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2 authors:

Antonello Eugenio Scorcu
University of Bologna

Roberto Zanola
Amedeo Avogadro University of Eastern Piedmont

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Antonello Eugenio Scorcu
University of Bologna
and The Rimini Centre for Economic Analysis, Italy

Roberto Zanola
University of Eastern Piedmont
and The Rimini Centre for Economic Analysis, Italy

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The Rimini Centre for Economic Analysis
Legal address: Via Angherà, 22 – Head office: Via Patara, 3 - 47900 Rimini (RN) – Italy
www.rcfea.org - secretary@rcfea.org

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A.E. Scorcu[+] and R. Zanola[°]

ABSTRACT

Different art objects are likely to be priced by means of different systems of hedonic characteristics; more precisely, different evaluation procedures for high and low price items are often postulated. However, the empirical evidence on this point is scant. The main purpose of this paper is to fill this gap by using the quantile hedonic regression approach. The empirical evidence, based on a data set of 716 Picasso paintings sold at auction worldwide, highlights the critical role of the price classes in determining the evaluation criteria of art items.

JEL Classification: D49
Key Words: hedonic price; auction; quantile regression; painting; Picasso.

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[+] University of Bologna, Department of Economics, Italy and Rimini Center for Economic Analysis (RCEA), Italy, antonello.scorcu@unibo.it
[°] University of Eastern Piedmont, Department of Public Policy and Public Choice, Italy and Rimini Center for Economic Analysis (RCEA), Italy, roberto.zanola@unipmn.it

1. **Introduction**

The price determinants of collectibles has often raised the interest of scholars of the field. Surveying the relevant empirical literature, Ginsburgh et al. (2006) noted that analyses often use the hedonic regression approach, with the price of an art item explained by a number of hedonic characteristics (author, genre, technique, dimension, etc.), market variables (auction house, city of sale, provenance of the object, etc.) and time dummies. The sign and the size of these price determinants emerge from an hedonic regression, and the corresponding market price index can be obtained from the estimated time dummy coefficients.

Empirical investigations often analyze the specification of the regression, or the stability of the estimated coefficients over time, as the collectors' preferences and the evaluation of the hedonic characteristics might evolve, exogenously or in relation to market booms and slumps. In any case, an implicit (albeit restrictive) assumption is that in given market and period, a single evaluation system is shared by low- and high-price art items.

Although there is an extensive literature on the hedonic approach [e.g. Candela and Scorcu, 1997; Locatelli-Biey and Zanola, 2005; Zanola, 2007; Collins et al., 2007, 2009], it seems that one basic point has been neglected, namely, the possible existence of a segmentation in the art market with respect to the market value of the items. One could hardly be surprised to learn that a different criterion is used in the appraisal of a masterpiece valued several million dollars and another one in the evaluation of a painting whose price might be a few hundred dollars. In fact art item characteristics evaluations can change across the sectional distribution of art prices, because those who bid for expensive items are likely to differ from those who buy relatively inexpensive items [Malpezzi, 2003]. Moreover, even the same collector might appreciate differently the characteristics in low- and high price items. Finally, paintings that reach an extraordinary evaluation within a group, the top lots, seem to behave differently from other items [Pesando, 1993; Mei and Moses, 2002].

The purpose of this paper is to analyze the existence of different hedonic models for cheap and expensive paintings. To this aim, an hedonic quantile regression framework is used, which allows the impact of art item characteristics to differ across price distribution. More precisely, by using a dataset of 716 Picasso paintings sold at auctions worldwide during the period 1988-2005, we address two questions:

- Is the assumption of homogeneous effects of covariates on prices, implicitly determined by the estimation of average effects, justified; or do effects differ at different quantiles of the price distribution?
- How do time-invariant and time-variant characteristics affect the returns from paintings?

The rest of the paper is organized as follows. Section 2 defines the model to be used. Data and functional form are presented in Section 3. The empirical evidence is discussed in Section 4. Section 5 concludes.

2. **Theoretical framework**

The hedonic OLS regression is commonly used in the analysis of the art market to determine the relationship between a set of characteristics of collectibles and their corresponding (hammer) prices. Such an approach relies upon the mean of conditional distribution of the dependent variable. However, to the extent that characteristics are expected to be valued differently across a given distribution of selling prices, the exogenous variables influence the parameters of the conditional distribution of the dependent variable differently. Neglecting this possibility might undermine the reliability of the results [Koenker and Bassett, 1978; Zietz et al., 2007].

Unlike OLS, quantile regression models allow for a full characterization of the conditional distribution of the dependent variable. The standard OLS hedonic regression minimizes the sum of the squared residuals:

$$\min_{\{\beta_j\}_{j=0}^{k}} \sum_i \left(y_i - \sum_{j=0}^{k} \beta_j x_{j,i} \right)^2 , \tag{1}$$

where y_i is the dependent variable at observation i; $x_{j,i}$ is the j regressor variable at observation i; and β_j the parameter of the implicit price of the j characteristic. By contrast, quantile model involves instead the minimization of a weighted sum of the absolute deviations in a median-regression context:

$$\min_{\{\beta_j\}_{j=0}^{k}} \sum_i \left| y_i - \sum_{j=0}^{k} \beta_j x_{j,i} \right| h_i, \qquad (2)$$

where the weight h_i is defined as $h_i = 2q$ if the residual for the ith observation is strictly positive or as $h_i = 2\text{-}2q$ if the residual for the ith observation is negative or zero. The variable q $(0<q<1)$ is the quantile to be estimated.

This flexible estimation method might be particularly useful in our framework, in which the price distribution of the art items shows a neat departure from normality. Figure 1 displays the empirical distribution function (EDF) for the hammer prices. The inverted 'L' shape of the EDF shows that many items are concentrated in the left-hand tail and that there is a long right-hand tail made up of relatively few items that have high selling prices. In these cases, the quantile regression procedure is less sensitive to outliers and provides a more robust estimator [Koenker and Hallock, 2001; Bassett et al. 2002]. Quantile regression models may also have better properties than OLS models in the presence of heteroschedasticity [Deaton, 1997].

[Figure 1 about here]

3. **Data and functional form**

The dataset considers 716 Picasso paintings sold at auction worldwide during the period 1988-2005. The data set is collected from the 2006 edition of the Art Price Index on CD-Rom. The use of a relatively homogeneous data set based on a single, well known painter, should reduce the effect of the several sources of artistic and market variability, except for the dimension we are interested in, the auction price distribution.

The publication contains records of paintings sold at the world's major auctions, and provides information on a number of variables: artist's name, nationality, title of the work, year of production, materials used, date and city of sale, auction price, pre-sale estimate (when available), dimensions, signature, and a number of further information that might vary from case to case. In the analysis we complement the data set with a series of indicators about the artistic styles of the painting. No information is provided on the provenance and the previous exhibitions of the items. Prices are gross of the buyers and sellers' transaction fees paid to auction houses and recorded in both local currencies and USD; all prices are however expressed in USD. In order to provide a sensible distribution of the "real" prices of Picasso paintings to be used in the regressions, nominal USD prices are deflated using US CPI prices (2000=100). All prices are then logged, in line with most of the relevant literature, in order to deal with heteroschedasticity.

[Table 1 about here]

The explanatory variables included in the study are dimension, style, media, salesroom and year of sale. The effects of the price distribution on the variables are shown in Table 1. We compute the average values for the (log of) prices as well for the independent variables, both for the full sample and the quantiles .20, .40. .60, .80, .95. In column (1) we show the means of the variables for the whole sample; in columns (2)-(6) we show the corresponding averages for the price classes considered. Some 'stylized facts' emerges neatly. The dimension is, on average, lower for the low price items (neglecting style and techniques). The Old Picasso Style is often associated with low prices, whereas the opposite holds for the Young Picasso Style. More precisely, the variables included in the regression are:

- *Dimension*: the surface of the painting, *area*, and the squared surface, *area2*, in squared meters.
- *Style*: different style periods are identified [Czujack, 1997]; Childhood and Youth (1881-1901), *style1*; Blue and Rose Period (1902-1906), *style2*; Analytical and Synthetic Cubism (1907-1915), *style3*; Camera and Classicism (1916-1924), *style4*; Juggler of the Form (1925-1936), *style5*; Guernica and the 'Style Picasso' (1937-1943), *style6*; Politics and Art (1944-1953), *style7*; and The Old Picasso (1954-1973), *style8* (excluded variable). As shown in Table 1, some stylistic period are much more frequent than others. The Blue and Rose period represents less than 2 per cent of the observations, whereas the most common, the Old Picasso Style (35 per cent of the total sales), is less frequent in the high price quantiles. Different styles have different weights,

and are unevenly distributed across price classes. In fact, quantile distributions are significantly different from the average full sample distribution[1].

- *Media*: a set of dummy variables, reflecting the technique adopted, is used: *canvas*, oil on canvas, the 67 per cent of the items auctioned; *panel*, oil on panel; *mixed*, mixed technique; and *medother*, all other media (excluded variable).
- *Salerooms*: Sotheby's and Christie's are known to be the leading auction houses in this kind of transaction while the most important art auction markets are in New York and London. We consider therefore some interaction dummies between salerooms and cities: *chriny*, for Christie's New York; *chrilon*, for Christie's London; *sothny*, for Sotheby's New York; *sothlon*, for Sotheby's London; *othauc* for all other locations (excluded variable). The most important market for the Picasso paintings is New York, followed by London, with few differences between Sotheby's and Christie's. Overall, the items auctioned by Sotheby's and Christie's represents the majority of the sales collected in the data set, but no obvious pattern in terms of prices classes emerges.
- *Year of sale*: a set of yearly dummy variables, d_t, with $t = 1988,.., 2005$, are introduced for each year between 1988 and 2005 (1988 baseline variable). Sales are spread quite evenly across the years under scrutiny, with notable exceptions, the years 1988 and 1991, with less than 2 percent of the total sales, and the year 1998, in which occurred the largest share of sales, 12.71 percent, mostly concentrated in the .80 quantile. The quintile distributions, however, are not significantly different with respect to the full sample distribution.

Formally, the following regression function form is set:

$$p_{it} = \beta_0 + \beta_1 area + \beta_2 area2 + \beta_3 style1 + \beta_4 style2 + \beta_5 style3 + \beta_6 style4 + \beta_7 style5 + \beta_8 style6 + \beta_9 style7 + \beta_{10} canvas + \beta_{11} panel + \beta_{12} mixed + \beta_{13} chriny + \beta_{14} chrilon + \beta_{15} sothny + \beta_{16} sothlon + \sum_{i=17}^{33} \beta_i d_i + \varepsilon_{it} \tag{3}$$

[1] A Shapiro-Wilks test is used to test for the normality of the differences between the average and the quantile yearly sales distributions. The results, not shown for the sake of brevity, are available upon request.

where p_{it} is the log-price of painting *i* sold at time *t*; and ε_{it} is the error term.

4. **Results**

In the following, firstly the whole sample standard hedonic price model is estimated to set a benchmark. Secondly, the quantile regressions are estimated in order to analyze the hedonic characteristics across the price distribution. The results are displayed in Table 2.

[Table 2 about here]

Column 1 shows the results for the OLS whole sample specification whereas the quantile regression results are shown in columns 2-6. Following Berndt et al. (1995), standard errors and variance-covariance matrices of the coefficients have been computed by using the White heteroschedasticity-robust procedure.

In column 1, dimension has a positive effect on prices, but at decreasing rate, as the squared area shows a negative sign, in line with several previous studies. All styles perform better than The Old Picasso style (the baseline variable): the Blue and Rose Period is the most appreciated by the collectors, followed by the Cubist period and the young Picasso. Oil on canvas displays a positive coefficient, whereas oil on panel is not statistically significant and mixed techniques shows a negative coefficient sign, compared to the other media class (the excluded variable). Finally, in line with previous studies, even controlling for other hedonic characteristics, Christies' and Sotheby's auction houses, located both in London and New York, sell at a premium with respect to the other auction houses (the excluded variable).

The evidence based on the whole sample shows in other words the expected results of a typical hedonic regression. As shown in columns 2-6 of Table 2, most of the coefficients are significantly different from zero at 1 per cent probability across quantiles; however, the R-squared of the overall sample regression is larger than the corresponding quantile regressions, because of the greater variability.

As for the quantile regression coefficients, a casual inspection might suggest a pattern roughly in line with the whole sample result, with the possible emergence of a stable ranking for artistic values. Some differences in the absolute size of coefficients across quintiles emerges for the style variable, whereas in relative terms The Blue and Rose Period is always the most appreciated, followed by Cubism, Young Picasso and the Juggler of the Form periods. Camera and Classicism, Guernica and Politics and Art (even if have a positive estimates and therefore perform better than the baseline Old Picasso style) are less appreciated. Like in the whole sample regression, the (log of) the price increases with the size of the painting, but at decreasing rate, with the size of the linear and (more neatly) squared term decreasing for the larger quantiles.

Differences among quintiles are more evident for the salesrooms, and the media coefficients: some variable, significant in the lowest quantile regressions, lose their significance in the higher quantile regressions. Also the yearly dummies follow idiosyncratic patterns.

However, a more formal evaluation requires to test for the equality of the coefficients across quantile regressions. In order to avoid problems arising in the presence of certain departures when solving minimization by linear programming [Deaton, 1997], we compute robust standard error estimates by bootstrap, with 1,000 replications. F-tests for each groups of variables on the lowest quintile versus the other quintile models is run and reported in Table 3. The null hypothesis of equal coefficients across quintiles cannot be rejected for the dimension, style and salerooms variables, whereas is rejected at the usual significance level for the media and the trend period. For the media variables this result might be in part due to the correlation between the media and the quintile: in the low quintiles *mixed techniques* or *other techniques* are relatively important, whereas in the high quintiles canvases prevail. The most striking outcome concerns the yearly dummies: low and high quintiles trends are clearly different, a result already known as the masterpiece effect [Mei and Moses, 2002].

[Table 3 about here]

With different values associated with the mean (OLS) regression and the quantile regression estimates, it is natural to evaluate the emergence of significant differences in the price dynamics of Picasso paintings. To this aim, the yearly dummy coefficients are used to calculate quantile-specific adjacent year regressions price indexes. These indexes measure the per cent change in price associated with the change from 0 to 1 of the dummy variables and they are given by $[100*(e^{\beta j}-1)]$, where β_j is the quintile-estimated coefficient. Table 4 and Figure 2 show both the whole sample and the quintile price index values.

[Table 4 about here]

[Figure 2 about here]

Figure 2 shows how the different specific price classes submarkets share several common short run adjustments, making difficult the recognition of the differences in the quantile trends. The boom of the late 80s is apparent for every series, as well the subsequent burst and the weak recovery that occurred over the period 1993-2003. Again the boom period of the 2003-05 emerges neatly from the time indices.

The imperfect synchronization of (price) cycles among price classes might affect the previous conclusions, as the use of a common base year influences the subsequent dynamics of the indexes. In order to develop a more balanced approach, in Table 5 we show the various 5-year returns computed over the periods 1988-1992, 1989-1993,…, computed using the Table 4 time dummies.

[Table 5 about here]

[Figure 3 about here]

Within a 5-year horizon, the burst of the bubble of the late Eighties lead to a period of significant losses for quantiles in the first years. However, with a careful (or lucky) selection of the investment period, remarkable rates of return can be obtained, as in the period 1993-1997. The same outcome emerges for specific quintiles, as in the period 1991-1995 for the highest quintiles.

On average, the return is higher for the high end of the market, but also more volatile, as shown in Figure 3.

The evidence in support of specific price characteristics for different quantiles is therefore strengthened.

5. **Conclusions**

Although the existence of different values for painting characteristics across different hammer price distributions may have been considered intuitive beforehand, to our knowledge, such a issue has never been empirically investigated. By contrast, the homogeneity of the systems of evaluation with respect to price levels has been the standard approach in the applied literature.

Quantile regression provides an intuitive way to evaluate the relevance of the price effect in the appreciation of the paintings. In this paper we use the quantile regression approach for analyzing the structure of the hedonic characteristics of 716 Picasso paintings sold at auctions worldwide during the period 1987-2005. We estimate a log-linear hedonic model both for the full sample and the .20, .40, .60, .80, and .95 quantiles of hammer price distribution. The empirical evidence suggests the existence of significant differences both in the way prices respond to characteristics (particularly in the media variables) and in the rates of return from an investment in Picasso paintings across different price ranges (the so called masterpiece effect).

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Figure 1. Empirical distribution function (EDF) of selling prices

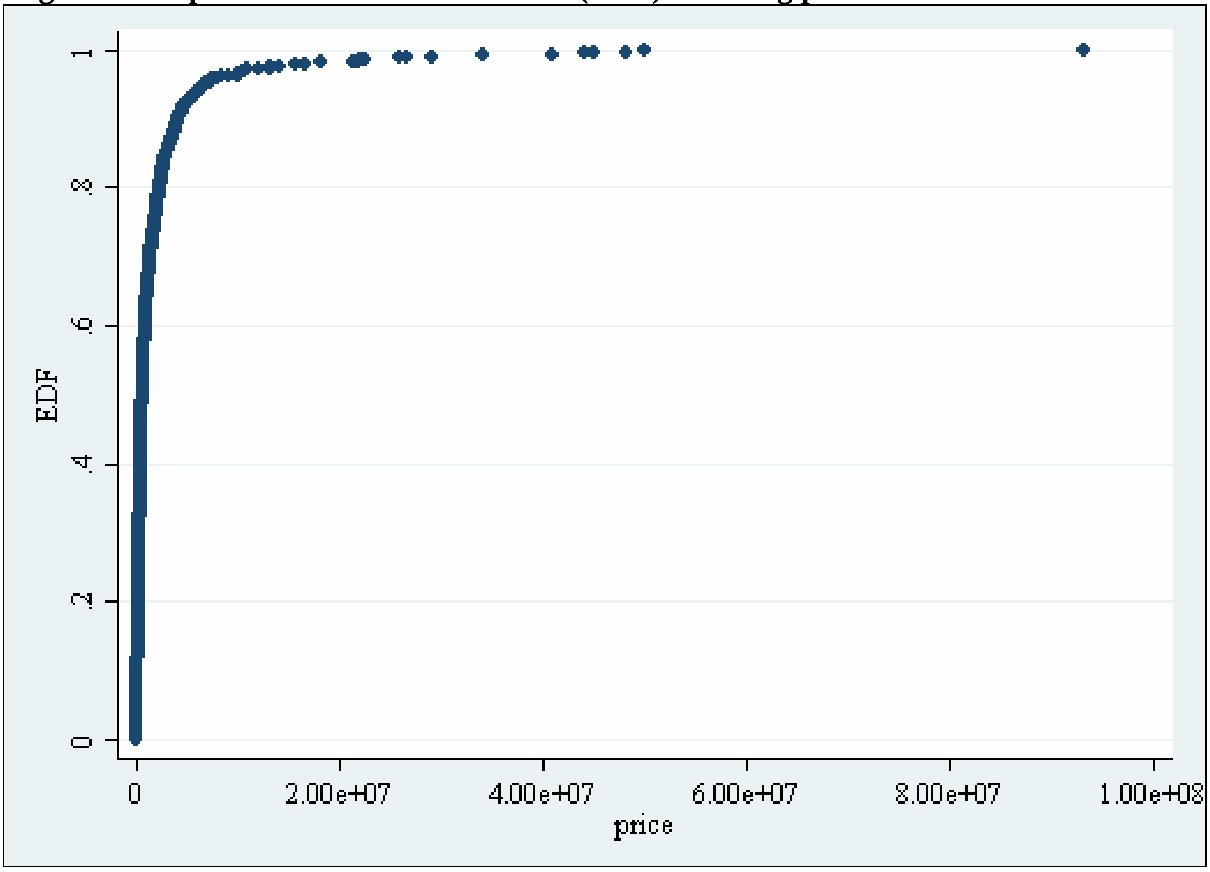

Table 1. Summary statistics

	Full sample		**Percentile**									
			.20		**.40**		**.60**		**.80**		**.95**	
	(1)		(2)		(3)		(4)		(5)		(6)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
price	2,122,799	5,984,123	118,987	83,834.55	350,470	85,597.45	655,989.4	162,247.2	1,512,689	519,238.3	3,866,488	1,362,944
area	.5171	.5275	.1586	.1757	.3285	.3117	.5032	.4270	.6568	.5577	.8371	.6087
area2	.5452	1.1117	.0558	.1269	.2044	.4772	.4342	.8275	.7402	1.2360	1.0678	1.4972
style1	.0564	.2309	.0611	.2404	.0282	.1660	.0652	.2478	.0634	.2445	.0588	.2364
style2	.0184	.1344	0	0	.0211	.1443	.0072	.0851	.0070	.0839	.0196	.1393
style3	.0589	.2356	.0534	.2258	.0563	.2314	.0580	.2345	.0493	.2172	.0980	.2989
style4	.1055	.3074	.1221	.3287	.1268	.3339	.0725	.2602	.1056	.3084	.0392	.1951
style5	.1043	.3058	.0382	.1923	.0775	.2683	.0870	.2830	.1056	.3084	.2157	.4133
style6	.1595	.3664	.2061	.4061	.0775	.2683	.1014	.3030	.1690	.3761	.2255	.4200
style7	.1472	.3546	.2137	.4115	.1479	.3562	.1159	.3213	.1479	.3562	.1372	.3458
style8	.3497	.4772	.3053	.4623	.4648	.5005	.4927	.5018	.3521	.4793	.2059	.4063
canvas	.7251	.4467	.4685	.5008	.7343	.4433	.7552	.4314	.8042	.3982	.8518	.3569
panel	.0580	.2340	.0699	.2559	.0559	.2306	.0909	.2885	.0629	.2437	.0370	.1897
mixed	.0557	.2294	.1608	.3687	.0350	.1843	.0070	.0836	.0210	.1438	.0370	.1897
other_tech	.1896	.3922	.4056	.4927	.1748	.3811	.1468	.3552	.1119	.3163	.0833	.2777
chrilon	.1505	.3578	.1608	.3687	.1259	.3329	.1888	.3927	.1888	.3927	.1204	.3269
chriny	.2666	.4424	.2517	.4355	.2657	.4433	.2587	.4395	.2797	.4504	.2222	.4177
sothlon	.1458	.3530	.1259	.3329	.1888	.3927	.1538	.3621	.1468	.3552	.1481	.3569
sothny	.2868	.4525	.1888	.3927	.2937	.4571	.2517	.4355	.2867	.4538	.4259	.4968
othauc	.1256	.3316	.2587	.4395	.1259	.3329	.1468	.3552	.0979	.2982	.0833	.2777

Table 1. Summary statistics (contd.)

	Full sample		Percentile									
			.20		**.40**		**.60**		**.80**		**.95**	
	(1)		(2)		(3)		(4)		(5)		(6)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
d88	.0140	.1174	0	0	.0140	.1178	.0070	.0836	.0140	.1178	.0278	.1651
d89	.0475	.2128	.0070	.0836	.0140	.1178	.0350	.0836	.0769	.2674	.0741	.2631
d90	.0670	.2503	.0140	.1178	.0350	.1843	.0559	.2306	.0909	.2885	.1759	.3825
d91	.0182	.1336	.0140	.1178	.0140	.1178	.0420	.2012	.0210	.1438	0	0
d92	.0335	.1801	.0489	.2165	.0559	.2306	.0210	.1438	.0280	.1655	.0185	.1354
d93	.0517	.2215	.0559	.2306	.1119	.3163	.0489	.2165	.0350	.1843	.0092	.0962
d94	.0461	.2098	.0699	.2559	.0559	.2306	.0699	.2559	.0070	.0836	.0370	.1897
d95	.0642	.2454	.0769	.2674	.0420	.2012	.0839	.2782	.0559	.2306	.0556	.2301
d96	.0517	.2215	.0769	.2674	.0839	.2782	.0420	.2012	.0350	.1843	.0185	.1354
d97	.0768	.2665	.0839	.2782	.0629	.2437	.0559	.2306	.0839	.2782	.0926	.2912
d98	.1271	.3333	.0489	.2165	.0839	.2782	.0909	.2885	.1119	.3163	.0741	.2631
d99	.0824	.2752	.2867	.4538	.1049	.3075	.1049	.3075	.0699	.2559	.0833	.2777
d00	.0475	.2128	.0280	.1655	.0420	.2012	.0559	.2306	.0280	.1655	.0833	.2777
d01	.0503	.2187	.0350	.1843	.0699	.2559	.0489	.2165	.0699	.2559	.0370	.1897
d02	.0531	.2243	.0629	.2437	.0559	.2306	.0559	.2306	.0559	.2306	.0370	.1897
d03	.0349	.1837	.0280	.1655	.0350	.1843	.0210	.1438	.0559	.2306	.0463	.2111
d04	.0601	.2378	.0280	.1655	.0420	.2012	.0559	.2306	.0699	.2559	.1018	.3039
d05	.0377	.1906	.0140	.1178	.0140	.1178	.0559	.2306	.0699	.2559	.0278	.1651

Table 2. Full sample and quantile regression (QR) results

	OLS		**QR**									
	(1)		**.20** (2)		**.40** (3)		**.60** (4)		**.80** (5)		**.95** (6)	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
area	3.7359***	.2078	3.5903***	.2713	3.5632***	.2691	3.3192***	.2761	3.3111***	.3216	3.1853***	.4439
area2	-1.1313***	.1023	-1.1613***	.1421	-1144***	.1458	-.9691***	.1490	-.9304***	.1386	-.8047***	.2094
style1	1.6202***	.2042	.9711**	.4494	1.5927***	.3154	1.6891***	.2152	1.7641***	.2497	2.0390***	.4826
style2	2.2070***	.3544	1.7832***	.5042	1.9731***	.4815	2.0475***	.5686	3.1895***	.7636	3.2695***	.5030
style3	1.8120***	.1816	1.2825***	.3381	1.6133***	.2443	1.5710***	.2426	1.8667***	.3136	2.2191***	.2804
style4	.9518***	.1180	.5566***	.1546	.6337***	.1508	.7094***	.1693	.9234***	.2149	1.5589***	.2755
style5	1.2603***	.1207	1.0189***	.1712	1.0480***	.1389	1.0390***	.1573	1.5893***	.2524	1.8825***	.2148
style6	.9309***	.1232	.4705***	.1478	.6479***	.2007	1.0169***	.1866	1.2914***	.1704	1.6429***	.2443
style7	.2710***	.1090	.3308**	.1433	.3040***	.1054	.3259***	.1066	.3188***	.1215	.3495***	.1366
canvas	.3880***	.1160	.6498***	.1824	.3617**	.1524	.2503**	.1207	.1874	.1618	.2322	.2168
panel	-.2826	.2209	-.2214	.5064	-.2554	.2766	-.2133	.2289	.1447	.2800	-.1093	.2830
mixed	-1.0104***	.2855	-1.2402***	.3683	-1.6714***	.5032	-.6297	.6021	-.5600	.3717	-.1662	.3710
chrilon	.3724***	.1406	.4241**	.2035	.3357*	.1826	.1481	.1761	.0892	.1913	-.1282	.3085
chriny	.3964***	.1401	.4562**	.2150	.4087**	.1802	.2156	.1761	.2122	.1921	-.0936	.2693
sothlon	.3104**	.1455	.2416	.2257	.3723*	.1736	.1671	.1890	.1608	.1902	-.2504	.2957
sothny	.5919***	.1371	.5598***	.2140	.5862***	.1736	.3122*	.1690	.3658**	.1673	.0532	.2900
cons	10.1871***	.2154	9.6212***	.3073	10.1133	.3060	10.7488***	.2661	11.0038***	.2459	11.6212***	.3491
	Yearly dummies		Yearly dummies		Yearly dummies		Yearly dummies		Yearly dummies		Yearly dummies	
R-squared	0.6388		0.4299		0.4014		0.4134		0.4284		0.5022	

***,**,*. significance at .01, .05, .10

Table 3. Test for the equality of the quantile hedonic regressions coefficients

	QR							
	.20 vs .40		**.20 vs .60**		**.20 vs .80**		**.20 vs .95**	
Variable	F	Prob > F	F	Prob > F	F	Prob > F	F	Prob > F
Dimension	0.97	0.3257	0.84	0.3606	0.69	0.4074	0.57	0.4505
Style	1.74	0.1091	1.73	0.1106	1.73	0.1124	1.73	0.1107
Media	3.81	0.0100	3.82	0.0100	3.82	0.0099	3.86	0.0094
Salerooms	1.48	0.2074	1.45	0.2166	1.41	0.2280	1.40	0.2324
Period	2.89	0.0001	2.80	0.0002	2.68	0.0004	2.65	0.0005

Table 4. Adjacent year regression indexes

	Full sample	Percentile				
		.20	.40	.60	.80	.95
d88	100.00	100.00	100.00	100.00	100.00	100.00
d89	179.10	172.25	246.25	170.70	166.60	162.26
d90	120.58	123.62	143.39	95.05	81.17	156.05
d91	67.11	72.64	82.79	49.91	46.92	48.82
d92	39.07	41.68	45.38	34.39	39.36	50.26
d93	31.85	20.74	58.61	35.54	32.10	37.42
d94	53.73	38.02	56.57	36.18	58.25	88.43
d95	52.63	44.55	55.43	37.53	55.30	82.20
d96	45.34	43.98	58.70	34.44	45.88	75.73
d97	77.51	59.36	81.50	65.93	85.69	117.23
d98	47.24	42.80	63.93	43.30	53.69	56.44
d99	70.29	51.82	81.82	61.66	89.33	102.33
d00	83.30	67.51	90.74	79.22	81.35	125.86
d01	67.78	63.83	72.38	50.95	47.59	120.32
d02	54.52	43.12	79.81	46.71	46.84	134.45
d03	71.56	75.85	88.33	55.94	53.14	76.95
d04	104.82	89.92	123.04	91.08	103.19	116.53
d05	118.79	117.94	149.87	91.66	106.83	198.18

Table 5. 5-year return

	return (full)	return (0.2)	return (0.4)	return (0.6)	return (0.8)	return (0.95)
1988-92	39.07	41.68	45.38	34.39	39.36	50.26
1989-93	17.78	12.04	23.80	20.82	19.27	23.06
1990-94	44.56	30.76	39.45	38.06	71.76	56.67
1991-95	78.42	61.33	66.95	75.20	117.86	168.37
1992-96	116.05	105.52	129.35	100.15	116.57	150.68
1993-97	243.36	286.21	139.05	185.51	266.95	313.28
1994-98	87.92	112.57	113.01	119.68	92.17	63.82
1995-99	133.56	116.32	147.61	164.30	161.54	124.49
1996-00	183.72	153.50	154.58	230.02	177.31	166.20
1997-01	87.45	107.53	88.81	77.28	55.54	102.64
1998-02	115.41	100.75	124.84	107.88	87.24	238.22
1999-03	101.81	146.37	107.96	90.72	59.49	75.20
2000-04	125.83	133.20	135.60	114.97	126.85	92.59
2001-05	175.26	184.77	207.06	179.90	224.48	164.71

Figure 2. Adjacent year regression indexes

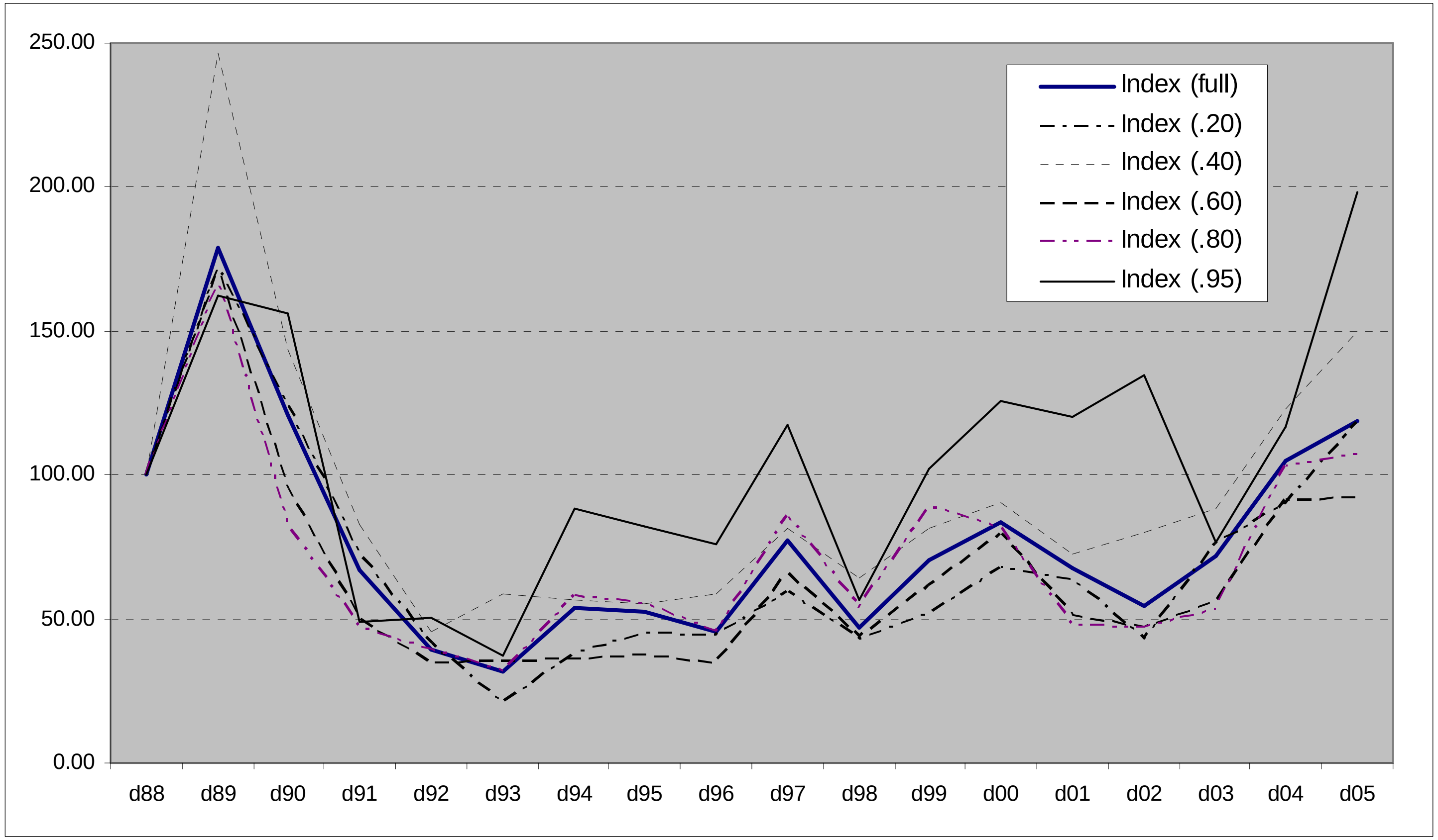

Figure 3. Average return and standard deviation of 5-year returns