1 Methods for Estimating Quality-Adjusted Price Indices: An Application to South African Art Prices

1.1 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 local and international auctions, both for the country's 'masters', including Irma Stern, JH Pierneef and Walter Battiss, and contemporary artists like William Kentridge (Naidoo, 2013). 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. Also in 2011, Bonhams in London sold Irma Stern's *Arab Priest* for a hammer prices of £2.7 million, a world record for a South African artwork at an auction. The increase in interest in South African art, both locally and abroad, has sparked a vibrant market for collectors and investors.

The increase in the popularity of South African 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 passion investments, which include art, antiques, wines and jewellery (Renneboog and Spaenjers, 2015). 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 purchased for potential value appreciation (Capgemini, 2010).

To date there has been little research on the South African art market and particularly trends in art prices. This is due, at least in part, to a lack of data on art prices (Campbell, 2009). 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 developments in the market.

The primary aim in this chapter is to explore methods for constructing quality-adjusted South African art price indices. It can be challenging to estimate accurate price indices for unique items such as artworks (Jiang, Phillips and Yu, 2014). Artworks have a low transaction frequency, which means that only a small part of the overall market is traded at any given time, while the prices of non-transacted items are unobservable. Artworks are typically unique, or heterogeneous, which means that the quality of items sold is not constant over time. The composition of items sold will generally differ between periods, making it difficult to compare prices over time (Hansen, 2009). These features present challenges for the measurement of the state of the market over time, and necessitate a different approach than is used for indices of traditional assets.

In this chapter three broad methodologies are used to develop price indices for South African art: central tendency, hedonic and hybrid repeat sales methods. Simple central tendency indices are estimated as a baseline to compare the results from the different methodologies. In this chapter it is argued 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 estimating implicit prices for a set of item attributes. A shortcoming of indices based on the hedonic method is that they may suffer from potential omitted variable bias.

The repeat sales method is an alternative estimation method for quality-adjusted price indices. Repeat sales indices suffer less from potential omitted variable bias, but have the shortcoming of potential sample selection bias. The repeat sales method controls for quality-mix changes, by tracking the same asset over time. Hence, only artworks that have sold more than once are utilised. The scarcity of repeat sales observations in the database limits the usefulness of the classical repeated sales approach in this case. In this chapter a simple hybrid repeat sales method is proposed for estimating alternative price indices for South African art. This approach addresses the problem of the scarcity of repeat sales observations and, to some extent, the potential omitted variable bias inherent in the hedonic method.

The internal validity of the indicators is assessed by comparing the indices calculated according to the different methodologies. In this way, the indices estimated with the hybrid repeat sales approach act as an internal validity test, to check that the results are not driven by the inherent biases of a specific method. The indices estimated with the hedonic and pseudo-repeat sales methods point to the same general trend in South African art prices, with a large increase in the run-up to the Great Recession and a flat trend after 2009. The indices for the different market segments indicate that the large price increases occurred in the more expensive or high-end parts of the art market, and especially for oil paintings. The external validity of the indices is assessed by testing their conformity to the price indices of other South African assets and available international art price indices. The indices are then evaluated directly in terms of smoothness or signal-to-noise metrics, in order to assess which index provides the most accurate measure of South African art prices over time.

In order to demonstrate how the estimated art price indices may be useful in exploring particular price patterns in the South African art market, this chapter studies the indices for evidence of a bubble in South African art prices. During this period many commentators claimed that the market was overheating and suggested the possibility of a bubble in the market (e.g. Rabe (2011); Hundt (2010); Curnow (2010)). A reduced-form bubble detection method is used to test for periods of mildly explosive behaviour in the art price indices. The evidence points to consistent evidence of an explosive period between 2006 and 2008. The bubble detection tests performed on the different market segments indicate that the bubble process occurred mainly for high-end oil and watercolour paintings.

The primary aim in this dissertation is to demonstrate aggregation methods that may be useful in overcoming specific data challenges, to create useful time-series indicators. In this chapter, various quality-adjusted measures of the mean of the distribution of growth rates in art prices are constructed. The chapter begins by discussing the different methodologies for constructing art price indices and then presents the data used to estimate the indices. The index results are subsequently presented, along with validity tests and an evaluation of the indices. The ancillary aim is to use time-series techniques to test for evidence of mildly explosive behaviour in the estimated art price indices. The chapter then presents the bubble detection framework and the results of the bubble detection tests.

1.2 Methodologies for Constructing Art Price Indices

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

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 for indices of traditional assets such as stocks and bonds. 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 of method.

1.2.1 Central Tendency Methods

The simplest method for constructing a price index is to calculate a measure of the central tendency of the price distribution. 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 advantages of being simple to construct and not requiring detailed data.

Despite its advantages, an index based on average prices does not account for the difficulties mentioned above. For assets such as artworks, central tendency indices may dependent more on the composition, or quality-mix, of assets sold than on changes in the underlying market. For instance, if there is an increase in the share of higher quality assets, a measure based on averages will show an increase in prices, even if the market prices remained constant. 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 compositional changes and turning points in asset price cycles, the average could be especially inaccurate (Hansen, 2009).

Stratified central tendency measures can control, to some extent, for compositional changes in assets sold over time, by dividing the sample into subgroups according to item attributes such as artist and medium. The central tendency for each subgroup is calculated, and the aggregate quality-adjusted index is then calculated as a weighted average of the indices for the subgroups. The Fisher index, which is the geometric mean of the Laspeyres and Paasche indices[1], is often recommended (Eurostat, 2013).

Stratified central tendency methods are currently used by several South African financial institutions to construct property price indices for South Africa, based on the finance applications they receive. ABSA and FNB publish mean property price indices, while Standard Bank publishes a median property price index.[2] The ABSA House Price Index, for instance, is based on the mean sales prices of properties categorised by house size and price segment (Aye *et al.*, 2014).

However, scholarly work rarely employs stratified central tendency indices, as these measures adjust only for the variation in the composition of assets across the subgroups. The ABSA House Price Index, for instance, does not control for changes in the composition 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 this, although some compositional 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, especially with regard to art price indices.

1.2.2 The Hedonic Method

The hedonic method is based on hedonic price theory, which is useful for the analysis of differentiated good pricing (Griliches, 1961). 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: $x_i = (x_{i1}, x_{i2}, x_{i3}, ., x_{iJ})$. 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 consumers purchase a particular good i, they have chosen a particular vector x of attributes (Rosen, 1974).

The price of the good is determined by the specific combination of attributes. The price of

[1]The Laspeyres price index P_L compares prices in the comparison period P^1 to prices in the base period P^0 for each stratum m, while holding quantity weights Q fixed in the base period 0: $P_L = \sum_{m=1}^{M} P_m^1 Q_m^0 / \sum_{m=1}^{M} P_m^0 Q_m^0$. The Paasche price index P_P compares prices in the comparison period P^1 to prices in the base period P^0 for each stratum m, while holding the quantity weights Q fixed in the comparison period 1: $P_P = \sum_{m=1}^{M} P_m^1 Q_m^1 / \sum_{m=1}^{M} P_m^0 Q_m^1$.

[2]http://propertywheel.co.za/wp-content/uploads/2016/07/HPI-Jun-2016.pdf;
https://blog.fnb.co.za/2016/07/fnb-property-barometer-house-price-index-jun-2016/;
http://propertywheel.co.za/wp-content/uploads/2016/05/April-House-Price-Index-Standard-Bank-1.pdf

good p_i is a function of its attributes x: $p_i = p(x_i) = p(x_{i1}, x_{i2}, x_{i3}, ., x_{iJ})$. The hedonic price function $p(x_i)$ specifies how the market price of a good varies as its attributes vary (Epple, 1987).

Rosen (1974) offers 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 are 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 $p_j(x_i) = \frac{\partial p}{\partial x_j}$. 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. Implicit prices are revealed to agents from the observed prices of differentiated goods and the attributes associated with them (Eurostat, 2013).

The hedonic method controls for compositional changes by assigning implicit prices to a set of value-adding attributes of an individual item. Thus, the hedonic approach can circumvent the problems of changes in composition or quality-mix over time (Hansen, 2009).[3] Hedonic regressions control for the observable attributes of an item to produce a price index for the 'standard asset' (Renneboog and Van Houtte, 2002). 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 ($t = 1, ..., T$); 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 ($j = 1, ..., J$) observed attributes of item i at time t; Z_{kit} is a set of k ($k = 1, ..., K$) 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 derived from the series of estimated coefficients: $\hat{\delta_1}, ..., \hat{\delta_T}$.

The most common form of the hedonic equation assumes that the implicit prices (i.e. the coefficients β_t and γ_t) are constant over the entire sample. However, when demand and supply conditions (e.g. tastes) change, the implicit prices of the attributes may change (Renneboog and Spaenjers, 2013). Another problem with this multi-period pooled model is that the

[3] According to Hansen (2009), there are various weighting approaches. An equal weighting of art price inflation rates is appropriate when measuring the price changes of a representative artwork. A higher weight should be given to the price changes of higher-value artworks when measuring changes in the value of the art stock (or a representative portfolio). This chapter focuses on the pure price changes for a representative artwork, assuming an equal weighting.

coefficients are not stable when data from additional periods are added to the sample. An adjacent-periods or chained regression can allow for shifts in parameters (Triplett, 2004). Separate regressions are estimated for adjacent time periods and the sequence of shorter indices are then chain-linked together to form the continuous overall index (McMillen, 2012). The coefficients, and therefore the implicit prices assigned to the attributes, are allowed to vary in each regression (Triplett, 2004).

1.2.2.1 The hedonic method applied to art prices

The majority of studies of art price indices have used hedonic models to construct the indices, due to the lack of repeat sales of artworks and the availability of information on many of their important attributes. Anderson (1974) first applied the hedonic method to art prices. More recent examples include Renneboog and Van Houtte (2002), who estimated an index for 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 (2015) who analysed art from the Middle East and Northern Africa region.

In estimating art price indices, studies typically 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 has been 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 will 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 subsample of selected artists. This approach is discussed in more detail below.

The choice of the attributes in a hedonic regression is limited by data availability and involves subjective judgement. Hedonic models typically include attributes that are 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).

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.[4] Nevertheless, the hedonic

[4] According to Triplett (2004), even if the hedonic coefficients are biased, it is not necessarily the case that the hedonic index will be biased. If the cross-sectional correlations between included and omitted attributes are the same as the time-series correlations, the hedonic index may be unbiased, even though the hedonic coefficients are biased. Changes in omitted attributes between two periods may offset the error in estimating the implicit prices of included variables. The bias therefore becomes an empirical matter, as the effect on the price index is important, not just the effect on the hedonic coefficients.

method may be especially appropriate for luxury consumption goods, where the willingness to pay for an item is often determined by a few key attributes. 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 such as real estate, and the omitted variable bias is often small in practice (Triplett, 2004; Renneboog and Spaenjers, 2013).

Bought-in lots (i.e. items that do not reach the reserve price and remain unsold) are always a problem when estimating 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. Including only items that systematically exclude ‘less fashionable’ artworks potentially introduces bias in the sample. Collins, Scorcu and Zanola (2009) used a Heckman selection model to address this issue. The results confirm a statistically significant sample selection problem, in line with similar studies on the property market.

1.2.3 The Repeat Sales Method

The repeat sales method provides an alternative method for estimating quality-adjusted price indices, based on price changes in items sold more than once. It was initially proposed by Bailey, Muth and Nourse (1963) to calculate house price changes, 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 growth rate in the distribution for each period (Kräussl and Lee, 2010). As a result, it does not require a measure of quality, only that the quality of each item be constant over time (Case and Shiller, 1987). Advocates of the repeat sales method argue that it controls more accurately for the attributes of goods, as well as for potential omitted variables (Jiang, Phillips and Yu, 2014).

The repeat sales model can be derived from the hedonic model if the hedonic model is differenced with respect to consecutive sales of items that have sold more than once (McMillen, 2012).[5] 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 at 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

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

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 derived from the series of estimated coefficients: $\hat{\delta_1}, ..., \hat{\delta_T}$.

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 for the omitted variables Z. Furthermore, it 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), and 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.[6] Items that have traded more than once may not be representative of the entire market. 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 occur only infrequently, which might be related to the high transaction costs involved. This substantially reduces the total number of observations available.

1.2.3.1 The repeat sales method applied to art prices

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. Mei and Moses (2002) constructed the seminal repeat sales index of art prices for the period 1875-2000. The returns for the index were compared with those of 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 price 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.

[6] The nature of sample selection bias is different in the hedonic and repeat sales approaches. The repeat sales method ignores single-sales observations, so that it may not be representative of the population. The hedonic method uses only sold items, so a bias may arise from unsold items.

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 not be 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.

1.2.4 Hybrid Methods

The major problem with the hedonic method is the potential for omitted variable bias, while the biggest problems associated with the repeat sales method are that it suffers from potential sample selection bias and that it discards single-sale observations. A number of hybrid models, 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 consisting of a fixed time effect and a random postal code effect, combined with an autoregressive component. The index was a weighted average of estimates from single-sale and repeat sales prices, with the repeat sales prices having a higher weight.

An interesting perspective, which is relevant to this chapter, is to view the repeat sales specification as an extreme solution to a matching problem. This is because 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, by some criterion, to cancel out as many as possible of the differences in attributes (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 a data preprocessing one that builds an estimation sample.

Guo *et al.* (2014) proposed a pseudo-repeat sales (ps-RS) method to estimate 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 were a limited number of repeat sales, similar to the South African art market. Secondly, new housing developments often included similar units within a residential complex. The idea was to match similar homes within each complex or building in order to construct a large pseudo-repeat sales sample.

As a matching criterion, Guo *et al.* (2014) 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 a distance metric smaller than a certain threshold were selected as pseudo-pairs. The threshold was a trade-off between the within-pair homogeneity and sample size, and was set flexibly.

All pseudo-pairs were then used in a ps-RS regression model. 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.

Taking within-pair first differences cancels out any attributes that 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 as independent variables, in differenced form, reflecting the hybrid specification. The ps-RS indices were derived from the coefficients of the time dummies. Guo *et al.* (2014) found that the ps-RS method controlled more adequately for quality-mix differences over time and produced a smoother index, indicating less random estimation error.

The approach is a hybrid model that 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 observations (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 model controlled for observable slave attributes, it may be sensitive to the presence of unobservable attributes. They created a matched sample that enabled the estimation of a repeat sales model for the changes in slave prices. Because they observed repeated sales of the same slave, the unobserved attributes would be similar for both transactions. They also allowed for the possibility that the observable attributes had changed between the date of initial purchase and the subsequent sale. They 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 was not dictating the results.

As previously mentioned, there is no consensus regarding the preferred approach to constructing quality-adjusted price indices, either theoretically or empirically. However, there is reason to believe that more advanced measures may provide a better guide to pure price changes than simple central tendency methods (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 summary of the South African art price literature. In the empirical sections, consideration is then given to the alternative approaches to gauge their performance and to establish whether they point to the similar aggregate trends.

1.2.5 South African Art Price Literature

Few studies have investigated South African art market prices. In an important contribution, 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.

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

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.[7]

Botha, Snowball and Scott (2016) used the CAPI to test the potential for art to be used

[7] The CAPI was estimated by the author on behalf of Citadel.

to diversify investment portfolios in the South African context. This might result if the art market exhibits different risk-return characteristics than conventional assets. To test this proposition, they used a VAR model, including the CAPI, the JSE All Share Index, the All Bond Index, and the ABSA House Price Index. They found that a positive shock to stock market returns was followed by a significant positive response in the CAPI in the following quarter. They concluded that South African art, as measured by the CAPI, would not aid portfolio diversification.

The primary aim in this chapter is to explore methods for constructing quality-adjusted South African art price indices. Various quality-adjusted measures of the mean of the distribution of growth rates in art prices are constructed, using central tendency, hedonic and hybrid repeat sales methods. Due to the limited number of repeat sales observations in the sample, a simple new hybrid repeat sales model is proposed as an alternative to the classical repeat sales method. The methods demonstrated in this chapter may be useful in constructing indices for other unique assets, such as real estate, antiques and wine, where the quality-mix of items differs over time, and where there is a lack of repeat sales.

The price indices estimated in this chapter build on the estimation of the CAPI. They are the first price indices for South African art in the academic literature, of the type often estimated internationally (e.g. Mei and Moses (2002), Renneboog and Van Houtte (2002), and Kräussl and Lee (2010)). The indices may be useful for an improved understanding of developments in the South African art market. By estimating more accurate measures of average price trends, it is possible to investigate particular price trends in the South African art market, such as bubble behaviour and potential portfolio diversification benefits. The following section presents the data used to estimate the indices.

1.3 Data: South African Art Auction Prices

As set out above, the aim in this chapter is to demonstrate methods for creating quality-adjusted South African art price indices. In this chapter, quarterly price indices are estimated for South African art from 2000Q1 to 2015Q3. The art price indices are based on the database of auction prices recorded by AuctionVault. The following section presents a brief discussion of public and private art market prices. The subsequent sections present the auction price data and the artwork characteristics used to estimate the South African art price indices.

1.3.1 Public and Private Art Market Prices

The literature on estimating art price indices has relied almost exclusively on publicly available auction prices.[8] Art is also sold privately, either directly by artists or through dealers. However, dealers' sales records are generally not available. Releasing such information may be damaging to dealers' businesses, and they have an incentive to give the impression that there is high demand for their artworks (Olckers, Kannemeyer and Stevenson, 2015).

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

Nevertheless, it is generally accepted that auction prices provide a benchmark that is used in the private market (Renneboog and Spaenjers, 2013). Anecdotal evidence suggests that private dealers are very aware of auction prices and follow them closely. Differences between auctions and private markets in terms of institutional arrangements, transaction costs, and available information might lead to different price levels for the same or similar artworks. However, in constructing price indices, the focus is not on the price levels of individual artworks, but on the trend in art prices over time.

Auction prices and private prices are likely to be correlated over time for similar artworks, even if their levels are different (Olckers, Kannemeyer and Stevenson, 2015). This is due to demand-side and supply-side substitution. The intuition is that there is a limit to how far prices can deviate before either demand-side or supply-side substitution forces them back in line (Stigler and Sherwin, 1985). Products can compete despite being priced at different absolute levels, as demand-side substitution depends on the willingness of marginal consumers to switch from one product to another as relative prices change (Davis and Garcés, 2010). If auction markets and private markets are substitutes to a certain degree, their prices should be correlated over time, even if the price levels are different.

Where the auction houses sell a particular artwork, buyers may or may not have similar artworks available as substitutes in private markets (e.g. from dealers or the artist's studio). If similar artworks are available (e.g. artworks by the same artist in the same medium or prints from the same series), to some extent there are substitutes available for buyers. Buyers would then be able to purchase the similar artwork at an auction or privately. Dealers, for instance, cannot charge exorbitant prices over time if similar works are selling for much less at auctions. The substitutes do not have to be perfect, nor do the prices have to be the identical (Hoehn *et al.*, 1999). All that is necessary is that they provide a competitive constraint. From the seller's perspective, an artwork sold at auction may also be sold privately. If auction houses charge a very high commission or fail to attract the desired hammer prices, sellers can substitute towards private markets.

In this way, auction markets and private markets may constrain each other, based on imperfect demand-side and supply-side substitution. If this is the case, one would expect auction and private market prices to be correlated over time. The substitution and price convergence may not necessarily occur immediately, depending on market efficiency and the diffusion of information, but over the longer term, prices in these markets should move together.

There is some empirical evidence that auction prices and private prices are correlated. Candela and Scorcu (2001) is one of the few studies to have access to private art market information. They used the prices from a leading gallery (Prandi) in Italy to construct price indices for private sales for the period 1977-1998. The indices were then compared with price indices based on auction prices. They found a high correlation between the indices, as well as evidence of a cointegrating relationship. They argued that this was due to substitutability between private and auctions markets, arbitrage by dealers between the markets, and the existence of common fundamentals. They also found that auction prices Granger-caused private market prices, while the converse was not true. Their results suggest that auction prices represent a benchmark for private market prices.

1.3.2 South African Art Auction Prices

Auction prices are the only consistently available price data for the South African art market. This chapter therefore relies on publicly available auction prices, similar to virtually all other studies estimating art price indices. As explained above, private sales prices are likely anchored by auction prices and are likely to be highly correlated over time for similar artworks, even if their levels are different (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 currently the only major international auction house with a dedicated South African art department, although competition is emerging from Christie's and Sotheby's. Bonhams 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 made only 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 eight auction houses[9] from 2000 to 2015. The database includes 52,059 sales by 4,123 different artists. The following characteristics are available for each auction record: auction house; date of auction; artist's name; title of work; medium; size; whether the artwork is signed, dated and titled; hammer price; and the number of distinct works in the lot. Like most studies, the database lacks information on buy-ins, and therefore the analysis is forced to disregard the potential sample selection problem.[10]

Figure 2.1 illustrates the number of auction lots sold in the sample over the period (2000Q1-2015Q4) 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. Total auction turnover echoed the increase in the number of lots over the period. At its peak in 2011, annual turnover in the sample had reached almost R400 million.

Figure 2.2 illustrates boxplots for the logarithm of the hammer prices for each year. The sample is highly positively skewed, with the overall mean price of R49,824 being much higher than the median of R7,000. There were a number of outliers, including the hammer price of over R30 million for Irma Stern's *Arab Priest* in 2011. Annual median sales prices increased substantially from R3,200 in 2003 to R10,000 at their peak in 2010. This confirms anecdotal evidence on the rise in popularity of the South African art market.

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

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

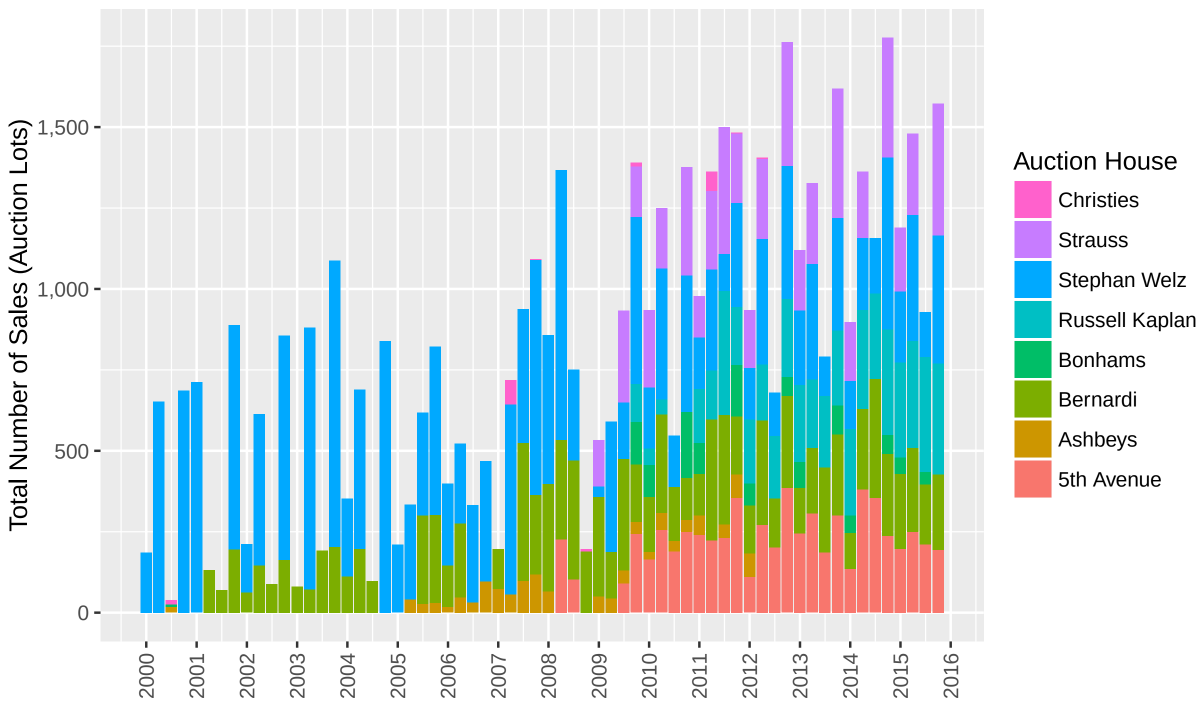

Figure 1: Total number of auction lots sold by auction house (2000Q1-2015Q4)

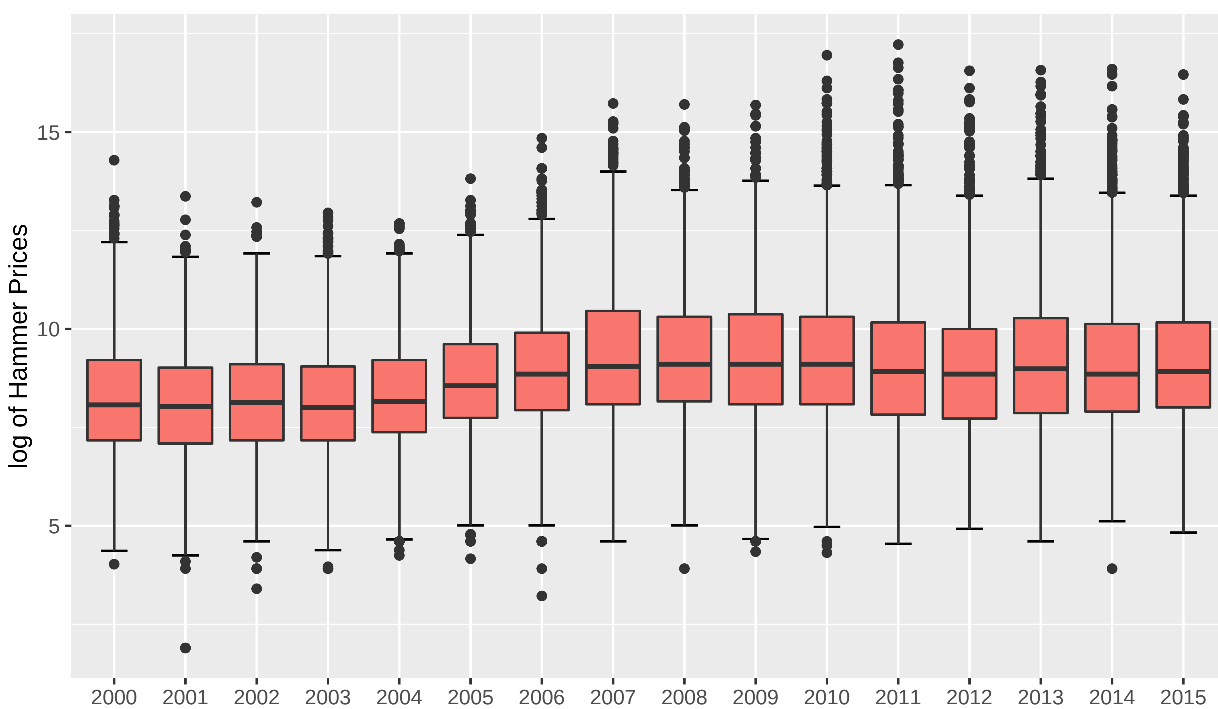

Figure 2: Boxplot of the logarithm of hammer prices

1.3.3 Artwork Characteristics

Hedonic art price models typically include characteristics that are 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, often some artists have to be excluded from the 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 two-step hedonic approach suggested by Kräussl and Van Elsland (2008). The models in this chapter 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 logarithm of the size of the artwork in cm^2. They also include size and medium interaction terms. This is particularly important for sculptures, as the size of a sculpture is usually only recorded in terms of its height (in cm). Figure 2.3 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.

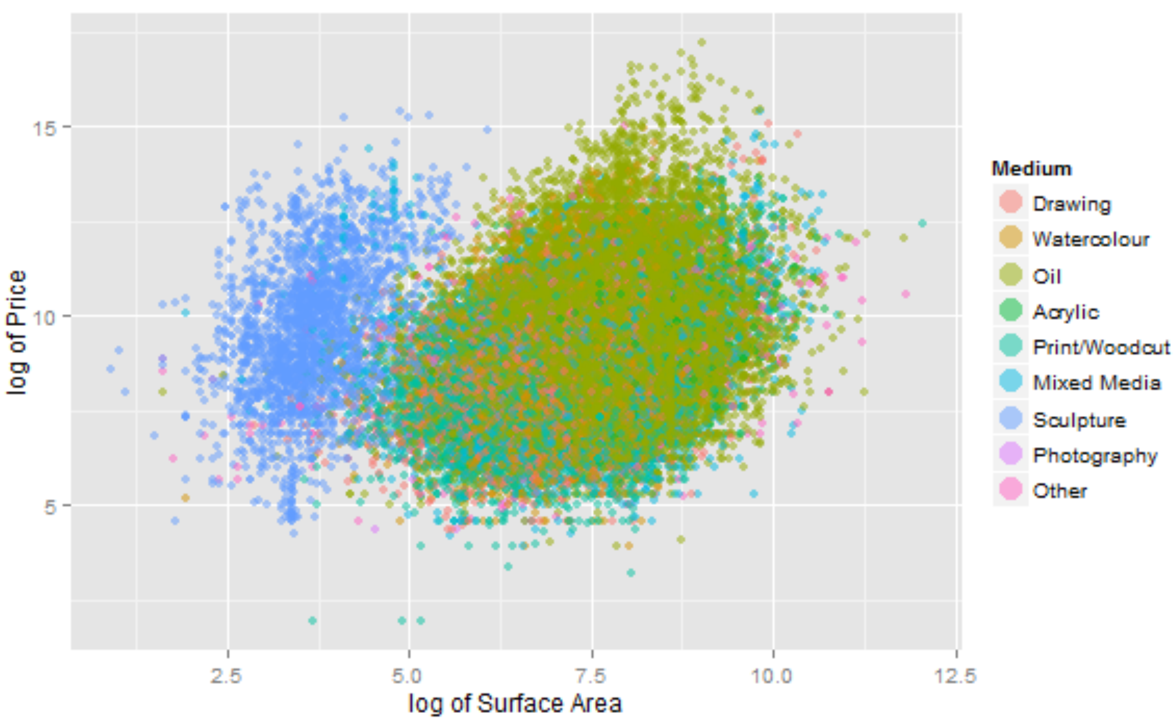

Figure 3: Relationship between prices and artwork sizes, by medium

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 more renowned auction houses offer higher quality work (Kräussl and Logher, 2010). Thus, the variables might pick up otherwise unobservable quality differences and do not necessarily reflect auction house certification (Renneboog and Spaenjers, 2013). 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 buyer's cost or the seller's revenue. 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 production stage the medium is associated with (e.g. preparatory drawings), or in some cases, the 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 defined in their data (Kräussl and Logher, 2010). The models in this chapter use the nine mediums defined in the dataset; the same mediums were 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, 2015). 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 corresponds to each artwork separately and not to the group. Moreover, it is possible that lots including more than one artwork fetch a lower price per artwork than if they are 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 growth in art prices in a specific period, relative to the common base period.[12]

[11] The 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 production has ceased. However, artists who are no longer alive are not able to build on their reputations, 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 the age of the artist were statistically insignificant in their South African sample.

[12] Because of the log transformation prior to estimation, the index reflects the geometric mean, rather than the arithmetic mean, of prices over time. 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 $I_t = \exp\left[\gamma_t + 1/2(\sigma_t^2 - \sigma_0^2)\right] * 100$, 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.

1.3.4 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, rather than only a selected subsample of artists. The approach involves estimating a continuous artist reputation variable, which is included in the regression instead of the artist dummy variables. The approach increases the sample size of artworks that can be included in the regression models and reduces selection bias.

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 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):

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

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

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:

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

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

The first step was to estimate the full hedonic model on a subsample of artists to obtain the characteristic prices (β_j). Following Kräussl and Van Elsland (2008), the subsample 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 was assumed that the characteristic prices are representative. In the second step, the artist reputation index was calculated for each artist relative to the base artist (Walter Battiss), i.e. the quality-adjusted prices for the works of artist y relative to artist 0. The reputation index was then used as a continuous proxy variable for artistic value in the hedonic models, instead of the artist dummies.

Figure 2.4 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 who sold only one artwork over the sample period. The results are very similar, in line with the findings in Kräussl and Van Elsland (2008).

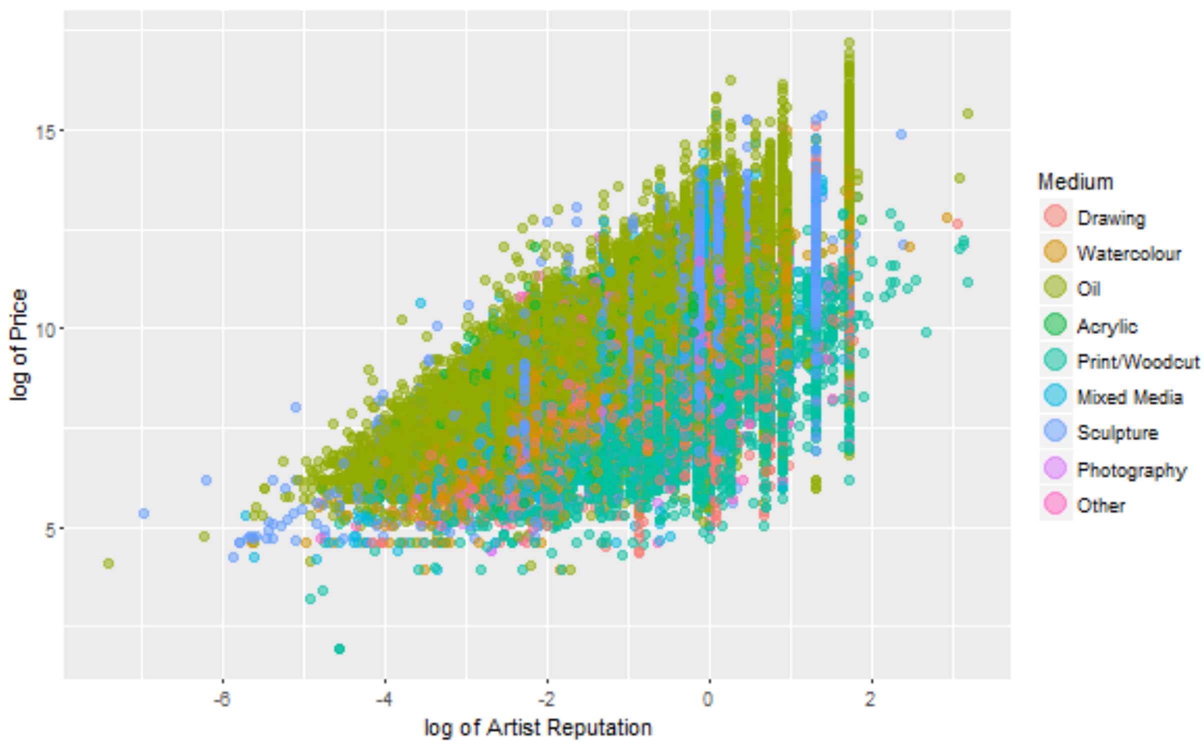

Figure 4: Relationship between prices and the reputation index

1.4 Index Results

This section presents the results for the three sets of quarterly art price indices, using central tendency, hedonic and hybrid repeat sales methods. The central tendency price indices act as a baseline in comparing the indices, but do not adequately control for compositional changes over time. Various indices are estimated with the hedonic regression method, which is able to control more adequately for compositional changes. A shortcoming of the hedonic method is that it has potential omitted variable bias. The repeat sales method is an alternative estimation method for quality-adjusted price indices. However, due to the scarcity of repeat sales observations in this case, a simple hybrid repeat sales method is proposed for estimating alternative quality-adjusted price indices for South African art.

The regression-based indices seem to point to the same general movement in South African art prices, with large prices increases in the run-up to the Great Recession and relatively flat prices after 2009. Also examined in this section are the different segments of the art market, in order to establish in which segments the marked price increases occurred. A few indices are also estimated for individual artists.

1.4.1 Central Tendency Indices

Two central tendency price indices are estimated at a quarterly frequency to act as a baseline in comparing the indices resulting from the different methodologies. The median index is simply the median price for each quarter. The Fisher index is a mix-adjusted central tendency index, which stratifies the sample into subgroups by artist and medium. The Fisher index is calculated as the geometric mean of the Laspeyres and Paasche indices. The base periods were allowed to vary for each index point, and the index points were then chained together to form the overall chain-link index.

Figure 2.5 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 the quality-mix or composition of the artworks sold between different periods.

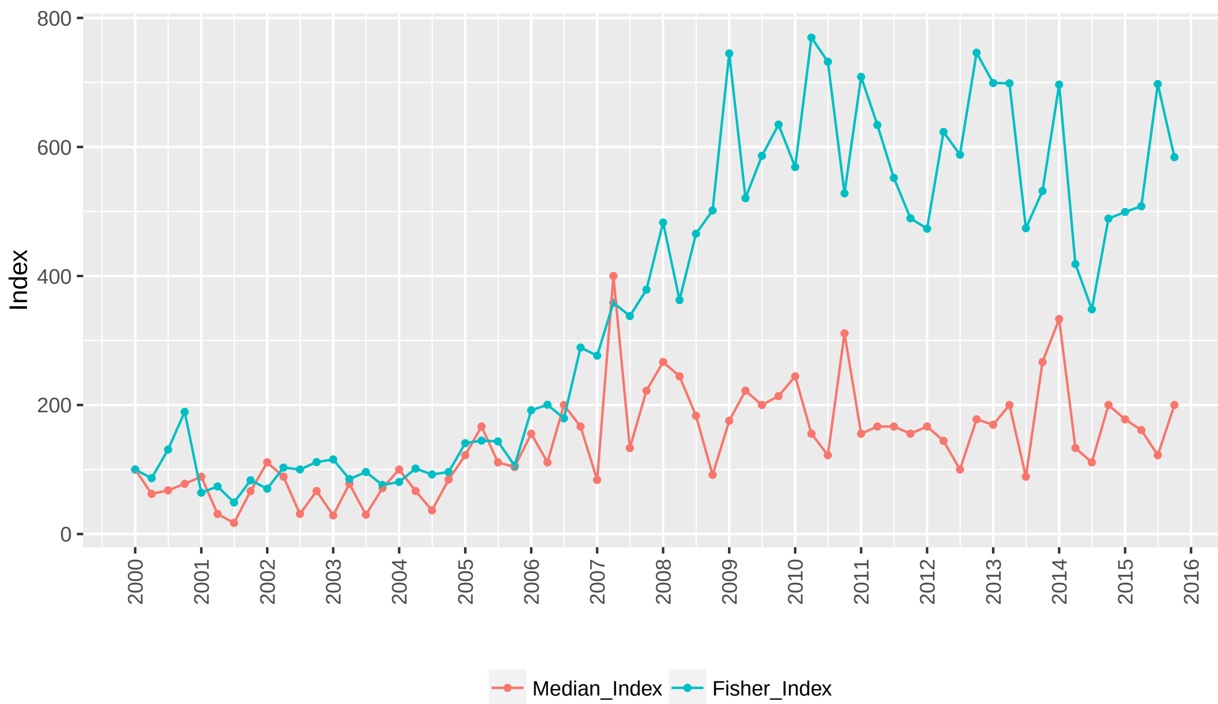

Figure 5: Central tendency index of South African art prices (2000Q1=100)

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 capture only a small portion of the differences in the quality of artworks sold between periods. The quality-adjusted measure does not take account of any changes in the quality-mix of artworks sold that are unrelated to artist and medium type. The stratified index also does not account for changes in the composition of artworks sold within each subgroup, in this case changes in the quality-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, echoing the findings in Els and Von Fintel (2010) for South African real estate. 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.

1.4.2 Hedonic Indices

The full pooled sample regression results are reported in Table 2.1. The coefficients are all significant and have the expected signs. The size of the artwork is highly significant and positive. 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 medium and size interaction terms are all negative and mostly significant, except for the sculpture size term, which is positive and significant. The authentication dummies are both positive and significant, as is the artist reputation variable. The number of works variable 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 large part of the variation in sales prices.[13] The time dummy coefficients were then used to calculate the full period pooled hedonic index.

To allow for shifts in the implicit prices, two adjacent-period or chain-linked indices were calculated by estimating separate models for adjacent subsamples. Selecting the length of the estimation window involves a trade-off. A shorter window decreases the likelihood of large breaks, but also reduces the number of observations used to estimate the parameters (Dorsey *et al.*, 2010). 1-year and 2-year estimation windows were selected, similar to Dorsey *et al.* (2010) in the context of real estate and Renneboog and Spaenjers (2013) in the context of art. This seems to be reasonable for the South African art market, where large auctions are held infrequently. The indices were then calculated by chain-linking the estimates together, as Figure 2.6 illustrates for the 2-year version of the index.

In the context of real estate, Shimizu, Nishimura and Watanabe (2010) suggests a so-called overlapping-periods hedonic regression method using multiple 'neighbourhood periods', allowing gradual shifts in the parameters. Parameters are estimated by choosing a specific estimation window size and shifting the period forward in rolling regressions. They argue that this method will be able to deal better with seasonal changes in parameters than adjacent-periods regressions. To apply this method, 5-year rolling regressions were run, which correspond to the rolling 5-year regressions used to estimate the Citadel Art Price Index. The estimation window was 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 are significant in virtually all cases. For example, the coefficient associated with the size of the artwork is 0.426 in the standard full hedonic regression, while the average coefficients

[13] The diagnostic tests indicate that there might be some problems with the assumptions of normality and homoscedasticity of the residuals. These assumptions are not crucial, however, as only the point estimates of the time dummy coefficients are of interest.

Table 1: Hedonic regression results

	Dependent variable:
	lnprice
lnarea	0.478*** (0.029)
ah_codeAshbeys	0.111*** (0.027)
ah_codeBernardi	0.125*** (0.013)
ah_codeBonhams	1.164*** (0.026)
ah_codeChristies	1.133*** (0.064)
ah_codeRussell Kaplan	0.127*** (0.015)
ah_codeStephan Welz	0.582*** (0.013)
ah_codeStrauss	1.100*** (0.015)
med_codeDrawing	−1.341*** (0.251)
med_codeMixed Media	−0.826*** (0.250)
med_codeOil	0.668*** (0.239)
med_codeOther	0.404 (0.278)
med_codePhotography	−0.827 (0.669)
med_codePrint/Woodcut	−0.757*** (0.243)
med_codeSculpture	1.233*** (0.248)
med_codeWatercolour	0.019 (0.255)
dum_signed	0.200*** (0.015)
dum_dated	0.048*** (0.007)
nr_works	−0.090*** (0.003)
lnrep	0.950*** (0.003)
Constant	5.562*** (0.243)
Medium Size Interactions	Yes
Quarterly dummies	Yes
Observations	51,454
R^2	0.789
Adjusted R^2	0.789
Residual Std. Error	0.768 (df = 51362)
F Statistic	2,111.353*** (df = 91; 51362)
Note:	*p<0.1; **p<0.05; ***p<0.01

from the other regressions are 0.44, 0.43 and 0.42. There are a few cases in which the estimated parameters fluctuate quite substantially. For example, the coefficient of the Strauss & Co auction house dummy varies between 1.04 in the pooled model and 0.77 in one the subsamples, indicating that structural changes may have occurred over the sample period.

Figure 2.7 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, with a rapid appreciation in the run-up to the Great Recession. The indices seem

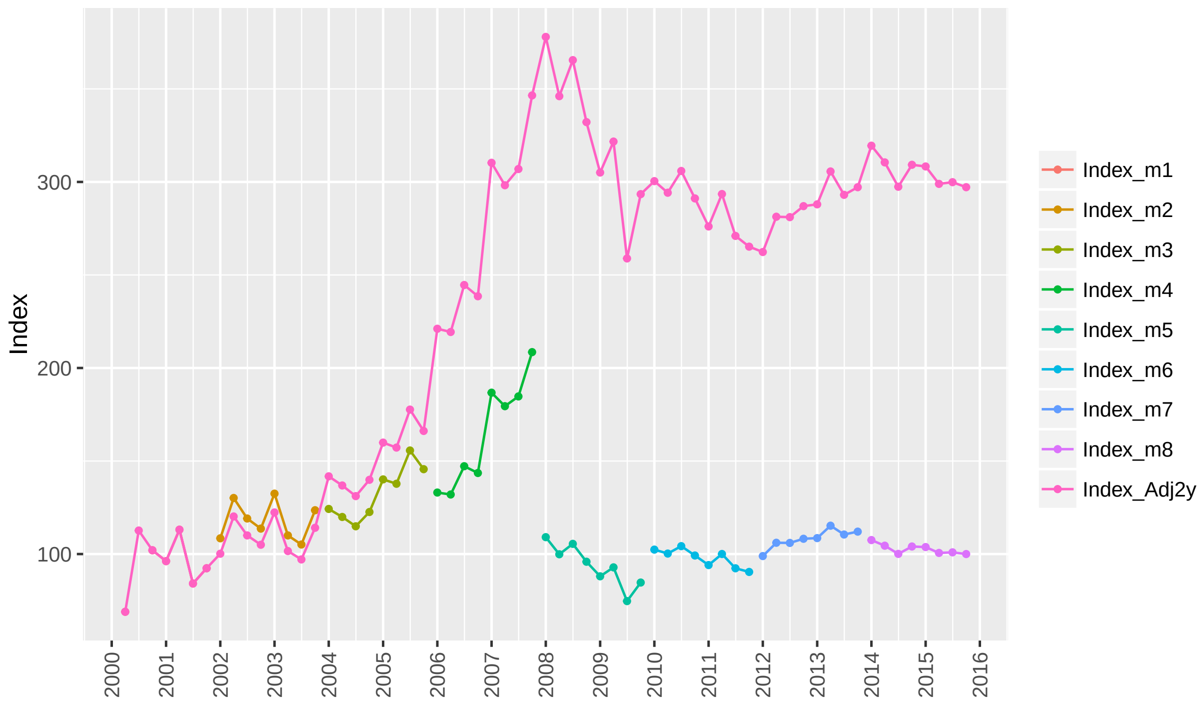

Figure 6: Chain-linked 2-year adjacent-period art price index

more plausible than the central tendency measures, supporting the case for regression-based measures. All four of the indices display dramatic increases in auction prices of more than 200% between 2003 and 2008. All four indices peak in 2008Q1, which is before the peak in sales and annual median prices in the sample. This conforms to the idea that there was a surge in the popularity of South African art over the period, as well as to the idea of the formation of a so-called bubble, with a dramatic rise and subsequent decrease in prices. The indices are all relatively flat after 2009, even in nominal terms.

The hedonic price indices therefore 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 might include, for instance, interaction terms (e.g. artist and medium combinations), squared terms, finer medium classifications (e.g. linocuts), or attributes such material, theme and style (e.g. canvas or landscape). 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, 2013).

In the following section, alternative art price indices were estimated using a hybrid repeat sales methodology, which should be less prone to omitted variable bias. If the alternative indices display the same kind of trend and the same marked increase in prices as the hedonic indices, this would provide more confidence that the results are robust to changes in methodology

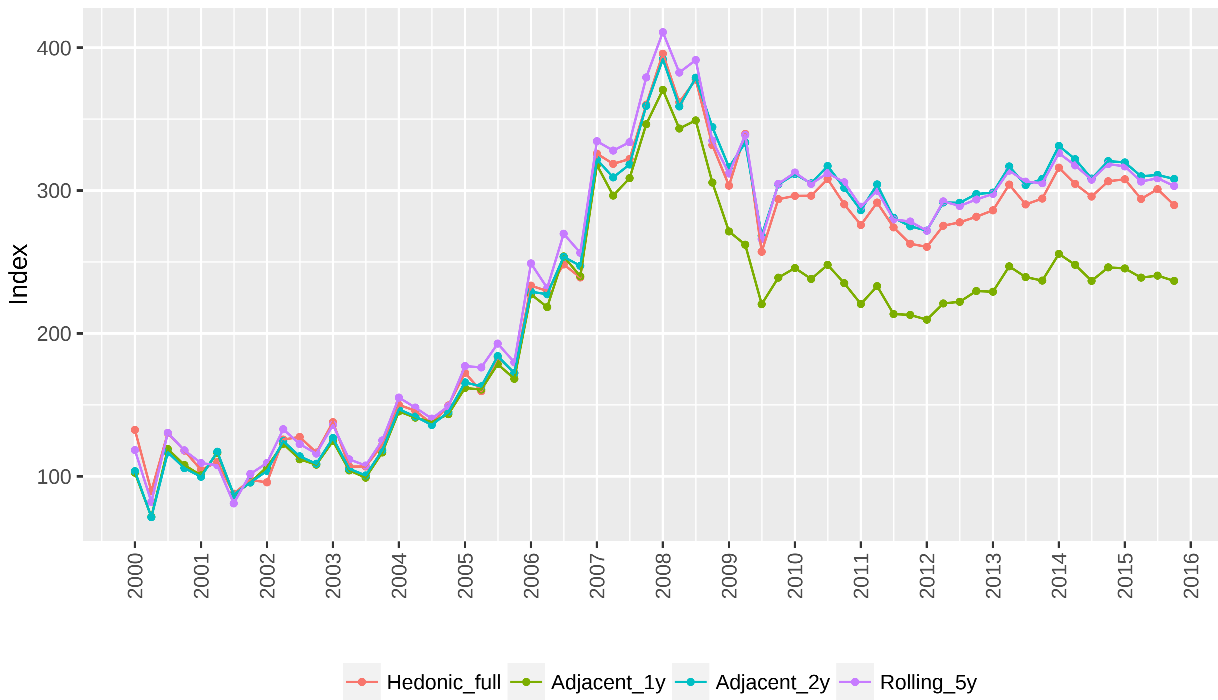

Figure 7: Hedonic index of South African art prices (2001=100)

and that omitted variable bias is not driving the results.

1.4.3 Repeat Sales and Hybrid Indices

The repeat sales method is less prone to potential omitted variable bias than the hedonic method, as it tracks 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 attributes: artist name, artwork title, size, 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 2.8 illustrates the index generated using the classical repeat 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.

In this chapter a simple new hybrid repeat sales model is proposed as an alternative. This procedure is similar in spirit to the 'pseudo repeat sales' (ps-RS) procedure suggested by Guo *et al.* (2014). Instead of requiring exact matches to form 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 for the estimation of a variant of the repeat sales index, which should address to some extent the potential omitted variable bias inherent in the hedonic method. The caveat is that even two artworks by the same artist of a similar size and in the same medium do not

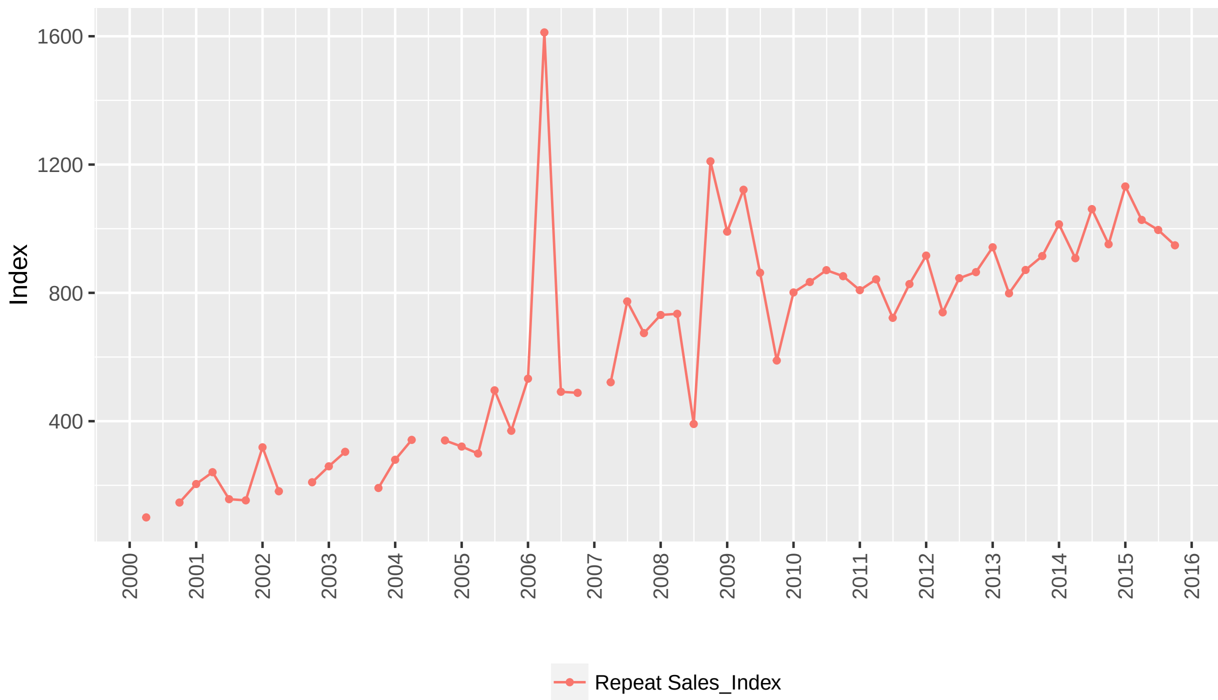

Figure 8: Repeat sales index of South African art prices (2000Q4=100)

necessarily serve as close substitutes (Olckers, Kannemeyer and Stevenson, 2015).

The first ps-RS sample was created by matching artworks on all the hedonic attributes, except for the title of the artwork. The matched pairs therefore have the same hedonic attributes except for the title of the artwork. Matching by these criteria increased 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 date on the artwork, i.e. the authenticity dummies. This increased the pseudo repeat sales sample to 7,965 sales pairs. This involved a trade-off between the within-pair 'similarity' and the sample size. Higher similarity is good for mitigating bias, while a larger size is good for reducing random errors (Guo *et al.*, 2014).

The differential hedonic equation was 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 these within-pair differentials in attributes, which are relatively small and easy to measure.

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 2.9 illustrates the two versions of the ps-RS indices. The indices point to similar cyclical trends in art prices over the sample period. 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, peaked in 2008Q1, and were relatively flat after 2009. The indices point to the same kind of marked increase in South African art prices as the hedonic indices, which provides more confidence in the results being robust to changes in methodology. In the following section, indices for different segments of the art market are estimated, in order to establish in which segments the marked price increases occurred. A few indices are also estimated for individual artists. In the subsequent section, the internal and external validity of the indices are assessed, and the indices are directly evaluated in terms of signal-to-noise metrics.

1.4.4 Market Segments and Artist Indices

Different segments of the South African art market may have exhibited different price trends over time. This section examines different segments of the market, in order to establish in which segments the marked price increases occurred. The market may be segmented in a number of ways, such as by price, artist value, and medium category. The caveat is that slicing the data thinly results in small sample sizes and more volatile indices. This makes it more difficult to discern a pattern and to distinguish the signal from the noise. The indices should therefore be interpreted with caution.

Fedderke and Li (2014) suggested that the South African art market should be segmented into three price ranges and found different hedonic relationships for the three market segments. The art market may be segmented for a variety of reasons, such as the following: first, wealthy individuals may be less tempted to buy artworks at the lower end of the market that do not signal the same social status; second, small investors are typically unable to purchase more expensive artworks; and third, more expensive artworks may be more prone to speculation (Renneboog and Spaenjers, 2013).

Historical rates of appreciation may therefore have varied across the price distribution

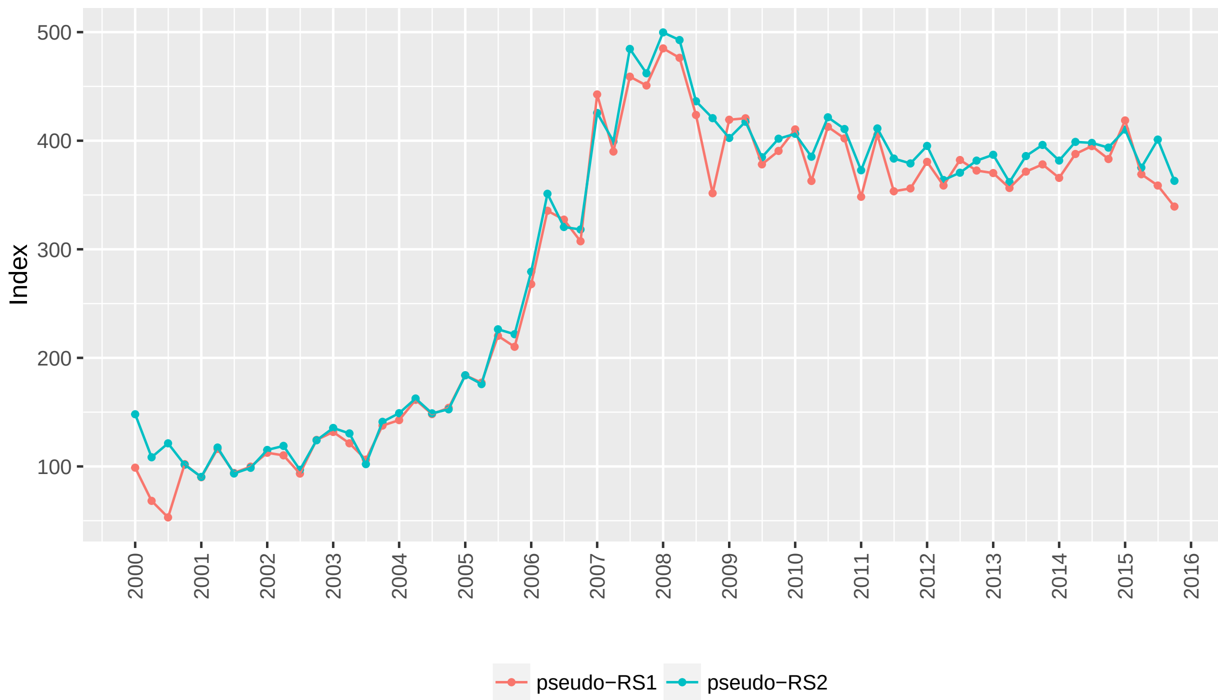

Figure 9: Pseudo-repeat sales index of South African art prices (2001=100)

(Renneboog and Spaenjers, 2013). In order to test this possibility, different parts of the price distribution may be investigated by estimating separate hedonic indices for each segment. This allows the characteristic prices to vary across the price distribution. Figure 2.10 illustrates the three indices for the bottom 25% of the price distribution ('Lower'), the interquartile range ('Middle'), and the upper 25% of the price distribution ('Upper').[14] The indices suggest that the dramatic price increases occurred in the upper part of the price distribution, which includes artworks with a hammer price of more than R22,000.

Quantile regressions provide an alternative means to investigate different parts of the price distribution and are also more robust to potential outliers. Quantile regressions can characterise the entire distribution of the dependent variable, as opposed to OLS regressions, which provide estimates for conditional means. Figure 2.10 illustrates the indices resulting from quantile regressions for the 25th, 50th, and 75th percentiles. The quantile art price indices do not exhibit large differences between the different segments. The lower end of the market seems to have depreciated slightly less after the peak in 2008.

Another potential segmentation is by medium category. It is possible that historical rates of appreciation have varied widely over time for different medium categories. Separate hedonic models may be estimated for each of the mediums. Figure 2.10 illustrates the indices for five

[14]The models are estimated with the full sample hedonic method. The models include dummy variables for all the artists that sold more than one artwork during the sample period. The adjacent-period hedonic and ps-RS models were used to confirm the results. In many cases, however, there are too few observations to estimate complete indices.

of the medium categories, which together account for 92% of the observations in the sample. Oil paintings are by far the largest category, representing 52% of the volume and 78% of the value of artworks in the sample. The indices indicate that oil was the medium for which there were the largest price increases.

Finally, the market may also be segmented by artist. In order to examine the price appreciation of the more expensive artists' work, the artists are ranked according to the average value of their artworks sold in the sample (i.e. average price per artwork). Separate hedonic regressions can then be estimated for the bottom 25% of the value distribution (i.e. for all artists in the lower part of the value distribution), the interquartile range, and the upper 25% of the distribution. Figure 2.10 indicates that prices increased more dramatically for artworks by the more expensive artists, which in this case includes the top 262 artists in terms of average price per artwork.

Overall, the results seem to indicate that the dramatic price increases occurred in more expensive or high-end parts of the art market, and especially for oil paintings.

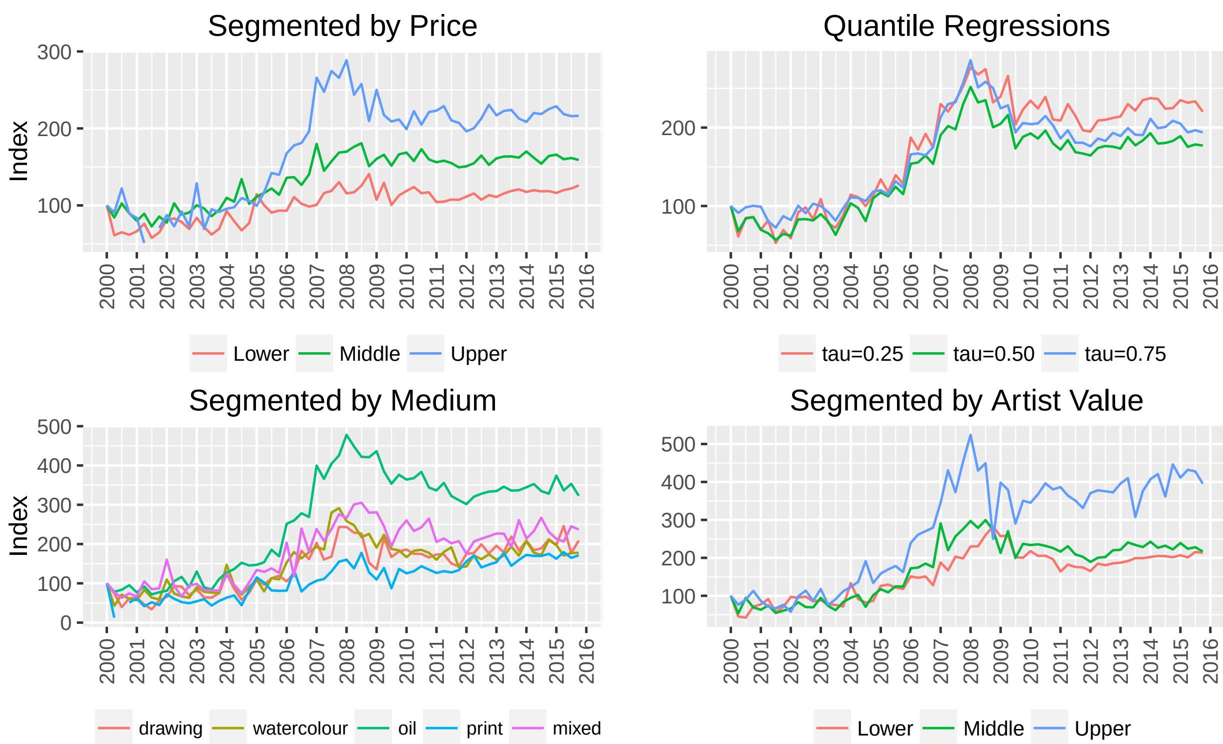

Figure 10: Art price indices for different market segments (2000Q1=100)

The sample may be further segmented in order to estimate separate indices for specific artists. Figure 2.11 illustrates indices for four of the leading South African artists, derived from separate hedonic models. Walter Battiss and Gregoire Boonzaier are the top selling artists in the sample in terms of number of sales (most observations). The Battiss index exhibits a sustained quality-adjusted price increase over the period, whereas the Boonzaier index exhibits a more pronounced cyclical pattern.

Irma Stern and JH Pierneef are two of the country's 'masters' and the top-selling artists in terms of turnover. The Pierneef index exhibits a strong increase over the period, but is quite volatile. The Stern index has some missing values towards the beginning of the sample period and is even more volatile. The quality-adjusted prices for Stern do not increase as much as one perhaps would have expected, given the record prices achieved during the sample period. This indicates that the record prices were in line with the model predictions. The large spikes in the Pierneef and Stern indices illustrate the small sample problem when slicing the data too thinly. In the quarters with large spikes, only a single artwork by each of the artists was sold. Although these artworks were not particularly expensive, they achieved hammer prices well above the model predictions, which is reflected in the index values.[15] Nonetheless, all four artist indices exhibited large spikes between 2006 and 2007.

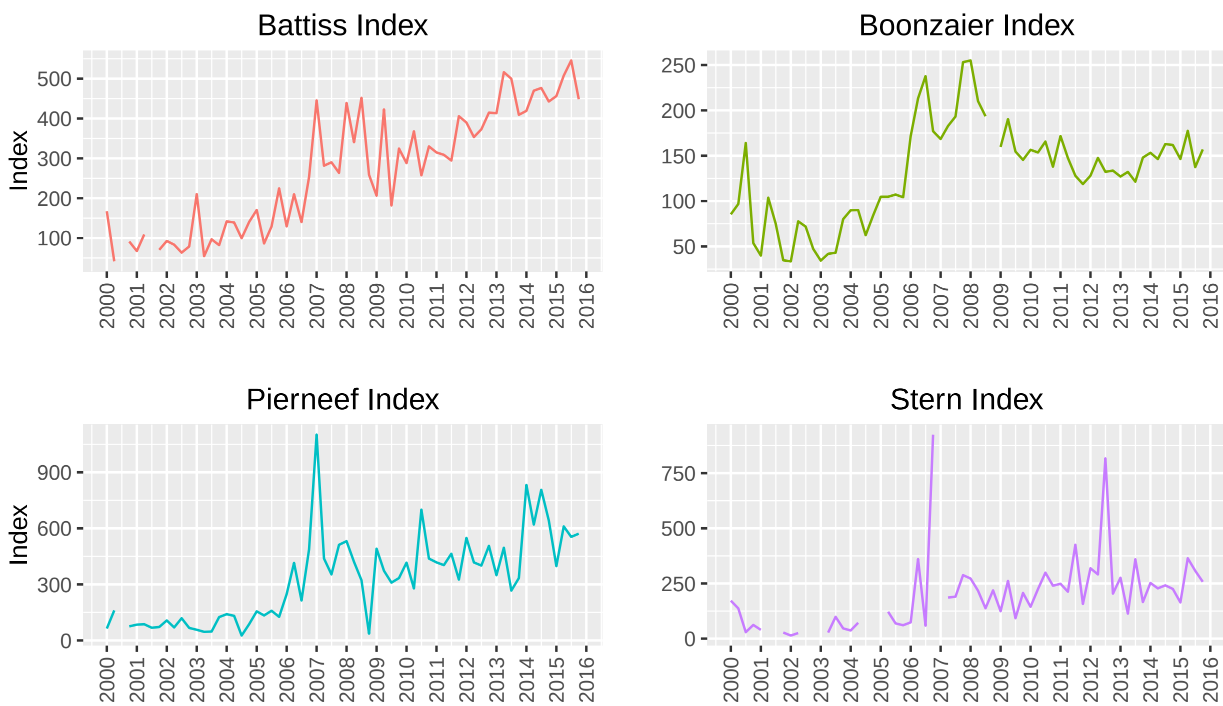

Figure 11: Art price indices for individual artists (2000=100)

1.5 Validity Tests and Evaluation

In this section, the internal validity of the indicators is assessed by comparing the indices estimated with the different methodologies, in order to determine whether they provide a consistent picture of price movements in the South African art market. In the absence of an existing South African art price index, as an external validity test, the art price indices are compared with other South African assets, as well as with available international art

[15]For instance, the large spike in 2006 in the Stern Index, was due to a single watercolour (gouache) painting *Lady of the Harem*, which sold for R2.2 million at Stephan Welz & Co.

price indices over the sample period. The indices are then evaluated in terms smoothness, to examine which index provides the most credible gauge of overall price movements in this specific case.

1.5.1 Internal Validity Test

The art price indices were first compared graphically. Figure 2.12 illustrates representative indices for the three methodologies: median values, the 1-year adjacent-period hedonic index and the second version (larger sample) of the ps-RS index. The two regression-based indices seem to point to a similar general trend in South African art prices. The simple median index, on the other hand, does not reflect this trend and is much more volatile than the regression-based indices. This implies that regression-based methods, which adjust for changes in the composition of artworks sold, provide better estimates of pure price changes for unique assets. The results echo the findings in Els and Von Fintel (2010) for South African real estate prices.

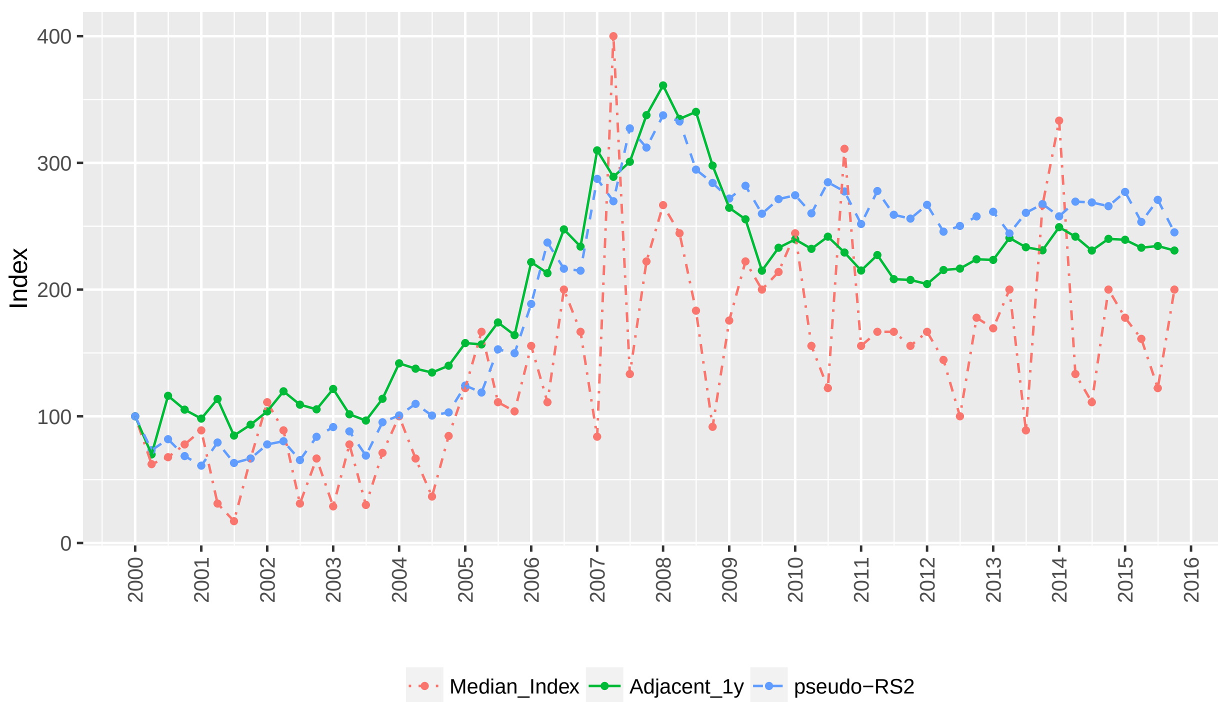

Figure 12: Comparing South African art price indices (2000Q1=100)

The hedonic and ps-RS indices exhibit similar trends over the sample period, although the hedonic index is at a lower level after 2009. Both measures indicate that the average price of a quality-adjusted artwork increased significantly between 2005 and 2008 and then declined sharply after the financial crisis, similar to other asset prices (Shimizu, Nishimura and Watanabe, 2010). Both indices are relatively flat after 2009 in nominal terms, implying that art prices decreased in real terms over latter part of the sample period.

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 acts as an internal validity test, to check that the results are not driven by the inherent biases of a specific method.

Table 2.2 reports the correlations in the growth rates between the various indices.[16] There is a significant positive correlation between the regression-based indices. This indicates that their general trends are similar, and are different from the simple median. The Fisher central tendency index is also significantly positively correlated with the hedonic indices. This shows that there is some consistency in the estimates from the different methodologies, which provides some confidence that the indices provide a reasonably accurate measure of the price movements in the South African art market. The following section compares the indices with other South African assets, as well as with available international art price indices. The subsequent section then evaluates the indices in terms of index smoothness.

Table 2: Correlations between art price indices (in growth rates)

	Median	Fisher	Hedonic	Adjacent-1y	Adjacent-2y	Rolling-5y	Repeat Sales	ps-RS1
Median								
Fisher	0.13							
Hedonic	0.03	0.38***						
Adjacent-1y	0.09	0.32**	0.90***					
Adjacent-2y	0.10	0.34***	0.95***	0.98***				
Rolling-5y	0.22*	0.35***	0.94***	0.94***	0.95***			
Repeat Sales	0.33**	0.00	-0.12	-0.08	-0.03	-0.09		
ps-RS1	0.06	0.13	0.49***	0.60***	0.59***	0.51***	0.17	
ps-RS2	0.05	0.13	0.49***	0.60***	0.60***	0.50***	0.34***	0.91***

1.5.2 External Validity Test

Figure 2.13 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 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 argue was as a consequence of the financial crisis. By the end of the period the international art price indices were around the same level as the South African art price indices. This suggests that the estimated indices provide reasonable estimates of pure price changes over the period.

[16]The first few periods of repeat sales estimates are often sensitive when the sample size is small, because of the lack of repeat sales in the first few quarters. In this case, very few artworks had been resold in the few quarters, making the index values very volatile. Indeed, there are no true repeat sales in the first three quarters of the sample period. Therefore, the first three index values were excluded from the comparison.

Renneboog and Spaenjers (2015) examine 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 of returns in the South African and international art price indices, reported in Table 2.3, are not significant.

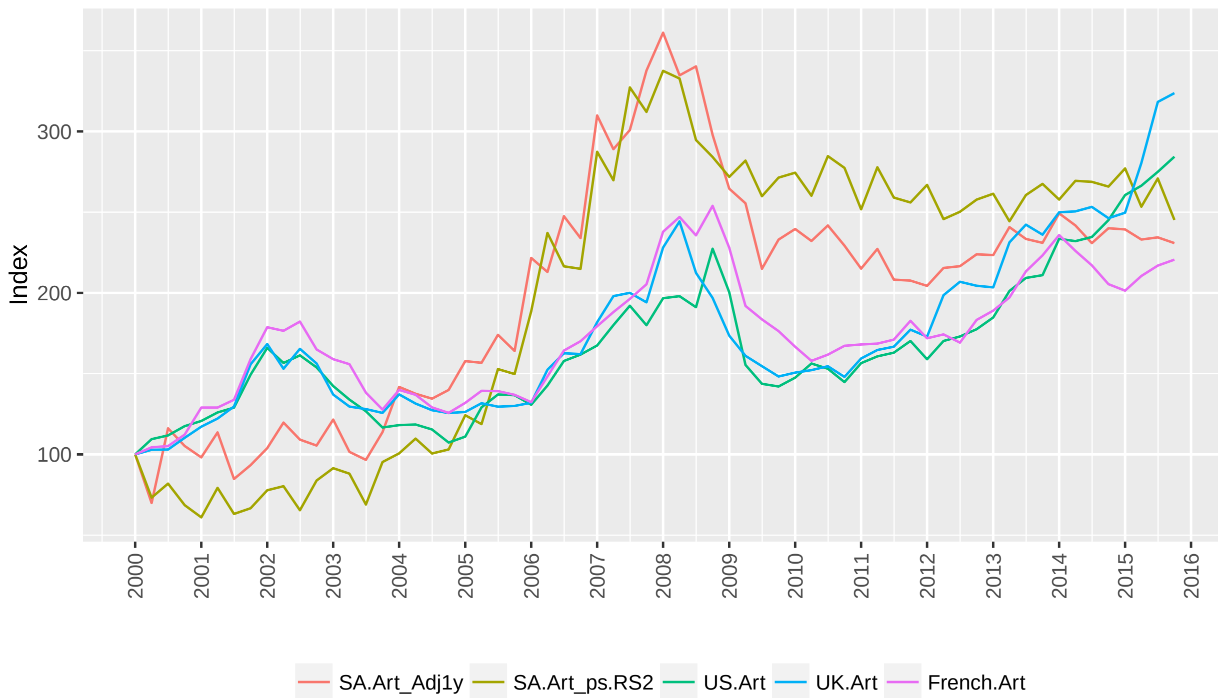

Figure 13: Comparing local and international art price indices (2000Q1=100)

Figure 2.14 provides a comparison of the two representative art price indices with indices for other South African assets: the JSE All Share Index, the All Bond Index, and the ABSA House Price Index. The correlations in returns between the art price indices and the equity and property indices, reported in Table 2.3, are positive and significant, although the coefficients are relatively low.

Table 3: Correlations between asset prices (in growth rates)

	SA.Art_Adj1y	SA.Art_ps.RS2
US.Art	0.00	-0.07
UK.Art	0.09	0.00
French.Art	0.08	-0.02
SA.Bonds	0.02	-0.05
SA.Equity	0.38***	0.39***
SA.Property	0.40***	0.39***

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. The equity and property markets peaked at around the same time as the art price indices. After 2009,

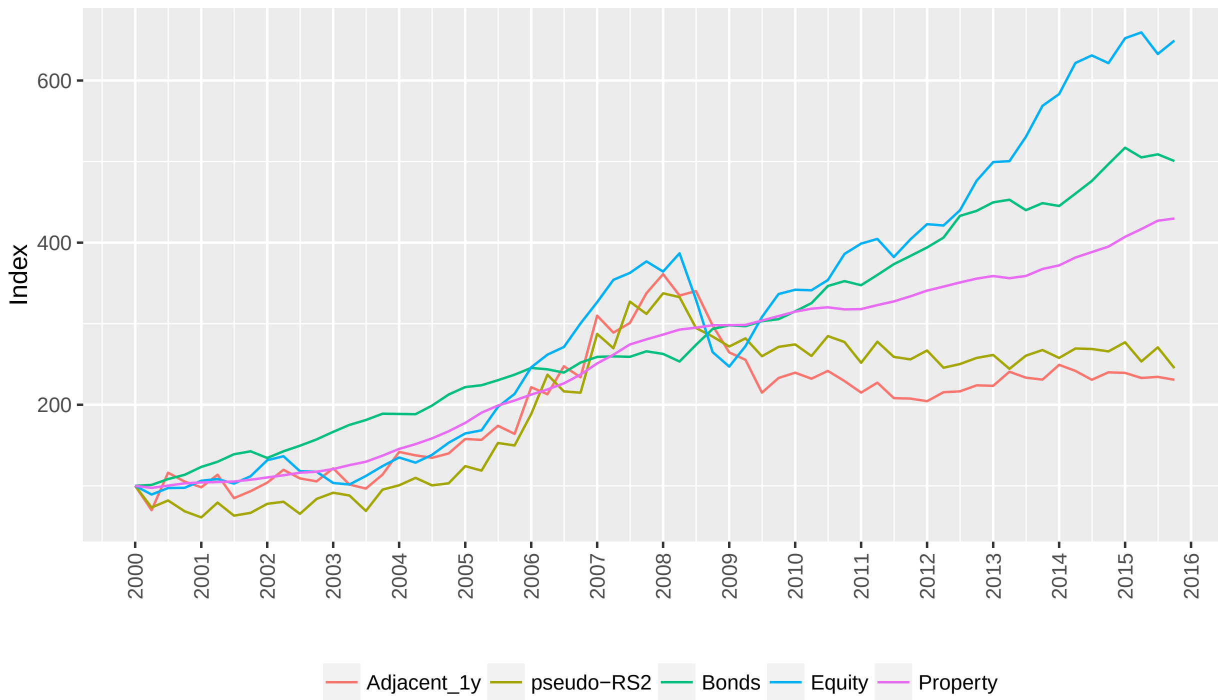

Figure 14: Comparing South African asset price indices (2000Q1=100)

however, the art price indices lagged substantially behind the other asset price indices. The art price indices were relatively flat, while the other asset price indices increased markedly.

The fact that local asset prices have increased much more than art prices over the entire period, suggests that the art price indices do not provide outlandish estimates of pure price changes over the period. It also implies that an investment in a 'standard artwork' or the art market in general would not have yielded comparable returns to other investment opportunities. Nevertheless, further research applications might use the art price indices to evaluate whether art would have formed part of an optimal investment portfolio, as is often done in the international literature (e.g. Campbell (2009) and Kräussl (2015)). This would be a more direct way of assessing the potential diversification benefits of art investments than in Botha, Snowball and Scott (2016). Further research might also evaluate whether specific segments of the South African art market (e.g. specific artists) would have yielded diversification benefits.

1.5.3 Evaluation

In this section, the indices produced with the different methodologies are directly evaluated, in order to assess which index provides the most accurate measure of South African art prices over time. This is not usually attempted for art price indices, given that most papers focus on a specific method. In other applications, the quality of price indices has often been evaluated based on the diagnostic metrics of the underlying regressions, such as the standard errors of the residuals (see e.g. Hansen (2009)).

However, Guo *et al.* (2014) argued that the regression residuals do not reflect errors in the price index itself, and hence do not directly reflect inaccuracy in the index returns. Even if an index is a perfectly accurate measure of the central tendency of price changes, the regression would still have residuals, and the time dummy coefficients may still exhibit large standard errors, resulting simply from the dispersion of individual art prices around the central tendency. When datasets become large, regression diagnostics can become impressive simply due to the size of the sample. In such cases, tests of economic significance are more valuable than tests of statistical significance. In this case, not all of the indices were generated with regression models. The regressions models that were employed differ in their specifications (in levels or first differences) and the underlying data sets used for estimation.

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

This is demonstrated in the following simple model:

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

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 is therefore important for users of the index. 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 in 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 of the index return ρ_{r^*}, can be derived as:

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

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

where σ_r^2 and σ_η^2 are the variances of the true return and the noise, and ρ_r is the first-order autocorrelation of the true return.

Volatility is a measure of the dispersion in returns over time. There is always true volatility, as the true market prices change over time. An ideal price index will filter the volatility induced by the noise to leave only the true market volatility. In addition to the true volatility, the noise in the index causes excess volatility in the index returns. Excess volatility decreases the first-order autocorrelation of the 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 more accurate art price index in the sense of less noise or random error.

Guo *et al.* (2014) suggested 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.

Another option is to compare the smoothness coefficients proposed by Froeb and Koyak (1994). The smoothness coefficient is defined as the average long-run variance of a time series divided by the average short-run variance. The idea is to obtain the spectral density of the time series, which shows the contribution of all frequencies to the data series. The smoothness measure is then taken as the average of the lower half of the frequency range (i.e. the low-frequency or longer-term movements) over the average of the upper half of the frequencies (i.e. the high-frequencies or shorter-term movements). In other words, the smoothness coefficient is the low-frequency portion divided by the high-frequency portion of the periodogram.[17] A higher smoothness coefficient indicates a larger share of variance in the low frequencies and a smoother time series.

Table 2.4 reports these four 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 volatilities, autocorrelations and HP filter deviations of the regression-based indices are around the same size. The 1-year adjacent-period hedonic index performs the best in terms of these metrics, with the lowest volatility Vol and highest autocorrelation $AC(1)$ in returns, the smallest deviation from its smoothed returns, and the highest smoothness coefficient. However, the smoothness coefficients of the regression-based indices are not significantly different.

1.5.4 Summary and Conclusion

This section has assessed the validity of the indices produced using the central tendency, hedonic and hybrid repeat sales methods. 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.

[17]The spectral density is smoothed using the Daniell window, which amounts to a simple moving average transformation of the periodogram values.

Table 4: Smoothness indicators

	Vol	AC(1)	HP-Deviation	Smoothness
Median	0.612	-0.416	22.11	-0.02
Fisher	0.284	-0.332	4.66	1.00
Hedonic	0.114	-0.323	0.75	1.09
Adjacent-1y	0.105	-0.246	0.63	1.39
Adjacent-2y	0.105	-0.303	0.63	1.10
Rolling-5y	0.112	-0.279	0.73	1.27
Repeat Sales	0.549	-0.403	17.76	0.65
ps-RS1	0.128	-0.360	0.95	0.94
ps-RS2	0.123	-0.342	0.87	1.16

However, the regression-based indices seem to point to the same general movement in South African art prices, with a large increase in the run-up to the Great Recession and a relatively flat trend after 2009. The fairly consistent picture offers some confidence that the indices provide a reasonably accurate measure of the price movements in the South African art market. The external validity tests also suggested that the art price indices provide reasonable estimates of price movements over time, although art prices have lagged substantially behind the asset price indices for other South African assets since 2009.

Moreover, the regression-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. The 1-year adjacent-period hedonic index performs the best in terms of these smoothness metrics. The implication is that the regression-based methods are useful in producing quality-adjusted price indices for unique items, when the composition or quality-mix is not constant over time.

This section has also investigated different segments of the market, in order to establish in which segments the marked price increases occurred. The results for the different market segments seem to indicate that the dramatic price increases occurred in more expensive or high-end parts of the art market, and especially for oil paintings.

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, remained remarkably stable over time. Even if the exact same artworks were not being resold, the same artists' work still made up the 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 before the crisis, 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.

The following section provides a study of the indices to test for evidence of a bubble in South

African art prices. In answering this question, the chapter turns to the literature on bubble detection. Specifically, the bubble detection tests proposed by Phillips, Wu and Yu (2011) are applied to the indices to test the hypothesis that South African art prices exhibited mildly explosive behaviour over the period.

1.6 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 (e.g. Rabe (2011); Hundt (2010); Curnow (2010)). 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 emerging and advanced economies suffered 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) and 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."

Case and Shiller (2003) define the term as "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 above levels that are 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, beyond a level sustainable by fundamentals, 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 intrinsic value, unless the materials used have a high value (Spaenjers, Goetzmann and Mamonova, 2015). 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 interpreted as the rent buyers are willing to pay to own the artwork over a given period. The rent can reflect aesthetic pleasure, but may also provide additional utility as a signal of wealth (Mandel, 2009). The price of an artwork should equal the present value of future private dividends over the holding period, and the expected resale value. The value of the dividend is unobservable and is likely to vary greatly among buyers, based on their motivations and characteristics (Penasse and Renneboog, 2014). Thus, it is almost impossible to 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 bubble detection method developed by Phillips, Wu and Yu (2011). The method is based on a right-tailed augmented Dickey-Fuller (ADF) unit root test, which is able to detect explosive behaviour 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 in 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 identify explosive periods in real estate prices in Singapore. The results suggested an explosive period from 2006Q4 to 2008Q1. Balcilar, Katzke and Gupta (2015) used the method to detect explosive periods in US real estate prices for the period 1830-2013 and found evidence of several bubble periods. Areal, Balcombe and Rapsomanikis (2013) used the methodology to test for 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 non-ferrous metals futures prices on the London Metal Exchange. They found that certain commodity futures markets exhibited bubble-like behaviour, with the majority of the bubble periods occurring 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 art market segments ('Post-war and Contemporary', 'Impressionist and Modern', '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 sample period.

1.6.1 Bubble Detection Framework

The most common bubble detection methods are based on the present value model and a rational bubble assumption (Yiu, Yu and Jin, 2013). 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 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 period 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 may be written as:

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

Rational bubbles occur when buyers are willing to pay more for an asset than the fundamental, as they expect the future price to be higher than its fundamental value (Yiu, Yu and Jin, 2013). If a rational bubble occurs, the asset price consists of a fundamental component and a bubble component. In other words, if there is a gap between the fundamental value and the actual price, an additional 'bubble component', B_t, is 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 a random variable of the following form:

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

.

Thus, the bubble component is included in the equation, with an expected value in period $t+1$ of B_t multiplied by $(1+r_f)$. The bubble component is called a 'rational bubble', as it is in line with the rational expectations framework (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 determined by the series F_t, which in turn is determined by γ_t. The current price of the asset 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 is a stochastic process for which the expected value in period $t+1$ is greater than or equal to the value in period t (Kräussl, Lehnert and Martelin, 2016). If there is no structural change in the fundamental process or explosiveness in the fundamentals, a period of explosive prices has a non-fundamental explanation. Mildly explosive behaviour in P_t (i.e. non-stationarity greater than a unit root) provides evidence of bubble-like behaviour. According to this theory, if a bubble exists, prices should inherit its explosive property (Areal, Balcombe and Rapsomanikis, 2013). Statistical tests can be formulated to detect evidence of explosiveness in the price series (Caspi, 2013).

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 during the process of bubble formation, the gap between the asset price and the fundamental value will exhibit explosive behaviour. They identified two scenarios in which the presence of a rational bubble is implied. 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 not cointegrated, their non-stationary behaviour provides evidence of a bubble. Diba and Grossman (1988) showed that explosive behaviour in prices is a sufficient condition for the presence of a bubble, if the fundamental value is not explosive.

However, unit root and cointegration tests are incapable of detecting explosive prices when a series contains periodically collapsing bubbles. Evans (1991) argued that explosive behaviour is only temporary, as bubbles eventually collapse, which means that explosive asset prices may appear more like stationary or I(1) series. Using simulated data, Evans (1991) showed that bubble detection tests could not differentiate between a stationary process and a periodically collapsing bubble. A series with periodically collapsing bubbles could therefore be interpreted by the standard unit root tests as a stationary series, leading to the incorrect conclusion that the series 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 between unit root processes and periodically collapsing bubbles, as well as identify the dates of their origin and collapse. The test proposed by Phillips, Wu and Yu (2011) involves repeatedly implementing a right-tailed unit root test. The method involves estimating an autoregressive model, starting with a minimum sample window size and incrementally expanding the window.

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.

The 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 testing directly for explosive behaviour, the test avoids the risk of misinterpreting a rejection of the null hypothesis due to stationary behaviour.

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

A limitation of the method is that it is designed to analyse a single bubble period. Phillips, Shi and Yu (2012) expanded the method to account for the possibility of multiple bubbles, by varying both the starting and ending points of the sample 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 bubble period, while the method of Phillips, Shi and Yu (2012) can identify multiple bubble periods. Simulations by Homm and Breitung (2012) indicated that the test worked adequately against other time series bubble detection tests and was particularly effective for real-time bubble detection.

1.6.2 Bubble Detection Results

In this section the South African art market is tested for 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 prices, deflated with the CPI (e.g. Kräussl, Lehnert and Martelin (2016), Caspi (2013) and Balcilar, Katzke and Gupta (2015)). In this case, there was only one potential bubble episode, so the Phillips, Wu and Yu (2011) method is sufficient to provide evidence of mildly explosive behaviour.

As explained above, the method involves estimating an autoregressive model, starting with a minimum fraction of the sample and incrementally expanding the sample window. The model starts with 3 years (i.e. 12 observations) and expands the sample by 1 observation each time. Each estimation yields an ADF statistic. In this case, there did not seem to be a deterministic drift present in the log real art price indices, and the intercept was not statistically significant at conventional levels. However, as the results could have been sensitive to model formulation, two versions of the autoregressive models were used: one without a constant or drift term and one with a drift term. Lags were included to take possible autocorrelation of the residuals into account, and the number of lags k was chosen with the Akaike Information Criterion.

Critical values for the tests were 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 is unrealistic for most economic and financial time series. They argue that a 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.[18]

[18]Phillips et al. (2014) suggest 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 where 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 $\eta \to \infty$ and a model with drift when $\eta \to 0$. The results may be sensitive to the value of η, so Phillips et al. (2014) recommend reporting the results for a range of values of η. In this case, different values of η produce qualitatively similar results.

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 period.

The method can be used to date stamp potential bubble periods. Figure 2.15 and Figure 2.16 illustrate the date stamping procedure for three representative series: median values, the 1-year adjacent-period hedonic index and the second version (larger sample) of the ps-RS index. Figure 2.15 illustrates the case of no drift term, while Figure 2.16 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 hedonic index, and breaches the 99% critical value.

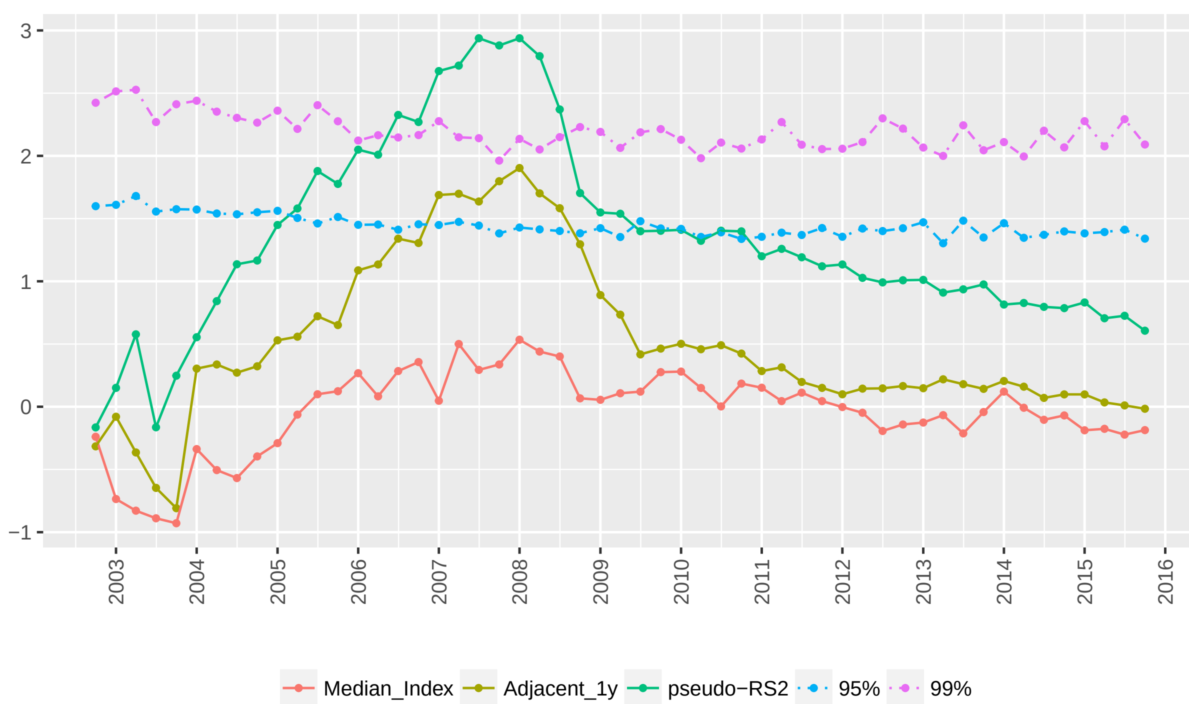

Figure 15: Test statistics and critical values for models without drift

Table 2.5 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 index in terms of smoothness (i.e. the 1-year adjacent index) suggests a period of bubble formation from 2007Q1 to 2008Q3. Phillips, Shi and

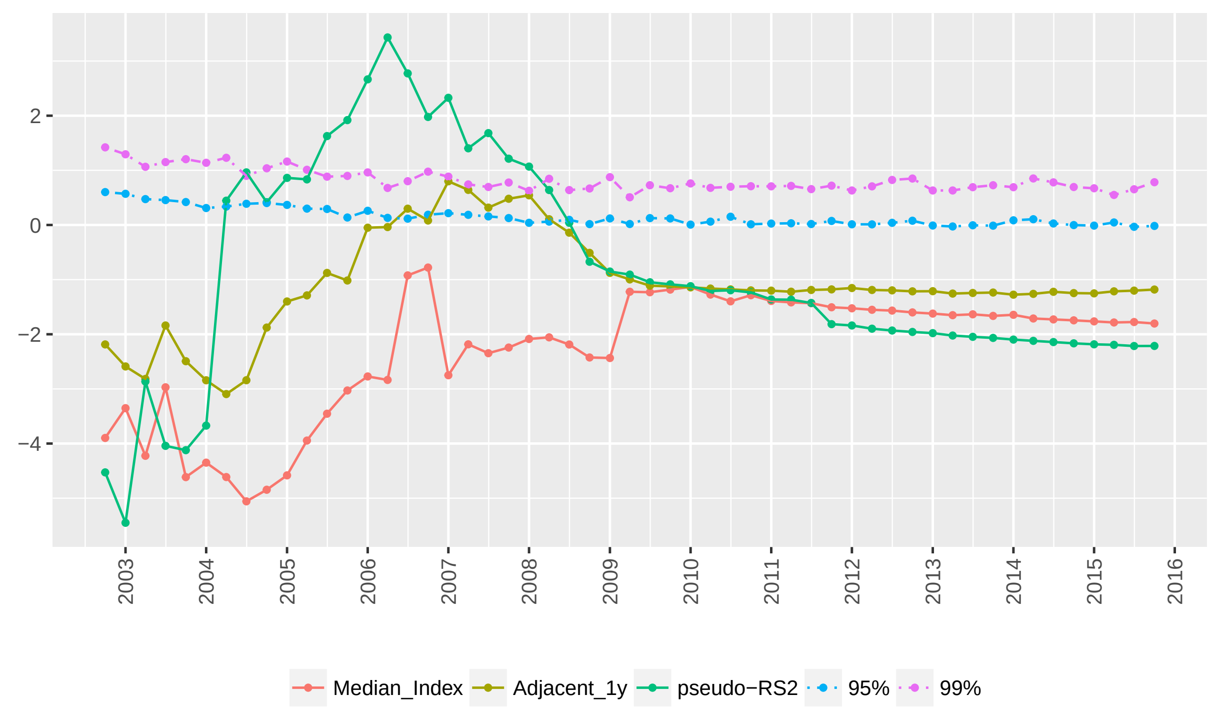

Figure 16: Test statistics and critical values for models with drift

Yu (2012) recommend that only explosive periods lasting more than log(T) units of time should be identified as bubble periods. In this case it implies that the bubble should be at least four quarters in length, and virtually all of the explosive periods identified satisfy this requirement.

Table 5: Dates of explosive price behaviour

	No Drift		Drift	
	Start	End	Start	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 Q2	2008 Q3	2007 Q1	2008 Q2
pseudo-RS1	2006 Q1	2010 Q1	2006 Q1	2008 Q2
pseudo-RS2	2005 Q2	2010 Q4	2004 Q2	2008 Q2

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 and for the 'American' art segments between 2005 and 2008, which also corresponds to the pre-financial crisis period. Interestingly, their findings point 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 flat since 2009.

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 with findings by Spaenjers, Goetzmann and Mamonova (2015), who observed that the timing of record prices does not always coincide with periods of general price increases. They argued that auction price records often occur in situations characterised by extreme supply constraints, resolution of uncertainty about the potential resale value, social competition among 'nouveaux riches', and idiosyncratic shifts in hedonic weights.

1.6.3 Market Segments

As discussed above, different segments of the South African art market exhibited different price trends over time. In this section the price indices for the different segments of the art market are examined, in order to establish how widely dispersed the bubble process was and which segments were responsible for the explosive price increases that occurred. The bubble detection tests were performed on the market segment indices defined above in terms of price, medium and artist value. Again, the caveat is that slicing the data thinly results in small sample sizes and more volatile indices. This makes it more difficult to discern a pattern and to distinguish the signal from the noise.

The results for the origination and termination dates are reported in Table 2.6. In terms of the price segments, the indices for the upper quartile (top 25%) of the price distribution, from both the OLS and quantile regressions, exhibit evidence of explosive behaviour. This implies that the explosive behaviour occurred mainly in the high-end segment of the art market.

In terms of the medium segments, the indices for watercolour and oil paintings show evidence of explosive behaviour according to both model formulations, with more limited evidence for prints/woodcuts and mixed media. In terms of average artist value, all three indices show evidence of explosive behaviour. This may be because the artist segment indices were estimated based on the average values for a specific artist and include their relatively cheap and more expensive artworks. This implies that the bubble-like behaviour occurred mainly for expensive artworks, and not necessarily for artworks by 'expensive' artists.

The explosive behaviour in art market prices therefore seems to have occurred mainly in the high-end oil and watercolour segments of the market. The origination and termination dates seem to be consistent in suggesting a bubble formation period between 2006/2007 and 2008.

1.6.4 Discussion

In this section the reduced-form bubble detection method developed by Phillips, Wu and Yu (2011) was applied to test for periods of explosive behaviour in the art price indices. The use of recursive tests enabled the identification of mildly explosive subsamples in the series. The results indicated that there was evidence of bubble-like behaviour in all of the regression-based art price indices, whereas the simple median index did not exhibit such behaviour. Again, this implies that it is important to control for the composition or quality-mix of items when estimating indices. The regression-based indices provide consistent results

Table 6: Dates of explosive price behaviour in the different market segments

	No Drift		Drift	
	Start	End	Start	End
price_lower				
price_middle				
price_upper			2007 Q1	2008 Q1
tau=0.25				
tau=0.50				
tau=0.75			2007 Q2	2008 Q1
drawing				
watercolour	2007 Q3	2008 Q2	2007 Q3	2008 Q1
oil	2006 Q2	2009 Q2	2006 Q2	2008 Q2
print	2007 Q4	2008 Q3		
mixed	2007 Q1	2009 Q2		
value_lower	2002 Q4	2010 Q1	2007 Q4	2009 Q2
value_middle	2006 Q3	2008 Q4	2006 Q1	2008 Q4
value_upper	2007 Q4	2008 Q1	2007 Q2	2008 Q1

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 bubble detection tests performed on the different market segments indicated that the bubble process occurred mainly in the high-end oil and watercolour segments. The origination and termination dates were also consistent in suggesting a bubble formation period between 2006/2007 and 2008.

The results 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. 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, previous findings in the literature have shown that preferences tend to be stable, even in the long run (Penasse and Renneboog, 2014).

The aesthetic dividend can also fluctuate as wealth fluctuates over time (Spaenjers, Goetzmann and Mamonova, 2015). The literature has provided evidence supporting this idea, with Goetzmann, Renneboog and Spaenjers (2011) finding cointegrating relationships between art prices and top income brackets. Mandel (2009) analysed the satisfaction derived from conspicuous consumption, which increases as the value of art increases. The 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 social status consumption. However, it is unlikely that aesthetic dividends, and factors such as collectors' preferences and wealth, exhibited similar explosive behaviour over the period.

Although the bubble detection 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 buyers are willing to pay more for an artwork than their private value, because they expect to resell it at a higher price in the future. Gérard-Varet (1995), for instance, argued that the sharp rise in world art prices in the late 1980s could be explained by a rational bubble. Although buyers believed that prices had reached unsustainable levels the in short run, the prospects for continued increases were sufficient to compensate for the risk of the bubble bursting. Prices may 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).

An artwork that would be too expensive under normal conditions might become more attractive during a bubble, because buyers might think they will be compensated by further price increases. Buyers may also be concerned that they will not be able to afford the artwork later. Large expected price increases may have a strong impact on demand if buyers think that prices are unlikely to decrease, so that the perceived risk associated with a purchase is minimal (Case and Shiller, 2003).

Penasse and Renneboog (2014) argued that limits to arbitrage induce a speculative component to art prices. Constraints on short selling and high transaction costs may lead to prices diverging from fundamentals, as they prevent arbitrageurs from pulling back prices to fundamental levels (Balcilar, Katzke and Gupta, 2015). When prices are high, pessimists would like to short-sell, but instead they 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 buyers in the future. The price of the option to resell the artwork in the future is the difference between their willingness to pay and their own optimistic valuation. The price of the resale option imparts a bubble component in art prices, and can explain price fluctuations unrelated to fundamentals. These market failures impede the ability to correct price inefficiencies and imply that periods of bubble-like behaviour could exist with little scope for arbitrage. This is especially relevant in 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 booms in volume were mainly driven by short-term transactions, which were interpreted as speculative transactions or trading frenzies. Given the high transaction costs in 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 the trading volume was high, they found that buyers tended to overpay, and earned negative returns in subsequent years. This provides evidence for the 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.

In general, speculative bubbles can act like self-fulfilling prophecies (Rosser, Rosser and

Gallegati, 2012). Prices increase because buyers expect them to increase, with this continuing expectation leading to higher demand, which causes further price increases. If some exogenous shock, such as the financial crisis, ends the price increases, the expectation ceases, and the demand suddenly disappears. Prices decline towards their fundamental value, where there is no expectation of price increases.

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 Impressionist art market in the second half of the 1980s. Hiraki *et al.* (2009) found a high 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 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 chapter, it does illustrate the usefulness of the art price indices for investigating developments in the South African art market.

1.7 Conclusion

The primary aim in this dissertation is to explore aggregation methods that may be useful in overcoming specific data challenges in order to create useful macroeconomic time-series indicators. This chapter has demonstrated aggregation methods to estimate quality-adjusted South African art price indices, using a relatively large microeconomic database of South African auction prices.

Estimating price indices for unique and infrequently traded items, such as artworks, can be challenging because the composition, or quality-mix, of items sold varies over time. Three broad methodologies were used to estimate quality-adjusted price indices for South African art: central tendency, hedonic and hybrid repeat sales methods. Each of the methods has strengths and weaknesses. The hedonic regression method is able to control more adequately for quality-mix changes than central tendency methods. A shortcoming of indices based on the hedonic method is that they may suffer from potential omitted variable bias. In this chapter, a new hybrid repeat-sales method was proposed to address the problem of a lack of repeat sales observations in the sample and to some extent the potential omitted variable bias inherent in the hedonic method.

The regression-based indices differed substantially from the central tendency indices. They produced better estimates of pure price changes, as shown by the smoothness metrics. This demonstrates the importance of regression-based methods for producing quality-adjusted price indices for unique assets. The regression-based indices seem to point to the same general movement in South African art prices, with a large increase in the run-up to the Great Recession and a flat trend after 2009. The relatively consistent picture offers some confidence that the indices provide an accurate measure of the general price movements in the South African art market. The indices for the different market segments indicated that the large price increases occurred in the more expensive or high-end parts of the art market, and especially for oil paintings.

To demonstrate the usefulness of the aggregation methods and the estimated time series, this chapter provided a study of the estimated South African art price indices for evidence of a bubble. A reduced-form bubble detection method was used to test for periods of mildly explosive behaviour in the art price indices. The results showed 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 in 2008. The bubble detection tests performed on the different market segments indicated that the bubble process occurred mainly in the high-end oil and watercolour segments of the market.

An attempt was made in this chapter at three contributions to the literature. The first was to explore and demonstrate aggregation methods to estimate price indices for unique and infrequently traded items, such as artworks, where the composition or quality-mix is not constant over time. These methods capture the central tendency of distribution of growth rates in prices. In addition, a simple new hybrid repeat sales method was proposed, which addresses the lack of repeat sales in the sample and to some extent the potential omitted variable bias of the hedonic method.

The hedonic and hybrid repeat sales methods demonstrated in this chapter may be useful in constructing indices for other unique assets, such as real estate, antiques and wine, where the quality-mix of items differs over time, and there is a lack of repeat sales. International real estate price indices often employ the repeat sales or hedonic methods to calculate quality-adjusted price indices. The repeat sales method, for instance, is used to calculate the S&P/Case-Shiller Home Price Indices in the US.

In South Africa, ABSA, FNB and Standard Bank currently use only stratified central tendency methods to construct their property price indices. These indices often do not correspond closely and often lead to different conclusions on changes in property prices, which illustrates that the indices have substantial shortcomings. This chapter has argued that the central tendency method does not adequately control for quality-mix changes, as was demonstrated for South African property prices by Els and Von Fintel (2010). Changes in the indices may be due to changes in the quality-mix of properties sold, rather than changes in the general price level of the property market. The use of repeat sales or hedonic methods would substantially improve property price indices in South Africa. Moreover, these techniques may be used to calculate the first quality-adjusted price indices for other unique items, such as wine and antiques, as more comprehensive microeconomic datasets become available.

The second contribution was to produce various quality-adjusted South African art price indices. The art price indices, reported in the Appendix below, are useful for investigating and understanding developments in the South African art 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. This would be a more direct way of assessing the potential diversification benefits of art investments than in Botha, Snowball and Scott (2016). Further research might also evaluate whether specific segments of the South African art market (e.g. specific artists) would have yielded diversification benefits. Conventional wisdom says that the top artworks by established artists tend to outperform the rest of the market (Mei and Moses, 2002). This so-called 'Masterpiece effect' may be investigated by examining the specific collections of artworks in the upper part of the price distribution.

The third contribution was to use the art price indices to test for evidence of episodes of mildly explosive prices, which demonstrates the usefulness of the 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 explosive behaviour in art market prices seems to have occurred mainly in the high-end oil and watercolour segments. Future research might further consider the drivers of the bubble formation process, in order to provide an explanation of the bubble episode. Potential factors that influenced the fluctuations in art prices over time, such as wealth effects, might also be investigated. The quality-adjusted art price indices estimated in this chapter can facilitate these inquiries and enable one to be more concrete about developments in the South African art market.

1.8 Appendix

Table 7: Art price indices (2000Q1=100)

Date	Median	Hedonic_full	Adjacent_1y	pseudo.RS1	pseudo.RS2
2000 Q1	100.00	100.00	100.00	100.00	100.00
2000 Q2	62.22	67.65	69.90	69.06	73.24
2000 Q3	67.70	98.31	116.15	53.67	81.92
2000 Q4	77.78	89.06	105.22	103.29	68.58
2001 Q1	88.89	78.88	98.15	91.06	61.03
2001 Q2	31.11	83.04	113.62	117.47	79.30
2001 Q3	17.22	66.34	84.78	95.07	63.14
2001 Q4	66.67	73.56	93.37	100.94	66.67
2002 Q1	111.11	72.33	103.86	113.84	77.79
2002 Q2	88.89	94.89	119.71	111.45	80.31
2002 Q3	31.11	96.29	109.16	94.46	65.43
2002 Q4	66.67	88.04	105.49	125.86	83.81
2003 Q1	28.89	104.10	121.58	133.22	91.47
2003 Q2	77.78	80.62	101.58	122.68	88.08
2003 Q3	30.00	80.70	96.61	107.48	68.97
2003 Q4	71.11	92.13	113.81	139.18	95.28
2004 Q1	100.00	113.23	141.79	144.28	100.66
2004 Q2	66.67	110.09	137.56	163.16	109.79
2004 Q3	36.67	103.22	134.52	149.85	100.56
2004 Q4	84.44	112.91	139.90	155.70	103.07
2005 Q1	122.22	130.13	157.77	186.05	124.25
2005 Q2	166.67	120.44	156.72	179.16	118.76
2005 Q3	111.11	138.49	174.06	222.76	152.84
2005 Q4	103.89	130.04	164.04	212.58	149.77
2006 Q1	155.56	176.14	221.66	270.93	188.65
2006 Q2	111.11	173.32	212.95	339.30	237.13
2006 Q3	200.00	187.35	247.51	331.05	216.46
2006 Q4	166.67	180.48	233.91	310.89	214.91
2007 Q1	83.89	245.81	309.88	447.67	287.39
2007 Q2	400.00	240.42	288.98	394.42	269.73
2007 Q3	133.33	243.01	300.87	464.20	327.24
2007 Q4	222.22	271.67	337.65	455.97	312.07
2008 Q1	266.67	298.57	361.12	490.53	337.50
2008 Q2	244.44	272.96	334.73	481.75	332.74
2008 Q3	183.33	284.90	340.26	428.52	294.68
2008 Q4	91.67	250.35	297.88	355.61	284.16
2009 Q1	175.56	228.94	264.54	424.09	271.84
2009 Q2	222.22	256.24	255.48	425.45	281.92
2009 Q3	200.00	194.02	214.92	382.50	259.86
2009 Q4	213.89	221.79	233.00	395.02	271.39
2010 Q1	244.44	223.53	239.58	415.09	274.43
2010 Q2	155.56	223.60	232.14	367.04	260.18
2010 Q3	122.22	232.43	241.76	417.49	284.71
2010 Q4	311.11	219.07	229.25	406.67	277.41
2011 Q1	155.56	208.16	215.03	352.31	251.76
2011 Q2	166.67	220.01	227.26	410.11	277.79
2011 Q3	166.67	206.91	208.22	357.44	259.03
2011 Q4	155.56	198.25	207.62	360.08	256.00
2012 Q1	166.67	196.62	204.35	384.85	266.90
2012 Q2	144.44	207.75	215.44	362.78	245.68
2012 Q3	100.00	209.57	216.55	386.57	250.23
2012 Q4	177.78	212.51	223.91	376.75	257.75
2013 Q1	169.44	215.90	223.41	374.40	261.40
2013 Q2	200.00	229.49	240.74	360.51	244.34
2013 Q3	88.89	219.03	233.41	375.71	260.59
2013 Q4	266.67	222.10	231.00	382.48	267.50
2014 Q1	333.33	238.42	249.26	369.90	257.79
2014 Q2	133.33	229.86	241.77	392.16	269.40
2014 Q3	111.11	223.18	230.81	399.53	268.77
2014 Q4	200.00	231.24	240.03	387.49	265.83
2015 Q1	177.78	232.30	239.31	423.43	277.07
2015 Q2	161.11	221.90	233.04	373.30	253.39
2015 Q3	122.22	227.06	234.39	362.78	270.84
2015 Q4	200.00	218.67	230.83	343.20	245.17

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