

# Art Price Index

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## 1 Introduction

Contemporary African art, long seen as a niche market, 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). For example, in 2011 Irma Stern’s “*Arab Priest*” set a world record hammer price of £2.7 million at auction (Bonhams), while “*Two Arabs*” sold for R19 million, a record for a South African auction house (Strauss & Co).

The increase in interest in South African art, both locally and abroad, has sparked a vibrant market for investors (Naidoo 2013). This increase in the popularity of art, 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 the Wall Street Journal reported that around 6% of total wealth was held in so-called passion investments, which include art, wine, antiques and jewellery. Of all these luxury goods, art is the most likely to be acquired for its potential appreciation in value (Capgemini 2010). Passion investments, and art in particular, are interesting examples of alternative assets, as they are durable goods with investment as well as consumption characteristics (Renneboog and Spaenjers 2014).

In times of economic uncertainty there is often an increase in demand for physical assets: as these have limited supply they are often considered relatively safe in times of financial turmoil (Warwick-Ching 2013). In addition, the demand for alternative assets is supported by their imperfect correlation with the stock market, which is thought to aid portfolio diversification. Alternative assets are also used as collateral for loans, or to take advantage of slacker regulatory and tax provisions.

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 answer some question around the development of this market. However, accurate valuation of real alternative assets like art can be difficult. These assets are heterogeneous and often involve large transaction costs for both buyers and sellers. They are less liquid than traditional assets and have a low transaction frequency, which makes it difficult to measure the state of the overall market, as only a small part of the overall market is traded at any given time.

This paper will attempt to estimate an accurate price index for South African art. The price indices are intended to be a summary of overall price movements in the art market. The indices are then be used to try to answer the questions of whether there was a large increase in prices in the run-up to the Great Recession and whether there is evidence for the presence of a bubble in the market, as is often claimed? Section 2 provides an outline of the methodologies applied in the literature and provides a brief literature review. Section 3 looks at the available data for South Africa. Section 4 reports the results from a number of potential estimation methods. Section 5 evaluates these

results and compares the indices to international art price indices. Section 7 introduces the bubble detection methodology and briefly looks at the literature. Section 8 reports the results of the bubble detection evidence. Section 9 concludes.

## 2 Estimation methodologies

An accurate measure is a prerequisite to analysing the art market to try and examine whether there was evidence of a bubble. The aim of this section is to establish a range of measures to answer the questions of .

The construction of price indices for real alternative asset markets 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 assets are unobservable. Secondly, the heterogeneity of individually unique assets means that the quality of assets sold is not constant over time. Thus, the composition of assets sold will generally differ between periods, making it difficult to compare prices over time (Hansen 2009). Constructing an index for individually unique assets, like art, 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) Naïve or central tendency methods
- b) Hedonic regressions
- c) Repeat sales regressions
- d) Hybrid models

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 or naïve methods

The simplest way to construct a price index is to calculate a measure of central tendency from the distribution of prices. As price distributions are generally skewed, the median is often preferred to the mean. These average measures have the advantage that they are simple and easy 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, naïve indices may therefore 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 (Hansen 2009). 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 (Eurostat 2013).

An improvement can be made by stratification of the data. Stratified measures control for variations in prices across different types of assets by separating the sample into subgroups according to

individual characteristics such as artist and medium.<sup>1</sup> Stratified measures are currently used by ABSA, FNB and Standard Bank, for instance, to construct property price indices for South Africa. However, scholarly work rarely employs central tendency indices. The repeat sales and the hedonic regression methods have dominated in the international literature.

## 2.2 Hedonic regression methodology

Artworks are heterogeneous assets, with a variety of characteristics that make them unique. The hedonic regression method recognises that the prices of heterogeneous goods can be described to some extent by their characteristics (Eurostat 2013). In the context of art, characteristics may include physical (e.g. medium) and non-physical attributes (e.g. artist reputation). The hedonic approach estimates the value attached to each of these attributes.

The hedonic approach entails regressing the logarithm of the sales price on the relevant attributes, as well as time dummies, which capture the “pure price effect” (Kräussl and Lee 2010). The standard hedonic model usually takes the following form:

$$\ln P_{it} = \alpha + \sum_{j=1}^z \beta_j X_{ij} + \sum_{t=0}^{\tau} \gamma_t D_{it} + \epsilon_{it}$$

where  $P_{it}$  represents the price of artwork  $i$  at time  $t$ ,  $X_{ij}$  is a series of characteristics of item  $i$  at time  $t$ , and  $\beta_j$  reflects the coefficient values (implicit prices) of the attributes,  $D_{it}$  is the time dummy variable, which takes the value 1 if item  $i$  is sold in period  $t$  and 0 otherwise, and  $\epsilon_{it}$  represents the error term.

The hedonic method therefore controls for quality changes by attributing implicit prices to a set of value-adding characteristics of the individual asset. Hedonic regressions control for the observable characteristics of an asset to obtain an index reflecting the price of a “standard asset” (Renneboog and Van Houtte 2002). It is also possible to allow the coefficients (the implicit prices assigned to characteristics) to evolve over time with the adjacent-period method (Triplett 2004).

Thus, the hedonic approach can circumvent the problems of heterogeneity of individually unique assets, changes in composition and quality, as well as the exclusion of single-sale data (a problem with repeat sales regressions) (Hansen 2009). However, the choice of the attributes in a hedonic regression and involves subjective judgement and is limited by data availability. If relevant variables are omitted or the functional form is incorrectly specified, it will result in omitted variable or misspecification bias, which will bias the parameter estimates and therefore the indices (Jiang, Phillips, and Yu 2014). Various studies have attempted to improve upon the basic methodology.

## 2.3 Repeat Sales Regression Method

The repeat sales methodology overcomes many of the problems by tracking the repeated sale of a specific asset over time. This method aggregates sales pairs and estimates the average return on the set of assets in each period (Kräussl and Lee 2010). The repeat sales method has often been applied

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<sup>1</sup>Ek het weergawes van hierdie indekse bereken, so ons kan hulle insluit as dit nodig is. The Fisher ideal index is often the recommended index formula, as it can be justified from several different perspectives (Eurostat, 2013). It is the geometric mean of the Laspeyres and Paasche indices. The Laspeyres index holds the quantity weights fixed in the base period, while the Paasche index holds the quantity weights fixed at the comparison period.

in the construction of real estate indices, where there is a lack of detailed information on each sale (which is necessary for the hedonic method).

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. The basic regression takes the following form:

$$\ln \frac{P_{t+1}}{P_t} = \sum_{i=1}^t \gamma_i d_i + \epsilon_i$$

where  $P_t$  is the purchase price for time  $t$ ;  $\gamma_i$  is the parameter to be estimated for time  $i$ ;  $d_i$  represents the monthly dummy variables (-1, 0, 1) indicating the occurrence of  $P_t$ ; and  $\epsilon_i$  is a white noise residual.

The repeat sales method avoids having to correctly specify the characteristics that determine asset value (a problem with hedonic models). By only using assets that have been sold at least twice, the method controls for other factors contributing to the variation in price growth. 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).

A disadvantage of the repeat sales method is that single-sale data is discarded. This is problematic for these assets because the resale of a specific item may only occur infrequently, which reduces the total number of available observations substantially. Another problem is the possibility of sample selection bias. Assets that have traded more than once may not be representative of the entire population of assets. 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). Several studies have investigated this source of bias and the size and direction of the bias has varied between samples.

## 2.4 Hybrid Models

A hybrid model approach involves a combination of the repeat sales and hedonic approaches. The hybrid formulation exploits the control of variation inherent in repeat sales pairs and avoids the problems of possible misspecification inherent in the hedonic methodology (Bester 2010). By combining the two methods, a hybrid approach tries to exploit all the sales data, and to address sample selection bias and inefficiency problems, in addition to the quality change problem (Eurostat 2013).

In the context of real estate, for instance, B. Case and Quigley (1991) used samples of single-sale and repeat-sale properties to jointly estimate price indices using generalised least squares regressions. More recently, Guo et al. (2014) developed a “pseudo repeat sales” procedure to construct more reliable price indices for newly constructed homes. Their procedure matched the sales prices of very similar new units in order to construct a large pseudo repeat sales sample. This approach is discussed in more detail below.

As mentioned, 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.

## 2.5 A Brief Literature Review

A number of academic studies have constructed art price indices for various art markets around the world. These studies have typically been interested in risk-adjusted returns to investigate whether the art market provides potential diversification benefits for an investment portfolio. The interest in investing in art has received a large boost recently from an increase in the availability of art price data (R. J. Campbell 2009).

These studies have typically relied on publically available auction prices.<sup>2</sup> Art is also sold privately, either directly from 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).

A few studies have utilised the repeat sales method to estimate art price indices. These studies have typically relied on a very large sales database due to the infrequency of repeat sales of individual artworks. Indeed, for artworks the resale of a specific item may occur only very rarely, which might be related to the very 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. These indices followed the (K. E. Case and Shiller 1987) methodology and were 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.

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. degrees of freedom). A common criterion has

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<sup>2</sup>Auctions account for around half of the art market according to The European Fine Art Fair Art Market Report 2014.

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

The 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 case, 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. The stability of the coefficients in a pooled regression can also become an issue as the number of periods expands. The adjacent-period method can deal with this by constructing a continuous time series through chaining a sequence of indices together. It allows the coefficients, and therefore the implicit prices assigned to the characteristics, to vary in each regression (Triplett 2004).

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.<sup>3</sup> The results confirmed a statistically significant sample selection problem, in line with similar studies in the property market.

### 2.5.1 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 surveying 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

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<sup>3</sup>The nature of sample selection bias is different in the approaches. The repeat sales method ignores all information on single sales, such that it may not represent the population. The hedonic method only uses sold items, so that bias may arise from unsold items.

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). Various sub-indices are also calculated. The estimation below will build on the CAPI in order to contribute to the research on the South African art market.

### 3 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 has two major South African art sales a year. 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 covers sales of South African art at 8 auction houses<sup>4</sup> from the year 2000 onwards. The database includes 49,955 sales by 4,361 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.<sup>5</sup>

The South African art market has grown markedly over the last decade. Figure 1 illustrates the increase in auction turnover over the sample period (2000-2015YTD) by auction house. In 2014 (the most recent full year), total sales had reached almost R300 million.

Figure 2 illustrates the increase in the total number of sales lots over the period, as well as the movement in the median sales price.

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<sup>4</sup>These are: 5th Avenue, Ashbeys, Bernardi, Bonhams, Christies, Russell Kaplan, Stephan Welz & Co and Strauss & Co.

<sup>5</sup>If the database included information on the artwork characteristics, censored regression techniques such as the Heckman selection model, could be used to look at the sample selection bias. But the dataset does not include the artworks that were bought-in, which means that it is a truncated sample. Unfortunately, truncated regression techniques cannot be performed to correct for the bias, as the cut-off points (i.e. the secret reserve prices) are different for each individual artwork and more importantly, unknown.

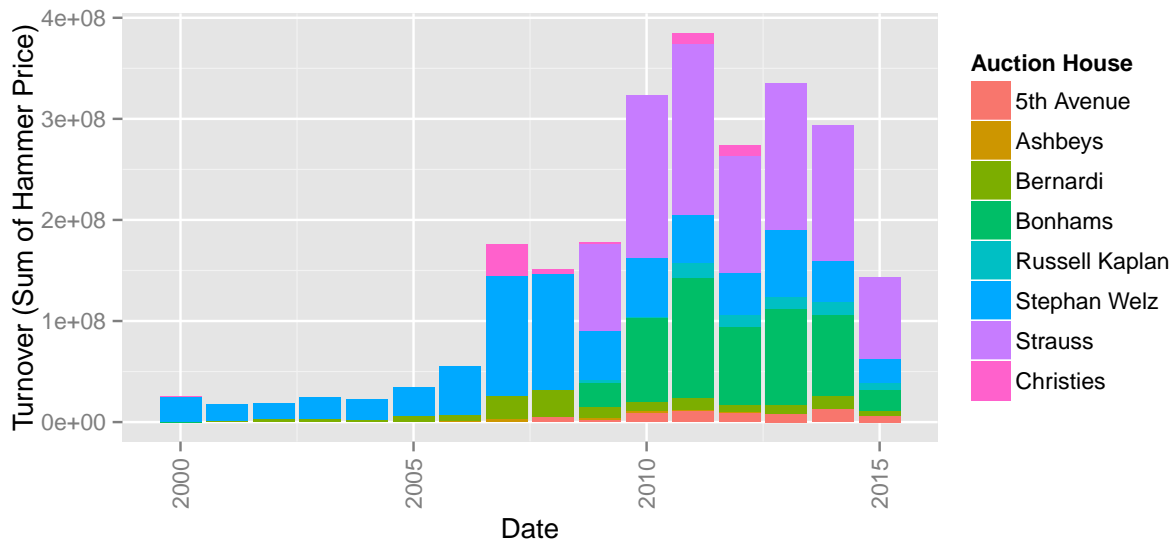


Figure 1: Turnover (sum of hammer prices) by auction house (2000-2015YTD)

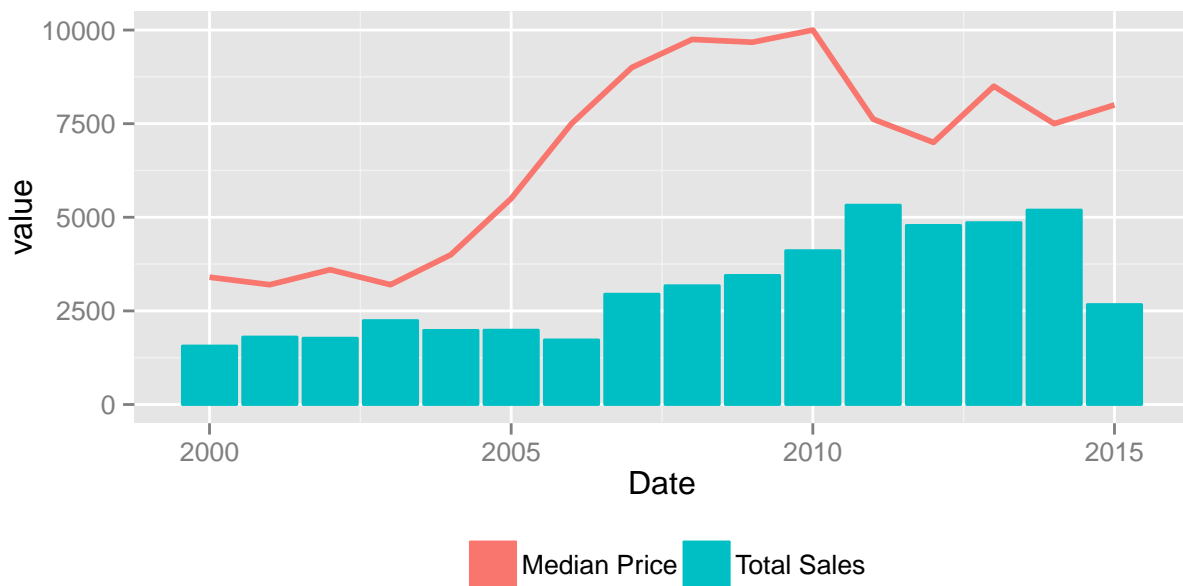


Figure 2: Median hammer prices and total sales (lots) at auction (2000-2015YTD)



Table 1 reports descriptive statistics for the hammer prices over the sample period. The mean price of R49,670 was much higher than the median of R7,000, indicating that the sample is skewed by very high prices for certain artworks.<sup>6</sup>

Table 1: Descriptive statistics of auction hammer prices					
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
20.00	2600.00	7000.00	49667.59	24000.00	30147660.00

## 4 The Hedonic Model

### 4.1 Artwork characteristics

Hedonic art price models typically include characteristics that are relatively easily observable and quantifiable. This section briefly discusses the main variables usually included in the hedonic models.<sup>7</sup>

*Artist reputation:* Dummy variables for the artists are usually included in the model. It is often the case some of the artists are excluded, 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 Kräussl and Van Elsland (2008) 2-step hedonic approach. The models are estimated using a continuous reputation variable, as explained below. 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.

*Size:* The most common variable used to describe the physical characteristics of an artwork is the size or surface area. Prices are expected to increase with size, up to the point that the work becomes too large (Renneboog and Spaenjers 2012). Squared values are therefore occasionally included to take non-linearities into account. Fedderke and Li (2014) found this to be the case for the South Africa art in their sample.<sup>8</sup> The models that follow use the natural logarithm of the surface area of the artwork in cm<sup>2</sup>. The models include an interaction term for sculpture size, as the size of a sculpture is usually only recorded as its height (in cm).

*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

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<sup>6</sup>Here we could illustrate some of the central tendency indices if we want to, in order to act as a baseline for the index comparisons. The naïve index, which is the median price for each quarter, shows a lot of variation in quarterly prices, but no clear cyclical trend emerges. The Fisher price indices are central tendency indices stratified by artist and medium. The fixed base Fisher index uses a fixed base to calculate the Laspeyres and Paasche indices (first and last quarter of the sample respectively). The other Fisher index allows the base periods to vary for each index point and the index points are then chained together. The results show a large amount of variation and no consistent picture emerges from these central tendency measures. This is probably because the artist and medium categories only capture a small portion of the variation in the quality of artworks that come to market between each period. The hedonic indices in the following section attempt to control for these quality changes by taking many more characteristics into account.

<sup>7</sup>Should some of the exploratory graphs comparing prices and various variables be included?

<sup>8</sup>The squared term is positive, however, which is contrary to expectations. It should have a negative sign, and it is not clear why this is the case. Should I still include it?

reflect auction house certification (Renneboog and Spaenjers 2012). Different auction houses charge different commissions to both buyers and sellers. 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, however, the auction house dummies should capture the different premiums charged by the auction houses.

*Mediums:* Average prices vary across mediums and studies typically include dummy variables for the different mediums as defined in their data (Kräussl and Logher 2010). 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. The models use the 9 mediums defined in the dataset, similar to Olckers, Kannemeyer, and Stevenson (2015).<sup>9</sup>

*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 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 are less valuable.

*Date dummies:* The models below include time dummies of a quarterly frequency, which are used to estimate the indices (i.e. the time dummy hedonic method).<sup>10</sup> The exponentials of the time dummy coefficients represent the appreciation in the value of art in that specific period, relative to the value of art in a common base period.<sup>11</sup>

Although are probably still omitted variables that influence prices, and thus may bias the coefficients

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<sup>9</sup>In a few cases studies have also differentiated between medium (e.g. oil) and material (e.g. canvas). The dataset includes enough detail in the latter years to identify the medium and the materials and this finer classification could be used as a robustness check? The subject matter or theme of an artwork can affect its value. A few studies (e.g. Renneboog & Spaenjers (2012) and Fedderke & Li (2014) have included controls for the theme of the artwork. Artwork can, for instance, be classified as portraits, landscapes, abstract works, etc. A classification of this kind would entail a much smaller sample, as the theme would have to be derived from the title of the artwork. Nevertheless, such classification could be carried out as a robustness check? 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. Nevertheless, the models could include this variable as a robustness check?

<sup>10</sup>The double imputation hedonic method is sometimes favoured by statistical agencies, e.g. Eurostat (2013). However, the double imputation index could not be implemented in this case, as the models and the variables changed too much between periods. For example, if an artist was not present in the next period, his/her new price could not be estimated.

<sup>11</sup>Such 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  $\sigma_t^2$  is the estimated variance of the residuals in period t (Renneboog & Spaenjers, 2012). In practice, however, this adjustment is often negligible (Hansen, 2009).

and the indices.<sup>12</sup> However, the bias is often small in practice (Triplett 2004; Renneboog and Spaenjers 2012). 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 real alternative assets like real estate.

#### 4.1.1 Continuous artist reputation variable: two-step hedonic approach

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 accounts for the degrees-of-freedom consideration, which limits the number of artist dummy variables that can be included. It increases the sample size, reduces inherent selection bias, and reduces the impact of outliers when there are few observations for a specific artist.

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 hedonic quality adjustment is a quantity measure of the mean change in the characteristics of assets sold in period  $t$  and  $t+1$ , valued by their implicit prices ( $\beta_j$ ):

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

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

Kräussl and Van Elsland (2008) argued 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:

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

where  $P_{i,y}$  is the value of painting  $i$ , created by artist  $y$ ;  $X_{ij}$  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 ( $\beta_j$ ). Following Kräussl and Van Elsland (2008), the sub-sample includes the top 100<sup>13</sup> artists in terms of volume, representing 53% of records and 92% of the value. The coefficients are similar to those for the full pooled model and it is assumed that the characteristic

<sup>12</sup>According 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 quantities 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.

<sup>13</sup>More artists can be included in the first step, but the estimation takes very long to process.

prices are representative. Next 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.

## 4.2 Estimation Results

The full pooled sample estimation results are reported in Table 2. The coefficients are all significant and have the expected signs.<sup>14</sup>

The implicit prices of hedonic characteristics (i.e. tastes) may change over time (Renneboog and Spaenjers 2012). One way to allow for gradual shifts in parameters is to employ an adjacent-periods regression, in which the models are estimated using only sub-samples of periods that are adjacent to each other. There are trade-offs 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).

Two versions of this method are estimated. Similar to Dorsey et al. (2010) in the context of real estate, adjacent-period hedonic models for 1-year estimation windows are calculated. This seems to be a reasonable compromise for the South African art market, where large auctions are held relatively infrequently. To increase the estimation sample size, the models are also estimated for every 2-year period, which is similar to Renneboog and Spaenjers (2012) in the context of art. The indices are then calculated by chain-linking the returns, as Figure 3 illustrates for the 2-year version of the index.<sup>15</sup>

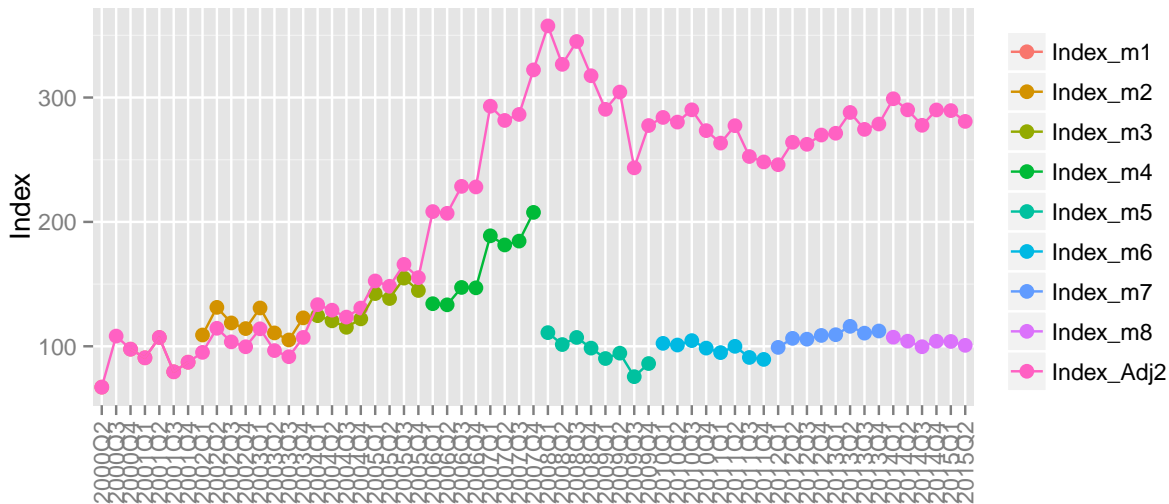


Figure 3: Chain-linked art price index from the 2-year adjacent-period regressions

In the context of real estate, Shimizu, Nishimura, and Watanabe (2010) suggested a so-called overlapping-period hedonic regression method using multiple “neighbourhood periods”. Specifically,

<sup>14</sup>The squared size term has the opposite coefficient (i.e. it is positive but should be negative), so I have excluded it for the time being.

<sup>15</sup>We can exclude this if it is unnecessary

Table 2: Hedonic Regression results

	<i>Dependent variable:</i>
	lnprice
lnarea	0.405*** (0.004)
ah_codeAshbeys	0.120*** (0.028)
ah_codeBernardi	0.126*** (0.014)
ah_codeBonhams	1.193*** (0.027)
ah_codeChristies	1.146*** (0.065)
ah_codeRussell Kaplan	0.137*** (0.016)
ah_codeStephan Welz	0.603*** (0.014)
ah_codeStrauss	1.129*** (0.016)
med_codeDrawing	−1.046*** (0.034)
med_codeMixed Media	−0.488*** (0.033)
med_codeOil	0.391*** (0.031)
med_codeOther	−0.339*** (0.046)
med_codePhotography	−1.666*** (0.095)
med_codePrint/Woodcut	−1.806*** (0.033)
med_codeSculpture	0.693*** (0.092)
med_codeWatercolour	−0.480*** (0.033)
lnsculpt_area	0.229*** (0.021)
dum_signed	0.219*** (0.016)
dum_dated	0.041*** (0.008)
nr_works	−0.095*** (0.003)
lnrep	0.949*** (0.003)
Constant	6.110*** (0.074)
Quarterly dummies	Yes
Observations	48,972
R <sup>2</sup>	0.782
Adjusted R <sup>2</sup>	0.781
Residual Std. Error	0.783 (df = 48889)
F Statistic	2,135.752*** (df = 82; 48889)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

they estimated parameters by taking a certain length as the estimation window and shifting this 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 also corresponds to the rolling 5-year regression used to estimate the CAPI. The estimation window is then shifted forward one year, which allows gradual shifts in the parameters.

The coefficients from these models are similar in magnitude to the full model and significant in almost 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.<sup>16</sup>

Figure 4 illustrates the resulting quarterly art price indices from these four methods, using the continuous artist reputation variable. The indices follow similar cyclical patterns over the period, although the index calculated with the 1-year adjacent-period method is slightly lower than the other indices, especially after the peak in 2008. As one would expect, the indices follow a similar cyclical pattern and appreciated rapidly in the run-up to the financial crisis.<sup>17</sup> These indices are also very similar to the indices based on the traditional time dummy method, which includes dummy for as many artists as possible, confirming the findings in Kräussl and Van Elsland (2008).<sup>18</sup>

## 5 Hybrid Models: The Pseudo Repeat Sales Method

The limited number of repeat sales observations in the database (514)<sup>19</sup> limits the usefulness of the repeated sales approach, as it leads to a very volatile index.<sup>20</sup> An alternative is to use the “pseudo repeat sales” (ps-RS) procedure recently introduced by Guo et al. (2014) in the real estate literature. It was used to construct more reliable price indices for newly constructed homes in China.

Guo et al. (2014) developed ps-RS procedure to deal with two unique 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, housing development in many high-density cities occurred with a high degree of homogeneity in the units built within the typical residential complex. The idea was then to match

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<sup>16</sup>We can include the average values of the coefficients in Table 2 if necessary? A formal Chow test can also be conducted to test for structural breaks in the coefficients. See Berndt (1991) for the use of Chow tests for hedonic functions.

<sup>17</sup>It will be interesting to compare this cyclical behaviour to other asset prices and to art price indices available for other countries, as we will do below.

<sup>18</sup>This section could also include diagnostic tests for the hedonic models. For instance, Olckers et al (2015) suggest the use of robust or clustered standard errors. The auction results include the sales of multiple artworks by the same artist, which is likely to violate the assumption that all the observations are independent. There are likely to be unobservable characteristics associated with the artists, which will lead the error term of artworks by the same artist to be correlated. They cluster the errors by the artist to test the effect this may have on the significance of the independent variables. Clustering increases the standard error by a large amount for all the variables.

<sup>19</sup>Unfortunately, the dataset does not uniquely identify each artwork. Repeated sales were identified by matching sales records using artist name, size, title, medium, and the presence of signature and date.

<sup>20</sup>According to authors specialising in repeated sales analysis, the repeated sales method should not be used for time frames of less than 20 years, unless the number of repeated sales is large (Fedderke & Li, 2014).

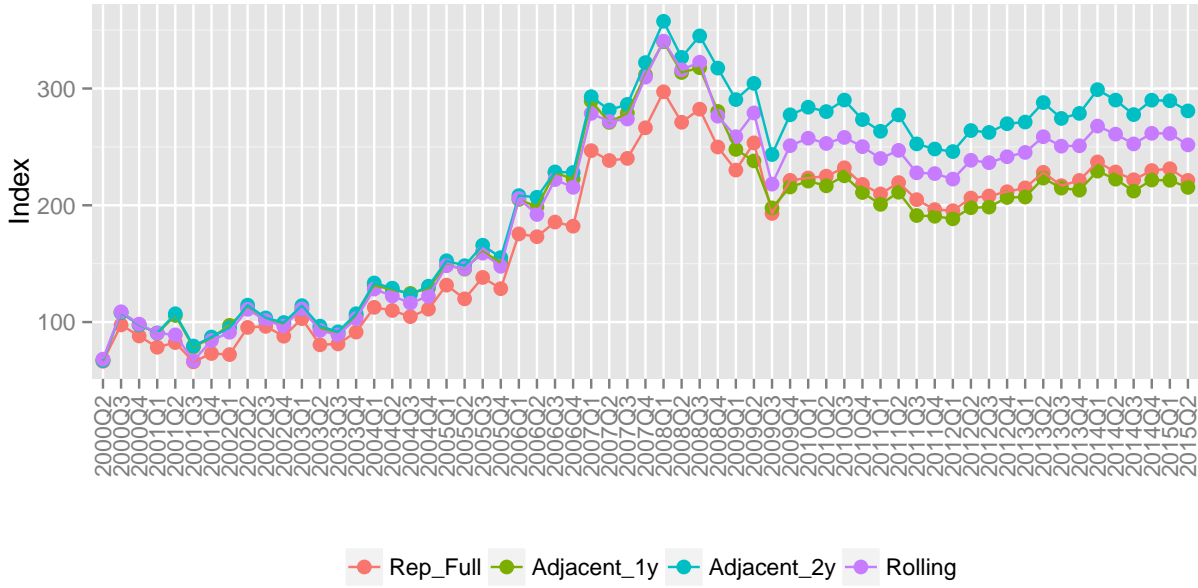


Figure 4: Hedonic South African art price indices (2000Q1=100)

similar homes within each complex or building in order to construct a large pseudo repeat sales sample. They argued that the ps-RS procedure could produce a more reliable and accurate picture of home price appreciation in markets with these features.

This procedure is similar to the matched-sample procedure proposed by McMillen (2012). This approach views the repeat sales model as an extreme solution to a matching problem: it requires an exact match to estimate an index, e.g. the same Van Gogh “*Wheat Field with Crows*” is tracked over time, to take account of as much of the variation in attributes as possible. The idea behind the ps-RS method (or imperfect matching) is that some assets may be similar enough to compare over time. For example, Van Gogh’s well-known *Sunflower* series, of which there are five versions, might be similar enough to be treated as repeated sales.

A hedonic matching criterion is used to create pseudo sales pairs and the repeat sales regression is then applied to these pseudo pairs. The approach is therefore a hybrid model of the type that has been demonstrated to have desirable features in the econometric literature. It mitigates two of the main difficulties of these models: lack of repeat sales data and potential omitted variable bias. It addresses the problems of small sample sizes and sample selection bias with repeated sales techniques by using all of the transaction data. This method has not been used in the art literature to date. The caveat is that artworks have few close substitutes and even two artworks by the same artist of a similar size and theme do not necessarily serve as close substitutes (Olckers, Kannemeyer, and Stevenson 2015).

## 5.1 Index construction methodology

Pseudo sales pairs can be generated when two non-simultaneous transactions share enough similarities in attributes. A distance metric is used to identify the most similar transactions for an artist across adjacent periods. For each artist, a hedonic model is estimated with physical attributes and time



dummies. The distance metric is based on the predicted value for each artwork excluding the time dummies (the non-temporal component). The distance metric between two sales is the absolute value of the difference between the two predicted log price values.

The threshold for this distance metric can be customised. At one extreme, only one pair with the smallest value of the distance metric can be selected. Alternatively, pairs with their distance metric smaller than a certain threshold can be selected. This is a trade-off between the within-pair homogeneity (for mitigating bias) and sample size (for reducing random errors).

Pseudo pairs are generated by matching each transaction with its most adjacent subsequent transaction. This is consistent with best practice in repeat sales regression estimation whenever a single property has more than two transactions in the sample. Thus, this matching process may generate many more pairwise observations than the number of individual transactions in the sample. No unnecessary redundancy is created in the pseudo dataset, however, because each pseudo pair is unique.

For a given artist  $j$ , artwork  $a$  in quarter  $t=r$  and artwork  $b$  in quarter  $t=s$  are adjacent transactions ( $s>r$ ), and the two make a matched pair. The differential hedonic regression (ps-RS) model is expressed as:

$$\ln P_{bsj} - \ln P_{arj} = \sum_{k=1}^K \beta_k (X_{bsjk} - X_{arjk}) + \sum_{t=0}^{\tau} \gamma_t d_t + \epsilon_{srabj}$$

where  $D_t$  is the dummy representing the time the sale occurs.  $D_t = 1$  if the later sale in the pair happened in quarter  $t=s$ ;  $D_t = -1$  if the former sale in the pair happened in quarter  $t=r$ ; and  $D_t = 0$  otherwise. The  $\epsilon_{srabj}$  term is the difference between the two error terms in the log prices of the two sales.

Within-pair first differencing will cancel out any variables for which the attributes are the same between the two units, including both observable and unobservable attributes. Only attributes that differ between the two units within a pair will be left on the right-hand side as independent variables, differenced between the second minus the first sale, reflecting the hybrid specification. This equation is then regressed over all the pseudo-pairs.<sup>21</sup> The ps-RS indices are then calculated based on the coefficients of the time dummies.

## 5.2 Pseudo Repeat Sales Results

This section applies the ps-RS methodology to the South African art market. The hedonic specification is used to generate pseudo sales pairs, for three selected distance metrics: namely the.. This creates . sales pairs.

The hybrid repeat sales model is then be used to generate the art price indices. Figure 5 illustrates the three versions of the ps-RS indices, as well as the traditional repeat sales index. The indices follow a similar pattern.

Guo et al. (2014) found that one of their ps-RS indices displayed practically the same long-term price growth trend as the hedonic index, essentially paralleling it. This implies that the omitted variable bias was not a serious problem in their case. The ps-RS index was much smoother with a lower volatility than the hedonic index, however, suggesting that the ps-RS index was better than

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<sup>21</sup>In order to make an apples-to-apples comparison, Guo et al (2014) employed a weighted least squares (WLS) regression to estimate the ps-RS index, where the hedonic attribute weights over time will be the same as those in the hedonic index.



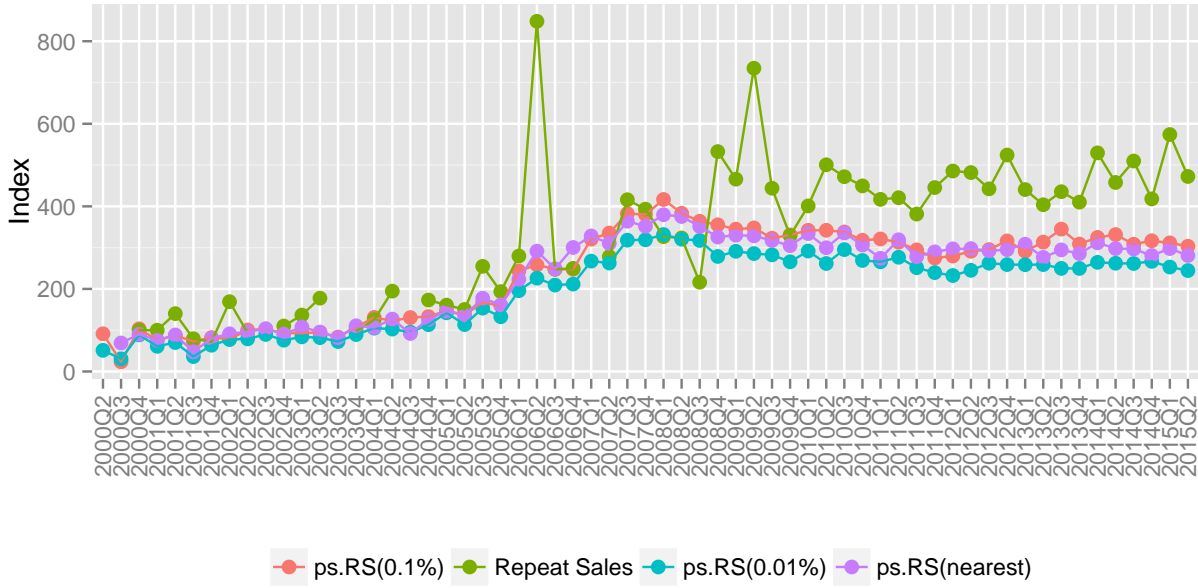


Figure 5: Pseudo repeat sales South African art price indices (2000Q1=100)

the hedonic index: with no more bias and less noise, as will be discussed in more detail below. The other two ps-RS indices did reveal a systematic difference from the hedonic index, suggesting that the type of physical quality attributes that the hedonic index cannot control for, did cause an upward bias in the index price trend. As the indices both tended to track below the hedonic index, it suggested that an improvement in omitted physical quality variables over time led to a positive bias into the index.

## 6 Comparison and Evaluation

### 6.1 Compare the different indices

As all of these approaches involve estimating unknown parameters, there is no way to know with certainty which price index is closest to the truth (McMillen 2012). This section will compare the different indices produced via the various central tendency, hedonic and pseudo-repeat sales approaches, in order to determine which provides the most accurate picture of the South African art market.

The indices can be compared and evaluated in a number of ways. The first step is to compare the indices from the three methodologies graphically. Figure 11 illustrates three representative indices for the three methodologies: the stratified central tendency index, the pooled hedonic index and the ps-RS index. There are large differences between the three measures, suggesting that adjusting for the composition and quality of artworks sold may provide better estimates of pure price changes.

Confidence intervals of the time dummy estimates can be constructed to see if they are statistically different. It is then possible to examine whether there is any overlap between the confidence intervals. For instance, Kräussl and Van Elsland (2008) constructed confidence intervals for the time dummy

estimates as follows:  $\exp(\gamma_t \hat{\sigma}_t^2 * \sigma_{\gamma_t})$ . Table 3 reports the proportion of the sample over which the various measures are statistically different. The median is, on average, statistically different to the more advanced measures for at least half of the sample. In contrast, the more advanced measures tend to be more similar, as there are fewer periods where the measures are statistically different.

The next step is to compare the fit of the models. Table 4 reports the RMSE and SSC comparing estimated price changes with the actual price changes. The RMSE statistics are very close for both the hedonic and ps-RS regressions. Similarly, the SSC statistics are close with approximately 50% of the variation in prices growth in the repeat sales sub-sample explained by each of the models. These results suggest that they are broadly equivalent in terms of model fit.

Table 4 also compares the average growth rates and standard deviations of the various indices. The comparison suggests that the regression-based indices tend to be smoother than the median, on average. Estimates of the pure price changes inferred from the hedonic and ps-RS approaches were very similar, although the average growth rates were higher with the hedonic models (Hansen 2009).

The correlations of the quarterly growth rates of the various indices can also be compared. The high correlations indicate that the general trends match across indices. The growth rates of the indices can also be compared in a graph: the dots in this panel are exactly on the 45 degree line, implying that these two indices are closely correlated with each other. It is also possible that there exist some lead-lag relationships between the indices. Pairwise Granger causality tests can be conducted to investigate such dynamic relationships between the indices. The null that the standard hedonic index does not cause the other indices can be rejected. On the other hand, the null that each of the other indices does not cause the standard hedonic index cannot be rejected. This implies that fluctuations in the standard hedonic index tend to precede those in the other indices.

To illustrate such lead-lag relationships between the five indexes, we compare them in terms of the timing of their turning points. All of the regression-based indices peaked in the first quarter of 2008, in contrast to the central tendency measures. The turn in the hedonic indices preceded the others. The indices also showed troughs after the financial crisis. (Shimizu, Nishimura, and Watanabe 2010). As the timing of turning points in the median did not coincide with those inferred from the more complex measures, there appeared to be several situations in which these measures have provided more consistent signals of the direction of pure art price changes (Hansen 2009).

## 6.2 Comparing index smoothness

The “signature” of random error in time dummy coefficient estimation for price indices is that it imparts “noise” into the index. Two indicators are often useful to quantify a comparison of the relative amount of noise between two or more indices: the volatility and the first-order autocorrelation (AC(1)) in the index returns. The index volatility and AC(1) directly reflect the accuracy of the index returns. Other things being equal, the lower the volatility and the higher the AC(1), the more accurate and less noisy is the index.

The volatility and AC(1) are signal-to-noise metrics, based directly on the index produced. Guo et al. (2014) argued that such metrics are more appropriate for judging the quality of price indices than the more traditional approach based on the diagnostic metrics of the underlying regression (e.g. standard errors of the residuals). However, the regression residuals do not represent error in the price index, and hence do not directly reflect inaccuracy in the index returns.

Even if an index was 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. This renders tests economic significance more interesting than tests of statistical significance. The signal-to-noise metrics directly reflect the economic significance of random error in the indices that are being compared. They are therefore more relevant indicators of index quality.

To explain the rationale, 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  $r_t$  (the log price difference) is the true return (the central tendency) of market art price in period  $t$ . The returns are arithmetically added across time to build the true market value level  $M_t$  (in logs).  $I_t$  is the index (beginning  $t$  periods ago at log value zero) as of the end of period  $t$ .  $\epsilon_t$  is the index-level random error, the error that causes noise and therefore matters from the perspective of index users. It can be modelled as white noise, with zero mean and zero correlation. The noise, unlike true market volatility, does not accumulate over time.

This leads to the formula for noise in the index return:

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

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

Based on this equation the standard deviation of the index return  $\sigma_{r_t^*}$ , which represents the volatility of the index (Vol) and the first order autocorrelation coefficient  $\rho_{r^*}$  (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  $\sigma_r^2$  and  $\sigma_\eta^2$  are the variance of the true return and the noise respectively, and  $\rho_r$  is the 1st order autocorrelation coefficient of the true return (which is usually positive in real asset markets).

Volatility is 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. The noise (random error) in the index adds to volatility in the index, in addition to the true volatility, and therefore causes excess volatility in the index. This excess volatility brings down the 1st order autocorrelation, as pure noise has an AC(1) value of -0.5. In the Vol equation, the lower  $\sigma_\eta^2$  (the less noise), the lower index volatility and the better the estimation of market return each period. Thus, lower Vol or higher AC(1) will indicate a better quality art price index in the sense of less noise.

Table 5 reports these two metric of index smoothness for the art price indices. The volatility measures of the ps-RS indices are much lower than that of the hedonic index. . . The ps-RS indices also have much higher first order autocorrelation coefficients than the hedonic index. This suggest that the ps-RS has less noise than the hedonic, and the smaller the matching space is, the better performance in terms of noise reduction. This is likely due to the ps-RS index controlling better

for the variation in artwork characteristics, given a sample size that is sufficient to mitigate purely random estimation error.

Guo et al. (2014) suggest another test of index quality in terms of minimising random error, which is based on the Hodrick & Prescott filter (HP filter). The HP filter is a spline fitting method that divides a time series into smoothed trend and cyclical components. The idea is then to examine which index has the least deviation from its smoothed HP representation. For each type of index the sum of squared differences between the index returns and its smoothed returns are calculated and compared. The results are reported in Table 5. The ps-RS index exhibits the smallest deviation from its smoothed representation.

### 6.3 In-sample and out-of-sample comparisons

Out-of-sample prediction tests offer another perspective on the reliability and robustness of the index estimation methodologies. To conduct this test, the sample is randomly divided into two sub-samples, and the index is estimated based on each of the sub-samples separately. The resulting indices can then be compared. The two indices in any pair are almost the same (no visually apparent differences) with high cross-correlation coefficients in the returns. Furthermore, we conduct mean-comparison tests between the two indices in each subsample pair with the null hypothesis as:

$H_0: \text{mean}(\text{Index1}_t - \text{Index2}_t) = 0$ ; where  $t$  indicates the period number.

The  $H_0$  could not be rejected, implying that the two indices based on two randomly constructed sub-samples are statistically indistinguishable from each other (Guo et al. 2014). Another option for evaluation would be to examine the predictive ability of the models. Kueth (2011) suggested evaluating the ability of a range of aggregate house price indices to predict house prices out-of-sample at the transaction level. Nagaraja, Jones, and Watchter (2014) compared the performance of their autoregressive index to four traditional repeat sales indices in terms of predictive ability.

In order to evaluate the indices, the transactions can be divided into two subsets: the training and the testing sets. These subsets can be separated either in time series (e.g. after a cut-off date) or randomly (e.g. the uniform distribution). The training set is used to estimate each of the index methodologies and the estimated coefficients are then used to create the predicted transaction prices in the testing set. Performance measures (such as the MAE and RMSE) can be used to examine the difference between the observed and predicted transaction prices, based on the coefficient estimates of the training set. This provides information on how well the models do when applied at the micro level. Predictions also provide a better quantitative measure of the effectiveness of the index in describing market trends. Table 6 reports the results for this metric. The ps-RS methods have RMSE values...

### 6.4 Compared to international art price indices (Artprice)

This section will compare the estimated South African art price indices to art price indices available for other countries over the sample period. Renneboog & Spaenjers (2014) examined the extent to which art prices generated in different auction markets moved together since the early 1970s. To investigate the co-movement between the art price indices, pairwise return correlation coefficients were calculated. They found that virtually all the correlations were significantly positive, although in some cases the correlations were relatively low. They also found that the average correlation

between international art markets was almost identical to that between the international equity markets in their sample (0.58).

Figure 12 illustrates the art price indices for the US, UK and France, calculated by Artprice, together with the preferred South African art price index. Similar to Renneboog & Spaenjers (2014), the results indicate that despite the cross-country variation in long-term returns, art markets often displayed similar cyclical patterns. For instance, art market suffered in the early 2000s, which were recessionary periods in most developed economies. The South African art market seems to be more volatile, with higher increases and steeper decreases.

## 6.5 Conclusion

We have looked at a number of methodologies used to estimate real asset price indices. We have tried a new method for the art market. We have assessed which methods produce the best indices. This index tries to capture the price movements in the South African art market over time. Such an index can then be used to investigate whether the South African art market has exhibited bubble-like behaviour over the sample period, focussing on a specific aspect of bubbles, namely explosive prices.

## 7 Bubble Detection

South African art prices experienced substantial increases in the run-up to the Great Recession. This section asks whether this markets has exhibited bubble-like behaviour since 2000. Over this period, both advanced and emerging economies have experienced severe financial crises. Yiu, Yu, and Jin (2013) argued that these crises were triggered by the collapse of bubbles in asset prices.

In studying “bubbles” it is important to define the term clearly. A popular definition is from Stiglitz (1990): *“[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.”* The main features implied by this definition are that prices increase beyond what is consistent with underlying fundamentals and that buyers expect excessive price increases.

The adverse effects of bubbles and their related crises have led to a large literature on bubble detection. The most commonly used detection methods are based on the present value model and the rational bubble assumption. According to the present value model, the price of an asset is equal to the present value of all its future incomes. This is the fundamental component of the asset price. Rational bubbles arise when investors are willing to pay more for an asset than the fundamental value, on the expectation that the price will exceed its fundamental value in the future (Yiu, Yu, and Jin 2013). The question is therefore whether price surges are generated by market fundamentals or by other drivers such as trend-following behaviour (Areal, Balcombe, and Rapsomanikis 2013). The problem then becomes whether one can observe the fundamental value of the asset.

It is particularly challenging to determine the fundamental value of artworks. Artworks usually have little inherent value, unless the materials used have a high intrinsic value (Goetzmann, Mamonova, and Spaenjers 2014). Artworks do not generate a future income stream (e.g. dividends) that can be discounted to determine the fundamental value, but rather a kind of convenience yield described as a “dividend of enjoyment” or “aesthetic pleasure” (Kräussl, Lehnert, and Martelin 2014). 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 (Penasse and Renneboog 2014).

## 7.1 Explosive prices

The difficulties in determining fundamental value have led to alternative methods to identify bubble-like behaviour in time series. These models typically define the price of an asset as the sum of a fundamental component, which is the discounted future stream of expected yields, and a bubble component, which is an expression that introduces bubble movements in the price over the fundamental component.

Given the different stochastic properties of the fundamental and the bubble components, early tests were based on unit root and cointegration tests. J. Y. 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 point to a bubble.

However, stationarity and cointegration tests are not capable of detecting explosive prices when a series contains periodically collapsing bubbles. Using simulated data Evans (1991) showed that these tests could not differentiate between a periodically collapsing bubble and a stationary process. A series that contained several bubbles could therefore be interpreted by the standard left-tailed unit root test as a stationary series, leading to an incorrect conclusion that the data contained no bubble (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) 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 fraction of the sample and repeatedly expanding the sample forward.

The model typically takes the following form:

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

where  $y_t$  is the asset price series,  $\alpha$ ,  $\rho$  and  $\phi$  are the parameters to be estimated,  $w$  is the sample window size,  $k$  is the lag order, and  $\epsilon$  is the error term.

A sample of ADF statistics are generated to test the null hypothesis of a unit root ( $\rho = 1$ ) against the right-tailed alternative of explosive behaviour ( $\rho > 1$ ). By looking directly for evidence of explosive behaviour, it 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 terminations dates by comparing the recursive test statistic to the critical values. Simulations indicated that the procedure worked satisfactorily against other recursive procedures and was particularly effective for real-time bubble detection (Yiu, Yu, and Jin 2013).

A limitation of the method is that it is designed to analyse a single bubble episode. P. C. B. 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).

A number of studies have used this method to investigate bubbles in a number of asset markets. In the context of art, Kräussl, Lehnert, and Martelin (2014) used the method to detect explosive behaviour in the prices of four different art market segments (i.e. “Impressionist and Modern”, “Post-war and Contemporary”, “American”, and “Latin American”). They found evidence of explosive behaviour in prices and identified two historical bubble episodes in the “Post-war and Contemporary” and “American” art market segments. Caspi, Katzke, and Gupta (2014) pointed out that although this method provides an efficient and consistent basis for identifying periods of explosive behaviour, it provides no causal understanding of these periods. Phillips, Wu, and Yu (2011) pointed out that it is compatible with several different explanations, including rational bubbles, herd behaviour, and exuberant and rational responses to fundamentals.

## 7.2 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. The method of P. C. B. Phillips, Shi, and Yu (2012) will be applied to the art price indices, in order to investigate whether the series have exhibited explosive behaviour over the period, especially in the run-up to the financial crisis. As explained above, this entails the recursive estimation of an autoregressive model, varying the sample over a feasible range of windows, and testing the hypothesis of explosive behaviour in the art price indices.

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