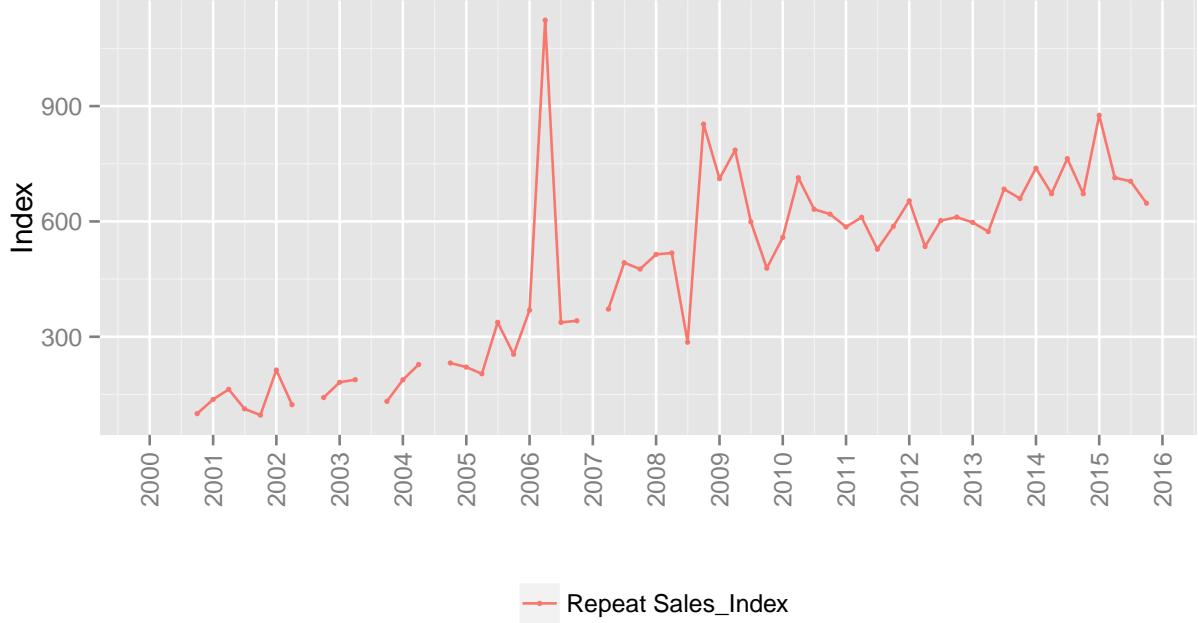


Figure 8: Repeat sales index of South African art prices (2000Q4=100)

An alternative is to use a procedure similar in spirit to the “pseudo repeat sales” (ps-RS) procedure suggested by Guo *et al.* (2014). Instead requiring an exact match to form a sales pairs, very similar artworks may be treated as repeat sales pairs. In this way the ps-RS method supplements the true repeat sales in the sample and mitigates the problem of small sample size. In so doing it allows the estimation of a variant of the repeat sale index. The caveat is that even two artworks by the same artist of a similar size and in the same medium do not necessarily serve as close substitutes (Olckers, Kannemeyer and Stevenson, 2015).

The first ps-RS sample is created by matching artworks on all the hedonic attributes, except the title of the artwork. The matched pairs therefore have the same hedonic attributes except for the title of the artwork. Matching by this criteria increases the number of repeat sales pairs to 6,642, which includes the 515 true repeat sales or exact matches. The second ps-RS sample allows the sample to increase further by matching on all the hedonic attributes except the title and the presence of a signature and a date on the artwork, i.e. the authenticity dummies. This increases the pseudo repeat sales sample to 7,965 sales pairs. This procedure involves a trade-off between the within-pair “similarity” (higher similarity is good for mitigating bias) and the sample size (larger size is good for reducing random errors).

The differential hedonic equation is then applied to the pseudo repeat sales samples, where

artwork i in quarter t and artwork h in quarter s form a matched pair ($t > s$):

$$\ln P_{it} - \ln P_{hs} = \sum_{j=1}^J \beta_j (X_{itj} - X_{hsj}) + \sum_{t=0}^T \delta_t G_{it} + \epsilon_{iths}$$

where G_{it} is again a time dummy equal to 1 if the later sale occurred in quarter t , -1 if the former sale in the pair occurred in quarter s , and 0 otherwise; and ϵ_{iths} again represents a white noise residual.

For the first ps-RS sample, the only remaining independent variable is the difference in the auction house dummies ($X_{it1} - X_{hs1}$). This takes account of possible differences in quality and commission structures. In the second ps-RS sample the independent variables represent the differences in the auction house dummies and the differences in the two authenticity dummies. The independent variables therefore include indicators of the relatively small and easy to measure within-pair differentials in attributes between the two items.

Thus, the ps-RS approach addresses the problem of lack of repeat sales data and to some extent the potential omitted variable bias inherent in the hedonic method. The pseudo repeat sales pairs include the 515 true repeat sales, or exact matches, where the model controls for all the observed and unobserved attributes by taking first differences. For the pseudo sales pairs, taking first differences will control for omitted variables when they are the same for the two items that form the pseudo sales pairs. For example, if Van Gogh's *Sunflowers* paintings are treated as repeat sales, taking first differences would control for attributes such as theme, style, material, prominence, and the stage of the artist's career. Other potentially significant variables might include an array of interaction and non-linear terms.

Figure 9 illustrates the two versions of the ps-RS indices. The indices point to similar cyclical trends in art prices over the sample period, although the “purest” pseudo repeat sales index is at a slightly higher level than the other index. The larger sample appears to reduce the volatility of the index, which is similar to the findings in Guo *et al.* (2014). Both indices appreciated rapidly in the run-up to the Great Recession and peaked in 2008Q1. The indices point to the same kind of marked increase in South African art prices as the hedonic indices, which provides more confidence that the results are robust to changes in methodology. The following section further compares and evaluates the different art price indices.

8 Comparison and Evaluation

This section compares the different art price indices in order to determine if they provide a consistent picture of price movements in the South African art market. The indices are evaluated in terms smoothness to examine which index provides the most credible gauge of overall price movements in this specific case. The art price indices are also compared to available international art price indices and other South African assets over the sample period, to check if the results are reasonable.

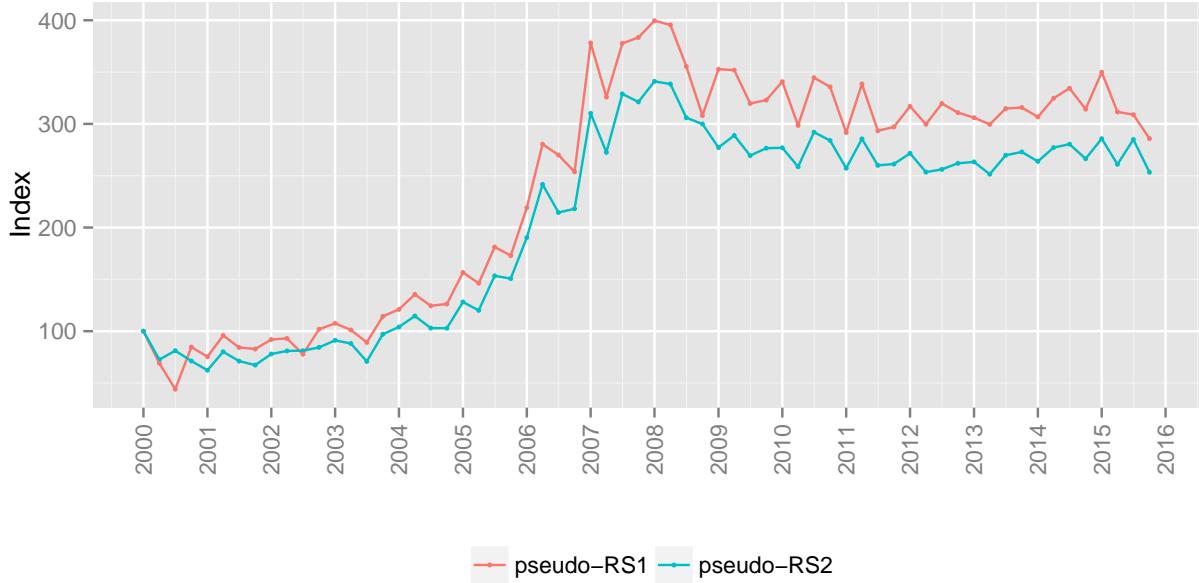


Figure 9: Pseudo repeat sales South African art price indices (2000Q1=100)

8.1 Comparison of the indices

The art price indices are first compared graphically. Figure 10 illustrates representative indices for the three methodologies: median values, the 2-year adjacent period hedonic index and the second version (larger sample) of the ps-RS index. The two regression-based approaches behave quite differently from a simple median. This implies that regression-based methods, which adjust for changes in the composition or quality-mix of artworks sold, provide better estimates of pure price changes for unique assets. The results confirm the findings for South African real estate in Els and Von Fintel (2014).

The hedonic and ps-RS indices exhibit remarkably similar trends over the sample period. Both measures indicate that the average price of a constant-quality artwork increased significantly between 2005 and 2008 and then declined relatively sharply after the financial crisis, similar to other asset prices (Shimizu, Nishimura and Watanabe, 2010). The fact that the regression-based indices are similar, even when the hybrid repeat sales indices are based on smaller subsamples of the data, implies that the potential omitted variable and sample selection bias may not be too pervasive in this case. The ps-RS method provides a type of robustness check on the hedonic indices.

Table 3 reports the correlations in the growth rates between the various indices.¹⁴ There is a significant positive correlation between the regression-based indices, and even the Fisher central tendency index. This indicates that their general trends are similar, and are different

¹⁴The first few periods of repeat sales estimates are often sensitive when the sample size is small. The first two index values are discarded because of the lack of repeat sales in the first few quarters. Indeed there are no true repeat sales in the first three quarters of the sample period.

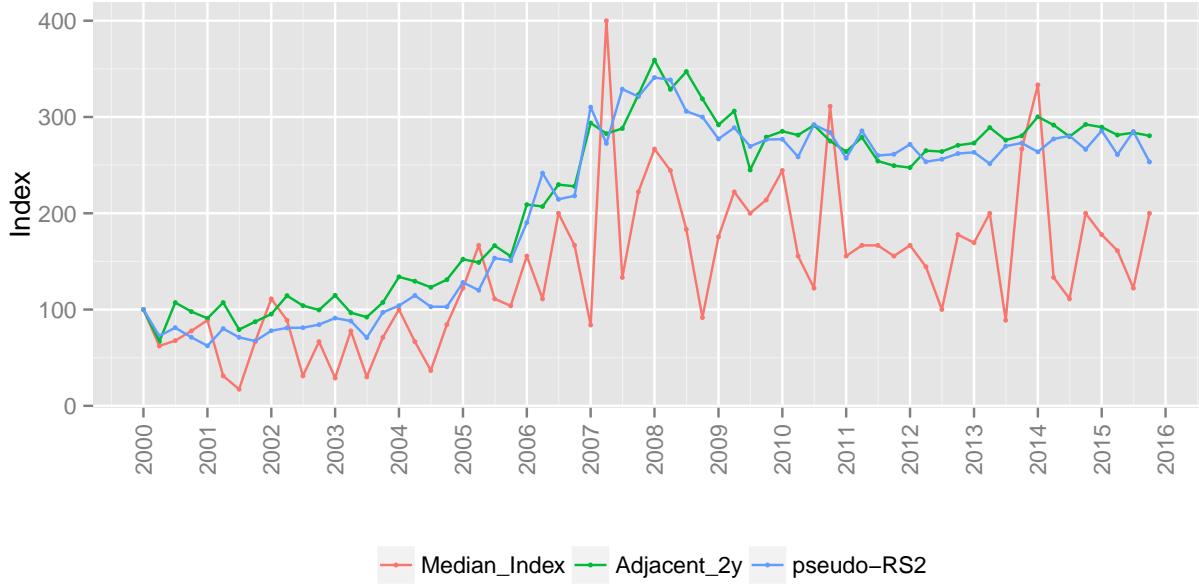


Figure 10: Comparing South African art price indices (2000Q1=100)

from the simple median. This shows that there is some consistency in the estimates from the different methodologies, and implies that they are approaching a sort of central tendency in art prices over the period. The following section compares the indices more formally by evaluating index smoothness.

Table 3: Correlations in growth rates (DLogs)

	Median	Fisher	Hedonic	Adj1y	Adj2y	Roll	RepSale	ps.RS1
Median								
Fisher	0.13							
Hedonic	0.03	0.40**						
Adj1y	0.11	0.35**	0.90***					
Adj2y	0.11	0.38**	0.94***	0.98***				
Roll	0.23	0.38**	0.94***	0.94***	0.95***			
RepSale	0.20	0.00	-0.11	-0.07	-0.03	-0.11		
ps.RS1	-0.01	0.08	0.48***	0.58***	0.56***	0.47***	0.12	
ps.RS2	-0.16	0.08	0.52***	0.59***	0.58***	0.46***	0.23	0.87***

8.2 Evaluating index smoothness

The quality of price indices has traditionally been evaluated based on the diagnostic metrics of the underlying regressions, such as the standard errors of the residuals. However, Guo *et al.* (2014) argued that this is an indirect way to evaluate the index. The regression residuals

do not represent errors in the price index, and hence do not directly reflect inaccuracy in the index returns. Even if an index is perfectly accurate, measuring the central tendency of market price changes in each period, the regression would still have residuals and the time dummy coefficients might still have large standard errors, resulting simply from the dispersion of individual art prices around the central tendency. Moreover, when datasets become large, the regression diagnostics are often impressively good simply because of the size of the sample. In such cases tests of economic significance are more valuable than tests of statistical significance.

Guo *et al.* (2014) suggested that signal-to-noise metrics, based directly on the index produced, are a more appropriate for judging the quality of the price index, as opposed to the underlying model. Random error in the coefficient estimation leads to “noise” into the index. Signal-to-noise metrics directly reflect the accuracy of the index returns and the economic significance of random error in the indices. The volatility (Vol) and the first order autocorrelations (AC(1)) of the index returns are signal-to-noise metrics that may be useful to compare the amount of noise in the indices.

Consider the simple model of random noise in the index:

$$m_t = m_{t-1} + r_t$$

and

$$I_t = m_t + \epsilon_t = \sum_{i=1}^t r_i + \epsilon_t$$

where m_t is the true market value level (in logs); r_t is the true return (i.e. the central tendency) of market prices in period t ; I_t is the index in period t ; ϵ_t is the index-level random (white noise) error. This random error causes noise in the index and therefore matters from the perspective of index users. The noise does not accumulate over time.

The index returns can be defined as follows:

$$r_t^* = I_t - I_{t-1} = r_t + (\epsilon_t - \epsilon_{t-1}) = r_t + \eta_t$$

where r_t^* is the index return and η_t is the noise component of the index return in period t .

The volatility of the index (Vol), which is the standard deviation of the index return $\sigma_{r_t^*}$ and the first order autocorrelation ρ_{r^*} (AC(1)) can be derived as:

$$Vol = \sigma_{r_t^*} = \sqrt{\sigma_r^2 + \sigma_\eta^2}$$

and

$$AC(1) = \rho_{r^*} = (\rho_r \sigma_r^2 - \sigma_\eta^2 / 2) / (\sigma_r^2 + \sigma_\eta^2)$$

where σ_r^2 and σ_η^2 are the variance of the true return and the noise respectively, and ρ_r is the first order autocorrelation coefficient of the true return.

Volatility is the dispersion in returns over time. There is always true volatility as the true market prices evolve over time. The ideal price index filters out the noise-induced volatility to leave only the true market volatility. In addition to the true volatility, the noise (random

error) in the index causes excess volatility in the index returns. Excess volatility decreases the first order autocorrelation in index returns. Less noise (lower σ_η^2) will lead to lower index volatility and higher AC(1). Other things being equal, the lower the volatility and the higher the AC(1), the less noisy and more accurate the index. Thus, lower Vol or higher AC(1) will indicate a better quality art price index in the sense of less noise.

Guo *et al.* (2014) suggest another test of index quality in terms of minimising random error that is based on the Hodrick-Prescott (HP) filter. The HP filter is a spline fitting procedure that divides a time series into smoothed trend and cyclical components. The idea is to examine which index has the least deviation from its smoothed HP component, by comparing the sum of squared differences between the index returns and the smoothed returns.

Table 4 reports these three metrics of index smoothness for the art price indices. The comparison suggests that that the regression-based indices are much smoother than the central tendency measures and the classical repeat sales index. The volatility and autocorrelations of the regression-based measures are around the same size. The larger sample ps-RS index performs the best in terms of these metrics, with lower volatility and higher AC(1) in returns, and a smaller deviation from its smoothed returns. Of the hedonic indices the 1-year adjacent period index performs best, although the differences are not large.

	Smoothness Indicators		
	Vol	AC.1	HPdev
Median	0.606	-0.414	22.34
Fisher	0.296	-0.477	5.24
Hedonic	0.130	-0.394	1.00
Adj1y	0.126	-0.342	0.93
Adj2y	0.126	-0.394	0.95
Roll	0.131	-0.364	1.02
RepSale	0.444	-0.408	12.01
ps.RS1	0.135	-0.390	1.10
ps.RS2	0.124	-0.285	0.92

8.3 Comparing the art price indices to other asset prices

To check that the estimated South African art price indices provide reasonable results, they can be compared to available international art price indices and other South African assets over the sample period.

Figure 11 illustrates the art price indices for the US, UK and France, calculated by Artprice, together with two representative South African art price indices. In contrast to the other art price indices, the South African art market index experienced a decrease at the start of the period. All of the art price indices increased substantially between 2005 and 2008, although the South African art price indices exhibited a steeper rise and higher growth rates. The Top 500 Art Market index in Kräussl and Lee (2010) also reflects this trend, with a sharp decline in 2008, which they argued was as a consequence of the financial crisis. By the end of the

period the international art price indices are around the same level as the South African art price indices. This suggests that the estimated art price indices provide reasonable estimates of pure price changes over the period.

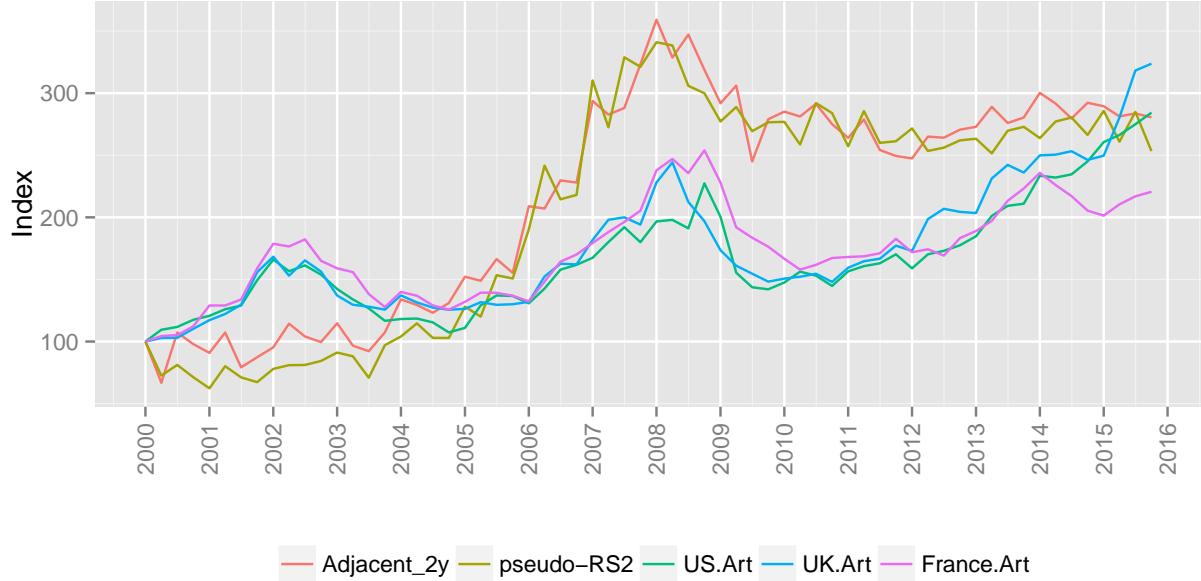


Figure 11: Comparing art price indices (2000Q1=100)

Renneboog and Spaenjers (2014) examined the extent to which art prices generated in Western auction markets moved together since the early 1970s. Despite the cross-country variation in long-term returns, art markets often displayed similar trends and most of the correlations in returns were significantly positive. In this case the correlations in returns between the South African and the international art price indices (not reported here) are not significant.

Figure 12 compares the two representative art price indices with indices for other South African assets: the JSE All Share index, the ABSA House price index and the Bond index. Local asset prices have increased much more than art prices over the entire period, which suggests that the art price indices do not provide outlandish estimates of pure price changes over the period. The equity and property markets also peaked at around the same time as the art price indices. The correlations in returns between the art price indices and the equity and property indices (not reported here) were positive and significant, although the coefficients were relatively low. After declining for the first few years of the sample, the art price indices experienced more rapid price appreciation between 2005 and 2008 than the other assets.

8.4 Summary and Conclusion

This section has evaluated and compared the art price indices produced according to three methodologies: central tendency, hedonic and hybrid repeat sales models. The regression-

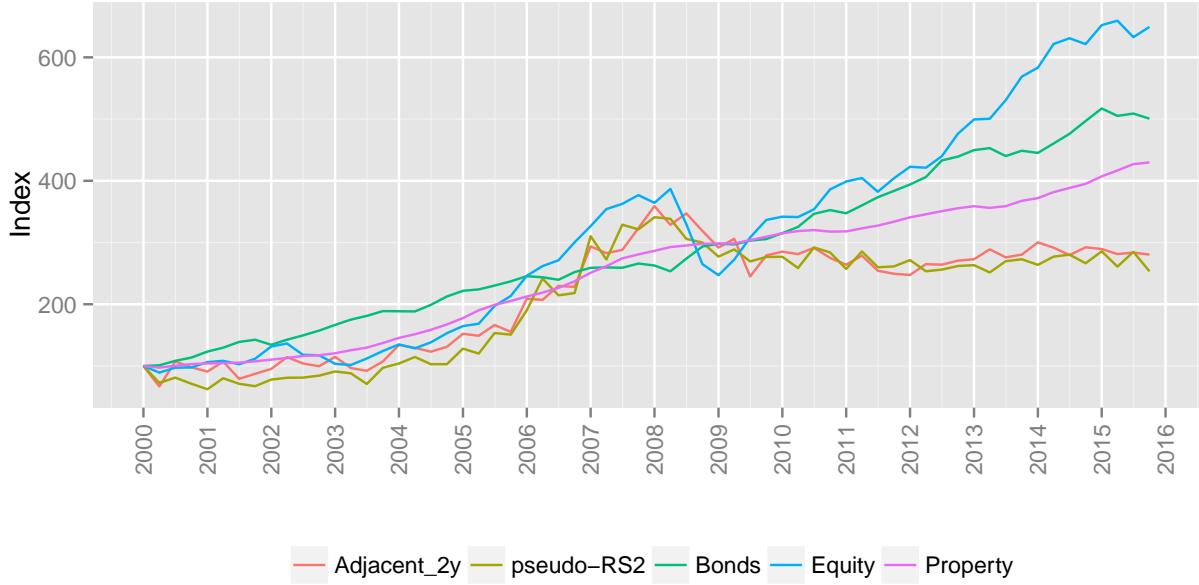


Figure 12: Comparing South African asset price indices (2000Q1=100)

based indices are significantly different from the central tendency measures and seem to produce better estimates of pure price changes. This is confirmed by the smoothness metrics and the consistent cyclical pattern displayed by the regression-based indices. This shows that regression-based methods are useful in producing quality-corrected price indices for unique assets.

Each of the regression-based methods employed above has strengths and weaknesses. The hedonic method may suffer from omitted variable bias, which would bias the indices, while the pseudo-repeat sales method may control for some of this omitted variable bias, but suffer more from possible sample selection bias. However, the regression-based indices seem to point to the same general movement in South African art prices, with a clear cyclical trend and a large increase in the run-up to the Great Recession. This increase was similar to international art price indices and traditional South African assets. The relatively consistent picture offers some confidence that the indices provide a relatively accurate measure of the price movements in the South African art market.

The large increase in art prices between 2005 and 2008 does not seem to be due to a fundamental shift in the types of artworks that were sold over that period. For instance, the top 100 artists in terms of volumes sold, which accounts for 60% of the volume traded and 90% of total turnover, has remained remarkably stable over time. Even if the exact same artworks were not being resold, the same artists' work still made up the vast majority of the market, and the hedonic model controls for the different artists. It is unlikely that the results are driven by sales of systematically better or higher quality artworks by specific artists that appreciated in price over that period, and by sales of systematically lower quality artworks by those artists after the crisis. Moreover, paintings are not sold at auction only to profit

from price appreciation or capital gains. A substantial portion of consignments come from the so-called three D's: Debt, Divorce and Death. In other words, many sellers are forced to sell their artworks, even if those artworks have not experienced the largest price appreciation.

In the following section the indices will be used to ascertain whether there is evidence for the presence of a bubble in the market over this period. In answering this question, the paper turns to literature on the bubble detection. The bubble detection tests proposed by Phillips, Wu and Yu (2011) are applied to the indices to investigate whether South African art prices exhibited mildly explosive behaviour over the period.

9 Bubble Detection

Record prices for South African artworks at local and international auctions, especially between 2008 and 2011, prompted many commentators at the time to claim that the market was overheating and suggest the possibility of a “bubble” in the market (Hundt, 2010; Curnow, 2010; e.g. Rabe, 2011). According to the indices generated above there was a substantial increase in South African art prices in the run-up to the Great Recession. This section uses the art price indices to investigate whether art prices exhibited bubble-like behaviour over the sample period.

Both advanced and emerging economies experienced severe financial crises around 2008. Yiu, Yu and Jin (2013) argued that these crises were triggered by the collapse of bubbles in asset prices. The adverse effects of bubbles and their related crises have led to a large literature on financial crises and the detection of bubbles in asset prices, including the seminal work by Kindleberger and Aliber (2005) the modelling approach by Phillips, Wu and Yu (2011).

The starting point is the definition of the term “bubble”. Stiglitz (1990) provided the following popular definition: “[*I*f the reason the price is high today is only because investors believe that the selling price will be high tomorrow - when ‘fundamental’ factors do not seem to justify such a price - then a bubble exists. At least in the short run, the high price of the asset is merited, because it yields a return (capital gain plus dividend) equal to that on alternative assets.”

According to Case and Shiller (2003), the term refers “*to a situation in which excessive public expectations of future price increases cause prices to be temporarily elevated.*” According to the New Palgrave Dictionary of Economics, “*bubbles refer to asset prices that exceed an asset’s fundamental value because current owners believe they can resell the asset at an even higher price*” (Brunnermeier, 2008). These definitions imply that the main features of a bubble are that prices increase beyond what is consistent with underlying fundamentals, and that buyers expect excessive future price increases. In other words, a bubble consists of a sharp rise in a given asset price, above a level sustainable by some fundamental values, followed by a sudden collapse (Kräussl, Lehnert and Martelin, 2016).

When it comes to the art market, however, it is particularly challenging to determine the fundamental value from which prices potentially deviate. In the case of stocks, dividends have been used to obtain the expected cash flow as a measure of fundamental value. Rents

and convenience yields can potentially be used for real estate prices and commodity prices (Penasse and Renneboog, 2014).

In contrast, artworks do not generate a future income stream (e.g. dividends or rents) that can be discounted to determine the fundamental value. Artworks usually have little inherent value, unless the materials used have a high intrinsic value (Goetzmann, Mamonova and Spaenjers, 2014). Instead, artworks are acquired for a kind of non-monetary utility or aesthetic dividend, sometimes described as “aesthetic pleasure” (Gérard-Varet, 1995). This dividend can be seen as the rent one would be willing to pay to own the artwork over a given period. It can reflect aesthetic pleasure, but may also provide additional utility as the signal of wealth (Mandel, 2009). The price of an artwork should equal the present value of these future private utility dividends over the holding period, plus the expected resale value. The value of this dividend is unobservable and is likely to vary tremendously across collectors, based on their motivations and characteristics (Penasse and Renneboog, 2014). Thus, it is almost impossible to clearly determine the fundamental value of art (Kräussl, Lehnert and Martelin, 2016).

To overcome this issue, this section follows Kräussl, Lehnert and Martelin (2016) in using a direct method of bubble detection developed by Phillips, Wu and Yu (2011). The approach is based on a right-tailed augmented Dickey-Fuller (ADF) test, which can detect explosive behaviour directly in time series. Phillips, Wu and Yu (2011) originally applied the method to stock prices. They showed that there was evidence of explosiveness in stock prices, but not dividend yields, implying that price explosiveness could not be explained by developments in fundamentals.

Since then various studies have used the method to investigate bubbles in a number of asset markets, including real estate, commodities and art. Jiang, Phillips and Yu (2014) employed the method to detect explosive periods in real estate prices in Singapore. The results suggested the existence of an explosive period from 2006Q4 to 2008Q1. Balcilar, Katzke and Gupta (2015) used the method to date-stamp periods of US housing price explosiveness for the period 1830-2013 and found evidence of several bubble periods. Areal, Balcombe and Rapsomanikis (2013) used the methodology to test for the presence of periods of explosive prices in agricultural markets and found that bubbles occurred for certain commodities, especially around 2007 and 2008. Figuerola-Ferretti, Gilbert and Mccrorie (2015) applied the method to examine the recent behaviour of non-ferrous metals futures prices on the London Metal Exchange. They found that certain commodity futures markets were prone to bubble-like phenomena and that the majority of the bubbles occurred between August 2007 and July 2008.

In the context of art, Kräussl, Lehnert and Martelin (2016) used the method to detect explosive behaviour in the prices of four different art market segments (*Impressionist and Modern, Post-war and Contemporary, American and Latin American*). They found evidence of explosive behaviour in prices and identified historical bubble episodes in the “Post-war and Contemporary” and “American” art market segments, around 2006-2008 and 2005-2008 respectively. The following section sets out the bubble detection framework used to test for the presence of bubble-like behaviour in South African art prices over the period.

9.1 Bubble Detection Framework

The most commonly used detection methods are based on the present value model and the rational bubble assumption. According to the present value model, under rational expectations, the price of an asset is equal to the present value of its future income stream, i.e. the expected fundamental value:

$$P_t = \frac{1}{1+r_f} E_t(P_{t+1} + \gamma_{t+1})$$

where R_f is the constant discount rate, P_{t+1} is the asset price at time t , and γ_{t+1} is the payment received (e.g. dividends, rents or a convenience yield) for owning the asset between t and $t+1$. When $t+n$ is far into the future, $\frac{1}{1+r_f} E_t(P_{t+n})$ does not affect P_t , as it tends to zero as n becomes infinitely large. The present value or market fundamental solution could be written as:

$$F_t = E_t \left[\sum_{i=1}^n \frac{1}{1+r_f} (\gamma_{t+i}) \right]$$

Rational bubbles arise when investors are willing to pay more than the fundamental value to buy an asset because they expect the asset price to significantly exceed its fundamental value in the future. When rational bubbles are present, the asset price is composed of the fundamental component and a bubble component (Yiu, Yu and Jin, 2013). In other words, if a gap between the market fundamental solution and the actual price exists and the terminal condition does not hold, an additional “bubble component”, B_t , has to be added to the solution of equation: $P_t = F_t + B_t$. In this case F_t is called the fundamental component of the price and B_t is any random variable that satisfies the following condition:

$$B_t = \frac{1}{1+r_f} E_t(B_{t+n})$$

Thus, the bubble component is included in the price process, and anticipated to be present in the next period with an expected value of $(1+r_f)$ multiplied by its current value. Being in line with the rational expectations framework, the bubble component is called a “rational bubble” (Kräussl, Lehnert and Martelin, 2016).

The statistical properties of P_t are determined by those of F_t and B_t . In the absence of a bubble, when $B_t = 0$, the degree of non-stationarity in P_t is controlled by the nature of the series F_t , which in turn is determined by the properties of γ_t . The current price of the commodity is therefore determined by market fundamentals: for example, if γ_t is an I(1) process then P_t would be an I(1) process.

When a bubble is present, if $B_t \neq 0$, current prices P_t will exhibit explosive behaviour, as B_t reflects a stochastic process in which the expected value of next period’s value, forecast on the basis of the current period’s information, is greater than or equal to the current period’s value (Kräussl, Lehnert and Martelin, 2016). In the absence a structural change in the fundamental process or explosiveness in the fundamentals, a period of explosive prices must have a non-fundamental explanation. Under the assumed properties of γ_t , the observation

of mildly explosive behaviour in P_t (i.e. non-stationarity of an order greater than unit root non-stationarity) will offer evidence of bubble behaviour. This expression embodies an explosive property and introduces “bubble” movements in the price over the fundamental component (Areal, Balcombe and Rapsomanikis, 2013). Thus, the theory predicts that if a bubble exists, prices should inherit its explosiveness property. This enables the formulation of statistical tests that try to detect evidence of explosiveness in the data (Caspi, 2013).

Given the different stochastic properties of the fundamental and bubble components, early tests were based on unit root and cointegration tests. Campbell and Shiller (1987) suggested a unit root test for explosiveness in prices, based on the idea that the gap between the asset price and the fundamental value will exhibit explosive behaviour during the process of bubble formation. They identified two scenarios that strongly suggest the presence of a rational bubble. In the first case, the asset price is non-stationary while the fundamental value is stationary. In the second, the asset price and fundamental value are both non-stationary (Yiu, Yu and Jin, 2013). In this case, if the asset price and its fundamental value are co-integrated, their non-stationary behaviour does not provide evidence of a bubble. Diba and Grossman (1988) showed that if fundamental values are not explosive, the explosive behaviour in prices is a sufficient condition for the presence of bubble.

However, unit root and cointegration tests are not capable of detecting explosive prices when a series contains periodically collapsing bubbles. Evans (1991) argued that explosive behaviour is only temporary in the sense that bubbles eventually collapse and that asset prices may appear more like I(1) or even stationary series than an explosive series, thereby confounding empirical evidence. Using simulated data Evans (1991) showed that these tests could not differentiate between a periodically collapsing bubble and a stationary process. A series containing periodically collapsing bubbles could therefore be interpreted by the standard unit root tests as a stationary series, leading to the incorrect conclusion that the data contained no explosive behaviour (Phillips, Wu and Yu, 2011).

A number of methods have been proposed to deal with this critique (Yiu, Yu and Jin, 2013). The recursive tests proposed by Phillips, Wu and Yu (2011) and Phillips, Shi and Yu (2012) are not subject to this criticism and can effectively distinguish unit root processes from periodically collapsing bubbles, as well as date-stamp their origin and collapse. The tests proposed by Phillips, Wu and Yu (2011) are based on the idea of repeatedly implementing a right-tailed unit root test. The method involves the estimation of an autoregressive model, starting with a minimum fraction of the sample and incrementally expanding the sample forward.

The model typically takes the following form:

$$\Delta y_t = \alpha_w + (\delta_w - 1)y_{t-1} + \sum_{i=1}^k \phi_w^i \Delta y_{t-i} + \epsilon_t$$

where y_t is the asset price series, α , δ and ϕ are the parameters to be estimated, w is the sample window size, k is the lag order, and ϵ_t is the white noise error term.

A sample of Augmented Dickey-Fuller test statistics are calculated from each regression. The null hypothesis of a unit root ($\delta = 1$) is tested against the right-tailed alternative of mildly

explosive behaviour ($\delta > 1$). The supremum value of the ADF sequence is then used to test for mildly explosive behaviour. By looking directly for evidence of explosive behaviour, the test avoids the risk of misinterpreting a rejection of the null hypothesis due to stationary behaviour.

The method also allows date-stamping of the origination and termination dates by matching the time series of the recursive test statistics to the critical value sequence. In other words, each element of the estimated ADF sequence is compared to the corresponding right-tailed critical values of the ADF statistic to identify a bubble period. The estimated origination point of a bubble is the first observation in which ADF value crosses the corresponding critical value (from below), while the estimated termination point is the first observation thereafter when the ADF value crosses below the critical value (Caspi, 2013).

A limitation of the method is that it is designed to analyse a single bubble episode. Phillips, Shi and Yu (2012) expanded the method to account for the possibility of multiple bubbles. The sample is extended by varying both the starting and ending points of the sample over a feasible range of windows. The moving window provides greater flexibility in choosing a subsample that contains a bubble (Yiu, Yu and Jin, 2013). Thus, the method of Phillips, Wu and Yu (2011) is consistent and particularly effective when there is a single explosive episode in the data, while the method of Phillips, Shi and Yu (2012) can identify multiple explosive episodes. Simulations by Homm and Breitung (2012) indicated that the procedure worked satisfactorily against other time series tests for the detection of bubbles and was particularly effective for real-time bubble detection.

9.2 Bubble Detection Results

This section tests whether the South African art market has exhibited bubble-like behaviour over the sample period, focusing on a specific aspect of bubbles: explosive prices. This section follows the convention of using the log value of real asset, deflated with the CPI (e.g. Kräussl, Lehnert and Martelin (2016), Caspi (2013) and Balciar, Katzke and Gupta (2015)). In this case there is only one potential bubble episode, so the Phillips, Wu and Yu (2011) method should be sufficient to provide consistent evidence of mildly explosive behaviour.

As explained above, the method involves the estimation of an autoregressive model, starting with a minimum fraction of the sample and repeatedly expanding the sample forward. The model starts with 3 years (i.e. 12 observations) and expands the sample by one observation each time. Each estimation yields an ADF statistic. In this case, there does not seem to be a deterministic drift present in the log real art price indices and the intercept is not statistically significant at conventional levels. However, as the results might be sensitive to model formulation, two versions of the autoregression models are used: one without a constant or trend and one with a constant or drift term. Lags are included to take possible autocorrelation of the residuals into account and the number of lags k is chosen with the Akaike Information Criterion.

Critical values for the tests are derived from Monte Carlo simulations of a random walk process, both including and excluding a drift term, with 2000 replications. In their original

study Phillips, Wu and Yu (2011) use a random walk without drift to estimate the null hypothesis. According to Phillips, Shi and Yu (2014), when the model is estimated with a non-zero drift it produces a dominating deterministic component that has an empirically unrealistic explosive form. They argue that these forms are unreasonable for most economic and financial time series and an empirically more realistic description of explosive behaviour is given by models formulated without a constant or deterministic trend. Nevertheless, as a robustness check the models were formulated with and without a constant or drift term included.¹⁵

The supremum ADF test statistics from both formulations are above the 95% critical values for each of the indices, except for the median index. Therefore, the null hypothesis of a unit root may be rejected in favour of the alternative hypothesis for each of the indices, except the median index. This provides evidence that real art prices experienced periods of explosiveness over the sample.

The method can now be used to date stamp potential bubble periods. Figure 13 and Figure 14 illustrate the date stamping procedure for three representative series: median values, the 2-year adjacent period hedonic index and the second version (larger sample) of the ps-RS index. Figure 13 illustrates the case of no drift term, while Figure 14 illustrates the case with a drift term. The figures compare the ADF test static sequence to the 95% and 99% critical value sequences. In both cases the test statistic sequences breach the 95% critical values in the run-up to the financial crisis (2005 and 2006 respectively), before falling below the critical values. The sequence of test statistics for the ps-RS index is higher than for the full sample hedonic index, and breaches the 99% critical value.

Table 5 reports the origination and termination dates for all of the periods of explosive behaviour, based on 95% critical values. The test statistic sequences for the hedonic indices all indicate a period of explosive prices beginning around 2006/2007 and ending in 2008. The test statistics for the ps-RS indices indicate periods of explosive behaviour that were slightly longer, beginning around 2005/2006 and ending in 2008 or even 2010, depending on the specification. The preferred method in terms of index smoothness (i.e. the ps-RS2 index) therefore suggests a slightly longer period of bubble formation. Phillips, Shi and Yu (2012) recommend that only explosive periods lasting more than $\log(T)$ units of time should be identified as bubble periods. In this case this implies that the bubble should be at least 4 quarters in length and virtually all of the explosive periods identified satisfy this requirement.

The dates identified correspond with many of the explosive periods identified in the literature for a range of assets. In the context of art, Kräussl, Lehnert and Martelin (2016) identified bubble periods for the “*Post-war and Contemporary*” art segment between 2006 and 2008

¹⁵Phillips, Shi and Yu (2014) suggested a random walk process with an asymptotically negligible drift might be useful for allowing for intermediate cases between a model with no drift and one with a drift term included, i.e. cases where there may be drift in the data but it may not be the dominant component. Such a model may take the following form: $y_t = dT^{-\eta} + \theta y_{t-1} + \epsilon_t$, where d , η and θ are constant, T is the sample size, and ϵ_t is the white noise error term. The deterministic component depends on the sample size T and the localising parameter η . When $\eta > 0$ the drift term is small relative to the linear trend. The null model becomes a model without drift when $\eta \rightarrow \infty$ and a model with drift when $\eta \rightarrow 0$. The results may be sensitive to the value of η , so they recommend reporting the results for a range of values of η . In this case, different values of η produce qualitatively similar results.

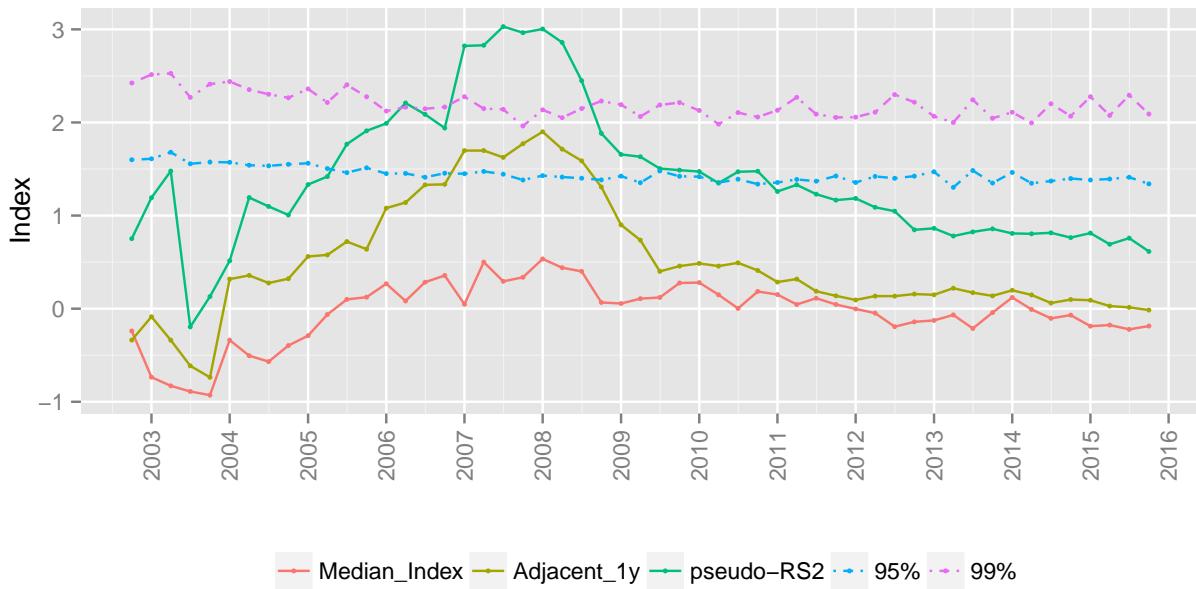


Figure 13: Test statistics and critical values for models without drift

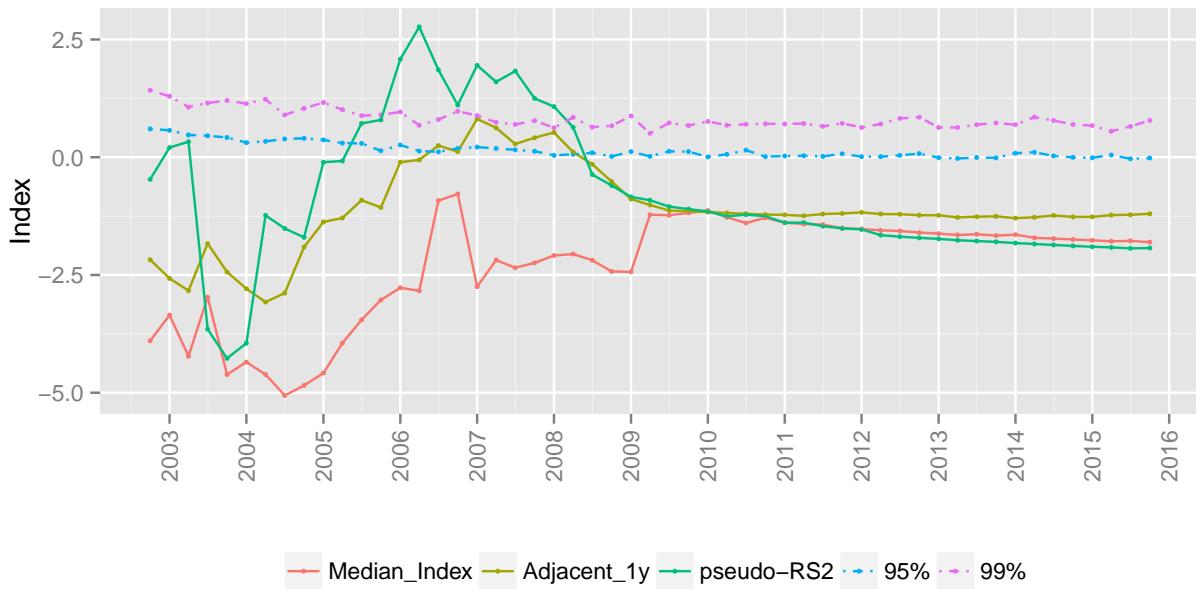


Figure 14: Test statistics and critical values for models with drift

Table 5: Dates of explosive behaviour

	None-Start	None-End	Drift-Start	Drift-End
Fisher_Index	2008 Q1	2010 Q3	2008 Q1	2009 Q2
Hedonic_full	2007 Q1	2008 Q3	2007 Q1	2008 Q2
Adjacent_1y	2007 Q1	2008 Q3	2006 Q3	2008 Q2
Adjacent_2y	2007 Q1	2008 Q4	2006 Q3	2008 Q2
Rolling_5y	2007 Q4	2008 Q3	2007 Q1	2008 Q2
pseudo-RS1	2005 Q3	2010 Q1	2006 Q1	2008 Q2
pseudo-RS2	2005 Q3	2010 Q4	2005 Q3	2008 Q2

and for the “*American*” art segments between 2005 and 2008, which also corresponds to the pre-financial crisis period. Interestingly, their data pointed to evidence in the formation of another bubble in these market segments around the start of 2011. This is not present in the South African art market, which has remained relatively flat since the 2010.

It is also interesting that many of the headline grabbing auction records for the South African art market occurred in 2011, well after the period of explosive behaviour. This corresponds to findings by Goetzmann, Mamonova and Spaenjers (2014), who observed that the timing of record prices does not always coincide with periods of general price increases. They argue that auction price records are often set in situations characterised by extreme supply constraints, social competition among “nouveaux riches”, resolution of uncertainty about the potential resale value, and idiosyncratic shifts from hedonic weights.

9.3 Discussion

This section has applied the reduced-form bubble detection method developed by Phillips, Wu and Yu (2011) to test for periods of explosive behaviour in the art price indices. The use of recursive tests enables the identification of mildly explosive subsamples in the series. The results indicate that there is evidence of bubble-like behaviour in all of the regression-based art price indices. Again, this implies that it is important to control for the composition or quality-mix of sales when estimating indices for unique items. The regression-based indices provide relatively consistent results in terms of the explosive periods in the South African art market, with a potential bubble most likely beginning in 2006 and ending in 2008.

The results implicitly assume that the aesthetic or utility dividends associated with South African art did not exhibit explosive behaviour over the period. Aesthetic dividends fluctuate over time as they depend on buyers’ willingness to pay for art, which in turn depends on preferences and wealth. However, preferences regarding art and culture would have had to fluctuate dramatically to explain the movements in art prices over the period. Even if trends can temporarily emerge for specific artists or schools of art, previous findings in the literature have shown that preferences tend to be very stable, even in the long run (Penasse and Renneboog, 2014). The aesthetic dividend can also fluctuate as wealth fluctuates over time (Goetzmann, Mamonova and Spaenjers, 2014). The literature has provided evidence supporting this idea, with Goetzmann, Renneboog and Spaenjers (2011) finding cointegrating

relationships between top incomes and art prices. However, it is unlikely that aesthetic dividends, or factors such as collectors' preferences and wealth, experienced similar explosive behaviour over the period.

Although the method provides a consistent basis for identifying periods of explosive behaviour, it does not provide an explanation of the bubble episode. The findings are compatible with several different explanations, including rational bubbles, herd behaviour, and rational responses to fundamentals (Phillips, Wu and Yu, 2011).

The periods of explosive prices could be compatible with a rational bubble, where investors are willing to pay more than their private value for an artwork, because they expect to resell later at a higher price. Gérard-Varet (1995) argued that the sharp rise in world art prices in the late 1980s could be explained by a rational bubble, where investors believed that although prices had attained unsustainable levels the short run, prospects for continued gains were sufficient to compensate for the risk that the bubble might burst. Prices increase at an accelerating rate because the probability of a crash increases and rational investors require an increasing risk premium to cover this higher probability of a crash (Rosser, Rosser and Gallegati, 2012).

Investors might think that an artwork that they would normally consider too expensive is now an acceptable purchase because they will be compensated by further price increases. During a bubble investors may also worry that if they do not buy now, they will not be able to afford the artwork later. The expectation of large price increases may have a strong impact on demand if investors think that prices are unlikely to fall, or not likely to fall for long, so that there is little perceived risk associated with a purchase (Case and Shiller, 2003).

Penasse and Renneboog (2014) argue that limits to arbitrage induce a speculative component to art prices. High transaction costs and short-selling constraints could lead to prices diverging from fundamental levels, as they prevent arbitrageurs from pulling back prices to fundamentals (Balcilar, Katzke and Gupta, 2015). When prices are high, pessimists would like to short sell, but instead simply stay out of the market or sell to optimists at inflated prices. Optimists may be willing to pay higher prices than their own valuations, because they expect to resell to even more optimistic investors in the future. The difference between their willingness to pay and their own optimistic valuation is the price of the option to resell the asset in the future. The price of the resale option imparts a bubble component in asset prices, and can explain price fluctuations unrelated to fundamentals. These market failures hamper the ability of markets to correct price inefficiencies and implies that periods of bubble-like behaviour could exist with relatively little scope for arbitrage. This is especially applicable to art markets, where transaction costs are high, short selling is not possible, and without a rental market the only possibility to make a profit is by reselling at a higher price (Penasse and Renneboog, 2014).

Penasse and Renneboog (2014) investigated this theory by looking at the behaviour of art prices and volumes. They found that the art market was subject to frequent booms and busts in both prices and volumes. They showed that volume was mainly driven by short-term transactions, which was interpreted as speculative transactions or trading frenzies. Given the high transaction costs that characterise the art market, it is unlikely that these artworks were purchased for the pure aesthetic dividends. The positive correlation between prices and

volumes was persistent across art movements, and was larger for the most volatile segments of the art market (i.e. Modern and Contemporary art). When trading volume was high, they found that buyers tended to overpay, in that high volume predicted negative returns in subsequent years. This provides evidence for resale option theory and speculative trading models of bubble formation, which predict that speculative trading can generate significant price bubbles, even if trading costs are large and leverage impossible.

Balcilar, Katzke and Gupta (2015) argued that large price increase in the short term could lead to higher allocation towards art as assets experiencing high capital growth. This, in turn, feeds into more demand and even higher prices, potentially driving an episode of unsustainable asset price increases, particularly as a result of factors inherent to art purchases, such as high transaction costs and difficulties with short-selling. Similarly, Mandel (2009) formalised the satisfaction derived from the conspicuous consumption that is increasing in the value of art. This part of the aesthetic dividend that is a signal of wealth could plausibly lead to price increases, which in turn could lead to another increase in the dividend related social status consumption.

In general, speculative bubbles can act like self-fulfilling prophecies. Prices increase because agents expect it to do so, with this ongoing expectation providing the increasing demand that keeps prices rising. If prices stop rising due to some exogenous shock like the financial crisis, this breaks the expectation and the speculative demand suddenly disappears, sending prices back towards their fundamental value, where there is no expectation of the price rising (Rosser, Rosser and Gallegati, 2012).

Kindleberger and Aliber (2005) argued that a boom in one market often spills over into other markets. A famous example in the context of art is the link between the boom in Japanese stock and real estate prices and the Impression art market in the second half of the 1980s. Hiraki *et al.* (2009) found a strong correlation between Japanese stock prices and the demand for art by Japanese collectors, leading to an increase in the price of Impressionist art during this period. Kräussl, Lehnert and Martelin (2016) found corroborating evidence of a bubble period in the “Impressionist and Modern” art segment between 1986 and 1991. During this period Japanese credit was freely available, backed by increasing values of stocks and real estate, which led to a consumption and investment spree through the wealth effect. Japanese investors invested heavily in international art and particularly French Impressionist art in the late 1980s. Luxury consumption by Japanese art collectors increased international art prices until the art bubble burst as a direct consequence of the collapse of the Japanese real estate market (Penasse and Renneboog, 2014).

Similarly, the run-up to the financial crisis saw large increases in asset prices and credit expansion. It is likely that these conditions contributed to the explosive behaviour in South African art prices between 2006 and 2008. The financial crisis caused the bubble to burst and led to a decline in South African art prices. While an in depth investigation is outside the scope of the paper, it does illustrate the usefulness of the art price indices to investigate developments in the South African art market.

10 Conclusion

This paper has estimated various price indices for the South African art market since the turn of the millennium. Three broad methodologies are used to estimate quality-adjusted price indices for South African art: central tendency methods, hedonic methods and hybrid repeat sales methods. The regression-based indices are significantly different from the central tendency measures and seem to produce better estimates of pure price changes. This demonstrates the importance of regression-based methods to produce quality-corrected price indices for unique assets.

Each of the methods employed has strengths and weaknesses. The hedonic method may suffer from omitted variable bias, while the pseudo-repeat sales method may control for some of this omitted variable bias, but suffer more from possible sample selection bias. However, the regression-based indices seem to point to the same general movement in South African art prices, with a clear cyclical trend and a large increase in the run-up to the Great Recession. This increase was similar to international art price indices and traditional South African assets. The relatively consistent picture offers some confidence that the indices provide a relatively accurate measure of the price movements in the South African art market.

The art price indices were then used to look for mildly explosive behaviour in prices over the sample period, using a reduced-form bubble detection method. The results indicate that there is evidence of bubble-like behaviour in all of the regression-based art price indices. The regression-based indices seem to point to consistent evidence of explosive prices in the run-up to the Great Recession, with the bubble period starting around 2006 and ending around 2008.

The art price indices are useful for investigating and understanding developments in the South African art market. In this paper the indices were used to look for evidence of a bubble in the market. Further research applications might consider the risk-return profile of art as an asset class and evaluate whether art could form part of an optimal investment portfolio. Conventional wisdom says that the top artworks by established artists tend to outperform the rest of the market (Mei and Moses, 2002). Another application would be to examine this so-called Masterpiece effect by looking at different parts of the distribution of art prices. Potential drivers or factors that influence the fluctuations in art prices over time, such as wealth effects, might also be investigated. The quality-corrected art price indices can facilitate these inquiries and enable one to be more concrete about developments in the South African art market.

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