Searching for the perfect risk-adjusted performance measure
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Welcome to the first edition of HedgeQuest, a new periodical themed report for the Hedge Funds and Fund of Hedge Funds community from the publishers of Hedgeweek.

This edition of HedgeQuest focuses on the theme of measuring Hedge Fund performance and includes contributions from some of the most active and original thinkers in this area.

We start with the search for the Holy Grail, the perfect risk adjusted performance measure (RAPM). Imagine if there existed a clear, easily interpreted measure, cheaply calculated from public information, which gave unambiguous and correct rankings of investments. Such a measure would of course put many consultants out of business and put far greater pressure on the investors to justify their performance. Perhaps it is just as well therefore that it probably doesn’t exist. But the search for the perfect RAPM has been very fruitful.

In this edition:

- **Simon Taylor**, Senior Research Associate at the Judge Institute of Management Studies at Cambridge University, provides a linking/overview article on the background to much of the analysis in the other contributions.

- **Arun Muralidhar** of M Cube Investment Technologies reviews the ever expanding “Greek alphabet soup” from the point of view of an institutional asset manager or Fund of Funds manager looking for practical investment decision making tools. Although not unique to the appraisal of hedge fund investments, this problem is a good place to show the context in which any particular measure or ratio has to be useful.

- **Milind Sharma** of Deutsche Bank argues that we must go beyond Sharpe ratios and other approaches that ignore the higher moments of investment return distributions. He discusses two RAPMs that offer real improvement: the Omega measure; and his own AIRAP (alternative investments risk-adjusted performance). The Omega measure is a very flexible tool based on non-parametric statistical analysis. Sharma’s AIRAP is derived from the economic theory of expected utility.

- **Con Keating** of the Finance Development Centre, who co-developed the Omega measure, explains why this measure works well. While acknowledging the value of the Sharpe ratio, he argues for a non-parametric approach to the analysis of investment returns (not just hedge funds). A recent Edhec survey reported that 57% of Fund of Funds managers consider the Omega measure either important or very important, suggesting that this measure is an increasingly established part of the alternative investment appraisal process.

- **Emmanuel Acar and Amy Middleton** of Bank of America analyse the use of drawdown as a measure. The appeal of a peak to trough asset fall is its concreteness, especially for investors concerned with capital preservation. This article extends the small but important literature on drawdown in using Monte Carlo analysis to derive drawdown statistics for some currency funds and shows that it is problematic to compare them. The underlying assumption of normally distributed returns is also questioned.

- **Jean-François Bacmann and Pierre Jeanneret** of RMF Investment Management examine a different performance approach, using factor analysis. They extend the important work of Fung and Hsieh in explaining fund of fund returns by various factors, improving the explanatory power. But they still find a statistically significant net investment contribution or alpha for Fund of Funds.
A brief history of performance ratios
by Simon Taylor

Early performance ratios grew out of the mean variance framework, were adapted for downside risk but have given way to newer measures better suited for hedge fund data.

Introduction: a background in economics

Investment performance measures have grown out of financial economics, a subject which has tended to emphasise formal rigour and analytical tractability over empirical realism. By assuming that mean and variance were sufficient to describe rational investor decision making framework, economists were able to develop the edifice of Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM).

These impressive theoretical frameworks dominate the world of applied corporate finance and investment decision making. This is despite the evidence of Mandelbrot and others that most financial data cannot be adequately described as Gaussian normal. Nor does CAPM work particularly well empirically. But MPT and CAPM are still widely used because they offer convenient and relatively easy “recipes” to follow.

The Sharpe ratio and its descendants

Out of the mean variance framework, one performance measure came to dominate investment appraisal, the Sharpe ratio, which divides the excess return of a portfolio (usually relative to the risk free rate) by its standard deviation, as a proxy for risk:

\[
\frac{R_p - R_f}{\sigma_p}
\]

where \( R_p \) is the return on the portfolio, \( R_f \) is the risk-free rate and \( \sigma_p \) is the standard deviation of the returns of the portfolio. This ratio shows the “price” of excess return in terms of risk (volatility). Sharpe revisited the ratio in 1994 and reinterpreted it as the return of a portfolio relative to some other portfolio (equivalent to being long one and short the other). This revised version is known as the information ratio.

Sharpe’s work has been extended and built on, for example by Treynor. The Treynor ratio replaces \( \sigma_p \), the volatility of the portfolio, with a measure of systematic risk. The intuition here is from the CAPM approach, namely that investors should only expect risk compensation for exposure to non-diversifiable or systematic risk.

Another set of developments was begun by Modigliani and Modigliani (the Nobel laureate Franco and his granddaughter). Known as \( M^2 \), their measure compares portfolios by leveraging or deleveraging them to the point where they have the same volatility (normally chosen to be the market volatility). This allows the portfolios to be compared simply by looking at the resulting returns. The fund with the highest \( M^2 \) will have the highest return for a given amount of risk. There is a further extension of this, developed by Muralidhar and called \( M^3 \), which additionally looks at differences in the correlations of the various portfolios being compared (see Muralidhar’s contribution in this issue).

The Sharpe ratio is still the bread and butter tool of investment management. It is easy to compute, relatively easy to understand, and has a fine theoretical pedigree behind it. The higher the Sharpe ratio for a portfolio, the better. (Unfortunately it is often quoted without any measure of statistical significance, even though this may render the numbers useless).
Downside risk measures

Many of the early hedge fund investors were high net worth individuals for whom capital preservation was paramount. So low volatility was less important than low downside volatility. This has given rise to two sorts of measures based on the downside risk: the Sortino ratio and Maximum Drawdown (MDD).

The Sortino ratio is closely related to the Sharpe ratio. It compares the return of a portfolio with a chosen Minimum Acceptable Return or MAR (which could be the risk free rate but need not be), and divides it by the downside semi-standard deviation, which measures only the volatility of returns below the MAR:

\[
\frac{R_p - MAR}{\sigma_{DD}}
\]

where \(\sigma_{DD}\) is the downside deviation of return. Sortino’s ratio appealed to the practitioners in the hedge fund world but was initially criticised for not being rooted in sound market theory, although that turned out to be a false criticism.

Maximum Drawdown (MDD) measures are often quoted in standard tables of hedge fund performance and describe the worst peak-to-trough fall in asset values experienced by the fund to date. Although widely quoted by practitioners, MDD was not widely analysed by academics until fairly recently. Some limitations are relatively clear: MDD can only be compared for funds with the same time scale and similar reporting frequency. One perverse result is that a very new fund almost certainly has a smaller MDD than a long established one, but it hardly follows that one should only invest in new funds.

Moreover MDD is a very inefficient statistic for describing a fund’s performance and carries a high potential level of error i.e. an investor should not reject or accept a fund on MDD alone. A measure such as the worst five trading days might be a superior measure because it uses more information about the historic returns.

MDD can be derived analytically as a formula for some return distributions but researchers have tended to preferred to use a Monte Carlo numerical approach. In other words, the estimated parameters of the return distribution (typically only the mean and variance) are used to generate a very high number of possible outcomes, of which the actual outcome is only one. Then the researcher (or investor) can pick a confidence level, say 95% or 99%, and see what the MDD would be. This should be a better guide to the underlying downside risk compared with the actual MDD.

Of course this approach only works if the underlying returns can be accurately captured by those parameters and they can be reasonably assumed to be stable. These are both strong assumptions and MDD is not a very reliable predictor (see article by Acar and Middleton in this issue).

MDD has also been incorporated in another variation on the Sharpe ratio, the Calmar ratio:

\[
\frac{R_p}{MDD - 10%}
\]

The compound return can be over any period but the norm is three years. An extension is the Sterling ratio, of which the most common form is:

\[
\frac{R_p}{MDD - 10%}
\]

Limitations of mean variance

The mean variance framework was adopted because it was tractable mathematically and seemed to fit with the empirical reality of financial data. In an age when computing power was expensive, it was highly desirable that empirical work could be largely confined to estimating just two parameters.

But there were always difficulties with this approach. The fundamental economic theory of decision making under uncertainty, pioneered by Von Neumann and Morgenstern (VNM) was only consistent with the mean-variance portfolio approach under rather limiting conditions, namely:

i) the investor’s utility function is quadratic (which implies they don’t care about higher moments, but also that investors have increasing absolute risk aversion, which seems implausible); or

ii) the investment returns are normal; or

iii) the risks are “small” in the sense that a second order Taylor approximation to the utility function is satisfactory.
It is commonly taken for granted that conventional financial data are normal distributed or near enough. Mandelbrot's recent book\(^2\) emphasises that this is a false assumption. But for much economic work the assumption of "small risks" has justified the use of mean variance analysis. Paul Samuelson, one of the greatest of economists, argued that in this case, "the mean-variance result is a very good approximation"\(^3\).

But for hedge funds, the mean variance framework is insufficient. Not only are the data markedly different from normally distributed. But the argument for the approximation of "small risks" is untenable too. Investors care about average volatility but they also can be presumed to care about larger and more abrupt moves in their portfolio.

**Dealing with higher moments**

The biggest problem with the Sharpe ratio and its spin offs remains their failure adequately to capture the higher moments of the distribution. If we reject the assumptions that investors don’t care about higher moments and that investment data can be characterised as Gaussian normal, then we need a new approach.

Sharma (2005) shows that the Sharpe ratio can be extended in a useful way by replacing the denominator by the value at risk (VaR) at say the 99% level. VaR, the expected return in a defined statistical set of worst cases, is typically based on a mean-variance normal distribution but can be modified to incorporate skewness and kurtosis using the Cornish-Fisher expansion to yield:

\[
\text{Modified Sharpe Ratio} = \frac{(R_p - R_f)}{\text{VaR}_{\text{CORNISH-FISHER}}}
\]

Although this is an improvement it still only takes the third and fourth moments into account. Sharma therefore proposes a measure called Alternative Investment Risk Adjusted Return (AIRAP), which draws on the economic theory of expected utility.

Expected utility theory, the outcome of VNM’s work, is a rigorous (although empirically questionable) model. In geometric terms, the shape of the utility function captures the investor attitude to risk. Figure 1 (taken from Milind Sharma’s article in this issue) shows the classic representation of expected utility as a concave function i.e. the investor is risk averse – he or she prefers a certain amount \(z\) to a risky combination of outcomes with the same mathematical expected value \(E(z)\). Thus \(U(E(z)) > E(u(z))\), where \(z\) is a linear combination of two possible outcomes \(z_1\) and \(z_2\).

**Figure 1: A concave utility function illustrating risk aversion**

Different utility functional forms allow economists to express different theories about risk. Investor risk aversion is largely taken for granted, but this is a very weak and general assumption, captured by the concavity of the utility function. Absolute risk aversion is a measure of this concavity (it is the ratio of the second to the first derivatives). Common sense suggests that absolute risk aversion declines with wealth ie a millionaire would pay more for a fair lottery ticket than a beggar.

Relative risk aversion takes the investor’s wealth into account. So a millionaire might have the same risk aversion, or even higher, than a beggar, when the downside risk is expressed as a percentage of his or her total wealth, rather than an absolute amount.

Economic theory allows for increasing, constant or decreasing absolute or relative risk aversion: what works best is an empirical matter, although not an easy one to settle decisively. But most often economists have tended to use a Constant Relative Risk Aversion (CRRA) model, which offers a reasonable compromise between empirical plausibility and mathematical convenience.

CRRA is the jumping off point for Sharma’s Alternative Investment Risk Adjusted Performance measure (AIRAP):
where $TR_i$ is the fund total return of the $i$th period and $p_i$ is the probability of that return; $c$ is the coefficient of relative risk aversion, which captures the shape of the utility function, and can take a number of values, so long as the same value is used for comparing different fund returns (see Sharma article in this issue).

Nonparametric approaches: Omega

The appeal of the Gaussian normal distribution is that it can be described by just two parameters, the mean and standard deviation, which simplifies computation enormously. Other parametric distributions, such as the Weibull or Gumbel, have the same usefulness. But financial return data don’t necessarily fit any of these distributions. Choosing parameters may amount to excessive simplification. The parameters may not even be well defined. An alternative approach is therefore the nonparametric one. Most statistics textbooks tend to have a brief section on nonparametric methods, though often limited to such relatively easy cases as Spearman’s rank correlation coefficient. Nonparametric tests are sometimes called distribution-free to emphasise that they don’t depend on any particular underlying distribution function behind the data. This is particularly apt when we don’t actually know the form of the underlying distribution function.

The main nonparametric approach to investment returns is the Omega function, created by Shadwick and Keating. This is a function which is mathematically equivalent to the distribution of returns and which allows an ordering of investments without specifying any utility function.

The starting point is the cumulative distribution function, which plots the ordered returns for an investment in a cumulative way. Figure 2 shows a density function for some daily hedge fund returns. This looks a bit like a normal distribution but with negative skew and high kurtosis ie a lot of extreme results but particularly on the downside. Perhaps unsurprisingly, this is data from a merger arbitrage fund.

The Omega function uses the information in the cumulative distribution to compare, for each chosen threshold return, the distribution weighted returns above that threshold versus the distribution weighted returns below. That ratio is then plotted graphically against the threshold returns. The Omega ratio is:

$$AIRAP = CE = \left[ \sum_i p_i (1 + TR_i)^{(1-c)} \right]^{1/(1-c)} - 1,$$

when $c \neq 1$ & $c \geq 0$

The same data can be shown in cumulative form. Figure 3 plots the returns ranked from worst daily return to best, with the cumulative distribution summing to 1 (which can therefore be thought of as ex post probabilities). Note that all of the data is retained here, we haven’t summarised it (and lost information) through the use of parameters.
\[
\Omega(L) = \frac{\int_{a}^{b} (1 - F(r))dr}{\int_{a}^{b} F(r)dr}
\]

where \((a, b)\) is the interval of returns and \(F(r)\) is the cumulative distribution of returns. The Omega function involves no estimation and therefore loses no data. A higher Omega is preferred to a lower for any specified return threshold. At the mean of the distribution the Omega function is one.

Omega is not uniquely designed for hedge fund use but in its ability to adjust automatically for higher moments it is particularly well suited to hedge fund data (see article in this issue by Keating).

**Factor analysis**

Drawing on the history of the Capital Asset Pricing Model (CAPM), researchers have tried to explain hedge fund and fund of fund performance in terms of a number of “factors” that might be equity market indices, interest rates, currency baskets and so on.

One motive for doing this is the attempt to show that hedge funds’ performance can be entirely explained by a combination of beta exposures that could easily be replicated statistically. If this were the case there would be no real alpha being generated and the investor is being charged excessive fees.

Another motive is to understand where the funds’ risk exposure is coming from, in order to better understand what the manager is doing and how the fund might be matched with others for optimal risk/return performance.

Famously, Fama and French showed empirically that the textbook CAPM explained stock returns rather poorly and that incorporating market capitalisation and book to price value did rather better. Fung and Hsieh (2002) and Naik and Aggarwal (2004), among others, have extended the Fama-French work into the world of alternative assets. Fund returns are regressed on a range of factors capturing equity, fixed income, currency, commodity and interest rate returns. Momentum and trend following effects can also be captured, the latter by using the concept of a "lookback straddle". This is an option strategy that pays the maximum difference between the highest and lowest prices of an asset over the maturity period. It therefore pays out what a trend follower would achieve with perfect foresight.

By modelling fund returns as a linear combination of these various explanatory factors, the residual or unexplained return of the fund can be interpreted as alternative alpha, a version of Jensen’s alpha. The fact that various authors including Bacmann and Jeanneret in this issue find positive alpha even after an exhaustive list of explanatory factors, should provide encouragement for investors.

Footnotes:
4. For example the gamble described in the famous St. Petersburg paradox, which Bernoulli used to demonstrate risk aversion, does not have a defined mean or variance.
5. A utility function would need to be specified if the difference between two portfolios were to be quantified.
6. Fama and French have recently argued that “despite its seductive simplicity, the CAPM’s empirical problems probably invalidate its use in application” *Journal of Economic Perspectives* (2004).
7. In the conventional CAPM model, Jensen’s alpha is the return generated by an asset or portfolio in excess of that predicted by its beta and the market risk premium ie excess return that indicates superior risk-adjusted investment performance. “The performance of mutual funds in the period 1946-64”, *Journal of Finance* (1968).
In the last year, every journal or magazine seemed to carry yet another piece on “alpha” versus “beta” or the next new performance measure termed “kappa” or “omega”. Some measures of performance go by the names of the inventors (unfortunately, not Greek) like the Sharpe ratio, Sortino ratio or M-square (Modigliani and Modigliani), Morningstar ratio or those of friends/family of the authors like the SHARAD (my measure which stands for Skill, History and Risk-Adjusted Performance – however, this is also my brother’s name).

In this note, we aim to help clients understand some of these measures and add a few Greek alphabets that seem to be missing in the debate, but which are important. Moreover, we will attempt to lay down some basic principles that a risk-adjusted performance measure should meet (based on theoretical and practical considerations) before the author can claim that this is the ultimate measure, replacing all others.

**Alpha and Beta, but where art Rho? Is sigma significant?**

The new paradigm espoused by all is “separate alpha from beta” and “do not pay alpha fees for beta,” but what does all this mean? Let us start from the perspective of a pension fund (the same would apply to an endowment, or insurance company or even hedge fund FoF), understand how they function and then put these terms into context by relating back to finance theory from where they came.

Typically, a Trustee Committee sets objectives for the fund and determines a long-term strategic asset allocation (SAA) for the fund. This SAA is typically of the form: 60% in Stocks (measured by the S&P500 index), and 4030% in Bonds (measured by the Lehman Aggregate Bond Index) and 10% in Alternatives (with a lot of murkiness as to whether the index is LIBOR + 5%, S&P 500 + 3% or even some HFRI-type index). I simplify greatly as there are typically many more asset classes and more stratification, but this will suffice for our purposes.

This benchmark is given to the investment team at a pension fund (which unfortunately many trustees do not trust entirely and hence consultants are hired) who are expected to implement this portfolio and ideally achieve the basic benchmark return and then some. However, trustees often do not want the staff to take too much risk relative to the SAA. Staff have two potential activities to beat the benchmark – make all investment decisions internally (very rare) or structure the portfolio optimally (e.g., either overweight/underweight stocks, keep some assets in cash or assign a manager the Russell 3000 stock index as a benchmark and manage the risk between the S&P500 and the Russell 3000) and hire external managers to implement these mandates.

We will focus on the latter, but again the problem is that the staff do not entirely trust that the managers are skillful and this is where the Greeks appear. The same would apply to pension funds that hire Hedge Fund FoFs, who then hire hedge funds managers. In this case, there is a potential doubling of delegation and more scope for “mistrust”.

**Greek Alphabet Soup and Risk-Adjusted Performance**

by Arun S. Muralidhar
The concept of beta has its origins in the Capital Asset Pricing Model, where the beta is a measure of covariance of an asset with that of the market portfolio. In investing parlance, very often when clients and asset managers refer to beta, they typically mean either the SAA or the market index to which they are measured (many of which would fail the required assumptions of the market portfolio of the CAPM). The two concepts of market portfolio and beta are completely different, but one would not know that if they read all the marketing pitches today about beta. Moreover, the true beta that a pension fund requires is relative to its liabilities – something the CAPM is completely silent about. Hence a lot of the discussion on “beta” is wrong for the average pension fund.

Alpha is also very loosely defined in investing parlance – many people use alpha to mean returns in excess of the benchmark index returns with no information at all about how correlated (or “rho”) these returns are to the benchmark (either SAA or market index). The correlation coefficient is very important because, ideally, to lower the risk of achieving a target rate of return the investor should find as many uncorrelated return (or ideally negatively correlated positive return) streams as possible. So the more appropriate definition of alpha, and largely an outgrowth of the hedge fund industry, is to consider the return streams that are uncorrelated with the SAA or market index. A good example of such a return stream in a classic pension portfolio is the pure excess return/cash generated from active currency strategy or from a “market neutral” hedge fund.

However, in the traditional mandates given out by pension funds, the manager was asked to beat the benchmark index and because the clients did not know exactly what the manager was doing back in their offices, they tried to ring fence their activities relative to the benchmark by monitoring their tracking error (or the volatility of excess returns). In the FoF case, this is compounded, though most investors would claim they care about absolute risk and not relative risk. There are three elements that go into a tracking error calculation – the volatility of the market index (or sigma of the index), the volatility of the external manager’s portfolio (or sigma of the manager) and the correlation of the manager’s performance with the benchmark index (or another rho).

For many years, investors and rating agencies looked solely at the excess return relative to a market index and divided them by some measure of risk to establish whether managers were good or bad. In some cases, the measure of risk was the tracking error (creating the information ratio or modified-Sharpe ratio), or a measure of volatility of only underperformance (creating the Sortino ratio), or alternative measures creating the Morningstar ratio (Gambera 2004). It took a seminal article, which it appears has not been widely read by researchers on risk-adjusted performance, by the late Franco Modigliani and Leah Modigliani (Modigliani and Modigliani 1997) to start to bring the focus back on sigma and also making measures of risk-adjusted performance become more user friendly. Their measure has many interesting implications for the Hedge Fund industry, with the focus on absolute risk.

Towards a higher standard for risk-adjusted performance measures

They pointed out that when offered a choice of investment alternatives relative to a benchmark (and the benchmark could even be LIBOR for hedge funds), investors should ideally look for two things: (a) a risk-adjusted performance measure that is expressed in percentage terms (i.e., return terms as that is what benefits can be paid from); and (b) help the investor construct better portfolios without getting hung up on the jargon. I use their starting point and my experience on different sides of the investment table to lay out a series of criteria that researchers should try to achieve in developing new risk-adjusted performance measures. These criteria are meant to help bridge the gap between theoretical rigor and practical value.

1) Expressed in the metric relevant to the investor

The late Franco Modigliani used to argue that getting a risk-adjusted performance measure as a ratio did nothing for the client and could often lead them to incorrect decisions. If the client could create measures of risk-adjusted performance that were...
expressed in return terms, then they could think about whether this return would be helpful to pay pension benefits or tuitions for endowments. As Modigliani-Modigliani in the \textit{M-square} measure demonstrate, an information ratio of -0.5 (manager A) may be better than an information ratio of 0.3 (manager B). It all boils down to a simple condition – if the volatility (sigma) of the manager A’s performance is very low and that of manager B very high, comparing returns is an apples-to-oranges comparison.

The returns relative to the benchmark cannot be compared until one normalizes for the differences in the sigmas. When one implements their M-square transformation, they show very credibly that a negative information ratio manager could be preferred in risk-adjusted return terms to the positive information ratio manager. We show why in the next section. The Omega ratio gives clients a measure of the performance profile relative to some performance threshold, but the M-square is cleaner as it is in percent terms.

\textbf{ii) Help with portfolio construction}

One of the other problems with ratios is what to do with them? For example, what does one do with a Sharpe ratio of 0.5 or an information ratio of 0.7 or an Omega of 1.2? Modigliani and Modigliani (1997) take a neat extension of the Sharpe measure to create risk-adjusted portfolios out of an investment possibility. In short, they used the risk-free asset (cash, assumed to have zero volatility) to lever or delever the active manager’s portfolio.

For example, if manager A (with a negative information ratio) took too little sigma risk, the investor can borrow cash to lever the manager allocation so that the sigma of the risk-adjusted portfolio (or as they called it, the RAP) is equal to that of the benchmark. Similarly, manager B may need to be delevered. Therefore, the additional value of their measure was it told the investor how much to allocate to different active strategies and how to balance that with allocations to cash, giving useful advice on whether leverage can help meet a performance threshold.

However, if the investor’s measure of risk is the tracking error as opposed to sigma (i.e., worried about relative risk rather than absolute volatility), then these two risk-adjusted portfolios may have the same sigma, but very different correlations to the benchmark. In other words, the two tracking errors could be different and hence the M-cube measure of performance was created to normalize for both the differences in volatilities and correlations (to achieve a target tracking error). The M-cube is an extension of the M-square and now gives the investor allocation information as to how to allocate to cash (risk-free asset); the benchmark (market portfolio or the asset with zero tracking error or “beta”) and the potential active strategy. Notice that none of the newer measures of performance for hedge fund strategies like the Kappa or the Omega (Kazemi at al 2004, Kaplan and Knowles 2004) or other ratios can offer this helpful advice to investors.

The value of this approach is that clients can hire a manager and without altering their strategy create appropriate exposures to “beta” and “cash” and thereby achieve the optimal portfolio rather than looking only for “alpha”, which appears to be a rare commodity – all the marketing pitches notwithstanding.

\textbf{iii) Incorporate the length of history or skill of the manager}

One of the shortcomings of all measures is that there is no time element to them and this is particularly vexing in the hedge fund world. Is an Omega over 2 years of data better than a lower Omega over 5 years of data? The problem investors have is (a) they would like to have some concept of the validity of the statistic (which reduces as the number of data points falls); (b) ideally compare managers with different lengths of data histories without throwing out any data; and (c) say something about the skill of the manager.

One of the issues with the old Sortino ratio was that picking up only observations when the return was less than the benchmark greatly reduced the sample set on which the sigma was calculated. This has been adjusted for in using bootstrap techniques to generate this ratio. It can be shown that including time could make the M-square and M-cube measures incorrect and hence a measure was proposed in Journal of Performance Measurement, called the \textit{SHARAD} (Skill, History and Risk-Adjusted performance), where time was used to
establish the confidence the investor could have that the manager was skillful and this was then multiplied by the risk-adjusted performance measure. This is a good fix but will suffer from the problem of requiring a unique objective function to make such a measure appropriate. We discuss this below in section v.

iv) Consistency
One interesting fact in currency management or CTAs is that the industry wide excess returns of managers and high relative to their tracking error. However, the returns are “lumpy” - i.e., performance is often achieved in a few months of the year. No institutional investor or FoF likes a positive “alpha” strategy with lumpiness as it requires explaining the same or defending it vis-à-vis the Trustee Board or a client.

Two statistics that can help capture the lumpiness of returns are the “hit-rate” (or number of positive periods divided by total number of periods), where anything above 50% is better than a coin toss and drawdown statistics, or how much and how long can you lose relative to a high water mark before you get fired. I like to call the drawdown statistics “Yield to Fire!” Most traditional risk adjusted performance measures do not tackle consistency and it typically relates to the emotional aspects of investing and delegating duties.

v) Satisfy complex objectives/satisfy higher moments
One of the knocks against the Sharpe ratio was that it assumes that investors have mean-variance preferences and hence did not capture higher moments such as skew and kurtosis. This could lead to potentially bad decisions to invest in strategies that had high blow up risk. The classic example here is a strategy to sell naked options, which gives many small positive returns, but could have one catastrophic negative return that bankrupts the investor, could have a good Sharpe ratio. This is where measures such as the Omega could dominate in capturing higher moments.

However, such a strategy is not a bad one if coupled with another that has the exact opposite profile like a classic trend strategy - many small losses with a few large gains. The combination of the two if properly designed (i.e., where the correlation between them is negative) can give a much better overall portfolio profile for the investor. Therefore, the Omega could penalize a strategy in isolation without giving an investor insight into what other strategy to combine the same with - which the M-square approach articulated very neatly.

vi) Ability to rank individual managers and combinations of managers
One aspect sorely lacking in the discussion is how various measures of manager risk-adjusted performance are helpful when clients hire not one, but multiple managers. Rarely, do FoFs, retail or institutional investors hire a single manager or mutual fund and hence the risk-adjusted performance measures or ranking schemes that cannot incorporate a portfolio approach can be misleading. For example, the Morningstar rating could lead to a retail investor buying a number of individually (highly) rated funds, but it has been shown that this can be a poor decision in the context of overall portfolio construction as the Morningstar technique does not lend itself easily to multiple manager portfolios.

Summary
This note set out to clarify some of the discussion on alpha, beta, rho, sigma, omega, kappa etc. and help highlight criteria by which future research on risk-adjusted performance measures can be directed. The goal of this list, by no means exhaustive, is to find good theoretical underpinnings to these measures yet find consistency with the practicalities of managing portfolios. The practical issues become much more relevant in managing institutional portfolios as there are multiple layers of decision making and with less than complete trust at all layers.

Moreover, investors rarely hire a single manager and this adds an additional layer of complexity. The goal of the investor is to maximize risk-adjusted return for whatever definition of risk, and simple ratios cannot help in this process. What this piece shows is that in the end investors may require more than one measure to satisfy complex objectives, but before the next researcher makes “gyro”ic (pronounced “herioc”) claims about the next new greek alphabet performance measure, that they check that they meet these basic criteria.

The author thanks the late Franco Modigliani and Sanjay Muralidhar for assistance and encouragement in developing these ideas. These are the personal views of the author and are theoretical in nature. They do not represent the views of Mcube Investment Technologies, FX Concepts, Inc. or any of their affiliates.
Two measures that address weaknesses of the Sharpe ratio are the Omega measure and Alternative Investments Risk Adjusted Performance metric.

The problem: traditional RAPMs can mislead

The most widely used traditional risk-adjusted performance measure (RAPM) is the Sharpe ratio, coined by its namesake and Nobel laureate William Sharpe in 1966. It has many desirable properties such as proportionality to the t-statistic (for returns in excess of zero) and the centrality of Sharpe-squared to optimal portfolio allocation. However, it is leverage invariant; it does not account for correlations; nor can it handle iceberg risks lurking in the higher moments. Worse yet, it can be ‘gamed’ by truncating the right tail of the returns distribution at the expense of a fat left tail (the periodic crashes).

A team of Yale professors has derived the optimal strategy to manipulate the Sharpe ratio, which comprises of shorting out of the money puts and calls in a specific ratio. They remark that, “the ‘peso problem’ may be ubiquitous in any investment management industry that rewards high Sharpe ratio managers.” It is now widely recognized that new RAPMs are required to deal with the complexities of the HF paradigm. An in-depth survey of emerging state of the art tools can be found in Barry Schachter’s 2004 compilation, Intelligent Hedge Fund Investing. The author’s research [Sharma (2004b)] has confirmed that high Sharpe ratios in hedge funds often represent a trade-off for higher moment risk.

One line of thought is to salvage the Sharpe ratio’s relevance while retaining the familiar form by replacing standard deviation in the denominator with an enhanced risk measure such as Modified VaR or AIRAP. In the parametric VaR case, assuming normality of returns, one obtains at the 99% confidence level:

\[ \text{VaR}_{\text{NORMAL}} = \mu - 2.32\sigma \]

The Cornish-Fisher expansion shown below can be used to modify VaR in order to include the impact of the skewness and kurtosis:

\[ \text{VaR}_{\text{CORNISH-FISHER}} = \mu - \Omega(\alpha)\sigma \]

\[ \Omega(\alpha) = z(\alpha) + \frac{(z(\alpha)^2 - 1)S}{6} + \frac{(z(\alpha)^3 - 3z(\alpha))K}{24} - \frac{(2z(\alpha)^3 - 5z(\alpha))S^2}{36} \]

Where \((1-\alpha)\) is the confidence level, \(z(\alpha)\) the critical value under normality, \(S\) is skewness, and \(K\) is excess kurtosis. Thus, the alternative formulations are:

Modified Sharpe Ratio = \(\frac{\mu - r_f}{\text{VaR}_{\text{CORNISH-FISHER}}}\)

or

\(\text{Modified Sharpe Ratio} = \frac{\text{Mean excess return}}{\text{AIRAP}_{RP(4)}}\)
where AIRAP RP(4) is the AIRAP based Risk Premium for the default value of CRRA = 4.

However, these ratios do inherit some of the limitations of the Sharpe ratio in addition to the fact that a four moment approximation does not include all higher moments and comes with its own convergence issues.

**New alternative RAPMs for hedge funds: Omega and AIRAP**

We now summarize two key alternatives for a new HF risk-adjusted performance measure:

i) Gain-Loss ratios such as that originally due to Antonio Bernardo and Olivier Ledoit [Bernardo and Ledoit (2000)] or a generalized version called Omega proposed by Con Keating and William Shadwick [Shadwick and Keating (2002)];

ii) utility based measures such as AIRAP proposed by the author that explicitly factor in risk-aversion. [Sharma (2004a)]

**Omega/ Gain-Loss Ratios:** Omega takes the ratio of the expectations above and below a given threshold L as shown in the formula below:

\[
\Omega(L) = \frac{\int_L^\infty (1 - F(x)) \, dx}{\int_0^L F(x) \, dx}
\]

The Omega function is calculated for all values of L in the interval [a,b]. Higher pointwise values of Omega are indicative of an investment with better upside to downside at those threshold points. The special case where the threshold L is zero corresponds to the ratio of gains to losses. Omega is mathematically equivalent to the returns distribution and hence incorporates all moments, although empirical results suggest that it is most sensitive to changes in mean and variance. Omega is monotonically decreasing from infinity to zero.

An intuitive restatement of Omega by Thomas Schneeweis and the CISDM faculty, [Kazemi et al] shows that it is essentially the ratio of a hypothetical European call and put on the underlying fund investment:

\[
\Omega(L) = C(L)/P(L)
\]

Omega does not explicitly factor in any risk-aversion parameter nor is a default value of the threshold L prescribed (to facilitate comparisons). While the lack of a simple threshold or/ single point of comparison across funds may be a source of confusion, it is clear that the choice of L used in analysis should be consistent with some notion of investor risk-aversion. The main benefit is that it Omega captures all observed higher moments without making restrictive distributional assumptions. Finally, an empirical limitation is sample size. Stability of estimates requires at least 40 to 50 observations.

**AIRAP (Alternative Investments Risk Adjusted Performance):** AIRAP has been proposed by the author (Sharma) [Sharma (2004a)] as the certainty equivalent risk-adjusted return corresponding to a CRRA (constant relative risk-aversion) representation of investor preferences. Simply put it is the implied equivalent return that the risk-averse investor desires with certainty in exchange for the uncertain return from holding risky assets. It allows us to decompose return into the risk premium earned and the risk-adjusted (AIRAP) component, thus enabling an apple-s to-apple facilitating an equitable comparison of HF performance.

A graphical interpretation of this the certainty equivalent return is shown in figure x below. The vertical axis is utility and the horizontal axis is return (or wealth). The shape of the utility function (the curved line showing utility for any given level of return) is concave, which captures the economic idea of risk aversion. A combination of returns z1 and z2 has the expected (ie probability-weighted) value E(z). Risk aversion means the investor value this combination less highly (so it lies beneath the utility function)

Figure 1: A concave utility function illustrating the idea of AIRAP or certainty equivalence
curve) of the certain outcome with the same value. The certainty equivalent of the probabilistic outcome is the lower value that generates the same utility for the investor, so the gap between $CE(z)$ and $E(z)$ is a kind of insurance premium.

For $TR_i = i^{th}$ period total fund return, $c = CRRA$ risk-aversion parameter, $i = 1,\ldots,N$ and $N =$ number of periods, the general solution is reproduced below. A default value of $c=4$ for risk-aversion is recommended to facilitate comparisons. Further, substituting $p_i =$ probability of the $i^{th}$ return$= 1/N$, provides a closed form solution that has a straightforward spreadsheet implementation.

$$AIRAP = CE = \left[ \sum_{i} p_i \cdot (1 + TR_i)^{(1-c)} \right]^{\frac{1}{(1-c)}} - 1, \quad \text{when} \quad c > 1 \& c \geq 0$$

and $AIRAP = \left[ \prod_{i} (1 + TR_i)^{p_i} \right] - 1, \quad \text{when} \quad c = 1$

AIRAP’s key merits are that: it captures all observed higher moments, penalizes for volatility and leverage in proportion with risk aversion; it works even when mean returns are negative; it can be formulated as a modified Sharpe ratio; downside variance is penalized more; it is invariant to wealth level and the closed form solution is as simple to calculate as the Sharpe ratio in a spreadsheet. The unrealistic assumption of normality is avoided and the limitations of mean-variance world are circumnavigated. Finally, AIRAP is unique in providing insights into the optimal level of leverage consistent with a given HF strategy.

**Using the new RAPMs: investing in HFs still stacks up**

The question remains - is the investor better off investing in HFs net of the higher moment risks assumed? The answer is in the affirmative but is subject to further research. Bypassing the zigzag of discovery we hone in on We highlight recent results, which revisit the optimal asset allocation problem using new RAPMs relevant to the HF paradigm. Jean-François Bacmann and Sebastian Pache Pache [Bacmann and Pache (2004)] investigate optimization with Omega and show that resulting portfolios are less prone to overweighting negatively skewed and leptokurtic styles than under mean-variance optimization. Maximization of the Omega ratio corresponds to maximizing the ratio of expected gains and losses with respect to some threshold.

The proof of the pudding lies in the eating. Since investors ultimately eat returns, it is heartening to note that their study attributes the highest outsample returns to optimizing RAPMs incorporating higher moments - evidence that investors ought to care, if not for the theoretical underpinnings, then at least for their bottom lines the sake of higher returns.

Maximizing AIRAP is tantamount to maximizing power utility. Operating in this framework, Bengt Pramborg and Niclas Hagelin (2004) have shown that even upon factoring in higher moment risks and survivorship corrections, it remains optimal to make significant allocations to hedge funds and FoHFs (figure 2 and table 1). In fact, they show that at times less risk averse investors may optimally choose to lever up and allocate all capital to HFs as proxied by the HFR composite index. Even the more risk averse investor would allocate as much to HFs as to equities (and significantly more than to bonds).

![Figure 2](source: Hagelin and Pramborg (2004))
Furthermore, they show that the incremental performance gains resulting from the inclusion of HFs to the traditional stock and bond mix can be both statistically significant and quite substantial. For the risk neutral investor the pickup in annualized geometric mean return ranges from 3.4% to 7.3% (when 2 times leverage is allowed), even after adjusting for survivorship bias and keeping volatility fixed.

Concluding thoughts
The rigorous study of HFs is still in its infancy. We provide some parting thoughts for the investors on measuring performance:

- Maintain the distinction between ex-post RAPM comparisons and their ex-ante relevance to out-sample performance.
- An assessment of investor risk aversion and loss threshold is critical to implementing paradigm RAPMs such as AIRAP and Omega. Be wary of traditional RAPM comparisons. Use of AIRAP or Omega would be prudent. HFs have many attractions and including them in asset allocation ought to be both desirable and optimal.

Table 1: Differences in growth rates between portfolios with and without adjusted hedge fund indices

The table displays the percentage differences in growth rates between portfolios for which investments in hedge funds are allowed and portfolios without hedge funds. Fund indices are adjusted for survivorship bias (HFRI), and for fees (FoF). Significance at the 10 percent level, at the 5 percent level, and at the 1 percent level is marked by *, **, and *** respectively.

<table>
<thead>
<tr>
<th>Portfolio Strategy</th>
<th>No Leverage Equity is SP500</th>
<th>Leverage Allowed Equity is SP500</th>
<th>Leverage Allowed Equity is MSCIW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HFRI</td>
<td>FoF</td>
<td>HFRI</td>
</tr>
<tr>
<td>EW</td>
<td>1.3***</td>
<td>0.5</td>
<td>1.3**</td>
</tr>
<tr>
<td>-60</td>
<td>2.0**</td>
<td>0.5</td>
<td>2.7**</td>
</tr>
<tr>
<td>-40</td>
<td>0.6</td>
<td>0.4</td>
<td>4.1***</td>
</tr>
<tr>
<td>-30</td>
<td>1.8*</td>
<td>0.4</td>
<td>4.5**</td>
</tr>
<tr>
<td>-20</td>
<td>1.8*</td>
<td>0.1</td>
<td>3.6**</td>
</tr>
<tr>
<td>-10</td>
<td>1.5</td>
<td>0.8</td>
<td>5.1***</td>
</tr>
<tr>
<td>-5</td>
<td>3.1**</td>
<td>2.3*</td>
<td>4.5**</td>
</tr>
<tr>
<td>-1</td>
<td>1.9</td>
<td>1.4</td>
<td>4.8**</td>
</tr>
<tr>
<td>0</td>
<td>2.1</td>
<td>2</td>
<td>5.1*</td>
</tr>
<tr>
<td>0.5</td>
<td>2.9*</td>
<td>2.5*</td>
<td>5.7*</td>
</tr>
<tr>
<td>1</td>
<td>3.4**</td>
<td>2.5*</td>
<td>7.3**</td>
</tr>
</tbody>
</table>

The Omega function and associated metrics offer a solution to the limitations of parametric approaches to investment performance appraisal.

In the welter of recent criticisms of the Sharpe ratio, it is easy to forget that the insights into performance evaluation due to Bill Sharpe were profound. But it is also obvious that the underlying assumptions of the ratio are far too simplistic for modern investment management, and that a non-parametric generalisation is needed.

To begin, it is worth dwelling briefly on the role of the risk-free rate in the Sharpe ratio. Without this element, the ratio is scale invariant, that is to say it cannot distinguish between sets of returns where the only difference is a question of leverage or gearing. The problem is that these distributions may have identical efficiency of production of return per unit of risk but the terminal values of the levered set are higher on average, a question of scale. With the interpretation of the risk-free rate as the cost of borrowing, however, this problem resolves.

There are related scale or exposure complexities for portfolios containing short positions.

While it is common to refer to the asymmetries of returns arising from the use of options or complex strategies as justification for more advanced methods, there is a much simpler and more direct rationale for the development of an accurate and discerning technique – our preferences are intrinsically asymmetric; we want the upside and not the downside to any investment.

Searching for a way to compare financial data

The fundamental problem is simple: we need to be able to compare distributions regardless of their empirical properties in a manner that is financially meaningful. The techniques, widely used in academia, known as Stochastic Dominance are not fit for this purpose.

There have been many attempts to advance from the mean-variance world of Sharpe, most notably with the development of the Sortino ratio. The denominator of this ratio is the downside deviation, a second order statistic, and proves its Achilles's heel. Choices are made correctly over downside potential but incorrectly over the upside.

There is also a substantial body of work in academic finance which questions the existence of higher order statistics for financial data; we can always calculate a sample statistic from a dataset but the question here is whether this converges to a finite value as we increase the sample size. This concern, while apparently an academic nicety, would have profound consequences for the risk management industry if irrefutably proven. Pragmatically, it means that we should avoid the use of higher order statistics if we can capture their information content in some other manner.

It is worth noting that there is a mathematical equivalence between the standard deviation of a distribution and the first order lower partial moment (at the mean) in the case of Normal distributions – another positive attribute of the Sharpe ratio.

Any definition of risk must capture the idea that it is fundamentally related to the rate of change of the object under consideration. In finance, where we are concerned with wealth and asset and liability values, this rate of change is simply return. If we wish to think about the riskiness of returns, then we are concerned with the rate of change of returns. In theory at least, the expected return of an asset must be positive.
for that asset to have value and the meaning of negative values is, to say the least, intellectually challenging—these are not liabilities.

These were the background concerns that led to the development of the Omega function and Omega metrics.

**The Omega function**

The Omega function for returns is mathematically equivalent to the returns distribution and consequently contains all information contained in the original data. It relies upon only the existence of the mean return and consequently is indifferent as the existence of higher order statistics. It is intuitive, being defined as the ratio of the upside pay-off to the downside pay-off relative to a threshold return, for the entire range of returns. Relative to single threshold this is: what do I win multiplied by how likely is it that I win divided by what do I lose multiplied by how likely is it that I lose—the comparison to the ratio of a put option to a call option is immediate.

Risk is defined as the rate of change of the Omega function. For the purposes of comparison risk it is convenient to use the relative (or logarithmic) rate of change, in the same manner that we use modified duration rather than Macaulay duration in bond analysis. Here risk is much richer than the global statistic, standard deviation, with which we are all familiar—now we can consider and quantify risk locally to a level of return.

The question remains of comparing Omega functions. The decision rule is simple. We prefer the higher valued function at any given threshold. We may simply consider the values at a single threshold, as many have done, but this can mislead critically. Only the entire function contains all of the information in the data. To compare Omega functions correctly we need a functional on the Omega function, which reduces it to a single number. One that rewards higher mean return together with higher concentration around the mean, that penalises asymmetric returns below the mean and rewards above. It should also reduce to the Sharpe ratio if returns are in reality normal. This is precisely what the Omega F2 metric does—and it demonstrates empirically a strong relation to realised values of wealth or asset values arising from both traditional asset management and alternative investment strategies.

**Conclusion: the superiority of non-parametric approaches**

A number of researchers have derived Omega functions from parametric models fitted to empirical data. If a distribution can be written in closed form, there is always a closed form expression for the Omega function. The problem at root is that the parameter estimation process is costly in terms of information discarded. The justification that these parametric models can easily be used predictively carries little substance; the choice of (parametric) model is critical and non-trivial. Non-parametric methods are certainly superior and their application holds the prospect of dismissing for ever the regulator’s mantra that past performance is no guide to the future.

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Footnotes:

1. Without the presence of the risk-free rate, the measure is known as the Information ratio.
2. There are many possible criticisms of the techniques utilised as Stochastic Dominance; perhaps the most elementary is that with increasing complexity, they apply to ever smaller classes of distribution and consequently rapidly lose relevance for the practitioner.
3. These have included many follies, such as the recently proposed ratio of upside to downside information ratios which would encourage downside while discouraging upside risk.
4. Technically this is the second order lower partial moment with respect to the Minimum Acceptable Return.
5. This dates to the work of Mandelbrot, Fama and Samuelson in the 1960s and is also evident in the recent work of Los and McCulloch.
7. A liability value distribution is the image about zero of an asset value distribution, which means that the symmetries differ.
8. Similarly we can think about returns locally to asset values—and gain insight into the options “smile”.
9. Including some who have failed to notice that they have generated nonsensical negative probabilities in the process.
Using Monte Carlo analysis to explore the limitations of drawdown statistics in comparing active currency indices.

Downside risk measures have received renewed attention recently. The most frequently quoted statistic of that sort within the hedge funds world is probably maximum drawdown; that is, over a defined period, the largest decline of the investment having once reached a peak. In simple terms it quantifies the biggest cumulative loss an investor could have made by entering and exiting the investment at the worse possible time.

Despite its practitioner's appeal, only a few academic articles have been written on the topic (Douady et al, 2000; Magdon-Ismail et al, 2004).

The analytical formula specifying the expected maximum drawdown is quite complex and as a consequence other authors have preferred using Monte-Carlo simulations (Burghardt et al, 2003; Harding et al, 2003). The expected maximum drawdown, as well as percentiles, can then be worked out as a function of a given investment mean, standard deviation and period length. The goal of this article is to quantify the empirical maximum drawdown of a variety of active currency indices and then compare retrospectively to the values obtained from a normal distribution with corresponding mean and standard deviation. Interesting differences between currency indices are then highlighted which in turn open up avenues for further research.

About active currency indices

Active currency indices can be very useful when trying to analyse the performance of foreign exchange managers. There are several such indices in existence including those provided by Stark, CISDM and Parker to mention just a few. Even though these indices possess relatively high correlation with one another over the period December 1989 to January 2005, Figure 1, differences are apparent especially with respect to the manager composition and the method by which the index returns are calculated. For example, the CISDM tracks over 40 currency programmes and compiles the returns on a median basis; whereas Stark uses a money-weighted approach and the Parker index includes 63 on an equally-weighted basis.

The differences between the indices are further highlighted when performance over the period in question is examined, Figure 2, this is true in terms of annualised mean returns and standard deviation. It is also apparent when examining the maximum drawdown statistics which range from -9.18% (Parker) through to -20.86% (Stark) and up to -28.69% (CISDM). Although one needs to question the extent to which these variations are due to the idiosyncrasies, in composition and constitution, of the individual indices. It could also be a function of survivorship or selection bias which would artificially inflate or deflate the returns of any of these indices.
but this aspect falls outside of the scope of this article.

Yet some clarity could be provided by examining a totally transparent index, namely the AFX. Developed by Lequeux and Acar (1998) the AFX index is based on three moving averages of lengths 32, 61 and 117 days and applied to a Bank of International Settlements (BIS) weighted portfolio of currencies. The performance statistics of the AFX can also be seen in Figure 2. The AFX index provided here is net of transaction costs but gross of fees. By twice leveraging the AFX index, denoted as “AFX_2”, and adding the Usd risk free rate, “AFX_2_RF”, the index provides a comparable risk/return profile to that of the other currency indices. As the AFX is fully replicable and therefore completely transparent, it provides a better understanding of the market inefficiencies being exploited and should aid in the assessment of risk.

A recent study by Middleton (2005) has shown that the majority of individual currency programmes, managed by either Commodity Trading Advisors or Overlay, show statistically significant correlation with the AFX index. For completeness purposes the performance of a passive buy and hold strategy (B&H) applied to a BIS-weighted portfolio is also shown, where positions are rolled using CME Futures contracts.

Are maximum drawdowns consistent with normally distributed returns?

Our study investigates whether the maximum drawdowns seen empirically are compatible with normally distributed returns assuming ex-post knowledge of the mean returns and standard deviation over the period. To calculate the maximum drawdown percentiles a Monte-Carlo experiment was conducted based on the historical mean and volatility parameters observed over the period December 1989 to January 2005. The simulations were performed 5,000 times and the 181-month maximum drawdown statistics collected. The 5th and 95th percentiles, together with the median and empirical maximum drawdown statistics are plotted in Figure 3.

The first thing one can observe from Figure 3 is that the confidence interval surrounding the maximum drawdown statistic is large, for example at the 5 and 95 percentile level the maximum drawdown values for the Stark index ranged from -38.07% to -14.54%. Interestingly the maximum drawdown of a passive currency investment falls below the 5th percentile.

A further observation can be made about the impact that leverage has on the maximum drawdown statistic. Whereas the return to risk ratio of the AFX index is identical regardless of leverage, see AFX and AFX_2 in Figure 2, the leverage does affect the maximum drawdown. For example, the

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**Figure 2: Descriptive Statistics of Currency Indices (End of Dec 89 – End of Jan 05)**

<table>
<thead>
<tr>
<th></th>
<th>B&amp;H</th>
<th>AFX</th>
<th>AFX_2</th>
<th>AFX_2_RF</th>
<th>CISDM</th>
<th>Stark</th>
<th>Parker</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annualised Average</td>
<td>0.63%</td>
<td>1.89%</td>
<td>3.79%</td>
<td>8.05%</td>
<td>8.78%</td>
<td>6.84%</td>
<td>9.79%</td>
</tr>
<tr>
<td>Annualised Standard Deviation</td>
<td>7.88%</td>
<td>6.69%</td>
<td>13.37%</td>
<td>13.43%</td>
<td>11.41%</td>
<td>12.07%</td>
<td>9.38%</td>
</tr>
<tr>
<td>Average/Standard Deviation</td>
<td>0.08</td>
<td>0.28</td>
<td>0.28</td>
<td>0.60</td>
<td>0.77</td>
<td>0.57</td>
<td>1.04</td>
</tr>
<tr>
<td>Maximum Drawdown</td>
<td>-41.77%</td>
<td>-111.99%</td>
<td>-21.13%</td>
<td>-20.40%</td>
<td>-28.69%</td>
<td>-20.26%</td>
<td>-9.18%</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.07</td>
<td>0.76</td>
<td>0.76</td>
<td>0.77</td>
<td>1.30</td>
<td>1.25</td>
<td>1.47</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>0.79</td>
<td>1.28</td>
<td>1.28</td>
<td>1.31</td>
<td>4.37</td>
<td>5.17</td>
<td>3.67</td>
</tr>
<tr>
<td>Correlation with AFX</td>
<td>0.13</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.74</td>
<td>0.73</td>
<td>0.86</td>
</tr>
</tbody>
</table>

**Figure 3: Empirical Maximum Drawdown versus results of the Monte-Carlo Experiment (5,000 simulations)**

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empirical maximum drawdown of the original AFX was -11.19%, however twice leveraging the index results in a maximum drawdown of -21.13% i.e. the relationship is not strictly linear. In addition Figure 3 also demonstrates the impact of the risk free rate on the maximum drawdown statistic. Using the 5th percentile values of AFX_2 and AFX_2_RF, -53.80% and -41.20% respectively, we see quite clearly how the deposit rate effectively ‘cushions’ substantially the maximum drawdown statistic over long period of times.

The results of the Monte Carlo experiment also show the significance of the maximum drawdown observed empirically for each of the three indices. For example the -28.69% maximum drawdown of the CISDM index is larger [in magnitude] than that expected, as indicated by the median value, but fails to be significantly large at the 5% level. Whereas the -20.26% maximum drawdown experienced by the Stark index over the period in question is lower than that expected but again is not significantly low at the confidence level set. However, the maximum drawdown observed empirically for the Parker Index was much smaller than that expected, -9.18% versus -13.65%, and beyond the 95th percentile.

Possible reasons for the “abnormal” drawdowns

There could be a few explanations for these “abnormal” maximum drawdowns. Firstly, the underlying distribution of returns may exhibit fat tails and that is apparent from the large excess kurtosis displayed for the three “managers” indices. Secondly, the volatility of returns may not have been constant though time because of at least three factors: stochastic market volatility; varying degree of leverage from single managers; and changing composition of the index which has on the most part increased the number of programmes. Figure 4 highlights for instance that the Stark two years rolling volatility dropped from almost 25% in December 1991 to less than 5% in January 2005 whereas the market volatility, as measured by the passive basket of currency pairs, has only gone down from 9.2% to 6.3%.

Having exhibited these stylised facts, it is legitimate to ask if the managers’ indices returns are comparable through time. Keeping this in mind, the losses exhibited in 2004 may actually exceed those generated in 1994 at constant risk exposure. On the other hand, the AFX index has tended to capture a more stable fraction (at around 85% over the total period) of the market volatility. For both of these reasons, smaller kurtosis and more stable volatility, the AFX index may represent a more accurate measure of the risk-adjusted performance of active currency managers.

Conclusion: drawdown statistics may not be comparable

This article has highlighted some basic properties of the maximum drawdown statistic. When applied to currency hedge funds indices, it becomes clear that results are not comparable for a number of reasons. As a consequence, transparent proxies may be useful for analysing the performance of foreign exchange managers, including the quantification of maximum drawdown.

Footnotes:
1. The opinions expressed in the article are those of the authors, and not of the authors’ employer.
4. www.parkerglobal.com/fxindex.htm
5. The following bid/ask spreads have been applied: Eur/Usd: 0.023%, Usd/JPY: 0.029%, Usd/CHF: 0.042%, Gbp/Usd: 0.027%, Eur/JPY: 0.030%, Eur/Gbp: 0.043%, Eur/CHF: 0.019%.
By extending earlier work on factor analysis of hedge fund performance the authors increase the explanatory power of factor while still showing evidence of alpha generation.

Introduction

In the last 10 years, the hedge fund industry has experienced a tremendous increase in its assets under management. According to TASS, the value invested in hedge funds jumped from 50 bn USD in December 1993 to 673 bn USD in December 2004. The attractiveness of the asset class has mostly been driven by the promise or ability to deliver absolute returns, especially since 2000, in the context of low interest rates and falling stock markets. Generating absolute returns is directly linked to the skill of hedge fund managers and their ability to implement complex strategies. Therefore, analysis of the alpha created by hedge fund managers is central to much of the literature in the field of hedge funds. In this paper, we focus on the alpha generated by funds of funds (FoF) as this type of investment constitutes the main vehicle many institutional investors use to gain hedge fund exposure.

The multi-factor analysis framework is useful for the study hedge fund performance and alpha measurement. However, in contrast to the long only world, the application of multi-factor analysis is complicated by the strategies followed by hedge fund managers. In particular, dynamic trading and option-like payoffs inherent in hedge fund strategies violate the buy-and-hold assumption of the standard measurement of Jensen’s alpha. Fung and Hsieh (2002) develop a new framework using asset-based style factors. These factors replicate the main strategies employed by hedge fund managers. Naik and Aggarwal (2004) propose an alternative model in which the non-linear payoffs are explicitly taken into account via call and put options.

We follow the approach of Fung and Hsieh (2002) in order to decompose the returns of funds of funds. In particular, we split the factors into two categories: “traditional” factors and replicating (or “alternative”) factors. We define as “traditional” risk factors the sources of risk commonly identified and recognised in the traditional investment universe. In order to incorporate hedge fund return characteristics into the factor decomposition analysis, we include “alternative” factors aiming to replicate one particular segment of hedge fund strategies, namely trend following strategies.

The paper is organised as follows. Section 1 describes the data set and our approach to the application of the traditional factors for the analysis. Section 2 discusses the construction of the factors replicating trend following strategies. Section 3 presents the results of the analysis we conducted using various FoF indices. Section 4 summaries our conclusions.

1. Data set and traditional factors

We analyse the returns of five FoF indices between January 1994 and January 2005. The five FoF indices are taken from HFR: HFRI FoF Composite, HFRI FoF Conservative, HFRI FoF Diversified, HFRI FoF Market Defensive, and HFRI FoF Strategic. HFRI FoF Composite comprises a diversified portfolio of hedge funds which is characterised by relatively low volatility due to the range of investment styles and strategies covered by the constituent managers. HFRI FoF Conservative includes funds dedicated to
conservative strategies such as arbitrage strategies. This index is characterised by low risk and market neutrality.

HFRI FoF Diversified should be close to HFRI FoF Composite in that it includes a broad variety of strategies. It should have minimal loss in down markets and superior returns in up markets. HFRI FoF Market Defensive includes short-selling and managed futures funds. It should be negatively correlated with equity markets and exhibit higher returns during down markets than during up markets. HFRI FoF Strategic will tend to exhibit superior return and the highest volatility characteristics because it includes funds investing in emerging markets, specific sectors and equity hedged strategies.

The traditional factors used in multi-factor analysis can be split into two categories: equity related factors and interest rate related factors. Following Fama and French (1993) and Carhart (1997), the equity related factors are the market factor (proxied by the S&P500), Small Minus Big (SMB), High Book-to-Market Minus Low Book-to-Market (HML) and the momentum factor. As shown by Asness, Krail and Liew (2001), hedge fund returns may exhibit a lag with respect to the market factor because hedge funds can entail illiquid investments. Therefore in our analysis we apply a one month lag to the market factor.

The interest rate factors are the monthly change in the 3-month US Libor rate and the monthly change in the 10-year US Govt Yield to take into account the dynamic of interest rates, and the change in high yield spreads to measure the impact of credit spreads on hedge fund returns.

2. Alternative factors
Fung and Hsieh (2001) have paved the way for the identification and analytical application of factors replicating trend following strategies. In particular, they have shown that a perfect trend follower should be able to capture the difference between the minimum price and the maximum price over a given time period. This type of profile is analogous to holding a lookback straddle. The value of this straddle can be obtained either through a theoretical formula (see Gatto, Goldman and Sosin (1979)) or by rolling over standard straddles on a daily basis (see Fung and Hsieh (2001) for a full description).

However, managed futures practitioners are not perfect trend followers. They mainly apply technical models providing signals that a trend is about to start or has already emerged. These models are based chiefly on moving averages and break outs. Moreover, these funds are likely to suffer during trendless and choppy markets characterised by short-term reversals and thin trading volumes.

In the Fung and Hsieh framework, the perfect trend follower will always be able to capture the difference between the maximum price and the minimum price. In other words, he will never be wrongly positioned, whereas some managed futures might be. Only the price of the lookback option, which depends largely on the volatility of the markets, may cause some losses. Therefore, we prefer to adopt a different methodology to replicate the risk-return profile of trend following strategies.

Our construction of factors replicating trend following strategies is based on moving averages for a diversified basket of 45 futures markets including stock indices, bond and short-term interest rates, currencies and commodities. It generalises the work of Lequeux and Acar (1998) on the trend following aspect of currency traders. More specifically, the technical trading rule is given by the position of the current futures price relative to its m-day moving average. Formally, the trading signal at time t-1, B_{t-1}, is given by the following rule:

\[ B_{t-1} = 1 \text{ if } P_{t-1} > \frac{1}{m} \sum_{i=1}^{m} P_{t-i} \] (long position)

\[ B_{t-1} = -1 \text{ if } P_{t-1} < \frac{1}{m} \sum_{i=1}^{m} P_{t-i} \] (short position)

where \( P_{t-i} \) is the closing price of the futures at day t-1, and m is the number of days in the moving average. The return of the trading rule, \( R_t \), is given by:

\[ R_t = B_{t-1} \times \frac{P_t}{P_{t-1}} - 1 \]

where \( X_t \) is the arithmetic return \((P_t/P_{t-1})-1\).

The strategy for a given futures market is composed of several trading rules determined by the length of the moving averages. Based on the Lequeux and Acar (1998) methodology with a correlation target
of 0.7 between the successive trading rules, we use four moving averages: 224 days, 117 days, 61 days, and 32 days. Finally, the strategies applied to the futures markets are aggregated to form five broad trend following categories: equity with 9 underlying markets, fixed income with 7 underlying markets, short-term interest rates with 11 underlying markets, currencies with 7 underlying markets, and commodities with 11 underlying markets.

In order to compare the Fung and Hsieh approach (FH PTFS)\(^2\) and ours (RMF TF), three different managed futures indices (Stark 300 trader index, TASS Managed Futures, and Barclays CTA index) are regressed on the FH PTFS as well as our RMF TF index (see table 1). The results of the adjusted R-square clearly show our trend following moving average methodology has better replicating power than the straddle lookback one. The adjusted R-square ranges between 0.58 and 0.72 for the moving average method against the 0.25 – 0.38 range for the Fung and Hsieh method. All RMF TF factors show a significant link to the indices whereas this is not the case for the FH PTFS on interest rates. The alphas found for the RMF TF are smaller – albeit they are still positive – than the ones obtained with the FH PTFS, which indicates that RMF TF provides a better mechanism for modelling the trend following behaviour of managed futures.

**Table 1: Regression results for managed futures indices against trend following indices**

<table>
<thead>
<tr>
<th></th>
<th>Fung and Hsieh PTFS</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Stark</td>
<td>CSFB</td>
<td>Barclay</td>
<td>Stark</td>
<td>CSFB</td>
<td>Barclay</td>
</tr>
<tr>
<td>Alpha annualised</td>
<td>11.33%</td>
<td>11.42%</td>
<td>9.26%</td>
<td>5.63%</td>
<td>5.22%</td>
<td>4.93%</td>
</tr>
<tr>
<td>Factor equity</td>
<td>0.038</td>
<td>0.056</td>
<td>0.030</td>
<td>0.230</td>
<td>0.298</td>
<td>0.175</td>
</tr>
<tr>
<td>Factor fixed income</td>
<td>0.032</td>
<td>0.032</td>
<td>0.022</td>
<td>0.695</td>
<td>0.679</td>
<td>0.468</td>
</tr>
<tr>
<td>Factor interest rate</td>
<td>-0.003</td>
<td>0.000</td>
<td>-0.006</td>
<td>2.991</td>
<td>3.299</td>
<td>2.360</td>
</tr>
<tr>
<td>Factor currency</td>
<td>0.043</td>
<td>0.045</td>
<td>0.048</td>
<td>1.007</td>
<td>1.305</td>
<td>0.892</td>
</tr>
<tr>
<td>Factor commodity</td>
<td>0.062</td>
<td>0.057</td>
<td>0.056</td>
<td>0.266</td>
<td>0.230</td>
<td>0.267</td>
</tr>
<tr>
<td>Adjusted R square</td>
<td>0.32</td>
<td>0.25</td>
<td>0.38</td>
<td>0.71</td>
<td>0.58</td>
<td>0.72</td>
</tr>
</tbody>
</table>

**Table 2: Multifactor regression results for the first time period**

<table>
<thead>
<tr>
<th></th>
<th>HFRI FoF Composite</th>
<th>HFRI FoF Conservative</th>
<th>HFRI FoF Diversified</th>
<th>HFRI FoF Defensive</th>
<th>HFRI FoF Strategic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha annualised</td>
<td>1.45%</td>
<td>6.10%</td>
<td>-0.63%</td>
<td>1.04%</td>
<td>1.55%</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>0.268</td>
<td>0.079</td>
<td>0.310</td>
<td>0.135</td>
<td>0.405</td>
</tr>
<tr>
<td>S&amp;P 500; lagged</td>
<td>0.067</td>
<td>0.039</td>
<td>0.071</td>
<td>0.073</td>
<td>0.093</td>
</tr>
<tr>
<td>Small minus large cap</td>
<td>0.172</td>
<td>0.056</td>
<td>0.172</td>
<td>0.022</td>
<td>0.321</td>
</tr>
<tr>
<td>Value versus growth firms</td>
<td>0.126</td>
<td>0.079</td>
<td>0.172</td>
<td>0.157</td>
<td>0.075</td>
</tr>
<tr>
<td>Momentum spread</td>
<td>0.195</td>
<td>0.140</td>
<td>0.230</td>
<td>0.110</td>
<td>0.189</td>
</tr>
<tr>
<td>Change in 3-month US libor</td>
<td>0.662</td>
<td>0.182</td>
<td>0.355</td>
<td>1.805</td>
<td>0.886</td>
</tr>
<tr>
<td>Change in 10-year US Gov yield</td>
<td>0.481</td>
<td>-0.575</td>
<td>1.789</td>
<td>-0.118</td>
<td>-0.087</td>
</tr>
<tr>
<td>Change in high yield credit spread</td>
<td>-1.575</td>
<td>-1.575</td>
<td>-0.973</td>
<td>-1.878</td>
<td>-2.618</td>
</tr>
<tr>
<td>Trend following equity</td>
<td>0.262</td>
<td>0.123</td>
<td>0.304</td>
<td>0.259</td>
<td>0.313</td>
</tr>
<tr>
<td>Trend following fixed income</td>
<td>0.006</td>
<td>-0.083</td>
<td>0.063</td>
<td>0.227</td>
<td>-0.022</td>
</tr>
<tr>
<td>Trend following interest rate</td>
<td>0.470</td>
<td>0.460</td>
<td>-0.027</td>
<td>1.821</td>
<td>0.587</td>
</tr>
<tr>
<td>Trend following currency</td>
<td>0.145</td>
<td>0.133</td>
<td>0.140</td>
<td>0.313</td>
<td>0.121</td>
</tr>
<tr>
<td>Trend following commodity</td>
<td>0.074</td>
<td>0.039</td>
<td>0.041</td>
<td>0.050</td>
<td>0.122</td>
</tr>
<tr>
<td>Adjusted R square</td>
<td>0.75</td>
<td>0.64</td>
<td>0.71</td>
<td>0.57</td>
<td>0.75</td>
</tr>
</tbody>
</table>

**Bold** means significant at the 5% level and **bold italic** means significant at the 1% level
3. Empirical analysis

Before regressing FoF indices on the selected variables, we need to evaluate whether changes in the sensitivities have occurred between January 1994 and January 2005. For that purpose, we run a breakpoint analysis in the context of the multi-factor regression. We use the sup F statistic (see Andrews (1993)) to test whether the parameters of the regression are changing between two sub-time periods.

For the five different FoF indices we find a breakpoint occurring in January/February 2000. This is consistent with the previous finding of Fung and Hsieh (2004). Moreover, this breakpoint corresponds to the end of the equity bull market and the start of the bear market. Therefore, in order to avoid stationarity problems, we identify two distinct time periods for the regression: January 1994 to December 1999, and May 2000 to January 2004. The two different resulting regressions enable us to identify changes in the sensitivities as well as the evolution of the alpha generated by funds of hedge funds.

Tables 2 and 3 display the results of the regression. The adjusted R square of all regressions is high at 57%-86%. The sensitivities are also fairly different across the FoF indices. This implies that the range of fund of funds on offer is rather broad and may accommodate a wide spectrum of potential investors. In particular, the link to the equity markets strongly depends on the type of fund of funds. For instance, the HFRI FoF Market Defensive index is mostly neutral with respect to the stock market.

The changes between the two time periods are particularly interesting. In the later period the beta with respect to the S&P500 has declined and the link to the equity trend following index has all but disappeared. Moreover, the various FoF indices show differences with respect to interest rates. The connection moves from close to neutral during the bull market to a bearish positioning in the second time period. Funds of funds seem to adapt particularly well to the changing interest rate environment. The link to credit spreads has also weakened but is still significant in the second period. The negative sensitivity shows that hedge funds profit from a tightening of credit spreads. Finally, the link to trend following strategies has been reinforced particularly on the currency side.

The alpha generated by the FoF indices is positive in most cases showing that funds of funds add value. Over the first time period, only the HFRI FoF Conservative index exhibits a significant alpha. The claim that large inflows in the hedge fund world are

<table>
<thead>
<tr>
<th>Table 3: Multifactor regression results for the second time period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimation period: May 2000 – January 2005</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Alpha annualised</td>
</tr>
<tr>
<td>HFRI FoF Composite</td>
</tr>
<tr>
<td>4.04%</td>
</tr>
<tr>
<td>HFRI FoF Conservative</td>
</tr>
<tr>
<td>4.89%</td>
</tr>
<tr>
<td>HFRI FoF Diversified</td>
</tr>
<tr>
<td>3.74%</td>
</tr>
<tr>
<td>HFRI FoF Defensive</td>
</tr>
<tr>
<td>5.84%</td>
</tr>
<tr>
<td>HFRI FoF Strategic</td>
</tr>
<tr>
<td>2.98%</td>
</tr>
<tr>
<td>S&amp;P 500</td>
</tr>
<tr>
<td>0.151</td>
</tr>
<tr>
<td>S&amp;P 500; lagged</td>
</tr>
<tr>
<td>0.039</td>
</tr>
<tr>
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<tr>
<td>Value versus growth firms</td>
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<tr>
<td>-0.053</td>
</tr>
<tr>
<td>Momentum spread</td>
</tr>
<tr>
<td>0.040</td>
</tr>
<tr>
<td>Change in 3-month US libor</td>
</tr>
<tr>
<td>-0.289</td>
</tr>
<tr>
<td>Change in 10-year US Gov yield</td>
</tr>
<tr>
<td>-1.217</td>
</tr>
<tr>
<td>Change in high yield credit spread</td>
</tr>
<tr>
<td>-0.691</td>
</tr>
<tr>
<td>Trend following equity</td>
</tr>
<tr>
<td>0.026</td>
</tr>
<tr>
<td>Trend following fixed income</td>
</tr>
<tr>
<td>0.101</td>
</tr>
<tr>
<td>Trend following interest rate</td>
</tr>
<tr>
<td>0.288</td>
</tr>
<tr>
<td>Trend following currency</td>
</tr>
<tr>
<td>0.179</td>
</tr>
<tr>
<td>Trend following commodity</td>
</tr>
<tr>
<td>0.003</td>
</tr>
<tr>
<td>Adjusted R square</td>
</tr>
<tr>
<td>0.84</td>
</tr>
<tr>
<td>Bold means significant at the 5% level and bold italic means significant at the 1% level</td>
</tr>
</tbody>
</table>

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destroying the alpha of fund managers is contradicted by the results of the second period, where the factor analysis shows that the alpha is more positive and significant than in the first time period. In other words, hedge funds continue to represent a very interesting investment opportunity in the current market environment.

4. Conclusion
Factor analysis of hedge fund returns offers a very powerful tool for understanding the risk profile of this type of investment. Our approach mixes traditional and alternative factors with the goal of synthetically replicating hedge fund strategies, using trend following strategies as a case study. This approach improves the quality of the regression as measured by the adjusted R square. A breakpoint analysis shows that the hedge fund environment changed at the end of the bull market period in 2000. In particular, funds of funds have adapted themselves to the subsequent environment in which we have experienced a bear market as well as declining and/or low absolute levels of interest rates. Finally, our analysis indicates that in the period since 2000 hedge fund investing has generated higher positive alphas than in the period between 1994 and 2000.

Footnotes:
1. These factors were obtained from the website of Ken French: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/
2. These factors were obtained from the website of David Hsieh: http://faculty.fuqua.duke.edu/%7Edah7/HFData.htm
The HFRI Fund of Funds Composite Index calculates FOF total average performance on a monthly basis for over 1000 FOFs that meet the Index qualifications. FOFs in HFR Database are also categorised into a series of sub-indices in four categories: Strategic, Diversified, Conservative and Market Defensive. Each fund meets a series of criteria based upon historical performance characteristics, standard deviation of returns, and underlying hedge fund investments. Figure 2 describes the relationship between the four HFRI FOF Indices and HFRI Fund Weighted Composite Index of single-strategy funds. While the FOF: Strategic Index exhibits both the highest (+38.8%) and the lowest (-9.8%) year-end return for the period, the FOF: Conservative Index has a decidedly more narrow performance spread and tends to track more closely the HFRI Composite Index.

Net asset flow in the Fund of Funds industry, seen against the backdrop of FOF performance in Figure 4, hit its peak in 2002 and has brought a tremendous influx of assets into the FOF industry, moving from $75 billion in 1998 to over $370 billion as of the end of Q1 2005, according to the latest HFR Q1 2005 Industry Report.

The FOF Rankings table, below, was

<table>
<thead>
<tr>
<th>Rank</th>
<th>Fund Name</th>
<th>Last ROR</th>
<th>ROR Year 5</th>
<th>STD Year 5</th>
<th>ShR Year 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>TS Multi-Strategy Fund, L.P.</td>
<td>31/3/05</td>
<td>24.09</td>
<td>4.13</td>
<td>4.62</td>
</tr>
<tr>
<td>2</td>
<td>CMA Fund III, L.P.</td>
<td>31/3/05</td>
<td>22.14</td>
<td>7.39</td>
<td>2.39</td>
</tr>
<tr>
<td>3</td>
<td>Edison Fund Ltd. (Class D)</td>
<td>31/3/05</td>
<td>21.09</td>
<td>7.25</td>
<td>2.31</td>
</tr>
<tr>
<td>4</td>
<td>Quest Trading Managers Limited – Class A</td>
<td>31/3/05</td>
<td>20.06</td>
<td>6.72</td>
<td>2.36</td>
</tr>
<tr>
<td>5</td>
<td>Fairfax Fund Ltd. (Class D)</td>
<td>31/3/05</td>
<td>19.31</td>
<td>7.21</td>
<td>2.12</td>
</tr>
<tr>
<td>6</td>
<td>Princeton Leveraged Fund, L.P. Class B</td>
<td>31/3/05</td>
<td>18.30</td>
<td>16.21</td>
<td>0.95</td>
</tr>
<tr>
<td>7</td>
<td>Middlesex Fund Ltd. (Class D)</td>
<td>31/3/05</td>
<td>17.59</td>
<td>9.04</td>
<td>1.54</td>
</tr>
<tr>
<td>8</td>
<td>Shakti Fund Ltd. Class A</td>
<td>31/3/05</td>
<td>17.05</td>
<td>9.33</td>
<td>1.45</td>
</tr>
<tr>
<td>9</td>
<td>Essex Fund Ltd. (Class A1)</td>
<td>31/3/05</td>
<td>16.52</td>
<td>7.81</td>
<td>1.65</td>
</tr>
<tr>
<td>10</td>
<td>Oxford Fund Ltd. (Class A)</td>
<td>31/3/05</td>
<td>16.12</td>
<td>7.36</td>
<td>1.70</td>
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<tr>
<td>11</td>
<td>Raleigh Fund, L.P.</td>
<td>31/3/05</td>
<td>15.15</td>
<td>8.20</td>
<td>1.43</td>
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<td>12</td>
<td>Feel Good Investment Fund Ltd. (Class A)</td>
<td>31/3/05</td>
<td>14.05</td>
<td>10.15</td>
<td>1.08</td>
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<td>13</td>
<td>Benchmark Plus Overseas Partners Fund Ltd. Fixed Income Fund</td>
<td>31/3/05</td>
<td>13.80</td>
<td>5.15</td>
<td>2.01</td>
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<td>14</td>
<td>Santa Barbara Holdings Ltd. (Class A)</td>
<td>31/3/05</td>
<td>13.67</td>
<td>4.93</td>
<td>2.07</td>
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<td>15</td>
<td>Sussex Trading Fund Ltd. (Class A)</td>
<td>31/3/05</td>
<td>12.95</td>
<td>7.88</td>
<td>1.24</td>
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<td>16</td>
<td>Permal Fixed Income Special Opportunities Ltd. (A preferred)</td>
<td>31/3/05</td>
<td>12.81</td>
<td>6.38</td>
<td>1.50</td>
</tr>
<tr>
<td>17</td>
<td>Mountain Avenue Partners, L.P.</td>
<td>31/3/05</td>
<td>12.81</td>
<td>6.22</td>
<td>1.53</td>
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<td>18</td>
<td>GAM Trading US$ Fund Inc.</td>
<td>31/3/05</td>
<td>12.12</td>
<td>16.19</td>
<td>0.62</td>
</tr>
<tr>
<td>19</td>
<td>Benchmark Plus Overseas Partners Fund Ltd. Equity-Hedge Fund</td>
<td>31/3/05</td>
<td>11.96</td>
<td>8.67</td>
<td>1.03</td>
</tr>
<tr>
<td>20</td>
<td>Santa Barbara Market Neutral Fund, LP Levered</td>
<td>31/3/05</td>
<td>11.55</td>
<td>5.39</td>
<td>1.55</td>
</tr>
<tr>
<td>21</td>
<td>Star Navigator Fund L.P.</td>
<td>31/3/05</td>
<td>11.37</td>
<td>4.61</td>
<td>1.76</td>
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<td>22</td>
<td>K1 Global</td>
<td>31/3/05</td>
<td>11.27</td>
<td>7.71</td>
<td>1.07</td>
</tr>
<tr>
<td>23</td>
<td>Canary Fund Ltd. (Class D)</td>
<td>31/3/05</td>
<td>11.14</td>
<td>4.34</td>
<td>1.83</td>
</tr>
<tr>
<td>24</td>
<td>Star Navigator Investments Ltd.</td>
<td>31/3/05</td>
<td>11.05</td>
<td>5.75</td>
<td>1.37</td>
</tr>
<tr>
<td>25</td>
<td>Summit Private Investments, L.P.</td>
<td>31/3/05</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
compiled from funds listed from HFR Database’s selection of over 1500 fund of funds (HFR lists over 4700 total funds in its distributed Database, and covers over 7000 funds internally). The chart ranks the 25 top-ranked funds in terms of performance, standard deviation and annualised Sharpe ratio over the five-year period ending March 31, 2005.

Figure 3 plots the growth of $1,000 since 1990 for each HFRI FOF Indices as well as for the HFRI Fund Weighted Composite Index. In this chart, the FOF: Strategic Index closely mimics the HFRI Fund Weighted Index over time, mainly due to the outstanding performance observed in Equity Hedge and Emerging Market strategies, which are at the foundation of the FOF:
Strategic Index funds. Figure 5 shows maximum drawdowns are generally unaffected by market swings, stressing the fact that hedge funds exhibit a lower beta correlation to the markets, especially in the last 4-year period, where net asset flows reached a historical high.

Joshua Rosenberg, President, Hedge Fund Research (HFR)
Figure 6  Estimated Growth of Assets / Net Asset Flow Fund of Funds 1990 – Q1 2005
References and further reading


REFERENCES

Brownian Motion*, Journal of Applied Probability, Volume 41, Number 3, March, 147-161


