

# Assessing Market Risk for Hedge Funds and Hedge Funds Portfolios

François-Serge LHABITANT

Union Bancaire Privée and Thunderbird, the American  
Graduate School of International Management

Research Paper N° 24  
March 2001

FAME - International Center for Financial Asset Management and Engineering

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François-Serge LHABITANT\*

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Still preliminary

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\* François-Serge Lhabitant, Ph.D., is Head of Quantitative Risk Management at *Union Bancaire Privée (Geneva)*, Professor of Risk Management at *HEC University of Lausanne*, and an Assistant Professor of Finance at *Thunderbird, the American Graduate School of International Management*. The opinions expressed in this paper reflect solely the views of the author and do not engage any institution he may belong to. I thank Dusan Isakov, Thierry Monnier and several Geneva GARP members for helpful suggestions and remarks. All comments are welcome. Email: [francois@lhabitant.net](mailto:francois@lhabitant.net)

# **Assessing Market Risk for Hedge Funds and Hedge Funds Portfolios**

**Abstract:** We suggest an empirical model to analyze the investment style of individual hedge funds and funds of funds. Our approach is based on a mixture of the style analysis approach suggested by Sharpe (1988), the factor push approach used in stress testing, and historical simulation. An interesting and straightforward extension of this model is the estimation of value-at-risk (VaR) figures. This extension is tested using a very intuitive implementation over a large sample of 2,934 hedge funds over the 1994-2000 period. Both the in-the-sample and the out-of-sample results suggest that the proposed approach is useful and may constitute a valuable tool for assessing the investment style and risk of hedge funds.

**Keywords:** hedge funds, style analysis, value at risk.

**JEL Code:** G10

*“The review team found that the due diligence and ongoing risk assessments of hedge funds were largely qualitative and lacked quantitative rigor.”*

Federal Reserve Board

March 24, 1999

## **1 Introduction**

Spurred by the increasing complexity of financial instruments and the large losses sustained by some major institutions, market participants have acknowledged the need for a unified method to measure risk that could be useful for both regulatory reporting and internal risk management purposes. As a result of important developments in financial risk modeling, Value at Risk (VaR) and scenario analysis have progressively become best practices for assessing the total market risk exposure of institutions. They are now being used within leading financial institutions and corporations, and are supported by the Basle Committee on Banking Supervision, the Group of Thirty, the Bank for International Settlements, and the European Union.

However, trading rooms have adopted VaR more readily than asset management firms. While most asset managers are particularly proficient at measuring returns and constructing benchmarks to evaluate performance, they argue that this expertise does not extend to the measurement of risk. Indeed, asset managers view risk management in general, and VaR in particular, as being inherently at odds with their primary business mandate: taking risks

Nevertheless, this situation should change rapidly, particularly for asset managers whose portfolio holdings are not transparent to investors at all times. We are particularly focusing on hedge funds, commodities trading advisors (CTAs), and other eclectic investment pools, whose private partnership structure or offshore location frees them from local regulation and disclosure requirements that apply to mutual funds and banks. For all of these, VaR could be used to communicate risk figures in simple terms, answering both regulators and investors' concerns without imposing disclosure of portfolio holdings.

Hereafter, we propose and test a practical framework for the quantification of the market and the specific risk of hedge funds and hedge funds portfolios ("funds of hedge funds"). Our model combines the style analysis approach of Sharpe (1988) with 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.

The structure of this article is as follows: Section 2 introduces the notions of hedge funds, market risk and VaR. Section 3 reviews the style analysis model introduced by Sharpe (1988) and its economic interpretation. Section 4 extends this model to take into consideration the various particularities of hedge funds. Section 5 suggests some applications, and Section 6 reports the results of the empirical tests. Finally, Section 7 concludes and opens the path to further discussion.

## **2 Hedge funds, Market risk and VaR**

Hedge funds have been embraced by investors worldwide and are now recognized as an asset class in their own right. Originally, hedge funds operated by taking a "hedged" position against a particular event or expectation (whether an increase or decrease in value), effectively reducing risk. Nowadays, some investment funds are categorized as hedge funds, but do not actually hedge anything. Indeed, the term "hedge fund" is applied somewhat indiscriminately and beyond the scope of its original meaning. It refers to any pooled investment vehicle that is not a conventional investment fund - that is, any fund using a strategy or set of strategies other than investing long in bonds, equities, money markets, or a mix of these assets. Consequently, hedge funds are better identified by their common

structural characteristics than by their “hedged” nature. These characteristics include, but are not limited to, active management, long-term commitment of investors, use of incentive fees, leverage, and broad discretion over the investment styles, asset classes and investment vehicles.

As with traditional investments, a major source of risk for hedge funds is market risk -- that is, the risk that the value of a fund’s assets declines because of adverse movements in market variables such as interest rates, exchange rates, or security prices. This risk can be increased by leverage, or reduced by hedging strategies. In addition, each fund has its own investment style and specific risk – that is, a risk that is independent of what the market is doing. For legal reasons, hedge fund managers have traditionally been very reluctant to disclose specifics about their operation or risks even to their own investors<sup>1</sup>, resulting in frequent criticisms. In addition, positions are often proprietary -- external knowledge of the positions could directly impact anticipated returns. Also, many investors do not have the tools required to gauge the risk of these positions, so that simple disclosure of positions is not necessarily the best option. The solution would be of course to disclose standardized risk information, so that investors could understand precisely what risk reports contain.

In April 1999, in response to the collapse of Long Term Capital Management, the President’s Working Group on Financial Markets<sup>2</sup> issued a report calling for a group of hedge funds to draft and publish sound practices for their risk management and internal controls. The answer<sup>3</sup> was the “Sound practices for hedge fund managers” report issued in February 2000, which developed some innovative recommendations, at least for the hedge fund industry. In particular, it suggested that hedge fund managers should employ a VaR (VaR) model for measuring and communicating the risk of loss for their portfolios.

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<sup>1</sup> See Lhabitant (2000) for a review of their major motives.

<sup>2</sup> 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.

<sup>3</sup> The answering group included representatives of the largest hedge funds in the industry: Caxton Corporation, Kingdon Capital Management, LLC, Moore Capital Management, Inc., Soros Fund Management LLC and Tudor Investment Corporation.

Let us recall that VaR aims to measure the magnitude of the likely maximum loss that a portfolio could experience over a finite time horizon at some specific confidence level. 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. The confidence level indicates the frequency of the maximum loss. The user sets the confidence level according to the purpose at hand (risk management, regulatory reporting, etc.) and within the limits of what is considered as “normal” market conditions<sup>4</sup>.

## **INSERT FIGURE 1 HERE**

VaR collapses the entire distribution of a portfolio’s returns into a single number (see Figure 1). It aims to do what virtually no other financial tool has ever attempted -- provide a unified framework for a meaningful, easy to interpret, aggregate measure of risks for portfolios composed of complex instruments with various market sensitivities, maturity and pricing mechanisms. While the definition of VaR is broad and encompasses – at least in theory – all sources of market risk for a portfolio, actually estimating VaR can be challenging in practice. Once the confidence level and holding period have been decided, the two next steps consist of forecasting large future movements of underlying markets and assessing the sensitivity of the portfolio to these movements. Various methods may be used, including parametric methods, extreme value estimates, or historical or Monte Carlo simulations. Each methodology has its own strengths and weaknesses<sup>5</sup>.

### **3 From factor models to style analysis**

Measuring market risk can be summarized as (i) finding a good model for assets’ returns and (ii) deriving assets’ risk exposures. Several descriptive model forms have been, and continue to be, applied in analyzing the sources of projected or realized assets’ returns. In the broadest, and most literal sense, most take the form of a linear factor model.

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<sup>4</sup> A VaR with a confidence level of 99 percent implies that the loss should not exceed the VaR in 99 cases out of 100. See for instance Jorion (1997) for relevant background material.

<sup>5</sup> See Jorion (1997) and Dowd (1998) for a review.

A linear factor model relates the return on an asset (be it a stock, bond, fund or any other asset) to the values of a limited number of factors. The basic equation of a multiple factor model takes the following form:

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

where:

- $R_t$  = the return on the asset at time  $t$
- $\alpha_i$  = the excess return (a constant) of the asset
- $F_{i,t}$  = the value of factor  $i$  at time  $t$
- $\beta_i$  = the change in the return on the asset per unit change in factor  $j$
- $N$  = the number of factors
- $\varepsilon_t$  = the portion of the return on the asset not related to the  $N$  factors

An analogy to the familiar relationship that quantity times price equals value provides an easy interpretation of equation (1). For a given asset, we can think of  $\beta_i$  as the quantity of type- $i$  risk in the asset and  $F_{i,t}$  as the reward of type- $i$  risk at time  $t$ . Thus, the product  $\beta_i \cdot F_{i,t}$  is the value of the contribution of type- $i$  risk to the expected return of the asset at time  $t$ .

The usefulness of a factor model depends crucially on the factor(s) chosen for its implementation. Equation (1) gives no guidance as to which factors should be considered. Selecting the correct factors to explain return dynamics is often more of an art than a science. Several techniques for factor identification have been proposed. They range from principal component analysis (PCA) to arbitrarily specified factors within one of the following categories:

- Factors pertaining to particular observable stock (firm) characteristics, such as a market index, sector index, amount of sales, P/E ratio, market capitalization, leverage, dividend yield, trading volume, etc. Something important to remember is that the corresponding factor should affect all assets under consideration; see for instance Fama and McBeth (1973).



- Macroeconomic factors, such as the shape or level of the term structure of interest rates, foreign exchange rates, industrial production, GDP growth, etc.; see for instance Blake, Elton, and Gruber (1995).
- Returns on relevant portfolios, which themselves capture the broader influences on the assets considered. Examples are decile portfolios sorted by size or P/E; see for instance Fama and French (1992)

Popular examples of theoretical factor models based on equation (1) include the single-factor CAPM and the generic Roll-Ross APT model, as well as fixed income models relying on duration and convexity and all derivative models relying on sensitivities (delta, gamma, etc.). On the practical side, numerous implementations are now available, such as the series of BARRA models, twenty-factor APT model from Advanced Portfolio Technologies Inc., six-factor model developed by Quantec Systems, Ltd, or Salomon Brothers Risk Attribution Measurement (RAM) model, among others.

An interesting application of factor models is the return-based style analysis initially suggested by Sharpe (1988). Return-based style analysis inverts 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 as follows:

$$R_t = \alpha + \sum_{i=1}^N \beta_i \cdot R_{i,t} + \epsilon_t \quad (2)$$

where  $R_t$  denotes the return on the fund at time  $t$ ,  $R_{i,t}$  is the return on index  $i$  at time  $t$ ,  $\beta_i$  is a factor loading that expresses the sensitivity of the fund's returns to index- $i$  returns, and  $\epsilon_{i,t}$  represents the portion of the fund's return not related to the  $N$  factors (idiosyncratic noise). The factor loadings must add-up to one, so that they can be interpreted as portfolio weights within an asset allocation framework.

$$\sum_{i=1}^N \beta_i = 1 \quad (3)$$

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

$$\beta_i \geq 0 \quad i = 1..N \quad (4)$$

The model in equation (2) subject to the constraints of equations (3) and (4) can easily be estimated by quadratic programming to provide point estimates for the factor loadings<sup>6</sup>. In practice, the indices represent pre-specified investment styles (e.g. value/growth, small/large caps, high/low dividend, etc.) or particular asset classes (stocks, bonds, real estate, etc.). Following Sharpe's recommendations, they should be mutually exclusive, exhaustive with respect to the investment universe, and have returns that differ. If some indices are too closely correlated or not mutually exclusive, the model will yield unstable or oscillating results from period to period. Likewise, if the set of indices does not span the investment universe, the methodology will fail in identifying a benchmark that consistently explains the fund's behavior.

Application of return-based style analysis has proven to be beneficial, but its results must be carefully interpreted. It is often incorrectly stated that the factor loadings correspond to the effective allocation of the fund's portfolio among the asset classes. In actuality, the most one can say is that the fund behaves "as if" it was invested using these factor loadings.

For an investor or a sponsor, return-based style analysis offers a major advantage: it allows the identification of the effective investment style of a fund, and this before obtaining end-of-year official figures<sup>7</sup>. This has important consequences for monitoring and judging a fund's investment behavior. For instance, it allows for the monitoring of portfolios' style characteristics at both the individual (i.e. fund) and at the aggregate (i.e. portfolio) levels. It

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<sup>6</sup> 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 (3) and (4) on the estimated coefficients, this is not a straightforward exercise. See for instance Gouriéroux et al. (1982).

<sup>7</sup> Although a fund's prospectus should obviously provide this information, recent research by DiBartolomeo and Witkowski (1997), Brown and Goetzmann (1997) and Kim, Shukla and Tomas (1999) presents evidence of serious misclassifications when self-reported investment objectives are compared to actual investment styles.

also allows the creation of style benchmarks for performance assessment, providing a detailed breakdown of the various contributions to return from investment styles. The return obtained by a fund in each month ( $R_t$ ) can be compared with the return on a mix of asset classes with the same estimated style ( $\sum \beta_i F_{i,t}$ ). This mix is a viable and identifiable alternative that can be easily replicated, and is an acceptable benchmark. The difference between the fund and its benchmark ( $\alpha + \epsilon_t$ ) is therefore, the net contribution from the manager, given its style.

A drawback of return-based style analysis is that it assumes style consistency through time, at least over the period of return measurement. A time series of data is used to perform a single constrained regression, providing a single style for the entire period. It is therefore common practice to use moving window regressions to incorporate new information and evaluate a manager's style shifting through time.

Style analysis works remarkably well for investment funds and traditional portfolios; see for instance the results obtained by Sharpe (1992). However, it performs poorly with hedge funds. The reasons are two-fold. First, the factors underlying hedge fund returns have not been fully identified yet in previous research. Second, hedge fund managers have different investment styles and market opportunities than traditional stock and bond fund managers. Typically, while the latter are strictly regulated and must hold primarily long positions in the underlying assets, the former have broad mandates, take long and short positions and use varying degrees of leverage in varying market conditions. This results in non-linear returns that can flaw the (linear) return-based style analysis. As an illustration, let us recall the major results from Fung and Hsieh (1998).

Applying principal component analysis to a sample of 2,525 U.S. mutual funds, Fung and Hsieh observe that there are 39 dominant investment styles. Most are sub-sets or mixes of nine broadly defined asset classes<sup>8</sup>. Given that mutual funds do not change their asset allocation frequently, style analysis has a large explanatory power with respect to mutual

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<sup>8</sup> These are: MSCI US, MSCI non-US, and IFC Emerging Market for equities; JP Morgan US Government Bonds, JP Morgan non-US government bonds, and Merrill Lynch High Yield Corporate Bond Index for fixed income; one-month eurodollar rate for cash; gold for commodities; and Federal Reserve's Trade Weighted Dollar Index for currencies.

funds' variations<sup>9</sup>. When applying the same methodology to a sample of 409 hedge funds and CTAs, the results differ dramatically. Fung and Hsieh identify five dominant styles, with two being linked to traditional asset classes (U.S. equity, and high-yield). The remaining three are dynamic trading strategies, i.e. non-linear functions of the traditional asset classes returns. Even worse, hedge funds often follow aggressive tactical asset allocations between these classes, resulting in the style analysis model having a very low explanatory power, and therefore, a reduced usefulness.

As a consequence, Fung and Hsieh suggest adding regressors to proxy the returns of these dynamic trading strategies. In particular, they use a non-parametric form of regression to find the corresponding dynamic trading strategy to replicates hedge fund returns. They observe that a twelve-factor model – nine asset classes and three trading strategies - provides better results, and could be used to assess the performance of hedge funds. Although we entirely support their proposition, recent academic research<sup>10</sup> has evidence that the existence of additional factors such as, convenience yields, market momentum, and other institutional features resulted in potential arbitrage opportunities for hedge fund managers. Accounting for these additional factors, while using monthly hedge funds quotes, would lead us to important estimation problems rather than to a solution.

## **4 Our model**

Fortunately, since Fung and Hsieh's research, new elements have occurred and may provide a solution to the problem. In 1999, Credit Suisse First Boston and Tremont combined their resources to create new benchmarks for hedge fund performance. The CSFB/Tremont Hedge Fund Indices offer several advantages with respect to their competitors:

- They are transparent both in their calculation and composition, and constructed in a disciplined and objective manner. Starting from the TASS+ database, which tracks over 2600 US and offshore hedge funds, the indices only retain hedge funds that have at least US \$10 million under management and provide audited financial statements. Only about 300 funds pass the screening process.

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<sup>9</sup> About 73% of the funds considered have a  $R^2$  higher than 0.80, and 56% have  $R^2$  higher than 0.90%.

<sup>10</sup> See for instance Chan et al. (1996) or Blake et al. (1999).

- They are computed on a monthly basis and asset-weighted. Funds are reselected quarterly to be included in the index, and in order to minimize the survivorship bias, they are not excluded until they liquidate or fail to meet the financial reporting requirements. This makes these indices representative of the various hedge funds investment styles and useful for tracking and comparing hedge fund performance against other major asset classes.
- They do not include the amount of funds of hedge funds and separate accounts. Therefore, each sub-index is mutually exclusive: this should allow the avoidance of most of the multi-collinearity problems in our regression/optimization approach.

Therefore, we suggest adapting the Sharpe (1988) return-based style analysis model by using as asset classes the nine CSFB/Tremont sub-indices, which are described in Table 1. For a given hedge fund, our model can be written as:

$$R_t = \alpha + \sum_{i=1}^9 \beta_i \cdot I_{i,t} + \varepsilon_t \quad (5)$$

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 Event Driven index at time  $t$

$I_{4,t}$  = return on the CSFB Tremont Global Macro index at time  $t$

$I_{5,t}$  = return on the CSFB Tremont Long Short Equity index at time  $t$

$I_{6,t}$  = return on the CSFB Tremont Emerging Markets index at time  $t$

$I_{7,t}$  = return on the CSFB Tremont Fixed Income Arbitrage index at time  $t$

$I_{8,t}$  = return on the CSFB Tremont Market Neutral index at time  $t$

$I_{9,t}$  = return on the CSFB Tremont Managed Futures index at time  $t$

We therefore assume that the return (and risk) on any hedge fund can be split in two components: one explained jointly by the nine systematic factors<sup>11</sup>, and the other that remains unexplained. The latter consists of a constant expected component ( $\alpha$ ), plus an unexpected one ( $\varepsilon_t$ ) with a zero mean and a variance denoted  $\sigma_\varepsilon^2$ .

Our model preserves the analytical tractability and ease of interpretation of Sharpe's model. Rather than referring to traditional asset classes modeled by passive indices, we simply use alternative asset styles represented by indices of active funds. Therefore, for a given hedge fund, the beta coefficients can then be seen as exposures to the different CSFB/Tremont styles. The alpha coefficient is the excess return generated by the hedge fund manager, taking into account its investment style.

Let us now discuss constraints on the sensitivities from Equations (3) and (4). Should we or shouldn't we impose constraints on the hedge funds' sensitivities? Following Fung and Hsieh's argument, we have decided to set no upward restriction on beta coefficients. The economic justification is the possibility of leverage. 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.

However, unlike Fung and Hsieh, we have decided to keep the lower boundary constraint. Although hedge funds may take short positions, we have to remember that our underlying indices are style indices, not standard asset class indices. 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?

## **5 Applications**

There are several possible areas of application for our model. The 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.

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<sup>11</sup> By systematic, we mean that the corresponding factors influence returns on all hedge funds.

Our multi-factor analysis can also be used for performance evaluation purposes. It helps in identifying what underlying ability, skill or flare has contributed to a fund manager's performance, as opposed to what might reasonably be expected by a fund manager with average abilities adopting the same investment style. It also allows the definition of benchmarks that are based on the characteristics of the strategies applied by the funds that are evaluated, in the spirit of Daniel et al (1997).

In the following example, we will focus primarily on a new application. Knowing the style exposure of a hedge fund, one can easily apply a two-step procedure to obtain its value at risk, that is, its maximum loss during a specified period of time at a given level of probability. The first step estimates systematic risk. Once we have mapped a hedge fund on the nine indices that constitute our risk factors, the idea is to “push” the price of each individual risk factor in the most disadvantageous direction and estimate the overall impact on the fund, accounting for risk factor correlation. This will give us the VaR due to market moves (i.e. style return moves). We call this first part the “value at market risk”. In a second step, we will add up the VaR due to the specific characteristics of the fund, that we will call “value at specific risk”.

Let us assume that we want a confidence level of 99% for the one-month VaR. Denoting by  $F_i^*$  the one percentile extreme move of index  $i$  returns over one month, the value at market risk for a fund  $P$  over one month is given by

$$\text{Value at Market Risk}_{P, 1M} = \sqrt{\sum_{i=1}^9 \sum_{j=1}^9 \rho_{i,j} \cdot \beta_i \cdot F_i^* \cdot \beta_j \cdot F_j^*} \quad (6)$$

where  $\rho_{i,j}$  is the correlation between monthly returns of hedge fund indices  $i$  and  $j$ . This formula is inspired by the one used in the variance/covariance method (e.g. Riskmetrics). The procedure to estimate extreme moves is based on extreme value theory and detailed in the appendix.

The second step estimates specific risk. We simply define specific risk ( $\sigma_\epsilon^2$ ) as the difference between total risk (observed fund variance  $\sigma_p^2$ ) and systematic risk (variance due to the market, i.e. the hedge fund style). We have:

$$\sigma_{\epsilon}^2 = \sigma_P^2 - \sum_{i=1}^9 \sum_{j=1}^9 \rho_{i,j} \beta_i \cdot \sigma_i \cdot \beta_j \cdot \sigma_j \quad (7)$$

By construction, the error terms  $\epsilon_{i,t}$  are non-correlated with the systematic risk, and distributed with zero mean and variance  $\sigma_{\epsilon}^2$ . We want to compute the one-percentile of the error term distribution. This can be done numerically, or parametrically if we assume a particular distribution for these error terms. For instance, if we assume a normal distribution, we can apply a factor push of 2.33 times  $\sigma_{\epsilon}$  (corresponding to a 99% confidence level for a normal variable) to obtain the specific risk of a hedge fund<sup>12</sup>.

$$\text{Value at Specific risk}_{P,1M} = 2.33 \times \sigma_{\epsilon} \quad (8)$$

The total VaR over a one-month interval is obtained by adding up market and specific risk figures, accounting for their zero correlation:

$$\text{VaR}_{P,1M} = \sqrt{(\text{Value at Market Risk}_{P,1M})^2 + (\text{Value at Specific Risk}_{P,1M})^2} \quad (9)$$

How does our VaR model compare to alternatives? VaR is nothing more than a measure of the tail of a distribution, however the key step when assessing the risk of a hedge fund is to model its return distribution. Given the scarcity of data and the low frequency of observations, performing a non-parametric estimation of a hedge fund return distribution is not feasible. Assuming a parametric distribution does not rely on any particular economic intuition, and adhering to the standard default of a normal distribution pattern would be non-realistic, since hedge funds typically have fat tails in comparison to normal distribution (i.e. unusual and extreme events tend to occur more frequently than that implied by the normal distribution).

Therefore, we believe our methodology is superior and provides more information in terms of the fund behavior, its areas of concentration and diversification benefits, its leverage with respect to the market -- and all without additional knowledge of the fund's positions. It also

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<sup>12</sup> If we do not want to assume that residuals are normally distributed, the Value at Specific Risk can be estimated by any other quantile estimation technique, since we have the time series of residuals ( $\epsilon_t$ ).



allows ease in applying unprecedented volatility levels or breakdowns in historical correlated markets, a critical component of the investment process of multi-manager portfolios.

## **6 Empirical tests**

### **6.1 Data and methodology**

A major source of difficulty in constructing a hedge fund sample is the lack of performance history. The majority of hedge funds started in the 1990s as private investment partnerships, and was not required to publicly disclose their performance and assets under management. Although this may create a selection bias, we are therefore restricted to focus solely on hedge funds that voluntarily reported their performance.

Our database is built from a series of historical quarterly snapshots from a number of hedge fund providers (Managed Account Reports, Hedge Fund Research, TASS+ and Evaluation Associates Capital Management). In total, it contains 5,228 distinct hedge funds and CTAs, with no restriction whatsoever on their assets under management or existing time. In particular, it includes defunct funds for the time of their existence.

To be selected in the sample used for this article, a hedge fund had to fulfill additional rules: a) The fund must have been reporting performance figures to one of the above-mentioned agencies for at least three years and one month between January 1994<sup>13</sup> and October 2000. b) The fund must have been managing at least \$5 million or an equivalent amount in another currency. c) The fund cannot be a managed account, but must have a legal structure (e.g. a limited partnership). This gave us a final sample of 2,934 investment vehicles, for which we computed monthly holding period returns based on net asset values expressed in U.S. dollars and accounting for eventual distributions.

We distinguish ten different investment styles, namely, Convertible Arbitrage, Short Bias, Event Driven, Global Macro, Long Short Equity, Emerging Markets, Fixed Income Arbitrage,

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<sup>13</sup> The January 1994 starting date for our sample coincides with the availability of CSFB/Tremont indices.

Market Neutral, Managed Futures, and Multi-strategy. Each of these styles corresponds to a CSFB/Tremont Hedge Fund index or sub-index for which monthly holding period returns in U.S. dollar terms are available starting from January 1994. Table 2 provides the standard deviation and correlation for the CSFB/Tremont hedge fund indices.

## 6.2 Fitting of the style-analysis model

The mapping of a particular fund in its corresponding category was performed according to the following rule. We use a 36-month historical window to estimate Equation (5). This provides us with nine exposure parameters (i.e. betas). If any exposure to an investment style represents more than fifty percent of the total fund exposure, the fund is mapped into this investment style. Otherwise, the fund is considered as being from the Multi-strategy style<sup>14</sup>. Then, we move one month forward the 36-month window and perform the same analysis using the new dataset. This allows us to capture style movements, if any. Consequently, a hedge fund can change his style on a monthly basis.

Table 3 gives key descriptive statistics of our total sample. Note all figures are expressed in terms of back-testing months rather than in terms of amount of funds in hedge fund, because of the frequent style changes. For a fund, a test period corresponds to the three-year sample period used to estimate style sensitivities. In total, we have 96,549 test periods. We use the resulting sensitivities to classify funds rather than the officially reported style, and we can observe that the largest category corresponds to multi-strategy (29,000 test periods), followed by convertible arbitrage (12,692 test periods) and event-driven (12,251). Surprisingly, very few funds confirmed their so-claimed emerging markets or global macro investment style (with 746 and 807 test periods, respectively). We also observed a large number of strategy changes throughout the life of the funds.

Table 4 provides some statistics about the style regression results. The R-square corresponds to the percentage of cross sectional variation explained by our nine-index style analysis. With an average R-square value of 0.56, there is strong evidence that our style indices capture the long-term behavior of hedge funds well. This was not granted a priority, because our style

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<sup>14</sup> A natural consequence of this particular mapping scheme is that the existence of diversified funds of hedge funds will result in double counting the underlying investment.

indices are constructed from a small sample of funds (less than 300), which implies that most of the funds considered in our sample were in fact not included in the style indices. The best fits are observed for the investment styles that have the least test periods (e.g. emerging markets, global macro and dedicated short). This is essentially due to the presence of outliers in other samples, since the median R-square values are often much higher than the average values.

### **6.3 VaR and backtesting**

We then compute the VaR according to the methodology described previously. Using the extreme moves of the style indices over the 36-month rolling window and each hedge fund sensitivities to these styles, we compute a one-month VaR figure for each hedge fund at a 99 percent confidence level, and compared it to the profits/losses realized by the fund over the next month, i.e. out of the estimation window. If the net asset value of a hedge fund experiences a drop larger than its VaR figure, the event is recorded as being an exception. Exceptions will be used later on to determine to what extent our VaR figures are consistent with the future risk of hedge funds.

#### **INSERT FIGURES 2 & 3 HERE**

Table 5 shows the average and volatility of VaR figures for hedge funds by investment styles as well as globally. The VaR is split into its value at market risk (VaMR) and value at specific risk (VaSR) components. All figures are expressed as a percentage of the net asset value to allow comparisons and aggregations across funds.

Overall, hedge funds have a monthly average VaR of 10.97 percent, which is split (on average) between a monthly VaMR of 8.07 percent and a monthly VaSR of 6.91 percent. However, the figures differ widely, both across investment styles and across time. The less risky investment style appears to be Event Driven (average VaR of 8.50 percent) and the riskier one is Emerging Markets (average VaR of 29.09 percent). Managed Futures, Global Macro and Dedicated Short styles experienced an overall decrease of their VaR, while all other categories increased their risk figures. The larger increase is observed for Emerging

Markets hedge funds, particularly after the Asian crisis of 1997. The major source of risk remains the market risk rather than the specific risk component.

The large VaR volatility figures (at least when compared to the average VaR for each category) give evidence to the wide variety of risks within a style. Therefore, as a rule of thumb, we can say that it is risky to assimilate a fund to a particular hedge fund index, even if the classification is based on effective returns rather than on a self-declared style. This could be somehow expected: two funds having the same investment strategy but different financial leverage will (and should!) exhibit very different value at risk figures.

#### **INSERT FIGURE 4 HERE**

Figure 4 details the number of exceptions aggregated on a month-to-month basis. In total, out of 96,549 test periods, 1,026 exceptions were observed, including 614 in August 1998 immediately after the LTCM crisis. The other major peaks observed correspond to the 1998 Asian crisis and the 2000 burst of the Internet bubble.

Table 6 regroups interesting statistics about these exceptions. Panel A shows the proportion of exceptions observed year by year for each investment style. The proportion of exceptions corresponds to a binary loss function. If a loss larger than the VaR is observed, it is counted as an “exception”. Each loss is equally counted, so that the magnitude of the loss does not matter so far. At time  $t$ , for a particular hedge fund, the loss function is therefore:

$$L_t = \begin{cases} 1 & \text{if } R_t \leq \text{VaR}_t \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

where  $\text{VaR}_t$  is the estimated VaR for month  $t$ , and  $R_t$  is the realized return figure at time  $t$ . If the VaR model is truly providing the level of coverage defined in its confidence level  $(1-\alpha)$ , then, one should observe that the average number of exceptions expressed in relative terms to be no more than  $(1-\alpha)$ .

The results from Panel A are somewhat mixed. The proportion of exceptions provides a point estimate of the probability of observing a loss greater than the VaR amount over one month

and at a 99 percent confidence interval. Considered globally, the exception rate is 1.06 percent, much higher than the expected one-percent level<sup>15</sup>. Fixed Income Arbitrage and Event Driven funds have the highest exception rate (1.84 and 1.47 percent, respectively). Note that these numbers have to be taken cautiously, given the longevity of the funds in our database. The back testing period being around 29 months on average, an average of one single exception per fund would result in an exception rate of 3.45 percent!

As a general rule, a large proportion of hedge funds (30.13 percent) experienced at least one exception during the 1998 LTCM crisis. To illustrate the impact of this single event on VaR figures, we repeat the experiment, but exclude August 1998 from our sample, assuming exceptions within this month were primarily due to the Russian default and/or the collapse of LTCM. As a result, the 1998-year and the overall average, look much better, with exception rates of 0.86 and 0.43 percent respectively.

Panel B of Table 6 provides some interesting statistics on the magnitude of observed exceptions. In absolute terms, each exception represented an average overstepping of 4.85 percent over the VaR. At a first glance, this number may appear small. However, expressed in relative terms, this corresponds to an average excess of 63.4 percent of the VaR. As expected, excluding the August 1998 month almost always resulted in lower figures.

## 7 Conclusion

Since the nineties, there has been a strong increase of interest in hedge funds due to their potential for enhancing the overall risk/return profile of traditional portfolios. However, the events of the third quarter of 1998 and the subsequent collapse of LTCM have highlighted the risks associated with hedge funds and prompted strong reactions from virtually all investors. Given the complexity involved with hedge funds strategies, there is a need for adequate tools for measuring and communicating their risk figures. An important challenge is to obtain some

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<sup>15</sup> Note that there are several tests to verify VaR systems; see for instance Kupiec (1995) or Lopez (1998). Unfortunately, the power of these tests is poor in small samples. In our case, we have a large number of funds, and this gives us a large number of test periods. But each fund has a short test history (at most seven years of observations, i.e. four years of test periods), due to the monthly quotes. We are therefore unable to rely on such tests to draw conclusions.

form of portfolio transparency from the individual hedge fund managers. Because of specific regulation, lack of liquidity, or other internal reasons, most hedge funds do not disclose their positions or their risk figures.

Our model proposes a simple tool to analyze the investment style of hedge funds, with possible applications for classification, monitoring, performance evaluation and risk management. The risks inherent in a hedge fund portfolio are a function of leverage, market volatility, diversification, and products and markets traded. VaR being a function of all the above, its use in risk disclosure and monitoring could significantly enhance the decision making at each stage of the investment process of hedge funds, from setting objectives to manager selection, asset allocation, risk monitoring, and performance evaluation.

On the computational side, our VaR model requires the estimation of extreme percentile returns of style indices (which is done once for all), and the calculation of the sensitivity coefficients of a hedge fund to style indices (which needs to be repeated for each fund). The resulting VaR can be split into a specific and a market (style) component, and the sources of the latter are also known.

Despite a relatively short observation period, we have tested our model on a large sample of hedge funds. The positive results should provide additional comfort to investment managers by indicating that the realized risks would not be significantly different from the expected ones. The major exception to the previous statement is the August 1998 month, which can be considered almost universally as a “non-representative” event.

However, despite these promising results, one should remember the definition of VaR and its limits. VaR should not create a false sense of security among fund managers, investors and bankers leading to higher leverage and larger exposure positions than would otherwise have occurred. This is definitely not the intended goal. It is important to recognize that VaR is not perfect and has limitations. It should be seen as a quantitative tool used to complement, but not replace, human judgment and market experience. Long Term Capital Management itself had a fairly sophisticated VaR system, based on historical data, to try to limit potential losses. However, the combination of the exceptional market conditions at the end of 1998 (spreads moving many standard deviations) with excessive leverage, led to a disaster.

There are numerous directions for future research. In particular, the framework presented in this paper does not incorporate all the risk components a hedge fund investor is exposed. For instance, we have completely omitted credit and liquidity risks<sup>16</sup>, which are also essential parts of the full risk picture of a hedge fund.

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<sup>16</sup> Note that the sound practice report also suggested that hedge fund managers should consider incorporating additional measures to capture asset liquidity. That is to say, the change in the value of an asset due to changes in liquidity of the market in which the asset is traded. Suggested measures of asset liquidity that might be captured include the number of days that would be required to liquidate and/or neutralise the position in question, and the value that would be lost if the asset in question were to be liquidated and/or neutralised completely within the holding.

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## Appendix 1: Estimating extreme moves

The estimation of extreme moves for hedge funds indices has to be performed very cautiously, since the whole methodology relies on the resulting values. In practice, extreme moves are nothing more than lower or upper extreme quantiles of a hedge fund index return distribution. However, estimating them using traditional statistical and econometric methods is generally not feasible. First, the underlying return distribution is not accurately known, which precludes the use of parametric methods. Second, most estimation procedures are targeted to provide a good fit in regions where most of the data fall, but are ill-suited to the assessment of tail behaviours, where by definition few observations fall<sup>17</sup>. Third, the required estimates are often way in the tails, far beyond the boundary of the range of observed data.

Fortunately, “Extreme Value Theory” (EVT) has emerged as a powerful approach for estimating extreme quantiles and probabilities. Unlike traditional approaches, EVT focuses on extreme values data rather than all the data, therefore fitting the tail (and only the tail). There are two different, yet related, approaches to modeling extreme values. The first one consists of fitting one of the three extreme value limit laws to the maximum of a time series, and much historical work was devoted to this approach (see Gumbel, 1958). The second one, and the one we will follow hereafter, is to consider exceedances over a given threshold.

Let  $r_1, \dots, r_N$  be the monthly return observations for a particular hedge fund index. These values are considered to be realizations of  $N$  independent and identically distributed random variables  $R_1, \dots, R_N$ . The order statistics of the sample  $\{r_1, \dots, r_N\}$  will be denoted by  $R_{(i)}$ , with  $R_{(1)} \leq \dots \leq R_{(N)}$ . We denote by  $F$  the cumulative return distribution. Let us say that we want to estimate the upper extreme quantile  $q_\alpha$ , defined by:

$$1 - F(q_\alpha) = \text{Prob}(R > q_\alpha) = \alpha$$

with  $0 < \alpha < 1/N$ .

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<sup>17</sup> This also applies to nonparametric methods such as kernel smoothing.

Traditional estimation methods assume a parametric approximation  $F \approx F_\theta$ , obtain an estimate  $\hat{\theta}$  based on the whole sample  $\{R_1, \dots, R_N\}$  and estimate the quantile  $q_\alpha$  as  $\hat{q}_\alpha = F_{\hat{\theta}}^{-1}(1 - \alpha)$ . Typical assumptions are the normal distribution (with mean  $\mu$  and variance  $\sigma^2$ , i.e.  $\theta = (\mu, \sigma)$ ) or any arbitrary fat-tailed distribution. However, cumulative distribution functions from various parametric models may have similar shapes over the sample range, but can differ significantly in their tail behaviors. Since most observations in the sample are central ones, the fit is generally adequate on average values, but ill-suited to the extreme observations. This leads to imprecise estimations, particularly when  $\alpha < 1/N$ ; see for instance Ditlevsen (1994). Fortunately, extreme value methods, and more particularly the extreme value theorem can help us in finding what the distribution of extreme quantiles should be.

Let us say that we choose a (high) threshold value  $u$  so that there are  $m$  values of  $r_i$  above the threshold. We denote  $y_i$  the differences  $r_i - u$ , with  $i = 1..m$ . Pickands (1975) shows that the probability distribution of  $y_1, \dots, y_m$  can be approximated by a generalized Pareto distribution, which has the following cumulative distribution function:

$$G(y; \sigma, k) = \begin{cases} 1 - \left(1 - \frac{ky}{\sigma}\right)^{\frac{1}{k}} & \text{if } k \neq 0 \\ 1 - e^{-\frac{y}{\sigma}} & \text{if } k = 0 \end{cases}$$

where  $\sigma > 0$  is a scale parameter, and  $-\infty < k < +\infty$  is a shape parameter. The support is  $y \geq 0$  if  $k \leq 0$ , and  $y \in [0, \sigma/k]$  if  $k > 0$ . The shape parameter  $k$  reflects the weight of the tail in the distribution of the parent variable  $X$  (low  $k$  values correspond to fatter tails). It also gives the number of finite moments of the distribution ( $k > 1$  when the mean exists,  $k > 2$  when the variance is finite, etc.). Depending on the value of  $\sigma$  and  $k$ , the generalized Pareto distribution reduces in special cases. For instance, normal, exponential, log-normal, gamma and Weibull distributions will result in a Gumbel distribution for extremes values ( $k=0$ ), while Cauchy, Pareto or student-t, or stable Paretian law returns will result in a Fréchet distribution for extremes values.

To summarize, the algorithm to estimate  $q_\alpha$  is as follows. Starting from  $N$  observations,

1. Choose a high threshold  $u$  so that  $m$  observations are greater than  $u$ . Keep these  $m$  observations, and denote the obtained excess returns  $(r_i - u)$  by  $y_1, \dots, y_m$ .
2. For high values of  $u$ , the probability distribution of  $y_1, \dots, y_m$  can be approximated by a generalized Pareto distribution, whose parameters  $\sigma$  and  $k$  can be estimated using maximum likelihood, method of moments or probability-weighted moments<sup>18</sup>.
3. The extreme quantile  $q_\alpha$  is then estimated by

$$\hat{q}_\alpha = u + \frac{\hat{\sigma}}{\hat{k}} \left[ 1 - \left( \frac{N \cdot \alpha}{m} \right)^{\hat{k}} \right]$$

In our case,  $N = 36$ , and we set arbitrarily  $m = 9$ , i.e. one fourth of the data is used to fit the extreme values distribution.

## Appendix 2: Alternative parameters

In addition to computing the 99 percent one-month VaR figure as described previously, we also performed additional tests on our sample.

First, the estimation of the funds' sensitivities to the style indices was performed using an exponentially weighted regression rather than a standard OLS. The goal of this particular weighting scheme was to set more emphasis on recent errors ( $\epsilon_t$ ) rather than older ones, in order to capture faster any investment style change from the fund manager, if any. The exponentially weighted average approach with a fixed weight parameter has been promoted fairly heavily by JP Morgan in their RiskMetrics (1996) package.

Second, in addition to 99 percent, we set the VaR confidence level at 97.5 and 95 percent. Remember that the choice of a particular confidence level depends very much on the application and users: internal risk management, external supervisory agencies, and financial statement users (VaR as a performance measure). A high confidence interval will ensure that alarms are not set off too frequently, while a lower level of VaR may be more appropriate to trigger more frequent discussions.

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<sup>18</sup> See Smith (1987) for maximum likelihood estimation, Hosking and Wallis (1987) for probability-weighted moments estimation, and Castillo and Hadi (1997) for more specific recommendations.

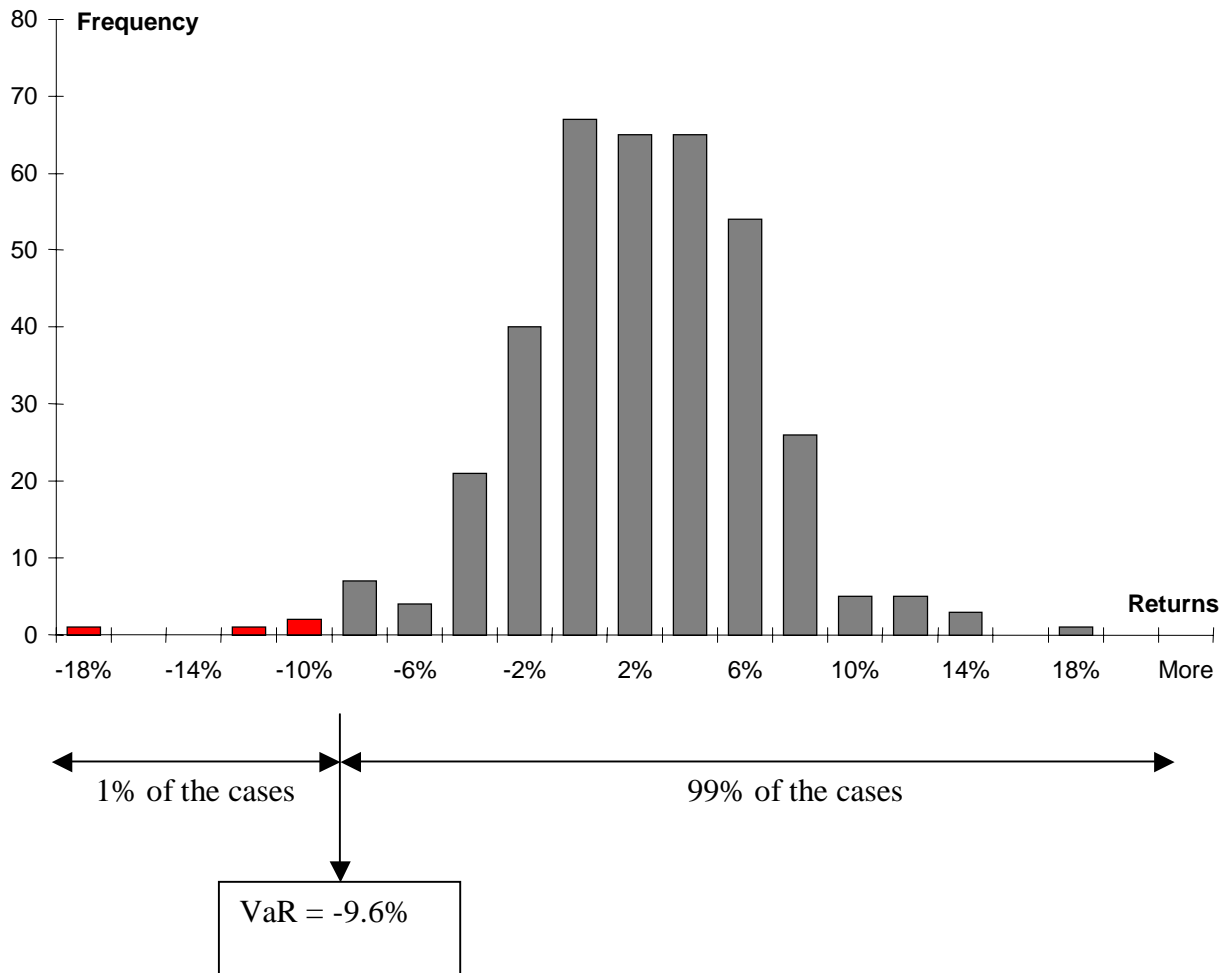
None of these “improvements” provided significantly different results with respect to the ones we reported in this paper. Using an exponentially weighted regression did not change much the funds’ style exposures or the VaR figures, and changing the VaR confidence level sensibly increased the number of exceptions.

**Table 1: Definition of hedge fund investment styles according to CSFB/Tremont**

<b>Category</b>	<b>Strategy</b>
Convertible arbitrage	Invest in the convertible securities of a company. A typical investment is to be long in convertible bond and short in stock of the same company.
Dedicated short-bias	Maintain consistent net short (or pure short) exposures to the underlying market.
Emerging markets	Equity or fixed income investing in emerging markets around the world
Market neutral	Exploit equity market inefficiencies by being simultaneously long and short matched equity portfolios of the same size within a country.
Event-driven	Equity-oriented investing designed to capture price movement generated by an anticipated corporate event (merger, acquisition, distressed securities, etc.)
Fixed-income arbitrage	Profit from price anomalies between related interest rate securities.
Global macro	Leveraged views on overall market direction as influenced by major economic trends and/or events.
Long/short equity	Equity-oriented investing on both the long and short sides of the market, with an objective different from being market neutral.
Managed futures	Systematic or discretionary trading in listed financial and commodity futures markets and currency markets around the world

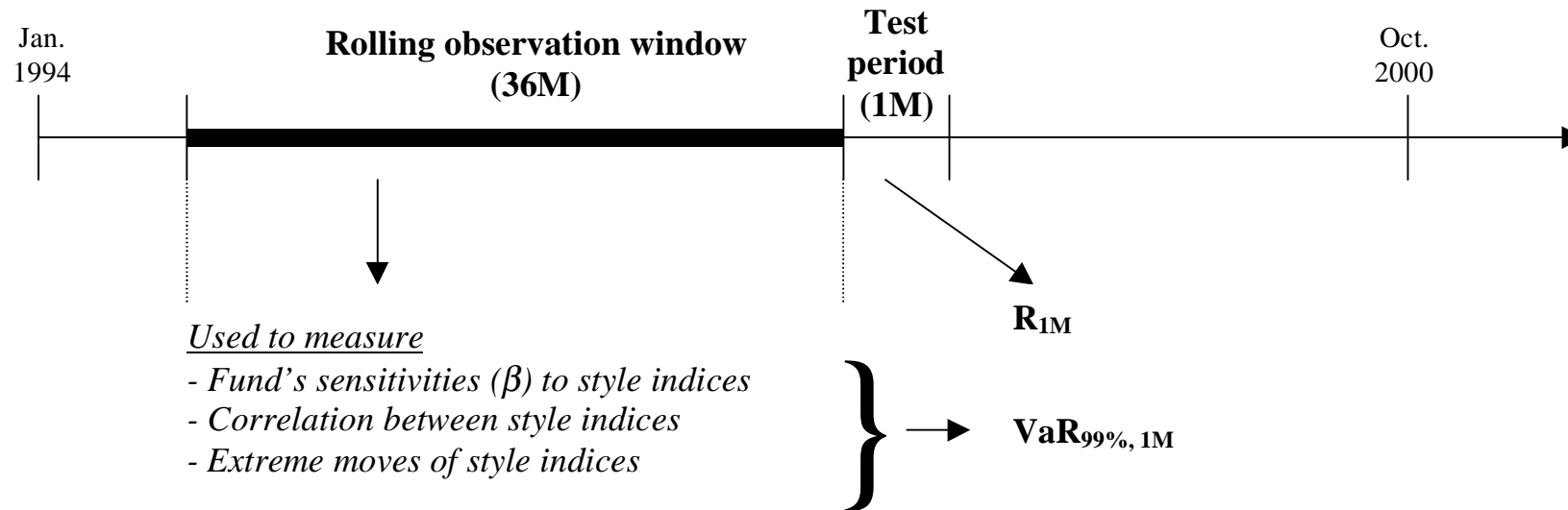
Source: CSFB/Tremont

**Figure 1: Computing VaR**



This figure illustrates the historical value at risk calculation in the case of the Morgan Stanley Capital Index USA, from December 1969 to October 2000, using monthly non-annualized data. On the histogram, the value at risk at a 99 percent confidence interval is equal to  $-9.6\%$ . This corresponds to the one-percent quantile of the return distribution, i.e. one percent of the observed values are lower than the VaR and 99 percent are higher than the VaR.

**Figure 2: Back-testing the VaR methodology**



The figure illustrates the methodology used to compute and back-test our VaR figures. All the data available during the observation window is used to “forecast” the VaR at a 99 percent confidence interval over a one-month holding period ( $VaR_{99\%, 1M}$ ). This value is compared to the realized return of the following month ( $R_{1M}$ ). Then, both the “rolling observation window” and the “test period” are shifted forward by one month, and the whole process starts again.



**Table 2: Correlation, extreme moves and volatility figures for hedge fund indices**

	Convertible Arbitrage	Dedicated Short Bias	Event Driven	Global Macro	Long Short Equity	Emerging Markets	Fixed Income Arbitrage	Market Neutral	Managed Futures
Convertible Arbitrage	1.00	-0.30	0.60	0.36	0.21	0.45	0.75	0.31	-0.61
Dedicated short bias	-0.30	1.00	-0.73	-0.14	-0.77	-0.72	-0.06	-0.56	0.30
Event Driven	0.60	-0.73	1.00	0.40	0.66	0.80	0.41	0.52	-0.53
Global Macro	0.36	-0.14	0.40	1.00	0.52	0.46	0.58	-0.05	-0.04
Long Short Equity	0.21	-0.77	0.66	0.52	1.00	0.75	0.23	0.30	-0.15
Emerging	0.45	-0.72	0.80	0.46	0.75	1.00	0.35	0.46	-0.38
Fixed Income arbitrage	0.75	-0.06	0.41	0.58	0.23	0.35	1.00	-0.01	-0.32
Market neutral	0.31	-0.56	0.52	-0.05	0.30	0.46	-0.01	1.00	-0.17
Managed Futures	-0.61	0.30	-0.53	-0.04	-0.15	-0.38	-0.32	-0.17	1.00
Volatility	1.83	6.41	2.54	4.20	4.76	6.67	1.66	0.76	2.89
Extreme move (99%)	-4.67	-8.68	-8.69	-9.38	-10.04	-18.39	-5.83	-0.69	-4.54

This table shows the correlation, volatility and extreme move figures for the hedge funds style indices at the end of September 2000. All values are computed from a historical sample of 36 months. Volatility and Extreme moves are expressed on a monthly basis.

**Table 3: Summary statistics on the hedge fund sample**

	<b>1997</b>	<b>1998</b>	<b>1999</b>	<b>2000</b>	<b>Total</b>
Convertible Arbitrage	1'780	3'560	4'093	3'259	12'692
Emerging	102	81	304	259	746
Event Driven	2'546	3'382	3'624	2'699	12'251
Long-Short Equity	2'998	2'803	3'199	2'344	11'344
Managed Futures	238	1'074	2'962	1'953	6'227
Market Neutral	1'362	1'656	3'946	4'033	10'997
Multi-Strategy	6'574	7'835	8'134	6'457	29'000
Fixed Income Arbitrage	3'094	3'278	2'904	2'606	11'882
Global Macro	240	160	219	188	807
Dedicated Short	163	163	188	89	603
All sample	21'094	25'990	31'572	25'887	96'549

This table shows the number of test periods for each investment style. Each test period corresponds to a three-year estimation period for one fund. Note that these numbers include defunct funds, if they were active during the corresponding year.

**Table 4: Fitting of the style analysis model (average R-square)**

	<b>1997</b>	<b>1998</b>	<b>1999</b>	<b>2000</b>	<b>Total</b>
Convertible Arbitrage	0.46	0.50	0.60	0.59	0.55
Emerging	0.68	0.78	0.75	0.76	0.75
Event Driven	0.50	0.53	0.66	0.64	0.59
Long-Short Equity	0.53	0.61	0.65	0.73	0.63
Managed Futures	0.42	0.65	0.68	0.65	0.66
Market Neutral	0.44	0.49	0.52	0.54	0.51
Multi-Strategy	0.47	0.50	0.55	0.54	0.52
Fixed Income Arbitrage	0.44	0.53	0.57	0.59	0.53
Global Macro	0.55	0.62	0.74	0.75	0.66
Dedicated Short	0.61	0.61	0.72	0.55	0.64
All sample	0.48	0.53	0.60	0.60	0.56

This table shows statistics on the average R-squares obtained when applying the nine-index style model of equation (5).

**Table 5: Value at Risk components (one month, 99% confidence) over time**

	Average VaMR					Volatility VaMR				
	1997	1998	1999	2000	Avg.	1997	1998	1999	2000	Avg.
Conv.Arbitrage	5.88	5.95	9.04	8.44	7.57	5.16	6.32	8.00	7.40	7.04
Emerging	9.88	29.52	28.71	29.94	26.65	5.06	19.70	13.19	14.42	13.74
Event Driven	5.13	5.27	7.14	7.20	6.22	4.63	4.70	5.21	5.96	5.14
Long-Short Eq.	6.77	8.12	10.20	14.10	9.58	3.63	4.75	6.36	8.63	5.99
Managed Futures	4.90	7.02	8.93	7.76	8.08	2.54	4.76	4.97	3.95	4.56
Market Neutral	5.55	6.46	8.50	8.80	7.94	4.38	4.74	6.73	7.15	6.38
Multi-Strategy	6.27	6.76	8.77	8.73	7.65	4.83	5.56	6.48	7.03	6.03
Fixed Inc. Arb.	5.79	7.77	10.72	11.98	8.90	5.30	7.24	7.78	8.00	7.11
Global Macro	8.02	8.34	8.67	8.26	8.31	4.87	4.69	4.62	4.01	4.58
Dedicated Short	11.95	10.62	10.79	7.71	10.60	5.60	4.76	4.94	5.14	5.11
All sample	6.10	6.83	9.15	9.55	8.07	4.70	5.75	6.68	7.18	6.25

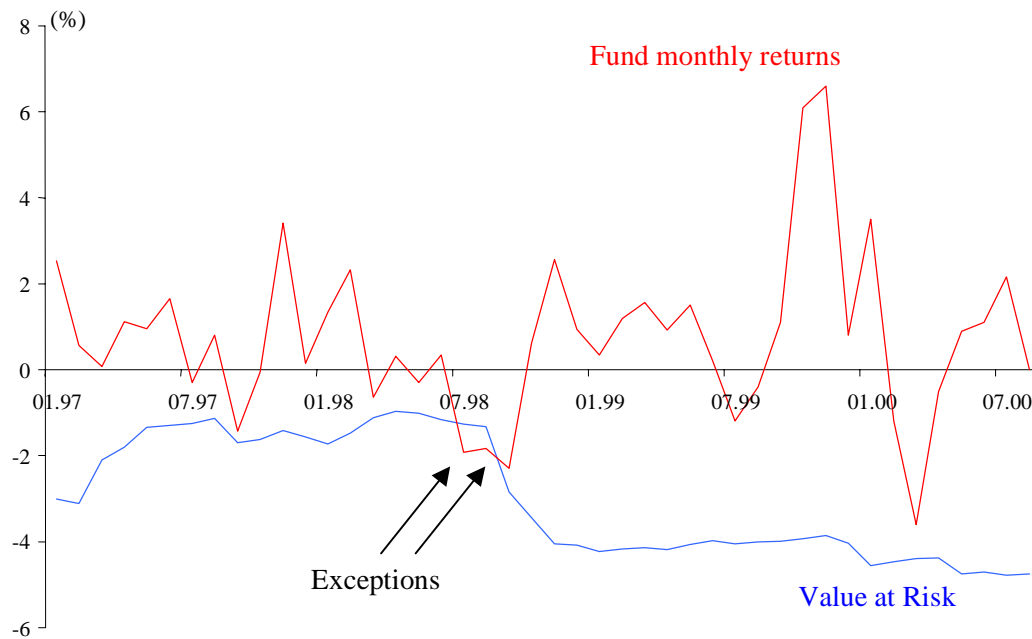
	Average VaSR					Volatility VaSR				
	1997	1998	1999	2000	Avg.	1997	1998	1999	2000	Avg.
Conv.Arbitrage	6.90	7.02	6.35	6.71	6.71	6.39	6.92	6.02	6.92	6.57
Emerging	5.13	9.76	11.58	12.74	10.90	2.05	6.87	5.14	6.61	5.63
Event Driven	5.93	5.69	4.63	5.17	5.31	5.60	5.11	4.44	5.89	5.21
Long-Short Eq.	5.79	5.80	6.77	8.63	6.65	3.67	3.57	4.58	5.64	4.38
Managed Futures	11.22	7.75	7.09	6.98	7.33	8.46	4.21	4.04	4.15	4.35
Market Neutral	6.46	6.62	7.60	7.85	7.40	4.88	5.00	5.35	5.14	5.17
Multi-Strategy	7.03	6.84	7.22	7.67	7.17	5.18	5.04	5.75	6.12	5.53
Fixed Inc. Arb.	7.47	6.55	7.47	8.43	7.43	7.14	6.12	5.73	5.89	6.26
Global Macro	7.52	6.29	4.93	5.03	5.99	4.55	4.20	2.90	2.98	3.74
Dedicated Short	7.89	7.64	7.40	8.38	7.74	4.17	3.44	3.18	3.07	3.53
All sample	6.76	6.58	6.82	7.45	6.91	5.53	5.34	5.28	5.83	5.48

	Average VaR					Volatility VaR				
	1997	1998	1999	2000	Avg.	1997	1998	1999	2000	Avg.
Conv.Arbitrage	9.29	9.60	11.33	11.04	10.48	7.96	8.97	9.69	9.85	9.31
Emerging	11.55	31.42	31.23	32.75	29.09	4.52	20.37	13.54	15.42	14.32
Event Driven	8.03	8.08	8.74	9.14	8.50	7.05	6.55	6.55	8.08	7.02
Long-Short Eq.	9.15	10.23	12.54	16.75	11.94	4.71	5.50	7.34	9.95	7.00
Managed Futures	12.43	10.82	11.56	10.62	11.17	8.57	5.71	6.12	5.39	5.94
Market Neutral	8.74	9.50	11.67	12.08	11.13	6.26	6.53	8.23	8.41	7.84
Multi-Strategy	9.73	9.97	11.68	11.91	10.83	6.65	7.02	8.22	8.95	7.75
Fixed Inc. Arb.	9.75	10.54	13.34	14.93	11.98	8.56	9.06	9.29	9.51	9.09
Global Macro	11.38	10.95	10.23	9.84	10.62	5.97	5.37	4.96	4.65	5.29
Dedicated Short	15.25	13.61	13.65	12.07	13.84	4.58	4.53	4.41	4.44	4.49
All sample	9.42	9.87	11.72	12.42	10.97	6.89	7.41	8.13	8.89	7.93

This table shows the average and the volatility of the value at market risk (VaMR), value at specific risk (VaSR) and value at risk (VaR) over time and split by investment style. All numbers are expressed as percentages of net asset values, and calculated using a one-month holding period and a 99% confidence interval.

**Figure 3: Back-testing the VaR**



This figure shows the results obtained from back-testing the VaR for a single hedge fund on a monthly (rollover) basis. In this example, the fund experienced two exceptions during the 1998 crisis. An exception is defined as a situation when within a month, the net asset value of a fund drops by more than the forecasted VaR at the end of the previous month.

**Table 6: Proportion of exceptions**

	Exception rate (%)							
	1997	1998	1999	2000	All	1998*	All*	Aug 98
Conv.Arbitrage	0.11	3.43	0.12	0.31	1.10	1.36	0.49	23.64
Emerging	1.96	3.70	0.00	0.00	0.67	0.00	0.27	60.00
Event Driven	0.63	4.46	0.25	0.15	1.47	0.56	0.39	41.49
Long-Short Eq.	0.10	2.75	0.03	0.38	0.79	0.19	0.16	36.73
Managed Futures	0.00	0.28	0.17	0.10	0.16	0.30	0.16	0.00
Market Neutral	0.59	3.20	0.13	0.22	0.68	0.59	0.29	33.33
Multi-Strategy	0.46	2.69	0.11	0.63	1.00	0.58	0.43	26.24
Fixed Inc. Arb.	0.78	5.40	0.03	0.65	1.84	2.19	0.92	36.60
Global Macro	0.00	2.50	0.00	0.53	0.62	1.37	0.38	14.29
Dedicated Short	0.00	0.61	2.13	0.00	0.83	0.68	0.85	0.00
All sample	0.45	3.34	0.13	0.39	1.06	0.86	0.43	30.13

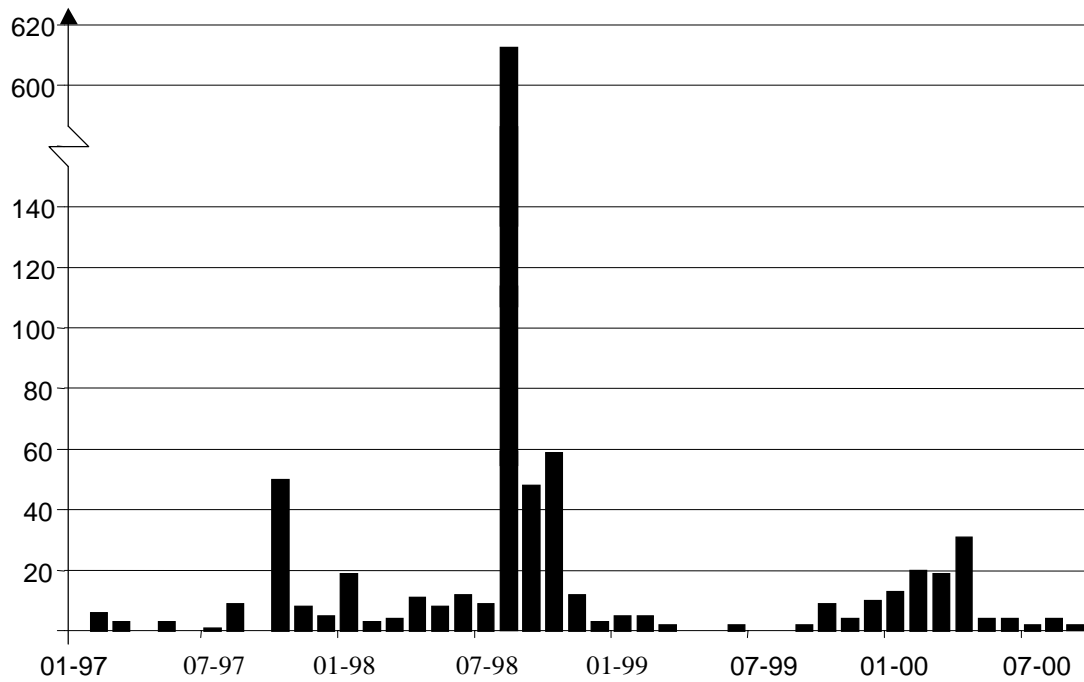
	Exception excess loss, as a percentage of NAV							
	1997	1998	1999	2000	All	1998*	All*	Aug 98
Conv.Arbitrage	3.10	4.08	6.60	1.22	3.95	2.05	2.32	5.22
Emerging	1.65	6.76			4.72		1.65	6.76
Event Driven	5.06	4.92	3.24	6.68	4.89	3.39	4.23	5.11
Long-Short Eq.	3.52	3.40	1.58	8.97	3.94	1.69	5.63	3.52
Managed Futures		0.45	0.40	2.15	0.77	0.45	0.77	
Market Neutral	10.23	4.60	3.10	3.06	4.92	5.70	5.68	4.38
Multi-Strategy	3.87	4.35	2.61	9.88	5.03	2.65	5.38	4.78
Fixed Inc. Arb.	4.48	6.31	0.73	2.44	5.79	4.36	4.05	7.45
Global Macro		3.25		0.12	2.62	0.82	0.59	5.68
Dedicated Short		5.67	2.04		2.76	5.67	2.76	
All sample	4.78	4.77	2.91	6.43	4.85	3.25	4.27	5.23

	Exception excess loss, as a percentage of VaR							
	1997	1998	1999	2000	All	1998*	All*	Aug 98
Conv.Arbitrage	23.4	60.6	55.0	7.1	56.0	38.2	34.0	73.3
Emerging	21.9	30.0			26.7		21.9	30.0
Event Driven	41.0	78.6	23.9	54.7	72.0	46.3	40.8	82.7
Long-Short Eq.	24.7	37.2	45.2	30.1	36.2	60.5	38.5	35.6
Managed Futures		9.4	2.9	23.0	8.8	9.4	8.8	
Market Neutral	55.3	52.6	49.8	49.5	52.3	58.7	53.7	51.3
Multi-Strategy	37.7	65.3	14.0	56.6	59.6	41.4	43.6	71.2
Fixed Inc. Arb.	35.4	98.0	2.4	40.2	86.2	75.9	60.4	110.9
Global Macro		32.5		0.7	26.1	5.0	3.6	60.0
Dedicated Short		35.3	11.4		16.2	35.3	16.2	
All sample	38.2	70.2	25.0	43.6	63.4	53.4	45.2	75.4

\* excluding August 1998.

This table shows the proportion of exceptions and their magnitude for each investment style from January 1997 to October 2000. An exception is defined as a situation when, within a month, the net asset value of a fund drops by more than the forecasted VaR at the end of the previous month. The absolute magnitude is expressed as a percentage of the net asset value. The relative magnitude is expressed relative to the forecasted VaR (loss to VaR ratio).

**Figure 4: Number of exceptions over time**



This figure shows the number of exceptions observed during each month from January 1997 to October 2000. An exception is defined as a situation when, within a month, the net asset value of a fund drops by more than the forecasted VaR at the end of the previous month.