“The multimanager approach in mutual funds investments”

Guido Abate (Italy)

The multimanager approach in mutual funds investments

Abstract

The multimanager approach in mutual funds investment is a methodology aimed at improving portfolio efficiency through diversification among managers, with the constraint of ensuring a limited deviation from the objectives defined by the asset allocation strategy. The aim of this article is the empirical comparison of two multimanager models. Arun S. Muralidhar has proposed a new performance measure named M^3, based upon the M^2 by Franco and Leah Modigliani. Muralidhar's M^3 model adjusts returns not only with regard to standard deviation, a commonly accepted measure of risk, but also to the correlation of the funds with their benchmark, in order to take into account also the risk caused by their tracking error volatility. His model is based upon the selection of managers using the M^3, a measure that is maximized in the optimal multimanager allocation. Gary T. Baierl and Peng Chen have focused on the misfit risk: they have created a model that replicates the target asset allocation using Sharpe's 'returns based style analysis' to estimate the style weights of each mutual fund. Then they maximize the selection Sharpe ratio, with the constraint of the strategic benchmark replication. The empirical study presented in this article makes use of more than three thousand mutual funds. The results show the prevalence of Muralidhar's approach, but this asset allocation has a higher exposure to non-normal risks than the one reached using the model of Baierl and Chen.

Keywords: multimanager approach, mutual funds investment, risk-adjusted performance, correlation-adjusted performance.
JEL Classification: G11, G23.

The multimanager approach. Introduction

Why diversify among managers: theoretical bases. Investors in actively-managed mutual funds are used to paying commissions for the excess return that managers say they can generate above a passive investment. This approach, if followed blindly, may lead to sub-optimal allocations. In fact, the average alpha[1] of active funds, net of fees, is less than zero (Sharpe, 1991).

In view of this fact, the purpose of this study is to understand whether it is possible to obtain a risk-adjusted return superior to the market return as a result of careful selection of funds and of investment allocation based on mathematical models. In fact, William Sharpe leaves open a window to active management: while, on average, managers do not provide value compared to a passive investment, it is still possible that some of them generate positive and persistent excess returns.

The multimanager approach: a definition. The multimanager approach in mutual funds investment is a methodology aimed at improving portfolio efficiency through diversification among managers, with the constraint of ensuring a limited deviation from the objectives defined by the asset allocation strategy.

It should be noted that the multimanager approach should provide tangible benefits in terms of diversification (Sharpe, 1981):

- among asset classes;
- of judgment;
- of management styles.

This diversification is based on the assumption that no manager can provide statistically significant and persistent excess returns if he applies his estimates to any type of asset class. Therefore, specialization and, at the same time, diversification among managers are necessary in order to lower the volatility of excess returns, provided that they are uncorrelated.

On the other hand, a third-party managed portfolio adds a new source of risk: the judgment risk, arising from the manager's choices, from his views, his coherence, his timing and efficiency. Consequently, this new type of risk must be lower than the benefits that are to be gained.

The implementation of the multimanager approach. The multimanager approach to portfolio construction requires, firstly, the definition of the asset allocation strategy, taking into account the risk profile of the investor. Only after its enunciation the process of funds selection does take place, along with diversification among managers, asset classes and styles of management.

In the selection of funds it is necessary to optimize a predefined objective function, which would result in the correct asset allocation.

In terms of management style, the multimanager approach has been conceived to efficiently combine both active investments, in which the manager frequently rebalances the portfolio according to his views, and passive investments, in which the replication of the benchmark is a priority, in a

[1] Alpha is defined as the average difference of returns between a fund and its benchmark. The standard deviation of this measure is the tracking error (TE).

logic that can often recall the core-satellite approach.

Precisely because of the presence of active managers, it is necessary to take into account and optimize the trade-off between the alpha and its volatility. The optimization methods taking into account both these factors are based on dynamic models. Instead, the static models are intended to minimize the distance between the actual asset allocation and the target.

In order to implement a multimanager portfolio it is necessary to resort to a hybrid model, which includes the characteristics of both the approaches described above.

The multimanager models. On the basis of the theory exposed above, it can be assumed that the mathematical formalization of the problems of asset allocation among managers is an interesting subject of study, having the purpose of identifying those methods that allocate the capital through automated processes, after the selection of the best managers on the basis of their risk-adjusted performance and, at the same time, also considering the investment in market indices.

The following sections are devoted to the analysis of two models designed for the application of the multimanager approach, which will also be compared through an empirical simulation.

The study conducted by Gary T. Baierl and Peng Chen (2000) makes extensive use of Sharpe's returns-based style analysis and uses, in order to select the best funds, risk and performance indicators that are standard in today's performance analysis.

On the contrary, the writings of Arun S. Muralidhar (Muralidhar, 2000, 2001a, 2001b, 2005) exhibit a different approach to measuring mutual funds performance and on such an innovative system his multimanager model is then built.

1. Correlation-adjusted performance: Muralidhar's M³

1.1. The impact of tracking error on funds scoring. Muralidhar, in order to structure the calculation of his indicator, starts from the recognition that the returns of a risk-adjusted portfolio (RAP), having the same volatility as the benchmark by construction (Modigliani & Modigliani, 1997), oscillate around its benchmark, even when its average is the same as the benchmark itself. In other words, the deviations of the portfolio generate a tracking error (TE). Moreover, since the calculation of the RAP does not take into account the possibility of investing in the benchmark, but only in the risk-free security, two RAPs may have different correlations with their common benchmark, and thus different alphas and TEs.

In fact, given a correlation $\rho_{I,B}$ between the fund *I* and its benchmark *B*, the TE is calculated as:

$$TE(I) = \sigma(r_I - r_B) = \sqrt{\sigma_I^2 - 2\rho_{I,B}\sigma_I\sigma_B + \sigma_B^2}. \quad (1)$$

Since the RAP of fund *I* has the same volatility as the benchmark, its tracking error is:

$$TE(RAP(I)) = \sigma_B\sqrt{2(1-\rho_{RAP,B})} = \sigma_B\sqrt{2(1-\rho_{I,B})}. \quad (2)$$

A minor correlation is related to a higher TE. Consequently, there are managers who have the ability to assume a 'correlation risk', as defined by Muralidhar, just as some managers can take advantage of the greater volatility of their portfolios in order to achieve higher unadjusted returns. Thus, a measure such as the RAP provides a better assessment for funds with a lower correlation with the benchmark, because they often have a higher average return thanks to their additional risk, not measurable by standard deviation alone.

1.2. Correlation adjusted portfolio. The problem that Muralidhar seeks to solve is to bring in a risk-return space, i.e. in two dimensions, what we have seen is actually a problem in three dimensions (risk, return, and correlation).

In the RAP, Modigliani uses the risk-free rate, with volatility equal to zero, to deleverage the portfolio and make its volatility equal to that of the index. Muralidhar, with the same logic, also uses the benchmark, which has alpha = 0, TE = 0, and $\rho = 1$, with itself, creating a correlation adjusted portfolio (CAP) with a TE, and thus a correlation, equal to the target. In this way, the returns of different funds are comparable not only with regard to the volatility, but also with respect to correlation with the benchmark, which is the same for all of them.

After setting a target value for the TE, we must calculate the allocation of the CAP into its components; the return of the CAP is:

$$r_{CAP} = a \cdot r_I + b \cdot r_B + (1-a-b)r_F, \quad (3)$$

with *a*: weight of fund *I*; *b*: weight of benchmark *B*; (1–*a*–*b*): weight of the risk free security.

Furthermore, the restrictions on the target TE imply the level of correlation that the CAP will have with the benchmark, specifically: if TE(CAP) = TE(target) then $\rho_{CAP,B} = \rho_{target}$. Thus:

$$\rho_{target} = 1 - \frac{TE(target)^2}{2\sigma_B^2}, \quad (4)$$

Given that the volatility of the CAP should be the same as the benchmark, the constraint $\sigma^2_{CAP} = \sigma^2_B$ must be satisfied:

$$\sigma^2_{CAP} = \sigma^2_B = a^2\sigma^2_I + b^2\sigma^2_B + 2ab\sigma_I\sigma_B\rho_{I,B}. \quad (5)$$

Given this constraint, the covariance between r_{CAP} and r_B is:

$$\rho_{target}\sigma^2_B = a\sigma_I\sigma_B\rho_{I,B} + b\sigma^2_B. \quad (6)$$

Solving for *b* we obtain:

$$b = \rho_{target} - a\frac{\sigma_I}{\sigma_B}\rho_{I,B}. \quad (7)$$

Finally, replacing *b* in the formula of the variance of CAP, we obtain the weight *a*:

$$a = +\sqrt{\frac{\sigma^2_B(1-\rho^2_{target})}{\sigma^2_I(1-\rho^2_{I,B})}} = \frac{\sigma_B}{\sigma_I}\sqrt{\frac{(1-\rho^2_{target})}{(1-\rho^2_{I,B})}}. \quad (8)$$

We imposed that *a* is positive because it is not possible to short a mutual fund, except those quoted on regulated markets. On the other hand, there are no restrictions on the sign of *b*, because, for example through a future, it is possible to short a benchmark. Moreover, if (1 – *a* – *b*) were negative, this would mean borrowing money, at the risk free rate, to be invested in *a* or in *b*.

1.3. The construction of multimanager portfolios in the M³ model. For the selection of mutual funds in a multimanager portfolio, Muralidhar suggests taking into account the relative risk budget, expressed by the target value of the TE, agreed with the investor or set by the funds manager. It is also necessary to consider the covariance matrix of the funds, and not only the covariance between each of them and the benchmark. The extension of the M³ model to the multimanager approach is based on theoretical foundations similar to those presented above.

K is defined as a portfolio of several managers, with $w_i \geq 0$ equal to the weight for the i-th manager in the share *a* of *K* invested in funds, and with $\sum_i w_i = 1$. Therefore, the fund manager has to maximize the return of the CAP(K):

$$max\, r_{CAP(K)} = max\left[a \cdot r_K + (1-a-b)r_F + b \cdot r_B\right]. \quad (9)$$

This function is subject to the same constraints of the CAP: its volatility must be equal to that of the benchmark and the correlation must be equal to the target level.

2. Baierl and Chen's model

2.1. Investors' objective. According to Gary T. Baierl and Peng Chen, the primary target for investors, in a mid-long term perspective, should be the achievement of their asset allocation target, as it has also been pointed out by other scholars (i.e. Ibbotson and Kaplan, 2000). The maximization of alpha, i.e. the differential between the yield of the portfolio and the benchmark, however, although very important, should be only a second best.

Moreover, investors must also be able to know what is the correct number of funds to be included in their portfolios, how much money they can allocate to each fund and whether an active or passive management is more convenient.

2.2. Multimanager allocation. After having set the target asset allocation, the investor has to select a group of funds such that the actual allocation will have the least deviation from the target. The best choice is based on three main themes of Baierl and Chen's model:

1) the use of style analysis, to determine precisely the asset allocation of the funds, so that the asset allocation generated by the model has the same proportions as the target;
2) the selection of portfolios based on their risk and return relative to the target allocation;
3) allocation in the funds must also be realistic with regard to the sums invested; therefore, short sales or investments under the minimum threshold are not allowed.

Before the introduction of the mathematical model, the terminology is formally defined:

m = number of asset classes;

n = number of mutual funds.

The subscript *i* is used for the range from 1 to *m* (*i* indicates an asset class), and *j* ranges from 1 to *n* (*j* indicates a fund).

$A_{i,j}$ = style weight of fund *j* in asset class *i*,

b_i = target allocation in asset class *i*,

α_j = alpha of the fund *j*,

$V_{j1,j2}$ = covariance of TE of funds *j*1 and *j*2,

M_j = minimum investment in fund *j*,

K = total investable amount,

w_j = allocation, in percent, to fund *j*,

λ = investor's tolerance to TE,

1 = n×1 vector of ones.

Matrix V can be assumed to be diagonal: the TEs generated by the managers are linearly independent.

Once the parameters that describe the performance of the managers have been defined, the investor has to solve the problem of allocating among funds. This allocation must:

- reach the target allocation share for each asset class;
- invest at least the minimum amount required by the threshold of each selected fund (lower than USD 10,000 in Baierl and Chen's article);
- be efficient in terms of alpha and TE.

More formally, we must choose $\boldsymbol{w}$ such that it is the solution of the following problem, recalling that $\boldsymbol{\alpha}$ is the vector of alphas:

$$min\ \boldsymbol{w}^T \boldsymbol{V} \boldsymbol{w} - \lambda \boldsymbol{\alpha}^T \boldsymbol{w}. \quad (10)$$

This problem is subject to the following constraints: the style weights of the investment in mutual funds must be equal to those of the investor's benchmark; the investment in each fund must be above the minimum threshold; and the portfolio weights allocated to funds must always be positive and sum to one.

This is a mean-variance optimization applied only to the active component of the portfolio return.

3. Empirical analysis

3.1. Sample and benchmarks. The sample consists of equity mutual funds; their monthly returns were downloaded from the Morningstar Direct database in the categories USA, Europe, Japan and Emerging Markets[1].

The selection covers the period of July 1998-June 2008 for a total of 120 months, but not all the mutual funds have 10 years of data, as the inception of some is more recent. Therefore, only those funds with a track record of at least 66 months have been taken into account.

The sample is affected by survivorship bias: only the funds still active at the end of the period of analysis are present, a fact that could result in yields, at least for the earlier years, higher than those of a hypothetical sample including ceased funds, since fund managers often close funds that have not generated an adequate performance (Brown et al., 1992).

[1] This database provides the returns gross of taxes of Italian mutual funds, therefore allowing their comparison to non-Italy-based funds. For a thorough analysis of the tax-induced dissimilarities between Italian and non-Italian funds see Savona (2006).

The 3,319 funds downloaded from the database are divided into the following asset classes[2]:

- Emerging Markets: 209;
- Europe: 869;
- Japan: 359;
- USA: 1,882.

The strategic benchmark is a synthetic index composed 99% of the MSCI AC World LCL, representative of all global stock markets, calculated in local currency, and the remaining 1% of the Citi EUR EuroDep 1 Mon EUR. The choice to include this latter index, representative of the money market, is due to the fact that mutual funds have to keep part of their net asset value in liquidity, in order to meet redemption requests from clients or to lower their exposure to markets in times of falling stock prices.

3.2. The sample composition. In order to classify the operators we have used the returns-based style analysis (RBSA), formulated by Sharpe (1992), i.e. a multivariate regression of the returns of each fund on the benchmarks representative of equity markets and the risk free rate.

These indices are as follows:

- MSCI EM LCL;
- MSCI Europe NR LCL;
- MSCI Japan NR JPY;
- MSCI USA NR USD;
- Citi EUR EuroDep 1 Mon EUR.

The MSCI indices have been selected as benchmarks of equity asset classes, while the last one shows the evolution of the 1-month interbank interest rate and is therefore a good proxy of the risk-free rate.

The benchmarks provided by MSCI, all denominated in local currency, were chosen in their NR version, a methodology in which dividends, net of tax, are reinvested in the index, making it a total return index.

Since Muralidhar does not impose restrictions on the classification of funds into each of the asset classes, it has been preferred, for sake of uniformity, to follow the lines suggested by Baierl and Chen. Specifically, to insert a fund into a given category, it is necessary that:

- the R^2 of the RBSA is at least 0.85, in order to prevent the selection of funds with inconsistent management style;

[2] We have not opted for a further subdivision into management styles due to the strong correlation existing between them, such that the allocation of a fund into a category (such as 'growth' rather than 'value') would have been arbitrary, especially taking into account the constraints imposed by the model of Baierl and Chen. Therefore, for the purpose of a multimanager allocation, it would have been incorrect to use samples comprising only a small number of funds, particularly in the early years.

- the R^2 of the regression on its benchmark is larger than or equal to 0.65, so that selected funds are representative of their asset class.

This study was conducted over 60 month rolling time windows for the in-sample analysis, which was necessary for the estimation of the parameters. Then, for six months each time, an out-of-sample simulation was carried out for empirical evaluation.

3.3. Muralidhar's multimanager model: empirical analysis. The implementation of Muralidhar's model has required, first, the estimation of the CAP of the funds for each of the four asset classes. This use of the CAP has allowed its further analysis: the positions in a ranking according to this index are very similar to those carried out with the RAP and the information ratio[1]. It is no coincidence, since the CAP takes into account both the risk-adjusted performance, measured by mean and standard deviation, as per the RAP, and the correlation-adjusted performance, which is measured by alpha and TE, the same ambit of the IR.

The application of this multimanager strategy, once the first seven funds in the ranking of the CAP have been selected, requires the choice of a single parameter: the target TE. Based on this value, the model calculates the different levels of exposure to active funds and to the benchmark: it will invest more in the former for higher values of target TE, while the investor will be more exposed to the index for a low TE. Moreover, since Muralidhar contemplates expressly the option of short selling the benchmark, the larger the target TE, the greater the propensity to isolate the positive alpha generated by active management through the short sell of the benchmark.

In order to make this model comparable to that of Baierl and Chen it has been necessary to select the same level of TE for both. Since this latter method does not require the input of the target TE, but of the risk tolerance parameter, the model of Baierl and Chen was the first to be implemented. Its TE was then measured empirically and its value, equal to 0.75%, used as a target in the simulation of Muralidhar's model.

We then proceeded with the optimization of the M^3 multimanager model, as outlined in section 1.3.

Table 1 shows the allocations calculated for the U.S. equity asset class for the out-of-sample period 7/2005-12/2005, changing the level of the target TE. Note that, as expected, the optimal choice of funds remains constant, while the proportion of the portfolio allocated to them varies.

Table 1. Simulation with different levels of target TE

Target Tracking Error	0,00%	1,00%	2,00%	5,00%
Rho(T,B)	1.000	0.976	0.902	0.388
Coefficient a	0.000	0.858	1.684	3.949
Coefficient b	1.000	0.138	-0.741	-3.641
Coefficient (1-a-b)	0.000	0.004	0.057	0.692
Columbia Value & Restructuring Z	13.37%	13.37%	13.37%	13.37%
FBP Value	33.80%	33.80%	33.80%	33.80%
Fidelity Advisor Equity Income I	0.00%	0.00%	0.00%	0.00%
Harbor Large Cap Value Instl	5.95%	5.95%	5.95%	5.95%
Hartford Value Opportunities HLS IA	46.88%	46.88%	46.88%	46.88%
Industry Leaders I	0.00%	0.00%	0.00%	0.00%
UBS U.S. Large Cap Equity Y	0.00%	0.00%	0.00%	0.00%
Mean return CAP (5/2005 - 10/2005)	0.980%	0.950%	0.880%	0.450%
MSCI USA NR (5/2005 - 10/2005)	0.980%	0.980%	0.980%	0.980%
Alpha	0.000%	-0.030%	-0.100%	-0.530%

3.4. The multimanager model by Baierl and Chen: empirical analysis. In this case as well, it was necessary to perform an evaluation of the funds in order to select the best ones. More precisely, the authors chose only three managers in each asset class, according to the following criteria:

1) the first in the ranking of the selection Sharpe ratio: it favors the efficiency of excess returns over the benchmark;
2) the greatest alpha: in this case it is the ability of the fund manager that is taken into account, but without considering the increased risk inherent in his decisions;
3) the lowest TE: regardless of the ability to provide excess returns, in this selection the aim is to avoid excessive deviations from the benchmark.

The first consideration that can be drawn from this selection method is the lack of interest in mean-variance efficiency of fund returns, because all the selection criteria focus on returns in excess of the benchmark. On the other hand, the positioning

[1] The CAP has a correlation with the RAP of 0.94 and with the IR of 0.92.

of the portfolio on the efficient frontier depends on the strategic asset allocation alone: as one of the optimization constraints is the replication of the benchmark, efficiency depends on the choice of this index. Furthermore, for the estimation of these parameters, both Baierl and Chen's article and the present work have used the RBSA, which provides a double benefit: it generates forward-looking estimates and the benchmark is not, as in Muralidhar, a single market index, but the style benchmark.

Therefore, the advantage in using the selection Sharpe ratio rather than the Information ratio is clear, because it has been estimated from a method (the style analysis) which clearly separates the contribution of the selection made by the fund manager from a passive investment in several indices, and not only in relation to just one of them, as happens in the information ratio.

Table 2 shows, as an example, the list of funds selected on the basis of the style analysis of the period of 7/2000-6/2005. The rank of each fund within its asset class is in bold and underlined. Where a fund is the first from the perspective of two different indicators, we select another one that is second in at least one of the two and that has the best relative position in the third ranking.

Observing the actual asset allocation of each fund, Table 3 shows that very often the style benchmark can differ significantly from the MSCI index of the asset class, even though, as explained in section 3.2, the classification of a fund within an asset class has been very strict. This misfit[1] is completely corrected, however, by the implementation of Baierl and Chen's model, because the target asset allocation is one of the constraints that must be satisfied, taking into account the RBSA carried out on every fund.

Table 2. Selection for Baierl and Chen's model

Asset class	Fund	Selection Alpha (%)	TE (%)	Selection Sharpe ratio	Ranking (Alpha)	Ranking (TE)	Ranking (SSR)
Emerging markets	Power Capital Navigator	-0.157	1.503	-0.105	50	**1**	53
	Sarasin EmergingSar-Global Inc	0.791	1.871	0.423	**1**	26	1
	The Emerging World Fund Inst Acc	0.744	1.907	0.390	2	30	**2**
Europe	GLG European Equity Fund A Acc	0.346	1.421	0.243	2	193	**2**
	Imi Europe Acc	-0.259	0.608	-0.426	131	**1**	299
	Pioneer Fds Top European Players E EUR ND Acc	-0.004	0.360	0.265	**1**	166	1
Japan	Nikko AM Japan Value Fund B	0.404	1.389	0.291	2	38	**1**
	UBS (CH) EF-Japan Inc	-0.178	0.387	-0.461	39	**1**	59
	Vitruvius Japanese-Equity JPY Acc	0.440	1.822	0.241	**1**	58	3
USA	American Century Equity Growth Inv	1.753	3.057	0.573	**1**	496	2
	JHT 500 Index Trust Ser I	1.386	1.838	0.754	6	346	**1**
	Wells Fargo Advantage Index Adm	0.066	0.226	0.293	310	**1**	107

Table 3. Style benchmark of the funds selected for Baierl and Chen's model (data as percentages)

Asset class	Fund	Citi 1M Euro Dep	MSCI EM	MSCI Europe	MSCI Japan	MSCI USA	R^2
Emerging markets	Power Capital Navigator	3.6292	82.7602	3.8003	0	9.8104	91.9235
	Sarasin Emerging Sar-Global Inc	6.4485	86.6703	0	6.8811	0	87.5478
	The Emerging World Fund Inst Acc	9.0336	86.1748	0	4.7916	0	86.7495
Europe	GLG European Equity Fund A Acc	2.3969	8.7775	80.0813	0	8.7443	91.5403
	Imi Europe Acc	6.4233	0	93.5767	0	0	98.2844
	Pioneer Fds Top European Players E EUR ND Acc	11.1523	0	88.8477	0	0	91.2048
Japan	Nikko AM Japan Value Fund B	6.9576	0	0	93.0424	0	89.689
	UBS (CH) EF-Japan Inc	1.051	0	3.3611	95.5879	0	99.1941
	Vitruvius Japanese-Equity JPY Acc	0	0	0	100	0	87.6353

[1] Discrepancy between the ex-post benchmark followed by the funds management and the ex-ante strategic allocation defined by the investor.

Table 3 (cont.). Style benchmark of the funds selected for Baierl and Chen's model (data as percentages)

Asset class	Fund	Citi 1M Euro Dep	MSCI EM	MSCI Europe	MSCI Japan	MSCI USA	R^2
USA	American Century Equity Growth Inv	0	2.9409	0	5.0794	91.9797	96.6677
	JHT 500 Index Trust Ser I	0.2608	0.4708	1.833	0.3487	97.0868	99.6945
	Wells Fargo Advantage Index Adm	0.5828	0.5570	1.7069	0.1152	97.038	99.7473

After this selection and preliminary analysis of the funds, the objective function, reported in section 2.2, has to be minimized, subject to all constraints, except for one: it is not useful to include only funds with an investment threshold lower than USD 10,000, since this constraint is redundant if a sufficiently large investment is assumed.

The only degree of freedom left by the authors is the decision of the investor's level of risk tolerance, represented by the parameter λ. However, since the model imposes the strict replication of the strategic asset allocation, large changes in the value of λ are needed in order to change the weights of the funds, as can be seen in the following table (data for the out-of-sample test period 7/2005-12/2005), in which benchmark indices have been included to emphasize the transition from active to passive investments.

Table 4. Sensitivity of asset allocation to variations in the coefficient of risk tolerance of the model by Baierl and Chen

λ	0.0005%	1.00%	5.00%	10.00%	50.00%
Power Capital Navigator	0.00%	0.00%	0.00%	0.00%	0.00%
Sarasin EmergingSar-Global Inc	0,02%	4.36%	5.07%	3.79%	2.09%
The Emerging World Fund Inst Acc	0.00%	2.11%	0.00%	0.00%	0.00%
GLG European Equity Fund A Acc	0.01%	5.57%	13.17%	26.20%	36.10%
Imi Europe Acc	0.00%	0.00%	0.00%	0.00%	0.00%
Pioneer Funds Top European Players E EUR ND Acc	0.01%	0.00%	2.58%	0.58%	0.00%
Nikko AM Japan Value Fund B	0.01%	2.77%	0.00%	0.00%	0.00%
UBS (CH) EF-Japan Inc	0.00%	0.00%	0.00%	0.00%	0.00%
Vitruvius Japanese-Equity JPY Acc	0.00%	6.36%	7.89%	8.02%	6.98%
American Century Equity Growth Inv	0.00%	9.26%	31.34%	30.39%	54.76%
JHT 500 Index Trust Ser I	0.02%	20.12%	22.22%	23.98%	0.00%
Wells Fargo Advantage Index Adm	11.98%	25.76%	2.03%	0.00%	0.00%
Citi EUR EuroDep 1 Mon EUR	0.93%	0.00%	0.00%	0.00%	0.00%
MSCI EM LCL	6.51%	0.00%	0.00%	0.00%	0.00%
MSCI Europe NR LCL	28.76%	23.71%	15.69%	7.04%	0.07%
MSCI Japan NR JPY	9.88%	0.00%	0.00%	0.00%	0.00%
MSCI USA NR USD	41.87%	0.00%	0.00%	0.00%	0.00%

As expected, an increase in the value of parameter λ causes a larger allocation in the active management, represented by the funds selected on the basis of their high alpha (see Table 2)[1].

In order to test the behavior of Baierl and Chen's model, the performance of the multimanager portfolio has been analyzed providing for the investment both in mutual funds alone, and in them and in the benchmark at the same time. The results were better in the case of investment also including the indices, both in terms of higher alpha and lower TE.

3.5. Performance comparison. In order to compare the two multimanager methods, a multiasset portfolio for Muralidhar's model had to be created, even though it had been designed to be used only for one asset class at a time. This portfolio, called CAP World, is a weighted average of the returns of individual multimanager allocations, in which the weights are those estimated by the style analysis of the MSCI AC World LCL index.

Then, from the comparison of the two models (for Baierl and Chen there is also the version with investment in the indices) with the strategic benchmark we can observe that, in terms of risk-return, the M^3 by Muralidhar allowed the composition of an efficient portfolio, as can be seen in Table 5.

Table 5. Risk-return of multimanager portfolios

	Arithmetic mean (%)	Standard deviation (%)	T-statistic	Sharpe ratio
CAP-K World	0.837	3.381	1.918	0.177
Baierl & Chen	0.717	3.339	1.664	0.143
Baierl & Chen (with indices)	0.743	3.323	1.732	0.152
Benchmark	0.715	2.904	1.907	0.164

[1] Note that in the Europe asset class the capital has been allocated mainly in the second-ranked fund because of its lower exposure to the short-term rate than the first-ranked fund.

On the other hand, if we also take into account the third and fourth distribution moments, the CAP has a higher risk, as shown in Table 6:

Table 6. Skewness and kurtosis of multimanager portfolios

	Skewness	Kurtosis
CAP World	-1.280	2.558
Baierl & Chen	-1.120	1.971
Baierl & Chen (with indices)	-1.141	2.097
Benchmark	-1.164	2.132

In addition, the alpha, relative to the strategic benchmark, is negative for Baierl and Chen, but positive for the CAP. It is striking that this latter portfolio has failed to fulfil its target TE (0.75%), departing from the benchmark to a lesser extent (see Table 7).

Table 7. Excess return relative to the benchmark

	TE (%)	TEV (%)	T-statistic	IR
CAP World	0.122	0.646	1.465	0.189
Baierl & Chen	0.002	0.746	0.020	0.003
Baierl & Chen (with indices)	0.028	0.700	0.311	0.040

Note: Note that the alpha of Muralidhar's M^3, even though positive, is still not significant with a confidence of 95%.

Conclusions

In light of the results, the multimanager approaches outlined in this article appear to be useful in selecting portfolios with an efficiency close to that of the market. In particular, the model by Baierl and Chen offers the advantage of allocating investments in compliance with the ex-ante asset allocation, thanks to constrained optimization that takes into account the style weights. This aspect is particularly important if we consider the relevant weight of strategic asset allocation as a determinant of portfolio performance (Brinson, Hood & Beebower, 1986).

On the other hand, the model by Muralidhar generates a better performance but, ignoring higher moments, can lead to allocations more exposed to non-normal negative returns. This problem could be corrected only resorting to optimization algorithms within a mean-variance-skewness-kurtosis framework as suggested by Davies, Kat and Lu (2009), a methodology that, on the other hand, would ignore the correlation between the fund and the benchmark.

The fact that portfolios' performances, relative to the benchmark, have strongly deteriorated since the inversion of the trend in the stock markets of the summer of 2007 (see Figure 1) can be interpreted as a further example of higher correlations between financial instruments in times of severe crisis (Jacquier & Marcus, 2001), which makes the task of those managers who are looking for opportunities to beat the benchmark more difficult. To explain the disappointing performance from mid-2007 to mid-2008 it is also possible to conjecture that the alphas of funds are partially generated through exposure to systematic risk factors that are not measured solely by the equity benchmarks used here for the style analysis. Several factor models have been proposed through the years, for example, fund managers might change the loadings of their funds, in part, according to the macroeconomic factors suggested by Chen, Roll and Ross (1986), or might invest a small part of their assets in synthetic portfolios constructed following the three-factor model by Fama and French (1996).

This suggests that the main problems of the multimanager asset allocation models in active mutual funds are the low persistence of the alphas, as shown in Table 7, and the difficulty in selecting managers capable of generating excess returns in situations of generalized sales, high volatility and increasing correlations between market factors.

The probable correlation between the managers' alphas is not taken into account by the two models studied in this article: Baierl and Chen assume that their variance-covariance matrix is diagonal, while Muralidhar, selecting funds only according to correlation-adjusted returns, ignores the links between the excess returns. Therefore, these approaches may lead to the construction of fund portfolios with highly correlated excess returns, amplifying the movements of their benchmark.

On the other hand, thanks to the selection process and to the optimization algorithms, these models can be useful for investors who wish to diversify their portfolios, but limiting their tracking error and seeking superior risk-adjusted returns.

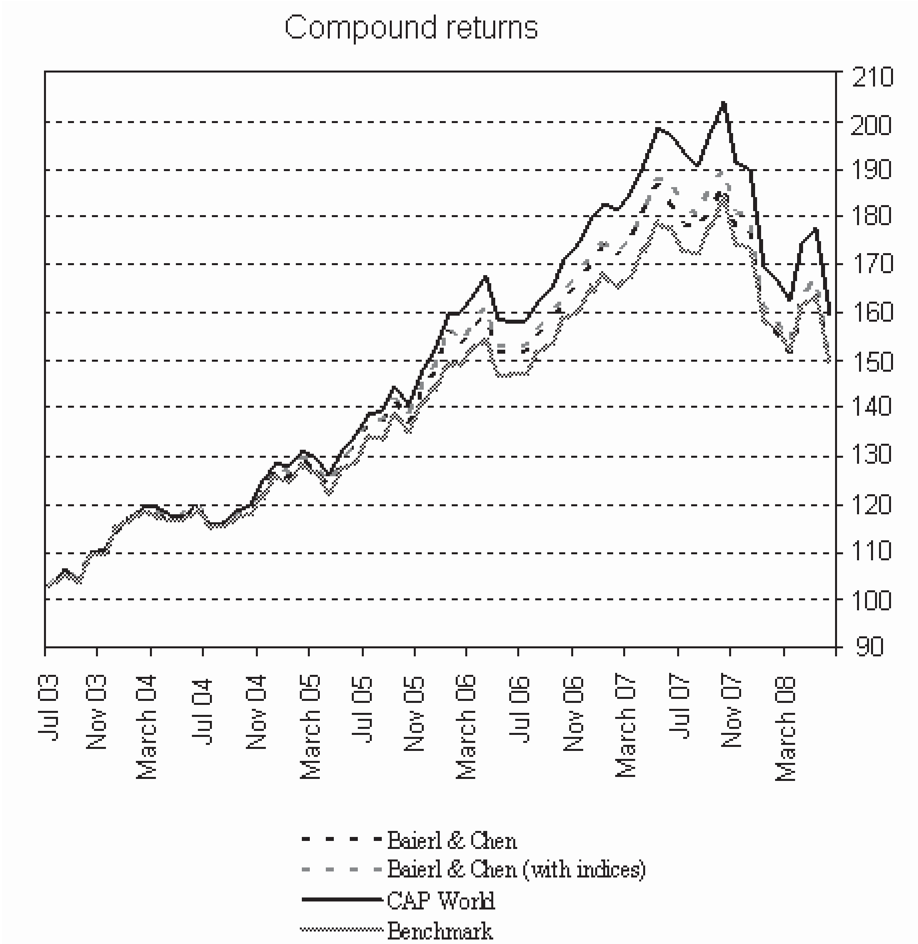

Fig. 1. Out of sample compound returns, 7/2003-6/2008; base=100: 6/2003

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