

# Assessing CTA Quality with the Omega Performance Measure

Winton Capital Management  
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## How to judge the quality of an investment?

	Sharpe	Sortino	Return	St Dev
Beach Discretionary	1.15	1.80	22.97	16.05
AHL Diversified	0.88	1.48	17.57	15.68
Transtrend Diversified	0.76	1.13	11.04	9.48
Rotella Standard Leverage	0.75	1.17	13.51	13.11
Winton Futures Fund	0.72	0.94	19.46	23.35
Grossman Global Macro Hedge	0.68	0.85	14.13	16.00
Aspect Diversified	0.65	0.91	15.06	19.00
Campbell & Co Global Diversified Large	0.59	0.68	11.38	13.63
Graham Global Investment	0.59	0.76	12.07	14.91
Grinham Diversified	0.53	0.76	8.93	10.19
BAREP Epsilon USD	0.51	0.62	10.40	14.11
JWH Global Diversified	0.46	0.59	13.86	28.31
Beach Systematic	0.39	0.46	9.20	16.84

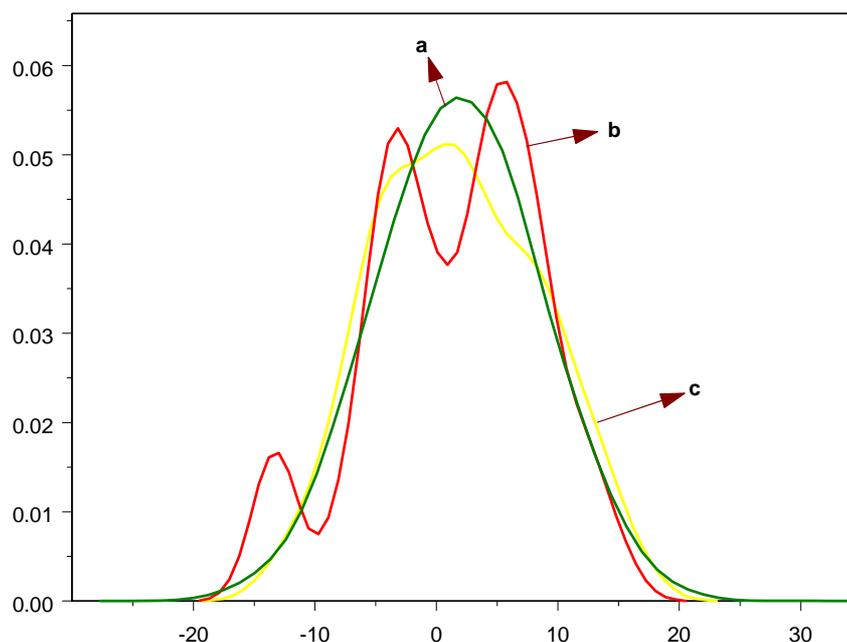
**Table 1.** Which is the best manager? A sample of top performing diversified CTAs ranked by annualised Sharpe ratio for the period October 1997-August 2003 (Aspect Diversified: December 1998-August 2003).

Rankings by Sharpe ratio are a common feature of hedge fund databases, and are frequently used as a first point of reference by investors selecting hedge fund managers. However, recent critiques of this popular performance measure have warned that when applied to hedge funds and managed futures it can hide more than it reveals about the pattern of returns, and that therefore these rankings are not only misleading but can prove dangerous for the unwary.

In this paper we use a recently introduced alternative performance measure called Omega ( $\Omega$ ) to assess Winton Capital Management's performance in the context of the managed futures industry, using the track records of a number of top performing diversified CTAs. The CTAs in our sample range from systematic programmes to global macro funds. Though we do not claim to have made a systematic selection, managers were included on the basis of long-term performance, size and reputation in the industry. In the light of a recent performance comparison by *EuroHedge* magazine (*EuroHedge Industry Research 2003*), closer attention will be paid to Winton's performance against AHL and Aspect Capital.

## Mean-Variance Performance Measures: A little knowledge is a dangerous thing

Over the past couple of years we have taken part in a lively critique of popular risk-adjusted performance measures, particularly the Sharpe ratio. Critics of the Sharpe ratio have pointed out that traditional mean-variance analysis is ill-suited to investment strategies which generate non-normal return distributions.



**Figure 1.** Three distributions with the same mean and standard deviation.

The risks of ignoring the precise shape of a return distribution are illustrated by the hypothetical graph in **Figure 1**, which illustrates three distributions which share the same mean and standard deviation but differ clearly in other significant respects. If they represented the return distributions of three funds, they would have the same Sharpe ratios, but would show markedly different propensities for extreme returns. Investors who place great emphasis on mean-variance based performance measures may be allowing themselves to believe that they are investing in the normal bell curve of (a) when in fact they are more likely to be investing in (c) or even (b). As it happens, (c) is the return distribution of an actual CTA, (a) is the normal distribution with the same mean and variance, while (b) is a distribution with the same mean and variance created by a random number generator.

Hedge funds in general are characterised by non-normal return distributions, both as individual funds (see recently Kat & Lu 2002), and when combined into portfolios or funds of funds (Kat & Amin 2003). Their divergence from

normality becomes apparent when higher moments of their return distributions (skewness and kurtosis) are taken into account. These give vital information about the shape of the return distribution, which is lacking in the mean-variance measures but is vital for assessing the risk of an investment, such as the propensity for extreme negative losses which is signified by the negative skewness of many hedge funds.

Similar limitations apply to the Sortino ratio, a modified mean-variance measure which uses only the downside volatility of a distribution. This has the advantage over the Sharpe ratio of removing from the calculation excess and frequently misleading data, which may, for instance, penalise a fund for extreme positive returns (Harding 2003). However, it adds no further information on the shape of the return distribution.

Because they convey no information on crucial aspects of the shape of the return distribution, simple mean-variance measures like the Sharpe & Sortino ratios tend to conceal and even understate certain types of systematic risks peculiar to hedge funds (Asness et al. 2001; Goetzmann et al. 2002; Lo 2001; Lux 2002).

## **Introducing Omega**

Practitioners have known instinctively that there is more information to be gleaned from historical returns than what is captured in the mean-variance measures, and that it must be possible to employ a more information-rich performance metric to enable safer and more meaningful investment decisions.

The search for an unequivocal and intuitive performance measurement has progressed with the introduction of Omega ( $\Omega$ ), a “universal” performance measure, which was designed to redress the information impoverishment of traditional mean-variance statistics (Keating & Shadwick 2002a, b). The Omega metric has two great advantages over traditional measures. Firstly, it is designed to encapsulate all the information about the risk and return of a portfolio that is contained within its return distribution, thus redressing the shortcomings discussed in the previous section. Secondly, its precise value is directly determined by each investor’s risk appetite.

Omega is the probability-weighted ratio of gains over losses at a given level of expected return. The ratio determines, in the words of the measure’s originators, “the quality of our investment ‘bet’ relative to the return threshold” (Keating & Shadwick 2002a).

We have used the Omega function to rate a number of managed futures managers with some very interesting results. Our analysis shows that the information drawn from the higher moments of managers’ return distributions can contradict the conclusions drawn from traditional mean-variance analysis. This confirms the warning from the critics (above) that highly significant

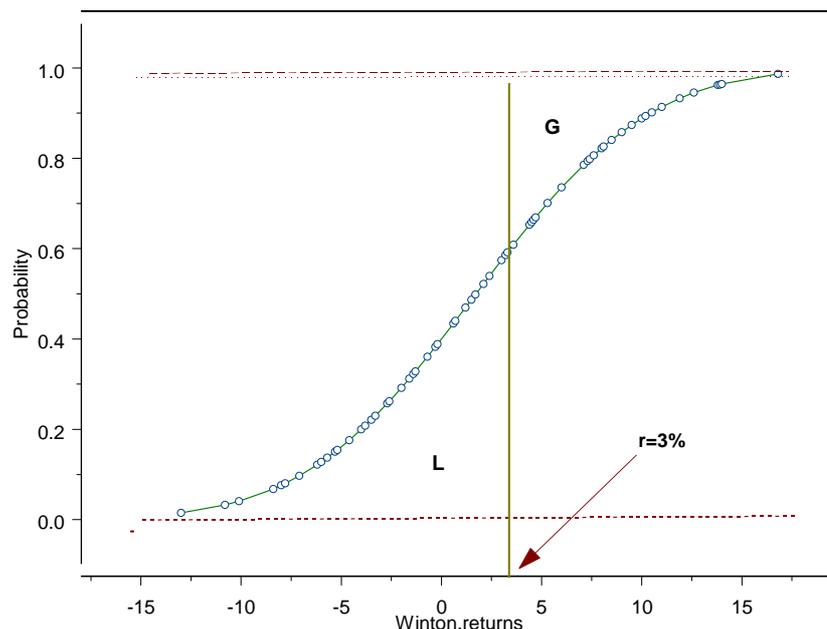
information is being ignored through over-reliance on the Sharpe, or even the Sortino, ratio.

## Omega Calculation

Following Keating and Shadwick, we will construct the Omega function step by step and then we will proceed to define it mathematically.

The only piece of information required to begin with is the return series of a fund or portfolio. The first step is to generate the empirical cumulative distribution function (CDF) of these returns.

The next step is to specify a specific level of return  $r$  which will be our threshold value. This threshold will be specific to each investor, and determined by their risk appetite. While one investor may be satisfied with any level of positive returns, another may regard gains of less than 2% as a loss. They would set  $r$  at 0% and 2% respectively. Using this threshold we can partition the CDF into two areas, say G and L (G stands for the gains area and L for the losses area - see **Figure 2**).



**Figure 2.** Cumulative distribution function (CDF) of the Winton Futures Fund (October 1997-August 2003).

What we have done so far is to partition the cdf of returns into a probability-weighted gains area (G) and a probability-weighted losses area (L). It is crucial to note that the loss threshold is an exogenous parameter and it is the input we need in order to apply the calculations in the next step according to the return objective of each individual investor.

Having completed these steps we can now define the Omega function:  $\Omega(r)$  as the probability weighted ratio of gains to losses subject to a given loss threshold  $r$ :

Definition: If  $(a, b)$  is the interval of returns and  $F$  is the CDF of these returns then we define the Omega function as follows:

$$\Omega(r) = \frac{\int_a^b (1 - F(x)) dx}{\int_a^r F(x) dx} = \frac{G}{L} \quad \text{for every level of return } r \quad (1)$$

In our example, we have used the monthly returns series of Winton Futures Fund and plotted the cumulative distribution function of these returns. Subject to a loss threshold  $r=3\%$  it is quite easy to see how we can implement the Omega calculation based on formula (1).

### Some properties of Omega – Remarks

Several features of Omega are worth noting at this point:

1. At a given level of return, using the very simple rule of preferring more to less, we should always prefer a portfolio with a higher value of Omega in comparison with one with a lower Omega. The portfolio with the higher Omega has a greater probability of delivering returns which match or exceed the  $r$  threshold. Thus, in practice, Omega allows us to compare returns for different asset classes and rank them according to their Omegas.
2. Omega goes beyond the mean-variance framework since it incorporates any higher moment effects (skewness, kurtosis and beyond). While traditional mean-variance approaches rely on an approximation of normality, Omega is, in a rigorous mathematical sense, equivalent to a return distribution, rather than an approximation of it (Keating & Shadwick 2002b). Using Omega to capture the behaviour of hedge fund return distributions gives a more information-rich, and therefore reliable, assessment of return versus risk.
3. An advantage of Omega calculation is that it requires no estimates of higher moments. There is also empirical evidence that it works reasonably well for relatively small samples.
4. The return threshold ( $r$ ) is set according to investor preference and situation, offering a tailored performance measure, while avoiding the tyranny of a benchmark<sup>1</sup>. The mechanism for rating investments at a

specific level of expected return offers a very useful tool, particularly in situations where investors need to overcome a return hurdle, such as those created by sales “wraps”.

5. For  $r$  equal to the mean ( $\mu$ ) return of an observed return series:

$$\Omega(r = \mu) = 1, \text{ since } G = L.$$

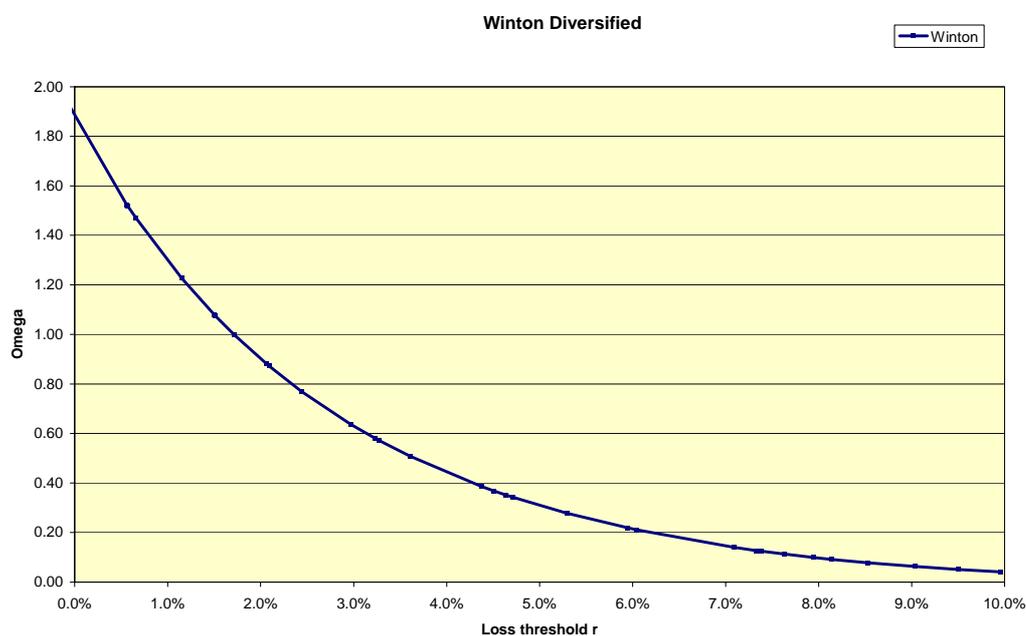
6. As  $r$  goes up, Omega goes down (i.e.  $\frac{\partial \Omega}{\partial r} < 0$ , for any  $r$ )

In the following section we use the Omega metric to compare Winton to a number of other CTAs.

### Empirical Analysis - Implementation

In our analysis we have used monthly returns data for the period October 1997-August 2003 since Winton’s inception<sup>ii</sup>. We have calculated Omega for thresholds  $r$  in the 0-10% range applied to monthly returns.

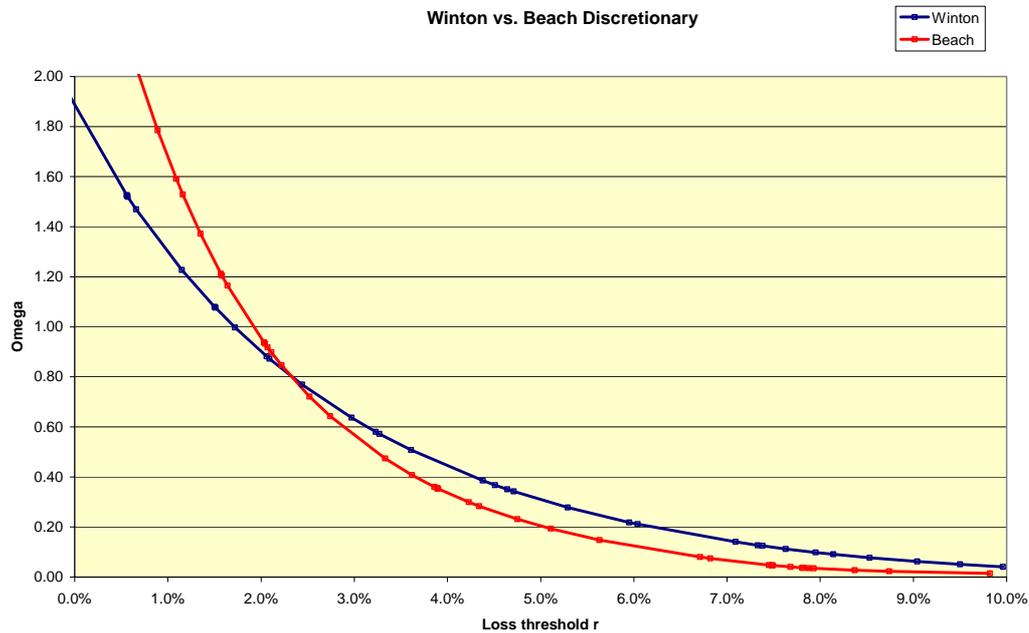
Plotting the results of the Omega calculation for Winton’s returns against the range of  $r$  values produces the expected downward curve (**Figure 3**) -(see Keating & Shadwick 2002b).



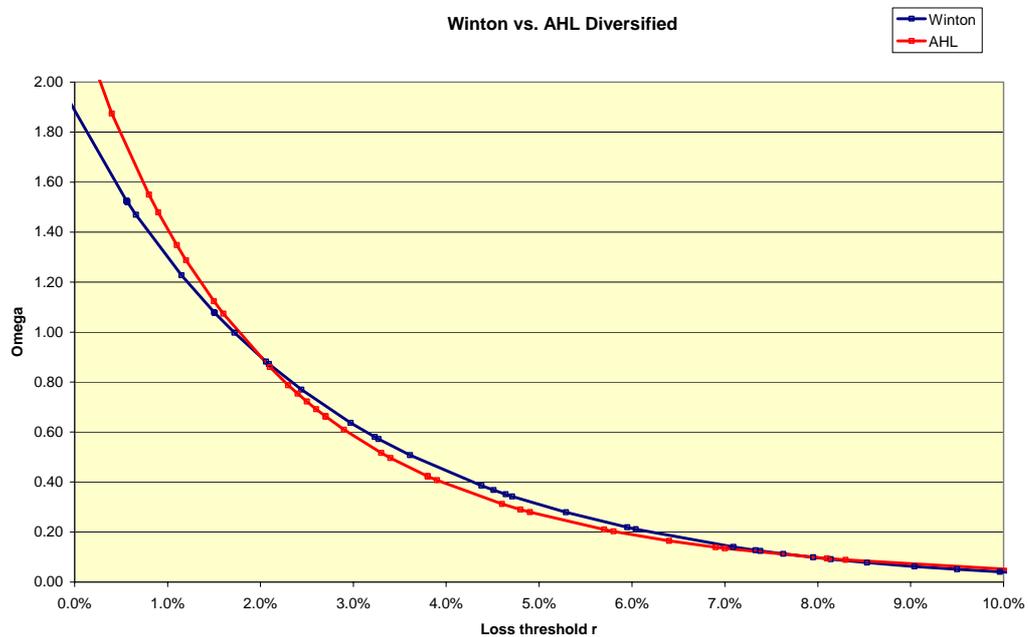
**Figure 3.** Omega curve for the Winton Futures Fund.

In the next step we compare Winton’s “Omega behaviour” to some of its peers in the managed futures industry. Specifically, we compare Winton’s performance with each of the funds in **Table 1**.

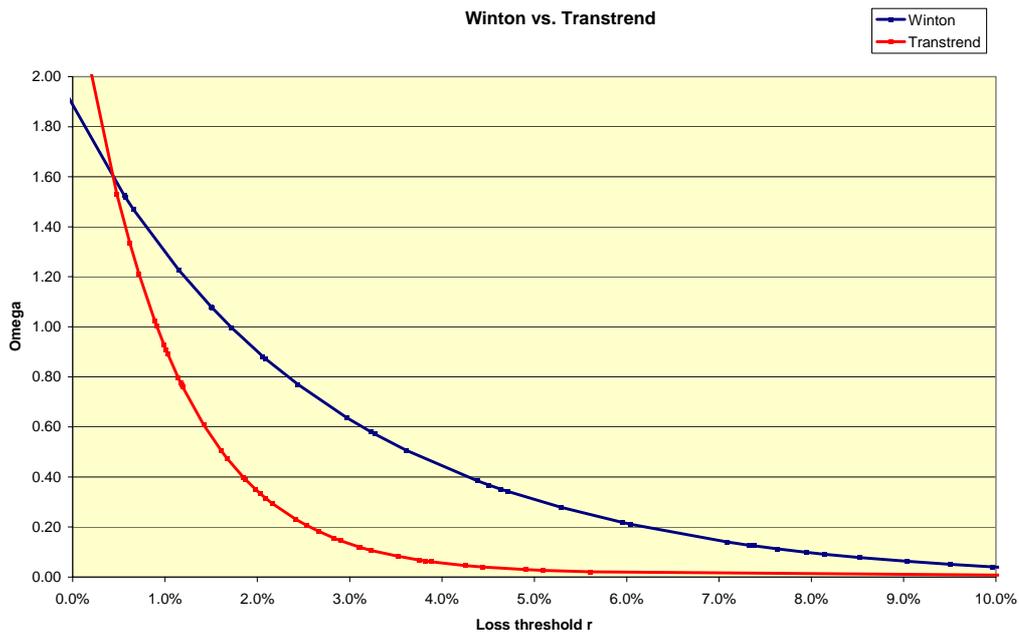
One-to-one comparisons are illustrated by **Figures 4-15**. **Tables 2-4** give revised rankings for these managers using Omega.



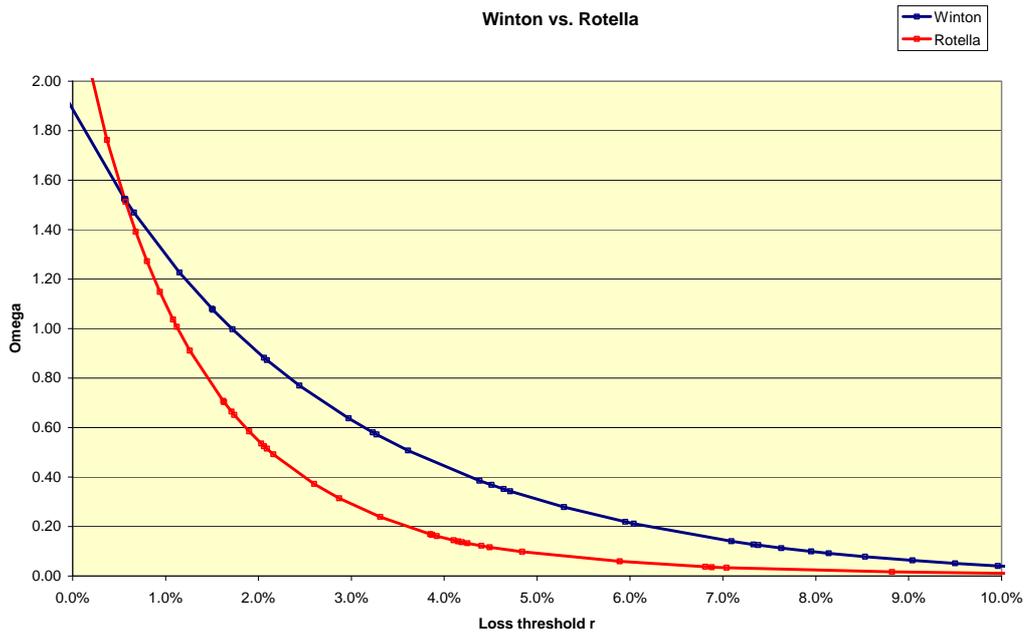
**Figure 4.** Omega curve for Beach Discretionary.



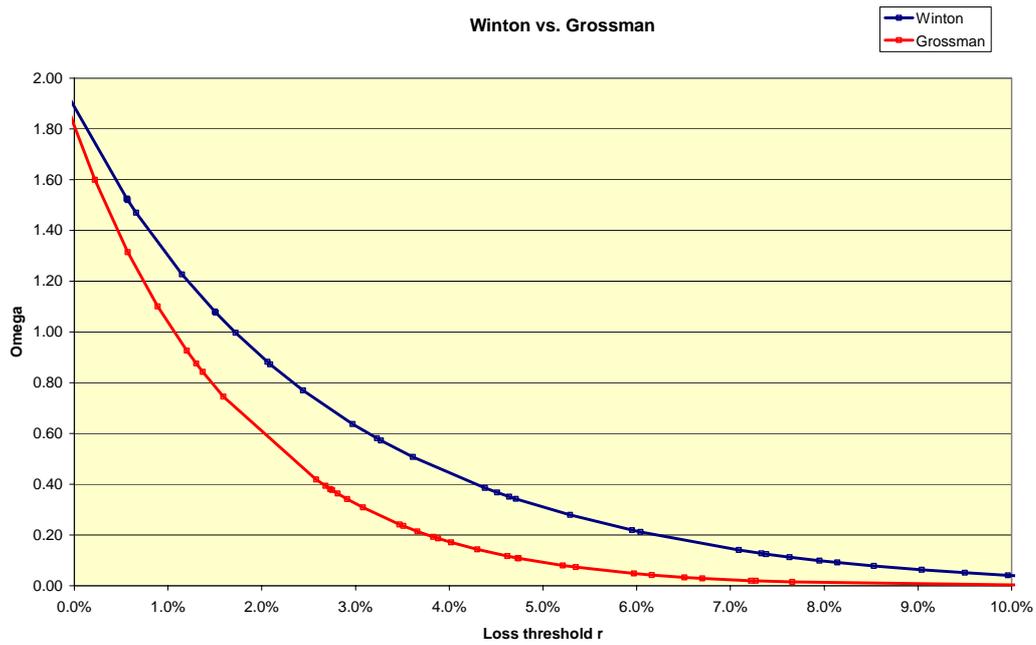
**Figure 5.** Omega curve for AHL Diversified.



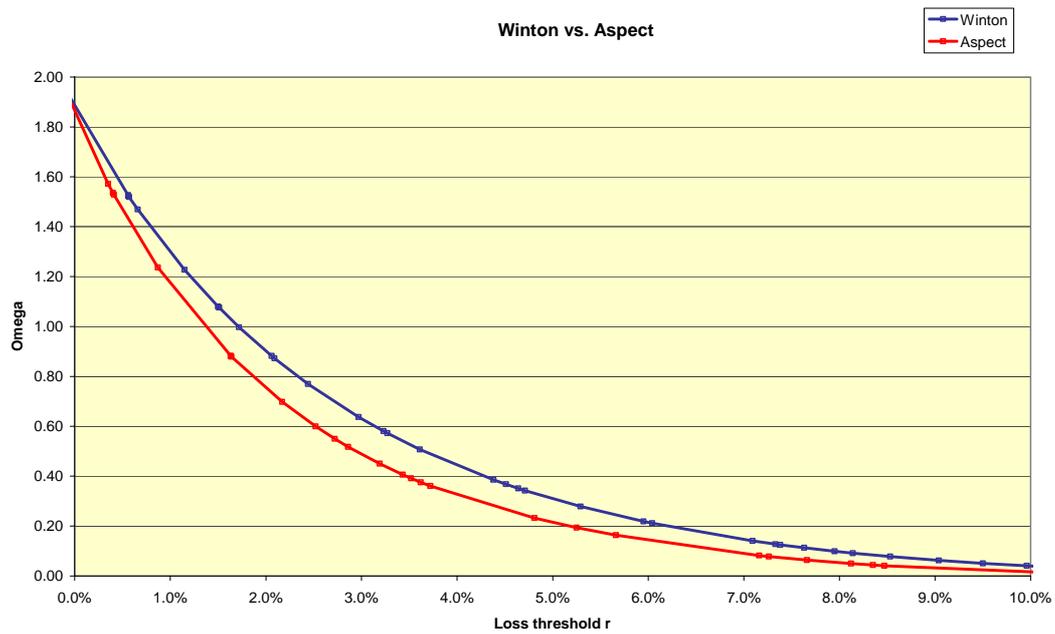
**Figure 6.** Omega curve for Transtrend Diversified.



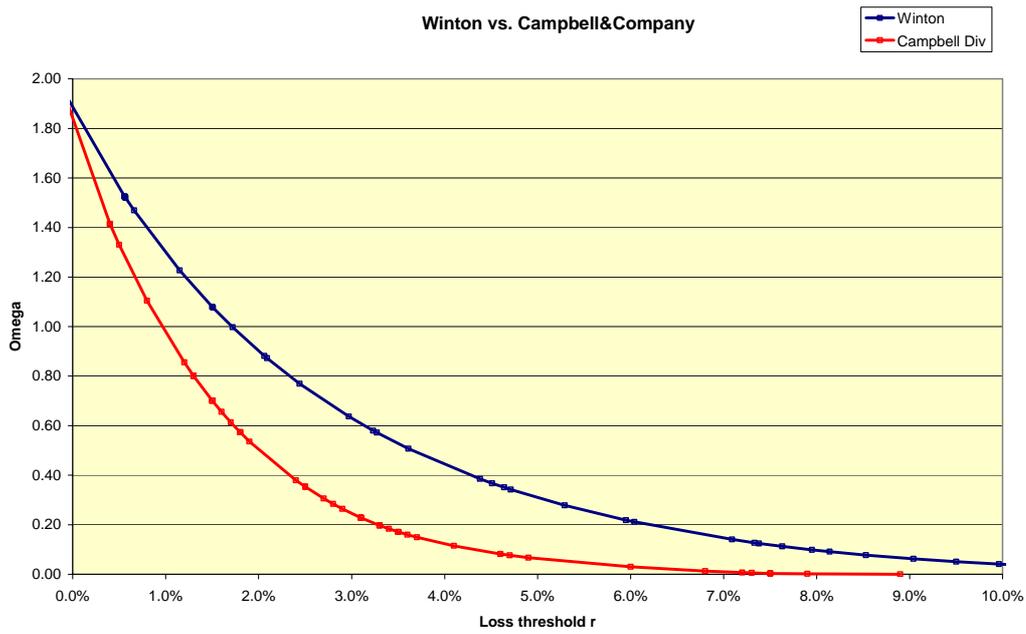
**Figure 7.** Omega curve for Rotella Standard Leverage.



**Figure 8.** Omega curve for Grossman Global Macro (QFS).



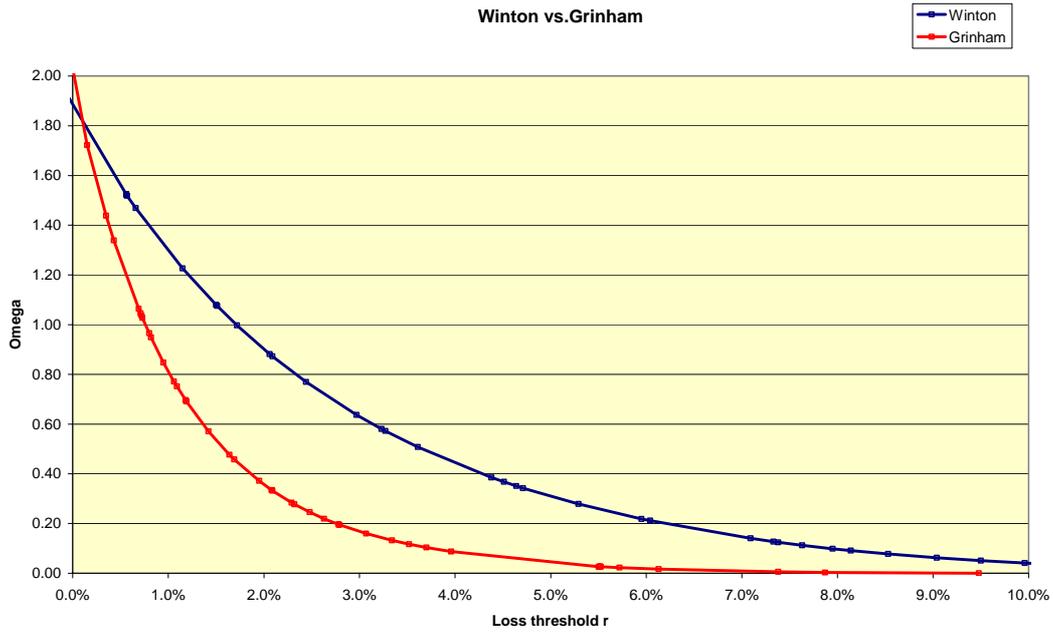
**Figure 9.** Omega curve for Aspect Diversified.



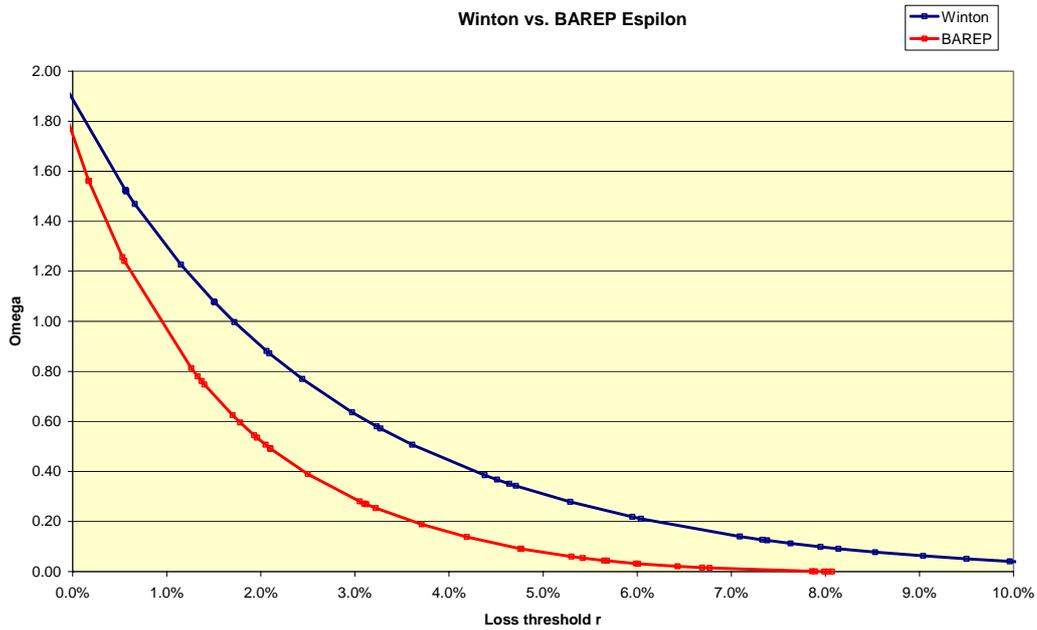
**Figure 10.** Omega curve for Campbell & Co. Global Diversified Large Portfolio.



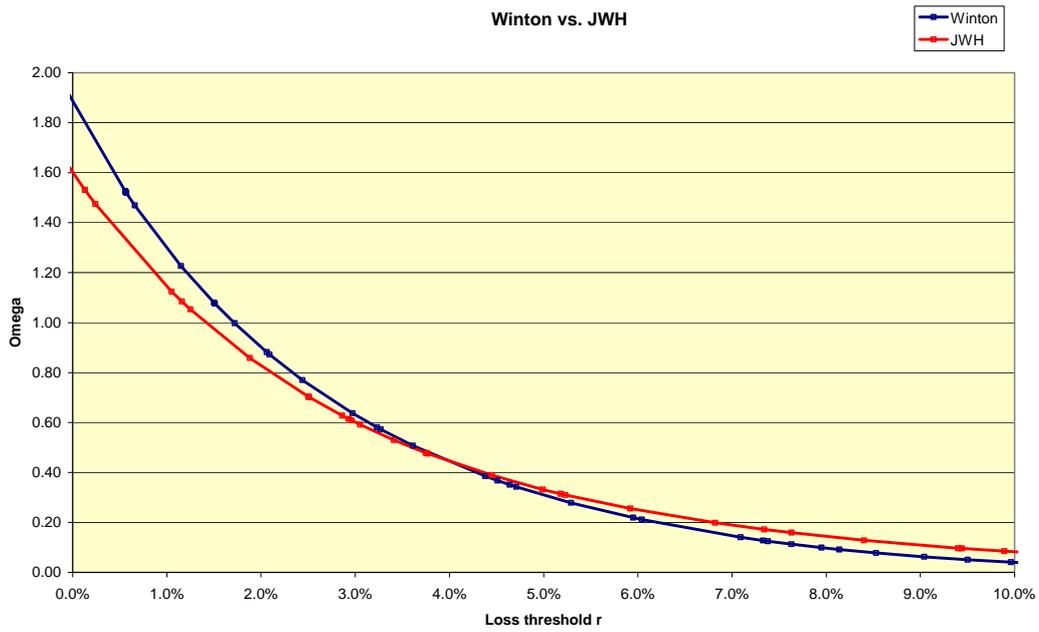
**Figure 11.** Omega curve for Graham Global Investment.



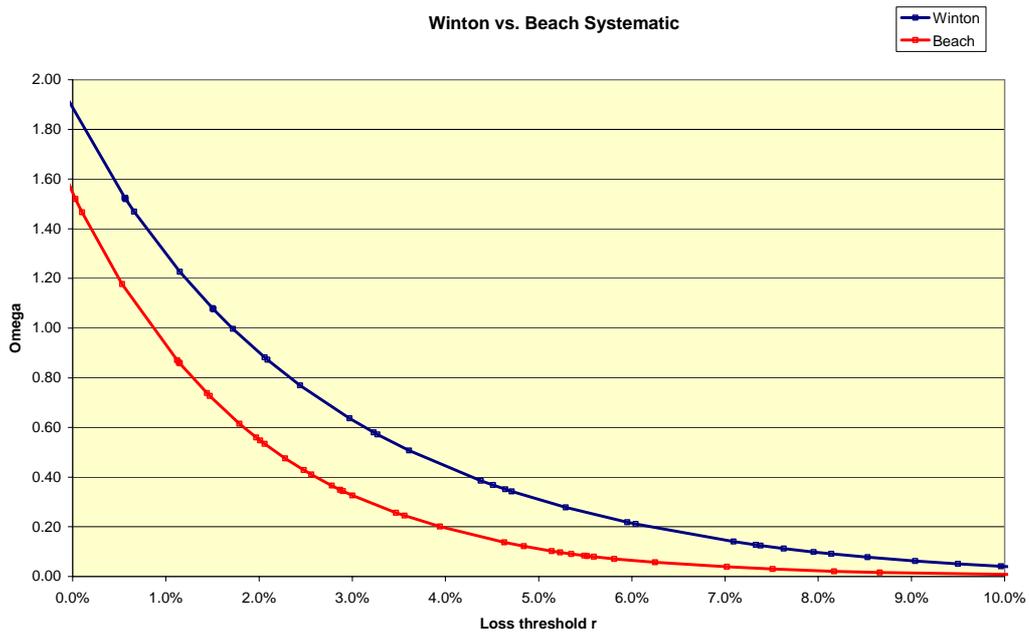
**Figure 12.** Omega curve for Grinham Diversified.



**Figure 13.** Omega curve for BAREP Epsilon.



**Figure 14.** Omega curve for JWH Global Diversified.



**Figure 15.** Omega curve for Beach Systematic.

<b>Omega</b>	<i>r=1%</i>	<i>Sharpe Rank</i>
<i>Beach Discretionary</i>	1.78	1
<i>AHL Diver.</i>	1.48	2
<i>JWH</i>	1.47	13
<i>Winton (Fund)</i>	1.47	6
<i>AHL Alpha</i>	1.34	3
<i>BAREP- Epsilon</i>	1.24	12
<i>Aspect Capital</i>	1.24	8
<i>Beach Systematic</i>	1.18	14
<i>Rotella Capital</i>	1.15	5
<i>Campbell &amp; Company.</i>	1.10	9
<i>Grossman</i>	1.10	7
<i>Graham Global</i>	1.03	10
<i>Transtrend</i>	0.93	4
<i>Grinham</i>	0.85	11

**Table 2.** Top performing CTAs ranked according to Omega for  $r=1\%$  average monthly return alongside their original Sharpe ratio rankings.

<b>Omega</b>	<i>r=3%</i>	<i>Sharpe Rank</i>
<i>Winton (Fund)</i>	0.64	6
<i>Beach Discretionary</i>	0.64	1
<i>AHL Diver.</i>	0.61	2
<i>JWH</i>	0.61	13
<i>Aspect Capital</i>	0.52	8
<i>AHL Alpha</i>	0.48	3
<i>Graham Global</i>	0.40	10
<i>BAREP- Epsilon</i>	0.39	12
<i>Grossman</i>	0.34	7
<i>Beach Systematic</i>	0.33	14
<i>Rotella Capital</i>	0.31	5
<i>Campbell &amp; Company.</i>	0.26	9
<i>Grinham</i>	0.20	11
<i>Transtrend</i>	0.16	4

**Table 3.** Top performing CTAs ranked according to Omega for  $r=3\%$  average monthly return alongside their original Sharpe ratio rankings.

<b>Omega</b>	<i>r</i> =5%	Sharpe Rank
<i>Winton (Fund)</i>	0.34	6
<i>JWH</i>	0.33	13
<i>AHL Diver.</i>	0.28	2
<i>Aspect Capital</i>	0.23	8
<i>Beach Discretionary</i>	0.23	1
<i>AHL Alpha</i>	0.16	3
<i>Beach Systematic</i>	0.12	14
<i>Graham Global</i>	0.12	10
<i>Grossman</i>	0.11	7
<i>Rotella Capital</i>	0.10	5
<i>BAREP- Epsilon</i>	0.09	12
<i>Grinham</i>	0.09	11
<i>Campbell &amp; Company.</i>	0.07	9
<i>Transtrend</i>	0.04	4

**Table 4.** Top performing CTAs ranked according to Omega for  $r=5\%$  average monthly return alongside their original Sharpe ratio rankings.

Several important points arise from these comparisons:

The rankings are radically reconfigured by the Omega metric, with many of the top ranking programmes according to the Sharpe ratio relegated further down the tables. Furthermore, the rankings differ considerably depending on where we have set the return threshold  $r$ . This indicates that the suitability of an investment is not an absolute, but is closely dependent on an investor's return specifications.

Winton performs substantially better in the Omega calculations, particularly for  $r$  values above 2.4%, indicating that it is well-suited to investors at all levels, but is especially advantageous for investors who demand higher returns. In six out of twelve comparisons Winton outperforms at all thresholds, while in all but one cases Winton returns higher Omega values at higher thresholds.

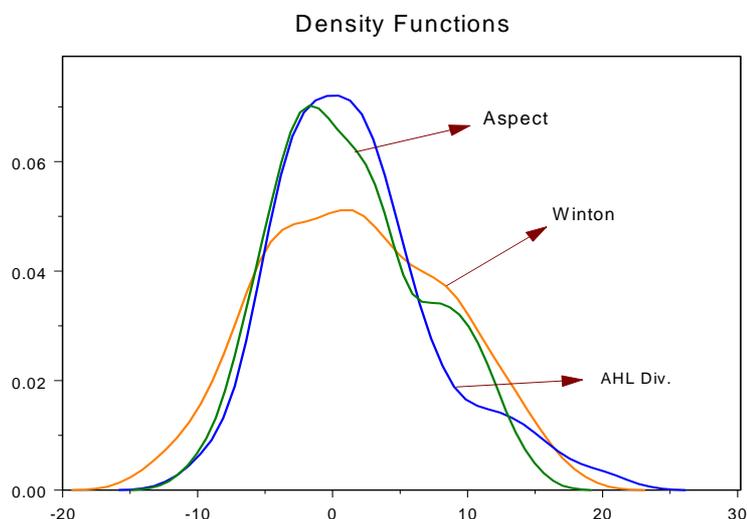
While there are some cases where the one-to-one comparison based on the Omega metric gives the same result as the Sharpe and Sortino ratios. This is the case for Winton vs. Grossman Global Macro Hedge (**Figure 8**), Winton vs. Aspect Diversified (**Figure 9**), Winton vs. Campbell & Co. Global Diversified Large Portfolio (**Figure 10**), Winton vs. Graham Global (**Figure 11**), Winton vs. BAREP Epsilon (**Figure 13**) and Winton vs. Beach Systematic (**Figure 15**). Where managers outperform Winton in the Sharpe rankings, the Omega rankings are more specific: these managers outperform Winton only for lower  $r$  values (up to  $r=2.4\%$  for Beach Discretionary (**Figure 4**),  $2.1\%$  for AHL Diversified (**Figure 5**),  $0.5\%$  for Transtrend Diversified (**Figure 6**) and  $0.6\%$  for Rotella Standard Leverage (**Figure 7**)), but Winton shows superior performance at the higher thresholds indicating that it offers better value for investors who demand higher returns.

Keating and Shadwick predict such reclassifications to arise when the higher moments of a distribution are highly significant (2002b). In these cases, as the more information-rich measure, Omega should override mean-variance metrics.

### Winton, AHL & Aspect: back to basics

We can explore these results in greater detail by returning to more familiar territory. We will limit our discussion to three programmes: Winton, AHL Diversified and Aspect Diversified by presenting some comparative statistics from the first four moments of their return distributions (mean, variance, skewness and kurtosis). This will allow us to fulfil two objectives. In the first instance, we will be able to look at the Omega results in more established terms. Secondly, the analysis will allow us to revisit the comparison between the three programmes discussed recently in the industry magazine *EuroHedge* (EuroHedge Industry Research 2003), a comparison which is salient in many investor's minds due to the "genetic" relationship between the three managers.

The probability density functions for the monthly returns of the three programmes (**Figure 16**) shows clearly that the distributions are far from normal, and indicates that a standard mean-variance analysis is likely to be misleading. The summary statistics on these distributions (**Table 5**) confirm this impression.



**Figure 16.** Probability density functions of the monthly returns of Winton (yellow), AHL Diversified (blue) and Aspect (green).

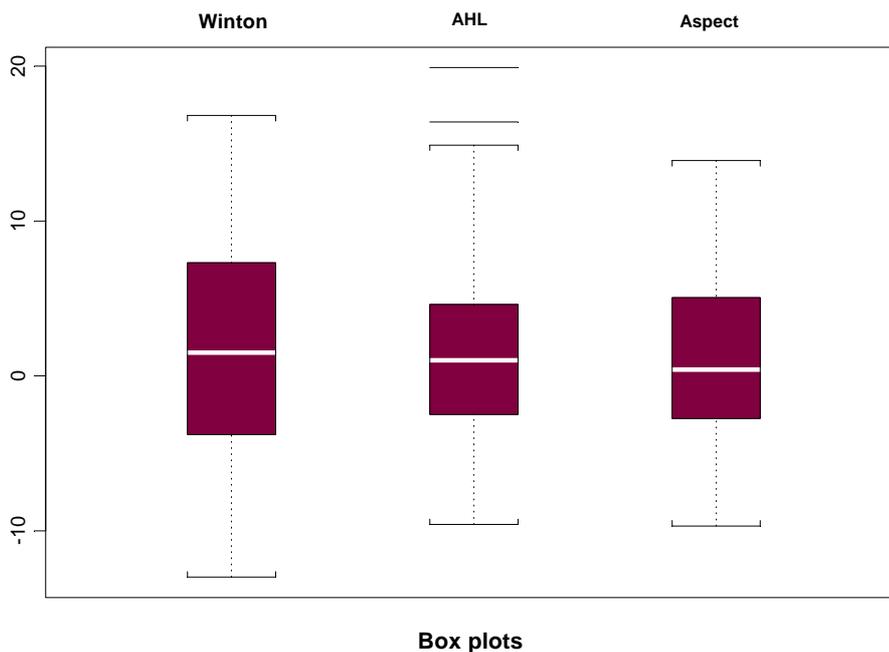
*** Summary Statistics for data in: Omega ***			
	Winton	AHL	Aspect
Min:	-13.0000000	-9.6000000	-9.7000000
1st Qu.:	-3.7250000	-2.4250000	-2.7250000
Mean:	1.7242857	1.7585714	1.3446429
Median:	1.5000000	1.0000000	0.4000000
3rd Qu.:	7.2500000	4.4250000	4.9250000
Max:	16.8000000	19.9000000	13.9000000
Std Dev.:	6.7931004	5.8666953	5.5238300
Skewness:	0.1054382	0.8709311	0.3456595
Kurtosis:	-0.6600990	0.8256165	-0.5902339

**Table 5.** Summary statistics of monthly returns for Winton, AHL Diversified and Aspect.

Winton's pure returns would put it in second place, between AHL and Aspect. However, Winton has the highest standard deviation of the three, and as a result would be considered the "riskiest" by conventional measures. The *Hedge Fund Review* analysis concluded on this basis that Winton's high performance may be attributed in part to the use of higher leverage, which results in greater volatility.

All three return distributions are positively skewed, meaning that they show a greater potential for large positive returns and a more limited potential for negative returns; however, Winton's returns exhibit the lowest coefficient of skewness of the three. On the other hand, Winton's distribution has the lowest kurtosis, which indicates that the returns are more dispersed about the mean.

Given the non-normality of all three distributions, it would be useful at this stage to examine how the monthly return values are actually distributed, as opposed to the "normalising" assumptions engendered by the mean and standard deviation. A series of box plots allows us to better visualise this information (**Figure 18**). A box plot is a graphical display of a five number summary (minimum value, 1st quartile, median, 3rd quartile and maximum value) and it effectively displays the locations of the basic characteristics of a distribution. A horizontal line within the rectangle represents the median and the top and bottom areas of the rectangle are the upper and lower quartiles. In the case of AHL the plot also shows two outliers, suggesting that the mean-variance description of the distribution is not painting an accurate picture.



**Figure 18.** Box plots of the distribution of monthly returns for Winton, AHL Diversified and Aspect.

The box plot represents the middle 50% of a distribution, which is the most significant portion in terms of probability mass and its positioning is less affected by outliers. We can see that for the case of Winton the main body of the data is located in the area (-3.725%, 7.25%) while for AHL and Aspect the corresponding ranges are (-2.425%, 4.425%) and (-2.725%, 4.925%) respectively. Winton's median return value is substantially higher, at 1.5%, than either AHL (1%) or Aspect (0.4%).

The plots show clearly that even though the main body of Winton's returns commences from a slightly lower level than the other two programmes, it extends significantly further into positive territory (7.25% compared to 4.425% and 4.925% respectively). Thus, while the dispersion of Winton's returns may make it appear risky by mean-variance measures, more detailed observation of the shape of the distribution shows them to be distributed mainly in the higher values, while the downside is not significantly lower than that of the two managers in this comparison.

In this section we have taken a longer route to reach these general conclusions. Moreover, juggling in the region of ten different measurements we are unable to make any definitive statements, or to differentiate between different return thresholds. The Omega measure allows us to make these comparative assessments using only one number, while matching our ratings to levels of investor preference.

## Conclusions

In this paper we used the new Omega performance measure to evaluate the results of the traditional Sharpe ratio rankings of CTAs. Our analyses have shown that radically different results are obtained when taking into account the non-normal features of CTA return distributions. This less idealised measure gives a much more accurate assessment of the risks involved in different trading programmes, and therefore offers a more reliable basis for comparison. A comparison of Winton with a number of high performing peers in the managed futures industry has in many cases reversed the impression given by the standard mean-variance measures and has demonstrated Winton to be one of the most competitive managers in the sample, particularly for investors seeking higher returns.

**Further information and research by Winton Capital Management can be found at <http://www.wintoncapital.com/>**

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## Endnotes

<sup>i</sup> Having formula (1) as starting point we could employ a more abstract framework in order to deal with more complex investor preferences. This is beyond the scope of this paper, but we mention some elements below (for further details see Darsinos & Satchell 2003).

In order to fully describe the risk preference/aversion of an investor for various levels of return it would be ideal if we could employ a utility function. This function would allow us to quantify clients’ trade-off between portfolio risk and expected return by assuming that investors can assign a welfare or ‘utility’ score to any investment portfolio.

If the investment outcome  $R$  is greater than the specified loss threshold  $r$  then we have some utility function  $G(R - r)$ , otherwise some other function  $L(r - R)$  would describe the resulting level of utility.

Based on the above remarks we can re-write formula (1) as follows:

$$U(r) = \frac{E[G(R-r)/R > r]}{E[L(r-R)/R \leq r]} \quad \text{for any level of } r \quad (2)$$

In this context, the function  $U$  is the expected utility of gains divided by the expected utility of losses.

In order to proceed any further with the numerical implementation of formula (2) we need to input the utility functions  $G$  and  $L$ , which would summarise the investor’s requirements. This provides us with the theoretical means of generalising the Omega function to incorporate more specific demands on the part of investors.

<sup>ii</sup> Returns for Aspect Diversified are only available for the period December 1998-August 2003, but have been included for the sake of completeness.

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