Journal of Cultural Economics **20:** 1–24, 1996.

The Relevance of Hedonic Price Indices

The Case of Paintings

OLIVIER CHANEL and LOUIS-ANDRÉ GÉRARD-VARET
GREQUAM, Marseilles, France

VICTOR GINSBURGH
Université Libre de Bruxelles and CORE, Brussels, Belgium

Abstract. We argue that for the case of heterogeneous commodities with infrequent tradings, such as paintings, it is relevant to base a price index on hedonic regressions using all sales and not resales only. To support this conclusion we construct a price index for paintings by Impressionists and their followers and compare the various estimators using bootstrapping techniques.

Key words: price index, heterogeneous commodities, returns on art investment

Introduction

Real assets, such as houses or paintings, are known to be illiquid: only a fraction of the stock is on sale during one run of the market. These are also heterogeneous commodities and the price of each unit depends, to some extent at least, on its own characteristics. In order to construct a price index for such markets, it is necessary to control for possible non temporal determinants of price variations. This is what motivated the estimation of "hedonic price indices", initiated by Court (1939), extended and used among others by Griliches (1971) for car prices and Ridker and Henning (1967) for housing.

These techniques produce indices of the market price for a standardized commodity by using the estimates of a regression of the sale price of a sample of commodities on their characteristics and on (some representation of) time. Because the correct set of characteristics is not known with certainty, it has been suggested, following Bailey, Muth and Nourse (1963), that the analysis be confined to commodities which have been sold more than once and to estimate an index by regressing the change in the (logarithm of the) price of each commodity on a set of dummy variables (one for each time period during which the commodity is hold). This is the so-called "repeat-sales regression" method which has been used to compute indices for property values or family houses by Palmquist (1980), Mark and Goldberg (1984), Case (1986), Case and Shiller (1987, 1989), Goetzmann (1990a), for paintings by Anderson (1974) and Goetzmann (1990b, 1993) or for prints by

Pesando (1993). Although the method avoids the difficulty of specifying the various quality characteristics, it does so at the cost of ignoring all the information on single transactions.

As observed by Shiller (1991), a repeat sales estimator is actually a hedonic estimator where hedonic variables consist only of commodity dummy variables, one for each commodity. This also suggests the possibility of using changed characteristics in a repeat sales regression by augmenting the set of hedonic variables. See Palmquist (1982) or Case and Quigley (1991). However, for markets characterized by infrequent trades, there is an advantage to an ordinary hedonic regression including all commodities, even those sold only once.

In this paper, we consider the market for paintings. Besides Anderson's (1974) and Goetzmann's (1990b) papers mentioned above, Stein (1977), Baumol (1986) and Frey and Pommerehne (1989) have also contributed to the issue. Most of these contributions were motivated by measuring the expected returns to investment in art. They consider the relationships between art and other assets, but they are not so much interested in constructing a price index for art markets. We argue that constructing such an index is a preliminary step to any sensible study of returns and that hedonic estimation provides a suitable method, since it allows combining information on single sales with information on repeat sales for commodities the characteristics of which may change over time.

Holub, Hutter and Tappeiner (1993) have criticized the approach in two respects. First, they rightly claim that it is meaningless to compute a unique price index comprising all painters, schools and artists.[1] Second, they argue that the repeat sales method does not really avoid the heterogeneity problem since results on homogeneous repeat sales are necessarily aggregated to produce a global index.

We provide a partial answer to both of their remarks, first by considering a relatively homogeneous market (Impressionist and Modern paintings), and second, by implicitly weighting the various artists appearing in our sample. Using all observations on sales provides many more observations and also avoids the difficult work of searching for paintings which have been sold twice at least. Unless the artwork sold is described by its number in a catalogue raisonné, one can never be sure that it is the same work: the title is often translated into the language of the country where it is sold; many works bear titles which make them undistinguishable (such as *Reclining Nude*, or *Still Life*); dimensions "change" because they are sometimes not accurately reported or measured, etc.

It is also worth noting that most (if not all) studies estimating returns for art markets are based on transactions at public auctions. Guerzoni (1994) pointed out that unobserved private sales (through galleries or other intermediaries) may also take place between sales at auctions. He shows that if one takes these into account (at least for Reitlinger's (1960, 1970) compendium used by most researchers), returns may turn out to be very different from those usually obtained. This adds to the reasons for which it may be better to use all the information (resales as well as sales) to compute returns. Finally, one cannot exclude the possibility of selection biases when using resales only: it may be the case that only "good" works (or on the contrary, only "lemons") appear often on the market.

In the first section we discuss alternative approaches to the construction of price indices. In Section 2, we briefly survey previous empirical findings on the art market. The third section is devoted to the presentation of the results that we have obtained using hedonic estimation. In Section 4, hedonic estimation is compared with two other widely used estimators (the geometric mean and the geometric repeat sales estimator), using bootstrap replications. We show that the hedonic estimator provides estimates that are much more precise than the two other estimators, even if the number of observations is identical. In the conclusion, we take up some issues concerning the art market as a financial institution.

1. On the Construction of Price Indices

In this section, we describe three possible estimators of price indices, obtained from observing a set of $2N$ transactions related to $i = 1, 2, \ldots, N$ different commodities (described in terms of some attributes or characteristics). For simplicity, we assume that each commodity has been the object of two transactions.[2] The set of dates (say, years) is $t = 0, 1, \ldots, T$ and defines possible periods (period t goes from date $t-1$ to date t) or market runs for the commodities. There exist data on prices for each commodity during some (here, 2) periods, but not for all commodities in every period. A transaction of commodity i in period t is indexed by subscripts (i, t).

The three estimators considered now are the geometric mean, the geometric repeat-sales estimator and the hedonic estimator. We illustrate our discussion using an example in which there are $2N = 12$ sales of $N = 6$ commodities at three possible dates ($T = 2$). Let p_{it} be the (log of the) price P_{it} of commodity i, sold at date t. Assume commodities 1 and 4 were sold in $t = 0$ and 1, commodities 3 and 5 were sold in $t = 1$ and 2 and finally, commodities 2 and 6 were sold in $t = 0$ and 2. We define a vector y with elements y_i (the logged differences of prices obtained at two dates) as follows:

$$y = \begin{pmatrix} p_{11} - p_{10} \\ p_{22} - p_{20} \\ p_{32} - p_{31} \\ p_{41} - p_{40} \\ p_{52} - p_{51} \\ p_{62} - p_{60} \end{pmatrix} .$$

The Geometric Mean Estimator

We write the following linear model:

$$y_i/\tau_i = \beta + \varepsilon_i , \tag{1.1}$$

where β is a parameter to be estimated and τ_i is a variable which takes as value the number of periods during which a commodity was hold by an owner (i.e. not sold); τ_i is thus equal to 1 for $i = 1, 3, 4$ and 5 and equal for 2 for $i = 2$ and 6; ε_i is a random disturbance with the usual properties. The variable y_i/τ_i is the annualized rate of return on commodity i. The parameter β can be estimated by running a regression of y/τ on a variable which takes the value one for each observation. It is trivial to check that the OLS estimate for β is the average of annualized return:

$$\hat{\beta} = \frac{1}{N}\Sigma_i y_i/\tau_i\,. \tag{1.2}$$

This is the estimator used by Baumol (1986) and Frey and Pommerehne (1989).[3] It is obviously very easy to compute, but its drawback is that it does not provide an index over time. Moreover, it puts equal weights on all annualized rates, irrespective of the length of time during which the commodity was held. For our example, (1.2) leads to:

$$\hat{\beta} = \tfrac{1}{6}\left[(p_{11} - p_{10}) + \frac{(p_{22} - p_{20})}{2} + (p_{32} - p_{31}) + \right.$$
$$\left. + (p_{41} - p_{40}) + (p_{52} - p_{51}) + \frac{(p_{62} - p_{60})}{2}\right]\,.$$

THE GEOMETRIC REPEAT-SALES ESTIMATOR

To derive this estimator, we construct an $N \times T$ matrix X. The columns of this matrix represent periods (not dates); observation i is in row i, which contains *ones* for periods during which the commodity was held and *zeroes* otherwise. For our case, this matrix is:

$$X = \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ 0 & 1 \\ 1 & 0 \\ 0 & 1 \\ 1 & 1 \end{pmatrix}\,.$$

The OLS estimator of the two coefficients β_1 and β_2 is given by:

$$\hat{\beta} = (X'X)^{-1}X'y \tag{1.3}$$

and leads, in our example, to the following system of two equations:

$$4\hat{\beta}_1 + 2\hat{\beta}_2 = (p_{11} - p_{10}) + (p_{22} - p_{20}) + (p_{41} - p_{40}) + (p_{62} - p_{60}),$$
$$2\hat{\beta}_1 + 4\hat{\beta}_2 = (p_{22} - p_{20}) + (p_{32} - p_{31}) + (p_{52} - p_{51}) + (p_{62} - p_{60}).$$

This can also be written:

$$\hat{\beta}_1 = \tfrac{1}{4}[(p_{11} - p_{10}) + ((p_{22} - \hat{\beta}_2) - p_{20}) + (p_{41} - p_{40}) + ((p_{62} - \hat{\beta}_2) - p_{60})],$$
$$\hat{\beta}_2 = \tfrac{1}{4}[(p_{22} - (p_{20} + \hat{\beta}_1)) + (p_{32} - p_{31}) + (p_{52} - p_{51}) + (p_{62} - (p_{60} + \hat{\beta}_1))].$$

If we now interpret $\hat{\beta}_1$ and $\hat{\beta}_2$ as being estimates of the mean rates of return in periods 1 and 2 respectively, $(p_{22} - \hat{\beta}_2)$ and $(p_{62} - \hat{\beta}_2)$ are estimates of the prices of commodities 2 and 6, had they been resold in year 1 instead of year 2, while $(p_{20} + \hat{\beta}_1)$ and $(p_{60} + \hat{\beta}_1)$ are estimates of the prices of the same commodities, had they been sold for the first time in year 1 instead of year 0. Once this interpretation is accepted, one immediately sees that $\hat{\beta}_1$ is the average return of the commodities sold in $t = 0$ and in $t = 1$, while $\hat{\beta}_2$ is the average return of the commodities sold in $t = 1$ and in $t = 2$.

Usually, the repeat-sales estimator is presented in a slightly different way. Let Ω be a $T \times T$ matrix constructed as follows: row t starts with t *ones*, while the other elements of the row are *zeroes*. For our example, this matrix is:

$$\Omega = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix}.$$

We then construct a matrix $Z = X\Omega^{-1}$ of explanatory variables. This leads to the following OLS estimator:[4]

$$\hat{\gamma} = (Z'Z)^{-1}Z'y. \tag{1.4}$$

Some straightforward matrix algebra shows that (1.4) can also be written:

$$\hat{\gamma} = \Omega\hat{\beta}, \tag{1.5}$$

which relates estimators (1.3) and (1.4). It implies that:

$$\hat{\gamma}_t = \sum_{\tau=1}^{t} \hat{\beta}_\tau,\ t = 1, 2, \ldots, T. \tag{1.6}$$

For our example, this means that $\hat{\gamma}_1 = \hat{\beta}_1$ and $\hat{\gamma}_2 = \hat{\beta}_1 + \hat{\beta}_2$. Since we can set $\hat{\gamma}_0 = \hat{\beta}_0 = 0$, the sequence $\exp(\hat{\gamma}_0)$, $\exp(\hat{\gamma}_1)$, $\exp(\hat{\gamma}_2)$ produces the price index over the three years.[5]

The Hedonic Estimator

We consider the vector of (logged) prices p, the elements of which are p_{it}. For convenience, we rank the observations for $t = 0$ first, then those for $t = 1$, etc., without taking into account that some of the prices concern resales of the same commodity. We also construct a matrix C of independent variables consisting of $2N$ rows and $T + 1$ columns, denoted $c_0, c_1, \ldots, c_T$. Element c_{it} is equal to *one* if a transaction on commodity i occurs in year t, and *zero* otherwise. For the example at hand, the (column) vector of prices is $(p_{10}, p_{20}, p_{40}, p_{60}, p_{11}, p_{31}, p_{41}, p_{51}, p_{22}, p_{32}, p_{52}, p_{62})$, while say, the first column of C contains 4 ones, followed by 8 zeroes.

We next estimate the parameters δ_t of the linear model:

$$p_{it} = \sum_{\tau=0}^{T} \delta_t c_{it} + \varepsilon_{it}\,, \tag{1.7}$$

where ε_{it} is a random disturbance. The OLS estimator is:

$$\hat{\delta} = (C'C)^{-1}C'p\,. \tag{1.8}$$

It is straightforward to check that the estimator for the price in year t is simply the average of the (log of) prices of the n_t commodities sold during that year:

$$\hat{\delta} = \frac{1}{n_t}\sum_i p_{it},\ t = 0, 1, \ldots, T\,. \tag{1.9}$$

Obviously, this is a sound approach as long as the same mix of commodities is sold in each year. This is where the hedonic approach will be useful since what it does is to homogenize sales mixes over time.

Consider now the set of commodities sold in a specific year t and assume that the price of a commodity i sold in t can be considered as a function of m time-invariant characteristics v_{ik}, $k = 1, 2, \ldots, m$ (e.g. the dimensions of a painting) and on n time-varying characteristics $w_{ij\tau}$, $\tau = 0, 1, \ldots, t$ (e.g. the changing owners of a painting), $j = 1, 2, \ldots, n$. Then, we can write that $p_{it} = f(v_{i1}, \ldots, v_{im}, w_{i10}, \ldots, w_{ilt}, w_{i20}, \ldots)$. We specialize the functional form to:

$$p_{it} = \sum_{k=1}^{m} \alpha_k v_{ik} + \sum_{\tau=0}^{t}\sum_{j=1}^{n} \theta_{j\tau} w_{ij\tau} + \delta_t + \varepsilon_{it}\,. \tag{1.10}$$

The parameters α_k and $\theta_{j\tau}$ appearing in (1.10) can be interpreted as (implicit) prices of the various characteristics describing the commodity, δ_t is the intercept and ε_{it} is a random error term. These implicit prices can be obtained by a regression of the prices on observable characteristics; once they are known, it is possible to compute, like in (1.9), the average price $\hat{\delta}_t$ of a characteristic-free commodity in year t:

$$\hat{\delta}_t = \frac{1}{n_t}\sum_i \left(p_{it} - \sum_{k=1}^{m} \alpha_k v_{ik} - \sum_{\tau=0}^{t}\sum_{j=1}^{n} \theta_{j\tau} w_{ij\tau} \right)\,. \tag{1.11}$$

The sequence of $\hat{\delta}_t$, $t = 0, 1, \ldots, T$ would then describe the price of an (artificial) characteristic-free commodity over time, and this can obviously be obtained by a hedonic regression pooling the sales over time, by combining (1.7) and (1.10):

$$p_{it} = \sum_{k=1}^{m} \alpha_k v_{ik} + \sum_{\tau=0}^{t}\sum_{j=1}^{n} \theta_{j\tau} w_{ij\tau} + \sum_{\tau=0}^{T} \delta_t c_{it} + \varepsilon_{it}\,. \tag{1.12}$$

The method easily allows for interactions between time and characteristics, if one believes that the prices of some characteristics (say, the ones which represent painters) may vary over time. For this, one merely has to introduce new variables $\omega_{kt} = v_k c_t$. The regression coefficients ζ_{kt} picked by these variables describe the time path of the implicit price of characteristic k. The two previous estimators can also provide such information, by computing the parameters on subsamples, e.g. painter by painter. However, given that the number of resales is small compared with the total number of sales, the coefficients would not be estimated with much precision.

Obviously, there are many other ways to specify the way in which prices depend on time. The $\sum_{\tau=0}^{T} \delta_t c_t$ formulation makes it possible to construct a price index. One can also introduce a variable t which takes the values $0, 1, 2, \ldots, T$ and specify (1.12) with a term ϕt, where ϕ would be an estimate of the price trend. One can also estimate different time trends over subperiods. For example, the time dependent term can be written $\phi_1 u_{1t} + \phi_2 u_{2t}$ with $u_{1t} = t$, $u_{2t} = t - \tau$ for $t > \tau$; the trend would then be ϕ_1 between 0 and τ and $\phi_1 + \phi_2$ afterwards.

COMBINING REPEAT-SALES AND HEDONIC ESTIMATORS

Case and Quigley (1991) try to use all the information and combine sales and resales (of houses) in a system of equations. For sales, they use a hedonic equation similar to (1.12), while a repeat sales equation is used for resales. The authors also distinguish resales for which characteristics have changed from other resales.

Though the results are extremely interesting – in particular, they provide estimates with small standard deviations – the suggestion is hard to apply to paintings, since characteristics are mainly described by qualitative variables, while Case and Quigley deal with (a small number of) continuous variables only. Since in our case time is represented by dummies, we would need to introduce a very large number of such ω_{kt} variables.

2. Real Rates of Return on Paintings: Existing Evidence

Anderson (1974) computes the (nominal) rate of return for each of the 1,730 paintings sold at least twice over the period 1653–1970, using Reitlinger (1960, 1970). Next, he runs a regression of returns on dummy variables representing subperiods[6] during which the painting was held before being resold, applying a variant of the geometric repeat sales procedure described in Section 1. He estimates a long term rate of return of 4.9% (3.8% in real terms). For the period 1950–1969, he also computes an average rate of return of 18% per year for Impressionists (166 observations), and 23% for Twentieth Century paintings (49 observations).

Goetzmann (1990b) uses repeat sales estimation[7] on two different databases (Reitlinger with 1,233 resales and Mayer with 1,714 resales); the second one includes data up to 1990. For the 1950–1987 period, he obtains a real rate of return of 10.5%,[8] but his long term rate is just around 3.3% between 1714 and 1986.

The work by Baumol (1986) is also based on Reitlinger, but introduces an extra constraint in selecting resales separated by more than 20 years.[9] The sample reduces to 650 observations. Baumol computes the real rate of return for each resale, and obtains a distribution of returns (for which normality cannot be rejected at the 5% probability level), leading to a mean (the geometric mean estimator) of 0.55% and a median of 0.85%. This is much smaller than the 2.5% real rate of return on (risk-free) financial assets, such as bonds, during the same period.[10] Baumol concludes that "art prices behave randomly" and that financial rationality alone is unable to explain why people buy and possess paintings.[11]

Frey and Pommerehne (1989) extend the data set used by Baumol to cover the 1961–1987 period, and draw similar conclusions on sales made during two subperiods: 1635–1949 and 1950–1987. The real rates of return on some 1,200 resales are respectively 1.4% and 1.7% (net of transaction costs estimated to amount to 0.4%); this is fairly close to Baumol's findings. For the same periods, real rates on financial assets reach 3.3% and 2.4%, with a standard deviation of 1.7%, implying a much lower risk than paintings (with a standard deviation of 5%). Thus, though art has be come a relatively better investment after the Second World War, it still achieves lower rates of return than low risk paper assets.

All these findings are based on a relatively small number of resales which makes it difficult to construct annual price indices.

3. Real Rates of Return on Paintings: New Evidence

We adopt the approach suggested in (1.12) and exlain the price of a painting by its characteristics. The first issue is related to defining characteristics. These may be the size of the work, the year in which it was sold, the year in which it was painted, the place of sale, the characteristics of the buyer and/or seller, the type of painting (still-life, nude, landscape, abstraction, etc.). Such a simple description is however insufficient to explain the price difference between, say Picasso and Miro, and one is necessarily led to include a "measure of the repute of individual artists" (Anderson (1974, p. 17)). To represent reputation, Anderson (1974) uses an "estimated price" for each artist. We chose to work with dummy variables representing artists.

We thus included in the set of characteristics a dummy for each artist[12] and the size of the work (height, width and surface). The auction house is included among the time-varying variables and the year of sale is the time variable. We decided not to use "schools", since there is little consensus on this matter, and several if not all artists have changed their style during their lifetime.[13] The "quality" of the buyer and/or the seller are, we think, important characteristics: there may be differences in the willingness to pay (or to sell) of a museum, a well-known collector, a Japanese insurance company or the Getty Foundation. Such information is unfortunately only seldom available.[14] Finally, we dropped all interaction terms which would have cost too many degrees of freedom in our regression and would also have made less meaningful the comparisons between estimators (Section 4).

Our data set is based on Reitlinger (1960, 1970),[15] and our interest is mainly centered on Impressionists, Post-impressionists and their "followers", but our sample includes *all* artists born after 1830 and having had auctions reported by Reitlinger between 1855 and 1970.[16] This makes for the 46 painters listed in Table I and for some 1,900 sales.[17] Obviously, Reitlinger's choice of artists is subjective, and ours is even more so, since we exclude for instance "old masters". This is of relatively little importance here, since our main purpose is to compare estimation methods.

Current prices were corrected for inflation using, like Baumol, the price index constructed by Phelps-Brown and Hopkins (1956) for the years 1855 to 1954; for more recent years, we used the US consumer price index (IMF, 1972). Prices were not corrected for possible transaction fees charged to buyers and/or sellers by auction houses; nor did we take into account costs of storing, restoring and insuring paintings.[18]

The table given in Appendix 1 reproduces our main results for a sample of equations that we estimated. In all cases, painter dummies, auction house dummies and dimensions are present. The equations differ mainly by how the temporal effects are taken into account: in Equation (1), we split the period into 4 subperiods (see Equation (3.1) below). In Equation (2), we use a trend over the whole period. In Equation (3), we introduce dummy variables for years (see Equation (1.12)) and we restrict observations to the period 1950–1969 only, since there are few sales per year for earlier years.

Note first that over 50% of the variance of the (log) of prices is explained by 60 to 80 variables. In many cases, the most interesting coefficients (i.e. those relative to variables representing time or trends, dimensions) are significantly different from zero at the 5% or even the 1% probability level.

The regression coefficients picked by artist dummies can be used to rank each painter according to the price of a "normalized" (i.e. ageless, standard dimension, sold in a standard auction house) painting of his. Such a ranking is given in Table I. It is based on Equation (3) which best fits the data. Since this model includes sales made between 1949 and 1969 only, it ranks the artists according to their prices in the late 1950's–early 1960's. It is interesting to look at these rankings with a 1990 eye which, given the more recent auctions, would probably rank Picasso much higher. This was far from being true some thirty years ago, where Picasso was "cheap" in comparison with Van Gogh, while Cezanne proved to be the most expensive painter. The coefficients picked by auction house dummies imply that Christie's performed rather poorly: an average sale makes some 10 to 20% less than at Sotheby's. The dimensions of the painting significantly contribute to explaining prices; since the logarithm of prices is a concave function of height and

Table I. Ranking of painters[a]

Rank	Painter	Coeff.	St. dev.	Index
1.	Cezanne	1.718	0.177	557
2.	Van Gogh	1.374	0.175	395
3.	Renoir	1.222	0.160	339
4.	Degas	1.159	0.169	319
5.	Seurat	1.155	0.215	317
6.	Manet	1.034	0.203	281
7.	Monet	0.976	0.168	265
8.	Sisley	0.911	0.173	249
9.	Pissarro	0.893	0.167	244
10.	Gauguin	0.889	0.177	243
11.	Matisse	0.862	0.188	237
12.	Picasso	0.824	0.164	228
13.	Lautrec	0.799	0.245	222
14.	Braque	0.769	0.168	216
15.	Fantin-Latour	0.727	0.200	207
16.	Modigliani	0.686	0.181	199
17.	Bonnard	0.629	0.159	188
18.	Rouault	0.246	0.177	128
19.	Gris	0.233	0.183	126
20.	Signac	0.181	0.187	120
21.	Vuillard	0.179	0.183	120
22.	Chagall	0.129	0.164	114
23.	Soutine	0.128	0.193	114
24.	Morisot	0.116	0.198	112
25.	Klee	0.061	0.176	106
26.	Rousseau	0.000	–	100
27.	Utrillo	–0.029	0.174	97
28.	Derain	–0.103	0.185	90
29.	Vlaminck	–0.156	0.162	86
30.	Dufy	–0.175	0.168	84
31.	Kandinsky	–0.198	0.177	82
32.	Redon	–0.202	0.185	82
33.	Cassat	–0.251	0.182	78
34.	De Staël	–0.274	0.189	76
35.	Leger	–0.327	0.180	72
36.	Miro	–0.401	0.188	67
37.	Van Dongen	–0.482	0.166	62
38.	Munnings	–0.605	0.180	55
39.	Ernst	–0.778	0.183	46
40.	Sargent	–1.372	0.210	25
41.	Whistler	–1.649	0.233	19
42.	Tissot	–1.919	0.265	15
43.	John	–2.162	0.204	12
44.	Burne-Jones	–2.317	0.201	10

Table I. *(Continued)*

Rank	Painter	Coeff.	St. dev.	Index
45.	Alma-Tadema	−2.794	0.234	6
46.	Lord Leighton	−3.649	0.234	3

[a] This ranking is based on Equation 3 reported in Appendix 1.

Table II. Growth rates of inflation-free prices

Time period	Growth rate
1855–1914	6.9
1915–1949	−3.1
1950–1960	22.4
1961–1969	4.3
1950–1969	13.8
1855–1969	4.9

width, the results imply that there exists an "optimal" size beyond which the price decreases.

We finally consider the effect of time. In Equation (1), the period 1855–1969 is split into four sub-periods (obtained after some experimentation, by spline techniques): 1855–1914, 1915–1949, 1950–1960 and 1961–1969. For each subperiod, we include a trend among the variables. More formally, Equation (1) is derived from model (1.12) as follows:

$$p_{it} = \sum_{k=1}^{m} \alpha_k v_{ik} + \sum_{\tau=0}^{t} \sum_{j=1}^{n} \theta_{j\tau} w_{ij\tau} + \phi_1 u_{1t} + \phi_2 u_{2t} + \phi_3 u_{3t} + \phi_4 u_{4t} + \varepsilon_{it} \,. \quad (3.1)$$

Since t is the year at which the sale took place, we have $u_{1t} = t$, $u_{2t} = t - 1915$ if $t > 1915$ and 0 otherwise, $u_{3t} = t - 1949$ if $t > 1949$ and 0 otherwise and $u_{4t} = t - 1960$ if $t > 1960$ and 0 otherwise. Therefore, the growth rates during the four subperiods are ϕ_1, $(\phi_1 + \phi_2)$, $(\phi_1 + \phi_2 + \phi_3)$ and $(\phi_1 + \phi_2 + \phi_3 + \phi_4)$, respectively. The results, reported in Table II, show that the growth rates of prices over the four subperiods are very different.

In Equation (2), a simple time trend βt is introduced over the whole period. The equation shows that the average trend is equal to some 4.8% per year. In Equation (3), a dummy is introduced for each year between 1950 and 1969. As shown in

Table III. Price index for paintings and for returns on common stocks[a] (1950–1969)

Year	Coeff.	St. dev.	Index	Comm. stocks index[b]
1949	0.000	–	100	100
1950	–0.138	0.229	87	110
1951	0.193	0.206	121	130
1952	0.731	0.217	207	150
1953	1.123	0.202	307	150
1954	0.862	0.177	236	229
1955	1.293	0.227	364	300
1956	1.186	0.316	327	311
1957	2.088	0.169	807	269
1958	2.179	0.169	883	381
1959	2.284	0.163	981	421
1960	2.349	0.155	1,047	416
1961	2.654	0.163	1,415	526
1962	2.781	0.155	1,613	474
1963	2.711	0.154	1,504	573
1964	2.705	0.155	1,494	661
1965	2.721	0.145	1,518	731
1966	2.567	0.147	1,303	633
1967	2.581	0.145	1,321	763
1968	2.998	0.143	2,005	814
1969	2.994	0.146	1,996	694

[a] The results are based on Equation (3) reported in Appendix 1.
[b] Calculations made on the basis of the Standard and Poors index, deflated by the US CPI.

(1.12), this makes it possible to construct a price index for the period 1950–1969. The coefficients are obtained from the following regression:

$$p_{it} = \sum_{k=0}^{m} \alpha_k v_{ik} + \sum_{\tau=0}^{t} \sum_{j=1}^{n} \theta_{j\tau} w_{ij\tau} + \sum_{t=1950}^{1969} \delta_t c_{it} + \varepsilon_{it} ,$$

where c_{it} is, as before, a dummy variable which takes the value 1 for a sale which occurred in year t, and 0 otherwise. The index so obtained is reproduced in Table III and is compared with the index of real returns on US common stocks. The table needs little comment and shows that during that period, paintings did much better than stocks.

Table IV. Comparison of real returns

Estimator	1855–1969	1855–1914	1915–1949	1950–1960	1961–1969
Hedonic regression est.	4.9[a]	6.9	–3.1	22.4	4.3
($N = 1,972$)					
Geometric mean est.	5.9	14.9	–3.2	18.4	6.8
($N =$)	(245)	(31)	(19)	(10)	(42)
Geometric repeat-sales est.	5.0[a]	6.0	–3.7	23.8	11.3
($N = 245$)					
Hedonic regression est.	5.0	6.9	–2.4	13.5	12.2
($N = 295$)					

[a] Obtained by a weighted average of subperiod returns.

4. Comparing Alternative Estimators

In this section, we compare the statistical properties of the three estimators discussed in Section 2. The first two have often been used by researchers, whose results are reported in Section 3, while the third is the hedonic estimator. Table IV reproduces annual returns resulting from the three different methods. The first line shows the results obtained with a hedonic regression run on the full sample of 1,972 observations (Equation (1) in Appendix 1). These are compared with three calculations based on resales only. In the first, we use the geometric mean estimator (1.2) to compute an average return over the whole period (245 resales) and *within* subperiods. In the second, we use the geometric repeat-sales estimator (1.3) to compute 10-year-subperiod returns (adapted to match our four subperiods). Finally, we also run a hedonic regression using resales only. As can be checked, the results are of the same order of magnitude and there is little reason to believe that the quality of resales is different from the quality of "all" sales.

Bootstrapping

We now show that the estimators have quite different properties. In particular, the use of the largest possible sample, which includes all sales, leads to estimates with much smaller variances. To do this, we use non-parametric bootstrap methods, which make it possible to describe the distributional properties of the estimates and not their means and standard deviations only.

We have computed 3,000 bootstrap replications for each of the three methods. In the regression and the GRS replications, we sample from the residuals of the computed regressions; in the geometric means replications, the drawings are taken from the observed individual rates of return.[19]

To make the comparisons as simple as possible, we estimate a unique parameter assumed to represent time, instead of introducing years (like in Table III) or subperiods (like in Table IV). The results, reproduced in Table V are all very close to

Table V. Comparison of annual returns obtained from bootstrapping

Method	"True value"	Bootstrap mean	Bootstrap stand. dev.	Minimum value	Maximum value
Geometric mean ($N = 245$)	5.90	5.92	0.92	2.22	9.53
GRS estimator ($N = 245$)	4.99	5.00	1.87	–2.44	12.34
Hedonic regression ($N = 1,972$)	4.88	4.88	0.25	3.93	5.85
Hedonic regression ($N = 490$)	4.88	4.87	0.51	2.99	6.53

the "true values" of the parameters obtained on the basis of our data (see column 1 of Table IV): all methods lead to unbiased estimates, but the standard deviations resulting from the hedonic regression are 4 to 8 times smaller.

The results are illustrated in Figures 1 and 2, where we compare the distributions of the bootstrap replications. Figure 1 clearly shows that the distribution of returns obtained with the hedonic regression model is much more concentrated than with geometric means and repeat sales regression methods.

To verify that these favorable results are not due to differences in sample sizes only (245 for resales methods and 1,972 when all sales are used), we computed 3,000 bootstrap replications using 490 random drawings[20] out of our observations instead of 1,972. The result is given in the last line of Table V (see also Figure 2, which compares the distributions), and again, the standard deviation of the hedonic regression is much smaller than the one derived with the two other methods. Hedonic regression seems thus significantly more accurate than methods based on resales only. Moreover, the geometric means method does better than repeat sales regression, but it cannot provide an index over time.

Though the means do not look too different, we wanted to check this more carefully and test formally whether the estimated coefficients were statistically different. For this, we use the classical statistic for comparing means:

$$\frac{|\alpha_1 - \alpha_2|}{\sqrt{\sigma_1^2/n_1 + \sigma_2^2/n_2}},$$

where α_1 and α_2 are two bootstrapped means, σ_1 and σ_2 are their standard deviations and n_1 and n_2 represent the number of observations on which their computations are based.[21, 22] The results, given in Table VI, show that there are significant differences, which seems to imply that resales and sales are not drawn from the same population.[23]

We have already stressed that hedonic regression makes it possible to compute annual price indices, without need to collect a large number of resales (if they can

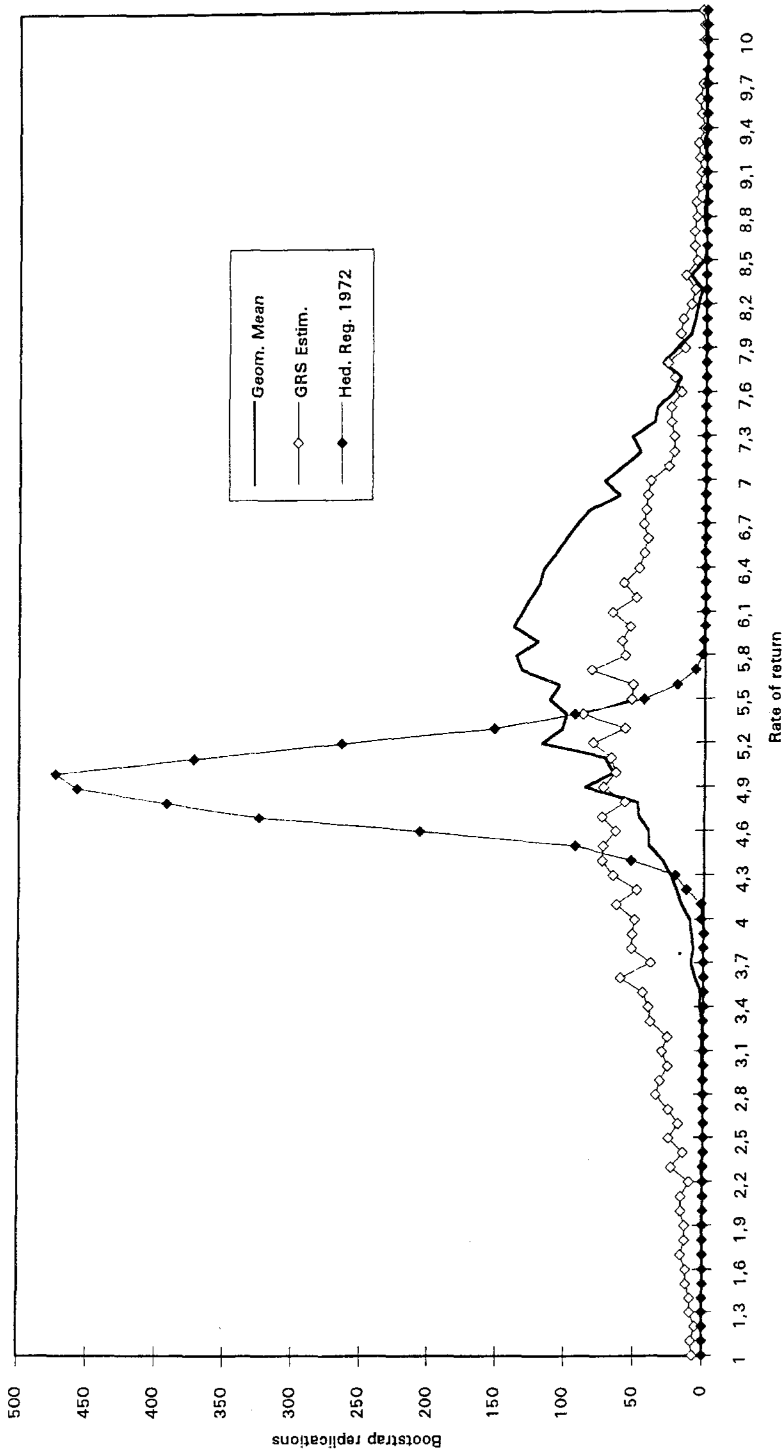

Figure 1. Comparison of the distributions of returns resulting from bootstrap replications.

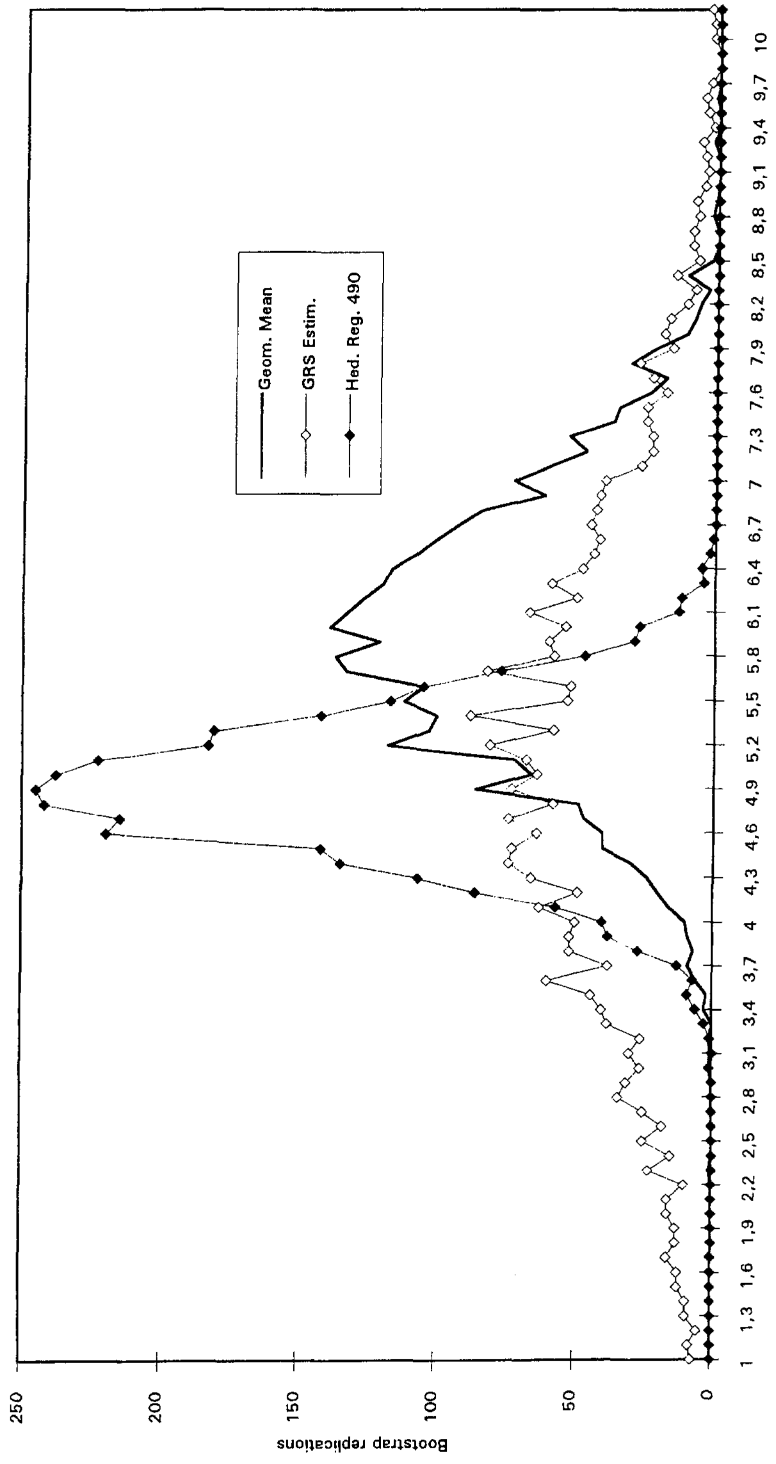

Figure 2. Comparison of the distributions of returns resulting from bootstrap replications.

Table VI. Are the results identical

Comparison between	Test-value
Hedonic (N = 1972) and Geom. mean	17.61
Hedonic (N = 1972) and GRS	1.00[a]
Hedonic (N = 490) and Geom. mean	16.63
Hedonic (N = 490) and GRS	1.07[a]
Geom. mean and GRS	6.90

[a] Equality accepted at the 5% probability level.

be found at all[24]). Therefore, it is of some importance to verify whether the annual coefficients associated to the time dummies in (1.12), as well as their standard deviations are meaningful. To verify this, we ran 3,000 bootstrap replications of Equation (3) in Appendix 1. Results appear in Table VII.

The first four columns concern the bootstrap replications and respectively give the means $\overline{\delta}_t$ (t = 1950 to 1969) of the coefficients obtained in the 3,000 replications, their standard deviations (computed as $\Sigma_i(\delta_{it} - \overline{\delta}_t)^2/3,000$), and the confidence intervals at the 95% level (based on the distribution of the 3,000 replications, leaving 2.5% at each tail). The four next columns give the regression coefficients $\hat{\delta}_t$, their standard deviations $\hat{\sigma}_t$, and the 95% confidence interval based on the standard deviations ($\hat{\delta}_t \pm 1.96\hat{\sigma}_t$). The last column in the table reports the difference between the confidence intervals obtained from the bootstrap replications and the hedonic regression. As can be checked, the hedonic coefficients and their standard deviations are very close to the bootstrapped means and standard deviations, so that the differences between the confidence intervals are negligible (except for the year 1955). This means that the standard deviations from the regression are an accurate measure of the precision with which indices over time are estimated by a hedonic regression.

5. Conclusions

In this paper, we suggest that price indices of paintings should be based on regressions using the full set of sales, and not resales only. To support this conclusion, we have constructed a price index for Impressionists. However, while taking the art market as an example, we did not consider other issues which seem essential, such as its efficiency.

There are good reasons to think that the art market should be less efficient than are financial markets: trades are infrequent, transactions are individualized, etc. However, we are not aware of any work confirming whether this is so, except for a few comments in Goetzmann (1990b). Indeed, some empirical results, such as Baumol's (1986) have been used to argue that, on the contrary, the art market is quite efficient. However, the observation that "returns" on paintings are smaller

Table VII. Comparison of annual indexes obtained from the regression equation and from bootstrapping

Year	Bootstrap				Regression				Δ range
	Mean	St. dev.	95% lb	95% ub	Coeff.	St. dev.	95% lb	95% ub	
1949	–	–	–	–	–	–	–	–	–
1950	–0.1362	0.2249	–0.5744	0.3245	–0.1380	0.2293	–0.5875	0.3114	0.0000
1951	0.1918	0.2050	–0.2342	0.5853	0.1927	0.2064	–0.2119	0.5974	–0.0102
1952	0.7319	0.2100	0.3151	1.1380	0.7310	0.2168	0.3061	1.1559	0.0229
1953	1.1239	0.1981	0.7343	1.5119	1.1229	0.2023	0.7265	1.5194	0.0153
1954	0.8595	0.1741	0.5134	1.1957	0.8618	0.1775	0.5139	1.2096	0.0135
1955	1.2930	0.2166	0.8638	1.7003	1.2933	0.2268	0.8487	1.7379	0.0527
1956	1.1884	0.3158	0.5603	1.8123	1.1861	0.3156	0.5674	1.8047	–0.0147
1957	2.0914	0.1663	1.7691	2.4121	2.0886	0.1687	1.7579	2.4194	0.0184
1958	2.1793	0.1664	1.8445	2.5008	2.1793	0.1686	1.8489	2.5097	0.0046
1959	2.2874	0.1610	1.9623	2.5994	2.2839	0.1634	1.9636	2.6041	0.0034
1960	2.3467	0.1541	2.0386	2.6594	2.3485	0.1553	2.0442	2.6528	–0.0121
1961	2.6554	0.1601	2.3413	2.9655	2.6540	0.1627	2.3351	2.9728	0.0135
1962	2.7829	0.1537	2.4864	3.0838	2.7809	0.1549	2.4774	3.0844	0.0097
1963	2.7103	0.1510	2.4069	3.0161	2.7111	0.1537	2.4099	3.0123	–0.0068
1964	2.7039	0.1518	2.4025	3.0002	2.7045	0.1545	2.4017	3.0074	0.0080
1965	2.7204	0.1422	2.4393	3.0102	2.7214	0.1450	2.4371	3.0056	–0.0024
1966	2.5672	0.1435	2.2893	2.8547	2.5673	0.1470	2.2792	2.8555	0.0109
1967	2.5816	0.1441	2.2941	2.8591	2.5812	0.1450	2.2970	2.8654	0.0034
1968	2.9990	0.1406	2.7220	3.2725	2.9984	0.1427	2.7187	3.2780	0.0089
1969	2.9929	0.1431	2.7142	3.2730	2.9943	0.1453	2.7096	3.2790	0.0107

than returns on bonds or other relatively secure assets cannot be taken as empirical tests of the efficiency of the art market.

As a matter of fact testing market efficiency by testing whether prices follow a random walk poses special problems when – as in the case of paintings – commodities are traded infrequently. As noted by Goetzmann (1990b), repeat sales estimation is particularly ill-suited for studying serial correlation of the market. More importantly perhaps, it seems that discussions on market efficiency have overlooked the fact that most statistical tests do not show that returns cannot be forecasted but only that these are not "very" forecastable. Models that have prices determined by fads may well imply that returns are not very forecastable.[25]

The hedonic methodology suggested here, applied to extended data sets, will provide a better basis for studying the predictability of returns and the efficiency of the art market.

Acknowledgments

We are grateful to W. Baumol, S. Bazen, R. Blundell, R. Davidson, A. Farber, Cl. Le Pen, M. Lubrano, P.-M. Menger, J. M. Montias, R. Moulin, M. Mougeot, J.-Cl. Passeron and M. Shubik for many useful comments, discussions and encouragements. Two referees provided extremely helpful suggestions which led us to a large number of revisions. The Musée Cantini (and especially Ms Creuset) and the Musée Longchamps in Marseilles were of great help in completing the data. Victor Ginsburgh acknowledges financial support from contract PAI no. 26 from the Belgian Government as well as support from Université Libre de Bruxelles.

Appendix

A. Regression Results

	Equation 1		Equation 2		Equation 3	
	Coeff.	St. dev.	Coeff.	St. dev.	Coeff.	St. dev.
Time periods						
1855–1914	0.062	0.006				
1915–1949	–0.082	0.010				
1950–1960	0.246	0.013				
1961–1969	–0.184	0.016				
Trend			0.048	0.002		
Individual years[a]					included	
Dimensions (inches)						
Height	0.036	0.006	0.024	0.005	0.036	0.005
Height squared ($\times 1,000$)	–0.246	0.074	–0.049	0.054	–0.259	0.060
Width	0.016	0.005	0.014	0.004	0.017	0.004
Width squared ($\times 1,000$)	–0.051	0.072	–0.091	0.046	–0.090	0.058
Surface ($\times 1,000$)	–0.066	0.124	0.013	0.117	–0.036	0.100
Auction houses						
Christie's	–0.406	0.089	–0.298	0.094	–0.258	0.077
Sotheby's	–0.194	0.078	–0.015	0.075	–0.104	0.068
Paris	–0.247	0.083	–0.305	0.085	0.042	0.078
New York	–0.156	0.080	–0.110	0.079	–0.045	0.071
All other[b]	0.000	–	0.000	–	0.000	–
Artists[a]	included		included		included	
Goodness of fit						
R^2	0.640		0.547		0.757	
Corr. R^2	0.630		0.534		0.747	
F-value	58.55		42.02		70.72	
Sample size[c]	1,972		1,972		1,751	
Degrees of freedom	1,913		1,916		1,676	

[a] We do not report all the results; see however Tables I and III.
[b] "All other" (299 observations) also includes "auction house not available" (159 observations).
[c] In Equation (3), only observations belonging to the period 1950–1969 are included.

B. The Bootstrap Method

The idea is to approximate with minimal assumptions, the unknown distribution F of a function of the observations z_i ($i = 1, 2, \ldots, n$) or of residuals of a regression $\hat{\varepsilon}_i$ ($i = 1, 2, \ldots, n$).

GEOMETRIC (OR ARITHMETIC) AVERAGE

The steps are the following:

(i) construct $\hat{F}$, the sample probability distribution, by putting mass $1/n$ on each observed data point z_i, $i = 1, 2, \ldots, n$;
(ii) draw a bootstrap sample $z_1^*, z_2^*, \ldots, z_n^*$ by randomly sampling n draws with replacement from $\hat{F}$; compute the value of the statistic θ^* (in our case, the real rate of return of paintings between 1855 and 1969);
(iii) repeat step (ii) a large number of times (say, M) and obtain M independent bootstrap replications $\theta^{*1}, \theta^{*2}, \ldots, \theta^{*M}$ and the boostrap distribution of $\theta^* = f(z^*, \hat{F})$.

Assuming M and n to be sufficiently large, it can be proved[26] that the distribution of θ^* is a consistent estimate of the true distribution of $\theta = f(z, F)$, where F is unknown.

GEOMETRIC REPEAT SALES OR HEDONIC REGRESSION

A regression is run, the estimated coefficients and residuals of which are the vectors $\hat{\beta}$ and $\hat{\varepsilon}$, respectively. Bootstrap samples are then drawn from these residuals, assumed to follow an unknown distribution F. The steps are:

(i) construct $\hat{F}$, the sample probability distribution, by putting mass $1/n$ on each estimated residual $\hat{\varepsilon}$, $i = 1, 2, \ldots, n$;
(ii) draw a bootstrap sample $\hat{\varepsilon}_1^*, \hat{\varepsilon}_2^*, \ldots, \hat{\varepsilon}_n^*$ by randomly sampling n draws with replacement from $\hat{F}$; compute the value of the statistic β^* (here, a vector of regression coefficients, obtained as $\beta^* = \beta + (X'X)^{-1}X'\hat{\varepsilon}$;
(iii) repeat step (ii) a large number of times (say, M) and obtain M independent bootstrap replications $\beta^{*1}, \beta^{*2}, \ldots, \beta^{*M}$ from which one can construct the bootstrap distribution $\beta^* = f(\hat{\varepsilon}^*, \hat{F})$.

Assuming again M and n to be sufficiently large, it can be proved[27] that the distribution of β^* is a consistent estimate of the true distribution of $\beta = f(\hat{\varepsilon}, F)$, where F is unknown.

Notes

1. This is also pointed out by Buelens and Ginsburgh (1993).
2. This simplifies exposition and is not too restrictive.
3. Actually, Baumol and Frey and Pommerehne have used the exact formula $^{(t-t')}\sqrt{P_{it}/P_{it'}}$ to compute the annual return of a painting sold in t' and subsequently in t. We use the approximation $(\ln P_{it} - \ln P_{it'})/(t - t')$ instead. The two lead to comparable results if P_{it} is close to $P_{it'}$.
4. This is the usual way to present the geometric repeat sales estimator, for which the matrix of independent variables Z has the same dimensions as X; element t in row i is -1 if the first sale of commodity i occured in year t; it is 1 if the resale occured in t and it is zero otherwise.
5. See Shiller (1991) for arithmetic repeat-sales estimators.

6. Anderson works with five year periods to compensate for the lack of data.
7. His procedure is more sophisticated than the one described in Section 2.
8. These figures are consistent with Stein's (1977) findings who, using the Capital Asset Pricing approach to value paintings, estimates the net return to be ... anything between 0 and 11% for the period 1946–1968.
9. This is apparently done in order to eliminate works "bought" by their owner in case reservation prices were not reached, or owners who "buy" at high prices in an effort to raise the market value of a painter or a work.
10. And also smaller than the rate of 3.8% found by Anderson, who uses *all* resales.
11. See also the paper by Buelens and Ginsburgh (1993), who show that this average is obtained from returns that are very different over subperiods and schools.
12. It is worth noting that Grampp (1989) for instance, considers that the name of the painter is part of the aesthetic object, no less than the painting itself. To make his point convincing, Grampp (1989, p. 131) suggests evaluating how "a dealer would fare if he (...) did not provide information about the paintings he offered for sale: no name, no title, no provenance, no references to works of art history or criticism, no dates. Nothing but the price".
13. Styles can be recovered easily from the results of the regressions by a suitable renormalization.
14. See however a recent paper by Pommerehne and Feld (1995).
15. In many cases, characteristics are missing in Reitlinger; for such cases, we have completed the data set using *Tout l'oeuvre peint de...*
16. With the exception of Bastien-Lepage, Jacob, Matthew and William Maris, Orchardson and Walker, who were dropped by Reitlinger in his 1970 additions and for whom he does not report sales after 1960. Note that we did not include artists *added* by Reitlinger in his 1970 volume since we would have missed their sales before 1960.
17. Reitlinger's compendium includes 2,986 sales, but we could only retrieve the dimensions for 1,972.
18. This is also the case in most studies, with the exception of Frey and Pommerehne (1989). Note that it is easier to take these costs into account in repeat sales than in hedonic regression methods.
19. See Appendix 2 for details.
20. The choice of 490 rather than 245 is based on the fact that Baumol and Anderson work on 245 resales, i.e. 490 pieces of information on prices.
21. The test is devised for comparing means in two independent samples. This is only approximately the case here, since the hedonic regression ($N = 1,972$) with 1,972 observations includes those resales for which we have all the characteristics (i.e. some 60% of all resales).
22. The number of observations is not the number of replications (3,000) but the number of cases on which each estimator is calculated (for instance, 245 in the case of the geometric mean).
23. This is confirmed by the result of a hedonic regression run with the 1,972 observations, in which we also include a dummy variable which takes the value *one* for resales. This dummy is significantly different from zero at the 1% probability level.
24. This is possible in the case of prints, since the several copies sold of the same print can be considered as resales of the same object. See Pesando (1993).
25. See Fama (1991) for a survey of the literature.
26. See Bickel and Freedman (1981).
27. See Freedman (1981).

References

Anderson, R.C. (1974) "Paintings as an Investment", *Economic Inquiry* 12: 13–25.

Bailey, M., Muth, J.F., and Nourse, H.O. (1963) "A Regression Method for Real Estate Price Index Construction", *Journal of the American Statistical Association* 58: 933–942.

Baumol, W.J. (1986) "Unnatural Value: or Art Investment as Floating Crap Game", *American Economic Review, Papers and Proceedings* 76: 10–14.

Bickel, P.J. and Freedman, D.A. (1981) "Some Asymptotic Theory of the Bootstrap", *Annals of Statistics* 9: 1196–1217.
Buelens, N. and Ginsburgh, V. (1993) "Revisiting Baumol's Unnatural Value or Art as a Floating Crap Game", *European Economic Review* 37: 1351–1371.
Case, K.E. (1986) "The Market for Simple Family Homes in the Boston Area", *New England Economic Review*, May–June: 38–48.
Case, B. and Quigley, J.M. (1991) "The Dynamics of Real Estate Prices", *Review of Economics and Statistics* 73: 50–58.
Case, K.E. and Shiller, R.J. (1979) "The Efficiency of the Market for Single Family Homes", *American Economic Review* 79: 125–137.
Case, K.E. and Shiller, R.J. (1987) "Prices of Single Family Homes Since 1970: New Indices for Four Cities", *New England Economic Review*, 44–56.
Court, A.T. (1939) "Hedonic Price Indexes with Automotive Examples", in *The Dynamics of Automobile Demand*. New York: The General Motors Corporation, pp. 99–117.
de la Barre, M., Docclo, S., and Ginsburgh, V. (1994) "Returns of Impressionist, Modern and Contemporary European Painters, 1962–1991", *Annales d'Economie et de Statistique* 35: 143–181.
Fama, E.F. (1991) "Efficient Capital Markets: II", *The Journal of Finance* XLVI: 1575–1617.
Freedman, D. (1981) "Bootstrapping Regression Models", *Annals of Statistics* 9: 1218–1228.
Frey, B.S. and Pommerehne, W.W. (1989) *Muses and Markets*. London: Basil Blackwell.
Goetzmann, W.N. (1990a) "Estimating Price Trends for Residental Property: a Comparison of Repeat Sales and Assessed Value Methods", Working Paper, University of Connecticut.
Goetzmann, W.N. (1990b) "Accounting for Taste: an Analysis of Art Returns over three Centuries", First Boston Working Paper Series FB-90-11, November.
Goetzmann, W.N. (1993) "Accounting for Taste: Art and Financial Markets over Three Centuries", *American Economic Review* 83: 1370–1376.
Grampp, W.D. (1989) *Pricing the Priceless, Art Artists and Economics*. New York: Basic Books Inc.
Griliches, Z. (1971), ed., *Price Indexes and Quality Change: Studies in New Methods of Measurement*. Cambridge, Mass.: Harvard University Press.
Guerzoni, G. (1994) "Testing Reitlinger's Sample Reliability", paper presented at the 8th Conference on Cultural Economics, Witten, August.
Holub, H.W., Hutter, M., and Tappeiner, G. (1993) "Light and Shadow in Art Price Competition", *Journal of Cultural Economics* 17: 49–63.
IMF (1972) "Supplement to International Financial Statistics", Washington, DC.
Mark, J.H. and Goldberg, M.A. (1984) "Alternative Housing Price Indices: an Evaluation", *AREUEA Journal* 12: 31–49.
Palmquist, R.B. (1980) "Alternative Techniques for Developing Real Estate Price Indices", *Review of Economic and Statistics* 62: 442–448.
Palmquist, R.B. (1982) "Measuring Environmental Effects on Property Values without Hedonic Regressions", *Journal of Urban Economics* 11: 333–347.
Pesando, J.E. (1993) "Art as an Investment. The Market for Modern Prints", *American Economic Review* 83: 1075–1089.
Phelps-Brown, H. and Hopkins, S.V. (1956) "Seven Centuries of the Prices of Consumables", *Economica* 23: 313–314.
Pommerehne, W.W. and Feld, L. (1995) "The Impact of Museum Purchase on the Auction Price of Paintings", manuscript, University of Saarland.
Reitlinger, G. (1960) *The Economics of Taste: The Rise and Fall of the Picture Prices 1760–1960*. London: Barrie and Rockliff.
Reitlinger, G. (1970) *The Economics of Taste: The Art Market in the 60s*. London: Barrie and Jenkins Ltd.
Ridker, R.G. and Henning, T.A. (1967) "The Determinants of Residential Property Values with Special Reference to Air Pollution", *Review of Economics and Statistics* 44: 246–257.
Rosen, S. (1974) "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition", *Journal of Political Economy* 82: 34–55.

Shiller, R.T. (1991) "Arithmetic Repeat Sales Price Estimators", *Journal of Housing Economics* 1: 110–126.

Stein, J.P. (1977) "The Monetary Appreciation of Paintings", *Journal of Political Economy* 85: 1021–1035.

Tout l'oeuvre peint de ..., Paris: Flammarion.