A NEW FINANCIAL METRIC FOR THE ART MARKET

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Abstract

This paper introduces a new financial metric for the art market. The metric, which we call Artistic Power Value (APV), is based on the price per unit of area (dollars per square centimeter) and is applicable to two-dimensional art objects such as paintings. In addition to its intuitive appeal and ease of computation, this metric has several advantages from the investor's viewpoint. It makes it easy to: (i) estimate price ranges for different artists; (ii) perform comparisons among them; (iii) follow the evolution of the artists' creativity cycle overtime; and (iiii) compare, for a single artist, paintings with different subjects or different geometric properties. Additionally, the APV facilitates the process of estimating total returns. Finally, due to its transparency, the APV can be used to design derivatives-like instruments that can appeal to both, investors and speculators. Several examples validate this metric and demonstrate its usefulness.

Keywords Art markets Hedonic models Paintings Auction prices

JEL Classification C18 D44 G11 G12 Z10

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Background

In the last thirty years, the art market –and more precisely, the market for paintings−has received an increasing amount of attention from economists, financial analysts, and investors. They have brought to this field many quantitative techniques already employed in more conventional markets. Not surprisingly, one topic that has received a great deal of attention is returns, specifically, how to compute returns for the art market. This is a challenging task not only because this market is still rather illiquid, at least compared with equities and bonds, but also because of its heterogeneity: every painting is essentially a unique object.

Several authors have employed hedonic pricing models (HPMs) to estimate returns (e.g., Chanel et al., 1994, 1996; de la Barre et al., 1994; Edwards 2004; Renneboog and Spaenjers 2013). Such models are suitable to manage product variety and can use all the available data. Their drawback, however, is that their application is limited by the explicatory power of the variables selected and sometimes it is difficult to fit a good model to the data (the academic literature frequently reports models with values of R^2 around 60% or below). Moreover, if the data are sparse (a common situation, especially for individual artists) the application of HPMs might not be possible (Galbraith and Hodgson 2012). An additional disadvantage of HPMs is the lack of stability that often affects the computation of the hedonic regression coefficients, coupled with the lack of reliability −not to mention the not-so-straightforward interpretation− of the time dummies (Collins et al., 2007).

A second alternative to estimate returns is to rely on repeat sales regressions (e.g., Anderson 1974; Baumol 1986; and Goetzmann 1993). While this approach has the advantage of using price data referring to the same object it has two disadvantages: a potential selection bias and the fact that it only employs a small subset of the available information. Ginsburgh et al. (2006) provide an excellent discussion on the merits of each approach plus a fairly complete literature review. Mei and Moses (2002); Renneboog and Spaenjers (2011); Higgs and Worthington (2005); Agnello and Pierce (1996); and artnet Analytics (2012) have dealt with the construction of art indices based on the two above-mentioned techniques or hybrid combinations of them.

The question of which approach is better to estimate returns still remains open. This issue is far more vexing than it appears. Superficially, it might be interpreted as a choice between two methods that lead to the same answer based on computational ease. However, there is no assurance that this is indeed the case. In fact, they might lead to different answers and it is not always clear which answer is the right one. Ashenfelter and Graddy (2003) have stated this point more forcefully: 'The hedonic index gives a real return of about 4 percent, while the repeat-sales index results in a real return of about 9 percent! Which is correct?'

Previous researchers have also focused on other topics. Just to name a few: Galenson (1999); Galenson (2000); Galenson (2001); Galenson and Weinberg (2000); and Ginsburgh and Weyers (2006) have looked at the creativity cycle of several artists (that is, the age at which they produced their best work). Renneboog and Van Houte (2002); Worthington and Higgs (2004); Renneboog and Spaenjers (2011); and Pesando (1993) have compared the returns of certain segments of the art market vis-à-vis more conventional investments. Coate and Fry (2012) and Ekelund et al. (2000) have investigated the death-effect in the price of paintings. Edwards (2004) and Campos and Barbosa (2009) have looked at the performance of Latin American painters. Scorcu and Zanola (2011) used a hedonic model approach to study Picasso's paintings, while Higgs and Forster (2013) investigated whether paintings which conformed to the golden mean commanded a price premium. And, Sproule and Valsan (2006) questioned the accuracy of hedonic models compared with the appraisals of experts.

Other issues that have been investigated, some of them still with inconclusive answers, are: whether the lack of signature affects the auction price of a painting; the importance of the auction house (in essence, Sotheby's or Christie's versus lesser known auction houses); whether masterpieces tend to underperform when compared to less expensive paintings; the correlation between the art market and the major equity and fixed income indices; whether an artist can be described, based on its creativity-cycle curve, as conceptual (early bloomer) or experimentalist (late bloomer); as well as the relationship between, withdrawing a painting from an auction, and its future sale price. All these analyses have relied on statistical and modeling techniques commonly used in financial and economic analysis.

In summary, although a great deal has been learned about the financial aspects of the art market in recent years, much needs to be understood, especially, from the investor's perspective. Therefore, the purpose of this paper is to contribute to this effort by introducing a new financial metric that can facilitate the understanding of some of the issues already mentioned. In addition, we want to shift the focus towards the investor's viewpoint and move away from the purely econometric models which, even though are interesting from an academic angle, offer little guidance to somebody concerned with pricing issues. Thus, our goal is twofold: (i) to provide a new tool to enrich the analysts' toolbox; and (ii) to facilitate the investors' decision-making process by making it easier to assess the merits of a painting using some simple quantitative analyses.

We should note that the application of HPMs and repeat sales regression models has so far focused, mainly, on estimating market returns aimed at building indices. Although these indices can be useful for performing econometric analyses and describing market tendencies, in general, they are less useful for investors. The chief reason is that investors are concerned with actual or realized returns (that is, total returns) instead of market returns (returns based on an ideal painting whose characteristics do not change over time). To put the point more forcefully: an investor has little use for an index that controls for quality and paintings' characteristics. In fact, the investor wants information that actually captures these features as well as supply-demand dynamics. The metric introduced herein (a point we discuss in more detail later) captures exactly that.

A New Financial Metric

Paintings, notwithstanding their artistic qualities, are essentially two-dimensional objects that can command ‒sometimes‒ hefty prices. Based on this consideration, it makes sense to express the value of a painting not using its price but rather a price per unit of area (in this study, dollars per square centimeter). We call this figure of merit Artistic Power Value or APV. By normalizing the price, the APV metric intends to offer the investor a financial yardstick that goes beyond the price, while not attempting to control for the specifics of the painting beyond its area.

The intuitive appeal of this metric is obvious: simplicity, ease of computation, transparency, and straightforwardness. In fact, there is already a well-established precedent for this approach. For example, prices of other two-dimensional assets, such as raw land, are frequently quoted this way (e.g. dollars per acre, or euros per hectare). The same approach is sometimes used to quote prices of antique rugs.

More recently, many artisans, print makers, digital printing firms, and poster designers have started to quote price estimates using this same concept. Moreover, considering that the cost of materials (an important component of the production cost) employed in creating these two-dimensional objects is often estimated on a per-unit-of-area basis, the idea of extending the same notion to express the value of the final product is not far-fetched.

Finally, the rationale for using the APV metric is not to negate the individuality of each painting or to trivialize the artistic process. It is really an attempt to synthetize in one parameter the financial value of a painting (or artists or body of work) with the goal of making comparisons easier. Additionally, many APV-based computations (a point treated in more detail in the subsequent section) can offer useful guidance for pricing purposes.

Alternatively, we can think of the APV as an attempt to find a common factor to compare and contrast the economic value of otherwise dissimilar art objects. If we accept the thesis that two paintings −even if they are done by the same artist and depict the same theme− are not only different but also unique, it is not possible to make a straight price-wise comparison. However, the APV metric, by virtue of removing the size-dependency, helps to make this comparison possible: in a sense the APV plays the role of unitary price.

The Data

Three data sets are employed in this study:

a. Data set A consists of 1,818 observations of Pierre-Auguste Renoir's paintings auction prices and their characteristics covering the period [March 1985; February 2013]. The database was built based on information provided by the artnet database (www.artnet.com).

b. Data set B consists of 441 observations of Henri Matisse's paintings auction prices and their characteristics covering the period [May 1960; November 2012]. The database was built based on information provided by the artnet database (www.artnet.com) and was supplemented by additional auction data from the Blouin Artinfo website (www.artinfo.com).

c. Finally, data set C consists of 2,115 observations of paintings covering the period [March 1985; February 2013]. This data set gathers information from six artists (Alfred Sisley, Camille Pissarro, Claude Monet, Odilon Redon, Paul Gauguin, and Paul Signac) and was based on auction information provided by the artnet database.

All prices were adjusted to January-2010 U.S. dollars (using the U.S. CPI index) and are expressed in terms of premium prices (when hammer prices were reported, they were modified and expressed in terms of equivalent premium prices). Observations where the selling price was below US$ 10,000 or the APV was less than 1 US$/cm2 were eliminated.

Sotheby's and Christie's dominate the data sets, as together they account for 86% of the sales.

The selection of artists was somewhat arbitrary. The chief consideration was to effectively examine the merits of the APV metric without regard to the qualities of the painters selected. Renoir was an ideal choice because of the high number of observations available, which were distributed over a long period of time, and without time gaps. This situation facilitates the comparison between the APV metric and the HPMs (which require many data points to be built). Matisse data had the advantage of being distributed over a longer time span, but included less observations, and had a few time-gaps. Data set C, despite its strong impressionist flavor, was not aimed at capturing in full the characteristics of the impressionist movement; it represents a group of painters who happened to live roughly at the same time and for which there were enough observations to make certain computations feasible. Nevertheless, and simply for convenience, in what follows we refer to this group as the Impressionists group. Renoir, despite his strong impressionist credentials was purposely left out of data set C. Otherwise, he would have dominated the group, making it highly correlated with data set A: an undesirable situation given the need to test the APV metric under different scenarios.

In summary, the selection of artists was not done with the idea of deriving any specific conclusion regarding these painters or the artistic tendencies they represented; the leading consideration was to showcase the attributes and benefits of the APV metric.

Table 1 summarizes the key features of the three data sets. **Table 2** describes in more detail the characteristics of the painters in the Impressionist group (data set C). Notice that the APV distribution is far from normal: the differences between the arithmetic mean (average) values and the medians are manifest, with the means always higher than the medians. Additionally, the values of the skewness and kurtosis reveal a strong positively skewed distribution with fat tails. The Jarque-Bera (JB) statistic and its corresponding p-value (close to 0.000 for each of the three data sets) indicate that the APV is not normally distributed. These facts should serve as a warning against APV-based projections based on normality assumptions. Finally, the relatively high values of the coefficient of variation for several artists (Renoir and Matisse exhibit the most variability) are somehow evidence of what experts already know: even masters are uneven producers and their paintings differ greatly in quality. Whether ranking artists by their average or median APV values is consistent with the critics' assessment of their merits, it is a topic we leave for others to decide

Table 1. Description of the three data sets and key statistics

	Data Set: A	**Data Set: B**	**Data Set: C**
Artist	Pierre-Auguste Renoir	Henri Matisse	Impressionists group
Born–Died	1841–1919	1869–1954	NA
Number of Sales	1,818	441	2,115
Period of Sales	Mar 1985–Feb 2013	May 1960–Nov 2012	Mar 1985–Feb 2013
Average APV (US$/cm^2)	646	803	537
Standard Deviation (US$/cm^2)	1,331	1,332	786
Coefficient of Variation	2.06	1.66	1.46
Median APV (US$/cm^2)	377	308	311
Skewness	15.56	3.87	4.86
Kurtosis	344.06	19.83	31.87
Jarque-Bera	9,040,581.38	8,328.44	97,801.30
JB *p*-value	0.000	0.000	0.000

Table 2. Detailed characteristics and key statistics of the artists included in data set C

Artist	**Number of Sales**	**Born–Died**	**Average APV (US$/cm^2)**	**Standard Deviation (US$/cm^2)**	**Coeff. of Variation**	**Median APV (US$/cm^2)**
Alfred Sisley	341	1839–1899	389	282	0.73	313
Camille Pissarro	586	1839–1903	432	335	0.78	338
Claude Monet	581	1840–1926	760	999	1.31	411
Odilon Redon	193	1840–1916	167	156	0.93	118
Paul Gauguin	167	1848–1903	1,138	1,631	1.43	465
Paul Signac	247	1863–1935	353	454	1.28	202

Applications of the APV Metric

This section is intended to demonstrate the usefulness of the APV metric with the help of some examples.

Comparisons among All Artists

The fact that the APV follows a highly non-normal distribution calls for comparisons to be based on the median rather than the average value. To this end we employ the median comparison test using the Price-Bonett variance estimation for medians (Price and Bonett 2001; Bonett and Price 2002), described in Wilcox's (2005) review of methods for comparing medians.

Table 3. Comparisons among the APV medians for all artists (1985-2012 sales only)

Median APV (diagonal) Difference between medians (off-diagonal) (US$/cm^2)	Henri Matisse[a]	Paul Gauguin	Claude Monet	Pierre-Auguste Renoir	Camille Pissarro	Alfred Sisley	Paul Signac	Odilon Redon
Henri Matisse[a]	513							
Paul Gauguin	NS	465						
Claude Monet	102**	NS	411					
Pierre-Auguste Renoir	136***	88*	34*	377				
Camille Pissarro	175***	127**	73***	39***	338			
Alfred Sisley	200***	152**	98***	64***	25*	313		
Paul Signac	311***	263***	209***	175***	136***	111***	202	
Odilon Redon	395***	347***	293***	259***	220***	195***	84***	118

NOTE: [a]: Median calculated from sales between 1985-2012 only;
NS: Not Significant; *p<.10; **p<0.05; ***p<0.01

Table 3 summarizes the results of such comparison. The median values for each artist are shown along the diagonal with the values decreasing from top-left to bottom-right: Matissse[1] has the highest value (513 US$/cm^2) while Redon the lowest (118 US$/cm^2). The

[1] In order to have similar periods for all comparisons among artists, we only considered the sales between 1985 and 2012 for Matisse.

remaining entries in the table can be interpreted, using matrix notation, as follows: the (i, j) entry represents the median APV value of artist j minus the median APV value of artist i. Hence, Pissarro's median APV exceeds that of Signac by 136 US$/cm^2 while there is no significant difference between Gauguin and Matisse's median APVs.

These calculations, trivial by all accounts, offer a convenient way to rank artists. They also offer useful guidance for pricing purposes.

Portrait versus Landscape Orientation for a Given Artist

Table 4. Comparisons of APV medians: portrait (vertical) versus landscape (horizontal) oriented paintings for each artist

	Portrait		Landscape			
Artist	**Number of Sales**	**Median APV (US$/cm^2)**	**Number of Sales**	**Median APV (US$/cm^2)**	**Portrait versus Landscape Difference US$/cm^2**	**P-Value**
Alfred Sisley	21	298	321	317	-19	NS
Camille Pissarro	132	327	450	346	-19	NS
Claude Monet	124	352	440	426	-74	<0.10
Henri Matisse	203	498	237	199	299	0.000
Odilon Redon	133	131	53	84	47	<0.01
Paul Gauguin	81	580	86	328	252	<0.05
Paul Signac	23	129	224	212	-83	<0.05
Pierre-Auguste Renoir	843	505	949	289	216	0.000

NOTE: Paintings with height=width are excluded from the table. NS: Not significant.

Certain painters, Modigliani for instance (not part of this study) decidedly preferred the portrait (or vertical) orientation. Sisley and Signac, on the contrary, favored the landscape orientation. **Table 4** compares, for all the artists considered here, the median APV as a function of the orientation using the median-comparison algorithm already described. The results are interesting and far from obvious. In the case of Sisley and Pissarro, the painting orientation does not affect the APV in a significant way. In the case of Matisse and Renoir, the difference in median APV values is highly relevant. More interesting is the fact that even though both were much better at doing portrait-oriented paintings, they did not seem to favor this orientation. They both painted −according to these sets of observations− roughly the same number of portrait-oriented paintings and landscape-oriented paintings (203 and 237 in the case of Matisse; 843 and 949 in the case of Renoir). Finally, Monet and Signac were better at doing landscape-oriented paintings, at least as seen by the market.

In conclusion, the orientation of a painting, in most cases, has a definite influence on its market value.

Comparisons of Different Subjects for the Same Artist

Tables 5, 6, and **7** display the median APV value, for each artist, as a function of three dummy variables, namely: (i) Still life; (ii) *Paysage*[2] and (iii) People (whether the painting shows one or several human figures regardless of the amount of detail); 0 refers to the absence of the condition.

Clearly, certain artists are more appreciated for certain topics: Redon (see **Table 5**) is more valued when executing still lives while the opposite happens with Renoir. *Paysages* painted by Matisse, Gauguin, and Renoir (**see Table 6**) are less desirable. And Gauguin, Renoir, and Matisse (see **Table 7**) commanded higher prices when their paintings included people. These considerations are useful when appraising paintings.

Table 5. Comparisons of APV medians: still-life versus no-still-life for each artist

	Subject: Still-Life=Yes		Subject: Still-Life=No			
Artist	**Number of Sales**	**Median APV (US\$/cm^2)**	**Number of Sales**	**Median APV (US\$/cm^2)**	**Difference US\$/cm^2**	**P-Value**
Alfred Sisley	NA	NA	NA	NA	NA	NA
Camille Pissarro	NA	NA	NA	NA	NA	NA
Claude Monet	59	279	522	424	-145	<0.05
Henri Matisse	69	335	372	308	27	NS
Odilon Redon	58	214	135	86	129	0.000
Paul Gauguin	24	821	143	411	409	<0.05
Paul Signac	NA	NA	NA	NA	NA	NA
Pierre-Auguste Renoir	364	302	1454	396	-94	0.000

NA: Not enough sales for this artist in this subject (<10 sales). NS: Not significant.

[2] For the sake of clarity we have used the French word *paysage* to refer to what in English is commonly termed landscape to avoid any misinterpretation since this term (landscape) was used in the context of the geometric orientation of the painting.

Table 6. Comparisons of APV medians: *paysage* versus *no-paysage* for each artist

	Subject: *Paysage*=Yes		Subject: *Paysage*=No			
Artist	Number of Sales	Median APV (US$/cm^2)	Number of Sales	Median APV (US$/cm^2)	Difference US$/cm^2	P-Value
Alfred Sisley	282	311	59	321	-10	NS
Camille Pissarro	325	342	261	340	2	NS
Claude Monet	410	424	171	355	69	<0.10
Henri Matisse	143	161	298	459	-298	0.000
Odilon Redon	42	61	151	135	-74	0.000
Paul Gauguin	58	288	109	649	-361	0.000
Paul Signac	103	218	144	200	18	NS
Pierre-Auguste Renoir	478	267	1340	429	-162	0.000

NS: Not significant.

Table 7. Comparisons of APV medians: people (one or many persons) versus no-people for each artist

	Subject: People=Yes		Subject: People=No			
Artist	Number of Sales	Median APV (US$/cm^2)	Number of Sales	Median APV (US$/cm^2)	Difference US$/cm^2	P-Value
Alfred Sisley	NA	NA	NA	NA	NA	NA
Camille Pissarro	71	267	515	348	-82	<0.05
Claude Monet	12	338	469	415	-77	<0.10
Henri Matisse	190	586	251	206	381	0.000
Odilon Redon	25	56	168	124	-67	<0.01
Paul Gauguin	31	1115	136	388	727	<0.01
Paul Signac	NA	NA	NA	NA	NA	NA
Pierre-Auguste Renoir	817	528	1001	285	243	0.000

NA: Not enough sales for this artist in this subject (<10 sales).

Life-Cycle Patterns

The idea behind this concept is to explore how the quality of an artist's paintings (using the APV metric as a proxy) evolves over time. That is, as a function of the age at which the painting was executed. Or more precisely, identify the period(s) at which the artist produced its most valuable work (financially speaking).

Figure 1. Pierre-Auguste Renoir Life-Cycle Creativity Curve

Figure 2. Henri Matisse Life-Cycle Creativity Curve

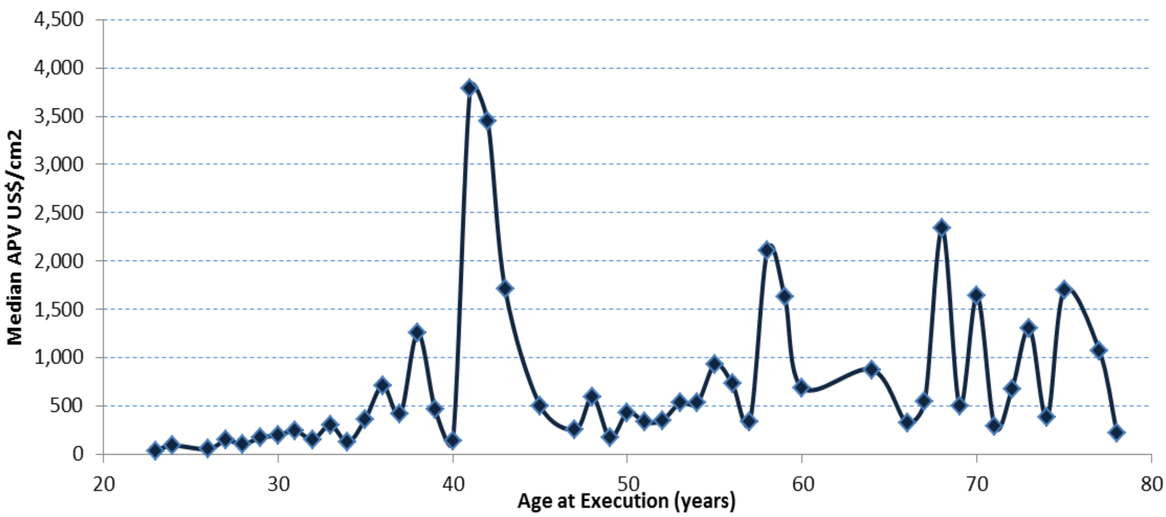


Figure 3. Claude Monet Life-Cycle Creativity Curve

Figure 4. Camille Pissarro Life-Cycle Creativity Curve

Figures 1, 2, 3, and **4** display the median APV values, as a function of the age-at-execution for Renoir, Matisse, Monet, and Pissarro; i.e., the artists for whom we had more than 400 observations.

The patterns shown are interesting as they reveal quite different tendencies. Renoir seems to have reached a peak around the mid-thirties and then experienced a slow decline. Matisse enjoyed a strong peak in his early forties, and a minor peak around his late fifties followed by a sequence of peaks and valleys in his late years. Monet's career is marked by two salient peaks: an early one (when he was thirty) and a later one (in his mid-sixties) while Pissarro's life is characterized by a more jagged curve that exhibited no significant decline in his old age and is more regular than those of either Monet and Matisse. This situation is somewhat consistent with the fact that his coefficient of variation (0.78 from **Table 2**) is lower than that of Monet (1.31) and Matisse (1.66).

Total Returns for Different Artists or Group of Artists

Tables 8, 9 and **10** present the year-to-year total returns for Renoir, Matisse and the Impressionists (based on the information provided by data sets A, B and C respectively) along with other key values. Notice the salient peak APV values (at year 1989 and then around 2007-2008) with their corresponding steep declines afterwards. They are consistent across the three data sets and are in agreement with trends already detected in the broader art market.

The total return computation is straightforward. First, we compute for each year, the average APV value (avg-APV). This is simply the sum of the APV values of all the paintings sold during the year divided by the total number of paintings sold. Then, the year-to-year total returns are computed based on the average APV values for two consecutive years. In short, the return between years *i* and *i+1* is simply [avg-APV_{i+1}/avg-APV_i] – 1.

We have purposely carried out this calculation using the average (mean) APV-value instead of the median. In general, it is customary to rely on the mean to estimate returns (regardless of the type of distribution) since the mean is better at capturing the influence of extreme values.

Leaving aside the ease of computation (undoubtedly an attractive feature) a valid question needs to be answered: What does this return mean?

The APV captures both, art market trends and supply-demand dynamics for the artist or artists considered, as it is based on actual sales. It does not intend to control the actual prices observed for any factor other than the area of the painting. Hence, the APV-based returns are really total (actual or realized) returns for the artist or artists in question (inflation has been removed since prices are expressed in January-2010 dollars).

Some academics might feel that these returns are contaminated, since we do not purposely control for factors such as the type of painting (subject matter), geometric features beyond the area, and the host of other variables that hedonic models normally employ to explain the price (dependent variable). The following analogy is useful to make our point that controlling for this factors, at least from an investor perspective, is not relevant.

Suppose you are looking at the possibility of buying IBM stock and you have computed the average return in recent years based on the observed stock price. This return would correspond to an actual (or total) return. Consider now that IBM's revenue (broadly speaking) comes from three sources: hardware, software, and consulting. Would you then attempt to control for revenue composition to arrive at a return figure reflecting the average or typical return? That is, a return based on an ideal revenue composition? Probably not. In fact, in all likelihood, the opposite is true. You want a return metric that actually captures the revenue composition variation. Well, the same goes for paintings. Renoir, for instance (and strictly from a return estimation standpoint) can be thought of as a company that sells multiple products (paintings), all with different features, and an investor certainly wants a metric that captures all that variability, which is exactly what the APV does. In summary, the fact that APV-based returns do not control for any factors beyond the area rather than being a weakness of the metric is a source of strength.

Table 8. Data set A: Pierre-Auguste Renoir, Key Statistics and Year-to-Year Total Returns

Year of Sale	Number of Obs.	Average APV (US$/cm^2)	APV Stand. Dev. (US$/cm^2)	95% Conf. Interval*	Coeff. of Variation	Year-to-Year Total Return (APV)
1985	32	360	347	241 - 479	0.96	
1986	41	446	432	319 - 575	0.97	0.239
1987	83	588	541	477 - 702	0.92	0.317
1988	70	1,051	1,098	795 – 1,308	1.04	0.788
1989	103	1,845	3,730	1,135 – 2,551	2.02	0.756
1990	93	1,415	1,960	1,018 – 1,804	1.39	-0.233
1991	31	426	336	313 - 540	0.79	-0.699
1992	43	491	525	336 - 649	1.07	0.152
1993	55	534	593	372 - 691	1.11	0.088
1994	45	370	281	287 - 453	0.76	-0.308
1995	75	386	428	288 - 484	1.11	0.045
1996	69	328	298	256 - 401	0.91	-0.151
1997	75	606	1,033	379 - 831	1.70	0.847
1998	77	409	695	250 - 569	1.70	-0.325
1999	75	437	435	339 - 537	1.00	0.068
2000	75	499	544	378 - 621	1.09	0.143
2001	49	430	663	248 - 615	1.54	-0.140
2002	38	485	495	331 - 641	1.02	0.128
2003	44	445	536	298 - 591	1.20	-0.081
2004	63	431	467	318 - 544	1.08	-0.032
2005	79	422	241	366 - 477	0.57	-0.020
2006	73	539	378	454 - 624	0.70	0.276
2007	94	667	657	530 - 799	0.99	0.237
2008	62	956	3,320	129 – 1,780	3.48	0.433
2009	59	442	356	352 - 532	0.80	-0.537
2010	65	541	481	423 - 663	0.89	0.223
2011	66	510	471	393 - 625	0.92	-0.057
2012	84	533	582	412 - 656	1.09	0.045

*The 95% confidence interval was computed based on a bootstrapping technique where we took 1,000 samples with replacement with size equal to the total number of observation in each year and computed a sample mean. The average and the standard deviation (standard error of the mean) based on the 1,000 means for each year was then computed for each year. We required a sample size of at least 10 observations to compute the confidence interval.

Table 9. Data set B: Henri Matisse, Key Statistics and Year-to-Year Total Returns

Year of Sale	Number of Obs.	Average APV (US$/cm^2)	APV Stand. Dev. (US$/cm^2)	95% Conf. Interval*	Coeff. of Variation	Year-to-Year Total Return (APV)
1960	2	70	34	NA	0.49	
1961	1	76	NA	NA	NA	0.092
1962	4	101	53	NA	0.52	0.333
1963	2	73	35	NA	0.47	-0.277
1965	3	64	33	NA	0.52	-0.067
1966	4	128	44	NA	0.34	1.014
1968	4	127	38	NA	0.30	-0.007
1970	7	222	87	NA	0.39	0.325
1971	5	63	65	NA	1.03	-0.716
1972	10	275	155	182 - 369	0.56	3.362
1973	7	620	800	NA	1.29	1.256
1974	9	413	516	NA	1.25	-0.334
1975	5	184	118	NA	0.64	-0.554
1976	10	141	57	104 - 178	0.40	-0.237
1977	9	248	163	NA	0.66	0.767
1978	9	173	105	NA	0.61	-0.302
1979	16	290	232	185 - 397	0.80	0.674
1980	7	253	124	NA	0.49	-0.128
1981	11	180	138	99 - 260	0.77	-0.290
1982	10	162	113	92 - 232	0.69	-0.097
1983	8	294	127	NA	0.43	0.810
1984	8	240	126	NA	0.52	-0.185
1985	11	306	200	189 - 424	0.65	0.278
1986	10	363	296	182 - 543	0.81	0.185
1987	13	446	300	288 - 604	0.67	0.228
1988	12	669	793	226 – 1,104	1.19	0.501
1989	12	1,411	1,252	722 – 2,096	0.89	1.108
1990	13	1,391	1,422	645 – 2,134	1.02	-0.014
1991	5	652	476	NA	0.73	-0.531
1992	9	1,134	974	NA	0.86	0.740
1993	11	710	766	280 – 1,127	1.08	-0.374
1994	6	362	357	NA	0.98	-0.489

Table 9. Data set B: Henri Matisse, Key Statistics and Year-to-Year Total Returns (continued)

Year of Sale	Number of Obs.	Average APV (US$/cm^2)	APV Stand. Dev. (US$/cm^2)	95% Conf. Interval*	Coeff. of Variation	Year-to-Year Total Return (APV)
1995	10	1,137	1,452	257 – 2,021	1.28	2.138
1996	6	227	113	NA	0.50	-0.800
1997	11	666	656	289 – 1,044	0.98	1.930
1998	12	406	441	164 - 651	1.09	-0.390
1999	12	701	616	355 – 1,045	0.88	0.725
2000	7	1,426	1,685	NA	1.18	1.035
2001	18	717	567	467 - 968	0.79	-0.497
2002	8	1,037	722	NA	0.70	0.446
2003	3	166	47	NA	0.29	-0.840
2004	9	2,034	2,440	NA	1.20	11.290
2005	7	1,127	1,632	NA	1.45	-0.446
2006	8	1,402	999	NA	0.71	0.243
2007	23	2,073	3,013	803 – 3,307	1.45	0.479
2008	20	1,371	1,314	789 – 1,951	0.96	-0.339
2009	8	1,865	3,031	NA	1.63	0.360
2010	11	3,090	2,208	1786 – 4,423	0.71	0.657
2011	7	844	1,181	NA	1.40	-0.727
2012	8	902	1,706	NA	1.89	0.069

*The 95% confidence interval was computed based on a bootstrapping technique where we took 1,000 samples with replacement with size equal to the total number of observation in each year and computed a sample mean. The average and the standard deviation (standard error of the mean) based on the 1,000 means for each year was then computed for each year. We required a sample size of at least 10 observations to compute the confidence interval.

Table 10. Data Set C: Impressionists Group, Key Statistics and Year-to-Year Total Returns

Year of Sale	Number of Obs.	Average APV (US$/cm^2)	APV Stand. Dev. (US$/cm^2)	95% Conf. Interval*	Coeff. of Variation	Year-to-Year Total Return (APV)
1985	60	227	190	177 - 275	0.84	
1986	58	243	196	193 - 292	0.81	0.070
1987	84	397	483	299 - 498	1.21	0.637
1988	72	790	1,321	493 – 1,094	1.67	0.988
1989	146	1,045	1,024	877 – 1,218	0.98	0.323
1990	62	648	395	546 - 749	0.61	-0.380
1991	36	404	466	263 - 543	1.15	-0.377
1992	40	307	240	232 - 382	0.78	-0.239
1993	60	333	249	269 - 398	0.75	0.084
1994	61	306	294	232 - 378	0.96	-0.082
1995	81	405	684	262 - 551	1.69	0.325
1996	69	373	405	276 - 465	1.08	-0.079
1997	87	438	510	334 - 544	1.16	0.173
1998	90	394	656	260 - 526	1.67	-0.101
1999	109	439	638	324 - 555	1.45	0.116
2000	80	582	897	385 - 784	1.54	0.325
2001	71	546	876	346 - 749	1.60	-0.062
2002	67	406	565	273 - 540	1.39	-0.257
2003	50	444	538	297 - 590	1.21	0.094
2004	75	502	945	286 - 720	1.88	0.130
2005	86	447	623	312 - 585	1.39	-0.109
2006	89	604	888	414 - 795	1.47	0.351
2007	105	863	1,170	635 – 1,091	1.36	0.429
2008	89	771	1,198	520 – 1,022	1.55	-0.106
2009	62	482	591	336 - 629	1.23	-0.375
2010	73	528	820	342 - 708	1.55	0.094
2011	58	464	532	330 - 601	1.14	-0.120
2012	95	645	787	479 - 807	1.22	0.388

*The 95% confidence interval was computed based on a bootstrapping technique where we took 1,000 samples with replacement with size equal to the total number of observation in each year and computed a sample mean. The average and the standard deviation (standard error of the mean) based on the 1,000 means for each year was then computed for each year. We required a sample size of at least 10 observations to compute the confidence interval.

Table 11. Year-to-year Total Returns (averages and standard deviations) and Cumulative Total Return, using the APV

APV	Data Set A: Renoir	Data Set B : Matisse	Data Set C: Impressionists
Average Total Return	8.16%	43.78%	8.30%
Standard Deviation Total Return	35.58%	172.19%	31.47%
Cumulative Total Return*	148.02%	1195.65%	284.21%

*Cumulative total returns computed for 27 years for Data sets A and C [1985-2012] and 52 years for Data set B [1960-2012].

Table 11 summarizes the year-to-year return results: (i) average year-to-year total returns; and (ii) cumulative total returns for the relevant time-periods.

Repeat Sales Vis-à-Vis the Entire (All-Sales) Data Set

Table 12. Comparisons of APV Medians and Total returns: all-sales versus repeat-sales for each artist

	All-sales			Repeat-sales		
Artist	Number of Sales	Median APV (US$/cm^2)	Avg. Total Returns	Number of Sales	Median APV (US$/cm^2)	Avg. Total Returns
Alfred Sisley	341	313	9.35%	118	327	20.23%
Camille Pissarro	586	338	6.41%	146	378	13.69%
Claude Monet	581	411	20.54%	176	476	47.70%
Henri Matisse	441	308	43.78%	160	249	21.98%
Odilon Redon	193	118	22.62%	36	91	64.39%
Paul Gauguin	167	465	57.98%	37	612	115.64%
Paul Signac	247	202	29.28%	90	180	27.18%
Pierre-Auguste Renoir	1818	377	8.17%	426	425	33.18%

Many analysts have estimated returns, for individual artists and groups of them, using only data from repeat sales. As pointed out before, a concern with this approach is that there could be a risk of selection bias. **Table 12** shows the median APV values for each of the artists considered using: (i) all the observations; and (ii) the repeat sales sub-set. In two cases (Matisse and Renoir) the differences in medians are significant at the 5% level. And, in four of the remaining six cases the discrepancies are marginally significant (significant at the 10% level). We have performed the comparison between the two data sets using the median (instead of the mean) because of the marked non-normality of these samples. Finally, and somehow expectedly, the estimated returns (based on year-average APV-values) are quite different for the two groups (all-sales versus repeat-sales). The fact that in most cases the returns are higher when computed based on repeat-sales set gives credibility to the hypothesis that paintings are more likely to be sold if they have increased in value.

All in all these findings support the view that a selection bias cannot be ruled out when dealing with repeat sales data and return estimates based on repeat sales regressions (despite the claim that one has controlled for all the relevant factors) should be regarded with caution because of this bias. The same goes for any other estimate based on repeat sales information.

In conclusion, the examples discussed in this section show that the APV metric is a useful tool that can provide a potential investor with a great deal of insight regarding the merits of an artist, groups of artists, or a particular painting.

Validation of the APV Metric

A useful way to assess the validity of the APV metric is to compare the results of calculations based on this metric and those obtained with other (more established) methods. HPMs, in spite of their shortcomings, constitute a sound basis on which we can build some tests to explore the reasonableness of the APV-based computations.

Total (Actual or Realized) Returns

A first examination consists of comparing the returns estimated with the APV metric and the returns calculated using HPMs.

In order to determine a fair yardstick for comparison purposes we carry out two steps. First, we estimate individual HPMs for each of the three cases (Renoir, Matisse, and the Impressionists) using the entire corresponding data set. And second, in each case, we evaluate the resulting HPM, for each year, using the average characteristics of the paintings sold during the year, to arrive at a representative price corresponding to each year, P_i (where i denotes a year index). The year-to-year HPM-based returns are computed based on these prices, using the expression $(P_{i+1}/P_i) - 1$. Thus, the idea is to use the HPM to estimate the total return.

The HPMs employ the natural logarithm of the painting selling price as the dependent variable. The independent variables (right-hand side of the regression equation) involve:

(i) linear and higher-order polynomial expressions based on the age of the artist at the time the painting was executed;

(ii) in the case of data set C a dummy (binary) variable to account for the identity of the painter;

(iii) linear and higher-order polynomial expressions based on variables associated with the geometry of the painting (area, height, width, aspect ratio, and diagonal) plus binary dummy variables accounting for medium (canvas) and special topics (nudes, still lives, flowers, etc.); and

(iv) a sequence of dummy (binary) variables associated with the year the painting was sold.

The corresponding adjusted R^2's (Renoir, Matisse, and Impressionists) are as follows: 0.75 (F= 137.47, p<.0001), 0.72 (F=18.78, p<.0001), and 0.67 (F= 77.39, p <.0001) respectively. In addition, we used White's (1980) test for heteroscedasticity and the null hypothesis of homoscedasticity in the least-squares residuals was not rejected in each of the three samples (results can be provided upon request).

Table 13 shows the comparison between the average year-to-year total return estimated with (i) the APV metric; and (ii) the HPMs applied as described before. Both estimates, in all three cases, are in close agreement. This fact is also consistent with the high correlation values reported as well as the visual comparison presented in **Figs 5, 6,** and **7**.

Table 13. Year-to-year total returns: averages, standard deviations, and correlations (APV and HPM)

	Data Set A: Renoir	**Data Set B : Matisse**	**Data Set C: Impressionists**
Average Total Return (APV)	8.16%	43.78%	8.30%
Standard Deviation Total Return (APV)	35.58%	172.19%	31.47%
Average Total Return (HPM)	7.64%	48.74%	8.36%
Standard Deviation Total Return (HPM)	38.12%	162.67%	33.35%
Correlation Total Ret. APV - Total Ret. HPM	0.79	0.89	0.82

It might not seem evident that this is a fair comparison. However, we should notice that by evaluating the HPMs for each year, with the typical features of the paintings sold that year, one is capturing the two effects that influence returns: the market trend (reflected in the

HPM coefficients associated with the time-dummy variables) and the specific characteristics of the paintings sold on a given year. The APV metric blends these two factors (market trends and paintings features) in one number. Therefore, the hedonic model framework (applied in the modified manner just described) seems appropriate to double-check the validity of the returns based on the APV metric.

Figure 5. Year-to-Year Total (APV and HPM) Returns for Pierre-Auguste Renoir Sales

Figure 6. Year-to-Year Total (APV and HPM) Returns for Henri Matisse Sales

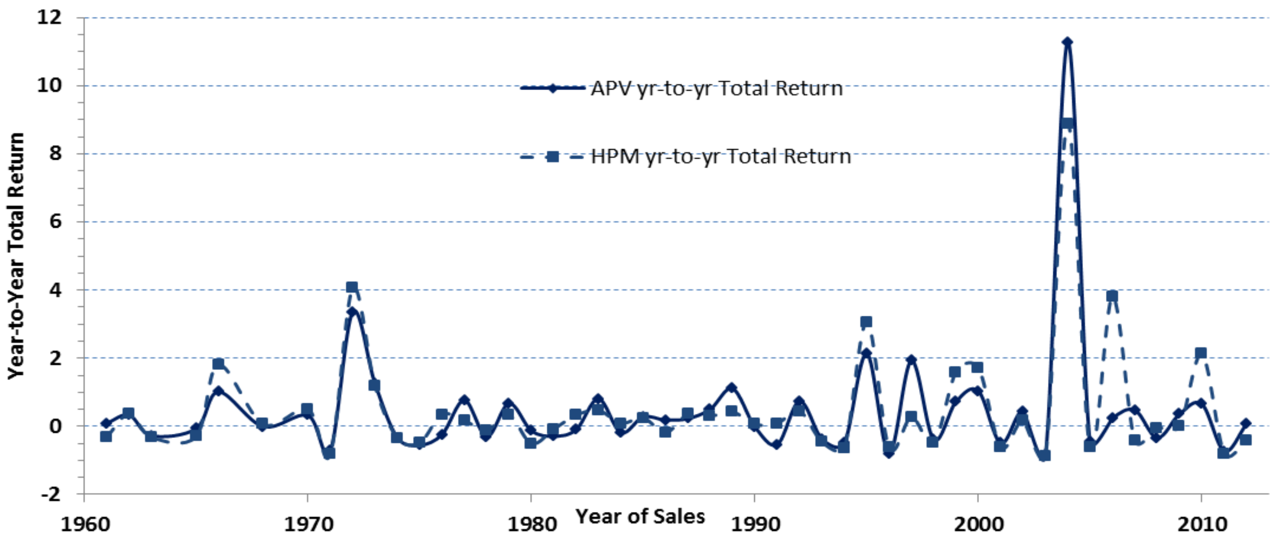
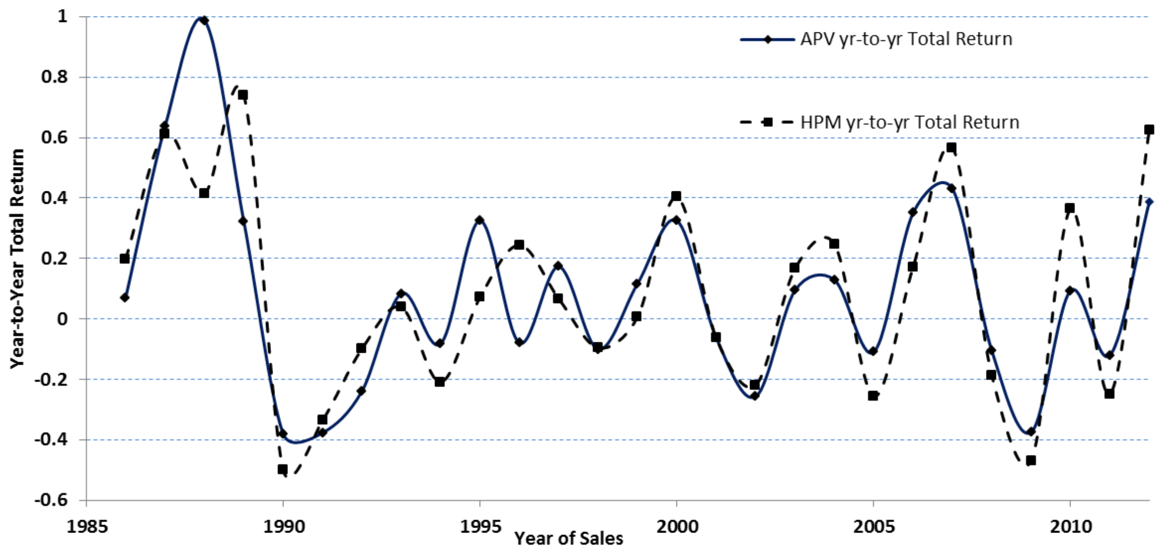


Figure 7. Year-to-Year Total (APV and HPM) for Impressionists Group Sales



Market Returns

Provided one has enough data, hedonic models can also be used to obtain an estimate of the market return (as opposed to total return) between two consecutive years using a model fitted just using the data corresponding to those two periods (unlike the previous section in which the returns were estimated using a HPM built based on the entire dataset). The market return, under this variation of the hedonic model framework (assuming a log-price dependent variable) is simply Exp(β) – 1, where β is the coefficient associated with the year-of-sale (dummy) variable (0 if the painting is sold during the first year, 1 if it is sold during the second year). This is, in principle, another test that can be used to verify the soundness of APV-based returns: does the APV metric render reasonable estimates of market returns? The only problem is that the APV metric, by its very definition, does not lend itself naturally to isolate the market effects and the supply-demand effects (specific features of the paintings actually sold) and therefore, one cannot estimate directly, using the APV metric, the market returns between two consecutive years. Thus, some modifications are required to design a test to check if the market returns implied by the APV metric make sense.

We tackle this in three steps. Let us assume that we have three consecutive years (*i*, *i+1, i+2*) each with several observations. First, we group in one set all the auction data for years *i* and *i+1* and compute APV(a), the average APV value considering all these observations as if they were made in the same year. Second, we group the data corresponding to years *i+1* and *i+2* in another set and compute APV(b), the average APV value considering all these observations as if they were made in the same year. And third, we estimate the market return between year *i+0.5* and *i+1.5* as λ = [APV(b)/APV(a)] – 1. The rationale for these calculations and assumptions is not straightforward, but it can be explained appealing to intuition.

By comingling in one set all the APV observations corresponding to two consecutive years (say, *i* and *i+1*) we are, in effect—if not nullifying at least mitigating—the influence of the variations in the individual paintings' characteristics. Thus, we are letting the market effect dominate. Furthermore, since APV(a) and APV(b) are based on adjacent years that actually overlap (year *i+1* is common), this also tends to minimize the effect of the differences in individual paintings' characteristics and privileges the market effects. This computational trick, which is actually tantamount to applying a low-pass filter to the time-history of APV values, is by no means perfect. But "smoothing" the time-history of the average APV values achieves the goal of reducing the effect of the individual paintings' characteristics. This estimated return corresponds to a (shifted) one-year period return simply because the "time-distance" between the center-points of two consecutive periods is *(i+1.5) – (i+0.5)* = 1.

We now need to estimate the market return between years *i+0.5* and *i+1.5* using a different approach to be able to make a meaningful comparison. To this end, we introduce a technique based on the HPM-framework applied to observations made in two adjacent periods (de Haan and Diewert 2011; Brachinger 2003). Consistent with the approach described in the previous paragraph we proceed as follows. We group all the information related to the paintings sold in years *i* and *i+1* in one set (keeping track of the "year-of-sale effect" by means of dummy binary variable) and fit a HPM to these data. The market return between year *i* and year *i+1* is estimated by $R_a = \text{Exp}(\beta_a)-1$ where β_a is the coefficient of the time dummy variable. We turn now to years *i+1* and *i+2* and determine a HPM analogous to the one estimated in the *i* and *i+1* case. Here, $R_b = \text{Exp}(\beta_b)-1$, where β_b denotes the coefficient of the time dummy variable, captures the market return from year *i+1* to *i+2*. Finally, $\omega = (R_a + R_b)/2$ provides an estimate of the market return between years *i+0.5* and *i+1.5*.

The above-mentioned calculations can only be carried out for Renoir and the Impressionist group. The Matisse data set (described in **Table 9**) contains several time gaps and lacks sufficient observations in most years; thus, for most consecutive years, it is not possible to fit a HPM. Consequently, the comparison between λ and ω, or, alternatively, the year-to-year market return estimated by (i) the APV-metric and (ii) the adjacent HPMs was only done for the two cases with enough data (Renoir and the Impressionists). In the case of Renoir, the values of the adjusted R^2 for the adjacent-period HPMs range from 0.67 to 0.82. For the Impressionists the adjusted R^2 values vary between 0.48 and 0.82.

Table 14. Average Year-to-Year Market Returns: Based on (i) APV and (ii) Adjacent HPMs, and their Correlations

	Data Set A: Renoir	**Data Set C: Impressionists**
Average Market Return APV	4.80%	6.61%
Standard Deviation Market Return APV	27.93%	26.21%
Average Market Return HPM	4.60%	6.26%
Standard Deviation Market Return HPM	18.99%	23.70%
Correlation Market Ret. APV – Market Ret. HPM	0.85	0.91

Table 14 summarizes the key comparison values. **Figures 8** and **9** compare graphically the time-history of year-to-year market returns for the two data sets considered. As in the case of the total returns the comparison validates the estimates provided by the APV metric as they show agreement with the estimates based on hedonic model techniques. This is also in agreement with the high correlation values reported (0.85 and 0.91). From **Table 14**, we appreciate that in both cases (Renoir and the Impressionists) the standard deviation of market returns estimated by the APV metric (27.93% and 26.21%, respectively) are higher than those given by the HPMs (18.99% and 23.70%). This is to be expected since the "smoothing" approach employed to derive market returns from APV data is only approximate (the HPM is better suited to separate these effects in a more clear-cut manner). In any event, the preceding comparison provides evidence that, again, in spite of its remarkable simplicity the APV metric can provide reasonable accuracy with an important economy of computation.

It is interesting to note that the standard deviation of the market returns (using either approach, APV or HPM) is markedly lower than the standard deviation of the corresponding total returns (35.58% and 31.47% from **Table 11**). Intuitively, this makes sense: total returns—by virtue of not controlling for the characteristics of the paintings—exhibit more variability.

Figure 8. Year-to Year Market Returns for Pierre-Auguste Renoir Based on (i) APV Metric and (ii) Adjacent HPM Approach

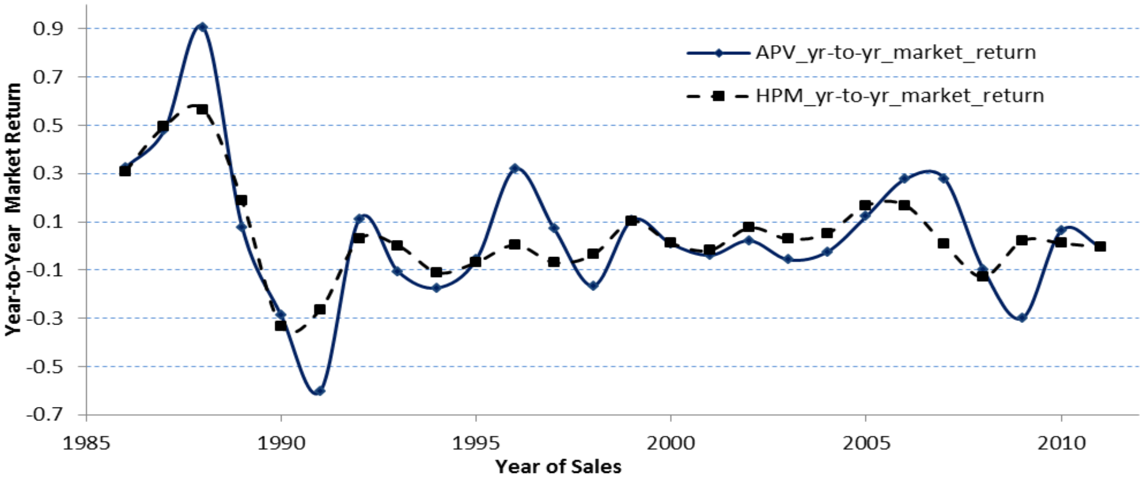
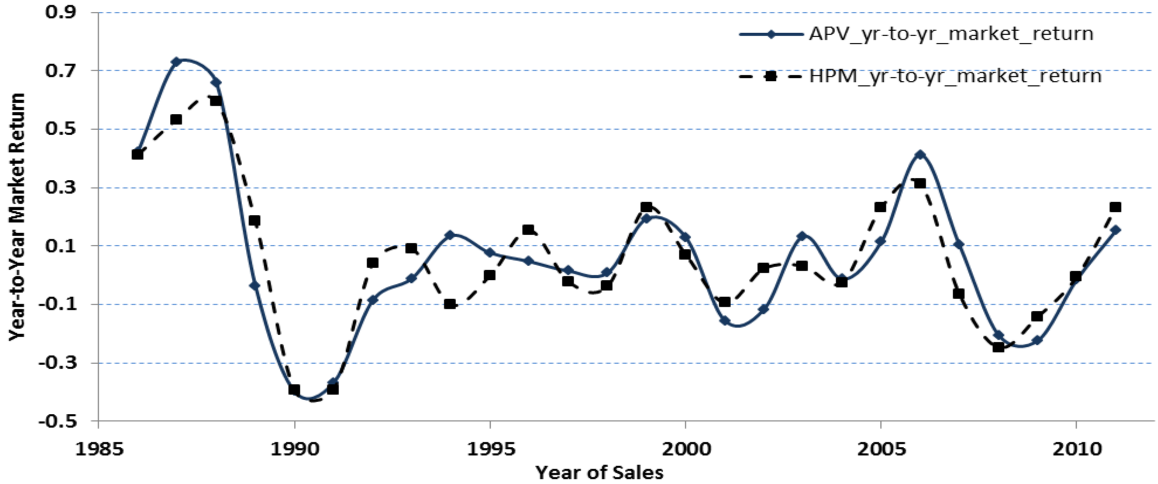


Figure 9. Year-to Year Market Returns for the Impressionists Group Based on (i) APV Metric and (ii) Adjacent HPM Approach



Life-Cycle Patterns

Hedonic models have also been used in the past to investigate the age at which an artist produced its most valuable work. Typically, a HPM is fitted to the entire data available (which normally cover several years) and then the natural logarithm of the average price versus the artist's age-at-the-time-the-painting-was-executed, based on such model, is plotted. That is, the hedonic pricing equation is evaluated, for each age, using the average characteristics corresponding to that age.

Figure 10. Life-Cycle Creativity Curve, Pierre-Auguste Renoir: Comparison between (i) Log of APV profile and (ii) Log of Price (from HPM) profile

Figure 11. Life-Cycle Creativity Curve, Henri Matisse: Comparison between (i) Log of APV profile and (ii) Log of Price (from HPM) profile

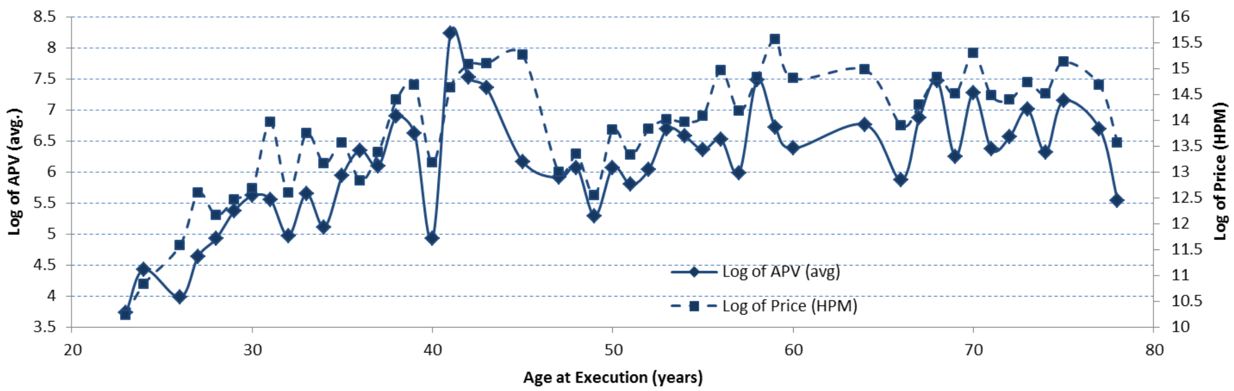


Figure 12. Life-Cycle Creativity Curve, Claude Monet: Comparison between (i) Log of APV profile and (ii) Log of Price (from HPM) profile

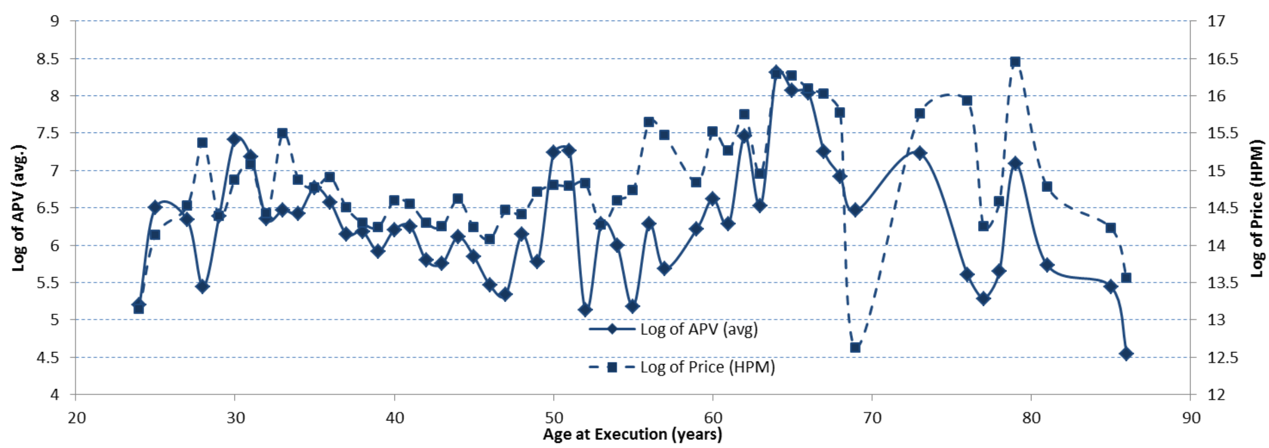


Figure 13. Life-Cycle Creativity Curve, Camille Pissarro: Comparison between (i) Log of APV profile and (ii) Log of Price (from HPM) profile

Figures 10, 11, 12, and **13** compare the curves obtained: (i) using the above-mentioned approach; and (ii) plotting the logarithm of the average APV versus age-at-execution. In this case we used the average APV rather than the median, since the HPM-based curves are normally done with the mean. The four artists considered were the only artists for whom we had more than 400 sales observations: Renoir, Matisse, Monet, and Pissarro. All four graphs show very consistent trends between the two curves. In essence, the HPM-curves do not seem to offer anything more than the simpler APV-based curves show.

A more interesting point becomes obvious when we compare these life-cycle curves with those displayed before in **Figs. 1, 2, 3,** and **4** which were obtained using the median APV instead of the log(average-APV) or log(average-price). Obviously, the first group of curves shows much more clearly the evolution of life cycle-patterns patterns. To some extent, this is to be expected, as the log-function tends to mitigate the effect of peaks and valleys. Furthermore, this phenomenon calls into question the benefits of building these curves using the log-function (regardless of the underlying variable) instead of using the real thing, that is, the actual variable −for example the APV (with no log applied).

To sum up, the APV-based calculations, in all cases considered, yielded very similar results to those obtained with the hedonic models. This provides good evidence that the APV metric, despite its simplicity, offers results consistent with conventionally accepted methods.

This high degree of consistency might seem surprising. However, the following two observations can explain, appealing partly to intuition, the success of the APV: (1) regressing the logarithm of the price on just the area of the painting, for the case of Renoir, Matisse, and the Impressionists, we obtained adjusted R^2's values equal to 0.37, 0.26, and 0.33

respectively. Recall that the R^2's values of the corresponding hedonic models were 0.75, 0.72, and 0.67 respectively. Hence, the APV metric −for all its roughness and simplicity− was able to explain, just by itself, almost half of what all the factors of the HPMs did; and (2) if we compute the correlation between the area of the paintings and the logarithm of the price for all the artists considered (Sisley, Pissarro, Monet, Matisse, Redon, Gauguin, Signac, and Renoir) we obtain the following (fairly high) values: 0.36; 0.65; 0.48; 0.51; 0.55; 0.59; 0.68, and 0.61 respectively. These observations provide some basis for making an argument that using the area of a painting as a normalization factor is not that eccentric or bizarre; it has some sound foundation.

Suggestions for Future Applications

APV-based Derivatives and Index Contracts

The market for paintings lacks a widely accepted index or indices that could be used to design derivatives contracts for hedging and/or speculative purposes. We reckon that the reason is that the most popular indices (Mei-Moses index, artnet.com family of indices, AMR indices, etc.) while effective for the purpose they were designed −namely, tracking broad market trends− are unsuitable for financial contracts. The reason is that they involve certain elements (proprietary databases, discretionary rules in terms of which sales should be included, ad hoc combinations of repeat sales techniques coupled with some undesirable features of HPMs) that make them opaque and −at least in theory− vulnerable to manipulation. In contrast, indices such as the S&P 500 or the Barclays Capital bond indices family −which are based on well-defined and transparent rules− are easy to reproduce and difficult to game. Not surprisingly, derivatives contracts based on these indices have enjoyed wide market acceptance.

We think that the APV metric provides a natural tool to create well-defined indices that could be the foundation for a derivatives art market. If one wishes to design an index to represent a specific market segment −for example, the Impressionists− the main point is to agree on the artists that should be part of the index. Once this issue is settled −a rule that must stay unaltered over time− what remains to agree upon is simply a mechanistic recipe to calculate the value of the index. For instance, it could be the average APV value of all the paintings sold in public auctions in the last twelve months as long as their values exceeded US$ 50,000.

A contract built around an index of this type could be used to gain exposure to this market or short it, in amounts much smaller than the typical price paid for a masterpiece. In that sense, these types of contracts could help to expand the investor base, and contribute to improve market liquidity. The operational details are similar, for instance, to those encountered in the agricultural derivatives market or commodities markets. This topic is presently under investigation by the authors.

Testing the CAPM Validity in the Art Market

Several authors have investigated the validity of the CAPM model within the context of the art market. Although the results have been mixed we also think they have been irrelevant. The reason is that most authors —erroneously in our view— have placed on the left-hand side of the equation estimates of the market returns (obtained, in general, via the time-dummy coefficients of a suitable hedonic model). We reckon that the correct approach is to place on the left-hand side of the CAPM equation estimates of total returns—not market returns. These returns, of course, can be easily obtained with the APV.

This suggestion might sound strange until one realizes that, for instance, if we were to apply the CAPM model to, say, IBM's stock (to go back to our initial analogy) we would place on the left-hand side of the equation the return based on the price of IBM stock over some time period: in short, the total return. We would never place on the left-hand side the IBM stock return computed after controlling for whatever market factors might influence it (composition of revenue, number of employees, technology changes, etc.)

In summary, it is quite odd that the validity of the CAPM within the art market context has been carried out using returns that do not capture supply-demand changes from period-to-period. At present, we are investigating this topic.

Conclusions

We have introduced an easy-to-compute financial metric suitable for two-dimensional art objects that is both intuitive and transparent. It has several appealing features: it is difficult to game since not much discretion comes into its evaluation (unlike hedonic models that are data intensive and often exhibit lack of stability); it can be applied to artists for whom there are few observations, albeit with all the caveats appropriate for small data sets; it facilitates comparisons between artists, between different types of paintings by the same artist, or, paintings done by the same artist at different life-periods; it is also appropriate to explore artists' consistency, by looking at its standard deviation or coefficient of variation; and, finally, it can be employed to construct well-defined total-return indices to create financial derivatives.

However, it must be emphasized that the main goal of this new metric is to offer an investor a useful yardstick that captures, after normalizing by the area, a representative price. It is not the aim of the APV to control prices for other characteristics or to build a market index based on a time-independent ideal painting. For these reasons the APV metric is ideally suited to compute actual returns.

In terms of estimating returns, the APV metric offers three attractive features: (i) unlike repeat-sales regression models, it uses all the available data; (ii) unlike HPMs, whose effectiveness can depend substantially on the variables chosen and the analyst's skill to select them, the APV gives a unique value: the actual total return; and (iii) APV-based returns can always be computed regardless of the number of observations. On the other hand, HPM-based returns can be computed only in the limited number of cases where one has enough data, with the caveat that the accuracy of such returns estimates is weakened by the explicatory power of the relevant model since the R^2 is never 1.

The comparison between APV-based total returns (or for that matter, any other figure of merit based on the APV metric) and a similar figure of merit based on HPMs techniques deserves some attention. The rationale for these comparisons is simply that hedonic models are, more or less, accepted as valid tools within the art market. Accordingly, some reasonable degree of agreement with a calculation based on hedonic models provides comfort that the new tool (the APV in this case) is not outlandish. In this regard, the examples described in the paper give validity to the soundness of the APV metric. At the same time, it should be mentioned that the examples presented here should be taken as a proof of concept and not as a definite claim of superiority in favor of the APV. We hope that other researchers will conduct more tests using the APV metric (and devise new applications) which, in due time, will lead to a more complete picture in terms of its advantages and drawbacks. Thus, we see the APV as a complementary tool to the conventional models, not as a substitute.

Although the topic of this paper has been to introduce a new tool to the analyst's toolkit, rather than questioning the virtues of the HPMs in the context of the art market, one thing is obvious: hedonic models, considering how data-intensive they are plus the additional limitations already mentioned, do not seem to offer a lot more insight than the simple APV metric −at least for the examples discussed in this study. Moreover, the high correlation observed between total returns computed using the APV and those based on HPMs reinforces this point.

In summary, we hope investors, financial analysts, and future researchers will be able to explore −and exploit− the merits of the APV metric. Our goal has been simply to introduce the tool, showcase a few applications, and perform some validation tests.

Finally, the main advantage of the APV is that it is a financial metric and not a modeling technique; therefore, it is what it is, and it can always be computed. In short, it can be useful or useless, but never wrong.

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