

Long and Short-term Portfolio Choices of Paintings¹

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Abstract

In their paper on price comovements of paintings, Ginsburgh and Jeanfils show that in three important markets (London, Paris and New York), prices of well-known and lesser known painters “move together” (are cointegrated). They conclude that therefore, an investor may be indifferent between the two groups of painters. We show that this is not the case, since well-known painters are less risky, and that though returns may be comparable, the share of well-known painters in a portfolio of paintings might be as high as 90%. We also construct long-run and short-run portfolios and show that these may be very different. These short-term portfolios give interesting insights which help in characterizing each of the three markets.

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1 Introduction

In a recent paper, Ginsburgh and Jeanfils (1995) (G&J) study the comovements between semestrial price indices of paintings by “Great Masters,” “Other Painters” and “US Painters” auctioned in three key art markets: London, Paris and New York. These price indices are constructed on the basis of hedonic regressions using prices obtained at auction between 1963 and 1992.²

G&J start with an error-correction model linking the returns of two price series in each market (GMs and OPs in London and Paris, GMs and USPs in New York³), and conclude that there is cointegration in all three cases. This means that, in each market, prices for both groups of artists “move together.” They could only find very weak evidence for short-run relations between stock and art markets, and no such link at all in the long-run. Furthermore, contemporaneous correlations between excess returns on paintings (measured as the difference between returns on paintings and the three months euro-rate on each country’s currency) and growth rates of the G7 countries are also very weak (0.14 for France, 0.31 for the UK and 0.13 for the US). Given these weak links, we have taken the shortcut to analyze portfolios for paintings in isolation from the rest of the economy.

Three additional insights are worth mentioning:

- (a) Returns on paintings are stationary.
- (b) GMs account, in all markets, for the common (non-stationary) trend. Intuitively, this implies that GMs are setting the (non-stationary) evolution of the market, which is then “followed” by OPs in London and Paris and by USPs in New York.
- (c) In each market, the difference between (the logarithms of) prices of GMs and OPs (or USPs) will, on average, remain constant *in the long run*.

The combined result of these findings is that, irrespectively of the market in which an investor wants to operate, “a portfolio of Van Gogh’s would do as well as a portfolio of Ginsburgh’s, if these appeared more or less regularly at auction” as suggested by G&J. Though true in terms of returns, this

²See the Appendix for details on the construction of these price indices.

³USPs appear quite seldom at auction in Paris and in London, while sales of OPs are infrequent in New York.

statement oversees the fact that identical long-run returns may have different variances and therefore, as taught by classical portfolio theory,⁴ an optimal portfolio will consist of GMs and OPs (or USPs) in different proportions.

However, another issue is also at stake. An optimal portfolio based on the findings obtained by G&J has a *long-run* connotation, since the cointegration relationship describes long-run behaviour. It might be that the portfolio has to be frequently reshuffled if one is interested in short-run operations.

In this paper we suggest a method to tackle this issue. The stationary structure linking the expected returns and their variances is combined with portfolio theory to produce dynamic estimates of the optimal portfolios.

The basic finding that the long-run portfolios are significantly different from the short-run ones may be the consequence of several facts, the volatility of returns being only one of them. The results also suggest a characterization of the three markets in terms of stability and of the role played by the group of Great Masters.

Of course, and as is the case in all our previous work in this field,⁵ the conclusions must be taken in due perspective. The data on art markets considered here are subject to many shortcomings. First, price series are based on auction data only, and miss other transactions which may turn out to be important.⁶ Secondly, transaction costs (which are neglected here and which are much higher than in the case of financial markets) will obviously prevent investors from reshuffling their portfolios very often.

The structure of the paper is as follows. In Section 2, we discuss some theoretical aspects and briefly sketch how to combine the classical, static optimal portfolio theory with cointegration results, in order to construct dynamic portfolios. Section 3 discusses the empirical results. Section 4 concludes with possible theoretical and empirical extensions.

⁴See e.g. Markowitz (1959).

⁵See for instance, Buelens and Ginsburgh (1993), and Czujack et al. (1996).

⁶See e.g. Guerzoni's (1995) interesting remarks on Reitlinger.

2 Long and Short-run Optimal Portfolios

2.1 Markowitz Long-run Optimal Portfolios

A Markowitz optimal portfolio is obtained as a combination of the available assets that maximizes the expected return of the portfolio, subject to the constraint that its variance should not exceed some bound (or that minimizes variance, subject to a constraint on the expected return).

Let $\pi_1 \geq 0$ and $\pi_2 \geq 0$ represent the weights of the two assets, with $\pi_1 + \pi_2 = 1$; r_1 and r_2 are their expected returns (first moments), σ_1^2 , σ_2^2 and σ_{12} represent their variances and covariance (second moments). Then, the expected return of the portfolio is given by

$$\pi_1 r_1 + \pi_2 r_2, \quad (1)$$

while the combined variance can be written

$$\pi_1^2 \sigma_1^2 + \pi_2^2 \sigma_2^2 + 2\pi_1 \pi_2 \sigma_{12}. \quad (2)$$

The optimal portfolio is obtained by choosing the weights that either maximize (1) subject to a constraint in which (2) is bounded from above, or that minimize (2) subject to a constraint in which (1) is bounded from below. By varying the bound in one or in the other problem, one obtains the efficient frontier which describes the best choices of π_1 and π_2 for given maximal variance, or for given minimal return.

In the case of two risky assets (GMs and OPs or USPs) and no riskless asset, it is easy to see that once the variance (or the expected return) is fixed, the problem is trivial, since weights have to be nonnegative and add up to one. Therefore, we have chosen to determine the portfolio with smallest variance, that is, the most conservative choice for an investor. It is easy to see that the solution to the problem

$$\min_{\pi_1, \pi_2} \pi_1^2 \sigma_1^2 + \pi_2^2 \sigma_2^2 + 2\pi_1 \pi_2 \sigma_{12} \quad (3a)$$

subject to

$$\pi_1, \pi_2 \geq 0, \pi_1 + \pi_2 = 1 \quad (3b)$$

is

$$\pi_1 = \frac{\sigma_2^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}}, \quad \text{if } \sigma_1^2, \sigma_2^2 \geq \sigma_{12}; \quad (4a)$$

$$\pi_1 = 1, \quad \text{if } \sigma_2^2 > \sigma_{12} \geq \sigma_1^2; \quad (4b)$$

$$\pi_1 = 0, \text{ otherwise.} \quad (4c)$$

Of course, in all three cases,

$$\pi_2 = 1 - \pi_1. \quad (5)$$

Markowitz's optimal portfolio approach—and all the developments that followed—assumes that the first two moments of the distributions of returns are constant. This condition is satisfied for the series studied by G&J;⁷ the moments of the observed returns series can thus be used to calculate (4) and (5) in London, Paris and New York.

Note that since we use minimum variance portfolios, the values of the expected returns do not play any role in the calculations—see equations (4)-(5). The investor is concerned with risk only.

2.2 Short-run Optimal Portfolios

If the expected moments of the distributions change over time, one should correct the long-run choice and design instantaneous optimal portfolios, which would, at every instant, take into account the best prediction of the values of these moments, given the past. This would show by how much the short-term optimal combination deviates from the static long-run portfolio, which befits a long-term investor. If the differences are small, holding the long-term portfolio would not be very risky. However, the dynamic portfolios are expected to vary considerably in unstable or highly volatile markets, adding insecurity to the long-term portfolio.⁸ Examining the series of optimal asset proportions can then help in characterizing the underlying markets. In the special case of the market for paintings—where, to the best of our knowledge no quantitative study of this kind has ever been performed—this can provide

⁷This is tested by Ginsburgh and Jeanfils (1995) using unit root tests on the logarithms of the price series.

⁸The whole discussion in this section is informal. The “insecurity” referred to has to do with the possibility for the long-term investor to liquidate his position at any moment. Actually, if one assumes that the investment period coincides with that of the observations—half-years—, dynamic portfolios would be the best choice if there were no transaction costs.

a further insight on the behaviour of agents, especially if wild movements are followed by reasonably stable periods.

Many possibilities exist for the updating of the variances and covariances. Since, as shown by G&J, the original price series are cointegrated, we will work with the related *error-correction model*, the residuals of which being used to update the second-order moments, through a *GARCH* formulation.

Cointegration and the Error-Correction Model

Cointegration⁹ studies the relation between 2 (or more generally, m) time series $y_{i,t}$, $i = 1, 2$; $t = 1, 2, \dots, T$ —in our case, prices of GMs and OPs or USPs— and combines both the long-run and the short-run within the framework of a unique model.

An example of such a model is:

$$\Delta y_{1,t} = \alpha_1(y_{1,t-1} - \beta y_{2,t-1}) + \gamma_{1,1}\Delta y_{1,t-1} + \gamma_{1,2}\Delta y_{2,t-1} + e_{1,t}. \quad (6)$$

In (6) first-order differences of the first series, $\Delta y_{1,t}$ are regressed on lagged first-order differences of both series,¹⁰ $\Delta y_{1,t-1}$ and $\Delta y_{2,t-1}$, and on lagged values of the levels of both series $y_{1,t-1}$ and $y_{2,t-1}$, which, however, appear under the form of $(y_{1,t-1} - \beta y_{2,t-1})$, assumed to represent the long-run equilibrium relation between the two variables, the so-called cointegrating relationship.

Along an equilibrium path, $\Delta y_{1,t-1} = \Delta y_{2,t-1} = \Delta y_{1,t} = 0$, so that $y_{1,t-1} - \beta y_{2,t-1} = -e_{1,t}/\alpha_1$. Taking expectations in this last expression, one gets $E y_{1,t-1} - \beta E y_{2,t-1} = 0$, which is the formal version of the long-run equilibrium relationship. In the short-run, variations in $\Delta y_{1,t}$ can be due to variations in $\Delta y_{1,t-1}$, or $\Delta y_{2,t-1}$ or to a disequilibrium in period $t - 1$, i.e., to the fact that $(y_{1,t-1} - \beta y_{2,t-1}) \neq 0$, even if $\Delta y_{1,t-1} = \Delta y_{2,t-1} = 0$. If $\alpha_1 < 0$, this will imply that any overshooting or undershooting of $y_{1,t-1}$ with respect to its equilibrium value $\beta y_{2,t-1}$ will be (partially) corrected in period t , so that the two series will not move too far apart from each other, for too long. This is the essence of the error-correction mechanism, as introduced by Davidson et al. (1978).

The full model will include a second equation which explains, in the same

⁹See Hamilton (1994), chapter 19 for a recent overview.

¹⁰In (6), there is only one lag, but in general, there may be more.

way, the short-run behaviour of $y_{2,t}$

$$\Delta y_{2,t} = \alpha_2(y_{1,t-1} - \beta y_{2,t-1}) + \gamma_{2,1}\Delta y_{1,t-1} + \gamma_{2,2}\Delta y_{2,t-1} + e_{2,t}. \quad (7)$$

Observe that in equations (6) and (7), all the parameters, including the error-correction coefficients α_1 and α_2 can differ, but that the long-run equilibrium relation between y_1 and y_2 ($y_{1,t-1} - \beta y_{2,t-1}$) is the *same* in both (6) and (7).

In our case, $y_{it}, i = 1, 2$ are logarithms of prices; therefore, their first differences $r_{it} = \Delta y_{it}$ represent returns. If model (6)-(7) is the best forecasting system for the returns, then, given the information I_{t-1} available at time $t - 1$, the anticipated part of r_{it} is given by

$$E(\Delta y_{it} | I_{t-1}) = \alpha_i(y_{1,t-1} - \beta y_{2,t-1}) + \gamma_{i,1}\Delta y_{1,t-1} + \gamma_{i,2}\Delta y_{2,t-1}, \quad (8)$$

while

$$\Delta y_{it} - E(\Delta y_{it} | I_{t-1}) = e_{it} \quad (9)$$

is the unanticipated part of the return. But this implies that in period $t - 1$, the best forecast for the variance of the return in period t will be

$$E((\Delta y_{i,t} - E(\Delta y_{i,t} | I_{t-1}))^2 | I_{t-1}) = E(e_{i,t}^2 | I_{t-1}),$$

so that the use of a *GARCH* model on the errors of the error-correction equation is a natural way of forecasting the second-order moments needed in the determination of the short-term optimal portfolios.

GARCH processes and the updating of second-order moments

In principle, the two variances and the covariance should be updated. However, as explained below, a shortcut will be used for the covariance.

We start with the dynamic variances, which will be defined by

$$h_{it}^2 = E(e_{it}^2 | I_{t-1}), i = 1, 2, \quad (10)$$

and taken as the volatility of the unanticipated part of the returns that can be predicted with the information I_{t-1} available in $t - 1$. Equation (10) is made operational through a *GARCH*(p, q) formulation.¹¹ According to this

¹¹See e.g. Hamilton (1994), chapter 21.

methodology, the conditional expectation $E(e_{it}^2 | I_{t-1})$ is written as a linear combination of the p past squares of the errors e_{it} and the q past expectations

$$h_{it}^2 = constant + a_1 e_{i,t-1}^2 + \dots + a_p e_{i,t-p}^2 + b_1 h_{i,t-1}^2 + \dots + b_q h_{i,t-q}^2, i = 1, 2 \quad (11)$$

Estimating models incorporating systems of equations such as (6), (7) and (11) is quite straightforward nowadays.

As for the covariance, we note that equation (4a) can be rewritten as

$$\pi_1 = (1 - (\sigma_1^2 - \sigma_2^2)/v)/2, \quad (12)$$

where $v = \sigma_1^2 + \sigma_2^2 - 2\sigma_{12}$, is also the variance of $(\Delta y_{1,t} - \Delta y_{2,t})$ which, given the results by G&J, who find that in (6)-(7), β is not significantly different from 1, is also the variance of the first differences of the cointegrated process. This implies that v is a function of second-order moments of the cointegrated process so that, as a shortcut to a multivariate *GARCH* we decided to keep v constant in (12), and update only the two variances σ_1^2 and σ_2^2 , using the *GARCH* processes defined in (11).

Computing short-run portfolios

Equations (6), (7) and (11) are estimated for each couple of return series in each of the three cities: (GMs, OPs) in London and in Paris (GMs, USPs) in New York. Then, the h_{1t}^2 and h_{2t}^2 forecasts given by (11) are used to implicitly update the covariance through

$$h_{12,t} = (h_{1,t}^2 + h_{2,t}^2 - v)/2. \quad (13)$$

Depending on the relative values of $h_{1,t}^2$, $h_{2,t}^2$ and $h_{12,t}$, one of the three formulas (4a) to (4c) is used for each semester, generating the time series of dynamic portfolios (π_{1t}, π_{2t}) in each market.

3 Empirical Results

Table 1 displays the first two moments of the GM, OP and USP returns in the three markets. One can easily compute the long-term minimum variance portfolios, using equations (4) and (5).

As can be seen, and though returns of GMs and OPs (or USPs) are not very different, the optimal portfolios contain very large shares of GMs. This is so because in all three markets, GMs have a much smaller variance than other painters. London and New York are the two places where Christie's and Sotheby's are present and where the best paintings produced by GMs are sold. Paris often sells less prestigious works, which are closer to those produced by OPs, so that the proportion of OPs is larger in a portfolio bought in Paris (15%) than in London (9%). Indeed, the GM/OP return-variance ratio is more than two times lower in London than in Paris. The situation is somewhat different in New York, the largest market for contemporary American painters: returns on both categories of artists (GMs and USPs) are almost identical, and the variance of USPs is much smaller than that of OPs in London and in Paris. As a result, the proportion of USPs in a portfolio bought in New York is relatively large (27%).

Figures 1 to 3 illustrate the series of returns for each class of painters in each market. All three series are very volatile, both for Great Masters and Other (or American painters), and one might expect that the *GARCH*-predicted variances, displayed in the upper and middle parts of Figures 4 to 6, will be highly fluctuating. Indeed, though the error-correcting filter attenuates this situation, the conditional variances do have significant peaks.¹² As expected, these are more dramatic for OPs, especially in Paris and for USPs.

This pattern generates the unstable dynamic portfolios represented in the lower part of Figures 4 to 6, where the continuous horizontal lines describe the proportions of GMs to hold in the long-term portfolios (see Table 1 and equation (4)), while the oscillating curves describe the corresponding sequences of short-term optimal proportions, computed on the basis of equations (6)-(12).

To interpret correctly these optimal short-run proportions, the reader should remember that, in the updating scheme we suggest to follow, the only parameters which are changing explicitly, are the variances of the returns. Let us briefly discuss the London market (Figure 4) as an example. Given the situation prevailing in the long-run, Markowitz's logic implies that larger deviations from the long-run share of GMs will take place when the condi-

¹²The reader should note the change in the vertical scale between Figures 1 to 3 and Figures 4 to 6.

Table 1
Return Statistics and the Long-Run Optimal Portfolios

	Characteristics of the Returns			LR portfolios
	Means	Variances	Covariances	
<i>London</i>				
Great Masters	0.052	0.044		0.916
Other Painters	0.033	0.412	0.007	0.084
<i>Paris</i>				
Great Masters	0.058	0.043		0.854
Other Painters	0.034	0.188	0.013	0.146
<i>New York</i>				
Great Masters	0.046	0.052		0.727
US Painters	0.047	0.115	0.014	0.273

Returns, variances and covariances are for semesters.

tional variances of GMs and OPs show sharply opposing trends. This means that the lower part of Figure 4 should be analyzed with the pair of *GARCH* results displayed in the upper part of Figure 4. The important drops in the share of GMs in 1972-2 and 1984-2 reflect the fact that the expected value of the GM/OP returns-variance ratio was much larger than the long-run ratio. The other decrease in 1988-1 comes one year after the global peak in the share, a movement which is the result of the large variations in the conditional variance of OPs in 1987-88.¹³

The analysis of the results shown in Figures 4 to 6 leads to the following observations.

(i) In all three markets, the dynamic short-run proportions can be quite far from the long-run ones. This is somewhat less pronounced in New York.

(ii) The percentage of GMs in the dynamic portfolios is reasonably higher

¹³The *GARCH* technique unfortunately emphasizes such variations.

than 50%, but usually lower than the share predicted on the basis of the long-run portfolio. Actually, in New York, and because they compete with American painters, Great Masters do not enjoy the same position as in the two European capitals, where they compete with lesser known painters.¹⁴ The result is that the short-run proportions of GMs in New York is clearly decreasing: American painters are gaining more and more popularity and importance. This point qualifies considerably the finding by G&J that GMs “lead” in all three markets. They do, indeed, in terms of *price levels*; however, in terms of risk, they are safer in London than in New York, for instance.

(iii) The lower quality of works sold in Paris, both for GMs and OPs, make it a more speculative market than London or New York. Investors deviating from the long-run portfolio may reap there the highest short-run profits as well as experience the largest losses.

Summing up, we could say that there is more speculation in Paris than in London and certainly in New York, where there is more “action,” since Great Masters are forced to compete on almost identical grounds with American painters. London seems to be a more solid market, though it can be seriously affected by sudden changes as in 1987-88.

4 Final remarks

The approach proposed can be extended in many ways. Estimation of the conditional volatility, for instance, can also be performed via the Kalman filter or via multivariate *GARCH* procedures, which would then encompass the prediction of the covariances between the series. However, as our purpose is not technical, we prefer to insist on the economic implications.

We have concentrated our discussion on minimum variance portfolios. This implies that the investor is blind to the levels of expected returns, provided that the variances do not change. This is of little importance in our special case, since, as can be seen from Table 1, returns on the two assets are roughly of the same size.

However, as is well-known, Markowitz’s theory produces a whole set of efficient portfolios, the “optimal” one being chosen according to the investor’s

¹⁴Note that in New York, returns for GMs and USPs are of the same order of magnitude.

preferences. An extension of the calculations in this direction is interesting, since we believe that it is important to describe the behaviour of agents on art markets. Of course this may open different possibilities of optimal portfolios whose dynamic characteristics should be interpreted in a proper context.

A simpler, though maybe also insightful development, would be to rerun the methodology including stocks or bonds as additional assets, though G&J have not found much evidence that stock and art markets are cointegrated. The oscillations of the optimal short-term proportions of GMs in a portfolio including art and financial assets could then be compared with some indicator of the business cycle, for instance. Finally, once optimal portfolios are calculated, further modelling along the lines of the Capital Asset Pricing Model (CAPM) is usually pursued.¹⁵ Such a study, which would include data on art markets, could perhaps add an interesting element to the debate on the testing of CAPM models.

5 Appendix on the construction of price indices

The return indices used in our calculations have been computed through hedonic regressions, as suggested in Chanel et al. (1996); one estimates the following equation:

$$p_{it} = \sum_{k=1}^m \alpha_k x_{ik} + \sum_{t=\tau_0}^{\tau_T} \gamma_t z_t + \epsilon_{it}, \quad (*)$$

where p_{it} is the (logarithm of the) price of a collectible i sold at time t , x_{ik} is a time-invariant idiosyncratic attribute of i ; $[\tau_0, \tau_T]$ is the time interval over which observations are available; z_t is a dummy variable which takes the value one if the work is sold in period $t \in [\tau_0, \tau_T]$, and zero otherwise; the γ_t are parameters to be estimated, and finally ϵ_{it} is an error term. The sequence $\gamma_{\tau_0}, \gamma_{\tau_1}, \dots, \gamma_{\tau_T}$ is used to construct the price or value index.

The data used to calculate value indices come from Mayer's (1963-1992) compendia *Annuaire des Ventes*. These yearbooks of public auctions are available since 1963 (sales of 1962); we thus cover the years 1962 to 1991. Three databases were compiled. Two of them concern European painters

¹⁵For a classical reference on this subject, see e. g. Huang and Litzenberger (1988).

born after 1830, thus excluding Old Masters; the third one is devoted to 20th century American painters.

The first contains some 25,000 sales of 82 well-known Impressionist, Modern and Contemporary European painters, selected in a fairly subjective way: we chose painters who lived (or at least spent part of their lifetime) in Paris, were frequently sold in public auctions (Dufy, Marquet, Van Dongen) and/or are well known (Cézanne, Gauguin, Seurat). For each of them, all sales collected by Mayer during the period 1962-1991 are included. We refer to those painters as ‘Great Masters.’ This database includes well-known painters only and can hardly be thought of as representing European painters in general. Therefore, we constructed a second database of European painters (‘Other Painters’) as follows. For each year (1962 to 1991), we draw 82 random numbers (within the set corresponding to the pages in each volume of Mayer’s compendia). The first painter appearing on each such randomly chosen page is selected and all his paintings sold during that year are included. The database contains over 6,000 sales, and hence approximately 200 paintings per year. A notable difference between the two databases is that each Great Master is followed over the 30 years time-span, while Other painters are not (except by chance). See de la Barre et al. (1994) for more details.

The third database (‘US Painters’), compiled by Demortier (1992) is concerned with the works of 139 American painters who were born after 1900 and/or died after 1965. This includes painters belonging to all “contemporary” currents (action painting, hard edge, minimal art, colorfield, hyperrealism and realism, pop art, bad painting, neo-geo, symbolism, naturalism, conceptual art, abstract expressionism, and precursors), and makes for over 6,000 paintings sold between 1962 and 1991.

In Mayer’s compendia, each sale is described by a certain number of characteristics (see below) and by a sale number, corresponding to a specific auction describing the location and the date of sale. It is therefore possible to construct monthly or quarterly indices. There are two reasons for having chosen to work with half-yearly indices. First, to compute monthly indices, more sales would be needed¹⁶ in order to obtain reliable indices and second, there are almost no auctions in July, August and September; this reason also

¹⁶For the ‘Other painters’ database, there are 6,000 observations over 30 years, i.e. an average of 17 observations per month or 50 per quarter; these are numbers which we thought of being too small to construct indices with higher than half-yearly frequency.

makes it clear why it would make little sense to construct quarterly indices.¹⁷

Though like financial markets, the art market is international (a Japanese collector can easily buy in London, Paris or New York), we consider three different geographical markets: the United States, the United Kingdom and France. Prices in the US and the UK are computed from all auctions at Christie's and Sotheby's New York (Parke Bennett until it was bought by Sotheby's) and London respectively; for France, all auctions collected by Mayer are included.

The characteristics we use to describe each work are limited by the fact that, beside the name of the artist and of the painting, the yearbooks give only a very rough description of the painting: the size of the work (height and width), the year in which it was painted (though not in all cases), the medium used, the place of the sale (saleroom, country) and the time of sale.

The model is estimated on the full sample of sales and resales. The x_{ki} variables describing characteristics are the following: dimensions (3 variables: height, width and surface); dummy variables for painters (82 for 'Great Masters', 139 for 'US painters') or for nationalities (25 for 'Other painters'); dummy variables for type of painting and/or medium (2 for 'Great Masters': painting or collage, 4 for 'Other painters': canvas, wood, cardboard, other; 15 for 'US painters'); 60 dummy variables z_t describing the dependence of prices over the sixty half-years 1962-1991.

Such regressions were thus run for 'Great Masters' in New York, London and France (3 indices), 'Other painters' in London and France (2 indices) and 'US painters' in New York (1 index). 'Other painters' hardly sell in the United States, while 'US painters' seldom appear at auctions in Europe.¹⁸ For further details see Ginsburgh and Jeanfils (1995).

¹⁷A year is divided into two "semesters" of unequal length: a seven months period (January-July) and a five months period (August-December); these are the two "seasons" usually taken into consideration by salerooms also, since, for calendar reasons, the last important sales before the summer holidays may take place either end of June or beginning of July: they should both be considered as belonging to the same "season."

¹⁸Prices are expressed in local currencies (dollars, pounds and FF for sales in New York, London and France respectively. We did not correct these data for inflation: since we have no information on who buys the paintings, it is not clear which inflation rate should be used to deflate the data.

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Figure 1
Returns of Great Masters (upper part)
and Other Painters (lower part) in London

Figure 2
Returns of Great Masters (upper part)
and Other Painters (lower part) in Paris

Figure 3
Returns of Great Masters (upper part)
and US Painters (lower part) in New York

Figure 4
Conditional variances of GMs (top), OPs (middle) and
Markowitz optimal proportions of GMs in London (bottom)

Figure 5
Conditional variances of GMs (top), OPs (middle) and
Markowitz optimal proportions of GMs (bottom) in Paris

Figure 6
Conditional variances of GMs (top), USPs (middle) and
Markowitz optimal proportions of GMs (bottom) in New York