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Investment Funds: What Next?

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Abstract

Investment funds provide a low cost method of sharing in the rewards from capitalism. Recently "alternative investments" such as hedge funds have grown rapidly and the trading strategies open to hedge funds are now becoming available to mutual funds and even to ordinary retail investors. In this paper we analyze problems in assessing fund performance and the prospects for investment fund sectors. Choosing genuine outperformers among top funds requires a careful assessment of non-normality, order statistics and the possibility of false discoveries. The risk adjusted performance of the average hedge fund over the last 10-15 is actually not that impressive, although the "top" funds do appear to have statistically significant positive alphas.

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1 Introduction

The mutual fund industry in the USA and UK has increased dramatically over the last 30 years. In the US and UK about 70% of institutional funds are actively managed and this rises to over 90% for retail funds. Hedge fund assets grew rapidly after 2000 and by 2006 US hedge fund assets amounted to around $800bn to $1 trillion – about 10% of mutual fund assets. On fund performance, the first key issue is whether active funds have an (ex-post) abnormal fund performance in terms of net returns to investors which is positive.[1] A second major issue is whether abnormal fund performance can be identified ex-ante and for how long it persists in the future.

To an economist, one's view of how the world works is probably a mixture of the elegance of particular theories, their empirical content and some good old fashioned "gut feeling" – a more polite term here might be "studied introspection". In this paper we want to apply this "holy trinity" as a basis for assessing the performance of investment funds. The paper is a highly selective and perhaps idiosyncratic view of the literature and we do not claim that the paper constitutes an exhaustive survey.[2]

The rest of this article is organized as follows. In Section 2 we discuss some broad issues in economic modelling and statistical inference, in Section 3 we discuss the performance of mutual funds and this is followed in Section 4 by a discussion of hedge fund performance. Section 5 concludes.

2 Economic Models and Statistical Inference

Let us start by noting some of the broad theoretical and statistical ideas that have influenced our views in this area. From textbook portfolio theory we have the elegant baseline mean-variance model but we do notice that as soon as we extend this to the "standard" intertemporal framework (perhaps the holy grail of economic modelling) we come across some major problems. These models are difficult to solve and invariably involve complex

[1] Taxes on capital gains and dividend disbursements also influence the return to investors, although lack of data on individuals' tax liabilities makes any adjustments difficult - so most studies use pre-tax returns.

[2] For a recent survey on theoretical issues on performance see Lehmann and Timmermann (2008) and on empirical evidence for mutual funds see Cuthbertson, Nitzsche and O'Sullivan (2006).

numerical solutions which make it difficult to believe that investors behave "as if" they use such models in asset allocation. However, intertemporal models do introduce the notion that hedging demands are potentially important - this depends on correlations between asset returns and "other variables" such as labour income (Viceira, 2001). As we might expect such models suggest that the demand for risky assets depends on the time horizon to retirement but results are very sensitive to slight changes in inputs. For example, if there is thought to be predictability in asset returns, the shift into risky assets predicted by such models is implausibly large (Campbell and Viceira, 1999). However, if we introduce parameter uncertainty then such effects are attenuated (Barberis, 2000). These models should form the basis for "default funds" for long term savings vehicles such as 401K (in the US) and the proposed "Brit Saver" schemes which will shortly be implemented in the UK (OECD, 2003, and Turner, 2006). However, it must be said that actual behaviour seems far removed from such optimal models as investors appear to use simple heuristics such as the 1/n rule when allocating amongst their risky assets (Bernartazi and Thaler, 2001) and can be encouraged to save more by simple pre-commitment rules (e.g. automatically increase savings when earnings increase). As far as mutual funds and hedge funds are concerned it is frequently the case that advocates of "picking winners" and adding such funds to an existing portfolio, base their advice on static mean-variance optimization - and charge high fees for doing so. Theory tells us this may not always be appropriate.

Conceptual difficulties with expected utility maximisation as a basis for 'microfoundations' in financial markets (see for example, Rabin, 2000), has led to alternatives where utility depends on *changes* in wealth (anchoring), where losses are much more 'painful' than gains (e.g. loss-aversion or disappointment aversion) and where individual's consider gains and losses in isolation (i.e. "narrow framing"). These changes have been important in understanding and explaining the equity premium puzzle and in extending factor models to explain investment fund returns.

When we turn to "empirical facts" that stand out, one is the success of the Fama-French 3 factor model in pricing assets and the accompanying empirical evidence that these may mimic genuine risk factors. Such a simple model does not do everything of course. It fails to price momentum portfolios (including those of mutual funds) and for that we need to add the Carhart (1997) momentum factor (Lesmond, Schill and Zhou, 2004).

2.1 Can You Count?

The next statistical issue to consider is how to interpret results which count the number of "winner funds". The standard approach to determining whether the performance of a single fund (or a single portfolio such as the average fund) demonstrates skill or luck is to choose a rejection region and associated significance level γ and to reject the null of "no outperformance" if the test statistic lies in the rejection region - 'luck' is interpreted as the significance level chosen. However, using $\gamma = 5\%$ when testing the alphas for each of m-funds, the probability of finding *at least one* lucky fund from a sample of m-funds is much higher than 5% (even if all funds have true alphas of zero).[3]

To see how simply counting the number of "significant" outcomes can mislead investors about the true "success" of particular strategy consider the results of Sullivan, Timmermann and White (2001) who note the vast number of studies that find calendar effects in stock returns and address the problem of whether this is due to 'chance' (data mining). They use over 100 years of daily returns data (on the S&P 500 and its futures index) to examine a huge set of up to 9500, possible calendar rules. Once the effects of undertaking a large number of tests has been accounted for they find that the best calendar rule does not yield a statistically significant ('reality check') p-value for 'predictability', where the latter is taken to be either the mean return or the Sharpe ratio.

In testing performance across many funds a balanced approach is needed. The false discovery rate (FDR) measures the proportion of lucky funds among a group of funds, which have been found to have significant (individual) alphas and hence the FDR 'measures' luck among the pool of 'significant funds' (Benjamini and Hochberg, 1999, Storey, 2002, and Storey, Taylor and Siegmund, 2004). Hence, (1-FDR) measures the proportion of "truly significant" funds - this is clearly useful information for investors.[4] So,

[3] This probability is the compound type-I error. For example, if the m tests are independent then Pr(at least 1 false discovery) = $1 - (1- \gamma)^m = z_m$, which for a relatively low value m=50 funds and conventional γ =0.05 gives $z_m = 0.92$ – a high probability of observing at least one false discovery.

[4] We use the usual language and terminology found in the statistical literature on false discoveries and error rates. The use of "truly significant" (sometimes "genuine" is used) should not be taken to mean that we are 100% certain that the proportion of funds among a particular group of significant funds have non-zero alphas – the FDR even if it is found to be zero, is still subject to estimation error. Also note that the FDR says nothing about the statistical significance of the alpha of any particular *individual* fund - conceptually, the FDR only applies to a group of significant funds. The FDR approach seems to have been first used in testing the difference between genes in particular cancer cells.

informed investors when forming portfolios need to know both the size of the significant alphas of individual funds and also the FDR amongst these alphas - we discuss this further below.

2.2 Masters of the Universe

We are used to seeing "press reports" which give impressive figures for the alpha of say the best fund of say 20% per annum (p.a.), which is statistically significant at the 1% level or better. If we are not careful this can be misleading for investors since the distribution of the return of the *best* fund is very different from the population itself and the standard critical values do not apply. This idea also has implications for survivorship bias since in some databases (particularly for hedge funds or private equity) we only observe the "best funds" - that is, those that have survived and hence this inflates the observed outcomes for performance.

A key empirical fact is that we require a considerable amount of data to obtain reasonable power for our test on alpha. For example, suppose alpha = 1.8% p.a. (0.15% per month (p.m.)) in the market model, R-squared = 0.9, beta = 1 and residual standard deviation is 1.5% p.m.[5] Then even with T = 270 months (>22 years) of data, power (for a one sided test) is only 50%, whereas if alpha is as large as 3.6% p.a., power equal to 50% is achieved with T= 68 (5.7 years) of data - see Lehmann and Timmermann (2008). Empirically this suggests that it is only in the tails of the cross-section of the performance distribution that we might have reasonably high power in detecting outperformance.

3 Performance: Factor Models

Risk adjusted mutual fund performance is usually measured using the alpha from factor models - a positive alpha implies that an investor can combine this fund with the "market portfolio" to obtain a Sharpe ratio higher than that which can be obtained using the benchmarks alone. [6] Unconditional models have factor loadings that are assumed to be time

[5] For convenience, we assume a benchmark Sharpe ratio of zero, but this does not affect the general point made.

[6] Semi-parametric "characteristic based measures" (Daniel et al., 1997), using stock holdings and stock trades are also used to measure performance - but results are broadly similar to those using factor models, so we do not report these in this paper (see Cuthbertson, Nitzsche and O'Sullivan, 2006).

invariant. Carhart's (1997) four-factor (4F) performance measure is the alpha estimate from:

$$r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} MOM_t + \varepsilon_{i,t},$$

where $r_{m,t}$ is the excess return on the market portfolio, SMB_t, HML_t and MOM_t are zero investment factor mimicking portfolios for size, book-to-market value and momentum effects, respectively. If $\beta_{4i} = 0$ the model is the Fama-French (1992, 1993) three-factor model while Jensen's (1968) alpha is the intercept from the CAPM one-factor (or market) model. Conditional models (Ferson and Schadt, 1996, Christopherson, Ferson and Glassman, 1998) allow for the possibility that a fund's factor betas and alpha may depend on lagged public information variables.[7] In what follows, 'statistically significant' refers to a 5% significance level (or better).

3.1 Average Performance

Most recent studies of mutual fund performance do not suffer from acute survivorship bias because databases at least for the US and UK have alive and dead funds. On average, US funds (over January 1975-December 2002 using around 1,700 mutual funds) have a net return alpha of about minus 0.5% p.a. (Kosowski et al., 2006). But it is also found that some subgroups of funds do seem to outperform their benchmarks (e.g. US growth oriented funds, Chen, Jegadeesh and Wermers, 2000, and Wermers, 2000). Much less empirical work on performance has been done on UK funds but the evidence suggests that the average fund over 1975-95 underperforms its benchmarks by around 1% p.a. (Leger, 1997, Quigley and Sinquefield, 2000, and Fletcher, 1997).

[7] Space constraints precludes discussion of market timing but the evidence seems to be quite conclusive that market timing is unlikely to provide profitable strategies after transactions costs and on a net return, risk adjusted basis (see inter alia Treynor and Mazuy, 1966, Henriksson and Merton, 1981, Jiang, Yao and Yu 2007, and Bollen and Busse, 2001).

3.2 Individual Funds

Kosowski et al. (2006) explicitly deal with the problem of inference when funds have been ordered according to their ex-post performance. They derive empirically (rather than analytically) the distribution of order statistics under the null of no outperformance. Compared to using standard critical values they find far fewer winner funds. However, funds ranked above the top 5th percentile (i.e. a maximum of about 90 funds) are statistically significant with α_{4F}^{net} in excess of 4.8% p.a. These "skilled" funds are all found to be in either the aggressive growth or growth styles.[8] Using a similar bootstrap approach on UK data (842 funds, 1975-2002), Cuthbertson, Nitzsche and O'Sullivan (2008) find that only 12 funds out of the top 20 are statistically significant (each at 10% significance level). For the UK, in contrast to the US results, skill appears to reside with equity income funds rather than 'all company' or small company funds. At the negative end of the performance scale using net return 4F-alphas, UK and US results strongly reject the hypothesis that most poor performing funds are merely unlucky.

As stated earlier, a simple count of all funds with 'significant' p-values ignores the possibility of some significant funds being "false discoveries". The 'false discovery rate' FDR - that is, the proportion of lucky funds among funds with positive significant (individual) alphas is around 55% for US funds, so in fact only 23 (of the 52 "statistically significant") top funds have genuine skill (i.e. about 2% of all US funds) - Barras, Scaillet and Wermers (2005). For the UK the FDR amongst winner funds (i.e. $\alpha_i > 0$) is 58% so only 9 funds truly outperform (1.3% of all 675 funds) - Cuthbertson, Nitzsche and O'Sullivan (2007). The FDR amongst loser funds is much lower (in the region of 10%) and it is found that about 15-20% of all US and UK funds have genuinely poor performance. Thus for the US and UK there are a much higher proportion of false discoveries among the best funds than among the worst funds - so the standard method of simply counting the number of funds with "significant" test statistics can be far more misleading for "winners" than for "losers".

[8] Note that these results although they deal with the issue of order statistics, are still subject to Type-I and Type-II errors, so use of "genuine" and "skilled" should be interpreted in the usual way. Results are largely invariant to use of an conditional/unconditional 4F model, to the minimum number of monthly observations used ($18 < T_{\min} < 120$) and ordering funds by alpha or t-alpha.

3.3 Persistence

It is important to assess whether there are ex-ante rules which can be used to choose funds which subsequently earn statistically and economically significant abnormal returns - in short whether there is persistence in fund performance. However, it is here that our caveat about data snooping bias comes to the fore. There have been so many different trading rules that have been tried (mainly on one US data set - CRSP), such that some may appear successful even though this may be due to luck.

Overall, studies of predictability on US mutual funds using statistical measures (e.g. correlation, regression or contingency tables), find evidence that poor performance persists for up to 3 years, while there is mixed evidence that winners repeat over periods in excess of one year (Grinblatt and Titman, 1992, Goetzmann and Ibbotson, 1994, Brown and Goetzmann, 1995, Elton, Gruber and Blake, 1996, and Carhart 1997, Teo and Woo 2001). Results on UK mutual funds are somewhat sparse but indicate there may be some short-run persistence while evidence for long-run persistence is rather weak (Leger 1997, Allen and Tan 1999, Lunde, Timmermann and Blake, 1999, Fletcher and Forbes 2002). However, such statistical measures of persistence do not necessarily imply an exploitable trading strategy - an issue we take up next.

Using the recursive portfolio approach of Carhart (1997) with the 4F model, recent US studies (e.g. Kosowski et al., 2006) have found some evidence of persistence by the top decile portfolio for a one-year rebalancing period and stronger evidence that worst funds persist. The source of this persistence is most likely to be a manifestation of the momentum effect in stocks which are 'accidentally held' by funds, rather than funds actively choosing stocks with a high loading on the momentum factor.

When we consider monthly or quarterly rebalancing and more sophisticated sorting rules for example, based on past forecast accuracy (Mamaysky, Spiegel and Zhang, 2004) or Bayesian approaches (e.g. Cohen, Coval and Pastor, 2005) or "active trades", which mainly turn out to be favourable IPO allocations (Kacperczyk, Sialm and Zheng, 2006) - US winners persist, with a top decile portfolio net return alpha in excess of 2.5% p.a. and loser persistence for the bottom decile around minus 4% p.a. There are far fewer studies of persistence using UK data and generally these find that past winners do not persist but past losers do (Quigley and Sinquefield, 2000, Fletcher, 1997, and Fletcher and Forbes, 2002).

4 Hedge Funds

The four most popular hedge fund styles are long-short equity (31%), event-driven (20%), global macro (10%) and fixed-income arbitrage (8%). Other key strategies include, event driven strategies (e.g. merger arbitrage\ risk arbitrage) and distress strategies/special situations (Tremont Asset Flows Report, 2nd quarter, 2005). These strategies are risky so the term 'hedge fund' is somewhat misleading. However, the term hedge fund is not a complete misnomer since many hedge fund styles seek to take long-short positions to hedge out any risks on which they do not wish to "place bets".

The collapse of Long-Term Capital Management (LTCM) in 1998 with a loss of $4bn capital and intervention by the Federal Reserve Board signaled the possibility of systemic risk from hedge funds. Because of the lack of transparency of hedge funds, regulators are becoming increasingly concerned about their activities.

4.1 Databases

Although data sources for the hedge fund universe are improving they are generally not as comprehensive and reliable as those for equity mutual funds - so databases often involve survivorship bias, back-fill bias (sometimes called "instant industry bias") and selection bias, (due to the fact that many hedge funds do not report to any database). Because many hedge funds have only short histories this makes statistical inference all the more difficult and as noted above raises issues of the power of test and the possibility of false discoveries. Some hedge funds hold illiquid assets (e.g. emerging market or distressed bonds) which may be difficult to value, so reported returns may be subject to "smoothing" and may be somewhat inaccurate on a month-to-month basis. This smoothing gives rise to autocorrelation in returns which can create problems when measuring the performance of hedge funds (Getmansky, Lo and Makarov, 2004). Of course, if hedge funds do hold large amounts of illiquid assets and they try to sell these assets in a crisis period (e.g. the Russian bond crisis of 1998) they may put additional downward pressure on prices, so the recorded prices might not reflect the "true" price they will be able to obtain. Also note that some funds might be closed to new investors, so the recorded returns are only attainable by existing investors (Fung et al., 2006).

4.2 Performance

You may remember that in one of the *Superman* films the character played by Richard Pryor had the idea of using the bank's computer system to collect all the nickels floating around in cyberspace and crediting them to his account. A partner of LTCM described hedge funds as making money by vacuuming up nickels (pennies) since they used arbitrage strategies – later, less charitable commentators described it as picking up nickels in front of a turbo-charged steam roller – because these arbitrage positions were highly leveraged (in LTCM's case by around 22:1 *on average* over June 1994-August 1997).

Let's have a look at some broad based statistics using the (value weighted) Credit Suisse/Tremont Hedge Fund index. Between 1994 and the middle of 2006 the buy-and-hold return on the hedge fund index was an average of 10.8 % p.a. (net of performance fees and expenses) with standard deviation of 7.8% p.a., compared with 10.3% average return for the S&P500 and standard deviation much higher at 14.5%. So the Sharpe ratio of the hedge fund is around twice that of the S&P 500 - one immediate question here is whether the standard deviation is a good measure of risk, particularly for hedge funds with serially correlated returns.

It is worth noting at the outset that trying to determine whether hedge funds "beat the market" is much more difficult than for mutual funds, which is not itself devoid of problems. This is because

- hedge fund databases may be incomplete
- adjusting returns for the risks inherent in hedge fund strategies is complex (and controversial) in part due to negative skewness and excess kurtosis in returns.
- returns from some illiquid strategies are difficult to correctly value
- we have a relatively short time span of data.

But here is some evidence on the matter. First, using over 3,000 hedge funds between January 1999 to March 2004, Ibbotson and Chen (2005) find that the average (net return) alpha is 3.7% p.a., which is much higher than the average for mutual funds which is around minus 1-2% p.a. The problem of assessing hedge fund performance on historic data is the possibility that hedge funds look relatively risk free (in terms of volatility) but are prone to very large losses (and possible insolvency) - as with Aramanth in 2006 and more controversially LTCM in 1998. Hedge funds might be acting very much like an insurance

company which sells catastrophe insurance (e.g. insurance against earthquakes). While there are no earthquakes the insurance company looks good. It pockets the premiums, has no claims, profits are high and not volatile – until that is, the rare event occurs (Lo, 2001).

Until recently there has not been a great deal of work on individual hedge fund performance because of a lack of reliable data. Early studies show that hedge funds have a high rate of attrition (Brown, Goetzmann and Ibbotson, 1999) and they give conflicting results on the risk adjusted performance of hedge funds and persistence in hedge fund returns. See, inter alia, Fung and Hsieh (1997) who find negative alphas, while evidence of a positive risk adjusted performance and some persistence in returns is noted by Agarwal and Naik (2000) - although the latter is possibly due to the 'style' adopted by the hedge fund rather than genuine manager skills (Brown, Goetzmann and Ibbotson, 1999, and Brown, Goetzmann and Park, 2001).

4.3 Fund Styles

What about the performance of particular fund styles. A recent study by Capocci and Hubner (2004) uses a multifactor model on a large database of over 2,700 hedge funds (including 801 'dead funds') concentrating mainly on the more recent (and accurate) monthly returns over the bull market period of 1994-2000. Funds are divided into around 20 style categories (e.g. long-short, emerging markets etc.). Overall there are around 25-30% of funds within any style category that have positive and statistically significant alphas, with around 5-10% having negative alphas and the majority of funds (i.e. around 60%) having zero alphas.[9] The market betas of the hedge funds are lower than those for mutual funds (at around 0.3-0.6) and for almost all funds, the coefficient on the (Small Minus Big) SMB factor is statistically significant. A subset of the funds also have a significant coefficient on the emerging bond return but only about 1/3 of funds show evidence of a statistically significant (High Minus Low) HML factor and about 15% of funds have a significant momentum factor. The R-squared for these multifactor regressions are mostly in the range 0.65-0.90. Hence, most hedge funds appear to have exposure to small cap stocks, while a smaller proportion are also exposed to emerging market bonds and momentum stocks. Unfortunately in only a few cases (i.e. long-short, convertible arbitrage, non-classified) do the positive alphas over the whole period 1994-2000, remain positive

[9] Of course as noted above, some of these will be false discoveries.

over sub-periods. The recent study by Kosowski, Naik and Teo (2007) find that in a sample of over 2,700 funds (January 1994-December 2002) all of the *individual* funds in the top 10% of hedge funds ranked by t-alpha have highly statistically significant large positive (seven-factor) *ex-post* alphas - while all of the funds in the bottom 10% have negative alphas but these are due to bad luck rather than 'bad skill'.

So, there is evidence that a randomly selected hedge fund will have a negative or zero alpha but the best hedge funds have positive and statistically significant alphas which exceed those for the top mutual funds. Although here one should not forget the rather acute problems in assessing risk-adjusted hedge fund performance (these are less severe when looking at mutual funds).

4.4 Persistence

What happens when we assess persistence by forming explicit portfolios of past winners and tracking their future performance? Short-term persistence, at three month horizons, in hedge fund *raw returns* has been found in early studies but such persistence does not occur at longer horizons (e.g. Brown, Goetzmann and Ibbotson, 1999, Agarwal and Niak, 2000, and Liang, 2000). Also note that Getmansky, Lo and Makarov (2004) argue that short-term persistence may be due to illiquidity in returns which gives rise to "return smoothing" and apparent persistence in returns. Capocci and Hubner (2004) sort hedge funds into deciles based on their past 1-year returns and they find that there is no persistence in performance for the top and bottom deciles. In contrast, Kosowski, Naik and Teo (2007), with annual rebalancing and ranking hedge funds based on their past "t-alpha", find that *all* decile sorted portfolios exhibit statistically significant forward looking alphas of between 4% and 6% p.a. over January 1994-December 2002. Clearly, 'winner persistence' is much stronger statistically and economically in hedge funds compared with (US or UK) equity mutual funds.

4.5 The Future of Hedge Funds

As hedge funds attract more institutional investors with fiduciary duties they will have to become more transparent about their trades and risk positions and perhaps to adopt specific benchmarks (e.g. a specific hedge fund index). Even now some fund-of-funds obtain

detailed and frequent information (sometimes daily) on hedge fund positions and risk measures. Also having to stay reasonably close to a benchmark may lead to less investment in highly specialized strategies for fear of tracking error or earning less than the benchmark - which would probably entail substantial outflows of funds. Mutual funds are also gaining more regulatory freedom to invest in derivatives so there is some convergence between the two sectors. There are also new products on the market which claim to successfully track the behavior of hedge fund *indices* (i.e. their average returns, volatility, skewness etc.) by using "mechanical" trading strategies (using highly liquid futures and options) that can be programmed with real time prices. These replication funds have much lower fees than fund-of-funds or a portfolio of individual hedge funds, so these may capture some of the capital which currently flows into the traditional hedge fund sector - why pay high management fees for something you can replicate at lower cost. (Goldman Sachs produced one of the first hedge fund replication portfolios in 2006 - see also Kat and Palaro, 2005). So convergence between mutual and hedge funds seems likely with a continuum of different types of fund.

Precisely which hedge funds to regulate will become more difficult as this convergence takes place. Regulation is likely to be based on rules about disclosure - with "hedge funds" who do not agree to disclosure requirements remaining in the unregulated sector. Whether this makes the markets more volatile is subject to much debate. Hedge funds may suffer from liquidity risk - they have highly levered positions and their risk strategy often depends on being able to get out of these positions with speed and little price impact. If liquidity is thin and banks begin to call in their loans because of fear of a collapse in the hedge fund and if there are many banks in this position (due to concentration risk), then hedge funds may in part contribute to systemic risk in financial markets. Clearly this was the view taken by the Federal Reserve in August 1998 over LTCM which had losses exceeding its capital of around $4bn. In addition, banks who are providers of lines of credit (i.e. bank loans for leveraged transactions) may also provide stock lending to funds (for short sales) and may also be counterparties to OTC derivative trades by hedge funds. Of course, these "facts" are as much an argument for the sensible regulation of the financial intermediary's credit risk as it is for the regulation of hedge funds themselves. In contrast to LTCM the $6bn losses of Amaranth in September 2006 seemed to cause minimum impact on markets and financial institutions.

5 Conclusions

In terms of ex-post performance recent US and UK studies find around 2-10% of funds in the extreme right tail have positive net return alphas and at least 20% of funds spread throughout the right tail have poor performance (Barras, Scaillet and Wermers, 2005, Kosowski et al., 2006, Kosowski, Naik and Teo, 2007, and Cuthbertson, Nitzsche and O'Sullivan, 2008). US data reveal that the top performers are in growth and aggressive growth styles, while in the UK, skilled funds tend to be in the income style rather than in growth or small cap funds.

What about hedge fund performance? This poses major data and modelling problems (Fung et al., 2006). The top hedge funds appear to have higher risk adjusted returns than mutual funds and past winner funds exhibit short term persistence. One can only suggest caution, both in terms of "picking winners" and also when adding hedge funds to an existing market portfolio in order to improve diversification. The lack of transparency and difficulty in assessing risk makes investment in hedge funds rather dangerous.

Hedge funds currently widen the area of choice for at least some sophisticated investors, whereas mutual funds widen the set of investments open to somewhat less sophisticated investors. These are two different clienteles and from an investor protection viewpoint there is no reason why the two cannot co-exist, in the same way that private equity also provides a different type of investment which caters to a different clientele. However, it is important that investors, particularly retail investors are informed in an unbiased way about the risk-return profiles of different investments. Given the massive funds available for "advertising" their funds and maybe an incentive for being "economical with the truth", there is a prima facie case for government working via truly independent organizations which have sufficient resources, to provide impartial information on risk-return profiles of funds.[10]

[10] OECD (2005) provides a survey of nascent programmes in developing financial education in member states. See also Cuthbertson, Nitzsche and O'Sullivan (2005).

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