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Evaluating Hedge Fund Investments: The Role of Pure Style Indices

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1 Introduction

Over the past decade, the hedge fund industry has grown – big time. According to estimates, the number of hedge funds increased from 2,000 to 8,000, assets under management went from US $67 billion to US $800 billion, and inflows of money to hedge funds have never been greater. This growth was essentially driven by the attractive risk-adjusted performance achieved by hedge funds, their ability to protect capital in negative equity markets, and the shrinkage in proprietary trading activities, which coincided neatly with a welter of hedge fund launches.

To a large extent, hedge funds have been marketed to potential investors on the basis of historical performance and low volatility. We all know that past performance is no guarantee of future returns, nor is volatility an adequate risk measure when returns are not normally distributed. When hedge funds were the only bright spark on an otherwise gloomy outlook, the need to understand their risks was practically non-existent. Getting access was the only thing that mattered. Things have changed however. Highly publicized hedge fund failures (e.g. Long Term Capital Management, Manhattan, Granite and Lipper Convertible) combined with the fiduciary responsibilities of institutional investors have spurred requests for more transparency and more sophisticated risk management systems. A survey conducted in May 2001 by the magazine *Investments & Pensions* demonstrated that lack of transparency and weakness of risk controls were the two biggest issues facing the alternative investment industry. Although a difference of opinion still remains between managers and investors on the issue of transparency, it is clear that the events above have triggered an increased industry-wide focus on risk management.

However, the nature of the hedge fund industry makes risk measurement challenging. First, traditional risk measures such as volatility are not always sufficient within the context of hedge funds. Many hedge fund strategies are dynamic by nature and display option-like payoffs, which violate the usual normality and linearity assumptions. Second, because the industry is unregulated or loosely regulated, many hedge fund managers are not required – and are even very reluctant – to disclose anything about their underlying investments[1]. Third, even with the most transparent managers, there is usually only relatively short time series of returns available, so that hardcore econometrics are not really feasible.

In April 1999, in response to the collapse of Long Term Capital Management, the President's Working Group on Financial Markets[2] issued a report calling for a group of

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1 Rather than holding units in a fund some investors have chosen to open managed accounts with hedge fund managers, whose positions mirror those of their publicly offered fund. These investors are the beneficial owners of the assets held by the managed account. They can monitor them with full transparency on a daily basis and ensure continued operation within the original risk budget. However, this approach is not yet mainstream.

2 The PWG comprises of the Secretary of the U.S. Department of the Treasury and the respective chairs of the Board of Governors of the Federal Reserve System, the Securities and Exchange Commission and the Commodity Futures Trading Commission.

hedge funds to draft and publish a review of sound practices for their risk management and internal controls. The answer came in February 2000 from representatives of the largest hedge funds in the industry – Caxton Corporation, Kingdon Capital Management, Moore Capital Management, Soros Fund Management and Tudor Investment. The "Sound Practices for Hedge Fund Managers" report developed some innovative recommendations, at least for the hedge fund industry[3]. In particular, it suggested that hedge fund managers should employ a consistent framework for measuring and communicating the risk of loss for their portfolios, such as a Value at Risk (VaR) model. Simply stated, VaR is the maximum loss that should be expected over a given time horizon under "normal market conditions". What constitutes normal market conditions is often defined in probabilistic terms as a degree of confidence, e.g. 99 or 95 percent of the time. The time horizon typically corresponds to a holding period hypothesis, which should reflect the features of the portfolio on which the risk is being measured.

Applying the concept of VaR to hedge funds is very appealing. Initially developed for trading desks, VaR has progressively become best practice for assessing the risk exposure of financial institutions and asset managers. It collapses the entire distribution of returns into a single number stated in terms of dollars or whatever currency is appropriate, so that senior managers and anyone without much technical knowledge can easily understand what it means. VaR is now widely used to communicate risk figures in simple terms, answering both regulators' and investors' concerns without imposing disclosure of portfolio holdings. Moreover, it can be developed for any kind of hedge fund and can easily be aggregated across portfolios of different kinds of instruments. However, VaR is also quite controversial. In the past, it has generated some intensely heated debates, primarily due to the diversity of methods available to calculate it.

So far, there are primarily three conventional paths for VaR estimation: parametric, historical, and Monte Carlo. The parametric method, also known as variance/covariance, is the most common form used in practice. However, it is not applicable to hedge funds because it assumes that returns are normally distributed and serially independent. Historical VaR uses history to predict the future. Unfortunately it is only as strong as the number and quality of the data points available, and back-collecting this data may prove cumbersome or even impossible in the case of hedge funds. In addition, hedge funds are known to change their allocations dynamically, so that available history may not be representative of the future. Finally, Monte Carlo VaR attempts to map out any possible return scenario for a hedge fund on a computer-generated model. Unfortunately, it is also a source of huge model risk in determining the likelihood of any given return scenario.

Our goal in this paper is to suggest a new framework for analysing hedge funds and hedge fund portfolios ("funds of hedge funds"), both from a return and a risk perspective. Our framework is designed so as to be consistent not only with the tools of modern portfolio theory but also with constraints imposed by practical implementation in a context where the

[3] The Managed Funds Association (MFA), a body representing the U.S. hedge funds industry, significantly updated this report in 2003.

presence of a variety of investment styles needs to be accounted for. It combines the style analysis of Sharpe (1988), the use of pure hedge fund indices of Amenc and Martellini (2002), and the factor push approach applied in stress testing and historical simulation. It is easy to implement, has a high explanatory power, and is not restricted by some of the assumptions that tie down traditional VaR approaches.

This paper is organized as follows. In section 2, we first discuss the application of factor models to analyze hedge fund returns and describe in particular the model introduced by Sharpe (1988, 1992) for assessing a fund's effective style mix, as well as the pure style indices that were created by the Edhec business school. We show how these tools can be combined to assess hedge fund returns. In section 3, we illustrate some applications in the domains of fund style assessment, style drift detection and VaR calculation. Finally, section 4 concludes and opens the door to further research.

2 Applying factor models to model hedge fund returns

As a result of the lack of transparency, factor-based models remain the workhorses of hedge fund risk management. They reduce the dimensionality and facilitate an understanding of hedge fund returns by decomposing them over a small number of better-known factors. Furthermore, their use is natural and consistent with standard asset pricing theory, as linear multi-factor models can be economically justified through equilibrium or arbitrage arguments[4].

2.1 Factor models

In a generic form, the econometric model of most multi-factor models is as follows:

$$R_t = \alpha + \sum_{i=1}^{N} \beta_i \cdot F_{i,t} + \varepsilon_t \qquad (1)$$

where R_t denotes the return on the considered fund at time t, $F_{i,t}$ is the value of factor i at time t, β_i is a factor loading that expresses the sensitivity of the fund's returns to factor-i, and ε_t represents the portion of the fund's returns not related to the N factors (idiosyncratic noise). Typically, a time-series regression is used to estimate the relationship between the returns on a particular fund and the various factors. Variations in fund returns that cannot be explained through betas are presumed to be fund specific, and hence non-correlated with any factor. A useful metric is the proportion of variance of R_t "explained" by the N factors, which is defined as the R-squared coefficient:

4 See for instance Merton's (1973) Intertemporal Capital Asset Pricing Model or Ross's (1976) Arbitrage Pricing Theory.

$$R^2 = 1 - \frac{\text{Variance}(\varepsilon_t)}{\text{Variance}(R_t)} \quad (2)$$

Of course, using a factor model leaves us with two very important questions: how many factors should we use (N), and which factors to select (F_1 to F_N)? In practice, selecting the right factors to explain return dynamics is often more of an art than a science, and the answer to both questions is usually a tradeoff between model risk and estimation risk. Several models have been suggested in the literature – see for instance Fung and Hsieh (1997, 2001), Amenc and Martellini (2004) or Lhabitant (2004).

Many researchers claim that though the linear dependence of asset returns on factors might be an oversimplification in Equation (1), other issues, e.g., the factor estimation process and the number and variability of factors, are more fundamental than the exact mathematical form of the dependence. We disagree with this opinion. These researchers may be right in the case of traditional assets. However, it is well known that a number of hedge fund investment styles have returns that are non-linearly related to fundamental risk factors, particularly because their return profile involves taking on some implicit long or short option risk – see Fund and Hsieh (1997, 2000) or Agarwal and Naik (2001). As a consequence, linear factor models will often exhibit little explanatory power when applied to hedge funds.

Nevertheless, model builders have adopted various strategies to enhance the ability of linear factor-based models to analyze hedge fund returns. Among these are: (i) increasing the number of factors; (ii) adding Bayesian priors; (iii) using adaptive statistics such as principal component analysis to determine implicit factors; or (iv) explicitly modeling the non-linearity of the relationship between the hedge fund and the factors[5]. Some of these strategies are simple, but fail miserably. Others are particularly appealing, but introducing non-linearity adds complexity to the mathematics of the models and is data-hungry. In addition, modeling non-linearity in ways that make sense from an asset management point-of-view is far from easy.

In our opinion, a much more pragmatic approach consists of identifying factors that capture the non-linearity of hedge fund returns, so that we can still use a linear factor model. That is, we are looking for new factors that are themselves non-linear with respect to the traditional risk factors. Obviously, the simplest solution is to use hedge fund indices as risk factors.

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5 For instance, Agarwal and Naik use stepwise regression to identify the independent variables, and find that a put or call option on an underlying variable is the most significant factor in the case of 54 percent of their funds.

Lhabitant originally suggested using as a set of factors the CSFB/Tremont hedge fund indices, one for each major investment style. These indices are transparent in both their calculation and their composition and they are constructed in a disciplined and objective manner. They are asset-weighted and computed on a monthly basis. Therefore, our empirical model becomes

$$R_t = \alpha + \sum_{i=1}^{10} \beta_i \cdot I_{i,t} + \varepsilon_t \qquad (3)$$

where

$I_{1,t}$ = return on the CSFB Tremont Convertible Arbitrage index at time t
$I_{2,t}$ = return on the CSFB Tremont Short Bias index at time t
$I_{3,t}$ = return on the CSFB Tremont Risk Arbitrage index at time t
$I_{4,t}$ = return on the CSFB Tremont Distressed Securities index at time t
I_5 = return on the CSFB Tremont Global Macro index at time t
I_6 = return on the CSFB Tremont Long Short Equity index at time t
I_7 = return on the CSFB Tremont Emerging Markets index at time t
I_8 = return on the CSFB Tremont Fixed Income Arbitrage index at time t
I_{9t} = return on the CSFB Tremont Market Neutral index at time t
I_{10t} = return on the CSFB Tremont Managed Futures index at time t

This model is in fact a specific case of a multiple linear regression analysis (statistical terminology) and of a factor model (financial terminology). It implicitly assumes that the return (and risk) on any hedge fund can be split in two components: one explained jointly by the ten systematic factors, and the other that remains unexplained. The latter consists of a constant expected component (α), plus an unexpected one (ε_t) with a zero mean and a variance denoted σ_ε^2. The former is systematic in the sense that it influences returns on all hedge funds.

2.2 From factor models to style analysis

An interesting extension to factor models is the return-based style analysis initially suggested by Sharpe (1988). Return-based style analysis inverses the causality of multi-factor models and asserts that a fund manager's investment style can be determined by comparing its returns with the returns of a number of selected passive indices. For a given fund, the econometric model is the same as in Equation (1), but with two additional constraints. First, the factor loadings must add-up to one, so that they can be interpreted as portfolio weights within an asset allocation framework.

$$\sum_{i=1}^{N} \beta_i = 1 \qquad (4)$$

Second, each factor loading must also be positive in order to meet the short-selling constraint that most fund managers are subject to.

$$\beta_i \geq 0 \qquad i = 1..N \tag{5}$$

The model in Equation (1) subject to the constraints of Equations (4) and (5) needs to be estimated by quadratic programming to provide point estimates for the factor loadings[6]. Under some conditions, it is also possible to derive the asymptotic distribution for the factor loadings. This allows for inferring confidence intervals and carrying out statistical significance tests. However, because of the constraints imposed by Equations (4) and (5) on the estimated coefficients, this is not a straightforward exercise – see for instance Gouriéroux et al. (1982).

Sharpe's return-based style analysis model has been successfully used with traditional assets. However, when applying it to hedge funds, Lhabitant (2001a, 2001b) suggests relaxing the constraint of Equation (4). The economic justification is the fact that hedge funds use leverage, so that their overall exposures (i.e. betas) may be higher than 100%. However, one should be cautious in interpreting a high beta, since this beta is relative to the average leverage of the CSFB/Tremont style index. In a sense, it is a relative indicator of leverage, but not an absolute one. By contrast, the lower boundary constraint of Equation (5) is maintained. Although hedge funds may take short positions, the CSFB Tremont indices used as factors represent investment styles rather than standard asset classes. Therefore, having a negative exposure to a particular style could be hard to justify economically. For instance, what would mean a negative exposure to the Short Bias style? To avoid embarrassing explanations, it is much simpler to force style exposures to remain positive.

2.3 Using pure style indices

For a long period of time, the CSFB/Tremont indices were the only high quality indices available in the hedge fund industry. As a consequence, the choice of risk factors in our above-described model was rather limited. However, as a result of the hedge fund growth, numerous other hedge fund indices have been recently set up. Unfortunately, as illustrated by Amenc and Martellini (2002) the high degree of heterogeneity of the offerings (multiple databases, varied construction methods, differing management principles) did not make the investors' search for a reference index that is representative of the hedge fund universe any easier.

Given that it is impossible to come up with an objective judgment on what is the best existing index, a natural idea consists of using some combination of competing indexes to reach a better understanding of what the common information about a given investment style would be. Amenc and Martellini explored this direction and proposed an original

6 Using a constraint implies that the model can no longer be estimated using a regular regression approach, but must be estimated using a constrained optimization procedure.

solution: a pure style index of indexes, build as the first component of a principal component analysis of competing indexes for each strategy. The Edhec Risk and Asset Management Research Center (www.Edhec-risk.com) is now calculating these indices on a monthly basis.

By construction, the Edhec Alternative Indexes are able to capture a very large fraction of the information contained in the data from the various competing indexes. In fact, one can show that there is no other linear combination of competing indexes that implies a lower information loss. In addition, they are systematically less biased than the indexes they contain. Since the competing indexes are affected differently by biases, searching for the linear combination of competing indexes that implies a maximization of the variance explained, leads to a minimization of the bias. These two characteristics are of great interest in the analysis of the behavior of hedge funds.

	HFR	**CSFB**	**EACM**	**Altvest**	**Hennesse**	**Van Hedge**	**CISDM**	**HF Net**	**Barclay**	**S&P**
Convertible Arbitrage	X	X	X		X			X	X	
CTA Global		X					X	X	X	X
Distressed Securities	X	X	X	X	X	X		X	X	
Emerging Markets	X	X		X	X	X	X	X	X	
Equity Market Neutral	X	X			X	X	X	X	X	
Event Driven	X	X	X	X	X		X	X	X	X
Fixed Income Arbitrage	X	X			X	X		X	X	
Global Macro	X	X		X	X	X	X	X	X	
Long/Short Equity	X	X		X				X	X	
Merger Arbitrage	X	X	X	X	X			X	X	
Relative Value	X		X	X	X	X		X		X
Short Selling	X	X	X		X	X	X	X	X	
Fund of funds	X			X		X	X	X	X	

Figure 1: List of Edhec alternative indices and their constituents as of December 2003

Our model for analysing hedge funds therefore becomes

$$R_t = \alpha + \sum_{i=1}^{12} \beta_i \cdot I_{i,t} + \varepsilon_t \qquad (3)$$

where

$I_{1,t}$ = return on the Edhec Convertible Arbitrage index at time t
$I_{2,t}$ = return on the Edhec CTA Global index at time t
$I_{3,t}$ = return on the Edhec Distressed Securities index at time t
$I_{4,t}$ = return on the Edhec Emerging Markets index at time t
$I_{5,t}$ = return on the Edhec Equity Market Neutral index at time t
$I_{6,t}$ = return on the Edhec Event Driven index at time t
$I_{7,t}$ = return on the Edhec Fixed Income Arbitrage index at time t
$I_{8,t}$ = return on the Edhec Global Macro index at time t
$I_{9,t}$ = return on the Edhec Long/Short Equity index at time t
$I_{10,t}$ = return on the Edhec Merger Arbitrage index at time t
$I_{11,t}$ = return on the Edhec Relative Value index at time t
$I_{12,t}$ = return on the Edhec Short Selling index at time t

In order to avoid co-linearity issues, we have not included the Edhec fund of fund index as a factor.

3 Applications

We now illustrate some of the possible areas of application for our model, using the Edhec pure hedge funds indices.

3.1 Static style analysis

First of all, our return-based style analysis can be used to monitor a hedge fund manager's investment style, regardless of his claimed exposure or categorization and without necessitating periodic disclosure of the funds' assets. This provides a useful indication as to the economic environment in which a given manager is likely to do well or poorly. It can also provide some evidence of both the probability and extent to which a particular hedge fund performance will diverge from any performance benchmarks it is measured against.

As an illustration, Figure 2 shows the beta coefficients provided by a style analysis made on one of the largest commodity trading advisors worldwide, the fund *Graham Global Investment Fund Diversified Portfolio*. At the end of 2003, our model identifies two style exposures for Graham, namely a 138% exposure to the CTA global style and an exposure of 21% to the dedicated short style. In reality, we know that Graham is a pure CTA fund, but its short positions on equity index futures generate a bias that our model captures and classifies as a dedicated short exposure. The R^2 of our model is 91%, which confirms the quality of our analysis.

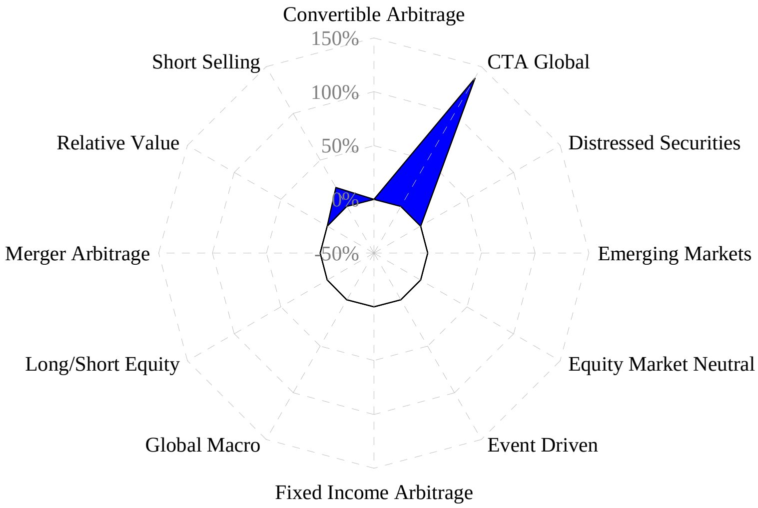

Figure 2: The style radar of *Graham Global Investment Fund Diversified Portfolio*

We also analyzed one of the largest existing multi-strategy fund of hedge funds at the end of December 2003. The results are represented in Figure 3. The style radar is very different from that of Graham. It seems more diversified, with important style allocations to market neutral managers (42%), followed by global macro (16%), long-short equity (15%), commodity trading advisors (15%), distressed securities and emerging markets (10% each). However, although the marketing brochure of this fund claims it is widely diversified across all investment styles, we can also see that there are no style allocations to fixed income arbitrage, merger arbitrage, event-driven or relative value strategies. The R^2 of our model is 69%, which is lower than for the case of a pure strategy fund, but still confirms the adequacy of our analysis.

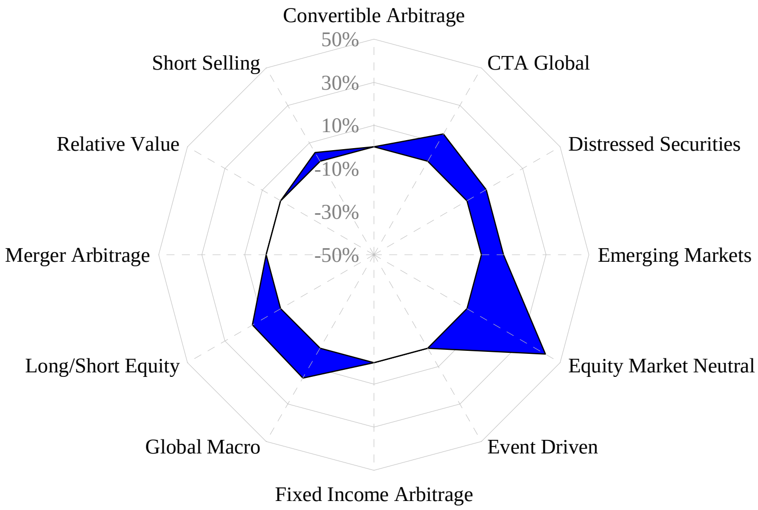

Figure 3: The style radar of a large multi-strategy fund of hedge funds

Clearly, our model provides useful insights into understanding the investment strategy of a particular hedge fund. Using hedge fund radars, it suddenly becomes easy to monitor what managers actually do, regardless of what they claim to be doing. It also helps in identifying hedge funds with a "pure " investment style and hedge funds with a diversified style or multi-strategy approach.

3.2 Style drifts

The major drawback of style analysis is that it implicitly assumes that style exposures are constant over the period examined. However, in practice, assuming a fixed style allocation over a long time is hardly sustainable. It is therefore necessary to apply style analysis in a dynamic way, for instance using a rolling window analysis. The process is as follows. We divide the period under study into two segments. Returns in the first segment, the sample period, are used as a basis for constructing the style benchmark. The sample period is then rolled forward month by month and the process is repeated for each period, allowing the style benchmark weights to vary.

By using rolling windows, the fund's investment style is constantly monitored, making classification and style exposures readily identifiable. Such a rolling style benchmark tracks the manager's actual returns much more closely than static benchmarks. It determines how the fund's styles may have changed over time. It also allows faster reactions to changes in management style ("style drifts"), and so provides an early warning of potential changes in future performance. This is particularly useful for institutional investors, who want to know whether funds adhere to their stated investment styles over time.

As an illustration, Figures 4 shows the evolution over time of the style allocation for our fund of hedge funds using a 36-month rolling window. The style drift towards less directional strategies is visible, with the progressive reduction of long/short equity and global macro style allocations in favor of equity market neutral and convertible arbitrage.

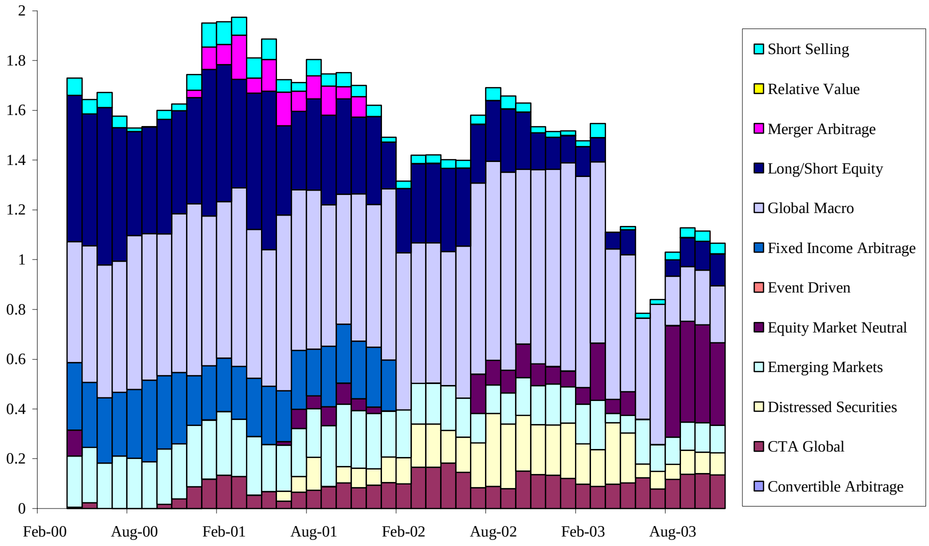

Figure 4: The style evolution of our fund of hedge fund

3.3 Calculation of VaR

Beyond its usefulness in analyzing hedge fund returns, our model can easily be extended to estimate VaR figures. Starting from β_i estimates provided by style analysis, the overall process to compute the VaR can be divided in four steps.

Step 1: Measure the VaR of all Edhec indices used as risk factors. This can be done by simply building up the empirical distribution for each hedge fund index and by measuring the relevant percentile. Let us denote by V_i the corresponding value for index i. Figure 5 shows the values of V_i for all considered strategies at the end of 2003.

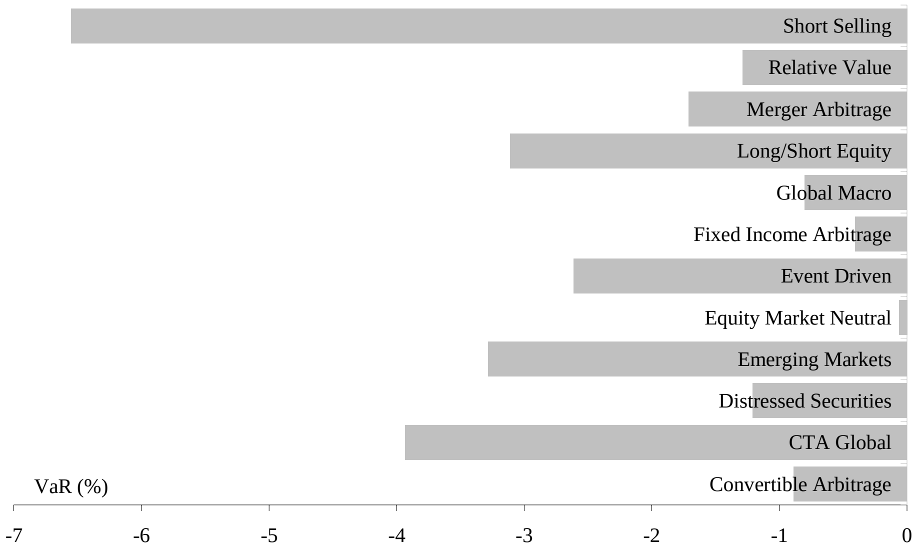

Figure 5: The VaR of all Edhec indices used as risk factors

Step 2: "Push" each individual style index to its VaR and estimate the overall impact on the fund, accounting for risk factor correlation. This gives us the VaR due to style index moves, which we call the "value at market risk". It is calculated as:

$$\text{Value at Market Risk} = \sqrt{\sum_{i=1}^{9} \sum_{j=1}^{9} \rho_{i,j} \cdot \beta_i \cdot V_i \cdot \beta_j \cdot V_j} \tag{4}$$

where $\rho_{i,j}$ is the correlation between returns of hedge fund indices i and j.

Step 3: Measure the VaR due to specific risk, that is, the VaR due to the residual terms (ε_t) in equation (3). This VaR component is called "value at specific risk". Estimating it can be done numerically by simply building up the empirical distribution of the residual terms for each hedge fund and by measuring the relevant percentile. Alternatively, we may use a parametric approach if we assume a particular distribution for these error terms. For instance, if we assume that residual terms (not hedge fund returns!) are normally distributed and we are looking for a 99 percent confidence level, the corresponding VaR is simply:

$$\text{Value at Specific Risk} = 2.33 \times \sigma_\varepsilon \tag{5}$$

where σ_ε is the volatility of the errors.

Step 4: The last step consists in aggregating the two VaR figures into one, accounting for their zero correlation[7].

$$\text{VaR} = \sqrt{(\text{Value at Market Risk})^2 + (\text{Value at Specific Risk})^2} \qquad (6)$$

This process gives us our final VaR number, expressed as a percentage of the fund's net asset value. It is interesting to observe that:

- Even if a hedge fund's returns are poorly explained by all the Edhec indices, its risk will be correctly accounted for through the specific risk component.
- The methodology does not require knowledge of the fund's positions. It simply requires that one runs the model to obtain style exposures.
- In addition to VaR figures, we can easily obtain VaR contributions of each investment style. This is a critical piece of information in the assessment of the concentration and diversification benefits of funds of hedge funds' portfolios.

As an illustration, at the end of year 2003, the one-month 99% VaR of our fund of fund was equal to -1.61%, which we can split in a value at market risk of –1.29% and a value at specific risk of –0.96%. By comparison, the VaR calculated using a normality assumption would be –1.77%. Looking backward and calculating a 36-month rolling value at risk, we can easily reconstruct the historical series of value at risk figures, and compare it to the fund of hedge funds returns – see Figure 6. In this particular case, we clearly see the decrease in the level of risk taken by the fund, as well as the absence of exceptions during the period considered.

[7] In reality, the two components display a zero correlation only if the positive-weights constraint is not binding, which is the case most of the time. Otherwise, a correlation term appears in equation (6). This correlation term is easy to estimate empirically.

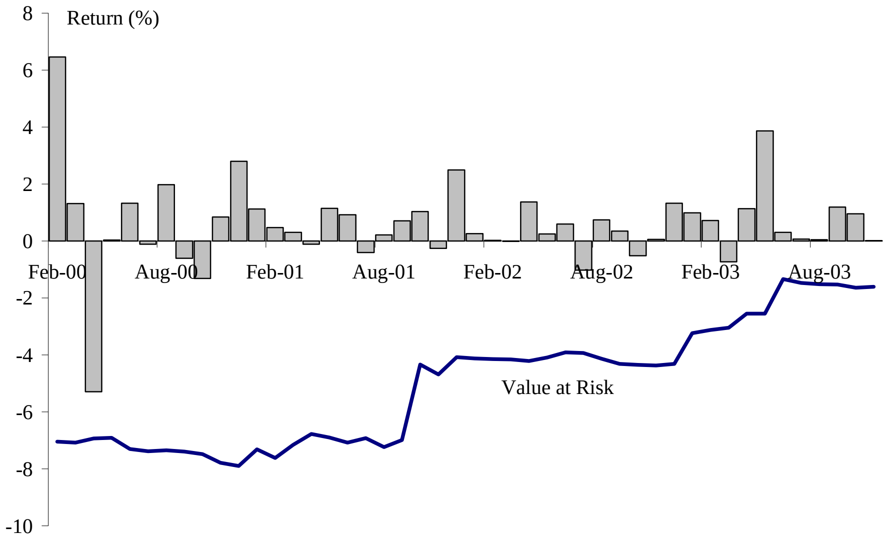

Figure 6: Backtesting the Value at Risk

4 Conclusion

Returns-based style analysis is a statistical evaluation technique that compares the fund's return to the returns achieved by a set of market indexes, each of which tracks a specific investment style. Originally developed for traditional long-only portfolios, it can easily be combined with pure style indices to create a powerful tool to understand the style behavior of hedge funds and funds of hedge funds, with possible applications for classification, monitoring, performance evaluation and risk measurement. Among its greatest advantages are its efficiency and impartiality. The only data needed are historical returns, and the method provides an assessment of the fund's behavior independent of its stated objective. Its results let investors make an informed decision about the role hedge funds can play in their portfolio. We believe it is a useful quantitative tool to complement, but not replace, human judgment and market experience.

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