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Performance and Performance Persistence of UK Closed-End Equity Funds

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Abstract:

Using a comprehensive data set of almost 300 UK closed-end equity funds over the period 1990 to 2013, we use the false discovery rate to assess the alpha-performance of individual funds with both domestic and other mandates, using self-declared benchmarks and additional risk factors. We find evidence to indicate that up to 16% of the funds have truly positive alphas while around 3% have truly negative alphas. Positive post-formation alphas using fund-price returns depend on the factor model used: there is some positive-alpha performance when post-formation returns are evaluated using a one-factor global model but substantial positive-alpha performance when using a four-factor global model.

Keywords : closed-end funds, performance, false discovery rate.

JEL Classification : C15, G11, C14

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Performance and Performance Persistence of UK Closed-End Equity Funds

1. Introduction

In the UK, closed-end funds (CEF) are an asset class which has often been overlooked by investors, who mainly focus on open-end funds. Nevertheless, particularly for retail investors, closed-end funds provide an attractive investment alternative to open-end funds, as fees are often substantially lower. Restrictions on advertising and a less favorable commission structure for financial advisors are reasons why closed-end funds have remained a niche market in the UK asset management industry. Investors in closed-end funds also have to consider changes in the discount, whereby the net asset value (NAV) of the fund and the price of the fund can diverge substantially – hence, the need to distinguish between the NAV return, which measures the performance of the fund manager, and the fund-price return to the investor.

Research on closed-end funds in the UK and US, has focused mainly on causes of the discount (Lee, Shleifer and Thaler 1990; Gemmill and Thomas 2002); relatively few studies focus on the performance of these funds and no studies (to our knowledge) have used closed-end funds to separate skill from luck by applying the false discovery rate (FDR). The impact of ‘luck’ in multiple hypothesis tests arises whenever we ask the question: ‘How many of our statistically significant results are likely to be ‘truly null?’ – that is ‘false discoveries’. In this paper we use the false discovery rate which measures the proportion of lucky funds among a group of funds, whose performance has been found to be statistically significant. We assess the alpha-performance of the UK closed-end funds over the period November 1990 to January 2013 using a monthly data set, free of survivorship bias. If we simply count the number of funds which are found to have a statistically significant performance measure, we run the risk of including funds which are truly null (i.e. Type I errors). For example, suppose the FDR amongst 20 statistically significant positive-alpha funds is 80%, then this implies that only 4 funds (out of the 20) have truly significant alphas - this is clearly useful information for investors. A key issue is whether this correction gives different inferences from the standard approach of simply ‘counting’ the number of significant funds with non-zero abnormal performance.

Another important element in performance measurement is the factor model used. We assess individual fund performance using self-declared benchmarks. However, noting that there may be style drift (Sensoy 2009), we augment this one-factor model with global factors related to

size, value, and momentum. No other studies, to our knowledge, attempt to measure closed-end fund performance using the funds' self-declared benchmarks.

We also address the issue of performance persistence. We sort funds into (decile) portfolios based on a number of different metrics which capture the skill of the fund manager (i.e. NAV performance). The portfolios are frequently rebalanced and we then assess the subsequent alpha-performance. This recursive portfolio approach is analysed for a number of different portfolio formation rules and factor models.

From a total of 330 UK closed-end funds, our final sample of around 300 funds over the period November 1990 to January 2013 provides a large comprehensive data set (largely free of survivorship bias). This paper contributes to the literature by assessing individual-fund performance relative to its self-declared benchmark (as well as other risk factors) and adjusts the number of statistically significant alphas for the presence of false discoveries. For individual fund performance we find that around 75% of funds neither statistically beat nor are inferior to their benchmarks – this applies across all three factor models used. Next, there is a much higher proportion of false discoveries among the worst (negative alpha) funds than amongst the best performing funds – so the standard method of simply counting the number of funds with 'significant' test statistics can be far more misleading for 'losers' than for 'winners'. Third, the truly significant positive-alpha and negative-alpha funds appear to be concentrated in the extreme tails of the cross-section of fund performance.

For persistence in performance, we find that sorting into decile portfolios on past performance produces some positive post-sort alphas using fund-price returns in a one-factor model but many more statistically significant post-sort alphas when using a four-factor model.

Previous Studies

Before examining the literature on the performance of CEF, it is worth briefly commenting on results from open-end funds. The literature on US open-end-fund performance is voluminous with less work being done on UK funds; most studies examine funds that invest domestically. It is well documented that the average US or UK open-end equity fund underperforms its benchmarks (Elton, Gruber, Das, and Hlavka 1993; Fletcher 1997; Blake and Timmermann 1998; Wermers 2000; Quigley and Sinquefeld 2000). However, the cross-section standard deviation of alphas for individual funds in both the UK and US is high, and while some studies do find a few funds with statistically significant positive alphas, many more funds record negative alphas (Malkiel 1995; Kosowski, Timmermann, White and Wermers 2006; Cuthbertson, Nitzsche, and O'Sullivan 2008; Cuthbertson, Nitzsche, and O'Sullivan 2012, Fama and French 2010.).

Studies which investigate possible sources of skillful and unskillful open-end funds are almost exclusively based on US data. Past winner funds attract additional fund flows (Del Guercio and Tkac 2008; Keswani and Stolin 2008; Ivkovic and Weisbenner 2009) and this may lead to diseconomies of scale (Chen, Hong, Huang and Kubik 2004; Yan 2008), dilution effects (Edelen 1999), distorted trading decisions (Alexander, Cici, and Gibson 2007; Coval and Stafford 2007; Pollet and Wilson 2008) or manager changes (Khorana 1996, 2001; Bessler, Blake, Luckoff, and Tonks 2010) – all of which in turn may affect future performance. At the other end of the spectrum, poorly performing funds are subject to ‘external governance’ (fund outflows) and ‘internal governance’ (manager changes) which also influence their future performance (Dangl, Wu and Zechner 2008; Bessler et al. 2010).

Closed-end funds, unlike open-end funds, are never forced to liquidate securities or purchase additional securities due to fund inflows and outflows. Instead, changes in demand for the fund lead to a widening or narrowing of the discount and hence changes in investors’ returns. Persistence in the performance may therefore be stronger than for open-end funds because sentiment in favour of a closed-end fund might lead to an increased demand for the fund by additional (retail) investors which, with a given fund size, may lead to higher future fund returns. In contrast, an increase in demand for a particular open-end fund will be met by an increased inflow and increased purchases across a wide range of stocks, where the future price impact may be relatively small. CEF’s can also invest in illiquid securities (Cherkes, Sagi, and Stanton 2009) and use leverage (Elton, Gruber, Blake, and Shachar 2013) – this may also result in more positive alphas and performance persistence of active strategies, than for open-end funds.

The literature on closed-end fund performance in the US and UK is relatively sparse. Bers and Madura (2000), using US funds with a domestic mandate, find evidence of positive persistence for NAV and fund-price returns, based on the correlation between estimated alphas in successive periods. Positive persistence is also found for US funds with a foreign mandate although the level of persistence is less than that for domestic funds (Madura and Bers 2002). More recently, Elyasiani and Jia (2011) evaluate fund-price and NAV persistence using 86 US equity funds. They find, however, evidence of only very weak persistence when the funds are evaluated against median risk-adjusted industry performance.

In the UK, Bangassa (1999) finds no evidence of individual funds with positive alphas and little evidence of positive alphas when funds are grouped into 10 investment styles. Using daily

data on 9 portfolios with both domestic and international mandates, Bangassa, Su, and Joseph (2012) find mixed evidence on alpha performance which depends upon the investment mandate and the factor model used.

In this paper we add to the literature by assessing the performance of individual UK closed-end funds using their self-declared benchmarks (and other risk factors) after adjusting for false discoveries. We also examine performance persistence using different sorting rules and different factor models for post-formation returns. The paper is organized as follows. In section 2 we briefly discuss the methodology behind the FDR and other methods of controlling for false positives in a multiple testing framework. In section 3 we look at performance models, in section 4 we present our empirical results; section 5 concludes.

2. The False Discovery Rate

The standard approach to determining whether the alpha of a single fund demonstrates skill or luck is to choose a rejection region and associated significance level 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 non-zero alpha-fund in sample of M-funds is much higher than 5% (even if all funds have true alphas of zero).¹ Put another way, if we find 20 out of 200 funds (i.e. 10% of funds) with significant positive estimated alphas when using a 5% significance level then some of these will merely be lucky.

In testing the performance of many funds a balanced approach is needed - one which is not too conservative but allows a reasonable chance of identifying those funds with truly differential performance. An approach known as the false discovery rate (FDR) attempts to strike this balance by classifying funds as 'significant' (at a chosen significance level) and then asks the question 'What proportion of these significant funds are false discoveries?' – that is, those that are truly null (Benjamini and Hochberg 1995; Storey 2002; Storey, Taylor, and Siegmund 2004). The FDR measures the proportion of lucky funds among a group of funds which have been found to have significant (individual) alphas and hence 'measures' luck among the pool of 'significant funds'. Storey (2002) and Barras, Scaillet, and Wermers (2010) provide a detailed account of the FDR methodology, so it is only briefly summarized below. The null hypothesis that fund-*i* has no skill in security selection (alpha) and the alternative of either positive or negative performance is:

¹ This probability is the compound type-I error. For example, if the M tests are independent then $\Pr(\text{at least 1 false discovery}) = 1 - (1 - \gamma)^M = z_M$, which for a relatively small number of $M=50$ funds and conventional $\gamma = 0.05$ gives $z_M = 0.92$ – a high probability of observing at least one false discovery.

$$H_0 : \alpha_i = 0 \qquad H_A : \alpha_i > 0 \text{ or } \alpha_i < 0$$

A 'significant fund' is one for which the p-value for the test statistic (e.g. t-statistic on alpha) is less than or equal to some threshold $\gamma / 2$ ($0 < \gamma \leq 1$). At a given significance level γ the probability that a zero-alpha fund exhibits 'good luck' is $\gamma / 2$. If the proportion of truly zero-alpha funds in the population of M-funds is π_0 then the expected proportion of false positives (or 'lucky funds') is:

$$[1] \qquad E(F_\gamma^+) = \pi_0 (\gamma / 2)$$

If $E(S_\gamma^+)$ is the expected proportion of significant positive-alpha funds, then the expected proportion of truly skilled funds (at a significance level γ) is:

$$[2] \qquad E(T_\gamma^+) = E(S_\gamma^+) - E(F_\gamma^+) = E(S_\gamma^+) - \pi_0 (\gamma / 2)$$

Varying γ allows us to see if the number of truly skillful funds rises appreciably with γ or not, which tells us whether skilled funds are concentrated or dispersed in the right tail of the cross-sectional distribution. An estimate of the true proportion of skilled (unskilled) funds π_A^+ (π_A^-) in the population of M-funds is:

$$[3] \qquad \pi_A^+ = T_{\gamma^*}^+ \qquad \pi_A^- = T_{\gamma^*}^-$$

where γ^* is a sufficiently high significance level which can be determined using the mean squared error criterion (Barras et al. 2010). The expected FDR amongst the statistically significant positive-alpha funds is:

$$[4] \qquad FDR_\gamma^+ = \frac{E(F_\gamma^+)}{E(S_\gamma^+)} = \frac{\pi_0 (\gamma / 2)}{E(S_\gamma^+)}$$

The proportion of truly positive-alpha skilled funds amongst the statistically significant positive-alpha funds is:

$$[5] \quad E(T_\gamma^+) / E(S_\gamma^+) = 1 - FDR_\gamma^+$$

The observed number of significant funds S_γ^+ provides an estimate of $E(S_\gamma^+)$. To provide an estimate of π_0 , the proportion of truly null funds in the population of M-funds, we use the result that truly alternative features have p-values clustered around zero, whereas truly null p-values are uniformly distributed, $U(0,1)$. To estimate $\hat{\pi}_0(\lambda)$ we can simply choose a value λ for which the histogram of p-values becomes flat and use:

$$[6] \quad \hat{\pi}_0(\lambda) = \frac{W(\lambda)}{M(1-\lambda)} = \frac{\#\{p_i > \lambda\}}{M(1-\lambda)}$$

where $W(\lambda)/M$ is the area of the histogram to the right of the chosen value of λ (on the x-axis of the histogram) – see Figure 4. For example suppose $\pi_0 = 100\%$ and we choose $\lambda = 0.2$. Then $W(\lambda)/M = 80\%$ of p-values lie to the right of $\lambda = 0.2$ and our estimate of $\pi_0 = 80\% / (1 - 0.2) = 100\%$ as expected. For truly alternative funds (i.e. $\alpha_i \neq 0$), the histogram of p-values has a “spike” near zero. But if the histogram of p-values is perfectly flat to the right of λ then our estimate of π_0 is independent of the choice of λ . So, if we were able to count only truly null p-values then [6] would give an unbiased estimate of π_0 . However, if we erroneously include a few alternative p-values then [6] provides a conservative estimate of π_0 and hence of the FDR.

The bias in the estimate of $\hat{\pi}_0(\lambda)$ is decreasing in λ (as the chances of including non-zero alpha-funds diminishes) but its variance increases with λ (as we include fewer p-values in our estimation). Hence an alternative estimate of π_0 is to choose λ to minimize the mean-square error $E\{\pi_0(\lambda) - \pi_0\}^2$ (Storey 2002, Barras et al. 2010)².

We use a bootstrap approach to calculate p-values of estimated t-statistics because of the non-normality in regression residuals (Politis and Romano 1994; Kosowski et al. 2006). The

² Barras et al. (2010) use a Monte Carlo study to show that the estimators outlined above are accurate, are not sensitive either to the method used to estimate π_0 or to the chosen significance level γ . The estimators are also robust to the typical cross-sectional dependence in fund residuals (which tend to be low in monthly data).

estimated factor model of returns is: $r_{i,t} = \hat{\alpha}_i + \hat{\beta}_i' X_t + \hat{e}_{i,t}$ for $i = 1, 2, \dots, M$ funds, where T_i = number of observations on fund- i , $r_{i,t}$ = excess return on fund- i , X_t = vector of risk factors, $\hat{e}_{i,t}$ are the residuals and \hat{t}_i is the (Newey-West) t-statistic for alpha. We draw a random sample (with replacement) of length T_i from the residuals $\hat{e}_{i,t}$ and use these bootstrap residuals $\tilde{e}_{i,t}$ to generate an excess return series $\tilde{r}_{i,t} = 0 + \hat{\beta}_i' X_t + \tilde{e}_{i,t}$ under the null hypothesis $\alpha_i = 0$. Using $\tilde{r}_{i,t}$ the performance model is estimated and the resulting t-statistic for the alpha-performance measure, t_i^b is obtained. This is repeated $B = 10,000$ times and for a two-sided, equal-tailed test the bootstrap p-value for the alpha of fund- i is:

$$[7] \quad p_i = 2 \cdot \min \left[B^{-1} \sum_{b=1}^B I(t_i^b > \hat{t}_i), B^{-1} \sum_{b=1}^B I(t_i^b < \hat{t}_i) \right]$$

where $I(\cdot)$ is a (1,0) indicator variable. The above 'basic bootstrap' uses residual-only resampling, under the null of no outperformance (Efron and Tibshirani 1993).³ A similar procedure is used for other hypothesis tests⁴.

3. Performance Models

Individual Fund Performance

The performance of individual closed-end funds can be measured using either fund-price returns or NAV returns – the latter measuring the performance of the manager of the fund and the former measuring the return to the investor. The difference between these two measures of performance is the change in the closed-end fund discount.

Our performance models are well known 'factor models' and therefore are only described briefly below. When considering the performance of individual fund excess returns we make use of the self-declared benchmark return of the fund (in excess of the risk-free rate), $r_{bi,t}$ and consider the following models:

³ Alternative bootstrapping procedures such as simultaneously bootstrapping the residuals and the independent variables, or allowing for serial correlation (block bootstrap) or contemporaneous bootstrap across all (existing) funds at time t , produced qualitatively similar results, hence we only report results for the 'residuals only' bootstrap.

⁴ The FDR seems to have been used first in testing the difference between genes in particular cancer cells (Storey 2002) and has recently been used in the economics literature to assess the performance of alternative forecasting rules in foreign exchange (McCracken and Sapp 2005), stock returns (Bajgrowicz and Scaillet 2012), hedge funds (Criton and Scaillet 2011) and to analyze US equity mutual fund performance (Barras et al. 2010).

Excess Benchmark Return Model (EBRM):

$$[8] \quad r_{i,t} - r_{bi,t} = \alpha_i + \varepsilon_{i,t}$$

One-Factor Benchmark Model (1FBM):

$$[9] \quad r_{i,t} = \alpha_i + \beta_{1i} r_{bi,t} + \varepsilon_{i,t}$$

Four-Factor Benchmark Model (4FBM):

$$[10] \quad r_{i,t} = \alpha_i + \beta_{1i} r_{bi,t} + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} MOM_t + \varepsilon_{i,t}$$

where $r_{i,t}$ is the excess return over the risk-free rate, and SMB_t , HML_t and MOM_t are global risk factors which capture size, book-to-market, and momentum, respectively (Fama and French 1993; Carhart 1997). The excess benchmark return model (EBRM) assumes the fund tracks its self-designated benchmark with zero expected tracking error. Recent studies (Sensoy 2009), however, have shown that many funds deviate from their self-declared benchmarks and this is accounted for in the one-factor benchmark model (1FBM) where the benchmark beta is not constrained to be unity, and in the four-factor benchmark model (4FBM) where global risk factors are also included. Equation [10] is widely used to measure open-end fund performance and should also be applicable to closed-end counterparts.

Portfolio Performance

In the sample, there are over 100 different self-designated benchmarks. Hence when considering the performance of *portfolios* of closed-end funds (e.g. equally-weighted portfolios) we cannot use the self-declared benchmark returns $r_{bi,t}$ because these may differ for each fund in the portfolio. Instead, we evaluate the return performance of portfolios (in excess of the risk-free rate) $r_{p,t}$, using the a global market return $r_{m,t}$ (in excess of the risk-free rate) in place of the self-declared benchmark; this gives a one-factor global model, (1FGM). When augmented by SMB_t and HML_t we obtain our three-factor global model (3FGM). Finally, adding a global momentum variable MOM_t our four-factor global model (4FGM) is:

$$[11] \quad r_{p,t} = \alpha_i + \beta_{1p} r_{m,t} + \beta_{2p} SMB_t + \beta_{3p} HML_t + \beta_{4p} MOM_t + \varepsilon_{p,t}$$

4. Data and Empirical Results

The sample comprises 298 closed-end equity funds traded on the London Stock Exchange. Of these 298 funds, 76 funds have a mandate to invest in UK markets; 59 funds in Far East and Asian markets; 46 funds in global markets and 43 funds in European markets. There are 52 specialist funds, the majority investing in hedge funds or private equity. The remaining 22 funds invest in the US and in emerging markets. There is a degree of subjectivity in this classification. When a fund has a mandate such as, say, 'Investing in European technology companies', we classify such a fund as 'European'. However when a fund has a mandate, say, 'Investing in technology companies' but without being restricted to a particular geographic region, such a fund is classified as 'specialist'. We classify a fund as 'global' where it has global mandate but is not restricted to investing in a particular industry or activity.

In cases where the fund declares a particular benchmark, the choice is clear-cut. However in many cases, and particularly early in the sample period, funds did not declare a particular benchmark. In these cases, a benchmark is selected that best matched the investment mandate of the individual fund. Thus, for example, the benchmark selected for Medicx plc - a closed-end fund launched in August 2006 and investing in primary healthcare properties in the UK - is the FTSE All Share Index for Healthcare Equipment and Services. For the 76 funds investing in the UK market, a total of 11 individual benchmarks are used.

Monthly NAV and fund-price returns (including reinvested dividends) for the individual funds are from Datastream. Most of the self-declared benchmarks are available from January 1975, but the global factors used in our multifactor models are only available from November 1990 onwards. Our sample period is therefore from November 1990 to January 2013. The global risk factors are from Kenneth French's website (converted into pounds sterling) with the one-month LIBOR as the risk-free rate. The analysis includes only those funds with at least 18 monthly observations, giving us NAV returns for 292 funds and fund-price returns for 298 funds; this is close to the entire universe of 330 UK closed-end funds.

Table 1 reports summary statistics for NAV and fund-price returns over the sample period. Three alternative models are used – the excess return benchmark model (ERBM), the one-factor benchmark model (1FBM) and the four-factor benchmark model (4FBM).

[Table 1 – here]

We consider first the results for NAV returns. The number of statistically significant positive alpha funds (at a 5% significance level) increases as we move from the most restricted model to the least restricted model. Thus, as we move from the ERBM to the 1FBM and to the 4FBM, the percentage of statistically significant positive alphas increases from 5.8% to 8.9% to 14.7%, respectively. On the other hand, the percentage of statistically significant negative alphas stays reasonably constant (around 5%) across all three models. The average NAV-return's alpha across all funds is negative for all three factor models – similar to results reported for open-end funds in the US and UK (see, for example, Kosowski et al. 2006; Cuthbertson et al. 2008; Fama and French 2010). The coefficient on the self-designated benchmark is constant at around 0.81 in the 1FBM and 4FBM models with the latter model indicating a positive loading on SMB_t and a negative loading on both HML_t and MOM_t . The average \bar{R}^2 increases from 61.5% for the 1FBM to 66.8% for the 4FBM - this suggests using the 4FBM when assessing the performance of individual funds. The average \bar{R}^2 for closed-end funds is higher than that found when similar factor models are estimated for hedge funds. For example, Capocci and Hubner (2004) report average \bar{R}^2 of 44% for a one-factor model and 60% for a four-factor model applied to hedge fund returns.

Results for fund-price returns are, for the most part, broadly similar to those for NAV returns although the number of statistically significant positive alphas is smaller while there are no negative alphas. The signs on the three factors are the same as those for the NAV returns but the factor loadings are larger. The average \bar{R}^2 using fund-price returns is lower than when using NAV returns – implying that the four factors fail to pick up all the variation in the discount. The main difference between the NAV and the fund-price regressions is that the former give negative average alphas whereas the latter give a positive average alpha for the 1FBM (0.36% p.a.) and 4FBM (1.53% p.a.). All three models for individual CEF returns have about 60-70% of funds with (statistically significant) non-normal residuals (Bera-Jarque test, at 5% significance level) – thus motivating the use of bootstrap procedures in testing fund performance.

To obtain further insight into the importance of the risk factors in explaining the performance of the average fund, we form an equally-weighted portfolio of all the funds and examine the recursive parameter estimates for the NAV and fund-price returns.

[Table 2 here]

For the one-factor global model (1FGM), the average alpha is positive but statistically insignificant for both NAV and fund-price returns (Table 2, Panel A). However, with the four-factor global model (Table 2, Panel B), the average alpha is positive and significant and all factors are statistically significant in both NAV and fund-price regressions. For fund-price returns, the recursive estimates of alpha (Figure 1), the betas for the excess market return, SMB_t and MOM_t coefficients are reasonably constant and well determined, with the HML_t factor less so (Figure 2)⁵. The above results point towards using a four-factor model when assessing the performance of a portfolio of funds, using either NAV or fund-price returns.

[Figures 1 and 2 here]

Individual Fund Performance and the FDR

In view of the above results, we first assess performance using NAV returns of individual CEF and the four-factor benchmark model (4FBM - equation [10]). We then discuss the false discovery rate results for the excess benchmark return model (EBRM - equation [8]) and the one-factor benchmark model (1FBM - equation [9]) as part of our robustness tests.

[Figure 3 here]

The distribution of alpha estimates (NAV returns) for the four-factor benchmark model shows a wide range of values (Figure 3). Most NAV-alphas are in the negative to 10.5% p.a. range but there are some funds in the extreme tails of the distribution which may have extremely 'good' or 'bad' security selection. This is important, since investors are more interested in holding funds in the right tail of the performance distribution and avoiding those in the extreme left tail, than they are in the average fund's performance. This emphasizes the importance of examining fund-by-fund performance (rather than the weighted average of all funds) and then correcting for false discoveries to provide an assessment of overall industry performance.

⁵ Recursive regression results are qualitatively similar when we use NAV returns.

Using NAV returns and the four-factor benchmark model (4FBM), we discuss estimates of the proportion of truly zero-alpha funds π_0 , positively skilled alpha-funds, π_A^+ and unskilled funds π_A^- among our total of M-funds. We then analyze the false discovery rate for the positive-alpha and negative-alpha funds taken separately; this allows us to ascertain whether such funds are concentrated in the tails of the performance distribution⁶.

Estimation of π_0

The histogram of bootstrap p-values for the 4FBM when testing $H_0 : \alpha_i = 0$ across funds is given in Figure 4. Exploiting the fact that truly null p-values are uniformly distributed [0, 1], the height of the flat portion of the histogram gives an estimate of the proportion of truly null-alpha funds π_0 . From Figure 4 a reasonable ‘eyeball’ estimate would be $\lambda = 0.2$ giving $\hat{\pi}_0(\lambda) = 0.8$.

[Figure 4 here]

Taking the four-factor benchmark model (4FBM) and our universe of all M-funds, the MSE-bootstrap estimator gives the percentage of truly zero alpha funds $\hat{\pi}_0(\lambda) = 76\%$ (se = 4.2), the percentage of negative-alpha funds $\hat{\pi}_A^- = 16.7\%$ (se = 4.0) and skilled funds $\hat{\pi}_A^+ = 7.5\%$ (se = 1.4) – Table 3. It is the estimate of $\hat{\pi}_0(\lambda)$ which determines our FDR (for alpha) and this is statistically well determined because the estimation uses data on a large number of null funds. Standard errors are in parentheses and are given in Genovese and Wasserman 2004 (and Barras et al. 2010, Appendix A). Hence in the whole population of funds, most have truly zero alphas, but there is a small proportion of funds with statistically positive or negative alphas. We now examine the location of these non-zero alpha funds.

As we increase the significance level γ , the number of statistically significant positive alpha funds S_γ^+ (Table 3, Panel A) and negative alpha funds S_γ^- (Table 3, Panel B) increases. However, FDR_γ^+ and FDR_γ^- also increase so that the proportion of truly skilled funds T_γ^+ and truly unskilled funds T_γ^- does not vary substantially with γ . This implies that the skilled and unskilled funds lie predominantly in the extreme tails (i.e. for $\gamma \leq 0.05$), rather than being evenly spread throughout the tails.

⁶ As noted below, the results using different models to estimate π_0 are qualitatively similar.

[Table 3 here]

The histogram of p-values when testing $H_0 : \alpha_i = 0$ for the excess benchmark return model (ERBM) and the one-factor benchmark model (1FBM) are similar to those for the four-factor benchmark model (4FBM) in Figure 4 (and are not presented here). This results in broadly similar values for π_0 as for the 4FBM - π_0 is equal to 86.5% for ERBM and 79.0% for 1FBM (Table 4, Panels A and B).

[Table 4 here]

Across the three models a salient feature is the resultant fall in FDR_γ^+ and the rise in the number of truly skilled funds T_γ^+ as we move from the Excess Return Benchmark Model (ERBM) to the one-factor benchmark model (1FBM in Table 4) and then to the four-factor benchmark model (4FBM in Table 3). For example, for $\gamma = 0.10$ we have FDR_γ^+ equal to 48.3%, 26.8% and 20.1% and T_γ^+ equal to 4.6% , 10.8% and 15.0% when moving from ERBM to 1FBM and to 4FBM respectively.

Turning now to negative-alpha funds, we find that as we move from the Excess Return Benchmark Model (ERBM) to the one-factor benchmark model (1FBM in Table 4) and then to the four-factor benchmark model (4FBM in Table 3), the number of truly negative skilled funds ($\gamma = 0.10$) remains largely constant with $T_\gamma^- = 4.9\%$, 2.6%, and 3.7% of the funds, respectively.

The above results which use self-declared benchmarks are not a like-for-like comparison across funds and this might influence the cross-section of alphas⁷. As a robustness test we therefore use a common global benchmark (in place of the self-declared benchmarks) but this does not appreciably alter the results in table 3. For example, if we take a significance level of $\gamma = 10\%$ then the number of truly skilled funds is $T_\gamma^+ = 15\%$ (se=2.6%) in table 3 (4FBM) and $T_\gamma^+ = 18.7\%$ (se=2.7%) when using the common global benchmark (4FGM) - so the results are qualitatively similar. For unskilled funds we have $T_\gamma^- = 3.7\%$ (se= 1.9%) in table 3 and $T_\gamma^- = 0.9\%$ (se= 1.6%) for the 4FGM – hence although the point estimates differ they are both statistically

⁷ This issue was raised by an anonymous referee.

equal to zero. In addition, using the self-declared benchmarks gives an average \bar{R}^2 of 66.6% (across all funds) while using the common global benchmark has an average \bar{R}^2 of 52.2%.

Persistence in Portfolios of CEF

Using NAV returns, we have established that there is some positive and some negative manager skill in security selection (alpha) when holding individual funds over the whole sample period. We now wish to examine whether forming portfolios by switching between different funds gives a positive-alpha performance in the post-formation period.

We form portfolios using a rolling window based on either the excess benchmark return model (EBRM) or on past t-alphas from the one-factor benchmark model (1FBM) – using NAV returns (ie. based on individual manager skill over the formation period). Our performance measure is based on fund-price returns in the post-formation period.⁸ We report results for post-formation alphas using a formation period of $f = 12$ months and for alternative holding periods $h = 12, 3, 1$ months. Because the post-formation portfolios contain funds with different investment objectives, it is not possible to estimate a post-formation factor model which incorporates all the self-declared benchmarks. Hence, we use the one- and four-factor global models to assess the post-formation alphas (for fund-price returns).

Post-formation decile-sorted portfolio alphas, together with their bootstrap p-values are reported for funds sorted by the excess benchmark return model (EBRM) in Table 5 and by the t-alpha of the one-factor benchmark model (1FBM) in Table 6. In each table, Panel A reports the results for the post-formation alphas of the one-factor global model (1FGM), Panel B reports those of the three-factor global model (3FGM) and Panel C those of the four-factor global model (4FGM).

[Table 5 here]

Funds Sorted using EBRM

When we sort funds based on the excess benchmark return model (EBRM) and evaluate the post-formation alphas for fund-price returns using the one-factor benchmark model (1FBM in Table 5, Panel A), we find about 4 out of the 10 decile portfolios have statistically significant post-formation alphas (at a 5% significance level) but there is no clear pattern of past ‘winners’

⁸ It seems unlikely that (predominantly) retail investors would be concerned with an active strategy where the post-formation performance is based on NAV returns, because investors cannot easily mimic this outcome since it requires detailed and timely information on portfolio weights used by managers.

remaining 'winners', except when we use $f, h = (12, 1)$ when there is persistence in winner funds for deciles 1 to 3. When evaluating the post-formation alphas using the three-factor global model (3FGM in Panel B) or four-factor global model (4FGM in Panel C), we find more positive post-formation alphas for all deciles and for all three combinations of (f, h) .

When moving from the one-factor global model (IFGM) to the four-factor global model (4FGM), the increase in the number of decile portfolios with statistically significant positive post-formation alphas is partly due to a reduction in residual variance (indicated by an increase in \bar{R}^2 of around 10% for each decile portfolio) and also to an increase in the point estimates of post-formation alphas. With the standard errors of the alphas remaining largely constant, the latter leads to an increase in the statistical significance of the decile portfolio alphas.

[Table 6 here]

Funds Sorted using t-alpha of 1FBM

The same pattern of results reported above, applies when funds are sorted on the t-alpha of the one-factor benchmark model (rather than EBRM) and evaluated using the global models (Table 6, Panels A, B, and C).

Irrespective of whether we form portfolios based on excess returns over fund-specific self-declared benchmarks EBRM (Table 5) or on the t-alphas of the one-factor benchmark model (Table 6), we obtain much stronger evidence of positive post-formation alphas, when using the four-factor global model (r_m, SMB, HML, MOM) rather than the one-factor global model (r_m) . This applies for all three rebalancing periods $h = 1, 3, \text{ and } 12$ months.⁹ These results are in contrast to those reported for the UK and US open-end fund industry using a four-factor model where there is little evidence of positive post-formation alphas and much stronger evidence negative post-formation alphas.

Funds Sorted using t-alpha of 4FBM

As a further robustness test we take account of the fact that for closed-end funds, price-returns (to the investor) may exhibit greater momentum than for mutual funds – since the premium or discount may persist (and this is not reflected in NAV returns). We therefore form portfolios of funds based on the t-alpha of the 4FBM (ie. including a momentum variable) using price-returns and use the 4FGM (with price-returns) as in table 6, to measure the post-formation

⁹ Recursive least squares analysis of the post-formation alphas reveals that it is only post-2001 that the alphas are statistically significant.

performance. We again find a substantial number of positive-alpha decile portfolios in the post-formation period (table 7)¹⁰.

[Table 7 here]

Which performance model should we use? For the four-factor global model, all four factors in the post-formation regressions are statistically significant for all deciles and the \bar{R}^2 's of 70%-75% suggest that these global factors capture most of the variability in fund-price portfolio returns. Whether the four-factor global model is the 'correct' model for closed-end funds could be debated but, for example, the four factors explain more of the variation in closed-end fund returns than do factor models applied to hedge fund returns – where positive alpha performance is also found. As both hedge funds and closed-end funds can hold heterogeneous portfolios and use leverage (whereas open-end funds cannot), this provides one possible reason for the positive post-formation alphas for closed-end funds.

5. Conclusion

We use the false discovery rate to assess the overall alpha-performance of UK closed-end funds using self-declared benchmarks and additional risk factors. We find evidence that around 16% of the funds in our sample have truly positive alphas (using a four-factor model that includes a self-designated benchmark or where the latter is replaced by a global benchmark). The number of truly negative alpha funds is around 1-4% of our sample of funds and is largely invariant to the factor model used. This is a better performance overall than UK and US open-end funds where around 0%-5% of the positive alpha funds and 25% of the negative alpha funds are found to be statistically significant.

Examining persistence in performance, we find that positive post-formation alpha fund performance depends on the factor model used – there is some positive-alpha performance when post-formation returns are evaluated using a one-factor global market model but substantial positive-alpha performance is found when using a four-factor global model. The magnitude of the alpha increases as global risk factors proposed by Fama-French (1993) and Carhart (1997) are included in our factor model. If we accept the four-factor global model, then decile portfolios of closed-end funds give rise to positive post-formation alphas and fund performance more

¹⁰ This variant was suggested by an anonymous referee. We also find qualitatively similar results when we form portfolios of funds based on the t-alpha of the four-factor global model 4FGM using price-returns (rather than the 4FBM) and also use the 4FGM (with price-returns) in the post-formation period (as in tables 6 and 7) - these results are available from the authors.

closely resembles the performance of hedge funds rather than open-end funds. We conjecture that this may be due to closed-end funds being able to use leverage and not having to change portfolio allocations due to fund inflows and outflows. Our overall results, from a performance perspective, suggest that there is prima facie evidence that closed-end funds could be a more attractive alternative to investors, (in particular retail investors) than open-end funds.

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Figure 1

Recursive Alpha: Fund-Price Returns, Four-Factor Global Model (4FGM)

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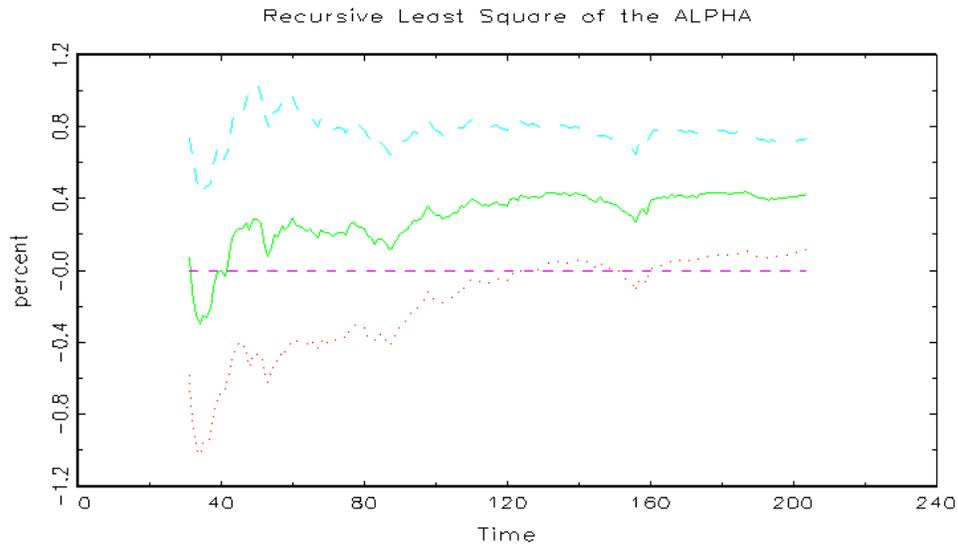


Figure 2

Recursive Factor Betas: Fund-Price Returns, Four-Factor Global Model (4FGM)

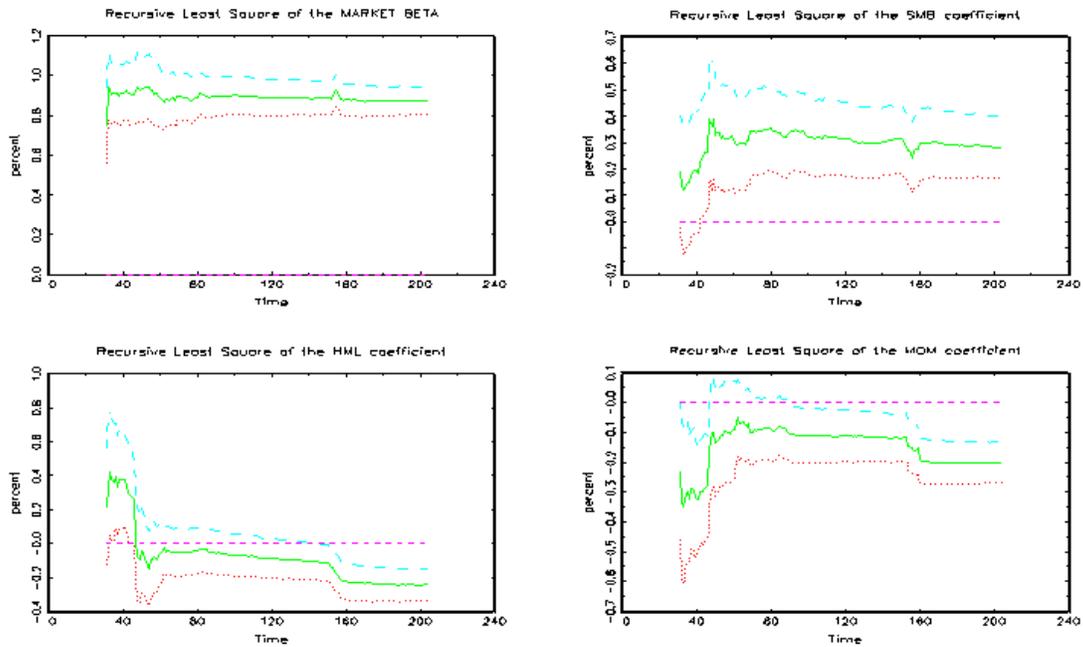


Figure 3

Alpha Estimates: NAV Returns, Four-Factor Benchmark Model (4FBM)

Alphas (percentage, per month) are estimated using a four-factor model (4FBM) including the self-declared benchmark and global factors for size, book-to-market, and momentum. The sample is from November 1990 to January 2013. Only funds with at least 18 monthly observations are included.

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Distribution of Alpha, 4 Factor Model

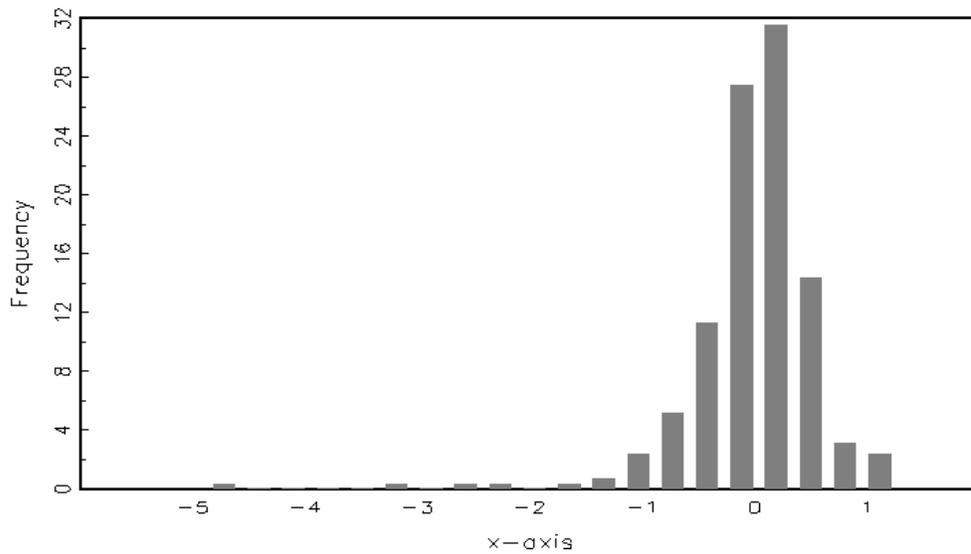


Figure 4

Alpha p-values: NAV returns: Four-Factor Benchmark Model (4FBM)

Bootstrap p-values under $H_0 : \alpha_i = 0$ for 292 funds with a minimum of 18 monthly observations over the period November 1990 to January 2013 for the four-factor model (4FBM), with NAV returns. The four-factor model (4FBM) includes the self-declared benchmark and global factors for size, book-to-market, and momentum.

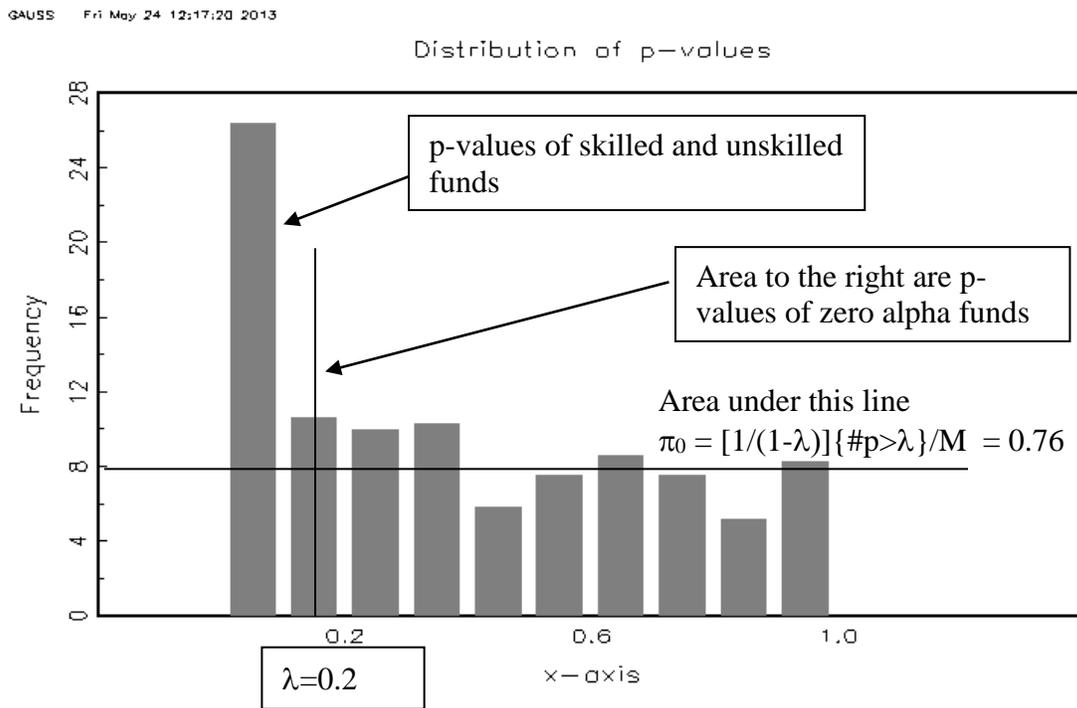


Table 1 Summary Statistics

This table reports summary statistics for all funds with at least 18 monthly observations. The sample period is November 1990 to January 2013. There are 292 funds with an average of 154 monthly observations for NAV returns and 298 funds with an average of 152 monthly observations for fund-price returns. We report averages of the individual fund statistics for both NAV returns and fund-price returns using 3 models, The models are the excess benchmark return model (EBRM), the one-factor benchmark model (1FBM) and the four-factor benchmark model (4FBM) which includes the self-declared fund benchmark and global factors for size, book-to-market, and momentum). Newey-West heteroscedastic and autocorrelation adjusted standard errors are reported. The percentage of funds with non-normal residuals is based on the Bera-Jarque B-J statistic. Statistical significance is at the 5% significance level (two tail test).

	Excess Benchmark Return Model		One-Factor Benchmark Model		Four-Factor Benchmark Model	
	EBRM		1FBM		4FBM	
	NAV>Returns	Fund-Price Returns	NAV>Returns	Fund-Price Returns	NAV>Returns	Fund-Price Returns
% statistically significant positive alpha	5.82%	3.02%	8.90%	3.69%	14.73%	10.07%
% statistically significant negative alpha	5.48%	0%	4.79%	0.67%	4.79%	0.34%
Alpha (stdv)	-0.0723 (0.5505)	-0.0056 (0.5920)	-0.0374 (0.5411)	0.0302 (0.6063)	-0.0115 (0.5739)	0.1275 (0.6281)
Self-declared benchmark (stdv)	-	-	0.8202 (0.2979)	0.8632 (0.3163)	0.8085 (0.2906)	0.8362 (0.3125)
SMB (stdv)	-	-	-	-	0.1760 (0.2858)	0.2503 (0.4091)
HML (stdv)	-	-	-	-	-0.0851 (0.3225)	-0.1145 (0.4336)
MOM (stdv)	-	-	-	-	-0.0288 (0.2219)	-0.1370 (0.3049)
Mean \bar{R}^2 (%)	N/A	N/A	61.50	46.01	66.84	50.97
% funds, non-normal residuals using B-J test	70.89%	65.10%	71.23%	66.44%	61.99%	59.73%

Table 2 Equally Weighted Portfolio of all CEF: Fund-Price and NAV Returns.

This table reports the estimated coefficients together with their t-statistics for the one-factor global model (1FGM) and the four-factor global model (4FGM) using an equally-weighted portfolio of all funds over the sample period January 1996 to December 2012. The 1FGM uses the excess return on a global stock market index. The 4FGM includes factors for the global stock market index and global size, book-to-market, and momentum variables. Figures in parentheses are t-statistics using Newey-West heteroscedastic and autocorrelation adjusted standard errors.

Panel A: 1FGM						
	Alpha	Market Return	SMB	HML	MOM	\bar{R}^2 (%)
Fund-Price Returns	0.1588 (1.05)	0.9239 (16.91)	-	-	-	74.30
NAV Returns	0.1087 (0.90)	0.8764 (25.68)	-	-	-	84.55
Panel B: 4FGM						
	Alpha	Market Return	SMB	HML	MOM	\bar{R}^2 (%)
Fund-Price Returns	0.4245 (2.67)	0.8721 (18.25)	0.2827 (4.49)	-0.2420 (-3.95)	-0.2014 (-4.26)	80.25
NAV Returns	0.2581 (2.48)	0.8428 (28.69)	0.2211 (5.23)	-0.2138 (-5.13)	-0.0854 (-3.05)	88.12

Table 3 False Discovery Rate: NAV Returns, Four-Factor Benchmark Model (4FBM)

This table reports the false discovery rate statistics for NAV returns using the four-factor benchmark model (4FBM). The four factors are the self-declared benchmark and the global risk factors SMB, HML and MOM. The sample period is from November 1990 to January 2013 using 292 funds with at least 18 monthly observations. p-values under the null $\alpha = 0$ are calculated based on 10,000 bootstrap simulations. Standard errors are in parentheses.

NAV Returns					
π_0	0.7583 (0.0417)				
π_A^+	0.0750 (0.0138)				
π_A^-	0.1667 (0.0401)				
Positive Alpha Funds (164 funds)					
Sign. Level, γ	# significant funds	FDR ⁺	S ⁺	T ⁺	F ⁺
0.05	42	0.1318	0.1438 (0.0205)	0.1249 (0.0216)	0.0190 (0.0010)
0.10	55	0.2013	0.1884 (0.0229)	0.1504 (0.0260)	0.0379 (0.0021)
0.15	65	0.2555	0.2226 (0.0243)	0.1657 (0.0302)	0.0569 (0.0031)
0.20	72	0.3075	0.2466 (0.0252)	0.1707 (0.0344)	0.0758 (0.0042)
Negative Alpha Funds (128 funds)					
Sign. Level, γ	# significant funds	FDR ⁻	S ⁻	T ⁻	F ⁻
0.05	15	0.3690	0.0514 (0.0129)	0.0324 (0.0141)	0.0190 (0.0010)
0.10	22	0.5032	0.0753	0.0374	0.0379

			(0.0154)	(0.0190)	(0.0021)
0.15	32	0.5190	0.1096 (0.0183)	0.0527 (0.0247)	0.0569 (0.0031)
0.20	36	0.6151	0.1233 (0.0192)	0.0475 (0.0292)	0.0758 (0.0042)

Table 4 False Discovery Rate: NAV returns, Excess Benchmark Return Model (EBRM) and One-Factor Benchmark Model (1FBM)

This table reports the false discovery rate statistics for two models. Panel A reports the statistics for the Excess Benchmark Return Model (EBRM) and panel B for the one-factor benchmark model (1FBM). The sample period is from November 1990 to January 2013 using 292 funds with at least 18 monthly observations on NAV returns. The p-values under the null $\alpha = 0$ are calculated based on 10,000 bootstrap simulations. Standard errors are in parentheses.

Panel A : EBRM						Panel B : 1FGM					
π_0	0.8659 (0.0408)					π_0	0.7903 (0.0450)				
π_A^+	0.0299 (0.0090)					π_A^+	0.0474 (0.0107)				
π_A^-	0.1041 (0.0399)					π_A^-	0.1623 (0.0440)				
Positive Alpha Funds (158 funds)						Positive Alpha Funds (156 funds)					
Sign. Level, γ	# Significant funds	FDR ⁺	S ⁺	T ⁺	F ⁺	Sign. Level, γ	# Significant funds	FDR ⁺	S ⁺	T ⁺	F ⁺
0.05	16	0.3951	0.0548 (0.0133)	0.0331 (0.0145)	0.0216 (0.0010)	0.05	26	0.2219	0.0890 (0.0167)	0.0693 (0.0178)	0.0198 (0.0011)
0.10	26	0.4863	0.0890 (0.0167)	0.0457 (0.0202)	0.0433 (0.0020)	0.10	43	0.2683	0.1473 (0.0207)	0.1077 (0.0241)	0.0395 (0.0022)
0.15	40	0.4741	0.1370 (0.0201)	0.0720 (0.0264)	0.0649 (0.0031)	0.15	53	0.3266	0.1815 (0.0226)	0.1222 (0.0289)	0.0593 (0.0034)
0.20	43	0.5880	0.1473 (0.0207)	0.0607 (0.0304)	0.0866 (0.0041)	0.20	58	0.3979	0.1986 (0.0233)	0.1196 (0.0332)	0.0790 (0.0045)
Negative Alpha Funds (134 funds)						Negative Alpha Funds (136 funds)					
Sign. Level, γ	# Significant funds	FDR ⁻	S ⁻	T ⁻	F ⁻	Sign. Level, γ	# Significant funds	FDR ⁻	S ⁻	T ⁻	F ⁻
0.05	14	0.4515	0.0479 (0.0125)	0.0263 (0.0137)	0.0216 (0.0010)	0.05	11	0.5245	0.0377 (0.0111)	0.0179 (0.0125)	0.0198 (0.0011)

0.10	27	0.4683	0.0925 (0.0170)	0.0492 (0.0204)	0.0433 (0.0020)	0.10	19	0.6073	0.0651 (0.0144)	0.0256 (0.0184)	0.0395 (0.0022)
0.15	38	0.4991	0.1301 (0.0649)	0.0652 (0.0260)	0.0649 (0.0031)	0.15	29	0.5968	0.0993 (0.0175)	0.0400 (0.0245)	0.0593 (0.0034)
0.20	41	0.6167	0.1404 (0.0866)	0.0538 (0.0301)	0.0866 (0.0041)	0.20	43	0.5367	0.1473 (0.0207)	0.0682 (0.0310)	0.0790 (0.0045)

Table 5

Persistence in Alpha: Funds Sorted by Alpha using NAV Returns and the Excess Benchmark Return Model (EBRM)

Funds are sorted into past 'winner' and 'loser' deciles using NAV returns and the Excess Benchmark Returns Model. The table reports alphas (and bootstrap p-values) for post-formation fund-price returns using the one-factor global model (1FGM, Panel A), the three-factor global model (3FGM, Panel B) and the four-factor global model (4FGM, Panel C). The formation (f) and holding (h) periods (f,h) are 12/12, 12/6 and 12/1 months. The 1FGM uses the excess return on a global stock market index, the 3FGM also includes global factors for size and book-to-market; the 4FGM adds a momentum variable. The investment horizon is 17 years (204 months), starting in January 1996 and ending in December 2012.

Panel A: 1FGM									
Deciles	(f,h) = 12/12			(f,h)= 12/3			(f,h)= 12/1		
	alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2	alpha	p-value	\bar{R}^2
1 - winner	0.2363	0.2230	0.5456	0.3714	0.1010	0.5490	0.7071	0.0093	0.5235
2	0.4144	0.0333	0.6393	0.4378	0.0257	0.6240	0.5936	0.0048	0.6145
3	0.2511	0.0906	0.7074	0.4370	0.0064	0.7209	0.5087	0.0024	0.7250
4	0.3092	0.0356	0.7307	0.2784	0.0586	0.7485	0.2576	0.0738	0.7532
5	0.1844	0.1503	0.7419	0.1936	0.1279	0.7408	0.2023	0.1205	0.7330
6	0.2952	0.0425	0.7426	0.2306	0.0780	0.7574	0.2176	0.0847	0.7719
7	0.2265	0.0685	0.7888	0.1869	0.1246	0.7622	0.1537	0.1617	0.7851
8	0.2958	0.0497	0.7389	0.2579	0.0981	0.7040	0.0844	0.3356	0.7121
9	0.2004	0.1649	0.6969	0.1555	0.2329	0.6696	0.0587	0.3985	0.6450
10 - loser	0.0400	0.4340	0.5957	-0.1795	0.2620	0.5812	-0.4600	0.0526	0.5879
Panel B: 3FGM									
Deciles	(f,h)= 12/12			(f,h)= 12/3			(f,h)=12/1		
	Alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2	alpha	p-value	\bar{R}^2
1 - winner	0.4951	0.0332	0.6433	0.6080	0.0099	0.6415	0.9326	0.0001	0.6041
2	0.5746	0.0036	0.6921	0.5851	0.0032	0.6715	0.7480	0.0001	0.6658

3	0.3456	0.0262	0.7317	0.5142	0.0011	0.7397	0.6149	0.0002	0.7565
4	0.3834	0.0141	0.7458	0.3759	0.0150	0.7684	0.3586	0.0167	0.7756
5	0.2785	0.0519	0.7616	0.2840	0.0412	0.7606	0.2932	0.0383	0.7528
6	0.3422	0.0226	0.7478	0.2639	0.0521	0.7611	0.2604	0.0504	0.7764
7	0.2315	0.0657	0.7948	0.2331	0.0774	0.7712	0.1954	0.1109	0.7892
8	0.3500	0.0282	0.7477	0.3221	0.0486	0.7156	0.1125	0.2881	0.7199
9	0.2566	0.1003	0.7034	0.2246	0.1417	0.6792	0.1295	0.2747	0.6565
10 - loser	0.1786	0.2397	0.6265	-0.0471	0.4362	0.6065	-0.3240	0.1261	0.6156

Panel C: 4FGM

Deciles	(f,h) = 12/12			(f,h)= 12/3			(f,h)=12/1		
	Alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2	alpha	p-value	\bar{R}^2
1 - winner	0.5924	0.0158	0.6535	0.6520	0.0068	0.6438	0.9685	<0.0001	0.6056
2	0.6720	0.0010	0.7071	0.6660	0.0007	0.6823	0.8118	0.0001	0.6726
3	0.4392	0.0054	0.7481	0.6054	0.0001	0.7564	0.6747	<0.0001	0.7634
4	0.4765	0.0025	0.7623	0.4655	0.0029	0.7822	0.4502	0.0041	0.7902
5	0.3992	0.0062	0.7892	0.3883	0.0063	0.7826	0.3990	0.0071	0.7755
6	0.5007	0.0009	0.7972	0.4159	0.0029	0.8079	0.3972	0.0026	0.8148
7	0.3725	0.0042	0.8346	0.3558	0.0115	0.8008	0.3369	0.0116	0.8277
8	0.5093	0.0012	0.7927	0.5280	0.0006	0.7871	0.3461	0.0197	0.8084
9	0.4537	0.0053	0.7685	0.4593	0.0057	0.7688	0.3788	0.0215	0.7580
10 - loser	0.3885	0.0434	0.6864	0.1989	0.2130	0.6773	-0.0634	0.3995	0.6955

Table 6 Persistence in Alpha: Funds Sorted by t-alpha using NAV Returns and the One-Factor Benchmark Model (1FBM)

Funds are sorted into past 'winner' and 'loser' deciles using NAV returns and the one-factor benchmark model (1FBM). The table reports alphas (and bootstrap p-values) for post-formation fund-price returns using the one-factor global model (1FGM, Panel A), the three-factor global model (3FGM, Panel B) and the four-factor global model (4FGM, Panel C). The formation (f) and holding (h) periods (f,h) are 12/12, 12/6 and 12/1 months. The 1FGM uses the excess return on a global stock market index, the 3FGM also includes global factors for size and book-to-market; the 4FGM adds a momentum variable. The investment horizon is 17 years (204 months), starting in January 1996 and ending in December 2012.

Panel A: 1FGM									
Deciles	(f,h) = 36/12			(f,h) = 36/3			(f,h) = 36/1		
	Alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2
1 - winner	0.3505	0.0573	0.6453	0.4652	0.0197	0.6180	0.6007	0.0027	0.6327
2	0.3676	0.0435	0.6604	0.4633	0.0111	0.7040	0.5735	0.0008	0.7221
3	0.1157	0.2832	0.7136	0.1856	0.1570	0.7520	0.2920	0.0565	0.7504
4	0.4123	0.0154	0.7237	0.3344	0.0454	0.7090	0.3944	0.0261	0.7226
5	0.2462	0.0933	0.7333	0.3589	0.0255	0.7434	0.1998	0.1544	0.7116
6	0.2365	0.1068	0.7330	0.1128	0.2818	0.7305	0.2672	0.0716	0.7349
7	0.1856	0.1556	0.7170	0.2899	0.0511	0.7329	0.1298	0.2174	0.7518
8	0.3578	0.0272	0.7467	0.0296	0.4428	0.7027	0.1333	0.2661	0.6617
9	0.3222	0.0491	0.7058	0.2287	0.1195	0.6909	0.0527	0.3911	0.7025
10 - loser	0.2227	0.1474	0.6621	0.2726	0.1133	0.6545	0.0817	0.3571	0.6429
Panel B: 3FGM									
Deciles	(f,h) = 36/12			(f,h) = 36/3			(f,h) = 36/1		
	alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2
1 - winner	0.4989	0.0077	0.6875	0.6126	0.0017	0.6621	0.7563	0.0001	0.6824
2	0.5001	0.0065	0.6965	0.6046	0.0002	0.7464	0.7033	0.0001	0.7595
3	0.2613	0.0799	0.7561	0.2983	0.0444	0.7771	0.4165	0.0080	0.7817

4	0.5061	0.0028	0.7430	.0.4446	0.0097	0.7352	0.5247	0.0019	0.7560
5	0.3268	0.0303	0.7515	0.4182	0.0102	0.7550	0.2560	0.0932	0.7227
6	0.2934	0.0568	0.7406	0.1602	0.1931	0.7351	0.3259	0.0335	0.7422
7	0.2225	0.1171	0.7204	0.3602	0.0202	0.7440	0.1806	0.1425	0.7580
8	0.4141	0.0114	0.7535	0.0878	0.3252	0.7096	0.1976	0.1722	0.6703
9	0.3679	0.0285	0.7124	0.2904	0.0648	0.7016	0.1256	0.2516	0.7139
10 - loser	0.2962	0.0781	0.6752	0.3467	0.0599	0.6667	0.1361	0.2757	0.6543

Panel C: 4FGM

Deciles	(f,h) = 36/12			(f,h) = 36/3			(f,h) = 36/1		
	alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2
1 - winner	0.6361	0.0005	0.7180	0.7316	<0.0001	0.6862	0.8709	<0.0001	0.7045
2	0.6443	0.0004	0.7313	0.6891	<0.0001	0.7589	0.7842	<0.0001	0.7713
3	0.3718	0.0214	0.7753	0.4088	0.0079	0.7970	0.5056	0.0011	0.7954
4	0.6284	0.0002	0.7681	0.5994	0.0007	0.7737	0.6716	0.0001	0.7892
5	0.4463	0.0054	0.7774	0.5553	0.0006	0.7887	0.3959	0.0149	0.7567
6	0.4083	0.0117	0.7636	0.2714	0.0694	0.7565	0.4441	0.0066	0.7671
7	0.3783	0.0127	0.7662	0.4935	0.0011	0.7776	0.3221	0.0202	0.7969
8	0.5929	0.0002	0.8105	0.2722	0.0604	0.7674	0.3925	0.0180	0.7360
9	0.5101	0.0018	0.7475	0.4713	0.0039	0.7619	0.3085	0.0348	0.7744
10 - loser	0.4528	0.0115	0.7164	0.5205	0.0070	0.7133	0.3204	0.0622	0.7058

Table 7 Persistence in Alpha: Funds Sorted by t-alpha using Fund-Price Returns and the Four-Factor Benchmark Model (4FBM)

Funds are sorted into past 'winner' and 'loser' deciles using fund-price returns and the four-factor benchmark model (4FBM). The four factors are the self-declared benchmark and the global risk factors SMB, HML and MOM. The table reports alphas (and bootstrap p-values) for post-formation fund-price returns using the four-factor global model (4FGM). The formation (f) and holding (h) periods (f,h) are 12/12, 12/6 and 12/1 months. The 4FGM uses the excess return on a global stock market index, global factors for size, book-to-market and momentum. The investment horizon is 17 years (204 months), starting in January 1996 and ending in December 2012.

Deciles	(f,h) = 36/12			(f,h) = 36/3			(f,h) = 36/1		
	Alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2	Alpha	p-value	\bar{R}^2
1 - winner	0.5234	0.0017	0.7635	0.5165	0.0019	0.7543	0.5028	0.0024	0.7583
2	0.4308	0.0074	0.7740	0.2746	0.0458	0.8000	0.2145	0.0902	0.8083
3	0.3474	0.0347	0.7418	0.3643	0.0255	0.7594	0.3184	0.0371	0.7704
4	0.4312	0.0060	0.7813	0.3883	0.0108	0.7639	0.4175	0.0111	0.7535
5	0.4655	0.0047	0.7620	0.6332	0.0002	0.7750	0.7980	<0.0000	0.7707
6	0.6034	0.0001	0.7916	0.5110	0.0020	0.7734	0.4634	0.0052	0.7429
7	0.4316	0.0095	0.7643	0.4275	0.0070	0.7472	0.4588	0.0066	0.7205
8	0.5927	0.0011	0.7308	0.5995	0.0009	0.7522	0.4465	0.0078	0.7634
9	0.6350	0.0002	0.7493	0.5762	0.0019	0.7414	0.7056	0.0001	0.7431
10 - loser	0.6581	0.0009	0.7010	0.7522	0.0002	0.7008	0.7370	0.0004	0.7093