Does the use of downside risk-adjusted measures impact performance rankings of UK investment trusts?

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Abstract

This paper investigates the impact of using different risk-adjusted measures of performance on the rankings of UK investment trusts. A sample of daily data on 109 trusts is analysed over a ten year period. Performance rankings were constructed on the basis of the Sharpe Ratio and several downside risk-adjusted performance measures (the Sortino ratio, excess return on Cornish-Fisher VaR, excess return on VaR, and excess return on Expected Shortfall). VaR and Expected Shortfall were computed using Filtered Historical Simulation (FHS), a hybrid methodology that combines the use of volatility models with bootstrapping techniques. The results based on Spearman´s rank correlations suggest that the choice of the performance measure does not have a significant impact on the ranking of UK investment trusts. A more detailed analysis, however, uncovers important differences between the performance rankings, reflected either in the number of funds that underperform/outperform the benchmark, the number of funds that maintain an equal order across rankings and the number of changes in the five top/bottom performing funds.

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Abstract

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1. Introduction

A critical issue in the area of portfolio performance evaluation is the choice of the appropriate measure used to quantify risk. Different risk measures have been developed and, consequently, different risk-adjusted performance metrics can be applied to the evaluation of investment portfolios. Besides well known risk-adjusted measures, downside risk-adjusted measures of performance can also be used to evaluate investment portfolios. This raises the question of whether or not the performance of investment funds is sensitive to the performance measure used.

The mean-variance paradigm of Markowitz (1952) is the theoretical basis for the development of the traditional framework established to assess risk-adjusted portfolio performance. The Sharpe (1966) ratio (SR) is probably the most important representative of the set of classic measures of risk used to adjust performance.

The limitations of mean-variance based models are a consequence of one of its major assumptions: that returns are normally distributed or, in a more general way, elliptically symmetric distributed. If returns do not follow an elliptically symmetric distribution the use of the mean-scale approach is questionable. Therefore, the assessment of performance in the presence of skewed distributions requires the use of non-standard measures to adjust for risk. The development of a downside risk measurement framework was the natural answer to the problems associated with the use of standard measures of risk in the context of highly skewed distributions. Generally speaking, downside risk measures focus on the returns that fall below a certain value, enabling us to look at the tails of the distribution.

Therefore, within the context of non-elliptical symmetry in returns, one might expect a lack of correlation between performance ranks based on traditional and downside measures of risk-adjusted performance. However, recent research in this area provides evidence suggesting no impact of the choice of a particular performance measure on the rankings between alternative investments. Pfingsten et al. (2004) compared rank correlations for several risk measures on the basis of an investment bank´s 1999 trading book and concluded that different measures result in largely identical rankings. Later, Eling and Schuhmacher (2005) also concluded for significant rank correlation between different performance measures. Their study focuses on hedge fund indices data from 1994 to 2003. Finally, Eling and Schumacher (2007) analysed individual hedge fund data instead of indices, but the results were the same in the sense that identical rank ordering across hedge funds was clearly identified. These authors conclude that despite significant deviations of hedge fund returns from a normal distribution, the first two moments seem to describe the distributions sufficiently well.

Despite its obvious potential, there is still a gap in the literature concerning the use of downside risk measures with performance evaluation purposes. The main objective of this paper is to contribute to this debate by providing evidence on the impact of using different risk measures to adjust performance. For that purpose, different performance measures will be computed on a data set of UK investment trusts. The contributions of this study in relation to the few previous studies in this area are fourfold. As far as we are aware of, this is the first study to investigate the impact of the use of standard and downside risk-adjusted measures of performance on the ranking of UK investment trusts.

Secondly, daily return series over a period of ten years are used. This is a much longer time period than those of the few studies on this particular issue.

Additionally, we provide a discussion on downside risk measures that can be used to evaluate portfolio performance and suggest the use of expected shortfall (ES), given its desirable properties as a measure of risk. There have been very few studies on the performance of investment portfolios using ES.

Finally, the value-at-risk (VaR) and ES measures of risk will be computed using a full valuation method based on a filtered historical simulation (FHS) procedure. As far as we know, performance ratios based on FHS estimates of VaR and ES have never been empirically tested. The computation of conditional VaR and ES under FSH is complemented with the estimation of unconditional VaR and ES. Unconditional VaR and ES are computed by extending the bootstrap procedures under FSH further ahead in time, in order to forecast the daily VaR and ES over a certain future time horizon.

Our first findings, based on Spearman´s rank correlations, suggest that the choice of the performance measure does not have a significant impact on the ranking of UK investment trusts. Accordingly, despite the rejection of the normality hypothesis and the strong evidence of negative skewness in investment trusts returns series, there seems to be little gain in abandoning classic measures like the SR. However, a subsequent analysis has uncovered important changes in the rankings of funds, suggesting that the use of different measures might indeed have some impact in relative performance assessment. Although not captured by the Spearman's rank correlation analysis, these impacts may be relevant for investors.

This paper is organized as follows. In Section 2 we discuss the literature on downside risk measures and its use in portfolio performance evaluation. In Section 3 we describe the methodology used to assess fund performance and estimate risk measures. Section 4 focuses on the data and on the empirical properties of the UK investment trust return series. Section 5 provides and discusses the empirical results. Finally, section 6 summarises the main results and presents some concluding remarks.

2. Literature Review

Based on the mean-variance approach, the well known traditional measures of performance (Jensen, 1968; Sharpe, 1966; and Treynor, 1965) use either the standard deviation or beta as risk measures. These measures are quite similar and, under certain market conditions, they produce rankings of portfolios that are not significantly different from each other. The use of traditional measures of performance is fully justified under the assumption of elliptically symmetric distributed returns. In fact, in the context of a traditional analysis of performance, it is often assumed that financial return series are normally distributed or at least that the hypothesis of an elliptically symmetric distribution is not rejected. Despite this, empirical evidence suggests that financial portfolio or asset returns are better fitted by distributions other than the normal (Bookstaber and Clarke, 1984; Mandelbrot and Hudson, 2004; and King and Wadhwani, 1990).

The assumption of elliptically symmetric returns can therefore be an issue of concern in evaluating portfolio performance. The SR can lead to misleading conclusions when returns are significantly skewed (Bernardo and Ledoit, 2000). In this case, the SR penalizes funds that have positive skewness and underestimates the risk of funds with negative skewness. It is a well known fact that investors have a preference for positive skewness, which means that upside risk is less important to investors than downside risk. If only the first and second moments are assessed, the negatively-skewed returns will generate the appearance of outperformance. Hence, asymmetric distributions require alternative evaluation approaches that integrate other moments of the distribution beyond the first and second moments. Higher moments of the distribution like skewness or kurtosis may also be of interest to investors (Arditti, 1968; Jean, 1971; Harvey and Siddique, 2000; and Prakash et al., 2003). Alternatively, some authors suggest that the entire distribution of returns should be considered (Hanoch and Levy, 1969, 1970; Whitmore, 1970; Meyer et al., 2005; De Giorgi, 2005).

In the presence of asymmetric empirical return distributions, the development of downside measures of risk (which are sometimes called safety measures) provide an alternative framework to assess risk adjusted performance.

The issue is whether the rankings obtained from these measures are different from those obtained in the context of the mean-variance paradigm. Pedersen and Rudholm-Alfvin (2003), using equity return data from global financial services institutions and UK micro-firms, compare a SR-based ranking with other alternatives that assess performance by using downside risk-adjusted measures. Applying Jarque-Bera tests and rank correlation analysis, they concluded that, for symmetric distributions of returns, there is a high correlation (80% in some cases) between the produced rankings resulting from the application of different measures of performance. On the other hand, on the context of asymmetric distributions of returns there is a significant absence of consistency in the measurement of performance, with the rank correlations dropping below 5% in some cases. These results enhance the importance of using an alternative performance evaluation framework when a departure from elliptical symmetry in the series of returns is identified. Most recently, Eling and Schumacher (2005,

2007) compared the SR with other downside measures of performance. Their results indicate that the choice of the performance measure does not affect the rankings of hedge funds. These findings are somewhat surprising considering that hedge fund returns differ significantly from a normal distribution.

Downside risk-adjusted performance measures include lower partial moments (LPM) measures of performance, such as the Sortino ratio (Sortino and Price, 1994) as well as performance measures using value-at-risk (VaR) and expected shortfall (ES).

The Sortino ratio is a direct parallel to the traditional SR. It compares the return of a portfolio with a chosen target return (which could be the risk free rate), and divides it by the semi-standard deviation. This ratio, developed by Sortino and Price (1994) was, at first, largely criticised for not being derived in the context of a market equilibrium theory.[1] However, Pedersen and Satchell (2002) added further motivation for the use of the Sortino ratio in a modified version using the risk return as the target return. As Pedersen and Satchell (2002) remark, this modified Sortino ratio is equivalent to the Sharpe ratio, except that standard deviation has been replaced by the semi-standard deviation in the denominator. The authors give support for the use of the modified Sortino ratio by placing it on a relevant theoretical foundation and by discussing its relative qualities in contrast with alternative approaches to assess performance. Moreover, Pedersen and Satchell (2002) have shown that there exists a utility-based one-period CAPM that promotes the use of the Sortino ratio, just like the traditional CAPM promotes the use of SR.

Throughout the years, VaR has become a standard measure of risk and has been receiving increasing attention by academics. VaR is commonly described in the literature (see for example, Bertsimas et al., 2004) as the lower α quantile of the distribution of portfolio returns.

Let $F(r)$ be a cumulative probability distribution of a random return R,

$$F(r) = P(R \leq r). \tag{1}$$

For some probability $\alpha \in (0,1)$ the VaR is generally defined as the α quantile of the distribution of the portfolio returns,

$$VaR_\alpha = q_\alpha = \inf\{r | F(r) \geq \alpha\}, \qquad \alpha \in (0,1). \tag{2}$$

VaR gives the size of the losses which may occur with probability no greater than α.

Alexander and Baptista (2003) and, more recently, Eling and Schumacher (2007) recommend the use of a VaR-based measure of performance that is closely related to the SR. In the particular context of hedge funds, Eling and Schumacher (2007) assess performance on the basis of VaR by applying a performance ratio that explicitly measures the excess return on VaR (ERVaR),

Under the assumption of elliptically symmetric distributions (with a mean equal or very close to zero) the proposed VaR-based measure of performance produces the same portfolio rankings as the SR. In the specific context of non-elliptically symmetric distributed returns, the portfolio with the highest ERVaR ratio may not be the portfolio with the highest SR.

[1] Leland (1999), for instance, states that the Sortino ratio is an *ad hoc* attempt to recognize the greater importance of downside risk.

VaR is a universal measure of risk, which means that it can be applied to any portfolio. Also, it has a clear probabilistic content and it is expressed in money, favouring its intuitive interpretation. VaR provides useful information but it cannot offer an exhaustive representation of an investor's preferences (Artzner et al., 1999). Furthermore, VaR presents several shortcomings. The most obvious shortcoming with respect to VaR is its threshold character. VaR is unable to differentiate between large and very large losses. Indeed, in the context of a VaR framework, the probability of losses and not its magnitude is of concern. Basak and Shapiro (2001) show that VaR investors often optimally choose a larger exposure to risky assets than non-VaR investors, and consequently incur in larger losses, when they occur. This is a direct consequence of the inability of VaR of not being able to penalize a potentially very large loss more than a large loss. This is particularly critical when dealing with non-normal heavy tailed distributions. In this context, the probability of a large loss is non-negligible and a risk measure that truly penalizes large losses is needed. By disregarding the loss beyond the quantile of the underlying distribution, VaR disregards the risk of extreme loss in the tail of the underlying distribution. Basak and Shapiro (2001) demonstrate that, due to this problem, the use of VaR increases the extreme loss in the tail of the distribution. In the context of options and loan portfolios, Yamai and Yoshiba (2002a) identified the same problem associated with the use of VaR.

Under non-elliptically symmetric distributed returns, VaR is unstable and difficult to work with due to its undesirable mathematical properties, such as the lack of subadditivity and convexity (Rockafellar and Uryasev, 2002). However, if the joint distribution of return is elliptically symmetric, VaR is subadditive and convex. In this particular context, VaR is proportional to scale and the two measures share the same properties (Yamai and Yoshiba, 2002b). Thus VaR, that was introduced as an attempt to measure risk under very general conditions, including portfolios with non-linear positions that usually exhibit asymmetric distribution returns, can only be used when the joint distribution function of the returns is elliptically symmetric. Consequently, the use of the VaR concept has no particular advantage over the use of Markowitz paradigm to assess risk-adjusted performance.

An alternative measure to VaR is expected shortfall (ES). Unlike VaR, ES has the desirable property of focusing on the size of the loss and not just on the frequency of losses.

The origins of ES can be traced down to Artzner et al. (1999), who have formalized an alternative measure of risk that they called tail conditional expectation. As defined by Artzner et al. (1999), tail conditional expectation coincides with the formalization of the ES presented next. The ES measures the expected magnitude of the losses, if the portfolio return drops below its α quantile (see, for example, Acerbi and Tasche, 2002),

$$ES_{\alpha} = E(R|R \leq q_{\alpha}), \forall\, \alpha \in (0,1). \tag{3}$$

ES is also known as conditional value-at-Risk (CVaR), a term introduced later by Rockafellar and Uryasev (2000) using an alternative integral notation. Assuming that returns are continuous and therefore the density, $f(r)$, exists along with all relevant integrals, ES may also be defined as,

$$CVaR_{\alpha} = \alpha^{-1} \int_{-\infty}^{q_{\alpha}} r f(r) dr. \tag{4}$$

CVaR/ES is therefore an expectation of the loss, conditioned that the loss is greater than or equal to VaR. Unlike VaR, ES is a well-behaved function in the sense that it is subadditive and therefore convex. Because of its convexity in relation to portfolio positions, ES has very tractable properties in terms of optimization (Rockafellar and Uryasev, 2002) and a global minimum is relatively easy to find.

ES is not a coherent measure of risk if the underlying random variable has a discrete probability space (Artzner et al., 1999). [2] With continuous probability distribution functions, ES is correctly defined as the conditional expectation beyond the VaR quantile. For discrete distributions, such as the histograms in empirical studies, a more careful definition of ES must be considered (see Acerbi and Tasche, 2002).

Independently but almost simultaneously, Acerbi et al. (2001) and Rockafellar and Uryasev (2002) develop a new definition of ES which is coherent under general distributions,[3]

$$ES_\alpha = \frac{1}{\alpha}E\left(RI_{\{R\leq q_\alpha\}}\right) + q_\alpha\left(1-\frac{F(q_\alpha)}{\alpha}\right), \tag{5}$$

Where $I_{\{Relation\}} = \begin{cases} 1, if\ Relation\ is\ true \\ 0, if\ Relation\ is\ false \end{cases}$.

The term $q_\alpha\left(1-\frac{F(q_\alpha)}{\alpha}\right)$ is the excess to be subtracted from the expected value $E\left(RI_{\{R\leq q_\alpha\}}\right)$ in the case that $F(q_\alpha) = P(R \leq q_\alpha) > \alpha$ (Acerbi et al., 2001). On the other hand, if $P(R \leq q_\alpha) = \alpha$, which occurs when the underlying probability distribution is continuous, the term is reduced to zero and the above definition of ES is equivalent to the definition of ES previously described in (4).

This new characterization of ES emphasizes its continuity with respect to α which in turn ensures the coherence of this risk measure.[4] Acerbi et al. (2001) show that ES satisfies subadditivity in full generality, with no assumptions at all on the probability distribution. They argue that ES represents a solid alternative for assessing relative risk as it has no restrictions of applicability.

Acerbi and Tasche (2002) propose an equivalent representation of ES as an integral of all the quantiles below the corresponding level. Introducing the so-called generalized inverse function,

$$F^{\leftarrow}(u) = \inf\{r|F(r) \geq u\}, \tag{6}$$

the authors show that ES_α can be simply expressed as the mean of $F^{\leftarrow}(u)$ on the confidence level interval $u \in [0,1]$,

$$ES_\alpha = \frac{1}{\alpha}\int_0^\alpha F^{\leftarrow}(u)du\,. \tag{7}$$

The above expression is equivalent to the one in Bertsimas et al. (2004), which defines ES as being the average of VaRs for all levels below α. Consider a sample of T returns. In order to estimate ES the sample of returns must be sorted in increasing order: $R_1 \leq R_2 \leq \cdots \leq$

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[2] Because they are not continuous with respect to the chosen confidence level, some measures of risk, when applied to discrete distributions, are very sensitive to small changes in the confidence level. This is the case of the ES as formalized by Artzner et al. (1999), Acerbi and Tasche (2002) and Rockafellar and Uryasev (2000).

[3] Artzner et al. (1999), after proving the lack of coherence of the tail conditional expectation for general distributions, proposed an alternative coherent risk measure which they termed worst conditional expectation. However, this measure cannot be implemented because it can only be applied when the entire distribution is known.

[4] See Rockafellar and Uryasev (2002) for a complete proof of the coherence of this new definition of ES.

R_T. The ES natural estimator is the average of the first $\alpha\%$, represented by the first k outcomes (where $k = [\alpha T]$),

$$ES_\alpha = \frac{1}{k}\sum_{i=1}^{k} R_i \,. \tag{8}$$

The above equation represents a natural non-parametric estimator of ES that does not rely on any kind of distributional assumptions with respect to the portfolio returns.

ES is proposed as a coherent measure of risk and a superior alternative to the industry standard VaR (Yamai and Yoshiba, 2002a). Despite all the positive features of ES as a measure of risk, it has not been fully exploited for performance evaluation purposes.

Incorporating ES as a measure of risk, Martin et al. (2003) presented an investment performance evaluation ratio called the stable tail adjusted return ratio (STARR), which provides a measure of excess return per unit of portfolio risk as measured by ES. The STARR was originally defined in the specific context of stable distributions and was presented as being a generalization of the SR.

Martin et al. (2003) recommend the use of stable distributions to compute ES. They argue that these distributions are more accurate in the modelling of extreme risk event probabilities, thus delivering more accurate risk estimates. Stable distributions are a class of probability distributions that allow skewness and heavy tails. Therefore there is a strong empirical argument to use stable distributions as many empirical financial series exhibit heavy tails and skewness. The overall stable distribution theory for finance is provided by Rachev and Mittnik (2000).

Since ES is a relatively new risk measure, there are few studies dealing with empirical testing of ES estimation methods. Giannopoulos and Tunaru (2005) argue that Filtered Historical Simulation (FHS) can provide an improved methodology for calculating ES. Recently, Harmantzis et al. (2006) conducted a study using indices as well as several currencies and concluded that, with respect to ES estimation, the historical simulation method is superior in accuracy while the use of parametric methods based on stable distributions overestimates ES.

One should note that advances that have been made in the context of VaR estimation should not be lost considering that the superior quality of VaR computation methodologies should also enable superior accuracy in the estimation of ES. In this sense, the problem of choosing the adequate method to estimate ES can benefit significantly by using advances in VaR estimation. Cutting-edge VaR estimation methods, like the methods that combine simulation techniques with the use of volatility changing models (FHS), can easily be adopted to estimate ES. By being free of any distributional assumptions in relation to the behaviour of the returns, these methods have a great flexibility in capturing all the empirical properties of the time series of returns under analysis, including skewness and kurtosis.

3. Methodology

3.1. Performance ratios

Different measures of risk-adjusted performance are considered for empirical computation, namely the Sharpe ratio (SR) and the three downside risk-adjusted measures of performance: the Sortino ratio, Excess return on VaR and Excess return on ES. To compute the risk-adjusted performance ratios, four different risk measures are used: standard deviation, lower partial moments (LPM), VaR and ES.

The SR (Sharpe, 1966) measures the relationship between the excess return and the standard deviation of the returns generated by a portfolio. For each portfolio p under evaluation, based on estimated values from a sample of daily returns $R_{p_1}, \ldots, R_{p_T}$ the SR is computed as:

$$SR_p = \frac{\bar{R}_p - R_f}{\sqrt{S_p^2}}, \tag{9}$$

Where $\bar{R}_p$ is the average daily return estimated for the portfolio over the sample period of analysis, R_f is the risk-free rate of return and $\sqrt{S_p^2}$ is the estimated standard deviation of the sample of portfolio daily returns.

Performance ratios based on downside measures of risk provide an alternative framework to assess risk adjusted performance. Three different ratios that are closely related to SR will also be used to empirically assess downside risk-adjusted performance: the Sortino ratio, Excess return on VaR and Excess return on ES. All these downside risk-adjusted measures of performance express a direct relationship between excess return and a specific downside measure of risk. Despite being based on downside risk measures, these are all relative measures of performance, like the SR, and therefore perfectly suitable to be used in the construction of portfolio ranks.

The version of the Sortino ratio that will be used for empirical application purposes is the one suggested by Pedersen and Satchell (2002), which represents the ratio between excess return and semi-standard deviation, as follows:

$$Sortino_p = \frac{\bar{R}_p - R_f}{SSD_p} \tag{10}$$

where, SSD_p is the estimated semi-standard deviation of the sample of portfolio daily returns.

The excess return on VaR ratio (ERVaR) is a performance ratio quite similar to the SR. The main innovation is that VaR takes the place of standard deviation as the selected measure of risk used to adjust the excess return of the portfolio. The ERVaR is the ratio between excess return and VaR:

$$ERVaR_p = \frac{\bar{R}_p - R_f}{\widehat{VaR}_{\alpha,p}}, \tag{11}$$

where $\widehat{VaR}_{\alpha,p}$ is the estimated value-at-risk (based on a sample of returns) of the risky portfolio p with the probability α.

Alternatively to the use of VaR as a risk measure to adjust the excess returns of the portfolio, the ES can be applied. The excess return on ES (ERES) corresponds to the ratio between excess return and ES.

$$ERES_p = \frac{\bar{R}_p - R_f}{\widehat{ES}_{\alpha,p}}, \tag{12}$$

where $\widehat{ES}_{\alpha,p}$ is the estimated (from a sample of returns) expected shortfall of the risky portfolio p , if the portfolio returns drop below its α quantile.

The ratio used in this study represents a more general version of the stable tail adjusted return ratio (STARR) introduced by Martin et al. (2003). In this study, excess returns on ES are defined in the context of general loss distributions and the estimation of ES is therefore not restricted to the assumption of stable returns distributions. Apart from this, the definition of STARR and the excess return on ES coincide. The empirical characteristics of the return series under investigation do not recommend the use of an ES estimator under a parametric framework. Therefore, the non-parametric estimator of the ES proposed by Acerbi and Tasche (2002) and Bertsimas et al. (2004) is used, as it does not rely on any restrictive assumption about the functional form of the empirical distribution of returns.

3.2. The computation of VaR and ES

The key feature of the parametric method to compute VaR is the assumption made about the probability distribution of the portfolio returns. In practice, the most frequent assumption is that the return distribution is a normal distribution. The normality assumption has the advantage of simplifying the estimation of VaR, since normal VaR (NVaR) can be directly derived from the standard deviation of the portfolio returns using a multiplying factor that will depend on the confidence level chosen,

$$NVaR_{\alpha} = \mu + Z_{\alpha}\sigma, \tag{13}$$

where μ is the mean, σ is the standard deviation of the portfolio returns and Z_{α} is the α quantile of the standard normal distribution.

While VaR is conceptually simple and flexible, for VaR figures to be useful they also need to be reasonably accurate. VaR is just an estimate, and its usefulness is directly dependent on its precision.

The simple analytic solution presented above in equation (13) does not hold when the financial time series under analysis exhibit some well known stylized facts. Besides skewness, financial time series often exhibit other types of distortions from normality, like for example fat tails. Focusing on the non-normality properties of the financial time series some analytical non-normal approaches to compute VaR need to be adopted. A commonly used approach to account for the non-normality in the return distribution consists on the use of the Cornish-Fisher expansion (Cornish and Fisher, 1937) to estimate VaR.[5] This approach makes use of certain additional parameters to allow for the fat tails or skewness and it was first introduced by Zangari (1996) to estimate parametric VaR of portfolios that include options. The Cornish-Fisher VaR (CFVaR), also known as Modified VaR (MVaR), is an estimator for VaR that estimates the true, unknown quantile function by its second order Cornish-Fisher expansion around the Normal quantile function. In fact, the rationale behind the Cornish-Fisher expansion is that one can obtain an approximate representation of any distribution with known moments in terms of the standard normal distribution. That is, the explicit polynomial expansions for the α quantile of a return distribution can be expressed in terms of the

[5] Favre and Galeano (2002), Amenc et al. (2003) and Gueyié and Amvella (2006) are some of the authors that used CFVaR in their studies.

standardized moments of the distribution and the corresponding quantile of the standard normal distribution (see Mina and Ulmer (1999) and Dowd (1998, Chapter 3), for details). The skewness and the kurtosis of the empirical distribution of the portfolio returns are incorporated in the estimation of the parametric VaR approximated by the application of the Cornish-Fisher expansion (Zangari, 1996) as follows:

$$CFVaR_{\alpha-\nu} = \mu + Z_{\alpha-\nu}\sigma, \tag{14}$$

where $Z_{\alpha-\nu}$ is the $(\alpha-\nu)$quantile of the standard normal distribution and ν is the adjustment provided by the Cornish-Fisher expansion,

$$\nu \approx \frac{1}{6}(Z_\alpha^2 - 1)SK + \frac{1}{24}(Z_\alpha^3 - 3Z_\alpha)E - \frac{1}{36}(2Z_\alpha^3 - 5Z_\alpha)SK^2, \tag{15}$$

where SK is the skewness and E is the excess kurtosis of the series of portfolio returns.

The Cornish-Fisher expansion presented above in equation (14) might not be reliable as an approximation of certain distributions that depart significantly from normality. In fact, in some situations the use of fully parametric methods to compute VaR might be totally inadequate. Any strictly parametric approach requires that the assumed parametric distribution must be adjustable as much as possible to the empirical data. Under certain specific circumstances (for example, when portfolios include non-linear positions), this might be a real difficulty. In such a case, an alternative method is required to estimate the true empirical portfolio return distribution in order to compute VaR.

Most recently, a new methodology has been developed in the literature to compute both VaR and ES. This new method successfully combines bootstrapping techniques with the use of parametric models and is generally known under de denomination of Filtered Historical Simulation (FSH). FHS was first proposed by Barone-Adesi et al. (1999). Under FHS the bootstrap process is applied to the residuals of a time series model (usually a GARCH-type model) used as a filter to extract autocorrelation and heteroscedasticity from the historical time series of returns. Despite being numerically intensive, FHS is quite simple to apply and as a result it is faster to implement than several more complicated methods. According to Hartz et al. (2006) FHS is also numerically extremely reliable. Additionally, the FHS methodology makes no assumptions about the distribution of the returns under analysis. Based only on the assumption of uncorrelated standardized residuals from an appropriate time series model, the use of the bootstrap resampling algorithm allows a computationally simple and feasible method to approximate the unknown return empirical distribution. Under FHS a bootstrap sample, generally denoted by R^*, of any size M, is generated. Based on this bootstrap sample the filtered historical simulated VaR and ES estimates can be easily obtained. VaR, under FHS, corresponds to the α quantile of the bootstrap sample generated under FHS,

$$VaR_{FHS,\alpha} = q_{\alpha,R^*}. \tag{16}$$

To obtain ES under FHS the bootstrapped returns must be ranked in increasing order: $R_1^* \leq R_2^* \leq \cdots \leq R_M^*$. The ES is the average of the first $\alpha\%$ returns in the sample of bootstrapped returns, represented by the first $K = [\alpha M]$ outcomes with M being the size of the bootstrap sample,

$$ES_{FHS,\alpha} = \frac{1}{K}\sum_{i=1}^{K} R_i^*. \tag{17}$$

In this study, the past performance of UK investment trusts will be assessed using these non-parametric VaR and ES estimators. By combining a non-parametric bootstrap procedure with a parametric modeling of the time series under analysis we are able to considerably improve the quality of the VaR and ES estimates.[6]

4. Data

From the total population of UK investment trusts alive on the 31st of March of 2006, those classified by the AITC into geographical sectors[7] were selected for analysis. Investment trusts classified by the AITC as split capital trusts were excluded from the study because of their dual nature.[8] Accordingly, 158 conventional investment trusts listed in the AITC were included in the initial sample. A 10 year series was defined as the minimum acceptable period of analysis. As a consequence, 44 trusts were excluded from the sample. Five additional investment trusts were also taken out of the sample because we were not able to find relevant price information about them on DataStream. As a result of this adjustment process, the sample was reduced to 109 investment trusts. Daily continuously compounded returns for each fund were computed using price information available on DataStream. From the total sample of 109 funds, 46 are investment trusts that invest in the UK and the remaining 63 invest outside the UK (Non-UK).

As one of the objectives of this research is also to analyse the position of a particular investment trust in relation to the market, the FTSE ALL-SHARE INDEX is used to proxy the market for benchmarking purposes. As a proxy for the risk free rate, the UK Interbank Overnight-Offered rate is used. Daily data for the benchmark and for the risk-free rate was also collected from DataStream.

A preliminary analysis on the empirical properties of the time series was performed.[9] This analysis was carried out to allow some conclusions on the distributional patterns of the data. For all trusts the skewness is different from zero, which constitutes the first indication that all the series are non-symmetric. Only 7 trusts (approximately 6,4%) exhibit positive skewness. For the great majority of the trusts (approximately 93,6%), the value of the skewness is negative. In addition, the value of the kurtosis is always greater than 3. For all

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[6] Baroni-Adesi et al. (1999), Pritsker (2001) and later Kuester et al. (2005), compare the performance of FHS with other parametric and non-parametric methodologies in the estimatation of VaR and conclude in favour of the superiority of FHS. Additionally, Giannopoulos and Turanu (2005) demonstrate how FHS can provide an improved methodology to compute ES. They argue that while resampling methods (such as FHS) are, in general, numerically intensive, they are quite simple to implement. Hence, it is faster to estimate VaR and ES with FHS than with other more sophisticated models. In addition, FHS is also numerically reliable (Hartz et al.,2006).

[7] As an alternative classification for the trusts, the AITC also organizes them into Specialists sectors. Most of the AITC trusts are included in both classifications. Only a few number of funds that appear in the Specialists sectors classification are not included in the list of trusts that are organized according to geographical sectors. Because of that and in order to avoid the duplication of trusts in our sample, only the classification into geographical sectors was considered for analysis and the trusts that are not included into this categorization were excluded from our study (these are mainly Private Equity trusts and trusts that are specialised in a specific economic sector, like for example Mining and Natural Resources).

[8] In this specific kind of trusts, capital and income shares are common.

[9] Although not presented here, the table with these figures is available from the authors upon request.

trusts, the application of the Jarque-Bera test[10] clearly rejects, for a confidence level of 99%, the hypothesis that the return data series are normally distributed. To further investigate the source of non-normality, the Jarque-Bera test was split into its skewness and kurtosis components and the components were tested separately. Only 10 trusts exhibit skewness values that are not statistically different from zero. For the remaining trusts skewness is statistically different from zero, indicating that the empirical series of returns are in general significantly (negative) skewed.

In addition, the hypotheses of independent returns and heteroscedasticity were also tested. Though independence has broader implications, the focus of this study will be on whether or not returns are uncorrelated. The Box-Pierce Q-Statistic was computed as well as Engle´s LM test. The results for the Box-Pierce statistics massively indicate the presence of serial correlation for a 95% level of confidence. When applied to the squared returns, the Box-Pierce Q-Statistic can provide evidence for the existence of heteroscedasticity. The null hypothesis of homoscedasticity was rejected with no exception. Finally, the application of Engle´s LM test to the squared returns gave further support for the presence of ARCH effects. With respect to all but one fund, the test detected significant autocorrelations for the 2^{nd}, 5^{th} and 10^{th} lag, at a 95% confidence level.

5. Empirical Results

The first step to the implementation of the FHS methodology (to estimate both VaR and ES) consists of a meticulous process of model fitting to select an appropriate volatility model. To ensure the validity of FHS the model selected to be used as a filter must necessarily pass the residual diagnostic tests for serial correlation and heteroscedasticity. Highly skewed and leptokurtic non-normal daily returns and a strong phenomenon of autocorrelation and heteroscedasticity are the main empirical properties of the data. Therefore, it is crucial to adopt a volatility model that properly deals with these empirical characteristics. For this purpose some GARCH-type models were estimated.[11] Letting m = 0,1,2,3 and n = 0,1,2,3, a set of ARMA(m,n) models, combined with alternative GARCH-type specifications for the variance equation were estimated with respect to each investment trust.[12] Alternative GARCH-type specifications were estimated and tested: GARCH (1,1); GARCH (1,1)-in-mean; GJR (1,1) and GJR (1,1)-in-mean.

From the total set of 64 estimated models for each time series under analysis, the best fitted model was selected. The first step for the selection of the best model for each fund is to perform a diagnostic check on the residuals for remaining serial correlation effects and also remaining heteroscedasticity. The well known Box-Pierce test was applied to the standardized residuals in order to investigate the presence of remaining serial correlation effects. When applied to the squared standardized residuals, the Box-Pierce test can give us a first indication of the correct specification of the variance equation by not rejecting the null hypothesis of

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[10] The results for the normality test as well as for autocorrelation and heteroscedasticity are also available upon request.

[11] The GARCH-type models were estimated using maximum likelihood (ML) approach according to the quasi-Newton method of Broyden, Fletcher, Goldfarb and Shanno. The results were obtained using Ox version 4.10 (see Doornik, 2007).

[12] For the estimation of the models the non-negativity and stationary conditions defined in the literature were considered.

homoscedasticity. Additionally the presence of remaining ARCH effects was investigated by the application of the Engles´s LM test and the Residual Based Diagnostic (RBD) of Tse (2002).

For each fund, only the models that passed simultaneously all the diagnostic checks (at a 95% confidence level)[13] were considered robust candidates to be selected as the best model. Next, considering the set of robust models for each fund, the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) were used in the comparison of the models and the final model selection was done by choosing the model which generates the lowest AIC and/or SIC. AIC and SIC are operational ways of trading off the complexity of an estimated model against how well it fits the data. It should be noted that SIC always provides a model with a number of parameters no greater than that chosen by AIC. The main purpose is to find the model that best fits the data with a minimum of free parameters. For those cases in which the AIC and the SIC do not select the same model, a log-likelihood ratio test (LRT) was applied to assess the statistical significance of the difference. In the case that the models selected by the two different adopted selection criteria are significantly different, according to the results provided by the application of the LRT, the model selected by the AIC was used as it is considered to be superior in terms of fit improvement. Otherwise, the simpler model was chosen and parsimony is ensured. For the great majority of the trusts under analysis, the fitted best model has an asymmetric specification for the variance equation. Table 1 presents these results.

[Insert Table 1 here]

Alternative risk-adjusted measures of performance are presented in table 2: the Sharpe ratio (SR), the Sortino ratio, excess return on value-at-risk (ERVaR) and excess return on expected shortfall (ERES). Two alternative versions of the excess return on VaR are computed. Firstly, the VaR is estimated using the Cornish-Fisher approximation (CFVaR). Secondly, the VaR (as well as ES) is estimated using the FHS method[14].

[Insert Table 2 here]

[13] Exceptionally, if for a particular fund there was not any model that passed simultaneously all the diagnostic checking at a 95% confidence level, the confidence level was changed to 99% and another round of the selection process took place. After that and if there still exist any funds that did not pass simultaneously all the diagnostic checking, at a 99% confidence level, those funds may still be considered for further analysis. On such a case, for a model to be considered for further appreciation it is only necessary that its residuals pass the serial correlation test, at a 95% confidence level.

[14] To obtain the 99% confidence level VaR_{FHS} and ES_{FHS} estimates of 100000 pseudo returns were generated through the implementation of a bootstrap (with replacement) procedure based on the residuals of the GARCH-type model previously fitted for each of the investment trust considered.

Performance rankings are then constructed for each of these measures. Rankings considering all funds as well as rankings for each of the two trusts subsamples (UK and Non-UK) are constructed (see appendix 1).

5.1. Rank Correlation Analysis

Spearman´s rank correlation test is used to assess the level of association between performance ranks. In the context of the Spearman´s ordinal measure of correlation, if the level of association between two rankings (constructed on the basis of two alternative measures of performance) is not statistically significant, we can conclude that the use of different performance measures impacts the ranking. In this case, the choice of the performance measure is critical as it may influence all the performance evaluation rankings. On the contrary, if the level of association between rankings is statistically significant, we can conclude that the use of different measures of performance does not lead to significantly different ranks and the results of performance evaluation are approximately the same no matter what measure is used to assess the performance. The results of the rank correlations are summarized in table 3.

[Insert Table 3 here]

With no exception, at a confidence level of 99%, all the performance measures display a significant level of association with respect to the traditional SR as well as in relation to each other. In summary, on the basis of these results, none of the downside risk-adjusted performance measures results in significant changes in the ranking of investment trusts when compared to the rankings based on the use of SR. In fact, according to these results, it does not seem to matter which measure is used to assess the performance of investment trusts. Because the application of downside risk-adjusted performance measures result in ranks that are similar to those produced in the context of SR, the use of the latter seems justified from an empirical point of view.

Next, the original sample of trusts (109 trusts) was split into two subcategories: UK Trusts (46 trusts that invest in UK) and Non-UK Trusts (63 trusts that invest outside the UK) The results for the Spearman´s rank correlation test for these subcategories are presented in tables 4 and 5.

[Insert Table 4 here]

[Insert Table 5 here]

The results obtained for the UK and Non-UK sub-samples are the same as those obtained for the global sample as all the performance measures display a significant level of association with respect to the Sharpe ratio as well as to each other.

The rank correlation analysis suggests that all performance measures lead to identical fund rankings, thus supporting the hypothesis that the choice of the performance measure does not have a significant impact on the relative evaluation of investment trusts, even in the presence of empirical distributions that exhibit (mostly) significant negative skewness. This type of evidence is somewhat puzzling as it is well known that the different performance measures are theoretically very distinct. As mentioned previously, under the SR a normal distribution is assumed for the return distribution and only the first two moments are of interest. By contrast, excess return on VaR and excess return on ES (in the context of FHS methodology) do not rely on any distributional assumption and therefore the asymmetry (or even the fat tails) of the empirical distribution are taken into account.

In addition, we analyze the mean and standard deviation of performance ratios computed with respect to our sample of trusts.

[Insert Table 6 here]

Among the five performance ratios, excess return on CFVaR presents the lowest mean and standard deviation. The mean and standard deviation are considerably higher for the Sortino ratio in comparison to any of the other performance ratios considered. Performance ratios based on CFVaR, VaR and ES exhibit a lower standard deviation (as well as a lower mean) in relation to the SR. The magnitudes of the standard deviation differ considerably between the Sortino Ratio and the other metrics. These findings might challenge the conclusions obtained from the Spearman's correlation in the sense that they might be interpreted as suggesting that the use of alternative performance ratios might produce different performance ranks. To further explore this issue, a refined analysis of performance rankings is performed in the next section.

5.2. A further analysis of performance rankings

As the findings obtained from correlation analysis suggest that performance ranks are similar, independently of the measure that is used to assess risk, a deeper analysis is required to further investigate this issue. Indeed, the significant rank correlations might hide some important differences in the ordering of the funds.

The first evidence on the existence of significant differences between the rankings on the basis of alternative performance measures is the rank order attributed to the benchmark (see appendix 1). Considering the total sample of trusts, the position of the benchmark varies from 68 (according to Excess Return on CFVaR) to 73 (according to Sharpe Ratio). This means that by changing the performance measure used from the Excess Return on CFVaR to the Sharpe Ratio there are 5 trusts that change from being underperforms to beating the market. If we focus on the subsample of UK trusts, the position of the benchmark varies from 33 (according to Excess Return on CFVaR, Excess Return on VaR and Excess Return on ES) to 36 (according to Sortino Ratio). Finally, for the sub-sample of Non-UK trusts the order of the benchmark changes from 36 (according to Excess Return on CFVaR) to 39 (according to Sharpe Ratio). It should be noticed that only Excess Return on VaR and Excess Return on ES always generate the same rank order for the benchmark (considering the total sample, UK sub-sample and also Non-UK sub-sample).

We further analyse the percentage of funds that exhibit the same rank order according to different performance metrics. As reported in table 7, the percentage of funds with the same rank order according to the use of two different measures of performance is at most of 11% on average (considering the sub-sample of Non-UK trusts).

[Insert Table 7 here]

For the total sample of trusts the percentage of funds with the same rank order according to the use of two alternative performance measures ranges from 5% (Sortino *versus* Excess Return on ES and Excess Return on CFVaR *versus* Excess Return on ES) to 30% (Excess Return on VaR *versus* Excess Return on ES). If we consider the sub-sample of UK trusts this percentage ranges from 1% (Sharpe Ratio *versus* Excess Return on CFVaR) to 23% (Excess Return on VaR *versus* Excess Return on ES). Finally, for the sub-sample of Non-UK trusts the same percentage ranges from 5% (Excess Return on CFVaR *versus* Excess Return on ES) to 26% (Excess Return on VaR *versus* Excess Return on ES).

Not surprisingly, the pair of performance measures Excess Return on VaR *versus* Excess Return on ES exhibits systematically and by far the highest percentage of equality in ranks. The general conclusion that can be drawn from this analysis is that the percentage of funds that are ranked in the same position according to different performance measures is very low.

An alternative approach to identify significant differences between rankings obtained from the use of different performance measures is to examine the number of changes in the top/bottom five funds. With respect to each performance ratio the top five and bottom five rankings were analysed (see appendix 2). Next, the number of changes in these rankings were tracked across the different pairs of performance measures. Table 8 summarizes the results for this analysis.

[Insert Table 8 here]

On average, with respect to the total sample, 42% of the trusts change in the top five ranking based on the use of alternative performance measures. This percentage is similar for the sub-sample of UK trusts (40%) and a little lower considering the Non-UK sub-sample (32%). For the total sample as well as for the two sub-samples, the bottom five ranking is more stable across the different pairs of performance measures. In fact, the percentage of trusts that change in the top five is always higher than the percentage of trusts that change in the bottom five ranking.

In sum, despite highly positive correlations between fund rankings in the context of the Spearman´s correlation analysis, a more detailed analysis between the performance ranks based on alternative measures shows several important rank changes that may not be neglected by investors.

6. Concluding remarks

Traditional measures of performance can produce biased estimates of fund managers abilities when returns are not elliptically symmetric distributed. Indeed, when dealing with highly negative skewed returns, it is expected that downside risk measures can be superior risk estimators. As a consequence, downside risk-adjusted measures of performance are considered, from a theoretical point of view, more accurate.

The purpose of this paper is to empirically analyze whether there is any impact on fund performance rankings from the use of traditional versus downside risk-adjusted performance measures. Different performance measures are computed for a data set of UK investment trusts The time series of returns from UK investment trusts exhibit significant negative skewness, a characteristic that is relevant for the use of downside risk-adjusted measures of performance. In this case, a significant impact on performance ranks based on traditional *versus* downside risk-adjusted performance is expected.

The first approach followed to assess the existence of significant differences in the rankings produced by alternative measures of performance involves the application of Spearman's rank correlation test. A high correlation was observed between all pairs of performance rankings, suggesting that the choice of the performance measure does not impact rankings of UK investment trusts significantly. These findings are consistent with Eling and Schumacher (2007), who reached similar conclusions in the context of hedge funds.

The Sharpe ratio assumes that the returns follow a normal distribution. In contrast, our VaR and Expected Shortfall estimates were computed on the basis of FHS, which is a distribution-free methodology and therefore particularly suitable to capture any empirical properties of the data. Considering the characteristics of our data (highly significant negative skewed returns), our high rank correlation findings are unexpected.

In order to clarify these puzzling results, we performed a more detailed analysis on the performance rankings. This analysis revealed important differences between the performance rankings, reflected either in the number of funds that underperform/outperform the benchmark, the number of funds that maintain an equal order across rankings and the number of changes in the five top/bottom performing funds.

Although these differences in performance rankings were not captured by the rank correlation analysis, their economic significance may be important to investors and fund managers. The persistence of these differences over time may also be of interest to further investigate the impact of using different risk measures to assess relative fund performance, an issue that deserves future research.

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Table 1 – List of best models used as filters for serial correlation and heteroscedasticity under FHS

This table list the best model fitted and selected for each of the investment trusts (identified by an IT code) and for the benchmark (the FTSE All share index represented by R900).

IT Code	Best Model Fitted	IT Code	Best Model Fitted	IT Code	Best Model Fitted
R10	GJR (1,1) ARMA (3,3)	**R171**	GJR (1,1) ARMA (3,3)	**R53**	GJR (1,1) ARMA (1,1)
R100	GJR (1,1) ARMA (3,3)	**R172**	GJR (1,1) ARMA (1,0)	**R55**	GJR (1,1) ARMA (3,3)
R102	GJR (1,1) ARMA (1,1)	**R173**	GJR (1,1) ARMA (2,0)	**R56**	GJR (1,1) ARMA (3,3) in-mean
R106	GJR (1,1) ARMA (1,2)	**R174**	GJR (1,1) ARMA (3,0)	**R60**	GJR (1,1) ARMA (2,1)
R107	GJR (1,1) ARMA (1,1)	**R175**	GJR (1,1) ARMA (1,1)	**R62**	GJR (1,1) ARMA (1,1)
R108	GJR (1,1) ARMA (1,1)	**R177**	GJR (1,1) ARMA (1,2) in-mean	**R64**	GJR (1,1) ARMA (2,0)
R109	GJR (1,1) ARMA (2,1)	**R178**	GJR (1,1) ARMA (3,3)	**R66**	GJR (1,1) ARMA (1,1)
R11	GJR (1,1) ARMA (3,1) in-mean	**R180**	GJR (1,1) ARMA (1,2)	**R69**	GJR (1,1) ARMA (3,3)
R110	GARCH (1,1) ARMA (3,3)	**R184**	GARCH (1,1) ARMA (1,1)	**R70**	GJR (1,1) ARMA (2,0)
R111	GJR (1,1) ARMA (3,3) in-mean	**R186**	GJR (1,1) ARMA (1,1) in-mean	**R72**	GJR (1,1) ARMA (1,1)
R112	GJR (1,1) ARMA (1,1)	**R187**	GJR (1,1) ARMA (3,3)	**R73**	GJR (1,1) ARMA (1,1)
R113	GJR (1,1) ARMA (1,1)	**R188**	GJR (1,1) ARMA (3,3)	**R74**	GJR (1,1) ARMA (1,1)
R114	GARCH (1,1) ARMA (3,3)	**R189**	GJR (1,1) ARMA (1,2)	**R75**	GJR (1,1) ARMA (2,1)
R115	GJR (1,1) ARMA (3,2)	**R193**	GARCH (1,1) ARMA (1,1)	**R76**	GARCH (1,1) ARMA (2,1)
R116	GJR (1,1) ARMA (3,3)	**R195**	GJR (1,1) ARMA (3,0)	**R77**	GARCH (1,1) ARMA (1,2)
R122	GJR (1,1) ARMA (1,1)	**R196**	GJR (1,1) ARMA (3,2)	**R78**	GJR (1,1) ARMA (3,3)
R123	GJR (1,1) ARMA (1,1)	**R197**	GJR (1,1) ARMA (3,3)	**R80**	GARCH (1,1) ARMA (1,1) in-mean
R126	GJR (1,1) ARMA (3,0)	**R198**	GARCH (1,1) ARMA (3,2)	**R81**	GARCH (1,1) ARMA (1,1) in-mean
R128	GJR (1,1) ARMA (1,1)	**R2**	GJR (1,1) ARMA (1,3)	**R82**	GJR (1,1) ARMA (1,0)
R129	GJR (1,1) ARMA (3,0)	**R21**	GJR (1,1) ARMA (1,1)	**R84**	GJR (1,1) ARMA (1,1)
R131	GJR (1,1) ARMA (2,0)	**R22**	GJR (1,1) ARMA (2,1) in-mean	**R85**	GJR (1,1) ARMA (1,2)
R134	GJR (1,1) ARMA (2,1) in-mean	**R23**	GJR (1,1) ARMA (0,0)	**R86**	GJR (1,1) ARMA (3,0)
R138	GJR (1,1) ARMA (1,1)	**R28**	GJR (1,1) ARMA (1,1)	**R900**	GJR (1,1) ARMA (0,0)
R141	GJR (1,1) ARMA (1,2)	**R29**	GJR (1,1) ARMA (3,3)	**R92**	GJR (1,1) ARMA (3,3)
R142	GARCH (1,1) ARMA (3,3)	**R3**	GJR (1,1) ARMA (1,2)	**R93**	GJR (1,1) ARMA (1,1)
R143	GJR (1,1) ARMA (3,3) in-mean	**R30**	GJR (1,1) ARMA (3,3)	**R94**	GJR (1,1) ARMA (1,1)
R144	GJR (1,1) ARMA (2,0) in-mean	**R32**	GJR (1,1) ARMA (1,1)	**R95**	GJR (1,1) ARMA (2,1) in-mean
R145	GJR (1,1) ARMA (2,2) in-mean	**R34**	GJR (1,1) ARMA (1,1)	**R96**	GJR (1,1) ARMA (3,3)
R147	GJR (1,1) ARMA (3,1)	**R38**	GJR (1,1) ARMA (2,0)	**R98**	GJR (1,1) ARMA (1,1)
R148	GJR (1,1) ARMA (1,1) in-mean	**R4**	GJR (1,1) ARMA (1,1)	**R99**	GJR (1,1) ARMA (1,1)
R150	GJR (1,1) ARMA (3,3)	**R41**	GJR (1,1) ARMA (3,0)		
R151	GJR (1,1) ARMA (1,2)	**R42**	GJR (1,1) ARMA (3,3)		
R152	GJR (1,1) ARMA (1,0)	**R43**	GARCH (1,1) ARMA (3,0)		

Table 2 – Estimates of performance measures

This table summarizes the results of the different performance ratios for each of the trusts in the sample (identified by an IT code) as well as for the benchmark (the FTSE All-Share represented by R900). The results for the benchmark are reported in bold.

IT Code	SR	Sortino	ERCFVaR	ERVaR	ERES	IT Code	SR	Sortino	ERCFVaR	ERVaR	ERES
R10	0.0186	4.2678	0.0025	0.0097	0.0063	R196	0.0039	0.6833	0.0012	0.0018	0.0016
R100	0.0117	1.8699	0.0040	0.0057	0.0047	R197	-0.0147	-2.0081	-0.0046	-0.0105	-0.0080
R102	-0.0107	-1.2568	-0.0023	-0.0061	-0.0047	R198	0.0337	8.2999	0.0063	0.0188	0.0121
R106	0.0131	1.8356	0.0045	0.0068	0.0050	R2	0.0195	2.6294	0.0035	0.0199	0.0146
R107	0.0095	1.8644	0.0022	0.0037	0.0028	R21	0.0079	1.0152	0.0027	0.0039	0.0033
R108	0.0198	3.2254	0.0068	0.0107	0.0082	R22	0.0090	1.1939	0.0028	0.0050	0.0037
R109	0.0352	5.1765	0.0089	0.0252	0.0181	R23	0.0051	0.8675	0.0018	0.0022	0.0018
R11	0.0065	1.3608	0.0022	0.0036	0.0028	R28	-0.0026	-0.5039	-0.0003	-0.0012	-0.0008
R110	-0.0047	-0.5596	-0.0017	-0.0025	-0.0020	R29	-0.0001	-0.0111	0.0000	0.0000	0.0000
R111	0.0024	0.2787	0.0007	0.0012	0.0008	R3	0.0109	1.5639	0.0024	0.0062	0.0046
R112	0.0337	7.0166	0.0110	0.0184	0.0141	R30	0.0596	15.2758	0.0184	0.0249	0.0180
R113	0.0064	1.1522	0.0023	0.0027	0.0022	R32	0.0020	0.3470	0.0005	0.0011	0.0009
R114	0.0372	8.2197	0.0065	0.0188	0.0154	R34	0.0685	33.4412	0.0103	0.0275	0.0151
R115	0.0289	3.7571	0.0077	0.0160	0.0121	R38	0.0032	0.5751	0.0010	0.0014	0.0011
R116	0.0175	3.4072	0.0046	0.0075	0.0062	R4	-0.0107	-1.2568	-0.0023	-0.0061	-0.0047
R122	0.0192	2.6133	0.0035	0.0146	0.0092	R41	0.0041	0.6919	0.0011	0.0020	0.0017
R123	-0.0053	-0.9103	-0.0012	-0.0028	-0.0022	R42	0.0129	2.8989	0.0022	0.0055	0.0040
R126	0.0040	0.8430	0.0011	0.0016	0.0013	R43	0.0220	1.9757	0.0027	0.0111	0.0064
R128	0.0278	6.8346	0.0069	0.0104	0.0075	R44	-0.0052	-0.6462	-0.0015	-0.0029	-0.0022
R129	0.0023	0.3175	0.0007	0.0014	0.0011	R45	-0.0049	-0.8343	-0.0018	-0.0026	-0.0021
R131	0.0053	0.9521	0.0015	0.0023	0.0019	R46	-0.0138	-2.0396	-0.0022	-0.0117	-0.0085
R134	0.0162	3.1641	0.0039	0.0097	0.0064	R47	0.0164	4.2676	0.0028	0.0084	0.0063
R138	0.0151	3.9423	0.0028	0.0089	0.0061	R49	0.0044	0.7782	0.0011	0.0032	0.0026
R141	0.0181	3.3597	0.0063	0.0076	0.0060	R5	0.0345	7.6784	0.0110	0.0137	0.0111
R142	0.0199	4.4735	0.0041	0.0107	0.0076	R52	0.0133	2.1493	0.0034	0.0071	0.0059
R143	0.0076	1.6689	0.0027	0.0039	0.0030	R53	0.0048	0.9071	0.0007	0.0018	0.0013
R144	-0.0002	-0.0381	-0.0001	-0.0001	-0.0001	R55	0.0215	5.0257	0.0029	0.0093	0.0069
R145	-0.0165	-1.8926	-0.0016	-0.0156	-0.0110	R56	0.0185	1.8480	0.0036	0.0132	0.0095
R147	-0.0077	-1.6760	-0.0014	-0.0070	-0.0055	R60	0.0140	2.0985	0.0043	0.0086	0.0064
R148	0.0351	8.4777	0.0051	0.0207	0.0141	R62	0.0457	8.0228	0.0151	0.0238	0.0188
R150	0.0031	0.4517	0.0006	0.0024	0.0016	R64	0.0471	9.3662	0.0111	0.0110	0.0090
R151	-0.0195	-2.0958	-0.0059	-0.0129	-0.0094	R66	0.0139	2.8858	0.0032	0.0069	0.0055
R152	0.0040	0.4424	0.0011	0.0032	0.0026	R69	0.0047	0.7272	0.0016	0.0027	0.0023
R154	0.0150	2.6972	0.0051	0.0057	0.0047	R70	0.0136	2.0164	0.0040	0.0083	0.0066
R155	-0.0156	-1.7005	-0.0046	-0.0102	-0.0084	R72	0.0194	2.8916	0.0052	0.0137	0.0113
R156	0.0291	12.4271	0.0056	0.0074	0.0052	R73	0.0494	12.6373	0.0076	0.0224	0.0168
R16	-0.0044	-0.6495	-0.0004	-0.0044	-0.0027	R74	0.0049	0.9932	0.0013	0.0018	0.0014
R167	-0.0073	-0.7977	-0.0022	-0.0038	-0.0031	R75	0.0256	5.6831	0.0050	0.0182	0.0134
R168	-0.0006	-0.0704	-0.0002	-0.0003	-0.0002	R76	0.0699	16.1532	0.0166	0.0250	0.0189
R169	-0.0163	-2.6425	-0.0058	-0.0065	-0.0056	R77	0.0160	3.7816	0.0029	0.0092	0.0066
R171	-0.0016	-0.2874	-0.0005	-0.0008	-0.0007	R78	0.0158	3.1444	0.0042	0.0101	0.0078
R172	0.0042	0.7251	0.0014	0.0018	0.0015	R80	0.0493	13.8547	0.0053	0.0175	0.0111
R173	0.0095	1.6111	0.0033	0.0055	0.0046	R81	0.0443	9.5457	0.0053	0.0106	0.0074
R174	0.0117	1.6093	0.0018	0.0110	0.0077	R82	-0.0056	-0.8202	-0.0016	-0.0031	-0.0025
R175	0.0052	1.0726	0.0017	0.0024	0.0019	R84	-0.0070	-0.9433	-0.0020	-0.0033	-0.0026
R177	-0.0067	-1.2773	-0.0014	-0.0024	-0.0018	R85	-0.0025	-0.3648	-0.0004	-0.0018	-0.0013
R178	0.0138	3.1527	0.0022	0.0085	0.0062	R86	-0.0120	-1.3583	-0.0040	-0.0073	-0.0061
R180	0.0097	2.0277	0.0029	0.0050	0.0040	**R900**	**0.0041**	**0.7829**	**0.0015**	**0.0022**	**0.0018**
R184	0.0037	0.8207	0.0009	0.0017	0.0013	R92	-0.0127	-1.3646	-0.0036	-0.0131	-0.0101
R186	0.0163	3.3785	0.0048	0.0052	0.0039	R93	0.0100	1.6311	0.0025	0.0053	0.0042
R187	0.0106	1.4825	0.0033	0.0056	0.0043	R94	0.0152	3.0157	0.0045	0.0063	0.0049
R188	0.0156	3.1955	0.0044	0.0062	0.0045	R95	0.0035	0.3376	0.0011	0.0026	0.0020
R189	0.0255	3.5795	0.0086	0.0174	0.0130	R96	0.0194	3.0154	0.0046	0.0212	0.0175
R193	0.0104	2.6241	0.0014	0.0036	0.0023	R98	0.0201	4.1171	0.0035	0.0108	0.0078
R195	0.0082	1.9853	0.0022	0.0028	0.0021	R99	0.0114	2.5542	0.0022	0.0073	0.0052

Table 3 - Rank correlation test results: Total sample (99% Confidence level)

This table summarizes the results obtained on the Spearman rank correlation test (at the 99% confidence level and considering all investment trusts of our sample) for the different risk-adjusted performance measures: Sharpe ratio, Sortino ratio, Excess Return on CFVaR, Excess Return on VaR and Excess Return on ES.

	Sharpe Ratio	Sortino	Excess Return CFVaR	Excess Return VaR	Excess Return ES
Sharpe Ratio		0.9791	0.9623	0.9735	0.9704
Sortino			0.9404	0.9352	0.9322
Excess Return CFVaR				0.9333	0.9405
Excess Return VaR					0.9970
Excess Return ES					

Table 4 - Rank correlation test results: UK (99% Confidence level)

This table summarizes the results obtained on the Spearman rank correlation test (at the 99% confidence level and considering only investment trusts of the UK subsample) for the different risk-adjusted performance measures: Sharpe ratio, Sortino ratio, Excess Return on CFVaR, Excess Return on VaR and Excess Return on ES.

	Sharpe Ratio	Sortino	Excess Return CFVaR	Excess Return VaR	Excess Return ES
Sharpe Ratio		0.9995	0.9957	0.9978	0.9972
Sortino			0.9945	0.9973	0.9965
Excess Return CFVaR				0.9935	0.9938
Excess Return VaR					0.9997
Excess Return ES					

Table 5 - Rank correlation test results: Non-UK (99% Confidence level)

This table summarizes the results obtained on the Spearman rank correlation test (at the 99% confidence level and considering only the investment trusts of the Non-UK subsample) for the different risk-adjusted performance measures: Sharpe ratio, Sortino ratio, Excess Return on CFVaR, Excess Return on VaR and Excess Return on ES.

	Sharpe Ratio	Sortino	Excess Return CFVaR	Excess Return VaR	Excess Return ES
Sharpe Ratio		0.9977	0.9945	0.9957	0.9953
Sortino			0.9936	0.9921	0.9921
Excess Return CFVaR				0.9900	0.9911
Excess Return VaR					0.9996
Excess Return ES					

Table 6 - Performance Ratios: Mean and Standard Deviation

This table presents the mean and the standard deviation of the different performance ratios: Sharpe ratio, Sortino ratio, Excess Return on CFVaR, Excess Return on VaR and Excess Return on ES

	Sharpe Ratio	Sortino	Excess Return CFVaR	Excess Return VaR	Excess Return ES
Mean	0.0119	2.7724	0.0027	0.0056	0.0041
Standard Deviation	0.0174	4.7237	0.0041	0.0088	0.0065

Note: Performance ratios ERCFVaR, ERVaR and ERES were estimated with a 99% confidence level.

Table 7- Equality of performance rankings

This table reports the number of investment trusts that exhibit the same rank order resulting from the use of alternative performance measures: Sharpe ratio, Sortino ratio, Excess Return on CFVaR, Excess Return on VaR and Excess Return on ES. These numbers are also expressed in percentage of taotal sample.

	Total Sample (109 trusts)		UK (46 trusts)		Non-UK (63 trusts)	
	Equality of ranks	Equality of ranks %	Equality of ranks	Equality of ranks %	Equality of ranks	Equality of ranks %
SR-Sortino	10	9%	14	13%	8	7%
SR-ERCFVaR	10	9%	1	1%	12	11%
SR-ERVaR	11	10%	9	8%	11	10%
SR-ERES	11	10%	5	5%	11	10%
Sortino-ESCFVaR	7	6%	2	2%	6	5%
Sortino-ERVaR	9	8%	7	6%	14	13%
Sortino-ERES	6	5%	5	5%	14	13%
ERCFVaR-ERVaR	7	6%	7	6%	7	6%
ESCFVaR-ERES	5	5%	6	5%	6	5%
ERVaR-ERES	33	30%	25	23%	29	26%
Average	10,9	10%	8,1	7%	11,8	11%
Maximum	33	30%	25	23%	29	26%
Minimum	5	5%	1	1%	6	5%

Table 8 – Number of changes in the top/bottom five rankings

This table reports the changes in the top/bottom five performing funds resulting from the different rsik-adjusted perforamce measures: Sharpe ratio, Sortino ratio, Excess Return on CFVaR, Excess Return on VaR and Excess Return on ES

	Total Sample (109 trusts)		UK (46 trusts)		Non-UK (63 trusts)	
	Changes in Top Five	Changes in Bottom Five	Changes in Top Five	Changes in Bottom Five	Changes in Top Five	Changes in Bottom Five
SR-Sortino	0	1	0	0	2	1
SR-ERCFVaR	3	1	2	1	1	0
SR-ERVaR	2	2	3	1	1	0
SR-ERES	3	2	3	1	1	0
Sortino-ESCFVaR	3	2	2	1	3	1
Sortino-ERVaR	2	1	3	1	3	1
Sortino-ERES	3	2	3	1	3	1
ERCFVaR-ERVaR	2	3	2	1	1	0
ESCFVaR-ERES	2	3	2	1	1	0
ERVaR-ERES	1	1	0	0	0	0
Average	2,1	1,8	2	0,8	1,6	0,4
Average %	**42%**	**36%**	**40%**	**16%**	**32%**	**8%**

Appendix 1 – Performance rankings according to different performance measures

Panel A – Total Sample

IT Code	SR	Sortino	ERCFVaR	ERVaR	ERES	IT Code	SR	Sortino	ERCFVaR	ERVaR	ERES
R10	29	20	53	30	36	R196	77	77	72	75	74
R100	49	51	34	50	47	R197	106	107	108	106	105
R102	101	99	103	100	100	R198	14	10	15	10	15
R106	47	54	28	45	45	R2	25	41	39	9	9
R107	57	52	62	60	61	R21	61	65	50	58	58
R108	24	30	13	25	22	R22	59	62	48	56	57
R109	10	17	8	2	3	R23	67	69	64	73	72
R11	63	61	58	61	60	R28	90	90	88	89	89
R110	92	91	98	92	92	R29	85	85	85	85	85
R111	82	84	82	83	84	R3	52	59	55	47	49
R112	13	14	5	12	11	R30	3	3	1	4	4
R113	64	63	56	67	66	R32	84	81	84	84	83
R114	9	11	14	11	7	R34	2	1	7	1	8
R115	16	25	10	16	14	R38	80	78	78	81	81
R116	32	27	26	40	37	R4	102	100	104	101	101
R122	28	43	37	17	20	R41	74	76	75	74	73
R123	95	97	92	94	95	R42	48	37	59	52	55
R126	76	70	73	80	79	R43	20	50	51	21	33
R128	17	15	12	28	27	R44	94	92	95	95	94
R129	83	83	81	82	82	R45	93	96	99	93	93
R131	65	67	67	72	70	R46	105	108	102	107	107
R134	35	32	35	31	34	R47	33	21	47	37	35
R138	40	23	49	34	39	R49	71	73	74	64	62
R141	31	29	16	39	40	R5	12	13	6	18	17
R142	23	19	32	26	26	R52	46	45	40	43	41
R143	62	55	52	59	59	R53	69	68	80	77	78
R144	86	86	86	86	86	R55	21	18	44	32	29
R145	109	106	96	110	110	R56	30	53	36	20	19
R147	100	104	94	103	102	R60	42	46	30	35	32
R148	11	9	22	8	10	R62	7	12	3	5	2
R150	81	79	83	71	75	R64	6	8	4	23	21
R151	110	109	110	108	108	R66	43	39	43	44	42
R152	75	80	76	63	63	R69	70	74	66	66	64
R154	41	40	21	49	48	R70	45	48	33	38	31
R155	107	105	107	105	106	R72	27	38	20	19	16
R156	15	6	17	41	43	R73	4	5	11	6	6
R16	91	93	90	99	98	R74	68	66	71	78	77
R167	99	94	101	98	99	R75	18	16	23	13	12
R168	87	87	87	87	87	R76	1	2	2	3	1
R169	108	110	109	102	103	R77	36	24	45	33	30
R171	88	88	91	88	88	R78	37	34	31	29	23
R172	72	75	70	76	76	R80	5	4	18	14	18
R173	58	57	42	53	50	R81	8	7	19	27	28
R174	50	58	63	22	25	R82	96	95	97	96	96
R175	66	64	65	70	71	R84	98	98	100	97	97
R177	97	101	93	91	91	R85	89	89	89	90	90
R178	44	33	57	36	38	R86	103	102	106	104	104
R180	56	47	46	57	54	**R900**	**73**	**72**	**68**	**69**	**69**
R184	78	71	79	79	80	R92	104	103	105	109	109
R186	34	28	24	55	56	R93	55	56	54	54	53
R187	53	60	41	51	52	R94	39	35	27	46	46
R188	38	31	29	48	51	R95	79	82	77	68	68
R189	19	26	9	15	13	R96	26	36	25	7	5
R193	54	42	69	62	65	R98	22	22	38	24	24
R195	60	49	60	65	67	R99	51	44	61	42	44

The benchmark is identified as R900.

Panel B – UK

IT Code	SR	Sortino	ERCFVaR	ERVaR	ERES	IT Code	SR	Sortino	ERCFVaR	ERVaR	ERES
R10	13	12	25	14	17	R38	38	38	36	38	38
R107	30	30	31	30	30	R41	36	37	35	35	35
R112	8	8	2	4	4	R42	25	23	28	25	27
R114	6	6	7	3	2	R45	41	41	44	42	42
R116	14	16	13	19	18	R46	45	46	46	46	46
R123	42	42	41	43	43	R47	15	13	23	18	16
R128	9	9	6	12	12	R5	7	7	3	7	6
R131	33	33	32	34	34	R53	34	34	38	36	36
R134	17	19	18	15	15	R64	4	5	1	8	8
R142	12	11	17	10	11	R66	23	24	20	21	20
R143	32	31	24	29	29	R73	2	3	5	2	1
R145	47	45	43	47	47	R75	10	10	11	5	5
R154	22	25	10	24	23	R77	18	15	21	16	14
R169	46	47	47	45	45	R78	19	21	16	13	9
R177	43	44	42	41	41	R80	3	2	8	6	7
R178	24	20	27	17	19	R81	5	4	9	11	13
R180	29	28	22	28	26	R84	44	43	45	44	44
R184	37	35	37	37	37	R85	39	39	40	40	40
R186	16	17	12	27	28	**R900**	**35**	**36**	**33**	**33**	**33**
R188	20	18	15	23	24	R93	28	32	26	26	25
R193	27	26	34	31	31	R94	21	22	14	22	22
R195	31	29	29	32	32	R98	11	14	19	9	10
R28	40	40	39	39	39	R99	26	27	30	20	21
R34	1	1	4	1	3						

Panel C – Non-UK

IT Code	SR	Sortino	ERCFVaR	ERVaR	ERES	IT Code	SR	Sortino	ERCFVaR	ERVaR	ERES
R100	24	22	17	26	25	R189	9	11	5	9	8
R102	58	57	58	57	57	R196	42	41	39	41	40
R106	23	24	14	24	24	R197	62	63	63	62	61
R108	12	13	7	16	14	R198	6	5	8	8	10
R109	4	7	4	1	3	R2	13	16	20	7	6
R11	31	29	31	31	31	R21	30	33	27	30	30
R110	53	52	56	52	52	R22	29	30	25	29	29
R111	45	47	45	46	47	R23	34	35	33	40	39
R113	32	31	30	35	35	R29	48	48	48	48	48
R115	8	10	6	10	9	R3	26	27	29	25	26
R122	16	17	19	11	13	R30	2	2	1	3	4
R126	41	36	40	44	44	R32	47	44	47	47	46
R129	46	46	44	45	45	R4	59	58	59	58	58
R138	19	9	26	18	20	R43	10	21	28	14	19
R141	18	12	9	21	21	R44	54	53	54	53	53
R144	49	49	49	49	49	R49	**37**	38	41	33	32
R147	57	61	53	59	59	R52	22	18	21	23	22
R148	5	4	12	6	7	R55	11	8	24	17	16
R150	44	42	46	39	41	R56	17	23	18	13	12
R151	64	64	64	63	63	R60	20	19	15	19	18
R152	40	43	42	32	33	R62	3	6	3	4	2
R155	63	62	62	61	62	R69	36	39	35	34	34
R156	7	3	10	22	23	R70	21	20	16	20	17
R16	52	54	51	56	55	R72	15	15	11	12	11
R167	56	55	57	55	56	R74	35	34	38	43	43
R168	50	50	50	50	50	R76	1	1	2	2	1
R171	51	51	52	51	51	R82	55	56	55	54	54
R172	38	40	37	42	42	R86	60	59	61	60	60
R173	28	25	23	28	27	**R900**	**39**	**37**	**36**	**37**	**37**
R174	25	26	32	15	15	R92	61	60	60	64	64
R175	33	32	34	38	38	R95	43	45	43	36	36
R187	27	28	22	27	28	R96	14	14	13	5	5

Appendix 2 - Top five and bottom five rankings according to the different performance measures

	SR	Sortino	Excess ReturnCFVaR	Excess Return VaR	Excess Return ES
Total Sample: Top Five Ranking					
1	R76	R34	R30	R34	R76
2	R34	R76	R76	R109	R62
3	R30	R30	R62	R76	R109
4	R73	R80	R64	R30	R30
5	R80	R73	R112	R62	R98
Total Sample: Bottom Five Ranking					
106	R197	R145	R86	R197	R155
107	R155	R197	R155	R46	R46
108	R169	R46	R197	R151	R151
109	R145	R151	R169	R92	R92
110	R151	R169	R151	R145	R145
	SR	**Sortino**	**ERCFVaR**	**ERVaR**	**ERES**
UK: Top Five Ranking					
1	R43	R34	R64	R34	R73
2	R73	R80	R112	R73	R114
3	R80	R73	R5	R114	R34
4	R64	R81	R34	R112	R112
5	R81	R64	R73	R75	R75
UK: Bottom Five Ranking					
43	R177	R84	R145	R123	R123
44	R84	R177	R45	R84	R84
45	R46	R145	R84	R169	R169
46	R169	R46	R46	R46	R46
47	R145	R169	R169	R145	R145
Non-UK: Top Five Ranking					
1	R76	R76	R30	R109	R76
2	R30	R30	R76	R76	R62
3	R62	R156	R62	R30	R109
4	R109	R148	R109	R62	R30
5	R148	R198	R189	R96	R96
Non-UK: Bottom Five Ranking					
60	R86	R92	R92	R86	R86
61	R92	R147	R86	R155	R197
62	R197	R155	R155	R197	R155
63	R155	R197	R197	R151	R151
64	R151	R151	R151	R92	R92