Financial Econometrics Research Centre

WORKING PAPERS SERIES

WP05-08

Performance Measurement with Loss Aversion

Gordon Gemmill, Soosung Hwang and Mark Salmon

Performance Measurement with Loss Aversion

Gordon Gemmill♦

Soosung Hwang[**]

and

Mark Salmon♦

July 4th, 2005

Abstract

We examine a simple measure of portfolio performance based on prospect theory, which captures not only risk and return but also reflects differential aversion to upside and downside risk. The measure we propose is a ratio of gains to losses, with the gains and losses weighted (if desired) to reflect risk-aversion for gains and risk-seeking for losses. It can also be interpreted as the weighted ratio of the value of a call option to a put option, with the benchmark as the exercise price. When applying the loss-aversion-performance measure to closed-end funds, we find that it gives significantly different rankings from those of conventional measures (such as the Sharpe ratio, Jensen's alpha, the Sortino ratio, and the Higher Moment measure), and gives the expected signs for the odd and even moments of tracking errors. However, loss-aversion performance is not more closely related to discounts on funds than are the conventional performance measures, so we have not found evidence that loss-aversion attracts investors to particular funds in the short-term.

Keywords: Performance Measurement, Loss Aversion, Prospect Theory, Closed-end-fund Puzzle.

JEL code: G11, G23

♦ Warwick Business School, University of Warwick, Coventry CV4 7AL

[**] Corresponding Author. Faculty of Finance, Cass Business School, 106 Bunhill Row, London EC1Y 8TZ, UK. Tel +44 (0)20 7040 0109, Fax +44 (0)20 7040 8881, Email s.hwang@city.ac.uk.

1 Introduction

Measures of portfolio performance, which take account both of risk and return, have evolved over the years in parallel with asset pricing theory, with the main focus on what constitutes risk. The Sharpe ratio (Sharpe, 1966) comes from portfolio theory and uses the variance of returns to measure risk. Treynor (1965) and Treynor and Mazuy (1966) use the CAPM beta as their measure of risk, while Jensen (1968) uses the CAPM alpha. Later measures have been based on the APT (Connor and Korajczyk, 1986 and Lehmann and Modest, 1987) and the Fama/French model (Carhart, 1997). Other approaches include the positive period weighting measure (Grinblatt and Titman, 1989) and measures based on the intertemporal marginal rates of substitution (Glosten and Jagannathan, 1994), the law of one price and/or no arbitrage (Chen and Knez, 1996), and the higher moments of the distribution (Hwang and Satchell, 1998).

Most of these measures assume that investors maximise expected utility, but this paradigm may be criticised for being inconsistent with experimental results. In particular, when taking decisions investors consider individual gains and losses rather than aggregating them into final wealth and the pleasure from a gain is not as great as the regret from a loss of the same size. This led Kahneman and Tversky (1979) to develop prospect theory, according to which investors maximise the weighted sum of a value function, where the 'value function' is calculated in terms of gains or losses rather than final wealth and the 'weights' are subjective (rather than objective) probabilities. If the gains and losses are measured relative to expectations rather than what happened in the recent past, then loss-aversion has been renamed "disappointment aversion" by Gul (1991) and this has been implemented by Ang, Bekaert and Liu (2004) and Fielding and Stracca (2003), among others.

The concepts of loss aversion and downside risk have been discussed for a long time by both academics and practitioners. Semi-variance, Value-at-Risk and downside beta are some well-known examples of downside-risk measures. Professional services such as Morningstar and Lipper have developed downside-risk measures to evaluate funds. If portfolio allocation is determined by downside risk, then performance measures should reflect this.

In this paper we propose a new measure of performance based on prospect theory and compare it, both theoretically and empirically, with other performance measures. The measure, which we denote as loss-aversion performance (LAP), is the ratio of gains to losses, both of which may be weighted by fractional powers. When the reference point is the benchmark portfolio, then gains and losses are 'tracking errors' and the measure is the ratio of positive tracking errors to negative tracking errors, each raised to a power. [1] Under the special case that both power terms are set to unity, our measure can be interpreted as the ratio of the price a call option to the price of a put option and is the same as the Omega performance measure of Keating and Shadwick (2002). Omega has been developed as an alternative method of presenting distributions of returns, but has not been related before to prospect theory.

The measurement of gains and losses is critical in implementing prospect theory. An interesting feature of investors is that they tend to take greater risks when they have experienced recent gains – the so-called 'house-money effect' (see, for example, Thaler and Johnson, 1990; Barberis, Huang and Santos, 2001). Because of the house-money effect, it is possible that performance measurement should take account of previous gains and losses as well as current gains and losses. For example, the poor performance of a fund in one period could be compensated to some extent by good performance in a previous period, or be regarded as remaining bad if there had been previous losses. Two of our three measures of loss-aversion performance allow for the house-money effect, as they incorporate lagged performance.

Using 42 UK closed-end funds, we first show some statistical properties of the LAP measure (in three particular specifications) as compared with the Sharpe (1966) ratio, Jensen's (1968) alpha, the Sortino ratio of Sortino and Van der Meer (1991), and the higher moment (HM) measure of Hwang and Satchell (1998). The new loss-aversion performance measures give different rankings from those of the conventional measures, but we do not find any significant differences between the three LAP variants and so conclude that the house-money effect is not relevant in our sample. Our results support

[1] Tracking error is defined in different ways in different studies. For example, Pope and Yadav (1994), Lee (1998), and Rudolf, Wolter and Zimmermann (1999) define tracking error as standard deviation of the difference between portfolio returns and benchmark returns, while Clarke, Krase, and Statman (1994),

the use of loss-aversion measures of performance. In particular these measures have highly desirable properties such as a positive relationship with a fund's tracking error and a negative relationship with its kurtosis. Other standard measures such as Jensen's alpha, the Sortino ratio, and the HM do not have these properties.

We also examine whether measures of performance can explain the discount on closed-end funds. If a performance measure is capturing what investors want, then it might be expected that the discount would be smaller for funds which "perform" well by that measure. We find that there is no simple relationship between discounts and any of the performance measures (traditional or otherwise) for the funds in our sample, so investor sentiment is not adequately captured in this way.

The paper is written as follows. In section 2 we develop the loss-aversion performance measure which is consistent with prospect theory. We also describe the alternative measures for performance which exist. In section 3 we compare the behaviour of LAP with the other measures empirically, using a set of monthly data on closed-end funds from May 1993 to April 2002. In section 4 we test whether LAP is more consistent with investor preferences than the other measures, assuming that such preferences are reflected in the discount on a particular fund. Section 5 draws together the conclusions of the study.

2 Performance Measures with Loss Aversion

2.1 Prospect Theory and Loss Aversion

According to prospect theory (Kahneman and Tversky, 1979), decisions are based upon relative gains and losses rather than upon the final wealth level (which is the key objective in conventional expected utility theory). Let W_t be the wealth of an investor at time t and let B_t be some appropriate benchmark wealth at time t relative to which an

---

Roll (1992) define tracking error as difference between portfolio returns and the benchmark portfolio returns. In this study we follow the second definition.

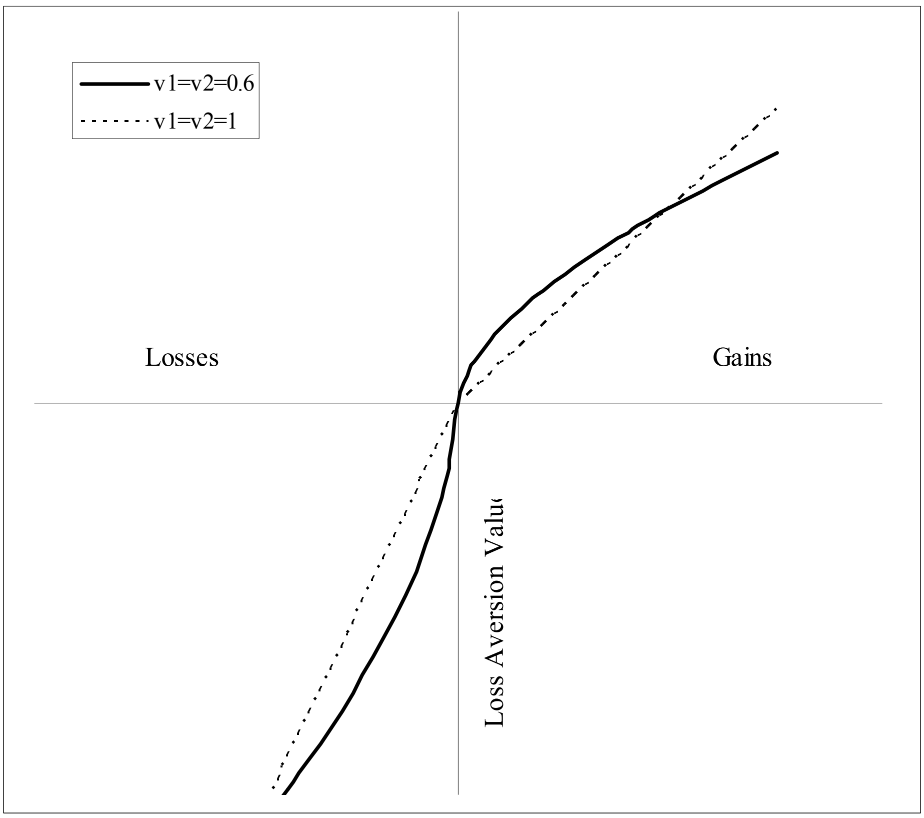
investor measures gains and losses. Gains are then measured as X_t, with $X_t=W_t–B_t$. The value function, V^S, is defined as

$$V^S = \begin{cases} X_t^{v_1}, \text{ if } X_t > 0, \\ -\lambda(-X_t)^{v_2}, \text{ if } X_t \le 0, \end{cases} \qquad (1)$$

where the parameters v_1, v_2 and λ are assumed positive. The two terms in (1) are respectively: gains raised to the power v_1; and losses raised to the power v_2 multiplied by a relative loss aversion coefficient λ.

Figure 1 plots the value function against losses and gains. Loss-aversion is generated by having $\lambda>1$, which leads to the kink at the origin of the diagram. Kahneman and Tversky (1992) and Benartzi and Thaler (1995), use $\lambda = 2.25$, while Ang, Bekeart, and Liu (2004) use a range of λ values which exceed unity and Fishburn and Kochenberger (1979) also present some evidence that $\lambda > 1$.

Figure 1 The Value Function V^S in Prospect Theory (with λ =2.25)



When $v_1 = v_2 = 1$, the investor is risk-neutral with respect to gain or losses and this is shown as the dotted line in Figure 1. In the case originally suggested by Kahneman and Tversky (1979), there is risk-aversion in gains ($v_1 < 1$) and risk-seeking in losses ($v_2 < 1$), which is shown as the solid line in Figure 1.

2.2 Loss Aversion with a 'House Money' Effect

We take account of two (of the many) extensions to prospect theory. First, risk-seeking (convexity, $v_2 < 1$) over losses is not generally supported; it is observed only when decision makers are asked to choose among prospects that involve only losses or gains, but not both. In other words, it is displayed if the frame of reference is one in which the investor cannot avoid making a loss. Barberis, Huang and Santos (2001) argue that for the choice of prospects that include both gains and losses, a loss aversion coefficient that is larger than one is the most important feature and so they set the two curvature parameters to unity. [2] Levy and Levy (2002), using stochastic dominance theory and experiments, also conclude that investors are not generally risk-loving over losses but are more likely to exhibit risk-aversion in both the gain and loss domains.

Second, investors who are "sitting on" prior gains may exhibit less pain for losses than those who are sitting on prior losses. The 'house-money effect' suggests that the value of λ should be smaller if there have been recent gains, an approach taken by Barberis, Huang and Santos (2001) in their study of the equity risk-premium.

To take account of the house-money effect and possible risk-aversion over losses, we propose two variants of the basic value function. In the first variant, which we call V^H (where superscrip H denotes "house-money"), we follow Barberis, Huang and Santos (2001) and make the loss-aversion coefficient λ depend on the previous gains and losses:

[2] In fact, when the two curvature parameters are set to any value close to one (e.g., 0.88), the degree of curvature is very small.

$$V^H = \begin{cases} X_t^{v_1}, \text{ if } X_t > 0, \\ -\lambda_t(-X_t)^{v_2}, \text{ if } X_t \le 0, \end{cases} \tag{2}$$

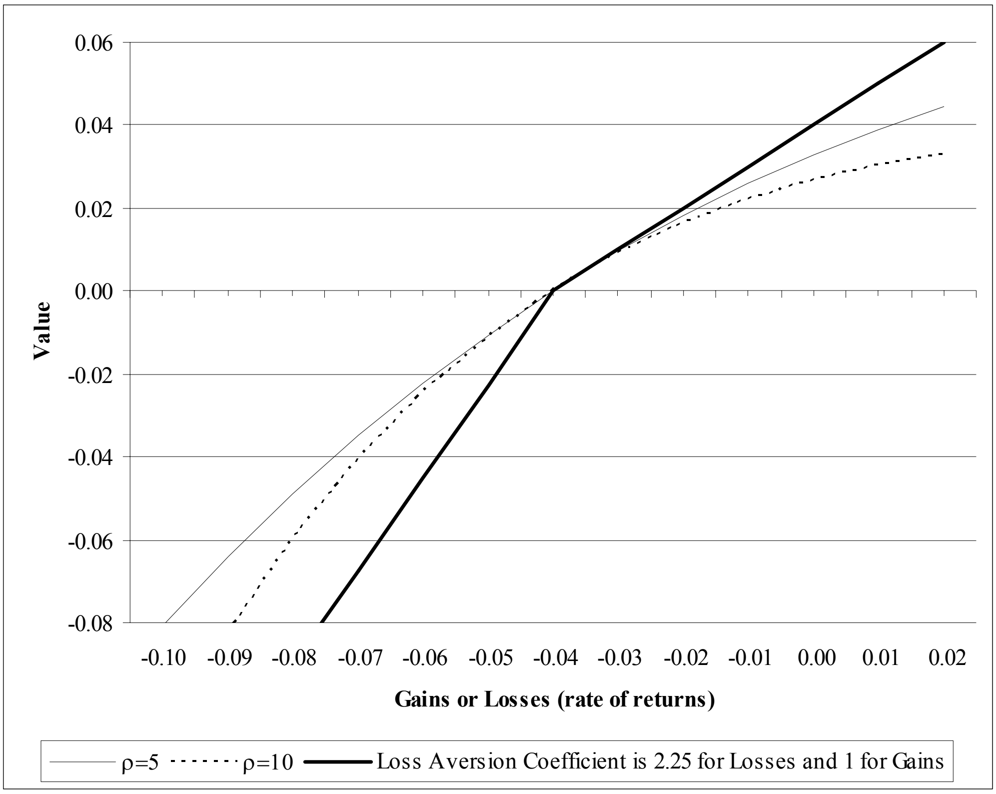
where $\lambda_t = \beta_0 - \beta_1 X_{t-1}$, $\beta_0 > 0$, and $\beta_1 > 0$. Therefore with previous losses (i.e., $X_{t-1} < 0$) we have $\lambda_t > \beta_0$ and hence the investor is more averse to losses, and vice versa.

In the second variant, we dispose of the two parameters v_1 and v_2 and replace λ_t by $\exp(-\rho_t X_t)$. The revised function is an 'exponentially weighted loss aversion' function, V^{EW}, which is defined as

$$V^{EW} = \exp(-\rho_t X_t) X_t, \tag{3}$$

where $\rho_t = \psi_0 - \psi_1 X_{t-1}$, $\psi_0 > 0$ and $\psi_1 > 0$. In this case there is no longer a sharp kink at zero in the value function. This is not as radical as it appears, because the "knife-edge" distinction between gains and losses around zero requires all investors to have the same benchmark. In financial markets there are many different choices of market indices for the benchmark. Although these are highly correlated, some small differences are inevitable and a small loss calculated with one index may be a small gain with another index. Figure 2 shows that for $\rho = 5$ or $\rho = 10$ the investor is assumed to be risk-averse in both the gain and loss domains, but the value function exhibits a smooth transition to be steeper in the loss domain, preserving loss-aversion.

Figure 2 Value Functions with Exponential Weights



2.3 Loss-Aversion Risk Measures

We have already argued that the benchmark will depend on the choice of a particular index. For portfolio managers it is sensible to calculate gains and losses at the present time as wealth in the previous period scaled-up by the rate of return on the risky index. The benchmark wealth for gains and losses is then $W_{t-1}(1+r_{bt})$, where W_{t-1} is wealth in the previous period and r_{bt} is the rate of return on the benchmark asset at time t.

Gains or losses from investing in a portfolio can then be expressed relative to the benchmark as:

$$X_t = W_{t-1}(r_{pt} - r_{bt}),$$

where r_{pt} is the portfolio return at time t. The prospect-theory value function in (1) can then be re-written using the benchmark as:

$$V^S = W_{t-1}^{v_1}\left[\left(r_{pt} - r_{bt}\right)^+\right]^{v_1} - \lambda W_{t-1}^{v_2}\left[-\left(r_{pt} - r_{bt}\right)^-\right]^{v_2}, \tag{4}$$

where superscripts $^+$ and $^-$ represent conditional gains and losses respectively. Thus for fund managers, the objective is to maximise the expected value function:

$$E[V^S] = W_{t-1}^{v_1} pE[((r_{pt}\text{-}r_{bt})^+)^{v_1}] - \lambda W_{t-1}^{v_2}(1-p)E[(-(r_{pt}\text{-}r_{bt})^-)^{v_2}], \tag{5}$$

where $p = prob(r_{pt} - r_{bt} \geq 0)$ and the expectation operator is calculated with subjective weights rather than with an objective probability density function.[3]

Viewed in this way, the expected value function in equation (5) is not conceptually very different from that used in traditional risk-return analysis. The first term on the right-hand side is what investors want, while the second term is what they want to avoid.[4] The trade-off between the two is reflected in λ, the loss-aversion coefficient. By comparison, a traditional mean-variance expected utility is:

$$E[u] = E[r_p] - \lambda_{MV}\sigma_{r_p}^2,$$

where λ_{MV} is a measure of risk-aversion and $\sigma_{r_p}^2$ is the variance of returns on the portfolio.

In fact, the expectation on the second component in (5), $(1-p)E[(-(r_p\text{-}r_b)^-)^{v_2}]$, is a special case of the risk measure suggested by Fishburn (1977). His measure is

$$R_F\left[r_\tau, v, r_p\right] = \int_{-\infty}^{r_\tau} \left|r_\tau - r_p\right|^v f(r_p)dr_p, \tag{6}$$

[3] According to prospect theory, people are observed to over-weight outcomes that are unlikely and under-weight outcomes that are highly likely. However, this subjective weighting function is not known and controversial. We do not consider the issue of subjective weights here.
[4] For simplicity, we omit the time subscript t where it is not required.

which includes the variance and semi-variance as special cases (in addition to standard deviation and semi-standard deviation). Using the objective probability density function, we can express the second component of (5) as

$$\begin{aligned}(1-p)E[(-(r_p\text{-}r_b)^-)^{v_2}] &= \int_{-\infty}^{r_b} \left|r_b - r_p\right|^{v_2} f(r_p)dr_p \\ &= R_F\left[r_b, v_2, r_p\right]\end{aligned} \qquad (7)$$

The difference between Fishburn's measure and our loss-aversion risk measure is that we allow any positive real number for v_2. [5]

2.4 Loss-Averse Performance Measures

As already noted, the first component in (5) represents what investors want (reward) and the second component is what they wish to avoid (risk). A simple loss-averse performance measure is then the ratio of the two,

$$LAP^S = \frac{pE[((r_p\text{-}r_b)^+)^{v_1}]}{(1-p)E[(-(r_p\text{-}r_b)^-)^{v_2}]}. \qquad (10)$$

Notice that the coefficient λ drops out, just as λ_{MV} is not required in the Sharpe ratio, because it is a constant. An important special case arises when the return on a risky benchmark portfolio is used. When we can define $TE \equiv r_p - r_b$, which is tracking error, and the simple loss aversion performance can be re-written as:

[5] The loss aversion risk measure does not belong to so-called "coherent risk measures". See Embrechts, Klüppelberg, and Mikosch (1997) and Artzner (1999) for a discussion.

$$LAP^{S} = \frac{pE[(TE^{+})^{v_1}]}{(1-p)E[(-TE^{-})^{v_2}]}. \quad (11)$$

The calculation of $E[(TE^{+})^{v_1}]$ and $E[(-TE^{-})^{v_2}]$ as well as *p=prob(TE>0)* requires an assumption on the probability density function (pdf) of tracking errors. Unfortunately the properties of tracking errors are not known, and even if r_p and r_b are normally distributed this does not imply that the tracking errors will be Gaussian. In the empirical tests below we use non-parametric methods (i.e. the empirical distributions) to overcome this difficulty.[6]

When the house-money effect is taken into account, the loss aversion coefficient λ_t is a function of previous performance and does not drop out. The revised performance measure becomes

$$LAP^{H} = \frac{pE[(TE_t^{+})^{v_1}]}{\lambda_t(1-p)E[(-TE_t^{-})^{v_2}]}, \quad (12)$$

where $\lambda_t = \beta_0 - \beta_1 TE_{t-1}$, $\beta_0 > 0$, and $\beta_1 \geq 0$. Likewise, the performance measure with exponential weights can be written as

$$LAP^{EW} = \frac{pE[\exp(-\rho_t TE_t^{+})TE_t^{+}]}{(1-p)E[\exp(-\rho_t TE_t^{-})(-TE_t^{-})]}, \quad (13)$$

where $\rho_t = \psi_0 - \psi_1 TE_{t-1}$, $\psi_0 > 0$, and $\psi_1 \geq 0$.

The interpretation of these performance measures with the house-money effect is as follows. When there are losses in the previous period ($TE_{t-1} < 0$), the loss aversion coefficient λ_t becomes larger and thus LAP^{H} shows worse performance than the

---

[6] We could assume a specific pdf for the calculation of the LAP^{S}; for example, Hwang and Satchell (2005) use Gaussian and mixed Gamma distributions. The mixed Gamma distribution is useful since it allows asymmetry and fat tails, while Gaussianity does not. In addition, the mixed Gamma distribution provides convenient analytical results for the LAP^{S}. We find that the LAP^{S} calculated with the non-parametric values of $E[(TE^{+})^{v_1}]$ and $E[(-TE^{-})^{v_2}]$ are very close to those with the mixed Gamma distribution. The results with the assumption of the pdfs can be obtained from authors.

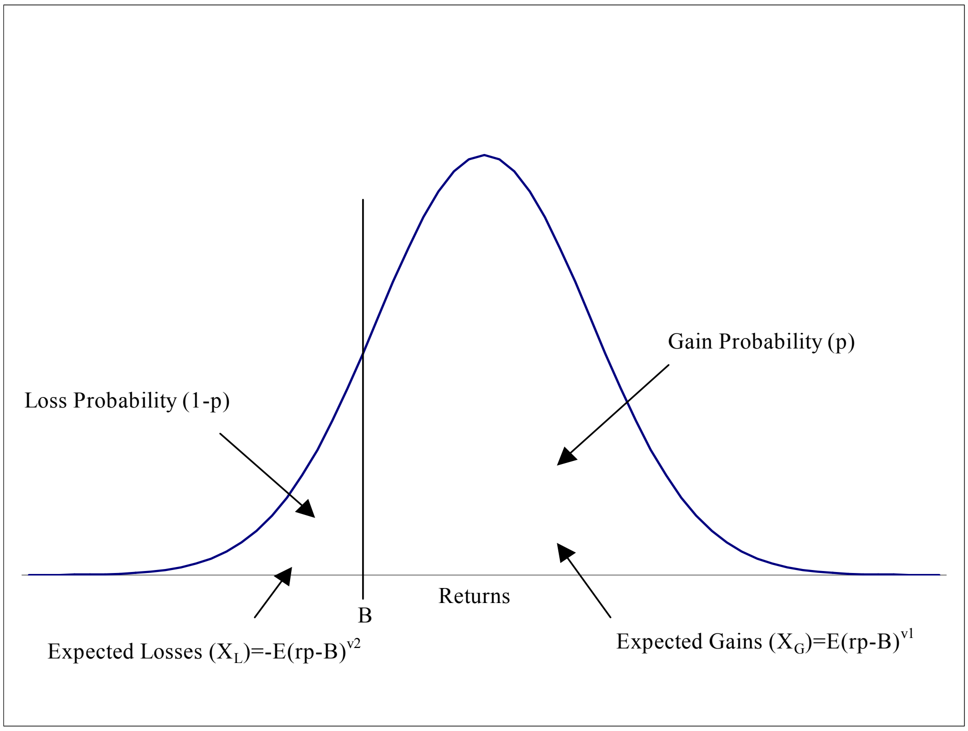
simpler LAP^S of (10). Therefore previous losses of a fund affect the current evaluation of the fund in a negative way.

Figure 3 demonstrates the conceptual simplicity of LAP^S , with the benchmark return set at B. (Note that for an absolute-return fund, such as a hedge fund, the benchmark might be set at, say, 5% per annum rather than as the return on an index.) LAP^S is equal to the probability of gains, *p*, times the expected (fractionally powered) gains of X_G, divided by the probability of losses, 1-*p*, times the expected (fractionally powered) losses of X_L.

When $v_1=v_2=1$, then LAP^S is equivalent to Keating and Shadwick's (2002) Omega. We can also note how pX_G is equal in value to an outperformance call option (relative to the benchmark, exercise price, *B*) and $(1-p)X_L$ is equal in value to an underperformance put at the same exercise price. If the distribution of excess returns were normal, then the values of these options could be easily computed with the Black/Scholes formula.[7]

[7] Given the ouperformance character of these options, there are two stochastic variables to take into account – the current portfolio and the benchmark portfolio. Consequently a model which allows for this becomes necessary, such as that of Margrabe (1978).

Figure 3 The Distribution of Returns and the Elements of the Simple Loss-Averse Performance Measure, LAP^S



2.5 Other Performance Measures

Turning to other measures of performance for comparison, the Sharpe (1966) ratio is simply the reward per unit of total variability:

$$SR = \frac{E(r_p - r_f)}{\sigma_p}, \tag{8}$$

where σ_p is the standard deviation of portfolio returns. The measure is easy to understand and widely used.

The Sortino ratio (Sortino and Van der Meer (1991)) changes the Sharpe ratio by measuring risk as deviations below the benchmark:

$$ST = \frac{E(r_p - r_f)}{\left((1-p)E[(-TE^-)^2]\right)^{1/2}}, \tag{9}$$

where the numerator is the same as that of the Sharpe ratio, but the denominator is replaced with semi-standard-deviation.

Using tracking errors can cause a serious problem for the Sharpe and Sortino ratios when ranking funds.[8] This is because if average tracking errors are around zero, these performance measures calculated with tracking errors could be negative for some funds. There is no simple way around this problem and so Sharpe and Sortino ratios are used in this study with a benchmark of the risk-free rate rather than in tracking-error form. [9]

Jensen's (1968) alpha, α_p^J, measures performance of a portfolio which is not explained by its CAPM beta:

$$\alpha_p^J = \mu_p - \beta_p \mu_m, \tag{14}$$

where

$$\mu_p = E(r_p - r_f),$$
$$\mu_m = E(r_m - r_f),$$
$$\beta_p = \frac{E\left[(r_p - E(r_p))(r_m - E(r_m))\right]}{E\left[(r_m - E(r_m))^2\right]},$$

and r_p represents the portfolio's return, r_f is the risk-free rate, r_m is the market (benchmark) return, β_p denotes the systematic risk of the portfolio. The measure is based on the assumptions that returns are Gaussian and investors have a quadratic utility function. When these assumptions do not hold Jensen's alpha is not appropriate.

[8] The Sharpe ratio is known as the information ratio when measured as outperformance, see Gupta, Prajobi and Stubbs (1999).

[9] Using tracking errors, we would rank a fund whose average value and standard deviation of tracking errors are –0.1% and 2% respectively (the Sharpe ratio is –0.05) higher than a fund whose average value and standard deviation of tracking error are –0.1% and 1% respectively (the Sharpe ratio is –0.1). However, because of the first fund's high volatility, it has higher probability of larger negative tracking errors, and for any risk-averse investor this fund would not be preferred to the second. A similar problem arises for the Sortino ratio.

A higher moment (HM) measure has been proposed by Hwang and Satchell (1998), based on an extension of the CAPM to three moments. It is

$$\alpha_p^{HM} = \mu_p - \psi_1 \mu_m - \psi_2(\beta_p - \gamma_p) \quad (15)$$

where

$$\psi_1 = \frac{\gamma_m^2 \gamma_p - (\theta_m - 1)\beta_p}{\gamma_m^2 - (\theta_m - 1)},$$

$$\psi_2 = \frac{\gamma_m \sigma_m}{\gamma_m^2 - (\theta_m - 1)},$$

$$\gamma_p = \frac{E\left[(r_p - E(r_p))(r_m - E(r_m))^2\right]}{E\left[(r_m - E(r_m))^3\right]},$$

$$\sigma_m = E\left[(r_m - r_f)^2\right]^{1/2},$$

$$\gamma_m = \frac{E\left[(r_m - E(r_m))^3\right]}{\sigma_m^3}, \text{ and}$$

$$\theta_m = \frac{E\left[(r_m - E(r_m))^4\right]}{\sigma_m^4}.$$

Note that γ_m and θ_m are the skewness and kurtosis of the market return, and β_p and γ_p are beta and coskewness, respectively. If the market returns are normal or investors' utility is governed by the mean and variance only, then $\psi_1 = \beta_p$ and $\psi_2=0$ and thus α_p^{HM} is equivalent to Jensen's Alpha. If this is not the case, the measure reflects both the skewness and kurtosis of the distribution of returns.

Jensen's alpha uses beta as risk measure while the higher moment (HM) performance measure uses beta and co-skewness as risk measures. Note that when beta is close to one (as in most mutual funds) Jensen's alpha becomes similar to average tracking error. Similarly, when co-skewness is small the HM measure is not different from average tracking error. It is beta and co-skewness respectively that could make these two performance measures different from average tracking error.

There are two other performance measures which we have considered. They are the Treynor and Mazuy (TM) (1966) measure and the positive period weighting (PPW) measure of Grinblatt and Titman (1989). However, we find that these two measures give virtually identical results to Jensen's alpha and so we do not include them.[10] We have also not included the commercial measures of downside risk used by Morningstar and Lipper. Until the middle of 2002 Morningstar had a measure which compared a fund's average underperformance in months when it underperformed with a similar measure for its category. This measure has been abandoned because many new funds in the late 1990s never underperformed relative to the benchmark. Lipper has a measure for the "preservation of capital" which is just the sum of negative monthly returns over 3, 5 and 10 year periods. A review of these and other industry measures may be found in Amenc and Le Sourd (2005).

3 Empirical Tests

3.1 Objectives and Data

In this section we compare the three LAP measures with the four conventional performance measures in an empirical context. The aim is to discover whether there is any difference in the rankings of funds when using alternative measures. If there is not, then the simplest possible measure should be adopted and there is no benefit of being concerned with loss aversion.

The analysis is based on two groups of UK closed-end funds which have very clear benchmarks: the first group of 19 funds has a benchmark of the FTSE AllShare index, and the second group of 23 funds has a benchmark of the FTSE SmallCap index. By using two groups, we are able to investigate the properties of the performance measures in different markets and also to cross-compare closed-end funds in different groups. The data are monthly over the period May 1993 to April 2002 and retrieved from Datastream. The analysis is made on net-asset values (NAVs) rather than prices,

[10] Cumby and Glen (1990), Grinblatt and Titman (1994), Hwang and Satchell (1998) and Hwang and

because managers are evaluated on that basis. Tracking errors are calculated by taking the returns of the benchmark from the returns of the individual closed-end funds' NAVs. Although the total of 42 funds which we use in this study is relatively small, that should not matter for discovering whether measures differ sufficiently to have an empirically recognisable impact.

Table 1 reports the basic statistical properties of the monthly returns for the 42 UK closed-end funds and two benchmark indices over the sample period. For the closed-end funds whose benchmark is the FTSE AllShare index (AllShare group), mean returns range from 0.7% to 1.2% (8.4% to 14.4% in annual terms) with standard deviations between 1.5% and 7.3% (5.2% to 25.3% in annual terms). The SmallCap funds show returns in the 0.2% to 1.6% range per month (2.4% to 19.2% in annual terms) and standard deviations between 3% and 8.6% (10.4% to 29.8% in annual terms).

Salmon (2002) also find these measures to be similar.

Table 1 Properties of Net Asset Value Returns and Their Tracking Errors

A. FTSE AllShare Index Funds

Benchmark Portfolio and Investment Trusts	NAV Log-returns						Tracking Errors						Rank Correlations between NAV log-returns and Tracking Errors	Discounts
	Mean	Std. Dev.	Skewness	Kurtosis	Normality (Jarque-Bera)	Autocorrelation with Lag 1	Mean	Std. Dev.	Skewness	Kurtosis	Normality (Jarque-Bera)	Autocorrelation with Lag 1		
FTSE AllShare index	0.008	0.038	-0.689	0.515	9.738 *	-0.008								
Albany	0.009	0.035	-0.542	0.242	5.555 *	-0.061	0.001	0.014	0.494	0.095	4.432 *	-0.123	-0.034	0.157
Bankers	0.009	0.040	-0.986	2.015	35.792 *	-0.052	0.001	0.014	-0.202	0.087	0.767	-0.067	0.260 *	0.059
Capital Gearing	0.009	0.021	-0.425	0.794	6.088 *	-0.055	0.001	0.028	0.433	-0.059	3.397	-0.076	-0.131	0.051
City Of London	0.009	0.042	-0.771	1.095	16.094 *	-0.038	0.001	0.012	0.173	1.735	14.082 *	0.210 *	0.407 *	0.015
Dres.Rcm Endow	0.007	0.015	1.827	5.270	185.069 *	-0.209 *	-0.001	0.040	0.582	0.091	6.130 *	-0.085	0.129	0.004
Edinburgh	0.007	0.042	-0.715	0.918	12.998 *	0.014	-0.001	0.010	0.404	0.935	6.871 *	-0.098	0.492 *	0.121
Edinburgh UK Tracker	0.008	0.038	-0.584	0.283	6.489 *	-0.021	0.000	0.006	1.294	1.455	39.676 *	-0.268 *	0.035	0.007
F&C Pep	0.008	0.037	-0.967	1.393	25.576 *	0.042	0.000	0.013	0.723	0.083	9.448 *	0.088	0.041	0.067
Finsbury Growth	0.008	0.046	-0.768	0.961	14.787 *	-0.039	0.000	0.016	-0.114	0.099	0.277	-0.119	0.597 *	0.103
Fleming Claverhouse	0.009	0.044	-0.667	0.671	10.039 *	0.013	0.001	0.012	-0.413	1.366	11.465 *	0.012	0.650 *	-0.010
Glasgow Income	0.011	0.046	-1.182	2.591	55.342 *	-0.043	0.003	0.025	0.131	1.090	5.655 *	0.042	0.545 *	0.047
Henderson Elec.&Gen.	0.007	0.052	-0.333	0.944	6.002 *	0.100	-0.001	0.030	0.388	3.574	60.192 *	0.209 *	0.598 *	0.090
Law Debenture	0.010	0.040	-0.976	1.701	30.156 *	-0.036	0.002	0.015	0.657	1.131	13.515 *	0.028	0.268 *	-0.093
Lowland	0.011	0.049	-1.166	4.011	96.897 *	0.029	0.003	0.031	0.635	6.099	174.644 *	0.092	0.541 *	0.078
Merchants	0.010	0.045	-0.964	1.813	31.521 *	-0.074	0.002	0.021	0.231	0.623	2.704	0.078	0.513 *	0.057
Murray Income	0.009	0.040	-0.898	1.624	26.377 *	0.051	0.001	0.017	1.478	5.811	191.276 *	0.370 *	0.239 *	0.074
Securities Tst.Sctl.	0.007	0.041	-0.802	1.186	17.904 *	-0.035	-0.001	0.015	0.337	0.056	2.058	-0.114	0.304 *	0.095
Temple Bar	0.010	0.041	-0.599	1.722	19.810 *	0.016	0.002	0.019	1.039	2.158	40.383 *	0.213 *	0.253 *	0.049
Welsh Industrial	0.012	0.073	2.346	14.780	1082.008 *	-0.011	0.003	0.063	3.156	18.377	1699.059 *	0.095	0.516 *	0.235

B. FTSE Small Cap Index Funds

Benchmark Portfolio and Investment Trusts	NAV Log-returns						Tracking Errors						Rank Correlations between NAV log-returns and Tracking Errors	Discounts
	Mean	Std. Dev.	Skewness	Kurtosis	Normality (Jarque-Bera)	Autocorrelation with Lag 1	Mean	Std. Dev.	Skewness	Kurtosis	Normality (Jarque-Bera)	Autocorrelation with Lag 1		
FTSE Small Cap	0.007	0.049	-1.148	4.464	113.398 *	0.181								
3i Sm.Quoted	0.008	0.056	-1.063	2.650	51.943 *	0.190	0.001	0.020	-0.731	2.499	37.718 *	0.091	0.511 *	0.132
Aberforth	0.013	0.046	-0.688	1.731	21.996 *	0.163	0.006	0.024	0.086	2.163	21.190 *	0.298 *	0.202 *	0.055
Britannic	0.007	0.052	-0.984	3.151	62.083 *	0.204 *	0.000	0.017	-0.480	2.832	40.237 *	0.193	0.236 *	0.136
Candover	0.016	0.038	3.492	17.584	1610.908 *	-0.162	0.009	0.061	1.535	4.477	132.583 *	0.003	0.212 *	-0.030
Dresdner Rcm	0.008	0.071	-0.112	3.107	43.667 *	0.352 *	0.001	0.038	1.102	8.355	335.979 *	0.443 *	0.634 *	0.172
Dunedin Enterprise	0.011	0.030	0.238	3.485	55.671 *	0.203 *	0.004	0.056	0.237	2.349	25.836 *	0.092	0.324 *	0.164
Dunedin Smaller	0.009	0.055	-1.176	4.312	108.586 *	0.207 *	0.002	0.022	-0.129	0.919	4.101 *	0.109	0.382 *	0.148
Electra	0.010	0.035	-0.339	4.993	114.244 *	0.039	0.003	0.039	0.184	0.690	2.755	-0.058	-0.024	0.151
Fleming Mercantile	0.010	0.047	-0.622	2.747	40.920 *	0.171	0.003	0.020	0.269	0.492	2.386	-0.044	0.152	0.150
Fleming	0.009	0.059	-0.951	3.208	62.599 *	0.243 *	0.002	0.024	-0.014	2.684	32.417 *	0.227 *	0.456 *	0.120
Gartmore	0.006	0.059	-0.618	2.406	32.933 *	0.343 *	-0.001	0.031	-0.342	3.287	50.716 *	0.383 *	0.420 *	0.152
Govett Strategic	0.007	0.051	-0.736	1.862	25.354 *	0.086	0.001	0.023	-0.406	1.081	8.230 *	-0.014	0.345 *	0.148
Henderson	0.002	0.078	-0.790	2.779	45.979 *	0.215 *	-0.005	0.051	-1.040	5.768	169.144 *	0.202 *	0.580 *	0.125
Henderson Strata	0.007	0.072	-0.444	2.521	32.150 *	0.268 *	0.000	0.047	-0.398	4.709	102.622 *	0.248 *	0.516 *	0.047
I&S.UK.	0.009	0.059	-0.530	1.539	15.718 *	0.259 *	0.002	0.030	-0.665	4.856	114.075 *	0.246 *	0.440 *	0.149
Invesco Eng.& Intl.	0.010	0.075	-0.798	3.991	83.154 *	0.239 *	0.004	0.037	0.315	5.661	145.994 *	0.297 *	0.824 *	0.133
Mercury Grosvenor	0.011	0.036	-0.435	5.080	119.553 *	0.015	0.004	0.053	0.305	3.611	60.348 *	0.046	0.262 *	0.178
Northern Investors	0.011	0.037	2.887	18.643	1714.135 *	0.101	0.004	0.051	1.004	2.311	42.177 *	0.092	0.208 *	0.166
Pantheon Intl.	0.011	0.039	2.985	16.356	1364.287 *	-0.109	0.004	0.058	1.287	3.353	80.419 *	0.041	0.348 *	0.188
Perpetual UK	0.012	0.049	-1.089	3.961	91.922 *	0.194	0.005	0.017	-0.259	1.627	13.115 *	0.045	0.126 *	0.097
Shires	0.009	0.048	-0.895	2.200	36.204 *	0.128	0.002	0.021	-0.130	1.954	17.493 *	-0.082	0.217 *	0.121
Thompson Clive	0.011	0.086	1.679	8.063	343.309 *	0.116	0.004	0.078	1.385	4.947	144.661 *	0.085	0.646 *	0.195
Throgmorton	0.006	0.052	-0.932	2.723	49.004 *	0.149	-0.001	0.018	-0.199	0.595	2.305	0.056	0.356 *	0.146

Notes: A total number of 108 monthly log-returns from May 1993 to April 2002 is used to calculate the statistics in the table. Tracking errors are calculated by taking appropriate benchmark portfolio log-returns from investment trust log-returns. The stars in the normality test and autocorrelation coefficient represent significance at the 5% level.

Most NAV returns (left half of Table 1) are negatively skewed and leptokurtic, leading to significant non-normality according to the Jarque-Bera statistics. In particular, the SmallCap NAV returns are more leptokurtic than those of the AllShare group. The non-normality suggests that performance-measures based on mean and variance may not capture downside risk satisfactorily. Another result in Table 1 is that in several cases high autocorrelation coefficients are found for funds in the SmallCap group, which may be due to the illiquidity of the small stocks which they hold.

The right-hand side of Table 1 reports the statistical properties of the tracking errors. For the AllShare group most of these tracking errors have means which are close to zero, as expected, but for the SmallCap group 20 of the 23 means are positive. By contrast, 16 out of 19 of the AllShare group show positive skewness, whereas only 11 out of 23 of the SmallCap group are positively skewed.

The results in Table 1 suggest that the distributions of the tracking errors are different from those of NAV returns. In particular, they tend to show less skewness and kurtosis than raw returns. Because of the non-normality for almost all distributions, *Pearson's* correlation coefficient may not be an appropriate tool to analyse the dependence relationships. For this reason we prefer to use *Spearman's rank order* correlations. The rank correlation coefficients between NAV returns and the tracking errors (penultimate column of Table 1) are positive and significant on average, but the levels are quite varied (ranging from –0.131 to +0.824). More than two thirds of the coefficients are less than 0.5. This suggests that performance based on tracking errors is likely to be quite different from that based on NAV returns.

Finally, the last column of Table 1 shows that during the nine years in our sample, 39 of the 42 funds traded on average at discounts to their NAVs.

Table 2 Performance Measures for the UK Investment Trusts

A. Performance Measures for the AllShare Group

	Sharpe Ratio			Jensen's Alpha (Multiplied by 100)			Sortino Ratio			Higher Moment (Multiplied by 100)			LAP[S] (v_1=0.75, v_2=0.95)		
	Values	WG	AG	Values	WG	AG	Values	WG	AG	Values	WG	AG	Values	WG	AG
Albany	0.134	6	14	0.166	8	21	0.546	6	8	0.167	13	26	2.780	5	9
Bankers	0.109	10	18	0.085	11	28	0.467	9	11	0.306	9	21	2.759	6	10
Capital Gearing	0.230	1	2	0.344	2	11	0.270	15	22	0.451	6	14	2.244	13	26
City Of London	0.109	11	19	0.082	12	29	0.572	3	5	0.172	12	25	2.934	3	6
Dres.Rcm Endow	0.152	2	8	0.219	6	18	0.085	19	38	0.286	11	24	1.713	18	40
Edinburgh	0.051	18	36	-0.166	19	41	0.298	14	20	-0.105	19	40	1.698	19	41
Edinburgh Uk Tracker	0.086	15	25	-0.021	15	35	0.927	1	1	-0.048	17	34	2.194	14	28
F&C Pep & Isa	0.102	13	22	0.051	14	32	0.481	8	10	0.300	10	22	2.349	11	23
Finsbury Growth	0.074	16	28	-0.069	16	37	0.299	13	19	0.087	16	31	2.311	12	25
Fleming Claverhouse	0.108	12	20	0.080	13	30	0.570	4	6	0.146	14	28	3.160	2	4
Glasgow Income	0.135	5	13	0.260	3	14	0.415	10	12	0.672	3	7	2.731	7	12
Henderson Elec.&Gen.	0.045	19	38	-0.162	18	40	0.113	18	37	-0.093	18	38	1.808	17	39
Law Debenture	0.137	4	12	0.204	7	20	0.656	2	3	0.462	5	13	3.240	1	3
Lowland	0.124	7	15	0.257	4	15	0.321	12	17	0.688	1	5	2.479	10	19
Merchants	0.111	9	17	0.131	9	24	0.370	11	15	0.463	4	12	2.520	9	18
Murray Income	0.115	8	16	0.122	10	25	0.481	7	9	0.405	7	15	2.618	8	15
Securities Tst.Sctl.	0.068	17	31	-0.077	17	38	0.268	16	23	0.111	15	29	1.989	15	33
Temple Bar	0.138	3	11	0.226	5	17	0.551	5	7	0.349	8	16	2.799	4	7
Welsh Industrial	0.094	14	23	0.355	1	10	0.227	17	27	0.686	2	6	1.930	16	36

B. Performance Measures for the SmallCap Group

	Sharpe Ratio			Jensen's Alpha (Multiplied by 100)			Sortino Ratio			Higher Moment (Multiplied by 100)			LAP^S (v_1=0.75, v_2=0.95)		
	Values	WG	AG	Values	WG	AG	Values	WG	AG	Values	WG	AG	Values	WG	AG
3i Sm.Quoted	0.059	16	33	0.089	16	26	0.230	9	25	0.154	14	27	2.584	8	16
Aberforth	0.174	4	5	0.612	2	2	0.602	2	4	0.608	6	9	4.125	2	2
Britannic	0.051	19	37	0.039	19	33	0.220	12	29	0.066	16	32	2.479	10	20
Candover	0.292	1	1	1.112	1	1	0.380	4	14	1.248	1	1	2.574	9	17
Dresdner Rcm	0.052	18	35	0.089	17	27	0.158	18	35	-0.063	18	35	2.185	16	30
Dunedin Enterprise	0.195	2	3	0.582	5	5	0.160	17	34	0.789	3	3	2.153	17	31
Dunedin Smaller	0.070	13	29	0.154	15	23	0.271	7	21	0.323	10	18	2.636	7	14
Electra	0.163	6	7	0.477	8	8	0.230	10	26	0.743	4	4	2.352	12	22
Fleming Mercantile	0.106	9	21	0.303	10	12	0.406	3	13	0.312	12	20	3.068	3	5
Fleming	0.078	11	26	0.208	13	19	0.300	6	18	0.287	13	23	2.788	4	8
Gartmore	0.029	21	40	-0.062	21	36	0.075	21	40	-0.095	21	39	1.977	19	34
Govett Strategic	0.055	17	34	0.069	18	31	0.170	16	33	0.088	15	30	2.344	13	24
Henderson	-0.037	23	42	-0.568	23	42	-0.070	23	42	-0.588	23	42	1.372	23	42
Henderson Strata	0.034	20	39	-0.009	20	34	0.071	22	41	-0.075	20	37	1.955	20	35
I&S.UK.	0.066	15	32	0.155	14	22	0.174	15	32	-0.004	17	33	2.448	11	21
Invesco Eng.& Intl.	0.077	12	27	0.262	11	13	0.238	8	24	0.316	11	19	2.668	6	13
Mercury Grosvenor	0.173	5	6	0.583	4	4	0.186	14	31	0.498	8	11	2.237	14	27
Northern Investors	0.178	3	4	0.604	3	3	0.225	11	28	0.813	2	2	2.193	15	29
Pantheon Intl.	0.152	7	9	0.571	6	6	0.188	13	30	0.651	5	8	2.014	18	32
Perpetual UK	0.148	8	10	0.510	7	7	0.722	1	2	0.599	7	10	4.743	1	1
Shires	0.090	10	24	0.234	12	16	0.322	5	16	0.327	9	17	2.733	5	11
Thompson Clive	0.068	14	30	0.413	9	9	0.129	19	36	-0.071	19	36	1.846	22	38
Throgmorton	0.019	22	41	-0.123	22	39	0.075	20	39	-0.121	22	41	1.906	21	37

Notes: The performance measures were calculated with 108 monthly log-returns from May 1993 to April 2002. The numbers in the column 'WG' are ranks within the AllShare or SmallCap group and the numbers in the column 'AG' represent ranks among all 42 investment trusts. LAP^S is the simple loss aversion performance measure without the house money effect.

3.2 Cross-sectional Properties of Loss Aversion Performance Measures

In Table 2 we report the LAP^S (with v_1=0.75 and v_2=0.95) [11] and the four other performance measures over the 108 monthly returns. There are three columns for each measure: the first, labelled 'values', gives the performance for the sample period; the second, labelled 'WG', gives the rank of a particular fund "within" its style group; and the third, labelled 'AG', gives the rank of a fund across "all" style groups.

Beginning with values, the Sharpe ratios and Sortino ratios are all positive except in one case. This is to be expected as they measure returns in excess of the risk-free rate rather than over the benchmark. The values for Jensen's alpha and the higher-moment measure are close to zero, as they measure returns relative to the benchmark index. The LAP^S values range from 1.4 to 4.7, indicating that the gain component in the numerator of equation (10) exceeds the loss component in the denominator of equation (10) by a relatively large margin for all funds.

Considering the WG (within group) rankings, the Sharpe and Jensen rankings are extremely similar: for the AllShare group, their rankings of funds differ by more than 3 places for only 3 funds out of 19 and for the SmallCap group differ by more than 3 places for only 1 fund out of 23. If we consider the three measures which specifically take account of the downside – the Sortino ratio, higher moment measure (HM) and LAP^S – we can also consider which, if any, of these gives a rank which is more than 3 places different from the other two. The result is that the HM differs from the other two measures in its ranking of the AllShare Group by more than 3 places in 11 out of 19 cases and in its ranking of the SmallCap Group by more than 3 places in 10 out of 23 cases. In fact the rankings with the HM measure are closely related to the rankings by the Sharpe and Jensen measures, which is not surprising because the HM is an extension of the CAPM on which the other two measures are based. So our first conclusion is that the Sharpe, Jensen and HM measures behave similarly, and that the Sortino and LAP^S measures are also closely related.

[11] These values are suggested by Hwang and Satchell (2005). We also considered a variety of other parameters, but the results were not much changed.

If we look at individual funds in the SmallCap group, Candover, Northern Investors, and Pantheon Intl. funds are ranked lower with the LAP^S than by the Sharpe ratio, Jensen's alpha, the Sortino ratio and the HM measure, which is because they are relatively less positively skewed in tracking errors than in returns. On the other hand, funds such as Perpetual UK, whose tracking errors are relatively more positively skewed and less leptokurtic, are ranked higher with the LAP^S than with the conventional measures. This result shows that LAP^S is more sensitive to higher moments than the other measures, even when compared with the "higher moment" HM measure.

Although the Sortino ratio shows rankings which are similar to those of the LAP^S in the SmallCap group, in the AllShare group its rankings of Glasgow Income, Welsh Industrial, Lowland, and Edinburgh UK Tracker are quite different from those of LAP^S. So the second conclusion is that the two downside measures – Sortino and LAP^S – are not empirically equivalent.

3.3 Time-Varying Properties of Loss Aversion Performance Measures

So far we have examined average rankings over all 108 months of data. It would be possible for two performance measures to give the same average rankings but to differ considerably in their time-series behaviour. Therefore we now use twelve individual monthly observations to produce a time-series of annual measures of performance. We also need to use time-series if we are going to compute LAP^H and LAP^{EW}, which take account of the previous year's losses or gains in order to allow for the house-money effect. Using this approach, we obtain a time series for each performance measure for each fund that consists of 9 annual observations from 1994 to 2002. (For the LAP^H and LAP^{EW}, only eight annual measures can be calculated since we require the previous year's gains and losses in their computation.) For the LAP^H, we set the values of $\beta_0 = 3$ and $\beta_1 = 15$, so that in 95% of cases the values of λ_t range from 1.5 to 4.5

depending on TE_{t-1}.[12] For LA^{EW} we choose $\psi_0 = 10$ and $\psi_1 = 100$, so that the values of $\exp(-\rho_t TE_{t-1})$ range from 1.1 to 4.4 in 95% of cases.[13]

Table 3 reports the average cross-sectional rank-correlation coefficients between the seven performance measures over the nine years, based on the whole sample of 42 funds.[14] The first result is that the three LAP measures are very closely related (correlations of 0.96 or higher), so that taking account of the house-money effect, which is included within LAP^H and LAP^{EW}, does not seem to matter for these funds. The second result is that the LAP measures are related more closely to Jensen's alpha than to the others – the correlation of the alpha and LAP^S is 0.751. This contrasts with a lower correlation of the Sharpe ratio with LAP^S, which is 0.591. Jensen's alpha is also closely related to the HM measure (correlation of 0.674). Although Jensen's alpha does not take account of asymmetry in the distribution of returns, it is apparent from the table that asymmetry is only of second-order importance in the fund rankings over time. Finally, despite the fact that the Sortino ratio and the LAP measures are concerned with downside risk, the Sortino ratio does not show a stronger relationship with the LAP measures than it does with the three traditional measures.

Table 3 Rank Correlation Coefficients between Performance Measures

	Sharpe Ratio	Jesen's Alpha	Sortino Ratio	Higher Moment	Loss Aversion Performance Measure		
					LAP^S (v_1=0.75, v_2=0.95)	LAP^H (v_1=0.75, v_2=0.95, β_0=3, β_1=15)	LAP^{EW} (ψ_0=10, ψ_1=100)
Sharpe Ratio	1.000	**0.719**	**0.680**	**0.446**	**0.560**	**0.592**	**0.562**
Jesen's Alpha		1.000	**0.392**	**0.674**	**0.707**	**0.751**	**0.742**
Sortino Ratio			1.000	**0.204**	**0.621**	**0.605**	**0.578**
Higher Moment				1.000	**0.478**	**0.492**	**0.517**

[12] We use $\beta_0 = 3$ so that $E(\lambda_t) \approx 3$ since $E(TE_{t-1}) \approx 0$. We set $\beta_1 = 15$ after trying several different values for β_1 from 3 to 30. When $\beta_1 = 10$ and the standard deviation of TE_{t-1} is 0.05, the values of $\beta_1 TE_{t-1}$ range from –1.5 to 1.5 in 95% of cases.

[13] When $\psi_0 = 10$ and $\psi_1 = 100$, we have $E(\rho_t) \approx 10$ since $E(TE_{t-1}) \approx 0$. In 95% of cases ρ_t belongs to the range between 5 and 15 when the standard deviation of TE_t is 0.05. For the LAP^H and LAP^{EW} we have tried several different parameter values, but our results do not show significant differences. For the curvature parameters of the LAP^H, we have used v_1=0.75 and v_2=0.95 as suggested by Hwang and Satchell (2005).

[14] We also did the analysis separately for the AllShare and SmallCap groups, but the results were not qualitatively different from those for the pooled sample.

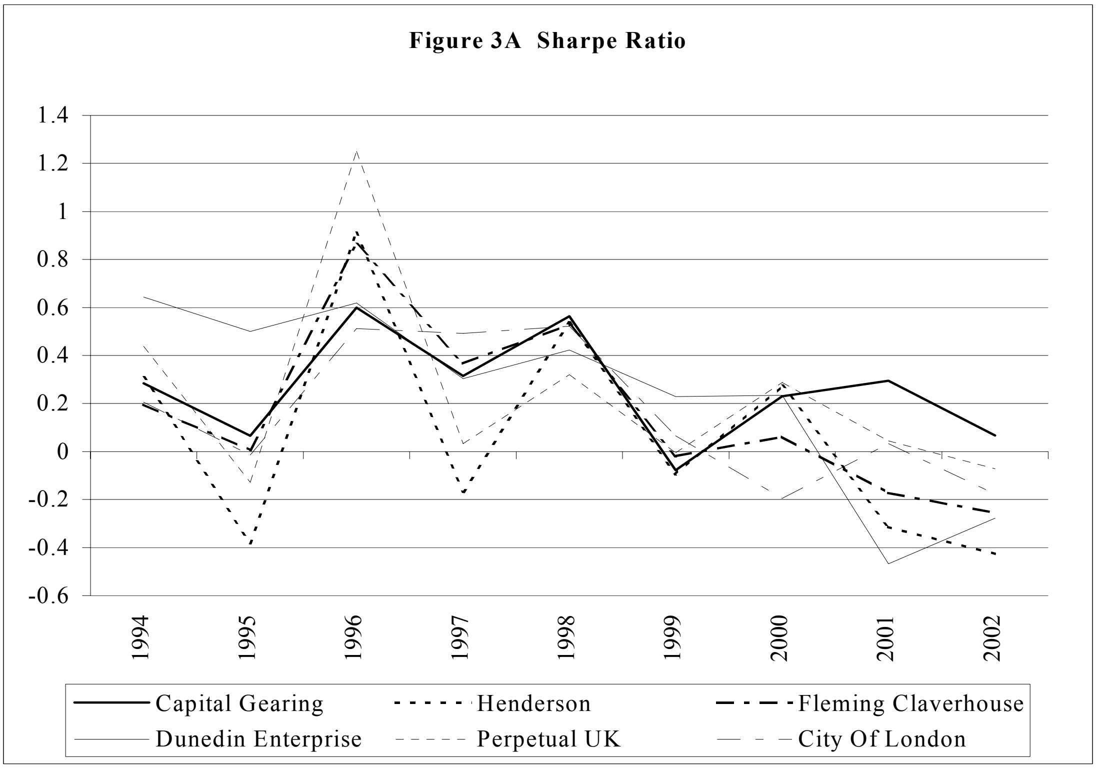
Loss Aversion Performance Measure	LAPM v_1=0.75, v_2=0.95					1.000	**0.997**	**0.969**
	LAP^H (v_1=0.75, v_2=0.95, β_0=3, β_1=15)						1.000	**0.966**
	EWLAP (ψ_0=10, ψ_1=100)							1.000
Rank Autocorrelation with Lag 1		**-0.106**	0.032	**-0.218**	0.053	-0.040	-0.048	-0.042

Note: The performance measures are calculated annually using 12 monthly returns. Rank cross-correlations between measures are then calculated each year using all 42 investment trusts, and then these correlation coefficients have been averaged over the 9 year period. The bold numbers represent significant at the 5% level.

Figure 3 plots each of the performance measures for six of the individual funds over the sample period. There is considerable variation over time with respect to which fund performs best, regardless of which measure of performance is used. Clearly the performance of these particular funds is not persistent and that is also indicated by the low rank-autocorrelations in the final row of Table 3.

Another feature which can be seen in Figure 3 is that the different performance measures do not behave the same in rising and falling markets. After the market fall of 2000, the Sharpe and Jensen measures become more dispersed across funds, whereas the Sortino measure becomes compressed and is similar for all six funds. By contrast, the LAP measures are largely unaffected by these market movements. Because they include lagged returns, the LAP^H and LAP^W measures are also more stable than the LAP^S that depends only on the last 12 months of data.

Figure 3 Performance Measures for Six Representative Funds over Time



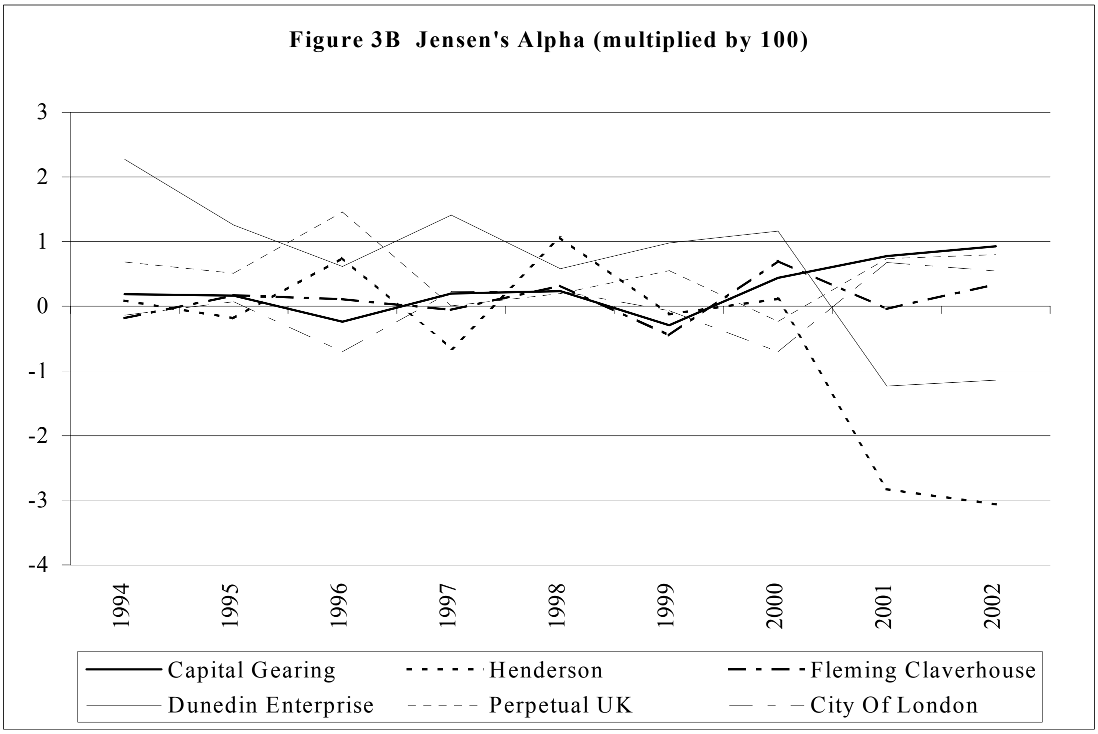


Figure 3C Sortino Ratio

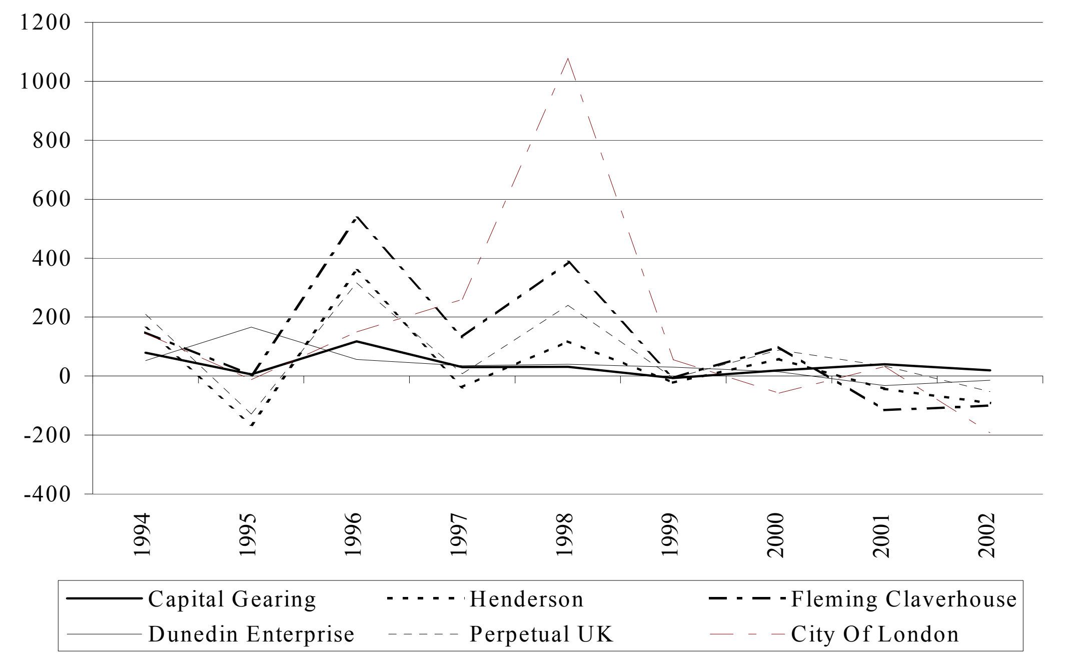


Figure 3D Loss Aversion Performance Measure (LAP^S)

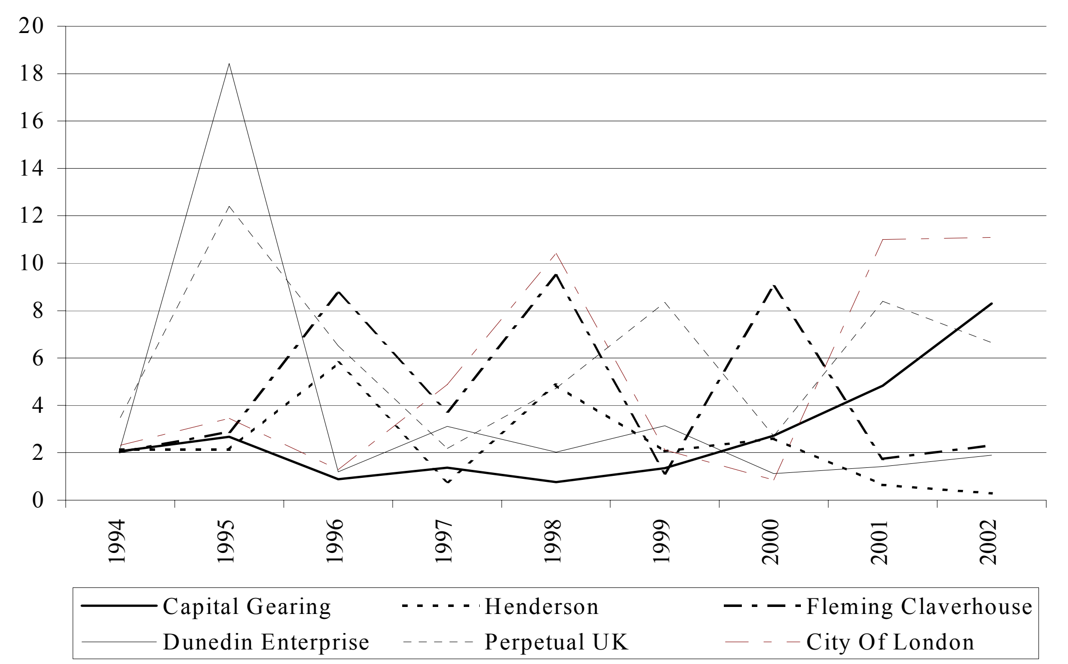


Figure 3E Loss Aversion Performance Measure with House Money Effects (LAP^{H})

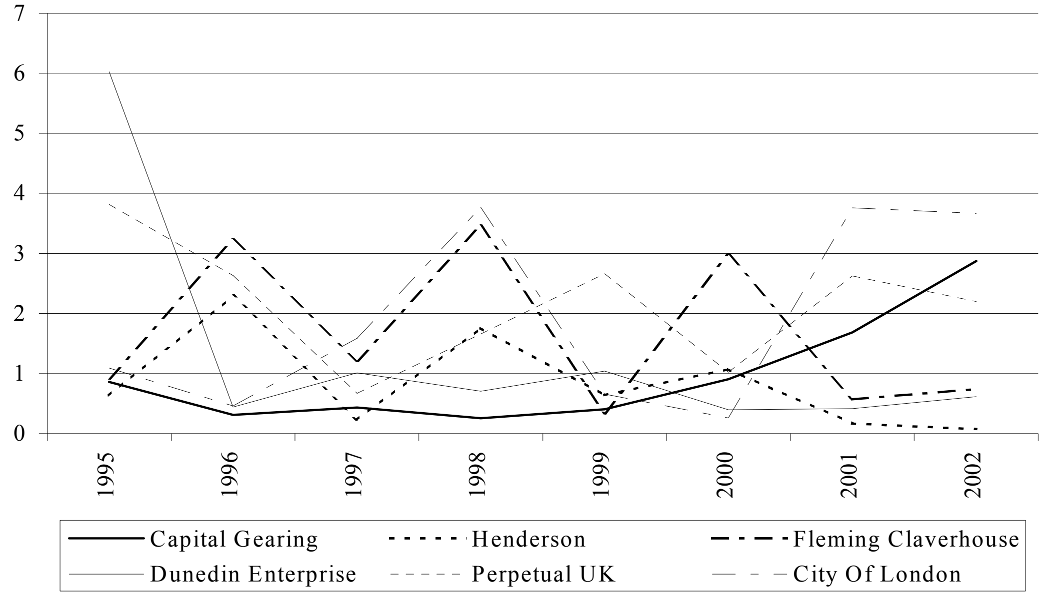
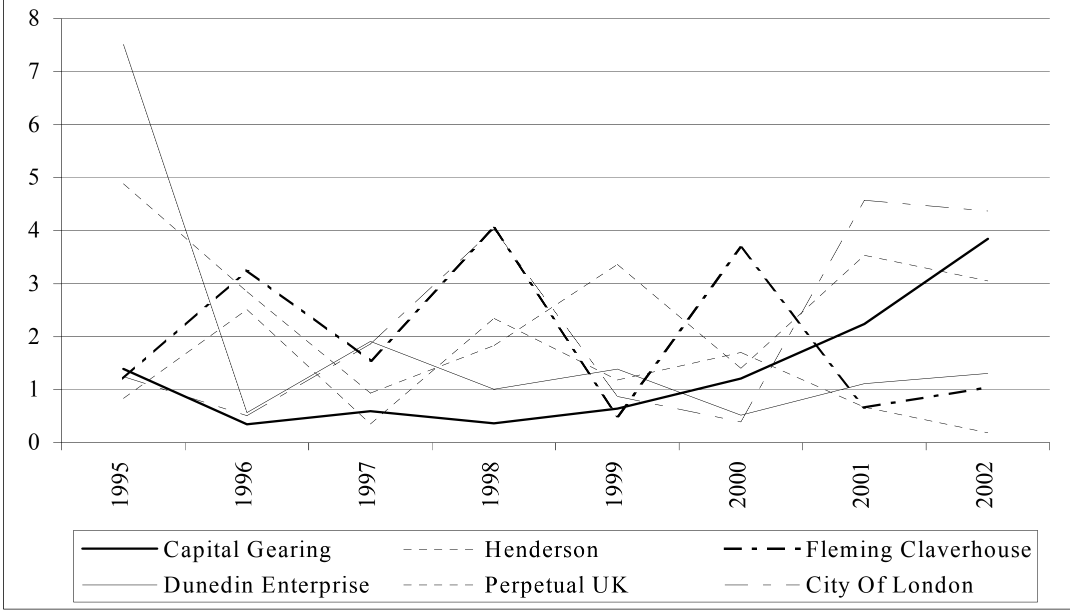


Figure 3F Exponentially Weighted Loss Aversion Performance Measure (LAP^{EW})



Finally in relation to Figure 3, the three LAP measures pick out City of London as a good performer in 1998, 2001, and 2002, but not in other periods, while the other conventional measures do not show City of London as a good performer at all. This is an example of how one fund could be preferred to the others if investors are loss-averse.

3.4 Do the Performance Measures Correlate with the Desired Moments of the Distribution?

From an investor's viewpoint, "good performance" is related positively to the mean and skewness and negatively related to the variance and kurtosis. Investors like larger first and third moments of the distribution (mean and skewness), while they dislike larger second and fourth moments of the distribution (variance and kurtosis) since these are measures of dispersion (risk). In Table 4 we report rank correlations between the performance measures and these moments of the distribution, both for NAV returns and for tracking errors.

Starting with the NAV performance in Panel A of Table 4, note first that we only give results for the four traditional measures (Sharpe, Jensen, Sortino, HM) because the LAP measures are only relevant for tracking errors. All four traditional measures are positively correlated with the mean and negatively correlated with the standard deviation, with the exception of the Sortino ratio. Jensen's alpha is the only measure to give a significantly positive correlation with skewness, and no measure gives a negative correlation with kurtosis. In fact the measures are positively related to kurtosis.

Turning to tracking-error performance in Panel B of Table 4, all of the correlations with the mean are again positive and significant. However, none of the correlations with the standard deviation are significantly negative except the LAP^{S}; the Sharpe ratio and Jensen's alpha even show significantly positive correlations with standard deviations. None of the skewness correlations are significant except for the LAP^{EW} , which shows a negative relationship with the skewness of tracking errors.[15] Only the LAP measures give significant negative correlations with kurtosis.

The results in Table 4, Panel B, tend to support the loss-aversion (LAP) measures. If tracking errors matter, then one of the LAP measures may be preferred by an investor because they are positively related with the level of tracking errors, and negatively related to volatility and kurtosis of tracking errors.

Table 4 Rank Correlation Coefficients between Performance Measures and NAV Log-returns and Tracking Errors

A. Cross-sectional Rank Correlation Coefficients between Performance Measures and the First Four Moments of NAV log-returns

The First Four Moments of NAV Log-returns	Sharpe Ratio	Jesen's Alpha	Sortino Ratio	Higher Moment
Mean	**0.856**	**0.649**	**0.807**	**0.395**
Std. Dev.	**-0.161**	**-0.139**	0.053	**-0.112**
Skewness	0.027	**0.209**	-0.083	**-0.199**
Kurtosis	**0.160**	**0.164**	**0.110**	**0.175**

B. Cross-sectional Rank Correlation Coefficients between Performance Measures and the First Four Moments of Tracking Errors

The First Four Moments of Tracking Errors	Sharpe Ratio	Jesen's Alpha	Sortino Ratio	Higher Moment	Loss Aversion Performance Measure		
					LAP^S (v_1=0.75, v_2=0.95)	LAP^H (v_1=0.75, v_2=0.95, β_0=3, β_1=15)	LAP^{EW} (ψ_0=10, ψ_1=100)
Mean	**0.626**	**0.746**	**0.641**	**0.484**	**0.898**	**0.903**	**0.879**
Std. Dev.	**0.111**	**0.224**	-0.038	0.091	**-0.128**	-0.069	0.017
Skewness	-0.054	0.024	0.013	-0.077	-0.061	-0.013	**-0.107**
Kurtosis	-0.089	-0.083	-0.027	-0.058	**-0.151**	**-0.135**	**-0.146**

Notes: All loss aversion performance measures and NAV and TEs statistics are non-normal with Jarque-bera statistics at 5% significance level and thus we calculate correlation coefficients based on ranks of the measures and the first four moments of NAV returns and tracking errors. The results are calculated by averaging 9 years cross-sectional rank correlations between performance measures and the four moments of NAV returns and tracking errors from May 1993 to April 2002 for 42 closed-end funds. The bold numbers represent significance at the 5% level.

[15] The negative relationship between the LAP^{EW} and the skewness of tracking errors however does not suggest inappropriateness of the measure since the LAP^{EW} is influenced by the previous years tracking errors.

4 The Closed-End-Fund Puzzle and Performance Measures

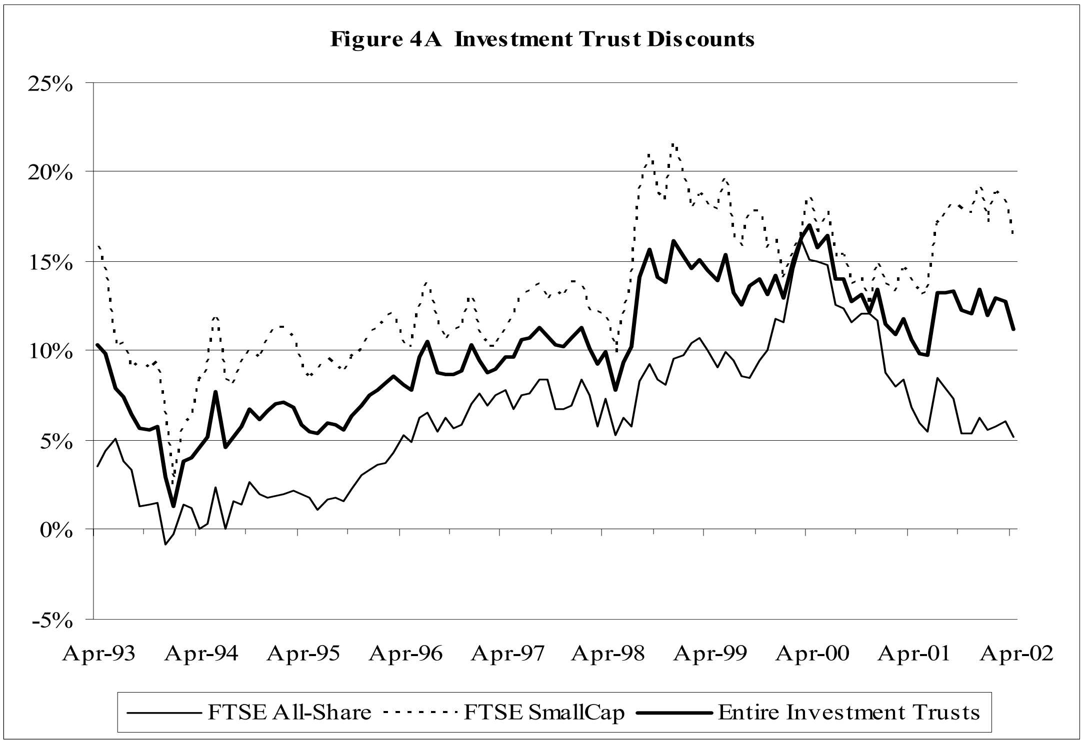
The main puzzle related to closed-end funds is that they trade at a discount to their net-asset values. This has already been noted for our sample in the final column of Table 1. The puzzle has been investigated by many authors and suggested reasons for its existence include management fees, tax liabilities, illiquid assets, past performance, agency problems, tax inefficiency, and market segmentation.[16] The failure of explanations based on efficient markets and rationality has led to a behavioural explanation, that the discount reflects the (irrational) sentiment of investors who are able to move prices within a wide channel because of limited arbitrage.[17]

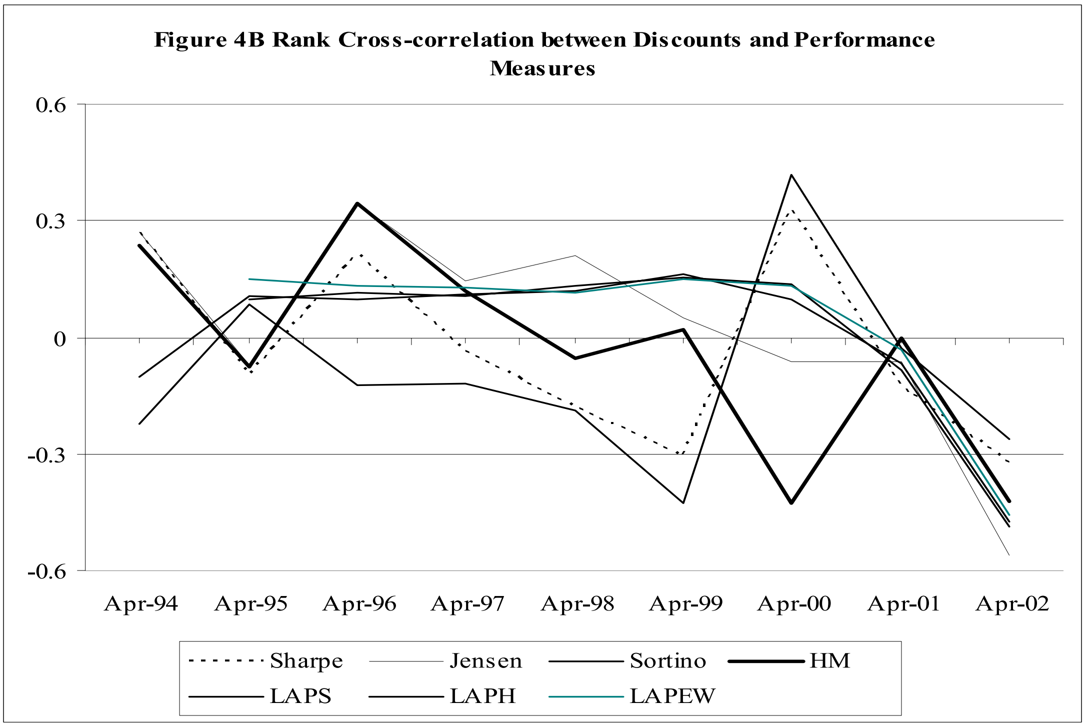
Figure 4A plots the average discounts of all UK closed-end funds over our sample period, together with the average discounts for the two sample groups (AllShare and SmallCap). There is an upward trend in the discount over the period, with the SmallCap discount always larger than that for the AllShare group, possibly reflecting the greater costs in replicating a portfolio of small-firm shares.

One way to consider the discount is that it is equal to one minus the familiar market-to-book ratio. If investors are happy with a fund's performance, they raise the market-to-book ratio and, for a closed-end fund, this is reflected in a smaller discount. The relevance of this to the present study is that "performance is in the eye of the beholder". If one performance measure is more reflective of investor preferences than another, then funds which perform well according to this measure should also have smaller discounts. That is the hypothesis which we are going to test.

[16] See Dimson and Minio-Kozerski (1999) for a literature survey on closed-end funds.
[17] See Zweig (1973), De Long, Shleifer, Summers and Waldmann (1990) and Lee, Shleifer and Thaler (1991) among others for early studies on the discount from the behavioural finance point of view. A more recent study by Gemmill and Thomas (2002) attributes changes in the discount to swings in sentiment, but the presence of a discount to management fees and limited arbitrage.

Figure 4 Investment Trusts Discounts and Performance Measures





In Panel A of Table 5 we examine whether discounts relate to the moments of the return distributions (either log returns or tracking errors) and in Panel B of Table 5 we examine whether discounts relate to each of the performance measures. All of the results in the table are based on annual rankings and correlations, so each number in the table is an average for the 9 years of results (or 8 years for LAP^{H} and LAP^{EW} , which require a one-year lag).

In Panel A the cross-sectional rank correlation coefficients between the discounts of the 42 closed-end funds and the first four moments of returns (i.e., mean, standard deviation, skewness and kurtosis) are given. This is done both for NAV returns (upper half of Panel A) and for tracking errors (lower half of Panel A). Few of the correlations are significant at the 5% level. We would expect the discounts to be smaller for funds which have higher NAV returns and this is supported by the negative values in the first row, but these are not statistically significant. Where there are significant correlations in Panel A, they suggest that discounts are larger: (i) for those AllShare funds which have high kurtosis; (ii) for those SmallCap funds which have a large standard deviation for their tracking errors.

Figure 4B plots the rank correlations between the performance measures and discounts year-by-year. A negative correlation would indicate that discounts are smaller when performance is good, but there is no clear "winner" in the contest to see which measure has the highest negative correlation. Measures which are worst in some periods are best in others. Panel B of Table 5 averages the annual data plotted in Figure 4B and confirms that discounts are not related to any of the performance measures: none of the correlations are significant. We hypothesised that the LAP measures would relate more closely to the discount than would the traditional measures, because investors exhibit loss-aversion, but we are not able to show that. The results do not support arguments that the discount is related to simple measures of past performance. Nevertheless, it remains possible that there is some more complicated relationship between past performance and discounts (see, for example, Chay and Trzcinka, 1999) which we have not properly specified, or that it reflects investors' views about future performance.

Table 5 Cross-sectional Rank Correlation Coefficients between Closed-end Fund Discounts and Various Statistics and Performance Measures

A. Rank Correlation between Discounts and the First Four Moments of NAV Log-returns and Tracking Errors

		All 42 Closed-end Funds	19 AllShare Funds	23 SmallCap Funds
Correlation between Discounts and the First Four Moments of NAV Log-returns	NAV Log-returns	-0.065	-0.044	-0.049
	Standard Deviation of NAV Log-returns	0.107	0.035	0.006
	Skewness of NAV Log-returns	0.075	-0.082	-0.009
	Kurtosis of NAV Log-returns	0.043	**0.188**	0.044
Correlation between Discounts and the First Four Moments of Tracking Errors	Tracking Errors	0.018	-0.044	-0.049
	Standard Deviation of Tracking Errors	**0.291**	0.070	**0.163**
	Skewness of Tracking Errors	-0.032	0.054	0.008
	Kurtosis of Tracking Errors	-0.017	-0.001	0.001

B. Rank Correlation between Discounts and Performance Measures

	All 42 Closed-end Funds
Sharpe Ratio	-0.028
Jesen's Alpha	0.029
Sortino Ratio	-0.096
HM Measure	-0.029
LAP^S, v_1=0.75, v_2=0.95	-0.026
LAP^H, v_1=0.75, v_2=0.95	-0.006
LAP^{EW}	0.035

Notes: The table is calculated with ranks on the NAV log-returns, tracking errors, and discounts for the 42 closed-end funds. Each year we calculate correlation coefficients based on ranks of the discounts and the first four moments of NAV returns and tracking errors. The results are calculated by averaging these 9 years cross-sectional rank correlations. The bold numbers represent significance at the 5% level.

5 Conclusions

In this paper we have developed three loss-aversion measures of portfolio performance which are consistent with the prospect theory of Kahneman and Tversky (1979). The simplest of these measures is closely-related to the Sortino ratio and the Omega measure of Keating and Shadwick (2002). The other two take account of the house-money effect, which implies more risk-taking by investors who have had recent successes. These loss-aversion-performance measures have great intuitive appeal, since they just compare weighted expected gains relative to weighted expected losses. They can also be interpreted as the value of an upside call option relative to a downside put option, with the benchmark return as the exercise price.

Performance measures are practical tools for investors. Two questions can be asked in relation to our new measures. The first is whether the new measures attribute different performance to funds than do traditional measures? The second is, even if there is a difference between the new measures and the old measures, do investors care about it? We use a sample of 42 closed-end funds observed monthly over the ten-year period, March 1993 to April 2002, to address these questions.

With respect to the first question, the loss-aversion measures do show different performance, particularly as they are applied to tracking errors and not to portfolio returns. They are positively related in cross-section to (positive) tracking errors, but negatively related to the volatility and kurtosis of such errors. The other measures do not behave in this way and are therefore less appropriate if the user is loss-averse. With respect to the second question, experimental evidence suggests that loss-aversion is important in many situations, but there is no evidence from the behaviour of discounts on the closed-end funds in our sample to suggest that investors bid-up the prices of funds which score well by any performance measure. Either our sample is too small, or loss-aversion does not matter, or investors are not basing their expectations of future performance on the recent past.

In sum, it is possible to estimate loss-aversion performance for funds and the measures are intuitively appealing and have theoretical support from prospect theory. However, it is not clear from our empirical analysis that investors do actually exhibit loss-aversion. More empirical studies of whether investors distinguish between funds on the basis of loss-aversion would be very helpful.

References

Amenc, N. and V. Le Sourd, 2005, “Rating the Ratings”, Edhec Risk and Management Centre, Lille.

Ang, A., G. Bekeart, and J. Liu, 2004, "Why Stocks May Disappoint," forthcoming, Journal of Financial Economics.

Artzner, P, 1999, Coherent Measures of Risk, Mathematical Finance 9(3), 203-228.

Barberis, N., M. Huang, and T. Santos, 2001, "Prospect Theory and Asset Prices," Quarterly Journal of Economics, 116(1), 1-53.

Benartzi, S. and R. H. Thaler, 1995, "Myopic Loss Aversion and the Equity Premium Puzzle", Quarterly Journal of Economics, 110(1), 73-92.

Burnes, J., Neilson, W., 2002. A Further Examination of Cumulative Prospect Theory Parameterizations. Journal of Risk and Uncertainty 24, 31-46.

Carhart, Mark M., 1997, "On Persistence In Mutual Fund Performance," Journal of Finance, 52(1), 57-82.

Chay, J. B. and C. Trzcinka, 1999, "Managerial Performance and the Cross-sectional Pricing of Closed-end Funds, Journal of Financial Economics 52, 379-408.

Chen, Z., and P. J. Knez, 1996. Portfolio Performance Measurement: Theory and Applications, Review of Financial Studies 9(2), 511-555.

Clarke, R. G., S. Krase, and M. Statman, 1994, “Tracking Errors, Regret, and Tactical Asset Allocation”, Journal of Portfolio Management, Spring, 16-24.

Connor, G., and R. Korajczyk, 1986. Performance Measurement with the Arbitrage Pricing Theory: A new Framework for Analysis, Journal of Financial Economics 15, 374-394.

Cumby, R., and J. Glen, 1990. Evaluating the performance of international mutual funds, Journal of Finance 45, 497-521.

DeLong, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann, 1990, "Positive-Feedback Investment Strategies and Destabilizing Rational Speculation," Journal of Finance 45(2), 374-397.

Dimson, E. and C. Minio-Kozerski, 1999, Closed-End-Funds: A Survey, Financial Markets, Institutions and Instruments 8(2), 1-41.

Embrechts, P., Klüppelberg, C., and T. Mikosch, 1997, Modelling Extremal Events for Insurance and Finance, Springer, Berlin.

Fielding, David and Livio Stracca, 2003, “Myopic Loss Aversion, Disappointment Aversion, and the Equity Premium Puzzle”, working paper no. 203, European Central Bank, Frankfurt.

Fishburn, Peter C, 1977. "Mean-Risk Analysis with Risk Associated with Below-Target Returns," American Economic Review, Vol. 67 (2) pp. 116-26.

Fishburn, P. C. and G. A. Kochenberger, 1979, "Concepts, Theory, Techniques; Two-piece Von Neumann-Morgenstern Utility Functions," Decision Sciences, 10, 503-518.

Gemmill, G. and Thomas, D., 2002. Noise Trading, Costly Arbitrage and Asset Prices: Evidence from Closed-End Funds, Journal of Finance 57, 2571-2594.

Glosten, L. R. and R. Jagannathan, 1994. A Contingent Claim Approach to Performance Evaluation, Journal of Empirical Finance 1, 133-160.

Grinblatt, M., and S. Titman, 1989. Portfolio Performance Evaluation: Old Issues and New Insights, Review of Financial Studies 2(3), 393-421.

Grinblatt, M., and S. Titman, 1994. A study of Monthly Mutual Fund Returns and Performance Evaluation Techniques, Journal of Financial and Quantitative Analysis 29(3), 419-444.

Gul, Faruk, 1991. "A Theory of Disappointment Aversion," Econometrica, Vol. 59 (3) pp. 667-86.

Gupta, Francis, Robertus Prajogi and Eric Stubbs, 1999. The Information Ratio And Performance, Journal of Portfolio Management, 26(1), 33-39.

Hwang, S. and M. Salmon, 2002, An Analysis of Performance Measures using Copulae, in J. Knight and S. Satchell eds., Performance Measurement in Finance: Firms, Funds and Managers, Butterworth-Heinemann, London."

Hwang, S., and S. Satchell, 1998. Evaluation of Mutual Fund Performance in Emerging Markets, Emerging Markets Quarterly 2(3), 39-50.

Hwang, S., and S. E. Satchell, 2005. The Magnitude of Loss Aversion Parameters in Financial Markets, Unpublished manuscript, Cass Business School.

Jensen, M, 1968. The performance of mutual funds in the period 1945-1964, Journal of Finance 23, 389-416.

Kahneman, D. and A. Tversky, 1979, "Prospect Theory: An Analysis of Decision Under Risk," Econometrica 47, 263-291.

Keating, C. and W. F. Shadwick, 2002. A Universal Performance Measure, Journal of Performance Measurement 6(3), 59–84.

Lee, W., 1998, “Return and Risk Characteristics of Tactical Asset Allocation under Imperfect Information”, Journal of Portfolio Management, Fall, 61-70.

Lee, M. C., A. Shleifer, and R. Thaler, 1991, “Investor Sentiment and the Closed-End Fund Puzzle”, Journal of Finance 46(1), 75-109.

Lehmann, B., and D. Modest, 1987. Mutual fund performance evaluation: A comparison of benchmarks and benchmark comparisons, Journal of Finance 42, 233-265.

Levy, M., and H. Levy, 2002. Prospect Theory: Much Ado About Nothing?, Management Science 48(10), 1334-1349.

Margrabe, W., 1978, “The Value of an Option to Exchange One Asset for Another”, Journal of Finance 33, 177-86.

Roll, R., 1992, “A Mean/Variance Analysis of Tracking Error,” Journal of Portfolio Management, 13-22.

Pope, P. and P. K. Yadav, 1994, Discovering Error in Tracking Error, Journal of Portfolio Management (Winter 1994), 27-32.

Rudolf, M., H. Wolter, and H. Zimmermann, 1999, “A Linear Model for Tracking Error Minimization,” Journal of Banking and Finance 23, 85-103.

Sharpe, W., 1966. Mutual Fund Performance, Journal of Business 39, 119-138.

Sortino, F. and Van der Meer (1991), Downside risk, Journal of Portfolio Management, 27-31.

Thaler, R. and E. Johnson (1990), "Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice," Management Science 36, 643-660.

Treynor, J., 1965. How to Rate Management of Investment Funds, Harvard Business Review 43, 63-75.

Treynor, J., and K. Mazuy, 1966. Can Mutual Funds Outguess the Market?, Harvard Business Review 44, 131-136.

Tversky, A. and D. Kahneman, 1992, "Advances in Prospect Theory: Cumulative Representation of Uncertainty," Journal of Risk and Uncertainty 5, 297-323.

Wermers, R., 1996, "Momentum Investment Strategies of Mutual Funds, Performance Persistence, and Survivorship Bias. Unpublished working paper, University of Colorado at Boulder.

Zweig, M. E., 1973, “An Investor Expectations Stock Price Predictive Model Using Closed-End Fund Premiums’, Journal of Finance 28, 67-87.

List of other working papers:

2005

1. Shaun Bond and Soosung Hwang, Smoothing, Nonsynchronous Appraisal and Cross-Sectional Aggreagation in Real Estate Price Indices, WP05-17
2. Mark Salmon, Gordon Gemmill and Soosung Hwang, Performance Measurement with Loss Aversion, WP05-16
3. Philippe Curty and Matteo Marsili, Phase coexistence in a forecasting game, WP05-15
4. Matthew Hurd, Mark Salmon and Christoph Schleicher, Using Copulas to Construct Bivariate Foreign Exchange Distributions with an Application to the Sterling Exchange Rate Index (Revised), WP05-14
5. Lucio Sarno, Daniel Thornton and Giorgio Valente, The Empirical Failure of the Expectations Hypothesis of the Term Structure of Bond Yields, WP05-13
6. Lucio Sarno, Ashoka Mody and Mark Taylor, A Cross-Country Financial Accelorator: Evidence from North America and Europe, WP05-12
7. Lucio Sarno, Towards a Solution to the Puzzles in Exchange Rate Economics: Where Do We Stand?, WP05-11
8. James Hodder and Jens Carsten Jackwerth, Incentive Contracts and Hedge Fund Management, WP05-10
9. James Hodder and Jens Carsten Jackwerth, Employee Stock Options: Much More Valuable Than You Thought, WP05-09
10. Gordon Gemmill, Soosung Hwang and Mark Salmon, Performance Measurement with Loss Aversion, WP05-08
11. George Constantinides, Jens Carsten Jackwerth and Stylianos Perrakis, Mispricing of S&P 500 Index Options, WP05-07
12. Elisa Luciano and Wim Schoutens, A Multivariate Jump-Driven Financial Asset Model, WP05-06
13. Cees Diks and Florian Wagener, Equivalence and bifurcations of finite order stochastic processes, WP05-05
14. Devraj Basu and Alexander Stremme, CAY Revisited: Can Optimal Scaling Resurrect the (C)CAPM?, WP05-04
15. Ginwestra Bianconi and Matteo Marsili, Emergence of large cliques in random scale-free networks, WP05-03
16. Simone Alfarano, Thomas Lux and Friedrich Wagner, Time-Variation of Higher Moments in a Financial Market with Heterogeneous Agents: An Analytical Approach, WP05-02
17. Abhay Abhayankar, Devraj Basu and Alexander Stremme, Portfolio Efficiency and Discount Factor Bounds with Conditioning Information: A Unified Approach, WP05-01

2004

1. Xiaohong Chen, Yanqin Fan and Andrew Patton, Simple Tests for Models of Dependence Between Multiple Financial Time Series, with Applications to U.S. Equity Returns and Exchange Rates, WP04-19
2. Valentina Corradi and Walter Distaso, Testing for One-Factor Models versus Stochastic Volatility Models, WP04-18
3. Valentina Corradi and Walter Distaso, Estimating and Testing Sochastic Volatility Models using Realized Measures, WP04-17
4. Valentina Corradi and Norman Swanson, Predictive Density Accuracy Tests, WP04-16
5. Roel Oomen, Properties of Bias Corrected Realized Variance Under Alternative Sampling Schemes, WP04-15
6. Roel Oomen, Properties of Realized Variance for a Pure Jump Process: Calendar Time Sampling versus Business Time Sampling, WP04-14

7. Richard Clarida, Lucio Sarno, Mark Taylor and Giorgio Valente, The Role of Asymmetries and Regime Shifts in the Term Structure of Interest Rates, WP04-13
8. Lucio Sarno, Daniel Thornton and Giorgio Valente, Federal Funds Rate Prediction, WP04-12
9. Lucio Sarno and Giorgio Valente, Modeling and Forecasting Stock Returns: Exploiting the Futures Market, Regime Shifts and International Spillovers, WP04-11
10. Lucio Sarno and Giorgio Valente, Empirical Exchange Rate Models and Currency Risk: Some Evidence from Density Forecasts, WP04-10
11. Ilias Tsiakas, Periodic Stochastic Volatility and Fat Tails, WP04-09
12. Ilias Tsiakas, Is Seasonal Heteroscedasticity Real? An International Perspective, WP04-08
13. Damin Challet, Andrea De Martino, Matteo Marsili and Isaac Castillo, Minority games with finite score memory, WP04-07
14. Basel Awartani, Valentina Corradi and Walter Distaso, Testing and Modelling Market Microstructure Effects with an Application to the Dow Jones Industrial Average, WP04-06
15. Andrew Patton and Allan Timmermann, Properties of Optimal Forecasts under Asymmetric Loss and Nonlinearity, WP04-05
16. Andrew Patton, Modelling Asymmetric Exchange Rate Dependence, WP04-04
17. Alessio Sancetta, Decoupling and Convergence to Independence with Applications to Functional Limit Theorems, WP04-03
18. Alessio Sancetta, Copula Based Monte Carlo Integration in Financial Problems, WP04-02
19. Abhay Abhayankar, Lucio Sarno and Giorgio Valente, Exchange Rates and Fundamentals: Evidence on the Economic Value of Predictability, WP04-01

2002

1. Paolo Zaffaroni, Gaussian inference on Certain Long-Range Dependent Volatility Models, WP02-12
2. Paolo Zaffaroni, Aggregation and Memory of Models of Changing Volatility, WP02-11
3. Jerry Coakley, Ana-Maria Fuertes and Andrew Wood, Reinterpreting the Real Exchange Rate - Yield Diffential Nexus, WP02-10
4. Gordon Gemmill and Dylan Thomas , Noise Training, Costly Arbitrage and Asset Prices: evidence from closed-end funds, WP02-09
5. Gordon Gemmill, Testing Merton's Model for Credit Spreads on Zero-Coupon Bonds, WP02-08
6. George Christodoulakis and Steve Satchell, On th Evolution of Global Style Factors in the MSCI Universe of Assets, WP02-07
7. George Christodoulakis, Sharp Style Analysis in the MSCI Sector Portfolios: A Monte Caro Integration Approach, WP02-06
8. George Christodoulakis, Generating Composite Volatility Forecasts with Random Factor Betas, WP02-05
9. Claudia Riveiro and Nick Webber, Valuing Path Dependent Options in the Variance-Gamma Model by Monte Carlo with a Gamma Bridge, WP02-04
10. Christian Pedersen and Soosung Hwang, On Empirical Risk Measurement with Asymmetric Returns Data, WP02-03
11. Roy Batchelor and Ismail Orgakcioglu, Event-related GARCH: the impact of stock dividends in Turkey, WP02-02
12. George Albanis and Roy Batchelor, Combining Heterogeneous Classifiers for Stock Selection, WP02-01

2001

1. Soosung Hwang and Steve Satchell , GARCH Model with Cross-sectional Volatility; GARCHX Models, WP01-16
2. Soosung Hwang and Steve Satchell, Tracking Error: Ex-Ante versus Ex-Post Measures, WP01-15
3. Soosung Hwang and Steve Satchell, The Asset Allocation Decision in a Loss Aversion World, WP01-14
4. Soosung Hwang and Mark Salmon, An Analysis of Performance Measures Using Copulae, WP01-13
5. Soosung Hwang and Mark Salmon, A New Measure of Herding and Empirical Evidence, WP01-12

6. Richard Lewin and Steve Satchell, The Derivation of New Model of Equity Duration, WP01-11
7. Massimiliano Marcellino and Mark Salmon, Robust Decision Theory and the Lucas Critique, WP01-10
8. Jerry Coakley, Ana-Maria Fuertes and Maria-Teresa Perez, Numerical Issues in Threshold Autoregressive Modelling of Time Series, WP01-09
9. Jerry Coakley, Ana-Maria Fuertes and Ron Smith, Small Sample Properties of Panel Time-series Estimators with I(1) Errors, WP01-08
10. Jerry Coakley and Ana-Maria Fuertes, The Felsdtein-Horioka Puzzle is Not as Bad as You Think, WP01-07
11. Jerry Coakley and Ana-Maria Fuertes, Rethinking the Forward Premium Puzzle in a Non-linear Framework, WP01-06
12. George Christodoulakis, Co-Volatility and Correlation Clustering: A Multivariate Correlated ARCH Framework, WP01-05
13. Frank Critchley, Paul Marriott and Mark Salmon, On Preferred Point Geometry in Statistics, WP01-04
14. Eric Bouyé and Nicolas Gaussel and Mark Salmon, Investigating Dynamic Dependence Using Copulae, WP01-03
15. Eric Bouyé, Multivariate Extremes at Work for Portfolio Risk Measurement, WP01-02
16. Erick Bouyé, Vado Durrleman, Ashkan Nikeghbali, Gael Riboulet and Thierry Roncalli, Copulas: an Open Field for Risk Management, WP01-01

2000

1. Soosung Hwang and Steve Satchell , Valuing Information Using Utility Functions, WP00-06
2. Soosung Hwang, Properties of Cross-sectional Volatility, WP00-05
3. Soosung Hwang and Steve Satchell, Calculating the Miss-specification in Beta from Using a Proxy for the Market Portfolio, WP00-04
4. Laun Middleton and Stephen Satchell, Deriving the APT when the Number of Factors is Unknown, WP00-03
5. George A. Christodoulakis and Steve Satchell, Evolving Systems of Financial Returns: Auto-Regressive Conditional Beta, WP00-02
6. Christian S. Pedersen and Stephen Satchell, Evaluating the Performance of Nearest Neighbour Algorithms when Forecasting US Industry Returns, WP00-01

1999

1. Yin-Wong Cheung, Menzie Chinn and Ian Marsh, How do UK-Based Foreign Exchange Dealers Think Their Market Operates?, WP99-21
2. Soosung Hwang, John Knight and Stephen Satchell, Forecasting Volatility using LINEX Loss Functions, WP99-20
3. Soosung Hwang and Steve Satchell, Improved Testing for the Efficiency of Asset Pricing Theories in Linear Factor Models, WP99-19
4. Soosung Hwang and Stephen Satchell, The Disappearance of Style in the US Equity Market, WP99-18
5. Soosung Hwang and Stephen Satchell, Modelling Emerging Market Risk Premia Using Higher Moments, WP99-17
6. Soosung Hwang and Stephen Satchell, Market Risk and the Concept of Fundamental Volatility: Measuring Volatility Across Asset and Derivative Markets and Testing for the Impact of Derivatives Markets on Financial Markets, WP99-16
7. Soosung Hwang, The Effects of Systematic Sampling and Temporal Aggregation on Discrete Time Long Memory Processes and their Finite Sample Properties, WP99-15
8. Ronald MacDonald and Ian Marsh, Currency Spillovers and Tri-Polarity: a Simultaneous Model of the US Dollar, German Mark and Japanese Yen, WP99-14
9. Robert Hillman, Forecasting Inflation with a Non-linear Output Gap Model, WP99-13
10. Robert Hillman and Mark Salmon , From Market Micro-structure to Macro Fundamentals: is there Predictability in the Dollar-Deutsche Mark Exchange Rate?, WP99-12
11. Renzo Avesani, Giampiero Gallo and Mark Salmon, On the Evolution of Credibility and Flexible Exchange Rate Target Zones, WP99-11
12. Paul Marriott and Mark Salmon, An Introduction to Differential Geometry in Econometrics, WP99-10

13. Mark Dixon, Anthony Ledford and Paul Marriott, Finite Sample Inference for Extreme Value Distributions, WP99-09
14. Ian Marsh and David Power, A Panel-Based Investigation into the Relationship Between Stock Prices and Dividends, WP99-08
15. Ian Marsh, An Analysis of the Performance of European Foreign Exchange Forecasters, WP99-07
16. Frank Critchley, Paul Marriott and Mark Salmon, An Elementary Account of Amari's Expected Geometry, WP99-06
17. Demos Tambakis and Anne-Sophie Van Royen, Bootstrap Predictability of Daily Exchange Rates in ARMA Models, WP99-05
18. Christopher Neely and Paul Weller, Technical Analysis and Central Bank Intervention, WP99-04
19. Christopher Neely and Paul Weller, Predictability in International Asset Returns: A Re-examination, WP99-03
20. Christopher Neely and Paul Weller, Intraday Technical Trading in the Foreign Exchange Market, WP99-02
21. Anthony Hall, Soosung Hwang and Stephen Satchell, Using Bayesian Variable Selection Methods to Choose Style Factors in Global Stock Return Models, WP99-01

1998

1. Soosung Hwang and Stephen Satchell, Implied Volatility Forecasting: A Compaison of Different Procedures Including Fractionally Integrated Models with Applications to UK Equity Options, WP98-05
2. Roy Batchelor and David Peel, Rationality Testing under Asymmetric Loss, WP98-04
3. Roy Batchelor, Forecasting T-Bill Yields: Accuracy versus Profitability, WP98-03
4. Adam Kurpiel and Thierry Roncalli , Option Hedging with Stochastic Volatility, WP98-02
5. Adam Kurpiel and Thierry Roncalli, Hopscotch Methods for Two State Financial Models, WP98-01