Art Market Performance Index

White Paper

1. Introduction

This document describes the construction of Art Market Research's (AMR) Art Market Performance Indexes and the methodology underlying their calculation.

AMR uses a disruptive and innovative approach to valuing art, departing from the conventional non-appraisal methodology.

The unique nature of each piece of art renders direct comparisons problematic, while like-for-like sales are sufficiently rare and distant in time that such sparse data do not lend themselves well to developing robust price indices.

Auction sales data, being rich due to the number and frequency of transactions, offer an unbiased assessment of the value of artworks at the point of sale, as the hammer price exceeds the maximum willingness to pay of all bidders except (perhaps) the buyer.

Since artists tend to specialise in particular types of work, combining auction sales data by artist allows "brand" values to be developed with hammer prices expressing the prevailing sentiment for an artist at the time of sale. Indices therefore reveal any *changes* in sentiment, and hence value, of artists over time.

2. Artist Price (AP)

2.1 Overview

Just as an investment bank might determine the market value of a company's shares before floatation on a stock exchange, AMR determines an average value for an artist whose works are put up for sale at auction. AMR calls this value the 'Artist Price' and makes the calculation for each artist in AMR's large database.

2.2 Frequency

The number of lots sold by an artist within a designated timeframe establishes a frequency of sales which are assessed from month to month. The categories are divided into *Frequent* ($\geq$ 60 lots sold in the sample window), *Medium* (11 to 59 lots sold) and *Rare* ($\leq$ 10 lots sold), denoted F, M and R, respectively. An example is shown in column D in Figure 1.

Figure 1: Example of frequency of sales categories: F = Frequent, M = Medium, and R = Rare.

Example: For a 24-month sample window of 2021-2022, the results were:

- F (frequent): 171 artists (2.47% of the total).
- M (medium) = 1,338 artists (19.36% of the total).
- R (rare) = 5402 artists (78.17% of the total).

Thinly traded artists

Most artists (approximately 80%) in a sample window are categorised as "rare" due to limited lots sold at auction. This rare class includes some of the rarest and most expensive works, so it is desirable to include these in an art price index. **The Art Market Performance Index includes F, M and R artists (see Section 3).** For those who feel all sufficiently thinly traded artists should not feature due to the sparsity of sales, see Art Market Performance Core (2.3).

2.3 Art Market Performance Core

The **Art Market Performance Core** index is a member of the Art Market Performance family of indexes and employs the same algorithms in its construction. 'Core' refers to artists whose works are sold regularly at auction. The index excludes artists with fewer than 30 sales in a two-year period.

Core Artists

Artists whose works are sold at least 30 times in a two-year period are considered 'core' constituents of the Art Market Performance family of indexes. The Art Market Performance Core consists exclusively of these artists which include some of the most popular and famous Painters, Sculptors, Printmakers and Photographers*. A list of these most frequently traded artists is updated and published monthly on the Art Market Performance Index.

*In cases where a large number works by the same artists are consigned to a single sale, the artist may be registered as a 'core' artist. These sales are rare and so average values can be considered negligble within the index as a whole.

2.4 Sampling

The Art Market Performance Index uses a number of leading auction houses globally from which to take a sample (for a complete list of auction houses, see 3.3 Auction house list). The auction houses chosen are selective about which works of art they take on consignment and this 'curation' of sales provides a basis for the list of artists tracked monthly. Sales at these auction houses also represent a significant proportion of global sales by value.

2.5 Sample Window

12-month, 24-month and 36-month duration sample windows were tested for a group of artists.

A 24-month window was chosen for the final 'Artist Price' calculation. (A 12-month window suffers from excessive changes in category sizes, while a 36-month window would not capture sentiment changes sufficiently quickly.)

2.6 Weighting

A weighted average is an average that has multiplying factors to give different weights to data at different positions in the sample window. 'Date insensitive' and 'date sensitive' weighted moving averages were tested.

Weighted Moving Average – Date Insensitive

This approach attaches weights to observations which decrease arithmetically, with older observations having the smallest weights.

Methodology

Suppose there are sales for a particular artist over the previous 24-month window. For *i = 1,2,…, N*, where *i = 1* is the oldest value and *i = N* is the most recent value, attach the weight:

$$\frac{2i}{N(N+1)}$$

and calculate the weighted average for the 24-month window as:

$$\sum_{i=1}^{N} \frac{2ix_i}{N(N+1)}$$

where *xi* is the *i*th sale value in the 24-month window. Examples are given in columns B and C for *N = 10* and *N = 12* in Figure 2.

	A	B	C	D	E	F	G
1	Weighted moving average examples						
2							
3	N = 10						
4							
5	Sale number	Weights (date insensitive)	Sale value		T_i	Weights (data sensitive)	
6	1	0.018181818	22000	22	4.318182	0.022055348	
7	2	0.036363636	20000	15	6.333333	0.032347844	
8	3	0.054545455	30000	14	6.785714	0.034658405	
9	4	0.072727273	35000	10	9.5	0.048521767	
10	5	0.090909091	35000	8	11.875	0.060652208	
11	6	0.109090909	40000	7	13.57143	0.069316809	
12	7	0.127272727	60000	7	13.57143	0.069316809	
13	8	0.145454545	50000	6	15.83333	0.080869611	
14	9	0.163636364	45000	5	19	0.097043533	
15	10	0.181818182	50000	1	95	0.485217665	
16							
17	Weighted moving average	=	44218			45596	
			=SUMPRODUCT(B6:B15,C6:C15)			=SUMPRODUCT(C6:C15,F6:F15)	
18							
19							
20	N = 12						
21							
22	Sale number	Weights (date insensitive)	Sale value		T_i	Weights (data sensitive)	
23	1	0.012820513	22000	24	5.791667	0.01864482	
24	2	0.025641026	20000	21	6.619048	0.021308366	
25	3	0.038461538	30000	18	7.722222	0.02485976	
26	4	0.051282051	35000	16	8.6875	0.02796723	
27	5	0.064102564	35000	14	9.928571	0.031962549	
28	6	0.076923077	40000	11	12.63636	0.040679608	
29	7	0.08974359	60000	9	15.44444	0.049719521	
30	8	0.102564103	50000	9	15.44444	0.049719521	
31	9	0.115384615	45000	7	19.85714	0.063925098	
32	10	0.128205128	50000	6	23.16667	0.074579281	
33	11	0.141025641	53000	3	46.33333	0.149158562	
34	12	0.153846154	60000	1	139	0.447475685	
35							
36	Weighted moving average	=	47885			52136	
37							

Figure 2: Examples of data insensitive and data sensitive weighted moving averages.

Weighted Moving Average – Date Sensitive

Like the date insensitive method, but this approach takes into account how recent the sales were in the 24-month window, with proportionally more weight placed on more recent sales. This differs from the date insensitive approach which treats sales as being uniformly spread over the 24-month window. Anticipating a degree of market sentiment may affect prices, the length of time which has passed should be modelled.

Methodology

Suppose there are N sales for a particular artist over the previous 24-month window. For $i = 1, 2, \ldots, N$, where $i = 1$ is the oldest value and $i = N$ is the most recent value, define:

$$T_i = \text{\# of months since the current month.}$$

For example, if observing the window January 2021 – December 2022, and if sale 1 occurred in January 2021, then $T_1 = 24$ and if sale N occurred in December 2022, then $T_N = 1$. The initial weights, $\widetilde{w_i}$, are then computed as:

$$\widetilde{w_i} = \frac{\sum_{i=1}^{N} T_i}{T_i}$$

which are then normalised to be in $[0,1]$, with the final weights, w_i, being:

$$w_i = \frac{\widetilde{w_i}}{\sum_{i=1}^{N} \widetilde{w_i}}.$$

Examples are given in columns D, E and F for $N = 10$ and $N = 12$ in Figure 2.

A date insensitive weighting computes different weights for works sold by artists in the same calendar month as only the order of sales is relevant. Date sensitive weighting ensures all works traded in the same calendar month are equally weighted. **The date sensitive approach was chosen for the final methodology.**

2.7 Smoothing

Data smoothing refers to a statistical approach of eliminating outliers from datasets to make trends more noticeable. It is achieved using an algorithm to eliminate statistical noise from datasets. Exponential smoothing is one of many modelling techniques commonly applied to smooth data in signal processing, acting as low-pass filters to remove high-frequency noise. It can also be extended to support data with a systematic trend or seasonal component.

Methodology

Let S_t denote the moving average value, based on sales price data $x_1, x_2, \ldots, x_t$. We then have for $t = 1$:

$$S_t = x_1$$

and for $t > 1$:

$$S_t = \alpha x_t + (1 - \alpha) S_{t-1}.$$

This procedure requires the specification of the smoothing parameter, α, where $0 < \alpha < 1$. The larger the value of α, the greater the weight attached to the most recent observation. Examples are given in columns C and D for α values of 0.50 and 0.20 in Figure 3.

There is no single "right" value for α. Different values were considered. **A set of parameters (α = 1, i.e. no smoothing, α = 0.50 and α = 0.20) is available with the final index to allow users to make their own choice.**

C7		fx	=0.5*$B7+(1-0.5)*C6	
	A	B	C	D
1	Exponential moving average			
2				
3				
4				
5	Sale number	Sale value	alpha = 0.50	alpha = 0.20
6	1	22000	22000	22000
7	2	20000	21000	21600
8	3	30000	25500	23280
9	4	35000	30250	25624
10	5	35000	32625	27499
11	6	40000	36313	29999
12	7	60000	48156	35999
13	8	50000	49078	38800
14	9	45000	47039	40040
15	10	50000	48520	42032
16	11	53000	50760	44225
17	12	60000	55380	47380
18				

Figure 3: Exponential smoothing examples.

3. Index Methodology

3.1 Overview
In data analysis there is no single "right" methodology to employ. Methodologies vary in terms of their frameworks, albeit in all cases the objective is to present a fair approach to analysis.

Three possible ways to construct an art price index are:
1. Hedonic regression-based index
2. Repeat sales regression-based index
3. AMR's Art Market Performance Index.

Hedonic regression decomposes artwork into its constituent attributes (such as artist, size, subject matter), with each attribute contributing to the overall value. The criticism is that such a piecemeal approach to valuation may not be a good representation of an artwork, due to the uniqueness of each painting. Rather, a hedonic approach is better suited to more fungible assets, like real estate (floor area, number of bedrooms etc.).

Repeat sales regression uses price data from repeat sales of the *same* paintings, allowing the exact return to be determined. The criticism is that repeat sales may be sufficiently rare and distant in time to form a meaningful continuous index.

Due to the above limitations, we advocate the AMR Art Market Performance Index.

The AMR Art Market Performance Index measures the performance of artworks sold at the leading auction houses worldwide, such as Christies, Sotheby's and Bonhams (see Section 3.3 for the full list).

The indexes are calculated using an Artist Price (AP) algorithm (see Section 2).

Artist price (AP) figures are ordered from high to low, and all the artist prices or the first 10,000 artist prices (whichever is the lower) are eligible for inclusion in the index.

The process is repeatedly monthly, so that a new list of artists is selected each month. It should be noted that there is minimal churn in the makeup of these artists month to month (as discussed in Section 3.2).

For all the data time points, including the base period, the sum of artist prices is computed – the Underlying Monetary Value (UMV).

An initial index for time point *t* is then computed as 1000 multiplied by the ratio of the sum at this time point to that of the sum in the base period. This process is repeated monthly.

The entire history of the series is smoothed with factors which decrease exponentially.

At any point in time, the index represents a comparison of the sum of 'Artist Prices' relative to the sum of 'Artist Prices' in the base period.

3.2 Eligibility and Index Composition

AMR's Art Market Performance Index employs an algorithm to select a list of APs each month.
An artist must have sold at least one of their works at auction in the previous 24-month period to be included in the monthly list of APs.

3.2.1 Index constituents retention analysis.

To test how constituents of the index might change over time, a calculation was made to track the percentage of artists who consistently appear in the list of APs over consecutive months (Fig. 4).

A sample data of 29 months was extracted for 447 artists, whose works were sold 30 times or more in a 24-month period (2018:01- 2020:05). The list of artists (comps) was compared in consecutive months – 2018:02 is compared to 2018:01 and so on. The results for the first two months were: of 447 artists in 2018:01 (total comps. column), 433 artists were present the following month 2018-02 (hit count column). See Figure 4 for full results.

Algorithm: changeIn% = 100 – (hitCount201802 / totalComps201801 * 100)
changeIn% = 100 – (433 / 447 * 100)
changeIn% = 100 – (0.96868 * 100)
changeIn% = 100 – 96.868
changeIn% = 3.132
consistency = 96.87%

	A	B	C	D	E
1	month	change in %	hit count	total comps.	Consistency
2	201801			447	
3	201802	3.13	433	450	96.87
4	201803	6.89	419	445	93.11
5	201804	2.70	433	444	97.30
6	201805	5.18	421	436	94.82
7	201806	5.28	413	428	94.72
8	201807	1.40	422	436	98.60
9	201808	0.92	432	434	99.08
10	201809	5.76	409	421	94.24
11	201810	4.51	402	417	95.49
12	201811	11.51	369	387	88.49
13	201812	3.62	373	394	96.38
14	201901	2.03	386	390	97.97
15	201902	1.79	383	391	98.21
16	201903	7.93	360	383	92.07
17	201904	3.92	368	381	96.08
18	201905	7.09	354	375	92.91
19	201906	7.47	347	366	92.53
20	201907	2.73	356	361	97.27
21	201908	0.83	358	360	99.17
22	201909	4.44	344	357	95.56
23	201910	6.44	334	346	93.56
24	201911	6.94	322	343	93.06
25	201912	5.25	325	340	94.75
26	202001	1.18	336	339	98.82
27	202002	4.13	325	328	95.87
28	202003	8.54	300	308	91.46
29	202004	3.25	298	301	96.75
30	202005	7.64	278	287	92.36

Figure 4: Index constituents retention analysis.

The resulting data, plotted in a chart, shows a consistency of at least 88.49% from one month to the next. This indicates reasonable stability in the core index constituents month to month (see 2.2 Frequency – Core Artists).

Index Composition test - % Change
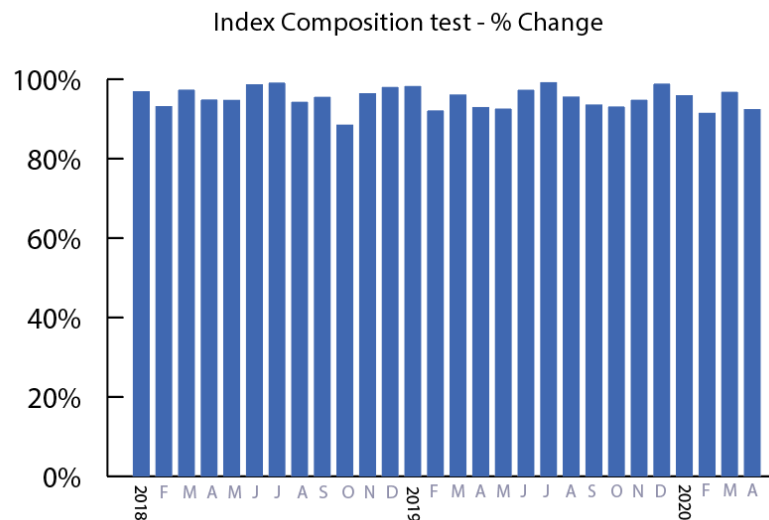
3.3 Auction House List

AMR tracks prices at the leading auction houses worldwide. The list of auction houses includes separate salerooms in different countries where they exist.

Percentages represent the weighting of each auction house in 2022.

Christie's	44.27%
Sotheby's	40.26%
Phillips	6.74%
Bonhams	1.77%
Seoul	0.86%
Artcurial	0.80%
Dorotheum	0.61%
Kornfeld	0.57%
Villa Grisebach	0.45%
Ravenel	0.39%

Heffel	0.35%
Saffron Art	0.35%
Tehran Auction	0.32%
Lempertz	0.31%
Bukowskis	0.22%
Smith & Singer	0.22%
Farsetti	0.19%
Strauss	0.18%
Claude Aguttes	0.17%
Rasmussen	0.15%
Tajan	0.13%
Couer D'Alene	0.13%
Beijing Poly Intl	0.12%
China Guardian	0.10%
Pandolfini	0.09%
Auctionsverket	0.06%
Morton Subastas	0.06%
Salcedo	0.05%
33 Auction	0.04%
Leonard Joel	0.03%
Meeting Art	0.01%
Stephan Welz	0.01%
Larasati	0.01%

3.4 Conversion of prices to GBP

AMR records prices of works sold at auction in different countries around the world. Auction House buyer's premium is removed to reveal the hammer price. Figures are converted to sterling on the day of sale (or day after if the sale is held on a weekend or holiday). AMR uses the Bank of England's website for information on daily spot rates.

James Abdey & Sebastian Duthy