Different risk-adjusted fund performance measures: a comparison

Pilar Grau-Carles,[1] Jorge Sainz and Luis Miguel Doncel

Department of Applied Economics I

Rey Juan Carlos University

Spain

Abstract

Traditional risk-adjusted performance measures, such as the Sharpe ratio, the Treynor index or Jensen's alpha, based on the mean-variance framework, are widely used to rank mutual funds. However, performance measures that consider risk by taking into account only losses, such as Value-at-Risk (VaR), would be more appropriate. Standard VaR assumes that returns are normally distributed, though they usually present skewness and kurtosis. In this paper we compare these different measures of risk: traditional ones vs. ones that take into account fat tails and asymmetry, such as those based on the Cornish-Fisher expansion and on the extreme value theory. Moreover, we construct a performance index similar to the Sharpe ratio using these VaR-based risk measures. We then use these measures to compare the rating of a set of mutual funds, assessing the different measures' usefulness under the Basel II risk management framework.

[1] Corresponding autor:
Pilar Grau-Carles
Department of Applied Economics I, Rey Juan Carlos University
Pº de los Artilleros s/n; 28032; Madrid; Spain
Email: pilar.grau@urjc.es

1 Introduction

Over the last few years different regulations designed to control the risk of managed funds and financial exposures have emerged based on the spirit of the so-called Basel I and Basel II accords, aiming to ensure the longevity of markets, reduce the probability of runs, and ensure transparency in markets. As a result, the Securities and Exchange Commission (SEC) now requires quantitative information on market risk (Alexander and Baptista, 2002), while in Europe two directives from the Commission — the European Union Savings Directive and the Market and Financial Instruments Directive (MiFID) — forces banks to, among other things, disclose information on counterparts and increase information on other risk issues (Doncel, Reinhart and Sainz, 2007).

In this framework, traditional measures of portfolio risk and performance, like the ones developed by Sharpe (1966), Treynor (1966) or Jensen (1968), may offer a superior and natural extension of the use of VaR measures (Alexander and Baptista, 2003). Sentana (2003) shows how the use of the latter approach with respect to the mean-variance approach, proposed in the three papers cited above, implies a cost to the manager that can be traced back to the design by the regulator. Nevertheless, as Liang and Park (2007) point out, traditional risk measures are not able to capture the exposure of current financial products, but the development of new measures is still in its infancy.

In the mean-variance approach, portfolio risk is measured using the standard framework described in Markowitz (1952), namely, using variance and covariance in the form of sigma or beta. Those measures of risk have been criticized from a behavioral point of view, as investors do not dislike variability per se and disregard higher moments of the return distribution. They like positive large returns or unexpected gains, but they are averse to losses. Thus, a way to avoid this objection is to take into account only losses or downside variability. A measure that can take into account only losses is Value-at-Risk (VaR), which represents a “worst case scenario” measure of risk. Following the definition issued in April 1995 by the Basel Committee on Banking Supervision, VaR is defined as *the maximum loss corresponding to a given probability over a given horizon.* This measure helps to determine capital adequacy requirements for commercial banks and can also be used to set limits on transactions and evaluate risk-adjusted investment returns. Because of its simplicity and intuitive appeal, VaR has become a standard risk measure.

Traditional VaR calculations assume that returns follow a normal distribution (Jorion, 2001), but deviations from the normal distribution are generally accepted, and financial return distributions show skewness and kurtosis, which become more pronounced with the frequency of the financial data (Cont, 2001). The existence of fat tails indicates that extreme outcomes happen more frequently than would be expected by the normal distribution. Similarly, if the distribution of returns is significantly skewed, returns below the mean are likely to exceed returns above the mean. In other words, ignoring higher moments of the distribution implies that investors are missing important parts of the risk of the fund.

Favre and Galeano (2002) introduced the modified VaR, which adjusts risk, taking into account skewness and kurtosis using the Cornish-Fisher (1937) expansion. This adjustment has been proved to be especially relevant in the analysis of hedge funds, as shown in Gregoriou and Gueyie (2003), Gregoriou (2004) and Kooli *et al*. (2005). Jaschke (2001) offers details and a thorough analysis of the Cornish–Fisher expansion in the VaR framework.

Another approach would be to model only the tail of the distribution, in order to precisely predict an extreme loss in the portfolio's value. Extreme value theory (EVT) provides a formal framework to study the tail behavior of the distributions. The use of EVT for risk management has been proposed in McNeil (1998), Embrechts (2000) and Gupta and Liang (2005), among others. The main advantage of EVT is that it fits extreme quantiles better than conventional approaches for heavy tailed data and allows the different treatment of the tails of the distribution, which, in turn, allows for asymmetry and separate study of gains and losses.

The novelty of this paper lies in the use of the VaR calculation of losses using EVT and applying it as a risk measure to construct a performance index similar to the Sharpe ratio. To our knowledge, this is the first time these measures have been compared, and this also represents the first empirical light to be shed on the theoretical advantages of these alternatives, thus paving the way for the use of new risk measures by industry practitioners. Using EVT allows for a better estimation of the distribution of extremes and, consequently, provides a better estimation of the risk associated with a portfolio. We will also compare the rating of mutual funds using the different risk-adjusted performance measures.

This paper is organized in five sections. Section 2 reviews the different classical performance measures used in the analysis and introduces the modifications to obtain more accurate estimations. In section 3 we present the data and the sample statistics. Empirical analysis is presented in section 4 as well as differences in funds' ranking. The final section provides a brief summary and some concluding remarks.

2 Performance measures

Performance measures are used to compare a fund's performance, providing investors with useful information about managers' ability. All the measures are dependent on the definition of risk, and there are different general classes of performance measures dependent on the definition of risk used. We divide risk-adjusted performance measures into two types: traditional performance measures, based on the mean-variance approach, and VaR-based measures.

2.1 Traditional mutual fund performance measures

Sharpe ratio: Developed by William Sharpe, its aim is to measure risk-adjusted performance of a portfolio. It measures the return earned in excess of the risk-free rate on a fund relative to the fund's total risk measured by the standard deviation in its return over the measurement period. It quantifies the reward per unit of total risk:

$$S_i = \frac{R_i - R_f}{\sigma_i}, \tag{1}$$

where R_i represents the return on a fund, R_f is the risk-free rate and σ_i is the standard deviation of the fund.

A high and positive Sharpe ratio shows a firm's superior risk-adjusted performance, while a low and negative ratio is an indication of unfavorable performance.

Treynor index: It is similar to the Sharpe ratio, except it uses the beta instead of the standard deviation. It measures the return earned in excess of a riskless investment per unit of market risk assumed. It quantifies the reward-to-volatility ratio:

$$T_i = \frac{R_i - R_f}{\beta_i}, \tag{2}$$

where R_i represents the return on a fund, R_f is the risk-free rate and β_i is the beta of the fund.

Jensen's alpha: It measures the performance of a fund compared with the actual returns over the period. The surplus between the returns the fund has generated and the returns actually expected from the fund given the level of systematic risk is the alpha. The required return of a fund at a given level of risk β_i can be calculated as:

$$R_i = R_f + \beta_i \left(R_m - R_f\right), \tag{3}$$

where R_m is the average market return during the given period. The alpha can be calculated by subtracting the required return from the fund's actual return.

2.2 Other performance measures

There are other ways to measure risk. One of the most popular is Value-at-Risk (VaR). Value-at-Risk, as a measure of financial risk, is becoming more and more relevant. Value at Risk is defined as the expected maximum loss over a chosen time horizon within a given confidence interval, that is:

$$P(loss > VaR) \leq 1 - \alpha\ , \tag{4}$$

where α is the confidence level, typically .95 and .99. Formally, Value-at-Risk is a quantile of the probability distribution F_X, or the x corresponding to a given value of $0 < \alpha = F_X\left(x\right) < 1$, which means

$$VaR_\alpha\left(X\right) = F^{-1}(x), \tag{5}$$

where F_X^{-1} denotes the inverse function of F_X.

The distribution function F_X is the distribution of losses and describes negative profit, which means that negative values of X correspond to profits and positive losses.

The use of VaR instead of traditional performance ratios presents several advantage. First, VaR is a more intuitive measure of risk because it measures the maximum loss at a given confidence interval over a given period of time. Second, traditional measures do not distinguish between upside or downside risk, but investors are usually interested in possible losses. Finally, several confidence levels can be used.

We present four different approaches to VaR: normal VaR, historical VaR, modified VaR and extreme value VaR.

2.2.1 Normal VaR

Traditional calculation of normal VaR assumes that the portfolio's rate of return is normally distributed, which means that the distribution of returns is perfectly described by their mean and standard deviation. It uses normal standard deviation and looks at the tail of the distribution. In general, if the (negative) return distribution of a portfolio R is $F_R \sim \mathrm{N}\left(\mu, \sigma^2\right)$, the value at risk for a confidence level α is

$$VaR_\alpha(R) = \mu + q_\alpha \sigma \,, \tag{6}$$

where q_α is the quantile of the standard normal distribution.

2.2.2 Historical VaR

The historical VaR uses historical returns to calculate VaR using order statistics. Let $R^{(1)} \geq R^{(2)} \geq \cdots \geq R^{(T)}$ be the order statistics of the T returns, where losses are positive; then the $VaR_\alpha(R) = R^{(T\alpha)}$.

The historical VaR is very easy to implement, makes no assumption about the probability distribution of returns, and takes into account fat tails and asymmetries. But it has a serious drawback: it is based only on historical data, and therefore it assumes that the future will look like the past.

2.2.3 Modified VaR

The normal VaR assumes that returns are normally distributed. If returns are not normally distributed, the performance measures can lead to incorrect decision rules. The modified VaR takes into account not only first and second moments but also third and fourth ones. It uses the Cornish-Fisher (1937) expansion to compute Value-at-Risk analytically. Normal VaR is adjusted with the skewness and kurtosis of the distribution:

$$z^{ConrishFisher} \approx z + \frac{1}{6}\left(z^2 - 1\right)S + \frac{1}{24}\left(z^3 - 3z\right)K - \frac{1}{36}\left(2z^3 - 5z\right)S^2, \qquad (7)$$

where z is the normal quantile for the standard normal distribution, S is the skewness and K the excess of kurtosis. The modified VaR is then:

$$VaR_\alpha(R) = \mu + z^{CornishFisher}\sigma, \qquad (8)$$

The modified VaR allows us to compute Value-at-Risk for distributions with asymmetry and fat tails. If the distribution is normal, S and K are equal to zero, which makes $z^{CornishFisher}$ equal to z, which is the case with the normal VaR.

The Cornish-Fisher expansion penalizes assets that exhibit negative skewness and excess kurtosis by making the estimated quantile more negative. So it increases the VaR but rewards assets with positive skewness and little or no kurtosis by making the estimated quantile less negative, thereby reducing the VaR.

2.2.4 Extreme value VaR

Extreme value theory (EVT) provides statistical tools for estimating the tails of the probability distributions of returns. Modeling extremes can be done in two different ways: modeling the maximum of the variables, and modeling the largest value over some high threshold. In this paper we will use the second because it employs the data more efficiently.

Let $X_1, X_2,...$ be identically distributed random variables with the unknown underlying distribution function $F(X) = P\{X_i \le x\}$, which has a mean (location parameter) μ and variance (scale parameter) σ. An excess over a threshold u occurs when $X_t > u$ for any t in $t = 1,2,...n$. The excess over u is defined by $y = X - u$. Balkema and de Hann (1974) and Picklands (1975) show that for a sufficiently high threshold, the distribution function of the excess y may be approximated by the generalized Pareto distribution (GPD) because as the threshold gets large, the excess function

$$F_u(y) = \Pr\{X - u \le y | X > u\}, \tag{9}$$

converges to the GPD generally defined as

$$G_{\xi,\sigma,u}(y) = \begin{cases} 1 - \left(1 + \frac{\xi}{\sigma} y\right)^{-1/\xi}, & 1 + \xi \frac{y}{\sigma} > 0, \; y \ge 0 \quad \text{if} \quad \xi \ne 0 \\ 1 - \exp\left(-\frac{y}{\sigma}\right), & y \ge 0 \qquad\qquad\qquad \text{if} \quad \xi = 0 \end{cases} \tag{10}$$

The parameter ξ is important, since it is the shape parameter of the distribution or the extreme value index and gives an indication of the heaviness of the tail: the larger ξ, the heavier the tail.

Having determined a threshold, we can estimate the GPD model using the maximum likelihood method.

The upper tail of $F(x)$ may be estimated by:

$$\hat{F}(x) = 1 - \frac{N_u}{n}\left(1 + \hat{\xi}\frac{x-u}{\hat{\sigma}}\right)^{-1/\hat{\xi}} \quad \text{for all} \quad x > u\,. \tag{11}$$

To obtain the VaR_{α} we invert (11), which yields

$$VaR_{\alpha} = u + \frac{\hat{\sigma}}{\hat{\xi}}\left(\left(\frac{n}{N_u}(1-\alpha)\right)^{-\hat{\xi}} - 1\right), \tag{12}$$

where u is the threshold, $\hat{\xi}$, $\hat{\mu}$ and $\hat{\sigma}$ are the estimated shape, location and scale parameters, n is the total number of observations and N_u the number of observations over the threshold.

A modified Sharpe VaR-based performance measure can be defined as the reward-to-VaR ratio, similar to the Sharpe and Treynor ratios but with the risk measured using the different VaR measures in the denominator, namely:

$$\varphi_i = \frac{R_i - R_f}{VaR_{\alpha}(R_i)}, \tag{13}$$

So we can calculate normal VaR, historical VaR, modified VaR and EVT VaR. The larger the ratio, the more reliable the fund is.

3 Data

European mutual funds have largely been neglected in risk and performance studies. The lack of reliable data, the data's fragmentation and the size of the market make it difficult to conduct studies (Otten and Bams, 2002). The only market that presents characteristics that may be similar to those of the US is the United Kingdom. For this reason in our study we use a sample of British equity mutual funds investing exclusively in the UK and onshore actively managed funds. By doing this we ensure the homogeneity in the country's risk exposure, reducing the unexpected variability.

Our data set comprises monthly returns on 239 UK mutual funds over 11 years, from January 1995 to December 2005. The data were provided by Morningstar. Morningstar mutual funds data have been widely use by researchers in the US, and since its merger with Standard & Poor's in Europe, Morningstar arguably represents the most comprehensive reference for analysis. Owing to the construction of the data set, we use only the data for funds that are active for the entire period, which, as pointed out by Carhart *et al.* (2002), may render an upward bias on persistence. Nevertheless, as Morningstar reports only funds that are active at the end of the period and the aim of this paper is to make comparisons among them, we don't find this issue to be especially relevant for our study. All mutual funds are measured gross of taxes, with dividends and capital gains, but net of fees. To calculate the excess return, we use the one-month government interest rate (T-bill equivalent), and for the market return, we use the FTSE 100 Index of the London Stock Market.

To illustrate the different methodologies and for the shake of simplicity, we have chosen the highest ten and lowest ten monthly averages return for the whole period. Table 1 summarizes detailed statistics of those funds.

INSERT TABLE 1

An examination of Table 1 shows that several funds have an asymmetric distribution. Upper fund returns have mostly negative skewness, indicating that the asymmetric tail extends toward negative values more than toward positive ones; however bottom fund returns show more negative skewness. According to the sample kurtosis estimates, the top ten fund returns show a higher level of kurtosis than the bottom ones. Table 1 also shows the highest and lowest month return for each fund: the highest one-month return is 60.5%, while the highest loss corresponds to the same fund (79.5%).

These results indicate that some funds do not follow a normal distribution. The results of three different normality tests and their p-values are in Table 2. The three tests used are: i) the Jarque-Bera, which is a goodness-of-fit measure of departure from normality, based on the sample kurtosis and skewness; ii) the Shapiro-Wilk, which tests the null hypothesis that the sample data come from a normally distributed population and iii) the Anderson-Darling test, which is used to test if a sample comes from a specific distribution. We can observe that the top ten show more departures from normality, while in the bottom ten, normality is clearly rejected only in one case. We also studied a qq-plot of returns against the normal distribution. In Figure 1 we can see that the departure from normality is small, but in some cases, we can see that there are extreme values, either on the right-hand side, on the left hand side, or both. In Figure 2, which shows a qq-plot of the top ten, relevant deviations from normality can be observed in the extremes, which means that the distributions are fat-tailed and have extreme values.

INSERT TABLE 2

4 Empirical results

In this section we report and discuss results of the different performance measures. Table 3 shows the results of the classical performance measures: Sharpe, Jensen and Treynor, as well as the ranking of the fund that would result from those indexes. As expected, the bottom ten has a smaller index than the top ten. Moreover, for the bottom ten we have negative Sharpe and Treynor indexes and Jensen's alpha, meaning that those funds are not able to beat the market.

INSERT TABLE 3

The other performance indexes are based on VaR. We have estimated $VaR_{0.05}$ and $VaR_{0.01}$ using the four different approaches discussed in section 2. To offer EVT VaR results we proceed with the generalized Pareto distribution (GPD) estimation. A crucial step in estimating the parameters of the distribution is the determination of the threshold value. We have selected the proper threshold, fitting the GPD over a range of thresholds looking at what level $\hat{\xi}$ and $\hat{\sigma}$ remain constant. Because of space constraints and for the ease of exposition, we do not present a detailed parameter estimation. Instead the model fit can be checked in Figures 4 and 5, with the fitted GPD distribution and the qq-plot of sample quantiles versus the quantiles of the fitted distribution.

$VaR_{0.05}$ and $VaR_{0.01}$ estimates are shown in Table 4. As expected, results for normal VaR and Cornish-Fisher VaR are similar for funds with little asymmetry and kurtosis. EVT VaR tends to be higher than the other VaR thresholds when the return distribution is not normal and presents asymmetries and kurtosis, which is more frequent in the top group. Additionally, the bottom 10 funds have, in general, higher VaR values than the top ones, which means they are more susceptible to extreme events.

At this stage, it is important to point out that normal VaR does not allow for asymmetries in calculating VaR, unlike the Cornish-Fisher expansion, which take into account asymmetries and fat tails. However, the extreme value approach is able to define the limiting behavior of the empirical losses and therefore allows us to study the upper tail separately.

INSERT TABLE 4

Since we use different performance measures, it is important to verify if the alternative approaches provide the same evaluation of funds. Since diverse ratios have special statistical properties and behaviors, it is interesting to see if they produce analogous fund rankings in our sample.

With regard to performance measures and rankings, Table 5 shows the results of the modified Sharpe ratio using the $VaR_{0.05}$ in Table 4. The rank from each ratio is also in the table. The bottom group exhibits a very small ratio, and they show similar ranking regardless of the method used for calculation. However, the results of the top group show more differences. To find out if they really produce similar results, we compared the rank order correlations of the top ten funds. Table 6 shows the Spearman and Kendall rank correlation.

INSERT TABLE 5

Not surprisingly, the Sharpe and the various VaR ratios exhibit higher correlations than do the Jensen and Treynor ratios. This is not unexpected, since Jensen and Treynor calculations include only the systematic component of risk, while the other measures also include residual risk. The normal VaR measure and the Sharpe ratio rate the ten top funds in the same order.[2]

INSERT TABLE 6

The modified VaR and EVT VaR also show a high correlation. With respect to the Kendall correlation, which is easier to interpret, the value of 0.867 indicates that there is an 87.6 percent greater chance that any pair will be ranked similarly

[2] If we take the whole sample of UK funds, the normal VaR and Sharpe ratios also show the highest correlation.

than differently. Consequently, the chance of disagreement in the ranking between modified VaR and EVT VaR is 6.6%; however, the chance between the Sharpe ratio and EVT VaR is 20%.

Taking into account that only modified VaR and EVT VaR ratios allow asymmetry and kurtosis, the results of those measures would be more accurate in the calculation of performance measures for funds with non-normal returns. As a preliminary conclusion, these findings indicate that the comparison between Gaussian funds and non-normal ones is better done using those measures, since they are better able to capture the risk behavior among them.

Our sample data do not show a high degree of asymmetry, and so the Sharpe and normal VaR ratios are highly correlated. In other words, risk measured through variance and the 0.95 quantile loss leads to the same ranking of performance measures.[3]

Only modified VaR and EVT VaR ratios would provide an intuitive measure of downside risk and offer reliable results if we explicitly account for skewness and excess kurtosis in the returns. Even though both measures take into account extreme events, only EVT VaR provides a full characterization of these extreme events defined by the quantile of the distribution. But the principal drawback of the EVT VaR approach is that it requires a data set with enough data because only data above a certain threshold are used for estimation. The calculation is not an

[3] The results of the Jensen and Treynor correlation using only ten funds are misleading because the sample is very small and negative; however, if we take the whole sample, the Spearman correlation is 0.74, and the Kendall is 0.67. Also, the rank correlation between the other indexes and Jensen's alpha is higher when considering the whole sample.

easy task, since it requires a careful threshold selection and the likelihood estimation of the generalized Pareto distribution, whereas the mean, standard deviation, skewness, and kurtosis of the return distribution used for the VaR measures of the Cornish-Fisher expansion can be easily obtained.

5 Conclusions

Evaluation of mutual fund performance is a key issue in an industry that has been rapidly evolving over the last few years; however, there is no general agreement about which measure is best for comparing funds' performance. In this paper we evaluate traditional risk-adjusted measures that are based on the mean-variance approach with others that use VaR to quantify risk exposure, empirically testing the appropriateness of each within a sample of UK mutual funds.

Using the variance as a measure of risk implies that investors are equally as averse to deviations above the mean as they are to deviations below the mean, though the real risk comes from losses. VaR is a measure of the maximum expected loss on a portfolio of assets over a certain holding period at a given confidence level, so it can be considered a more accurate measure of risk.

Different approaches have been proposed to estimate VaR. The historical VaR uses the empirical distribution of returns. It does not make any assumption about data distribution and takes into account stylized facts such as correlation asymmetries; however, it supposes that future VaR estimates would behave like past VaR estimates. Also, an accurate estimation requires that the number of data in the data set be large enough. The other VaR methods make assumptions about the distribution of returns. Traditional VaR is obtained from the normal distribution, but there is much evidence that financial returns depart from normality due to asymmetry and fat tails; consequently, normal-VaR results are usually underestimated.

Modified VaR using the Cornish-Fischer correction and VaR measures based on extreme value theory take into account this fact. The Cornish-Fisher expansion allows investors to treat losses and gains asymmetrically; consequently, in the presence of skewness and kurtosis, the VaR estimation would be more accurate than ones calculated with the normal VaR. The approach based on EVT estimates an extreme distribution, usually the generalized Pareto distribution, using only extreme values rather than the whole data set and offers a parametric estimate of tail distribution.

Taking into account VaR-based risk measures that emphasize losses instead of losses and gains as the variance, it seems reasonable to use VaR as a risk measure. So the Sharpe ratio can be modified using this risk measure. We have compared these modified Sharpe ratios with the original one and with the two other well-known traditional performance measures: the Treynor ratio and Jensen’s alpha. The rankings generated from each measure have been also compared.

We studied monthly returns of UK mutual funds, and we selected for the study the ten funds with the lowest and highest monthly average returns. For the distribution of the bottom ten, we reject that they follow normal distribution in all but one case. On the other hand, the upper ten show a higher degree of asymmetry and kurtosis, and we can reject normality in half of the cases. Also, we have calculated VaR using four different approaches, and EVT VaR is the one that gives higher results for probabilities of 0.05 and 0.01.

Regarding the ranking of performance measures, from the bottom sample we obtained the same ranking regardless of the measure used, except for the Jensen and Treynor measures, which also show a high rank correlation. However, for the top data set, the ranking is not the same. If we consider rankings from the modified Sharpe index calculated with the Cornish-Fisher VaR and EVT-VaR, more accurate measures in the presence of non-normal distribution, both are highly correlated and present a lower correlation with the other measures. So we recommend employing when trying to rank the performance of different funds, especially in the presence of non-normal data, such as returns from hedge funds or more frequently sampled returns.

Acknowledgements

Authors want to thank for Financial Assistance from the Ministerio de Educación y Ciencia, Research Project MTM2006-15433. We would also like to thank Mark Roomans, from Morningstar Spain. Any possible errors contained are the exclusive responsibility of the authors.

References

Alexander, G. J and Baptista, A. M. (2002) Economic Implications of Using a Mean-VaR Model for Portfolio Selection: A Comparison with Mean-Variance Analysis, *Journal of Economic Dynamics and Control*, 26, 7-8, 1159-1193.

Alexander, G. J and Baptista, A. M. (2003) Portfolio Performance Evaluation Using Value at Risk, *Journal of Portfolio Management*, 29, 93-102.

Balkema, A. A. and de Hann, L. (1974) Residual Life Time at Great Age, *Annals of Probability*, 2, 792-804.

Carhart, M.M., Carpenter, J.N., Lynch, A.W. and Musto, D.K. (2002) Mutual Fund Survivorship, *Review of Financial Studies* 15, 1439-1463.

Cont, R. (2001), Empirical Properties of Asset Returns: Stylized Facts and Statistical Issues, *Quantitative Finance*, 1, 223-236.

Cornish, E. A. and Fisher, R. A. (1937) Moments and Cumulants in the Specification of Distributions, *Review of the International Statistical Institute*, 5, 307–320.

Doncel, L., Reinhart, W. and Sainz, J. (2007) Should Investors Study: A Note on Financial Risk and Knowledge. *Anales de Economía Aplicada 2007*, 234-245.

Embrechts, P. (2000) Extreme Value Theory: Potential and Limitations as an Integrated Risk Management Tool, *Derivatives Use, Trading and Regulation*, 6, 449-456.

Favre, L. and Galeano, J. A. (2002) Mean-Modified Value-at-Risk Optimization with Hedge Funds, *Journal of Alternative Investments*, 6, 21–25.

Gregoriou, G. N. (2004) Performance of Canadian Hedge Funds Using a Modified Sharpe Ratio, *Derivatives Use, Trading & Regulation*, 10, 2, 149-155.

Gregoriou, G. N. and Gueyie, J-P. (2003) Risk-Adjusted Performance of Funds of Hedge Funds Using a Modified Sharpe Ratio, *Journal of Wealth Management*, 6, 3, 77-83.

Gupta, A. Liang, B. (2005) Do Hedge Funds Have Enough Capital? A Value at Risk Approach. *Journal of Financial Economics* 77, 219–253.

Jaschke, S.R. (2001) The Cornish-Fisher-Expansion in the Context of Delta-Gamma-Normal Approximations, *Journal of Risk*, **4**, 4, 33-52.

Jensen, Michael J., (1968) The Performance of Mutual Funds in the Period 1945-1964, *Journal of Finance*, 23, 389-416.

Jorion, P (2001) *Value at Risk: The New Benchmark for Controlling Market Risk*. McGraw-Hill.

Kooli, M., Amvella S.P and Gueyie J.P. (2005), Hedge Funds in a Portfolio Context: A Mean-Modified Value at Risk Framework, *Derivatives Use, Trading and Regulation*, 10, 4, 373-382.

Liang, B. and Park, H. (2007) Risk Measures for Hedge Funds: A Cross-sectional Approach, *European Financial Management*, 13, 2, 201-207.

Markowitz, H. M. (1952). Portfolio Selection, *Journal of Finance*, 7, 1, 77-91.

McNeil, A. (1998) Calculating Quantile Risk Measures for Financial Return Series Using Extreme Value Theory, Preprint, ETH Zürich.Monitor, 1, 4-12.

Otten, R. and Bams, D. (2002) European Mutual Fund Performance, *European Financial Management*, 8, 75-101.

Picklands, J. I. (1975) Statistical Inference Using Extreme Value Order Statistics, *Annals of Statistics*, 3, 119-131.

Sentana, E. (2003) Mean-Variance Portfolio Allocation with a Value at Risk Constraint. *Revista de Economía Financiera*, 1, 1 4-14.

Sharpe, W. F. (1966) Mutual Fund Performance. *Journal of Business*, 39, 119-138.

Treynor, Jack. L. (1966) How to Rate Management Investment Funds, *Harvard Business Review*, 43, 63-75.

Zangari, P. (1996) *A VaR Methodology for Portfolios That Include Options*, RiskMetrics.

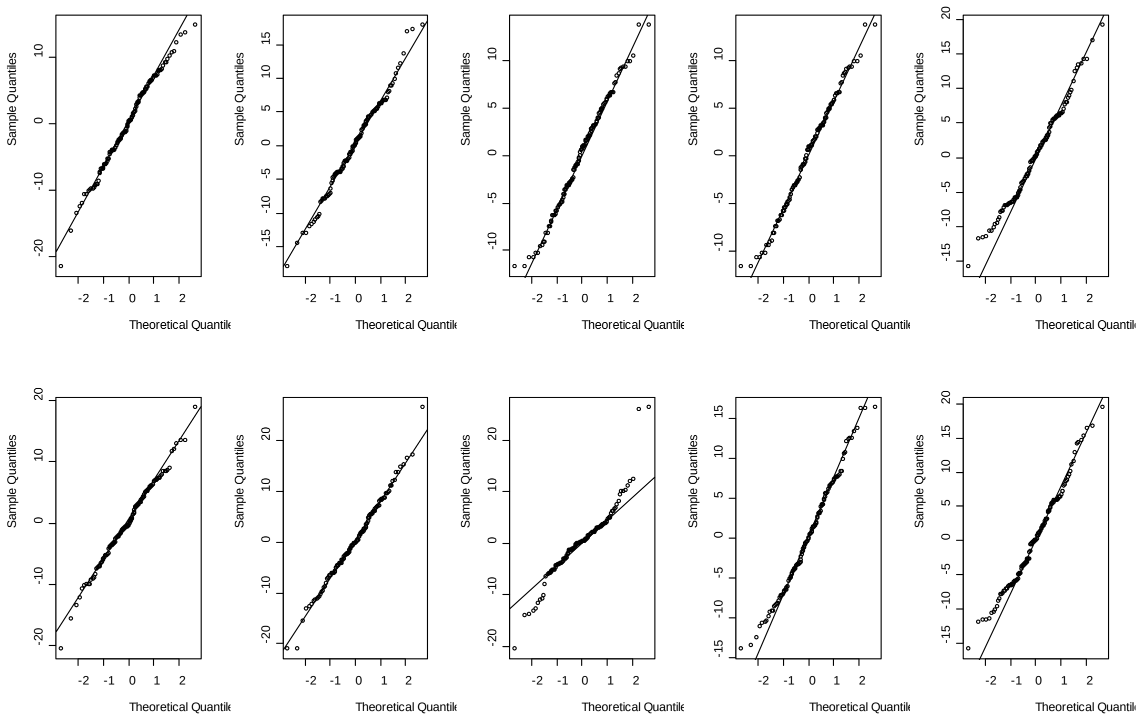

Figure 1: q-q plots against the normal distribution for the bottom ten funds.

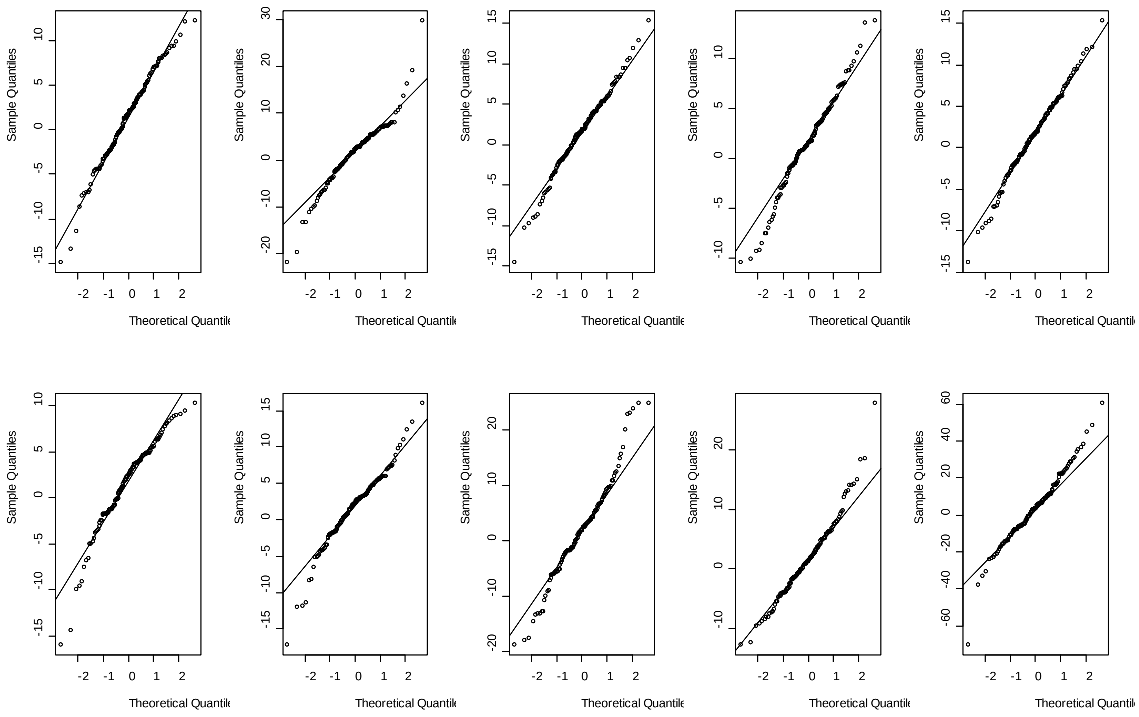

Figure 2: q-q plots against the normal distribution for the top ten funds.

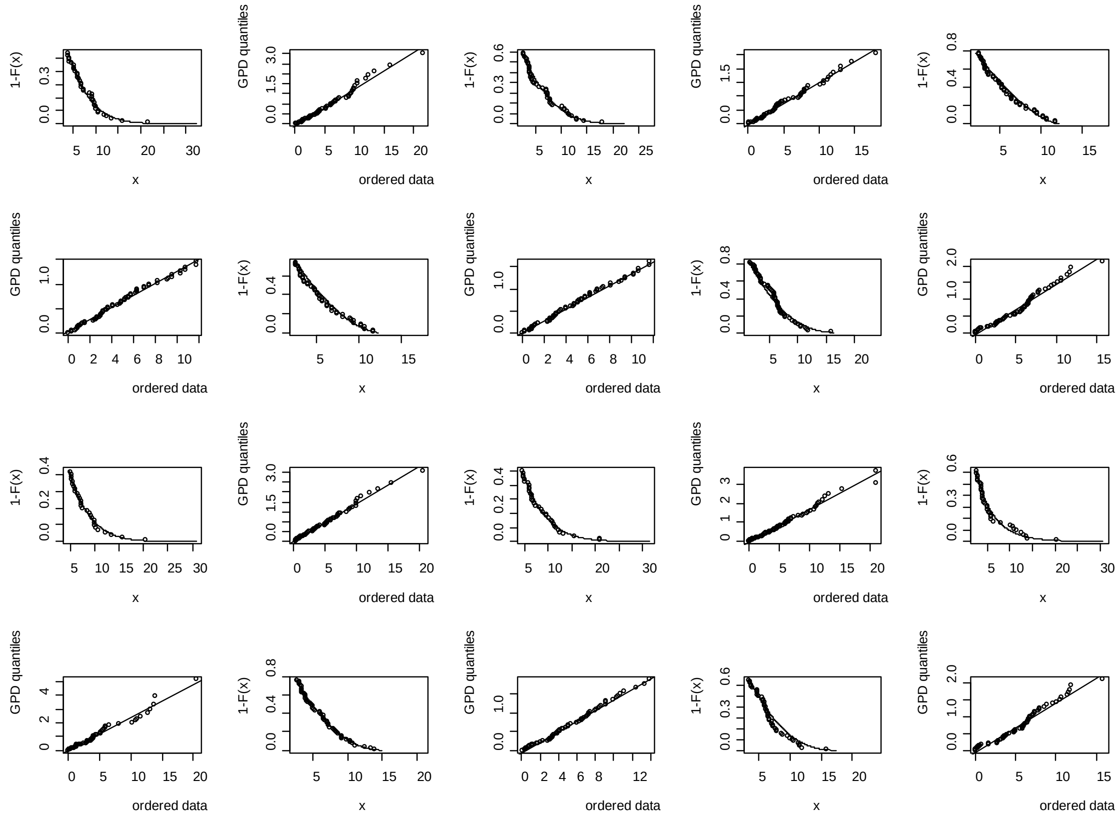

Figure 3: (Left) Fitted GPD distribution (dots) and empirical one (solid one) and (right) q-q plots of sample quantiles versus the quantiles of the fitted distribution for the bottom ten funds.

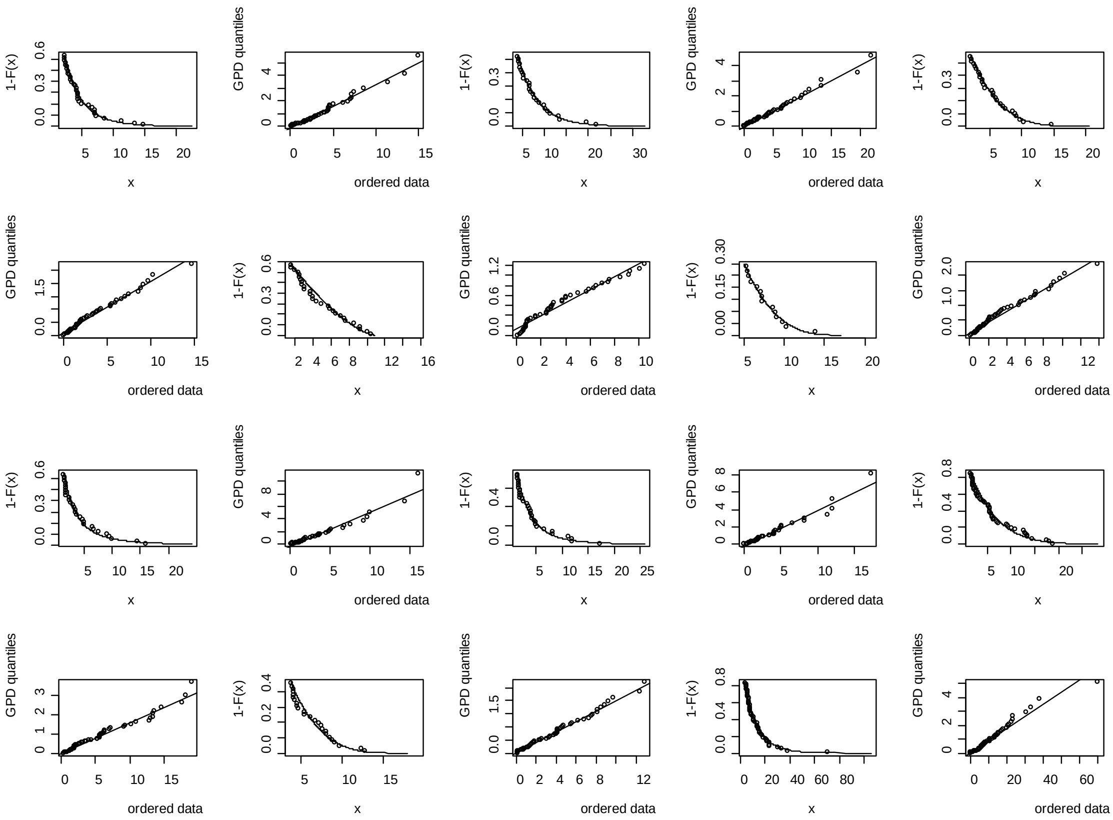

Figure 4: (Left) Fitted GPD distribution (dots) and empirical one (solid one) and (right) q-q plots of sample quantiles versus the quantiles of the fitted distribution for the top ten funds.

Table 1: Descriptive statistics of the top ten and bottom ten average return funds.

Panel A: Bottom 10 funds					
Mean	Std.	Max.	Min.	Sk.	Ku.
-0.002	6.672	14.934	-21.498	-0.236	-0.136
0.050	6.632	17.934	-18.002	0.032	0.103
0.080	5.636	13.712	-11.713	-0.019	-0.567
0.127	5.633	13.778	-11.638	0.002	-0.548
0.146	6.651	19.202	-15.840	0.297	-0.198
0.147	6.378	18.895	-20.506	-0.132	0.335
0.171	7.713	26.480	-21.025	0.143	0.531
0.212	6.234	26.352	-20.446	0.579	4.066
0.216	6.754	16.394	-13.878	0.244	-0.498
0.244	6.931	19.498	-15.877	0.345	-0.244
Panel B: Top 10 funds					
Mean	Std.	Max.	Min.	Sk.	Ku.
1.319	5.058	12.182	-14.900	-0.390	0.231
1.331	6.670	29.765	-21.934	-0.049	3.103
1.414	4.959	15.328	-14.597	-0.252	0.500
1.470	4.671	13.823	-10.472	-0.170	0.285
1.526	5.033	15.327	-13.883	-0.231	0.270
1.605	4.611	10.282	-16.008	-0.966	1.623
1.632	4.898	16.023	-17.239	-0.570	1.922
1.697	8.399	24.776	-18.913	0.282	0.740
1.771	6.453	27.880	-12.853	0.665	1.454
3.499	17.921	60.549	-70.528	-0.130	1.929

Mean=sample mean; Std. = Standard deviation; Max.=maximum observed monthly return; Min.= minimum observed monthly return; Sk.= Skewness; Ku. = Kurtosis

Table 2: Descriptive statistics of the top ten and bottom ten average return funds.

Panel A: Bottom 10 funds					
J-B	p-value	S-W	p-value	A-D	p-value
1.297	0.523	0.991	0.565	0.304	0.567
0.148	0.929	0.992	0.671	0.311	0.550
1.554	0.460	0.990	0.453	0.273	0.663
1.435	0.488	0.990	0.479	0.251	0.735
2.115	0.347	0.988	0.293	0.459	0.259
1.210	0.546	0.993	0.804	0.271	0.670
2.342	0.310	0.992	0.702	0.230	0.804
103.401	0.000	0.921	0.000	2.559	0.000
2.501	0.286	0.987	0.240	0.368	0.425
2.909	0.234	0.984	0.137	0.587	0.124
Panel B: Top 10 funds					
J-B	p-value	S-W	p-value	A-D	p-value
3.852	0.146	0.986	0.207	0.284	0.625
56.245	0.000	0.944	0.000	1.803	0.000
3.114	0.211	0.991	0.544	0.423	0.315
1.272	0.529	0.986	0.202	0.649	0.088
1.768	0.413	0.993	0.771	0.309	0.554
36.774	0.000	0.948	0.000	1.408	0.001
29.238	0.000	0.962	0.001	1.352	0.002
5.287	0.071	0.974	0.012	0.982	0.013
22.687	0.000	0.972	0.008	0.714	0.061
22.483	0.000	0.976	0.018	0.628	0.100

J-B: Jarque-Bera test; S-W: Shapiro-Wilk test; A-D: Anderson-Darling test

Table 3: Classical mutual fund performance measures

Panel A: Bottom 10 funds						Panel B: Top 10 funds					
Sharpe	Rank	Jensen	Rank	Treynor	Rank	Sharpe	Rank	Jensen	Rank	Treynor	Rank
-0.025	10	-0.372	10	-0.234	10	0.228	7	1.014	9	2.346	7
-0.017	9	-0.311	9	-0.169	9	0.175	10	0.959	10	1.602	10
-0.015	8	-0.075	3	2.371	1	0.252	5	1.119	8	2.724	2
-0.007	7	0.008	1	0.237	2	0.279	3	1.165	7	2.656	3
-0.003	6	-0.166	6	-0.039	8	0.270	4	1.229	6	2.944	1
-0.003	5	-0.221	8	-0.027	7	0.312	1	1.278	4	2.530	4
0.001	4	-0.191	7	0.007	6	0.299	2	1.298	3	2.475	5
0.007	3	-0.078	4	0.105	4	0.182	9	1.267	5	1.648	9
0.008	2	-0.091	5	0.101	5	0.249	6	1.414	2	2.386	6
0.011	1	-0.075	2	0.145	3	0.186	8	2.910	1	2.236	8

Table 4: VaR results of the different approaches

Panel A: Bottom 10 funds							
$VaR_{0.05}$				$VaR_{0.01}$			
Norm-VaR	Hist-VaR	Mod-VaR	EVT-VaR.	Norm-VaR	Hist-VaR	Mod-VaR	EVT-VaR
10.977	10.289	11.449	13.697	15.524	15.259	16.608	18.641
10.858	11.237	10.784	13.193	15.378	14.085	15.384	16.626
9.190	9.531	9.286	10.481	13.031	11.412	12.365	11.572
9.138	9.442	9.197	10.295	12.977	11.317	12.246	11.542
10.794	9.956	10.270	12.231	15.326	11.796	13.787	14.650
10.344	9.967	10.542	12.896	14.690	14.894	15.849	17.793
12.516	11.522	12.122	14.638	17.772	19.225	17.976	20.182
10.043	10.870	8.544	12.685	14.292	13.872	18.350	19.652
10.893	10.107	10.501	11.636	15.496	13.081	13.650	13.437
11.158	10.321	10.527	12.599	15.881	11.837	14.037	14.932
Panel B: Top 10 funds							
$VaR_{0.05}$				$VaR_{0.01}$			
Norm-VaR	Hist-VaR	Mod-VaR	EVT-VaR	Norm-VaR	Hist-VaR	Mod-VaR	EVT-VaR
7.001	7.098	7.552	9.846	10.448	12.814	12.460	15.452
9.641	9.927	9.315	14.439	14.186	17.759	19.269	21.918
6.743	7.242	7.054	10.248	10.123	10.121	11.740	13.567
6.213	7.252	6.415	9.228	9.397	9.862	10.344	10.320
6.753	7.192	7.061	10.283	10.183	10.121	11.458	13.031
5.979	6.669	7.175	10.774	9.121	13.062	15.765	22.774
6.425	5.800	7.058	11.375	9.763	12.029	14.613	21.464
12.118	13.104	11.332	15.303	17.842	17.991	17.804	21.459
8.844	8.103	7.489	10.002	13.242	11.567	13.354	12.715
25.978	22.294	25.948	34.442	38.191	36.590	48.099	53.696

Norm-VaR: normal-VaR; Hist-VaR: Historical-VaR; Mod-VaR: modified VaR using Cornish-Fisher expansion;
EVT-VaR: extreme-value-VaR calculated form the GPD estimation.

Table 5: VaR-based performance measures

Norm-VaR	Rank	Hist-VaR	Rank	Mod-VaR	Rank	EVT-VaR	Rank
Panel A: Bottom 10 funds							
-0.015	10	-0.016	10	-0.015	10	-0.012	10
-0.011	9	-0.010	9	-0.011	9	-0.009	9
-0.009	8	-0.009	8	-0.009	8	-0.008	8
-0.004	7	-0.004	7	-0.004	7	-0.004	7
-0.002	6	-0.002	6	-0.002	6	-0.002	6
-0.002	5	-0.002	5	-0.002	5	-0.001	5
0.000	4	0.000	4	0.000	4	0.000	4
0.005	3	0.004	3	0.005	2	0.004	3
0.005	2	0.005	2	0.005	3	0.004	2
0.007	1	0.008	1	0.007	1	0.006	1
Panel B: Top 10 funds							
Norm-VaR	Rank	Hist-VaR	Rank	Mod-VaR	Rank	EVT-VaR	Rank
0.165	7	0.163	7	0.153	7	0.117	7
0.121	10	0.117	9	0.125	10	0.081	10
0.185	5	0.172	6	0.177	6	0.122	6
0.210	3	0.180	5	0.203	3	0.141	2
0.201	4	0.189	4	0.193	5	0.132	4
0.241	1	0.216	2	0.201	4	0.134	3
0.228	2	0.253	1	0.208	2	0.129	5
0.126	9	0.117	10	0.135	8	0.100	8
0.181	6	0.198	3	0.214	1	0.160	1
0.128	8	0.150	8	0.128	9	0.097	9

Table 6: Spearman and Kendall correlation of the performance measures for the top 10 funds

	Sharpe	Jensen	Treynor	Norm-VaR	Hist-VaR	Mod-VaR	EVT-VaR
Sharpe	1	0.248	0.782	1.000	0.891	0.770	0.745
Jensen	0.2	1	-0.006	0.248	0.394	0.394	0.297
Treynor	0.644	-0.067	1	0.782	0.636	0.588	0.673
Norm-VaR	1.000	0.200	0.644	1	0.891	0.770	0.745
Hist-VaR	0.733	0.378	0.467	0.733	1	0.879	0.782
Mod-VaR	0.644	0.378	0.378	0.644	0.733	1	0.927
EVT-VaR	0.600	0.244	0.511	0.600	0.600	0.867	1

Statistics in the top half of the matrix represent Spearman rank correlation coefficients; numbers in the lowest half correspond to Kendall values