Art Market Returns: Misgivings and Certainties

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Dr. Ventura Charlin; V.C. Consultants; Avenida Los Leones 1300, Suite 1202; Santiago, Chile; (+56) (2) 2789-7447; ventcusa@gmail.com.

Professor Arturo Cifuentes; Faculty of Economics and Business, University of Chile; Santiago, Chile; (+56) (2) 2977-2101; arturo.cifuentes@fen.uchile.cl.

ABSTRACT

Paintings are −among other things− financial assets. The most basic piece of information regarding a financial asset is probably its return, or, more appropriately, the potential return that it can offer. Not surprisingly, many scholars have devoted a fair amount of effort to explore how to compute returns for such assets.

Unfortunately, after more than forty years of efforts, many fundamental issues regarding returns remain unsolved. In this paper we address two issues that somehow have been overlooked by previous research: (i) how the choice of metric influences the computation of estimated returns; and (ii) the importance of taking into consideration the error propagation in the computation of these estimates. We conclude that estimating returns for paintings is far more difficult than previously believed; there is no unique or best solution; and perhaps more relevant, the errors associated with these estimates are quite substantial.

Keywords Art markets Hedonic pricing Repeat Sales Paintings Returns

JEL Classification C18 D44 G11 G12 Z10

INTRODUCTION

Paintings, notwithstanding their artistic merits, are also financial assets, which, very often, fetch incredible prices. Therefore, it should not be surprising that many scholars have explored the merits of paintings as investments. This trend got started about forty years ago and the focus has been mainly on how to estimate returns for the art market (e. g., Agnello and Pierce 1996; Anderson 1974; Ashenfelter and Graddy 2003; Baumol 1986; Renneboog and Spaenjers 2013; Renneboog and Van Houtte 2002). This is critical, since an assessment of the benefits of investing in any asset has to go hand-in-hand with a comparison against the merits of other options. Usually, the basic elements for such comparisons are returns and their key characteristics: expected values, volatilities, correlation with other assets, their market betas, etc. Therefore, the need to have a reliable and well-accepted method to estimate returns is paramount.

Unfortunately, despite significant efforts, much remains to be understood regarding returns within the art market: from how to compute them, to what they actually capture, depending on the metric or method employed. For example, the two most popular approaches to compute returns are the hedonic pricing method, via time-dummy coefficients, and the repeat-sales regression. However, scholars are still pondering why they sometimes give different results (e. g., Ashenfelter and Graddy 2003).

A more vexing question is whether returns estimated with repeat-sales data are actually biased −as some researchers have pointed out− despite the many approaches introduced to correct such estimates. Even if we accept that hedonic models are superior (a fairly contentious assumption), the merits of using adjacent/chained hedonic models, that is, using two-consecutive periods, vis-à-vis the advantages of using models based on longer time-stretches, have not been fully explored. Furthermore, the real meaning of a return based on an ideal −time-independent and unaltered− painting poses a few yet-to-be-settled interpretation challenges. And, if we also add to these issues the fact that price indices based on time-dummy coefficients do not meet Fisher's monotonicity condition (Fisher 1922), it is easy to understand why estimating returns in this market is still an open question (Melser 2005; Charlin and Cifuentes 2014).

The most compelling evidence that the art market really needs an easy-to-understand, easy-to-verify, and transparent way of computing returns is that no market for art derivatives has yet emerged. The most popular indices (the Mei-Moses index is a good example) are still based on opaque rules that makes them impossible to replicate by third parties.

In this context, our paper seeks to address two issues: (i) the relevance of selecting different metrics to estimate returns; and (ii) the importance of accounting for error propagation when estimating returns.

THE DATA

We employ two datasets based on realized auction premium prices as provided by the www.artnet.com website. They cover the 1992-2012 period and the artists considered are Renoir (1,367 observations) and Bonnard (485 observations). The prices are expressed in 2010 U.S. dollars (adjusted via the U.S. CPI index). Table 1 summarizes the key aspects of both datasets. The Artistic Power Value (APV) refers to the price per unit of area (Charlin and Cifuentes 2014).

Table 1. Detailed characteristics and key statistics of the artists in the study.

Variable	Pierre-Auguste Renoir	Pierre Bonnard
Number of Sales	1,367	485
Number of Repeat-Sales Pairs	140	65
Price (in US$)		
Average	797,924	701,109
Standard Deviation	1,933,136	1,294,323
Geometric Mean	298,143	327,713
Median	267,395	319,762
Minimum	11,496	11,291
Maximum	28,045,202	11,355,673
APV (in US$/cm^2)		
Average	503	228
Standard Deviation	888	265
Geometric Mean	347	145
Median	337	146
Minimum	29	2
Maximum	26,425	1,878

ESTIMATING RETURNS

The most challenging question when estimating returns for paintings is actually a conceptual issue rather than a computational one: What do we mean by the real or correct return? This difficulty can be appreciated with more clarity if we resort to an analogy. Suppose we need to estimate the return associated with an investment in XYZ, a company that is traded in the global stock markets. The return can obviously be computed by looking at the stock price variation during the relevant period; that's it, there is no ambiguity here.

Far more important is to realize that a return computed this way, is not only based on a well-defined concept, but also, this return has no error associated with it. This return is not an estimate, is the real thing. Its computation is based on two numbers: the stock price at the beginning and at the end of the period, which are exact and therefore not affected by errors. Thus, this return computation has no error. Furthermore, this return is a total return: it captures all the effects that influence the price of XYZ, from supply-demand dynamics in the broadest sense of the term to the specifics of XYZ; we are not controlling for any factors.

Clearly, if the same painting is sold twice, the computation and the interpretation of the return is trivial: it is a total return; i.e., a return that takes into consideration all the factors that affect the price, from general market forces to the specific features of the painting in question. Therefore, if we have several matched sales (repeat-sales regression approach) what we are doing is computing an average total return estimate. We are not controlling ─as some academics believe─ for anything. This is not necessarily bad; quite the contrary, it is just a matter of knowing how to interpret these results. Unfortunately, repeat sales account for a small fraction of the art market. Hence, the need to use all the data available forces us to look into other alternatives.

Hedonic pricing models are a popular alternative. The idea is to fit a model using all the data, and to estimate the returns by means of the time-dummies of the ordinary least-squares regression. Such return, leaving aside the violation of the monotonicity condition that might result in spurious values, poses an intriguing question: What does this return capture? How do we interpret it? Clearly, it is in not a total return since we are controlling for a number of factors; which is the idea at the root of the hedonic model. It is simply a return associated with an ideal (average) painting which is unchanged, with constant characteristics over time. While the interpretation of this return is uncertain, one thing is obvious: we should not expect this return to be close to the repeat sales-based return (leaving aside sample bias issues) because the time-dummies-based return is not a total return.

An additional challenge comes from the time periods considered. Or more to the point, from the way we decide to partition the dataset time-wise. If we employ one hedonic model to cover all the periods, the most common choice according to the academic literature, we can probably get a higher R^2. However, the underlying assumption at the root of this approach is that the investors' preferences (utility function) remain constant over time. Given the nature of this market, this assumption is difficult to defend. Painters' popularity is notoriously time-dependent. On the other hand, if we chose the other extreme, namely, using a sequence of adjacent (chained) hedonic models, while we could account for variations in tastes over time, we could encounter numerical instabilities. These models are often associated with lower R^2's as a result of being based on less data points.

Finally, all these considerations lead unequivocally to one conclusion: the need to explore other alternatives to estimate returns is warranted.

OUR APPROACH

This study considers five different approaches to estimate returns.

[1] Based on the change in the geometric mean of the price.
[2] Based on the change in the geometric mean of the APV (price per unit of area, that is, dollars/cm^2). The APV metric is discussed in detail in Charlin and Cifuentes (2014).
[3] Based on the time-dummies of a hedonic model fitted to the entire period (1992-2012) at once.
[4] Based on a sequence of hedonic models using two consecutive periods (chained/adjacent hedonic models).
[5] The conventional WLS regression approach for matched sales, that is, applied to the repeat-sales set of observations.

An important feature of our analyses, given the fact that we are estimating returns based on input data that are subject to error (time-dummy regression coefficients, or geometric means for a specific year, etc.) is to also compute the error associated with the estimate. This is critical for any estimate is useless unless one has an idea of the magnitude of the error associated with it. Previous researchers have overlooked this issue; yet, it will be clear that neglecting it can lead to a misinterpretation of the results.

Broadly speaking, if two variables x and y (both subject to errors, δx and δy, respectively) are used to compute F= F(x, y), we denote the error associated with estimating F(x, y) as δF. This error (δF) can be estimated by means of the following expression: $(\delta F)^2 = (\partial F/\partial x)^2 (\delta x)^2 + (\partial F/\partial y)^2 (\delta y)^2$. This formula provides the basis to estimate the relative errors associated with the return estimates specified previously. The standard errors (SE) of the time-dummy coefficients and the geometric means can be used as a proxy to estimate the errors in the primitive variables (δx and δy in this framework).

RESULTS

Table 2 shows the year-to-year and average (for the period 1992-2012) returns using the five different approaches described before, in the case of Renoir.

As expected, the estimates are quite different, as they capture different things. The returns based on the geometric mean of the price are an attempt (however crude) at capturing a total return. Given its high variability, it is not surprising that these returns exhibit the second largest relative error. The APV-based returns, which also aim to capture a total return, but just controlling for the area of the paintings, show the least error and they have the advantage of being more intuitive and easy-to-compute, since not much discretion comes into the calculation. The time-dummies-based returns are difficult to interpret due to the reasons explained before, but they certainly do not attempt to estimate total returns. The adjusted R^2 associated with the conventional hedonic model [3] is 0.79; the adjusted R^2's associated with the chained-adjacent models [4] are in the [0.62-0.84] range. The discrepancy between the two time-dummies-based returns −[3] and [4]− raises even more issues regarding this approach since it shows that such return estimates are heavily dependent on the way the time periods are partitioned. The return based on repeat-sales shows the highest relative error due to the reduced number of observations.

Table 2. Pierre-Auguste Renoir returns and corresponding relative errors based on five different approaches: (1) Price (Geometric Mean); (2) APV (Geometric Mean); (3) Hedonic Model (Time-Dummies); (4) Chained/Adjacent Hedonic Model (Time-Dummies); and (5) Repeat-Sales Model (Weighted Least Squares).

	(1) Price		(2) APV		(3) Hedonic Model		(4) Chained/Adjacent Hedonic Model		5) Repeat-Sales Model	
Period	**Return (Geom. Mean)**	**Return Relative Error**	**Return (Geom. Mean)**	**Return Relative Error**	**Return (Time Dummies)**	**Return Relative Error**	**Return (Time Dummies)**	**Return Relative Error**	**Return (WLS)**	**Return Relative Error**
1992 - 1993	4.61%	26.99%	-1.97%	17.78%	2.51%	12.29%	11.65%	15.85%	1.16%	20.55%
1993 - 1994	-41.62%	25.71%	-8.60%	15.38%	-9.69%	17.78%	-16.72%	18.26%	-10.20%	28.68%
1994 - 1995	2.11%	22.56%	-9.62%	12.25%	-10.37%	17.29%	-7.77%	18.57%	-2.83%	33.10%
1995 - 1996	3.46%	19.32%	-12.61%	12.59%	-1.34%	16.43%	14.79%	18.41%	-13.04%	30.96%
1996 - 1997	57.68%	21.55%	43.82%	14.00%	17.96%	16.45%	6.13%	16.15%	29.13%	31.33%
1997 - 1998	-36.14%	22.62%	-29.91%	14.73%	-23.39%	16.31%	-17.42%	16.42%	-13.24%	24.78%
1998 - 1999	30.89%	21.60%	24.66%	13.93%	12.64%	16.32%	23.96%	19.62%	-1.98%	27.87%
1999 - 2000	8.80%	22.84%	11.03%	13.38%	-1.96%	16.32%	7.91%	15.04%	0.27%	28.40%
2000 - 2001	-13.67%	25.52%	-18.31%	15.47%	3.14%	17.05%	-24.01%	15.28%	-20.42%	26.93%
2001 - 2002	19.72%	30.32%	21.56%	18.32%	11.84%	18.43%	21.92%	22.79%	7.01%	32.67%
2002 - 2003	8.57%	30.24%	-3.03%	17.27%	-1.02%	18.61%	1.22%	18.45%	-19.62%	34.26%
2003 - 2004	-7.35%	25.53%	-5.72%	14.44%	3.67%	17.56%	-6.60%	16.68%	49.97%	45.71%
2004 - 2005	-16.96%	20.16%	19.03%	11.47%	18.26%	16.56%	10.63%	15.93%	11.04%	27.95%
2005 - 2006	49.04%	17.97%	25.58%	8.49%	27.06%	16.51%	7.53%	11.80%	-8.16%	22.55%
2006 - 2007	-7.44%	18.59%	11.70%	9.18%	13.98%	16.34%	-5.34%	9.92%	38.22%	22.57%
2007 - 2008	-9.26%	21.40%	-15.31%	13.17%	-6.45%	16.53%	-24.89%	12.21%	-11.16%	21.82%
2008 - 2009	-36.96%	23.38%	-20.53%	14.33%	-30.73%	17.12%	1.90%	19.57%	-4.65%	30.50%
2009 - 2010	59.25%	22.42%	21.27%	12.24%	28.86%	16.95%	39.09%	18.68%	21.11%	27.99%
2010 - 2011	-6.73%	22.29%	-9.35%	12.57%	-11.05%	16.90%	-33.82%	12.45%	-13.18%	19.03%
2011 - 2012	-1.70%	20.41%	0.57%	12.93%	15.62%	16.61%	28.78%	19.83%	2.62%	21.87%
Avg. Return	3.32%		2.21%		2.98%		1.95%		2.10%	
Relative Error	104.25%		62.21%		74.96%		75.51%		127.91%	
Return Range	(-0.14%, 6.77%)		(0.84%, 3.59%)		(0.75%, 5.21%)		(0.48%, 3.42%)		(-0.59%, 4.79%)	

Table 3. Pierre Bonnard returns and corresponding relative errors based on five different approaches: (1) Price (Geometric Mean); (2) APV (Geometric Mean); (3) Hedonic Model (Time-Dummies); (4) Chained/Adjacent Hedonic Model (Time-Dummies); and (5) Repeat-Sales Model (Weighted Least Squares).

	(1) Price		(2) APV		(3) Hedonic Model		(4) Chained/Adjacent Hedonic Model		(5) Repeat-Sales Model	
Period	Return (Geom. Mean)	Return Relative Error	Return (Geom. Mean)	Return (Time Dummies)	Return Relative Error	Return Relative Error	Return (Time Dummies)	Return Relative Error	Return (WLS)	Return Relative Error
1992 - 1993	-21.92%	36.28%	-47.75%	-28.54%	33.17%	29.02%	-28.54%	33.17%	-50.58%	38.47%
1993 - 1994	50.56%	36.50%	7.40%	87.70%	59.50%	42.57%	87.70%	59.50%	110.58%	92.84%
1994 - 1995	20.15%	34.96%	38.34%	-24.01%	27.65%	42.31%	-24.01%	27.65%	-25.29%	34.64%
1995 - 1996	-22.97%	27.74%	-28.58%	-12.40%	31.90%	40.77%	-12.40%	31.90%	-25.86%	48.75%
1996 - 1997	-48.09%	28.45%	-20.71%	15.34%	30.55%	41.00%	15.34%	30.55%	20.59%	63.81%
1997 - 1998	86.54%	27.03%	69.34%	12.35%	25.63%	39.79%	12.35%	25.63%	0.51%	43.20%
1998 - 1999	5.43%	27.46%	6.14%	27.55%	22.97%	38.73%	27.55%	22.97%	-3.39%	35.61%
1999 - 2000	-1.05%	34.24%	-13.34%	-51.80%	19.29%	40.38%	-51.80%	19.29%	-8.31%	37.85%
2000 - 2001	1.34%	34.08%	-3.10%	38.64%	41.91%	42.22%	38.64%	41.91%	34.74%	42.88%
2001 - 2002	-12.77%	32.84%	-7.29%	-4.79%	40.14%	43.42%	-4.79%	40.14%	-31.49%	55.19%
2002 - 2003	21.10%	46.27%	46.23%	-16.55%	60.87%	43.76%	-16.55%	60.87%	42.43%	110.26%
2003 - 2004	-37.69%	45.97%	-35.27%	-11.43%	107.62%	43.52%	-11.43%	107.62%	9.17%	73.72%
2004 - 2005	189.56%	39.92%	80.33%	95.34%	110.12%	42.90%	95.34%	110.12%	-4.63%	54.75%
2005 - 2006	-5.23%	35.23%	28.31%	-1.06%	27.31%	40.08%	-1.06%	27.31%	15.65%	43.71%
2006 - 2007	-30.98%	29.75%	-20.68%	-27.00%	22.95%	39.67%	-27.00%	22.95%	37.69%	33.89%
2007 - 2008	-22.94%	35.26%	-35.18%	-34.71%	35.14%	40.52%	-34.71%	35.14%	-21.21%	27.40%
2008 - 2009	36.03%	40.60%	8.92%	70.23%	68.03%	42.56%	70.23%	68.03%	-7.95%	33.89%
2009 - 2010	7.70%	35.95%	18.80%	12.54%	43.09%	42.92%	12.54%	43.09%	5.16%	37.19%
2010 - 2011	-15.82%	31.58%	-20.19%	-21.13%	35.92%	41.07%	-21.13%	35.92%	-22.82%	32.18%
2011 - 2012	-4.42%	34.03%	12.06%	-6.69%	40.54%	40.88%	-6.69%	40.54%	-3.15%	36.06%
Avg. Return	9.73%		4.19%		3.89%		5.98%		3.59%	
Relative Error	157.03%		132.92%		183.44%		227.20%		237.62%	
Return Range	(-5.55%, 25.00%)		(-1.38%, 9.76%)		(-3.24%, 11.02%)		(-7.60%, 19.56%)		(-4.94%, 12.13%)	

Finally, the obvious: the relative errors associated with these estimates are substantial. This suggests that: (i) estimating returns without reporting the errors is unlikely to be of any use (it just gives a false sense of accuracy); and (ii) previous research and findings related to art market returns, correlation with other assets, and volatilities −since for the most part were based on return estimates whose errors were neither computed nor reported− are to be regarded with a great deal of skepticism. Table 3, which shows the results for Bonnard, displays some of the same trends, except that the average return estimated with the hedonic model is lower than the average return estimated with the adjacent model. The adjusted R^2 associated with the hedonic model [3] is 0.62; the adjusted R^2's associated with the adjacent models [4] fluctuate between 0.43 and 0.74. However, the discrepancies between these two returns − [3] and [4] − remain high. Overall, the relative errors are much higher than those associated with Renoir due to the smaller size of the dataset.

Tables 4 and 5 report the different correlation values among the five different return metrics for Renoir and Bonnard respectively. The low correlations between the returns obtained with the conventional hedonic model and the chained/adjacent model for both artists (0.61 for Renoir and 0.46 for Bonnard), raise many doubts. The question is, in essence, what is the "right" time-partition to obtain the "correct" estimate? Leaving aside all the other considerations and drawbacks already pointed out, this is an indictment on the use of hedonic models in the context of returns. Moreover, the low correlation between the returns estimated with the repeat-sales approach and all the other estimates, gives validity to the view that this subset of sales (repeat-sales) does not have the same characteristics of the complete universe.

Table 4. Pierre-Auguste Renoir: Correlations among the returns based on five different approaches: (1) Price (Geometric Mean); (2) APV (Geometric Mean); (3) Hedonic Model (Time-Dummies); (4) Chained/Adjacent Hedonic Model (Time-Dummies); and (5) Repeat-Sales Model (Weighted Least Squares).

Return	(1) Price	(2) APV	(3) Hedonic Model	(4) Chained/ Adjacent Model	(5) Repeat-Sales
(1) Price	1.00				
(2) APV	0.80	1.00			
(3) Hedonic Model	0.76	0.82	1.00		
(4) Chained/Adjacent Model	0.59	0.60	0.61	1.00	
(5) Repeat Sales	0.28	0.49	0.45	0.29	1.00

Table 5. Pierre Bonnard: Correlations among the returns based on five different approaches: (1) Price (Geometric Mean); (2) APV (Geometric Mean); (3) Hedonic Model (Time-Dummies); (4) Chained/Adjacent Hedonic Model (Time-Dummies); and (5) Repeat-Sales Model (Weighted Least Squares).

Return	(1) Price	(2) APV	(3) Hedonic Model	(4) Chained/ Adjacent Model	5) Repeat-Sales
(1) Price	1.00				
(2) APV	0.82	1.00			
(3) Hedonic Model	0.57	0.75	1.00		
(4) Chained/Adjacent Model	0.67	0.47	0.46	1.00	
(5) Repeat Sales	0.13	0.20	0.20	0.46	1.00

CONCLUDING REMARKS

In summary, the results shown before indicate that: (i) return estimates in the case of paintings are subject to such large errors that any conclusion based on such returns should be examined with great skepticism; (ii) the high variability observed depending on the metric employed adds even more uncertainty to any potential conclusion; and (iii) of all the alternatives employed, the APV is possible the best choice to estimate returns, due its clear interpretation, stability, and ease of computation (no discretionary decisions are involved in its computation). That said, Baumol's characterization of art market investments as a floating crap game seems to also apply to the computation of returns in such market (Baumol 1986).

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