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Hedge Funds Investing: A Quantitative Look Inside the Black Box

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Abstract:

There is an increasing amount of evidence that shows the benefits of considering hedge funds as an asset class at the strategic asset allocation level. The investors' greatest challenge remains the identification of desirable investment vehicles, since very little formal quantitative analysis of hedge funds has been done in the past. In this paper, we suggest an innovative approach to hedge fund investing, which is valid at the individual fund level as well as at the aggregate portfolio level (e.g. portfolio of hedge funds). This approach only relies on hedge funds historical returns. We provide several illustrations, including static and dynamic style analysis, benchmark construction, performance assessment, and value at risk calculations.

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1 Introduction

The consequences of globalization have dramatically eroded traditional asset allocation dogmas. International assets move more and more in lockstep fashion and fail to fulfill their diversification promises, particularly in turbulent times. Consequently, investors have broadened their investment horizons and started seeking alternative asset classes, among them, hedge funds.

Investors commonly view hedge funds as the phenomenon of the 1990s. From a few hundred players ten years ago, the hedge fund industry has expanded to several thousand today with double-digit annual growth. With capital under management under \$100 million, most of the newcomers are small, but a few dozen funds had a capital base larger than \$1 billion at the end of 2000.

Hedge funds have traditionally managed capital for high net worth individuals, family offices, and endowments. More recently, a broad range of institutional investors (including pension funds in the Netherlands, Switzerland, Scandinavia as well as US funds) has also expressed an increased interest in hedge funds. It is likely that this interest will continue in the near future, increasing the role of hedge funds within traditional asset-allocation models.

Surprisingly, there is still no universally accepted definition of what constitutes a hedge fund. Functionally, hedge funds and proprietary trading desks pursue similar goals: hiring professional investment managers, rewarding them by performance-linked fee and implementing a large diversity of strategies often involving leverage, derivatives, hedging and short positions to exploit market inefficiencies. Organizationally, however, there are substantial differences: hedge funds are typically private pooled investment vehicles with high minimum investments and infrequent redemption opportunities.

Another key characteristic of hedge funds is that they dislike disclosing information about their investment process and/or market bets. The reasons are twofold. First, hedge funds are often registered as offshore companies or limited partnerships to avoid the restrictive registration and investment requirements of mutual funds. Consequently, publishing performance figures, portfolio compositions, or other informative statistics could be considered by regulators as public solicitation and therefore illegal. Second, hedge funds are often taking concentrated and leveraged positions in illiquid markets or securities. Disclosing them publicly could wipe out future expected gains or harden the ability of unwinding these positions when necessary.

However, given the sector's growing significance and the increasing turbulence of markets, this situation is hardly sustainable. The collapse of Long Term Capital Management LP in 1998 raised serious concerns for credit providers, trading counterparties and market regulators. Investors, chastened by the 1997 Asian crisis, the 1998 Russian crisis, the 1999 Brazil crisis and the year 2000 Internet bubble burst now want to closely monitor their assets. Last, but not least, banks, investment consultants and funds of hedge fund managers require having a clear view of hedge funds' risk and return profiles before including them on any recommended list.

Given the increase in investors' interest, there is an urgent need of quantitative methods of analyzing hedge funds and provide meaningful information while respecting their privacy. Most hedge funds are now providing their net asset value on a regular and voluntary basis (e.g. monthly) to commercial data vendors such as TASS, Altvest, Hedge Fund Research, Managed Account Reports, etc. Although subject to a survivorship bias, these net asset values are probably the most reliable source of data publicly available today on the hedge fund industry. They incorporate what hedge funds actually do, not just what they say they do.

Our goal in this paper is therefore to propose an alternative approach to hedge funds analysis, which can be summarized as "let the data speak". It relies essentially on an extension of Sharpe's (1992) return-based style analysis technique for mutual funds. This extension takes into account the particularities of hedge funds, such as the ability to go short and to use leverage. It is easy to implement and only requires a small amount of data. Last, but not least, its results are easy to understand, even by non-quantitative investors.

The structure of this paper is the following. Section 2 discusses the quantitative aspects of our model and its assumptions. Section 3 illustrates several potential applications such as static and dynamic style analysis, benchmark construction and performance assessment. Section 4 proposes an interesting and straightforward extension to compute the value at risk of a hedge fund. Section 5 summarizes our findings and opens the door to further developments.

2 The hedge fund analysis model

As mentioned already, our analysis of hedge funds uses a time series of net asset values as a raw input. Let us denote by NAV_t the net asset value of a hedge fund at time t . From the fund's net asset values, returns are derived as follows:

$$R_t = (NAV_t - NAV_{t-1}) / NAV_{t-1} \quad (1)$$

Next, we postulate a multi-factor model to explain the time-series of returns. If we denote $F_{k,t}$ as the value of factor number k at time t and we use N distinct factors, our multi-factor model can be expressed as:

$$R_t = \alpha + \sum_{k=1}^N \beta_k F_{k,t} + \varepsilon_t \quad (2)$$

We can interpret the intercept term of the model as the portion of return unexplained by the factor model.

Multi-factor models are useful tools to describe the return structure of investment funds. The major difficulty in implementing them is the identification of common and relevant factors. Two approaches compete for this task. The first one consists in deriving endogenously a set of implicit factors using principal components analysis. This ensures an optimal fitting of the model, but the difficulty then lies in the economic interpretation of the implied factors. The second approach consists in specifying exogenously a set of factors that we believe or know to be relevant. The economic interpretation is then straightforward, which makes it the preferred method for investment analysis.

Which factors should be considered? The answer is relatively straightforward for traditional money managers, given their limited investment flexibility. For instance, Sharpe (1992) used fifteen global stock and bond indices to describe the cross sectional returns of U.S. equity funds, and Elton, Gruber, and Blake (1995) preferred a series of fundamental economic variables for U.S. bond funds. However, the situation is different for alternative money managers. First, they have a larger set of potential investments available, may use leverage or short selling, and can invest in illiquid assets since they do not offer daily redemption. Second, they attempt to provide investors exposure to unique and uncorrelated sources of return, i.e. returns driven by factors not easily explained by the factors common to traditional investments. Third, the benchmarks they use are of little help for this task, because they are hurdle rates (such as T-Bill rates) for absolute performers rather than benchmarks for trackers.

This explains why academic research on the sources of hedge fund returns is much less developed than for traditional funds. As an illustration of the recent approaches proposed and without attempting to be comprehensive, let us mention the following papers. On the single factor side, Irwin et al. (1994) used a simple managed futures benchmark and McCarthy et al. (1997) suggested a single index with Bayesian adjustment for leverage. On the multiple factor side, Mitev (1995) suggested using five implied factors, identified as trend following strategies, surprise or stop-loss control models, agricultural markets, spread-strategies (primarily interest rate) and fundamental economic factors or global markets. Fund and Hsieh (1996) demonstrated the role of dynamic trading and investment approaches (distressed, global/macro, systems, systems/opportunistic, and value). Liang (2000) relied on eight asset classes (S&P 500, MSCI world and MSCI emerging for equity, Salomon Brothers world government bond and Salomon Brothers world corporate bond indices for bonds, Federal Reserve Bank trade-weighted dollar index for currency, gold price for commodities, and one-month Eurodollar deposit for cash): Finally, Schneeweis and Spurgin (1998) combined a very large number of hedge fund indices, CTA indices, and traditional asset class indices.

All these models rely on regression-like analysis. Our approach is somehow different and motivated by the following considerations: a) Unlike equity or bond mutual funds, the lack of a single factor that describes the return process of hedge funds highlights the emphasis that should be placed upon investment style rather than on the general return process. b) Static buy and hold portfolios, such as equity and bond indices, fail to capture the dynamic asset allocation and derivatives usage of hedge fund managers. We therefore start from an asset allocation perspective, namely, Sharpe's (1992) return-based style analysis model, which is equivalent to equation (2) plus some constraints.

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

Category	Strategy
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

Sharpe's model uses as factors returns on representative asset classes. These asset classes must be 1) mutually exclusive; 2) exhaustive with respect to the investment universe; and 3) have returns that differ. Since traditional asset classes are not really representative of hedge funds behaviour, we are using hedge fund indices. Several broad-based hedge fund indices are now publicly available to benchmark the performance of the industry. However, given the substantial diversity in hedge funds strategies, we rather considered hedge fund style indices, which group funds based on their managers' self-described strategies. In the following analysis, we are using the nine CSFB/Tremont style indices family (see Table 1), mostly because of their quality, transparency, and adequate weighting scheme¹. However, we could repeat our analysis using any other family of hedge fund indices.

¹ CSFB/Tremont hedge fund indices publicly disclose their calculation methodology and the index constituents. The selection rules are simple: at least \$10 million of assets under management and audited statements. Surprisingly, less than 300 hedge funds out of the 3000 in the TASS database fulfill them. CSFB/Tremont hedge fund indices are also the only asset-weighted indices of the hedge fund industry. This very desirable property corresponds to a momentum strategy, i.e. winners (losers) naturally increase (decrease) their relative weight in the index. In contrast, all other hedge fund indices are equally weighted, which corresponds to a contrarian allocation, i.e. selling winners and buying losers at regular time intervals.

Thus, our model becomes:

$$R_t = \alpha + \sum_{i=1}^9 \beta_i \cdot I_{i,t} + \varepsilon_t \quad (3)$$

where

I_1 = return on the CSFB Tremont Convertible Arbitrage index

I_2 = return on the CSFB Tremont Dedicated Short Bias index

I_3 = return on the CSFB Tremont Event Driven index

I_4 = return on the CSFB Tremont Global Macro index

I_5 = return on the CSFB Tremont Long Short Equity index

I_6 = return on the CSFB Tremont Emerging Markets index

I_7 = return on the CSFB Tremont Fixed Income Arbitrage index

I_8 = return on the CSFB Tremont Market Neutral index

I_9 = return on the CSFB Tremont Managed Futures index

Sharpe's model also imposes two restrictions on the beta coefficients in order to interpret them as asset allocation weights: all betas must be positive (i.e. no short positions) and their sum should equal one (i.e. the portfolio is fully invested). In our case, we kept the first constraint², but relaxed the second one to account for the relative leverage possibility. Therefore, our model can be seen as a constrained regression and needs to be solved by quadratic programming³.

² Being short an investment style is rather hard to justify economically. For instance, what would mean being short the "Dedicated Short Bias" style?

³ This raises some technical difficulties if one needs to obtain the asymptotic distribution of the beta coefficients, for instance to build confidence intervals.

3 Applications

We now suggest several applications for our model at both the individual hedge fund and the overall hedge fund portfolio level.

Clearly, our model provides useful insights to understand the investment strategy of a particular hedge fund. If one considers the CSFB/Tremont indices as purely synthetic⁴ hedge fund portfolios whose objective is to deliver a particular set of risk/return characteristics, the betas of equation (3) can be interpreted as exposures to each of these investment styles. As an illustration, Figure 1 represents graphically the nine betas that we obtained for two existing hedge funds. The shapes of these graphs (that we call “hedge funds radars”) allow for an immediate style classification. The first fund is a pure convertible arbitrage hedge fund ($\beta_1=0.41$, all other betas below 0.04). The second fund is a fund of hedge funds that appears to be diversified across styles. Its highest exposures are in the convertible arbitrage ($\beta_1=0.22$), market neutral ($\beta_8=0.22$) and global macro styles ($\beta_4=0.19$), and moderate exposures in long-short equity ($\beta_5=0.15$), emerging markets ($\beta_6=0.13$) and event-driven ($\beta_3=0.07$, all other betas below 0.01).

Thus, 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 approach. This is specifically useful for funds of hedge funds and multi-manager portfolios, which offer investors an efficient way of diversifying risks across a number of managers and strategies. Are they effectively diversified across styles? A single fund radar will help answer this question. Moreover, for those who prefer a quantitative indicator, a useful indicator of style concentration is the following Herfindahl-Hirschman-like concentration index, computed by adding the squared (adjusted) style exposures:

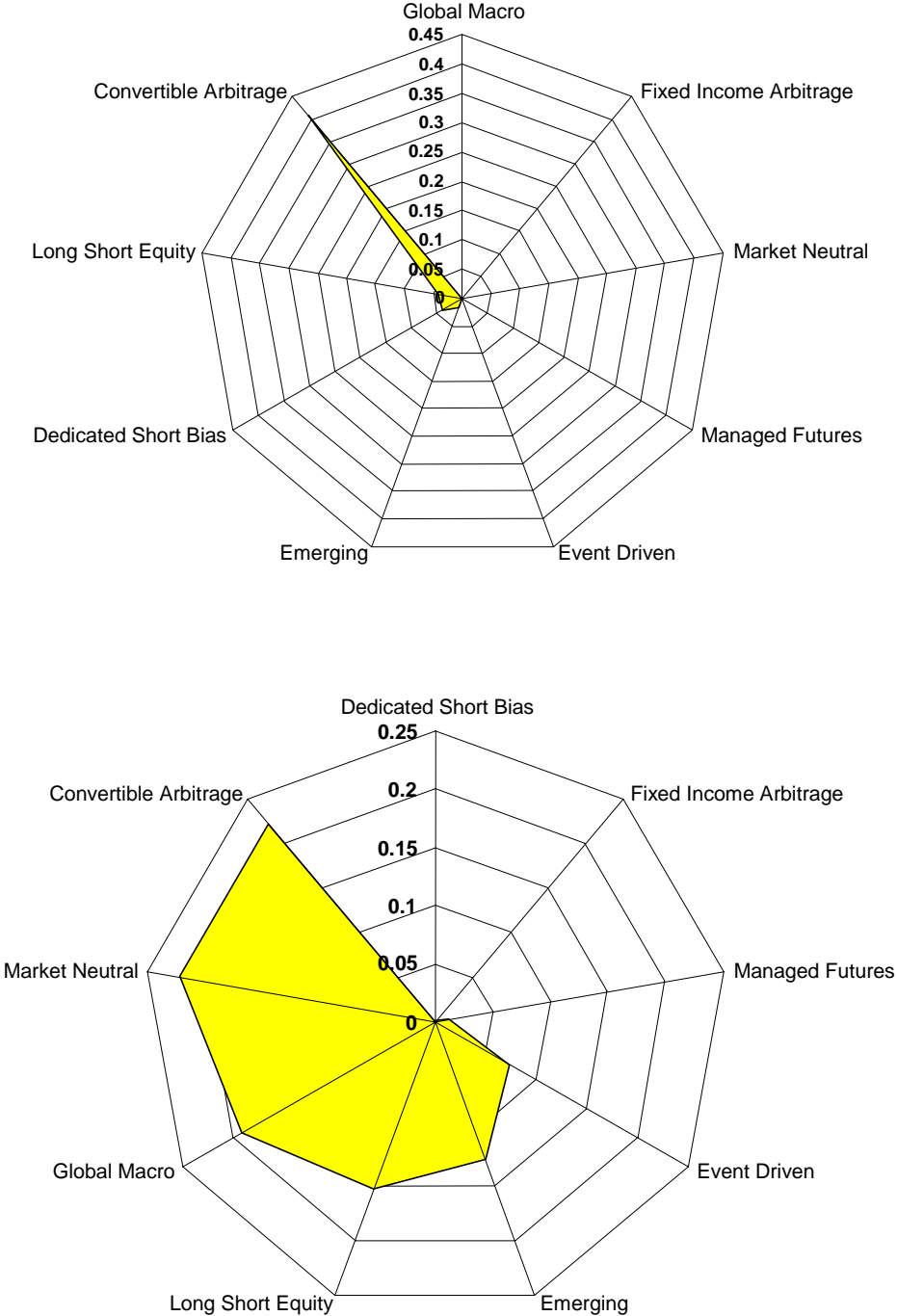
$$HHI = \sum_{i=1}^9 \left(\frac{\beta_i}{\sum_{j=1}^9 \beta_j} \right)^2 \quad (4)$$

Adjustment is necessary here, because the sum of the exposures can be significantly different between two funds, since they do not sum to 100%. As an illustration, if we compute the concentration indices for the two hedge funds of our previous example, we obtain 0.66 for the convertible arbitrage hedge fund, and 0.18 for the fund of funds.

⁴ Although CSFB/Tremont indices consider a relatively small number of hedge funds with respect to concurrent indices, they are not easily investable. First, the high minimum investment in each fund suggests that a substantial amount of capital would be required to track the index. Second, the liquidity and redemption policies of individual hedge funds would not allow for an unambiguous rebalancing scheme, leading to an increase of the tracking error.

Figure 1: Hedge fund style radars

The figure shows the hedge fund radars obtained for a convertible arbitrage fund (top) and a fund of hedge fund (bottom). The sensitivities (i.e. style-beta coefficients) are estimated using three years of historical data.



Hedge fund radars also open new doors to benchmarking hedge fund performance. The asset allocation implied by the radar provides a perfect natural benchmark against which the fund returns should be compared. Of course, it does not necessarily correspond to the tactical asset allocation of the fund. However, over the considered period, what one can affirm is that the fund behaved “as if” it effectively had this asset allocation. And the quality of this approximation is easily verified using the r-square indicator obtained when estimating equation (3).

$$R^2 = 1 - \frac{\text{Var}(\epsilon)}{\text{Var}(R)} \quad (5)$$

However, a fund radar only provides a static picture of a hedge fund’s behavior. Our model also allows for a dynamic assessment of a hedge fund’s behavior. By using a rolling observation period, it is possible to build up a series of radars that represent the evolution of the fund’s exposures over time. These can also easily be represented graphically, allowing for verifying the stability of the fund’s behavior.

As an illustration, Figure 2 shows the dynamic behavior of the two funds considered previously. For our first fund, the exposure to convertible arbitrage appears only since the first quarter 1999. Before this, the fund was clearly exposed to the long-short equity, event driven and market neutral styles. This evidences that the track record of this fund will not be the one of a pure convertible arbitrage fund, although the fund is now almost only exposed to this style. By contrast, the fund of hedge funds appears diversified since it was created.

4 Risk management and value at risk

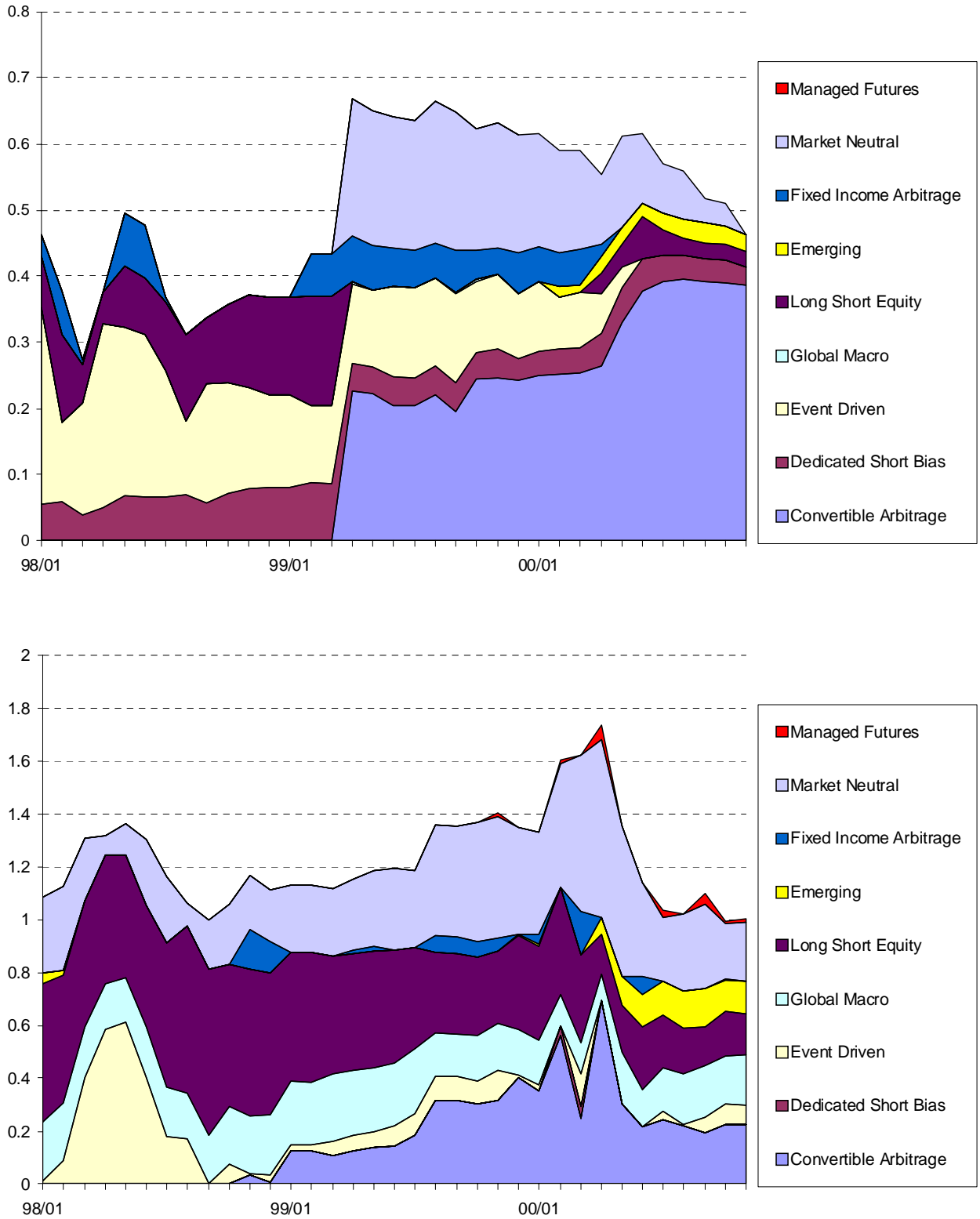
Another key application of our model is in the domain of risk management. Although the quantitative measurement of risk is essential, given the wide investment latitude of hedge fund managers, there is no real consensus on risk measures for hedge funds. Some funds simply claim to focus on absolute returns and do not even consider producing risk figures. Others provide a plethora of risk indicators, including volatility around the mean (although their return distributions are non-symmetric), drawdowns (related to the length and depth of a decline in portfolio value), downside risk measures (related to the statistical probability of not achieving a certain return), and other inadequate information⁵.

Most hedge funds are still reluctant to provide value at risk (VaR) figures -- that is, their expected maximum loss during a specified period at a given level of probability. This is surprising, for at least two reasons. First, the world’s leading financial institutions and proprietary trading desks have now adopted VaR, with the strong support of rating agencies and market regulators. Second, VaR would be an invaluable tool for monitoring risks at both overall portfolio and individual hedge fund level, allowing fund managers to communicate intuitive and easy to understand risk measures without going into the intricate details of complicated or proprietary trading strategies.

⁵ See Lhabitant (2000) for an illustration.

Figure 2: A dynamic view on hedge fund style

The figure shows the historical evolution of the sensitivities (i.e. style-beta coefficients) for a convertible arbitrage fund (top) and a fund of hedge fund (bottom).



Our model helps fill in this gap. From the style exposure of a hedge fund, one can easily apply a two-step procedure to obtain its VaR. Let us assume for instance that we want a confidence level of 99 percent for the one-month VaR⁶. The first step consists of “pushing” each individual risk factor in the most disadvantageous direction (at the one percentile value of its historical distribution) and estimating the overall impact on the fund, accounting for the risk factors correlation. This gives us the VaR due to market moves (i.e. style indices moves), that we call “value at market risk”. Mathematically,

$$\text{VaMR} = \sqrt{\sum_{i=1}^9 \sum_{j=1}^9 \rho_{i,j} \cdot \beta_i \cdot F_i^* \cdot \beta_j \cdot F_j^*} \quad (6)$$

where $\rho_{i,j}$ is the correlation between monthly returns of hedge fund indices i and j , and F_i^* is the one percentile extreme return of style index i returns over one month.

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

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

By construction, the error terms ε_t of equation (3) are non-correlated and normally distributed with zero mean. Since we want a 99 percent confidence level, we can apply a factor push of 2.33 times σ_ε (corresponding to a 99% confidence level for a normal variable) to obtain the specific risk of a hedge fund. Mathematically, the value at specific risk (VaSR) is given by

$$\text{VaSR} = 2.33 \times \sigma_\varepsilon \quad (6)$$

To obtain the total VaR figure, simply add up market and specific risk figures, accounting for their zero correlation:

$$\text{VaR} = \sqrt{(\text{Value at Market Risk})^2 + (\text{Value at Specific Risk})^2} \quad (7)$$

Note that the procedure can easily be adapted to implement stress-scenario analysis, such as breakdown in correlations. If we apply this model to the two hedge funds that we considered previously, we obtain the following results. The convertible arbitrage fund has a VaR equal to 7.73% of its net asset value, which we can split into a VaMR of 2.11% and a VaSR of 7.42%. The fund of hedge funds has a VaR equal to 7.88% of its net asset value, which we can split into a VaMR of 5.83% and a VaSR of 5.31%. As expected, the proportion of specific risk is larger in the pure-style hedge fund than in the diversified one.

⁶ The choice of the holding period depends upon the time needed to liquidate a portfolio. It typically varies from one day for a trading portfolio to thirty days for a fund with a monthly redemption policy. The choice of the confidence interval is also relatively subjective. Banks typically use 95% to 99% as confidence intervals for measuring and reporting VaR.

How trustworthy is our approach? We back-tested this VaR model on a sample of 2934 hedge funds from January 1994 to October 2000. Using a three-year observation period, we computed funds' exposures, the market parameters, and the funds' VaRs (one month, 99% confidence level). Then, we compare the VaR of each fund with the profit and loss of the following month. If the loss is greater than the VaR figure, this is recorded as an exception. On a total of 96,549 three-year observation periods, 1'026 exceptions were observed. This gives an exception rate slightly higher than expected (1.06% versus 1%). However, things have to be taken with precaution, since 614 of these exceptions occurred in August 1998 immediately after the LTCM crisis, which can be qualified as an abnormal market situation. If we exclude this month from our sample, the exception rate falls to 0.43%, a rather conservative figure⁷.

⁷ See Lhabitant (2001) for detailed back-testing results.

Table 2: Correlation, extreme moves and volatility figures for Tremont/CSFB 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
Index Volatility	1.83	6.41	2.54	4.20	4.76	6.67	1.66	0.76	2.89
Index extreme move	-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.

5 Conclusions

For a long time, due to the lack of transparency, hedge fund investing was more an art than a science, mostly based on qualitative analysis and due diligence. The collapse of numerous large players (LTCM, Granite funds, etc.) and the increasing turbulence of financial markets has evidenced that qualitative approaches, although critical and necessary, were not sufficient. Given the complexities involved with hedge fund strategies, there is a need to introduce new quantitative tools.

Our model attempts to fill in this gap. Relying only on net asset values, it determines the exposures of a hedge fund to several investment styles. This makes it a useful tool to assist investors and fund managers in monitoring their portfolios, determining whether the benefits are in line with expectations and assumptions made in asset allocation, verifying the diversification benefits or highlighting the risks concentrated with any hedge fund manager or investment strategy. A simple extension will transform our model into a powerful risk management tool able to compute the value at risk of a hedge fund as well as the marginal risk contributions of each investment style an investor is exposed to.

Of course, some may argue that historical data may not be representative of the future. Our answer will be very pragmatic. First, we successfully back-tested our model on a large sample of hedge funds, from January 1994 to October 2000. Second, historical data will always be useful to assess past performance and to understand what were favorable and unfavorable outcomes. Third, over the years, our discussions with several hedge fund managers led us to believe that the vast majority of their funds may have unpredictable performance (because their returns depend on too many variables and the number of past observations is too small to make any inference), but have some form of partially predictable behavior (e.g. investment philosophy, stop-loss, etc.). This is why past information, knowledgeably and intelligently interpreted, will always be better than no information.

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