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Separating Skill from Luck in REIT Mutual Funds[*]

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Separating Skill from Luck in REIT Mutual Funds

Abstract

This study uses a bootstrap methodology to explicitly distinguish between skill and luck for 80 Real Estate Investment Trust Mutual Funds in the period January 1995 to May 2008. The methodology successfully captures non-normality in the idiosyncratic risk of the funds. Using unconditional, beta conditional and alpha-beta conditional estimation models, the results indicate that all but one fund demonstrates poor skill. Tests of robustness show that this finding is largely invariant to REIT market conditions and maturity.

Separating Skill from Luck in REIT Mutual Funds

1. Introduction

The last two decades have seen a substantial increase in the extent of institutional investment in the Real Estate Investment Trust (REIT) sector. Prior to the onset of what is often referred to as the modern REIT era in 1992, average institutional ownership was only 14% (Chan et al., 2003), yet increased to over 60% by 2005 (Lin et al., 2009). The impact of this increase has been directly or indirectly examined in a large volume of research in recent years and has been shown to have contributed to factors such as the increase in the number of analysts covering the sector (Wang et al., 1995), the reduction in spreads (Below, et al., 1996 and Bhasin et al., 1997), flow of funds affects resulting from increased institutional investment (Downs, 1998) and the impact on volume and volatility (Cotter & Stevenson, 2008 and Jirasakuldech et al., 2009). This is in addition to the large literature that has considered the altering dynamics in the sectors investment characteristics, in particular, its relationship with mainstream stocks (e.g. Glascock et al., 2000, Clayton & MacKinnon, 2001 and Case et al., 2010) and the nature of REIT systematic risk (e.g. Crain et al., 2000, Feng et al, 2006, Ambrose et al., 2007).

In addition, the last twenty years have also seen a large degree of growth in the number of dedicated REIT mutual funds. As Hartzell et al. (2010) note, the number of dedicated funds increased from 16 in the early nineties to 132 unique funds by 2005, while fund ownership as a percentage of the sector's market capitalization increased from under 2% in 1992 (Ling & Naranjo, 2006) to over 14% by 2005 (Hartzell et al., 2010). While a growing literature has considered the performance of Real Estate Mutual Funds (REMFs), the majority have tended to apply conventional performance measurement tools. Like all investment funds REMFs are largely judged upon their performance history, with Jensen's Alpha being one of main measures of fund performance used. Of the 64 active US REMFs listed on *MorningStar.com* in mid-2008 the trailing average alpha over 3-years is 0.125% with 33 achieving positive alpha. These results would imply that on average REMF managers out-perform and create investor value, while some managers have exceptional skill. However, alpha in its traditional form does not delineate between skill and luck. This separation of performance is of importance as it is likely that at least some of the funds perform very well, or indeed badly, not due to the relative skill of the manager but due to luck.

In contrast to previous studies of REMF performance, this paper applies a methodological approach that explicitly distinguishes between the skill and luck of a fund manager. It examines the issue using a cross-sectional bootstrap methodology similar to that used by Cuthbertson et al. (2008). While previous studies of REMFs have provided mixed evidence with respect to whether the average REMF outperforms, they have all assessed performance on an aggregate basis using standard test statistics. This approach implicitly assumes that a funds idiosyncratic risk has a known parametric distribution, namely normal. However, it is shown that many funds, especially those in the extreme tails of the performance distribution, are likely to exhibit non-normality in their idiosyncratic risk. These are precisely the funds that potential investors will be most interested in identifying: extreme winners to invest in and extreme losers to avoid. In addition, where non-normality is present standard asymptotic results do not apply and test statistics based on standard critical values, as used in the existing literature, may give misleading inferences. The cross-sectional bootstrap methodology used in this study allows for the separation of skill and luck in the performance of individual funds, even when idiosyncratic risk is highly non-normal, as in the extreme tails of the distribution.

The results show that in the majority of cases not only do REMFs underperform in terms of displaying stock selection ability, but that this underperformance is significantly worse than that which could be attributed to luck alone. These findings are also consistent across different sub-samples. The remainder of the paper is set out as follows. The following section briefly reviews the existing work on dedicated REIT funds. Section 3 considers the methodological framework adopted in the current study, while the following section details the data used in the paper and the performance evaluation models tested. Section 5 discusses the empirical findings, while Section 6 provides concluding comments.

2. Previous Studies on Real Estate Mutual Fund Performance

Previous studies of REMF performance have tended to apply conventional performance measurement tools. However, one of the key differences in the results centers around the sample period examined. Whereas earlier studies (e.g., Kallberg et al, 2000 and Gallo et al., 2000) largely found evidence of outperformance by fund managers, more recent studies have largely reported a lack of significant performance. Kallberg et al. (2000) is one of the earliest comprehensive examinations of REMFs. Using a sample of 44 funds, from a period covering 1986 through 1998, they find active management can add value, reporting significantly positive alphas. These results are also broadly consistent irrespective of whether single index or multi-factor models are used, whether the alphas are allowed to be time varying and whichever benchmark index was used. For example, using a standard single-index model they find that the average alpha is 0.068 when compared to the NAREIT index of publicly traded REITs. The average alpha remains significant and highly positive when the real estate index used is the Wilshire Real Estate Index (17.3%) or the Wilshire REIT index (6.5%). Only when a multi-factor model is used, that includes the S&P 500, risk-premiums for size and growth and bond excess returns, does the average figure fail to be significantly positive. Of further interest is that these figures are substantially higher than those found in most studies of general equity mutual fund, which generally have reported negative average alphas. Kallberg et al. (2000) however recognise that intercepts can capture the effects of model misspecification and run a cross-sectional regression of the reported alphas against reasonable determinants of performance (such as fund size and expense ratio) to ascertain whether they are actually capturing excess returns. They find that total assets and turnover are significant determinants of alpha but that a dummy for passive style (versus active) is negatively correlated and significant. They therefore attribute *some* of the apparent out-performance to active style, which can be viewed as a proxy for skill.

Gallo et al. (2000) also measure alpha, for a sample of 24 REMFs between 1991 and 1997, using single and multi-index models. They find the sampled funds outperformed by an average 5.3% when compared to the Wiltshire Real Estate Index (single-index model). Using Sharpe's (1992) effective-mix test they find that the superior performance is largely due to overweighting in out-performing property types relative to the Wilshire Real Estate Index, specifically apartments and healthcare, the latter being excluded from the index completely. They find 94% of performance is attributable to allocation by property sector, whilst they infer just 6% is due to allocation to other asset classes and stock-selection within property sectors. They therefore distinguish between macro forecasting (sector-picking) and micro-forecasting (stock-picking) and conclude that the majority of forecasting performance is due to macro-level decisions.

Whilst Kallberg et al. (2000) and Gallo et al. (2000) reported supportive evidence with respect to the performance of REMFs, more contemporary studies have found little or no evidence of out-performance. Studies such as O'Neal & Page (2000), Lin & Yung (2004), Rodriguez (2007) and Chiang et al. (2008) all fail to identify any evidence of significant outperformance. The recent paper by Hartzell et al. (2010) extends the analysis conducted in previous work in a number of ways, specifically in terms of model specifications and benchmarks. The alternative benchmarks used adapt conventional ones in the following form. Initially, three and four-factor models based on those proposed by Fama & French (1993) and Cahart (1997) are used incorporating size, book-to-market and momentum factors. However, a key difference in the Hartzell et al. (2010) paper is that the portfolios used in the construction of the factors are purely based on REITs not stocks overall. Secondly, the authors use returns of portfolios sorted by the property type and finally, a combination of the above two approaches is used, incorporating size, book-to-market and property type. While the primary results concur with other recent work in finding a lack of evidence in favour of outperformance, Hartzell et al. (2010) find that outperformance can be achieved with respect to the primary benchmark indices (e.g. FTSE-NAREIT and Dow Jones Wilshire) by tilting the REMF portfolio towards small cap REITs, including non-REIT securities such as Real Estate Operating Companies (REOCs) and by adopting a momentum strategy.

The issue relating to the benchmarks is important in a REIT context and the results of Hartzell et al. (2010) in this respect do effectively capture the fact that the primary benchmark indices are not only constrained to REITs, therefore excluding firms such as REOCs, but are also heavily weighted in large cap REITs by definition as they are value weighted. The FTSE NAREIT indices includes all US listed REITs with a market capitalisation above $100m, while the cut-off for the Dow Jones Wilshire REIT index is $200m. Furthermore, irrespective of these explicit constraints, the fact is that the REIT sector is characterised as being dominated on a market capitalization basis, by a small number of firms. The results also show how controlling for non-REIT investment (e.g. REOC) is important. The incorporation of non-REITs sees an increase in the R-squared's reported by Hartzell et al. (2010), particularly in the case of the single-index models, and results in a reduction in the estimated abnormal performance. While size effects and momentum also provide valuable insights, the property type factors explain less of the cross-sectional variation. Furthermore, Hartzell et al. (2010) find that there is a low correlation between alphas highlighting the issue of benchmark selection.

With respect to the momentum issue, not only is this consistent with the broader mutual fund literature (Cahart, 1997), but in addition, there is a large degree of evidence relating to the REIT sector. Ling & Naranjo (2006) find evidence of REIT performance significantly impacting upon future capital flows, a finding that would also be supportive of the momentum profits observed in REIT studies such as Chui et al. (2003) and Hung & Glascock (2008, 2010). A recent study by Derwell et al. (2009) explicitly considers momentum profits in the context of REMFs. The effect of incorporating a REIT specific momentum factor is a reduction of the positive alpha's previously reported. However, the interpretation of the results does have to be addressed carefully. While Derwell et al. (2009) argue that the findings indicate that previously reported performance studies of REMF's may have over-estimated the extent of managerial skill, it should however be noted that while the inclusion of a momentum factor has been clearly illustrated of being of importance in explaining fund performance, it can argued that perhaps this is actually a key component of active management and what a manager is being remunerated for.

3. Bootstrapped Methodological Framework

Assuming that if all fund managers have no skill, the '*true*' alpha of each fund can be seen as being normally distributed, with a mean of zero and a known standard deviation, which differs for each fund. This standard deviation is what we refer to as the '*luck*' distribution. We can order the best ex-post performing fund, on the basis of alpha, as number one. If however, we impose an alpha of zero then it is likely that we would sample a different estimate of alpha due to this distribution of luck. While the most likely re-sampled alpha is zero, we may sample a value at the extreme of the distribution and that the funds ranking is no longer first. The same applies for each fund in the sample. Overall, the greater the variance of the '*luck*' distributions of alpha, the more likely the funds are to be re-ordered. This becomes especially relevant when performance distributions are idiosyncratic and non-normal. By re-sampling once, with $\alpha = 0$ for all i funds by using the residuals, we have i alphas, which can be ordered. By repeatedly re-sampling n times and choosing the highest alpha each time we can obtain the complete distribution of alpha under the null hypothesis of no out-performance for the best-performing fund. This is simply the 'luck' distribution for the best performing fund. Similarly, this can be obtained for the second best performing fund by choosing the second highest value of alpha sampled in each of the n samples and so on.

This is the methodological approach taken here, specifically using residual only re-sampling. This is achieved as follows. Firstly, we estimate the factor model in question for the fund. From the residuals from this estimation we draw a random sample, with replacement. Re-sampling is of length T, where T is the number of observations for the fund. These re-sampled bootstrap residuals are then used to generate a simulated excess return series for the fund in question, under the null-hypothesis of no abnormal performance ($\alpha = 0$), with the chronological ordering of the factor returns unaltered. Based on the simulated returns series, the factor model is estimated and the first bootstrapped estimates of alpha obtained. This process is then repeated for all i funds and the alpha's ordered. This process is repeated 1,000 times in order to generate the 'luck' distributions for each ordered fund as explained above.

We can therefore compare the ex-post value of alpha for each fund with its concomitant luck distribution. If the ex-post alpha is higher than (say) the 1% right tail cut-off point then we can reject the null hypothesis of no out-performance with 99% confidence and reasonably conclude that the excess return of the fund is due to skill. This approach has the advantage that each 'luck' distribution contains information about the 'luck' experienced by *all* funds and not just that of the fund in question, as the re-sampled alphas are ordered *each* time.

Three recent papers have considered the issue of mutual fund performance in terms of the skill present. Kosowski et al. (2006) examine 1,704 US mutual funds between 1975 and 2002. They find the proportion of funds with genuine skill is between 30-40% for the period 1975 to 1989, although it falls to 5% for 1990 to 2002. Cuthbertson at al. (2008) apply the bootstrap methodology utilised in the current paper to a sample of 842 UK equity funds from 1975 through 2002, finding that 12 of the top 20 funds have genuine skill but that below the top 3% of funds any out-performance is due to luck. They also find that the 'genuine' out-performers are not necessarily those producing the best ex-post alphas. This highlights the difficultly in using conventional measures in identifying skilful managers in relation to poor performance, Cuthbertson et al. (2008) find evidence of value-destruction due to 'poor skill', rather than simply bad luck, for between 20-40% of those funds with negative alphas. The key difference between the approach adopted in Kosowski et al. (2006) and that proposed by Cuthbertson et al. (2008) and also followed here is that Kosowski et al. (2006) apply the bootstrap approach on a fund-by-fund basis. This therefore accounts only for the luck experienced by each respective fund in isolation as the bootstrapped alphas are not reordered. Fama & French (2009) adopt a slightly bootstrapping approach. They simulate the cross-sectional α estimates. This is achieved by initially setting α to zero by subtracting the α estimate from the fund's monthly return. The primary difference in the two approaches is that the Fama & French (2009) captures the cross-correlation of the returns of the funds as the same sample period is used for each fund and that they effectively jointly sample fund returns and the explanatory returns. In contrast, the Kosowski et al. (2006) and Cuthbertson et al. (2008) approach ensures that the number of months of returns for an individual fund is matched in terms of the simulations[1].

One further issue does warrant note is that Kosowski et al (2006) and Fama & French (2009) both provide evidence that value/income fund managers were less likely to provide skill. Kosowski et al. (2006) for example, find that the top-performing funds are generally growth rather than income funds[2]. This may therefore beg the question as to why consider the performance of REMFs, which virtually by definition are income/value funds. There are two reasons for this. One is that Cuthbertson et al. (2008) found that in their sample of UK fund managers skill tended to be demonstrated mostly by income rather than growth funds. The second is concerned with the increased size of the REMG sector over the last two decades. This together with the changing dynamics of the underlying REIT market may lead to differentiated findings.

4. Data and Model Selection

The data set used in this paper consists of monthly returns for 80 REMFs for the sample period January 1995 through May 2008. The data consists of 64 active and 16 dead funds, thus survivorship bias is eliminated. The criterion for inclusion in the sample was a minimum of 15 monthly observations. Where a fund offers multiple share classes, only the single fund with the lowest expense ratio was included. This decision was made as the study is concerned with management performance rather than investor returns per se and that the funds with lower charges exhibit returns closer to raw performance. Share classes were therefore selected in the following order, depending on availability: Institutional (Class I/Y, which offer lower fees because of the larger minimum investment required); Class-A (charge a front-end load with a lower annual management charge than Classes B and C); Class-B (charge a redemption fee on sale); Class C (don't charge a front-end load or redemption fee and concomitantly charge higher annual fees). A few funds also offer a Class Z share, for employees of the firm, and this was chosen when it had the lowest expense ratio.

To allow for more accurate factor model estimation in the calculation of the alphas, only funds investing a minimum of 80% of assets in publicly listed US real estate firms were included. This focuses the study on the performance of US REMFs, which have a more established history, and avoids applying diverse international benchmarks to disparate REMFs, which it was felt would lack precision. Tracker funds were also eliminated as the study is concerned with stock-selection ability. Of the 119 currently active REMFs recognised by Morningstar, 42 invest globally; 3 are trackers; 9 had insufficient data available and one, the Pimco Real Estate Real Return Fund, holds a significant proportion of non-real estate assets (Treasuries). Of the 23 dead REMFs in existence during the period under consideration and where data was available, 3 invested globally, 2 were trackers and 2 had insufficient data available for inclusion. Returns were calculated from bid price to bid price, with income from dividends reinvested. The returns are therefore gross of taxes on dividends and capital gains tax on growth, and net of management fees[3].

For model selection, monthly total returns are used for all factors. The market factors tested are the FTSE NAREIT US Real Estate Index; the FTSE NAREIT US REIT Index and the Dow Jones Wilshire REIT index. The factor representing the size effect, SMB, is the difference between the returns of the Dow Jones Wilshire Large-Cap and Small-Cap indices[4]. The factor representing the premium for value stocks, HML, is the difference between the returns of the Dow Jones Wilshire Mid-Cap Value and Mid-Cap Growth indices. The risk-free rate used to calculate excess returns is the one-month return of the Merrill Lynch 3 Month US T-Bills index. The variables used in the conditional models for the lagged public information variable, z_t, are the dividend yield on the S&P500 index and the one-month risk-free rate as above. Descriptive statistics for the sample funds and indexes are presented in the appendix. Of note is that the Sharpe Ratios shows that, on average, the funds underperformed the benchmarks by a significant margin during the sample period. The mean Sharpe Ratio of the 80 REMFs was 0.10 compared to 0.29 for the Wilshire All REITs index, indicating inferior risk-adjusted performance compared to a relevant benchmark.

The paper initially compares a number of alternative models in the estimation of alpha. The primary results are best on a single model, with the selection based on the Schwartz Information Criterion (SIC) and the statistical significance of the constituent parameters to determine a 'best-fit' model for each of three classes of model outlined below. The first form of model used is the traditional unconditional model, with time-invariant alphas and betas. The standard single-index version of Jensen (1968) can be displayed as follows:

$$R_{it} - R_{ft} = \alpha_i + ß_i (R_{mt} - R_{ft}) + \varepsilon_{it} \tag{1}$$

Where R_{it} is the return on fund *i* in period t.

R_{ft} is the risk-free rate (30-day Treasury Bill in period t).

R_{mt} is the single-index return on the relevant benchmark index.

The multi-factor version, as adapted from Fama & French (1993) can be shown as:

$$R_{it} - R_{ft} = \alpha_i + ß_i (R_{mt} - R_{ft}) + ß_{si} (R_{st} - R_{lt}) + ß_{gi}(R_{gt} - R_{vt}) + \varepsilon_{it} \tag{2}$$

Where R_{mt} here is the return on the benchmark.

$R_{st} - R_{lt}$ is the difference between small and large-cap returns.

$R_{gt} - R_{vt}$ is the difference between growth and value returns.

In additional to the conventional form of performance evaluation models conditional specifications are also used in the form proposed by Ferson & Schadt (1996). Conditional models control for look-ahead bias as a fund's factor betas may be dependent on lagged public information variables (z_t). Betas may therefore be time variant due to changes in this information set (such as changes in company dividend policy) or because managers alter portfolio weights depending on this lagged information and so alter their beta. In the case of the single-index model the conditional specification can be expressed as:

$$R_{it} - R_{ft} = \alpha_i + ß_{0i} (R_{mt} - R_{ft}) + ß_{zi\text{-}1} [z_{t-1} * (R_{mt} - R_{ft})] + \varepsilon_{it} \tag{3}$$

The next form of model specification considered is the conditional alpha-beta model (Christopherson et al., 1998), which allows for alpha to also depend linearly on the lagged public information set *z*:

$$R_{it} - R_{ft} = \alpha_{0i} + \alpha_{zi\text{-}1}\,(z_{t\text{-}1}) + ß_{0i}\,(R_{mt} - R_{ft}) + ß_{zi\text{-}1}\,[z_{t\text{-}1} * (R_{mt} - R_{ft})] + \varepsilon_{it} \quad (4)$$

This can be similarly generalised to a multi-factor model. The variables used for z_t here are the one-month T-Bill yield and the S&P500 dividend yield.

The above models assume that returns are of a linear functional form, however market timing models account for the fact that when managers expect the market to go up they may increase their factor beta accordingly in order to gain expose to upside volatility thus leading to the returns being of a quadratic functional form. In other words, successful market timing is doubly rewarded as the sectors they overweight in become even more significantly weighted in their portfolio as prices rise. The two main specifications of the model examined are that of Treynor & Mazuy (1966) and Henriksson & Merton (1981). The Treynor & Mazuy (1966) model can be specified as:

$$R_{it} - R_{ft} = \alpha_i + ß_i\,(R_{mt} - R_{ft}) + \gamma_{im}\,[R_{mt} - R_{ft}]^2 + \varepsilon_{it} \quad (5)$$

Where $\gamma_{im} > 0$ = the unconditional measure of market timing ability. The Henriksson & Merton (1981) market timing model can be shown as follows:

$$R_{it} - R_{ft} = \alpha_i + ß_i\,(R_{mt} - R_{ft}) + \gamma_{im}\,[R_{mt} - R_{ft}]^+ + \varepsilon_{it} \quad (6)$$

Where $[R_{mt} - R_{ft}]^+ = \max\ \{0, R_{mt} - R_{ft}\}$.

These models can be generalised to conditional models. If managers do have the ability to time the market then a linear model biases alpha upwards, as it exaggerates the skill or luck in sector-weighting. Controlling for market timing focuses alpha as a measure of stock selection, rather than sector weighting, thus making the measurement more robust.

The models were then estimated for all 80 funds and the cross-sectional average statistics calculated. Model selection was based on the Schwarz Information Criterion (SIC), which measures the efficiency of a parameterised model in predicting the dependent variable, while imposing a penalty for complexity (additional variables). SIC is an increasing function of the number of parameters and a decreasing function of the residual sum of squares and so it is desirable to minimise SIC. Exhibit 1 presents the cross-sectional results for the single-factor unconditional model using all three indices examined; NAREIT Real Estate; NAREIT REITs and Wilshire REITs. The Wilshire REIT index, which excludes smaller securities included by NAREIT, was found to have the best explanatory power (Lowest SIC and Adjusted R^2 of 0.71). This suggests that REMFs tend to invest in larger, more liquid real estate securities, which an examination of their holdings supports. Exhibit 1 also presents results for the other models examined, using the Wilshire REIT index as the market factor. The results reported here are for models using the S&P500 dividend yield as the conditional variable and the Treynor-Mazuy (1966) market timing factor, which were consistently found to be statistically more significant than their alternatives. The highlighted models indicate the best in the i) unconditional, ii) conditional beta and iii) conditional alpha-beta classes.

Fama and French premiums for small-cap and value stocks did not provide more efficient model estimation than the single-index model in any class. This is perhaps unsurprising as most US REITs tend to be small to medium in size relative to other equities and because REIT cash flows are derived from stable rental income, they tend to be value-type stocks. Market timing factors were also not significant in either the Treynor-Mazuy nor Henriksson-Merton specifications. This makes intuitive sense as evidence has shown the REIT market to be increasingly homogenous across sectors (e.g. Chong et al., 2010)[5]. While early studies of REMF performance use multi-factor models, they do not use SIC to determine the efficiency of estimation, which it is felt is the most robust specification criterion.

Exhibit 2 presents the cross-sectional estimation results for the three best-fit models. Around 85% of funds have non-normal errors, using the Jarque-Bera statistic, highlighting the limitation of traditional asymptotic test statistics. As noted in the introduction standard performance test statistics implicitly assume that a funds idiosyncratic risk has a known normal parametric distribution. Non-normality leads to a position whereby test statistics based on standard critical values may lead to misleading inferences. In addition, it is also those funds that display non-normality in their idiosyncratic risk that investors will wish to identify. Furthermore, the proportion of funds with non-normal errors is higher than that reported in either the Kosowski et al. (2005) or Cuthbertson et al. (2008) papers, who reported figures of 48% and 64% respectively. This therefore provides additional rationale as to the methodological approach adopted in the current study. The Adjusted R^2 across all three models is around 0.70, which suggests that the factor models reasonably explain fund performance. As the SIC is lowest for the unconditional model, there is little support for the use of a conditional framework. The unconditional single-index model is therefore used as the 'baseline' model for later tests of robustness[6].

5. Empirical Findings

Exhibit 3 presents the ex-post alphas for the 80 REMFs using each class of model. In all three best-fit models, the cross-sectional average alpha takes on a negative and statistically insignificant value: -0.55% per month (-6.8% annually) for the unconditional model; -0.54% per month (-6.7% per annum) for the conditional beta model and -0.57% (-7.1% per annum) for the conditional alpha beta model. Using the unconditional model, only 5 of the 80 funds (6%) deliver abnormal return; using the conditional beta model 7 funds (9%) created value and using the conditional alpha-beta model 9 (11%) deliver alpha. This is consistent with other studies of US Mutual Funds such as Blake & Timmermann (1998), although it contrasts with earlier studies of REMFs such as Kallberg et al. (2000) and Gallo et al. (2000), who both find positive cross-sectional average alpha using a single-index model. It should be remembered that if a fund simply matches the benchmark performance, it would be expected that a small negative alpha would be observed due to transaction costs and management fees. However, the magnitude of average under-performance reported here is relatively large and provides further rationale as to the consideration of to what extent fund performance is due to luck[7].

Of particular interest in the context of this study is the relatively large cross-sectional standard deviation of the alpha estimates: 0.38% per month for the unconditional model; 0.39% for the conditional beta model and 0.69% for the conditional alpha-beta model. This suggests that there may be a significant number of funds in the extreme tails of the distribution of abnormal return. Exhibits 4, 5 and 6 show histograms of the cross-sectional distribution of the alpha estimates for all funds from the three models. There is a wide spread of estimates and a significant number of funds in both tails of the distribution for all three models.

Exhibit 7 presents the summary bootstrap results for the unconditional (Panel A), conditional beta (Panel B) and conditional alpha-beta (Panel C) models. The first row in each panel indicates the ex-post alpha of the Best (Max), Worst (Min) funds and the funds at 5th, 10th, 20th and 50th percentiles. The second row shows the bootstrap p-values based on the luck distribution for alpha (under the null of no out-performance). The third row offers interpretation, indicating whether that fund's ex-post alpha demonstrates skill or luck at the 1% significance level – i.e. whether it is in the extreme tail of the luck distribution. It also states whether this is due to good or poor skill/luck – i.e. whether the ex-post alpha is in the left (poor) or right (good) tail. For example, if we take the worst performing fund (ex-post) using the unconditional model, we see it has an ex-post alpha of -2.51% per month. The p-value of 0.005 indicates that it is in the extreme tail of the luck distribution – i.e. its alpha is genuinely due to management ability, as opposed to luck. The fact that row 3 indicates this is due to *good* skill means that the ex-post alpha is in the extreme right tail of the luck distribution for the worst performing fund. By way of illustration, Exhibit 8 illustrates the location of the best performing fund's ex-post alpha within its luck distribution. Although it has an actual ex-post alpha of 0.99%, it can be seen to be in the extreme left tail of its distribution of luck – and therefore indicative of poor skill rather than simply luck.

In the period January 1995 to May 2008, all but one of the 80 sampled REMFs were found to have an ex-post alpha due to poor skill. In other words, all but one fund's ex-post alpha was in the extreme left tail of the luck distribution of alpha meaning they all underperformed relative to how they would be expected to simply due to luck. The one fund that behaved counter to this was in fact the worst performing fund, which, as outlined above, was found to have produced a negative alpha due to 'good skill'. Although, counter-intuitive to label under-performance 'skilful' it is simply to say this fund did not perform as badly as we would expect it to given the distribution of luck. The results are also consistent across all three classes of model.

The use of the non-parametric bootstrap is motivated by the idea that extreme performers are likely to exhibit non-normal risk and therefore will change position more frequently than median performers. This is supported by the estimation output as the distribution of extreme performers is more widely dispersed. Using the baseline unconditional model, the best and worst performing funds' residuals have standard deviations of 0.188 and 0.168 respectively, while the median fund's residuals have a much lower standard deviation of 0.016. This can be seen in Exhibits 9, 10 and 11. The histograms show that the residuals of the best and worst funds are widely dispersed compared to the median fund which is normally distributed and has lower variance. This high variance generates wide dispersion in the performance of funds at the top and bottom of the performance scale, with the bootstrapped alphas being reordered more frequently.

It could be argued that the findings presented here are due to the high cross-sectional variation of alpha i.e. variable rather than simply poor management performance per se. An alternative version of this methodology, which does not reorder the bootstrapped alphas but instead creates the distribution of luck for each *individual* fund, should therefore be considered. This method was used by Kosowski et al. (2006) to study US mutual fund performance. Overall, the results, which are displayed in Exhibit 12, show that the five funds that had positive ex-post alpha were found to demonstrate genuine management skill, while the remaining 75 funds destroyed value. Using this alternative assessment, therefore, the findings are similar to using alpha in its traditional form. However, the results do highlight the importance of the central methodology expounded here: capturing idiosyncratic risk is critical to a proper assessment of management performance. Variable performance is potentially poor performance and of central concern to investors. Re-running history for a single fund ignores the other possible distributions of luck encountered by other funds but these other luck distributions provide valuable information. To ignore this would be to assume that each fund operates in an independent environment, impacted by unique factors that do not affect other funds. The wide and over-lapping dispersion of fund performance disabuses us of such a notion. Luck, of course, doesn't discriminate. It is random and affects all funds, albeit in different ways, at different times.

As noted earlier in the paper, some of the earlier studies of REMF performance, particularly those examining data prior to 2001, provide evidence of management out-performance. In addition, the REIT market has been through quite distinct phases in terms of its performance over the last two decades. Firstly, the recent poor performance of the REIT sector could influence the overall findings. Secondly, the late nineties were also characterised by relatively poor REIT sector performance. However, subsequent to the 2000 tech crash, REITs were one of the best performing US equity sectors. Furthermore, this post 2000 period also saw a large increase in trading volume in the sector and continued maturity of the sector. Therefore, in order to examine whether the results are time-varying and as an additional test of robustness, we examine REMF performance over two sub-periods. We consider two periods of January 1995 to March 2000 and from there until December 2006. For the 27 funds that had a minimum of 15 observations in each sub-period, the bootstrap methodology was performed using the baseline unconditional model for both sub-periods. The results are presented in Exhibit 13. Overall, in Period 1, one fund demonstrated genuine skill in out-performance while all others genuinely destroyed value. In Period 2, all 27 funds demonstrated genuine negative alpha. This indicates that not only are the overall findings are not unduly biased by factors such as the performance of the sector in recent years, but that on a more general level, the results are largely invariant to the time-period studied. The fact that the results are similar in quite differing market conditions does provide additional weight to the empirical results reported.

6: Conclusion and Implications

The parametric bootstrap methodology presented here finds that none of the 80 REMFs, over a long sample period, exhibit stock selection skill. It is important to note that the methodology used does not consider performance per se. Rather it considers whether the performance achieved, whether it be good, bad or indifferent, can be attributed to skill or luck. The empirical findings show that even apparently successful funds ex-post display '*poor*' skill in that they perform significantly worse than they would be expected to simply due to luck. In addition, it is found that poor REMF performance is invariant to the time period or market conditions assessed. Even pre-2000, when the REIT market was less mature and less heavily traded, REMF managers demonstrate poor skill. It should be noted that these results are quantitatively different to previous studies of non-real estate mutual funds that use a similar bootstrap methodology, which find some genuine out-performers and under-performers, though not necessarily those at the top or bottom of ex-post performance (Cuthbertson et al, 2008). The parametric bootstrap methodology implemented in this study is an alternative to traditional alpha in that it distinguishes between skill and luck. It also offers a sensitive treatment of idiosyncratic risk, which it has been demonstrated is especially significant for the extreme performers investors are primarily interested in. It accounts for the luck experienced by all funds and in doing so offers an inbuilt test of the persistence of skill versus luck.

The fact that our findings do not indicate substantive outperformance warrants consideration as to what factors could be influencing and impacting upon the performance of REIT Mutual Funds. In practical terms REMF Managers have a number of constraints that can limit their ability to outperform the benchmark. These constraints may mean that not only are less likely to be observed outperforming, but that their performance can be attributed to so called poor skill rather than luck. To begin with it is also possible that REIT Mutual Fund managers are constrained by internal asset allocation policies. It is quite common to see fund managers having to operate under allocation constraints that effectively limit their ability to partake in substantial degrees of active management. However, this would not alone explain the results obtained. A key element that could explain not only our findings but also those reported in Hartzell et al. (2010) is the size of the REIT sector. The REIT market is characterised by a relatively small number of large cap firms and a large number of small to mid-cap REITs. This can be seen in that in November 2008 the average market capitalization of Equity REITs was \$1.3bn and that 60% of firms had a market cap below \$1bn, which would classify them as small stocks. Even prior to the downturn in the market at the end of 2006 the average figure stood at \$2.9bn and more than a third (36%) had market caps of less than a billion. This structural issue also impacts the benchmarks. The fact that the primary REIT benchmarks are value-weighted means that a small number of large firms, such as Boston Properties, Simon

Property Group and Vornado, will act as the primary driving forces of the indices. Whilst Hartzell et al. (2010) finds that tilting their portfolios into small cap REITs can lead to REMF outperformance the practicalities of investment in the sector will impose constraints on a fund's ability to do so. The smaller firms will naturally display reduced liquidity and be less heavily traded. This alone would limit a manager's ability to wholeheartedly shift the portfolio out of the relatively small number of large cap REITs.

However, the impact of the structure of the sector could possibly come through in other respects as well, and in particular the contrast in recent studies of REMF performance. Whereas recent studies have largely found a lack of evidence pointing to outperformance, earlier studies often did find empirical evidence of fund outperformance. As noted earlier in this paper, and by Hartzell et al. (2010) and Ling & Naranjo (2006), not only has the REIT sector grown substantially since the early nineties, but so did the REIT Mutual Fund sector. The increased flow of funds into the sector, particularly in the 2000 to 2006 period could have had a number of implications. Firstly, it may actually have had a constraining effect on strong performing REMFs as the placement of such funds would be limited by the structure of the sector. Effectively, less capital may have been able to be directed towards smaller REITs due to lower market capitalization and reduced liquidity. Secondly, the constraints in fully exploiting performance in small cap REITs may also help to explain the results reported by Hartzell et al. (2010) and Derwell et al. (2009) with respect to momentum profits. Again, managers may have been less able to exploit such momentum profits in the small-cap REIT sector due to a combination of the large scale flow of funds entering the REMF sector and the reduced liquidity in small cap REITs.

Finally, the amount of funds entering the sector may have contributed to the observed worsening performance. Barras et al. (2010) find a combination of an increasing numbers of fund and worsening performance since the early nineties in relation to the general mutual fund sector. The hypotheses proposed relating to the worsening performance include; increased stock market efficiency, the increased number of funds leading to a higher proportion of poorer managers and the impact of increased search costs for outperforming funds. The implications could be that the increased flow of funds into REMFs led to that capital not being solely directed towards strong performing managers but spread more evenly.

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Tables and Figures

Exhibit 1: Cross-Sectional Results of Examined Models

	R^2	Adjusted R^2	SIC
Panel A: Unconditional			
Wilshire REIT	0.71	0.71	-4.534
NAREIT REIT	0.70	0.69	-4.431
NAREIT Listed	0.71	0.71	-4.508
S&P500	0.17	0.15	-3.115
F&F* (Wilshire)	0.73	0.71	-4.459
Wilshire & Timing	0.72	0.71	-4.500
F&F (Wilshire) & Timing	0.73	0.71	-4.422
Panel B: Conditional Beta			
Conditional Wilshire	0.72	0.71	-4.480
Conditional Wilshire & Timing	0.72	0.71	-4.445
Conditional Wilshire & Conditional Timing	0.73	0.71	-4.396
Conditional F&F	0.74	0.71	-4.304
Conditional F&F & Timing	0.75	0.71	-4.266
Conditional F&F & Conditional Timing	0.75	0.71	-4.241
Panel C: Conditional Alpha Beta			
Conditional Alpha; Conditional Wilshire	0.72	0.71	-4.428
Conditional Alpha; Conditional Wilshire & Timing	0.73	0.71	-4.392
Conditional Alpha; Conditional Wilshire & Conditional Timing	0.74	0.71	-4.353
Conditional Alpha; Conditional F&F	0.75	0.71	-4.265
Conditional Alpha; Conditional F&F & Timing	0.75	0.71	-4.226
Conditional Alpha; Conditional F&F & Conditional Timing	0.76	0.71	-4.118

Notes: Exhibit 1 displays the cross-sectional results for different benchmarks for the unconditional performance models. Panels B and C display the cross-sectional results for the conditional models solely using the Wilshire REIT Index. The results for the alternative benchmarks can be obtained from the authors on request. F&F denotes the Fama & French Multi-index model

Exhibit 2: Cross-Sectional Results of Best Models

	Unconditional	Conditional Beta	Conditional Alpha-Beta
Average Alpha	-0.00552	-0.00537	-0.00573
	0.179)	(0.185)	(0.269)
Standard Deviation of Alpha	0.00384	0.00396	0.00689
Number Positive / Negative Alphas	5 / 75	7 / 73	9 / 71
Unconditional Beta			
Wilshire	0.925	0.904	0.901
	(0.006)	(0.005)	(0.008)
Conditional Beta Variable			
Wilshire * Z_{t-1} (Dividend Yield)	-	17.590	23.352
		(0.423)	(0.417)
Model Selection Criteria			
Adjusted R^2	0.71	0.71	0.70
SIC	-4.553	-4.480	-4.428
Residuals not normally distributed (% of funds)	86	84	89
Equally-Weighted Portfolio			
Alpha	-0.00368	-0.00537	-0.0037
	(0.011)	(0.015)	(0.015)

Notes: Exhibit 2 displays the cross-sectional results for those models determined to be the best-fitting specifications. P-values are displayed in parentheses.

Exhibit 3: Ex-Post Alphas

Fund Name	Unconditional	Conditional Beta	Conditional Alpha-Beta	Fund Name	Unconditional	Conditional Beta	Conditional Alpha-Beta
Fund 1	-0.011	-0.010	-0.010	**Fund 41**	-0.008	-0.008	-0.011
Fund 2	0.003	0.003	0.003	**Fund 42**	-0.002	-0.002	-0.003
Fund 3	-0.006	-0.006	-0.005	**Fund 43**	-0.007	-0.006	-0.004
Fund 4	-0.007	-0.007	-0.005	**Fund 44**	-0.007	-0.007	-0.008
Fund 5	-0.002	-0.002	-0.002	**Fund 45**	-0.016	-0.016	-0.018
Fund 6	-0.001	-0.001	-0.001	**Fund 46**	-0.016	-0.020	-0.001
Fund 7	-0.001	0.001	-0.002	**Fund 47**	-0.007	-0.007	-0.007
Fund 8	-0.006	-0.006	-0.006	**Fund 48**	-0.005	-0.004	-0.024
Fund 9	-0.010	-0.010	-0.011	**Fund 49**	-0.003	-0.003	-0.003
Fund 10	-0.010	-0.010	-0.016	**Fund 50**	-0.005	-0.005	-0.005
Fund 11	-0.002	-0.002	0.001	**Fund 51**	-0.011	-0.011	-0.011
Fund 12	0.002	0.002	0.002	**Fund 52**	-0.006	-0.006	-0.007
Fund 13	-0.005	-0.005	-0.006	**Fund 53**	-0.008	-0.008	-0.007
Fund 14	-0.003	-0.003	-0.003	**Fund 54**	-0.005	-0.005	-0.007
Fund 15	-0.006	-0.006	-0.006	**Fund 55**	-0.002	-0.002	-0.001
Fund 16	-0.005	-0.005	0.001	**Fund 56**	0.001	0.001	0.006
Fund 17	-0.007	-0.006	-0.005	**Fund 57**	-0.001	-0.001	-0.001
Fund 18	-0.002	-0.003	-0.002	**Fund 58**	-0.003	-0.003	-0.003
Fund 19	-0.007	-0.007	-0.009	**Fund 59**	-0.003	-0.003	-0.004
Fund 20	-0.016	-0.016	-0.015	**Fund 60**	-0.009	-0.009	-0.009
Fund 21	-0.001	-0.001	-0.001	**Fund 61**	-0.003	-0.003	-0.004
Fund 22	-0.015	-0.015	-0.023	**Fund 62**	-0.006	-0.007	-0.006
Fund 23	-0.004	-0.004	-0.004	**Fund 63**	-0.010	-0.010	-0.007
Fund 24	-0.003	-0.003	-0.003	**Fund 64**	-0.007	-0.007	-0.004
Fund 25	-0.014	-0.014	-0.018	**Fund 65**	-0.004	-0.004	-0.005
Fund 26	-0.003	-0.003	-0.005	**Fund 66**	-0.005	-0.005	-0.001
Fund 27	-0.003	-0.003	-0.004	**Fund 67**	-0.003	-0.003	-0.007
Fund 28	-0.004	-0.004	0.000	**Fund 68**	-0.004	-0.003	0.006
Fund 29	-0.003	-0.003	-0.004	**Fund 69**	0.010	0.010	0.010
Fund 30	-0.005	-0.005	-0.007	**Fund 70**	-0.011	-0.011	-0.010
Fund 31	-0.004	-0.004	-0.006	**Fund 71**	-0.007	-0.007	-0.006
Fund 32	-0.009	-0.010	-0.012	**Fund 72**	-0.003	-0.004	-0.005
Fund 33	-0.007	-0.008	0.000	**Fund 73**	0.000	0.000	-0.001
Fund 34	-0.003	-0.003	-0.004	**Fund 74**	0.001	0.001	0.000
Fund 35	-0.005	-0.005	-0.005	**Fund 75**	-0.002	-0.002	-0.002
Fund 36	0.000	0.001	0.000	**Fund 76**	-0.008	-0.007	-0.007
Fund 37	-0.007	-0.005	-0.008	**Fund 77**	-0.005	-0.006	-0.006
Fund 38	-0.005	-0.006	-0.004	**Fund 78**	-0.025	-0.019	-0.025
Fund 39	-0.005	-0.005	-0.002	**Fund 79**	-0.001	-0.001	-0.003
Fund 40	-0.019	-0.019	-0.039	**Fund 80**	-0.002	-0.002	0.000
Mean	**-0.0055**	**-0.0054**	**-0.0057**	**EW Portfolio**	**-0.004**	**-0.004**	**-0.004**

Notes: Exhibit 3 reports the ex-post alphas for each fund, estimated using the best-fitting models in each category.

Exhibit 4: Cross-Sectional Alpha – Unconditional Model

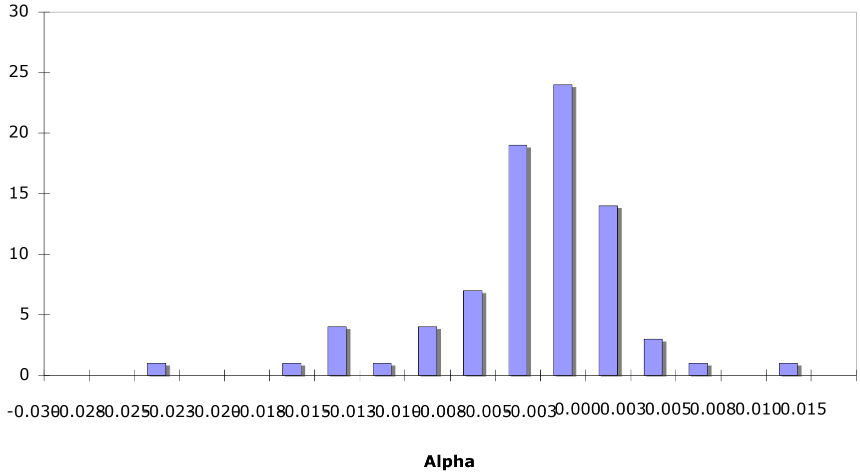


Exhibit 5: Cross-Sectional Alpha – Conditional Beta Model

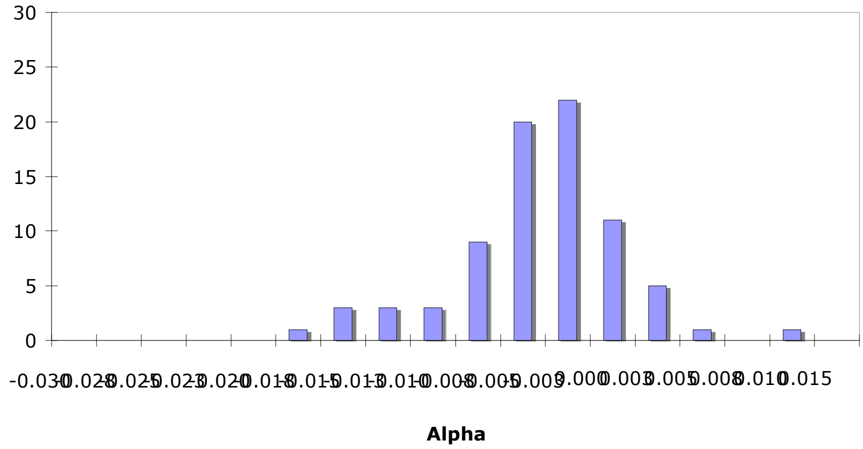
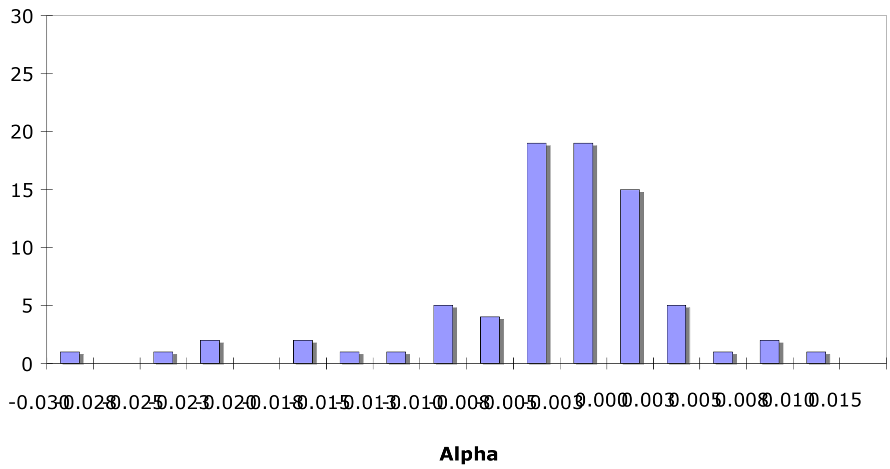


Exhibit 6: Cross-Sectional Alpha – Conditional Alpha Beta Model



Notes: Exhibits 4, 5 and 6 display histograms of the distribution of the ex-post alpha's displayed in Exhibit 3.

Exhibit 7: Bootstrap Results of REMF Performance

Panel A: Unconditional Model

	Min	5%	10%	20%	Median	20%	10%	5%	Max
Ex-post Alpha	-0.0251	-0.0158	-0.0110	-0.0092	-0.0049	-0.0022	-0.0006	0.0009	0.0099
P-value	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
@ 1%	GOOD SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL

Panel B: Conditional Beta Model

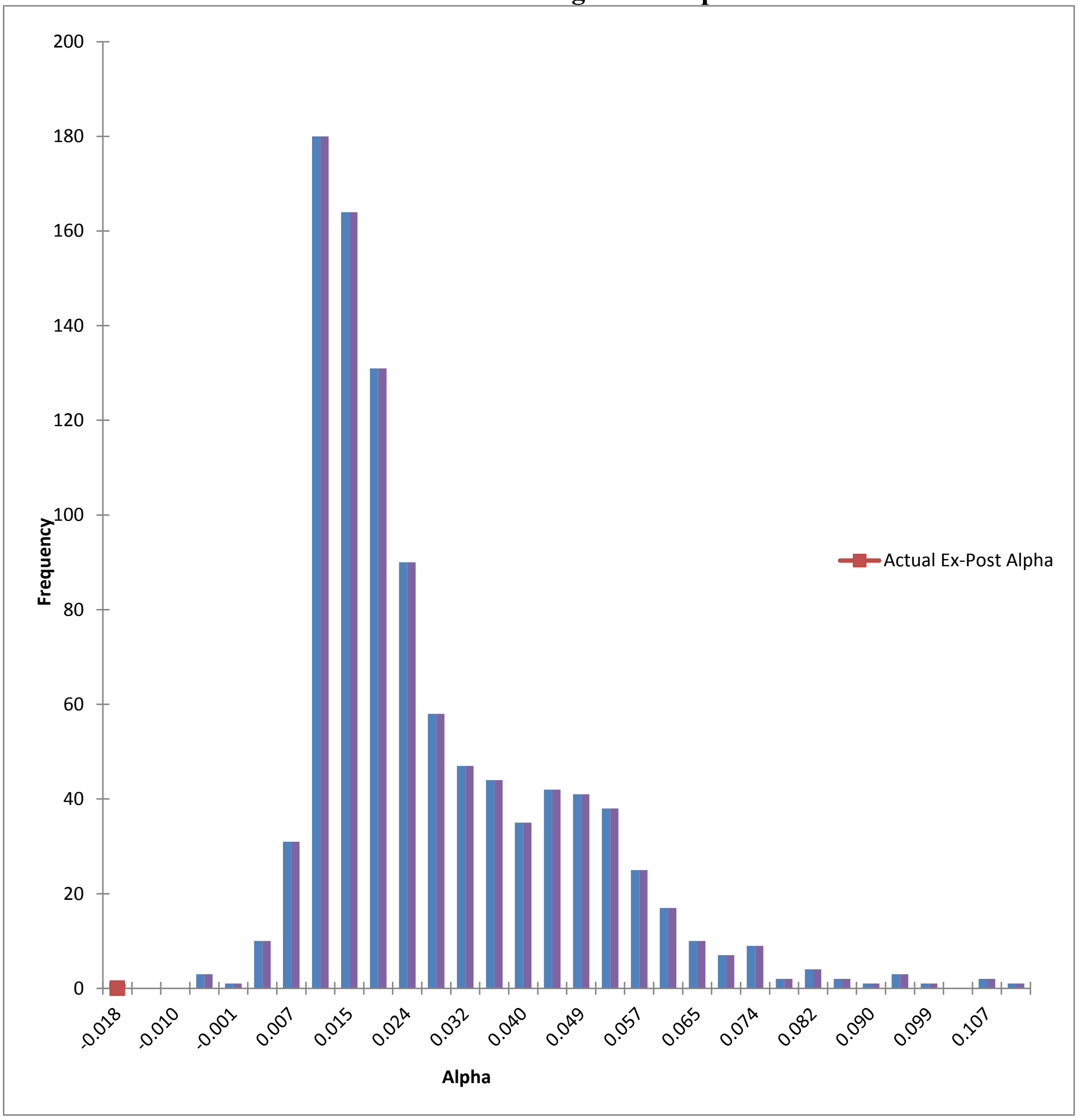
	Min	5%	10%	20%	Median	20%	10%	5%	Max
Ex-post Alpha	-0.0196	-0.0158	-0.0107	-0.0093	-0.0049	-0.0018	-0.0004	0.0012	0.0097
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00
@ 1%	GOOD SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL

Panel C: Conditional Alpha-Beta Model

	Min	5%	10%	20%	Median	20%	10%	5%	Max
Ex-post Alpha	-0.0395	-0.0178	-0.0117	-0.0094	-0.0046	-0.0010	0.0003	0.0028	0.0098
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00
@ 1%	GOOD SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL

Notes: Exhibit 7 presents the summary bootstrap results for each class of performance model.

Exhibit 8: Luck Distribution of the Best Performing Fund ex-post



Notes: Exhibit 8 displays the location of the best performing fund using the unconditional model within its luck distribution.

Exhibit 9: Residuals of Best Performing Fund

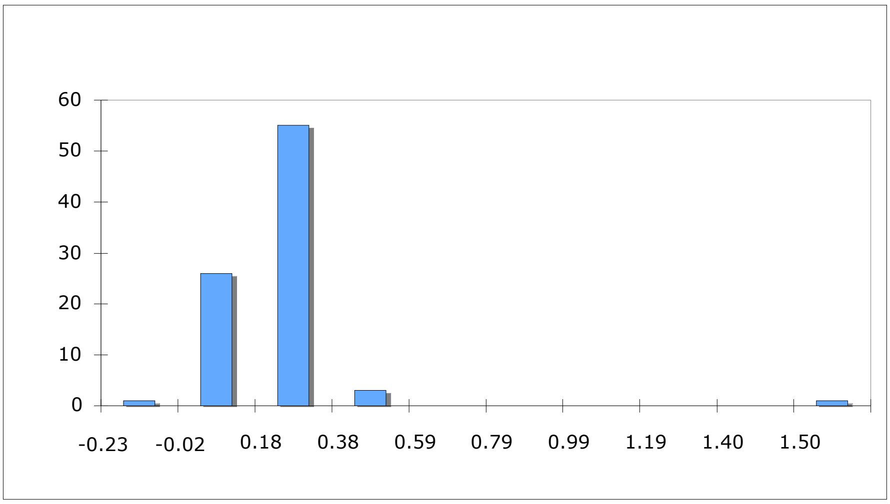


Exhibit 10: Residuals of Worst Performing Fund

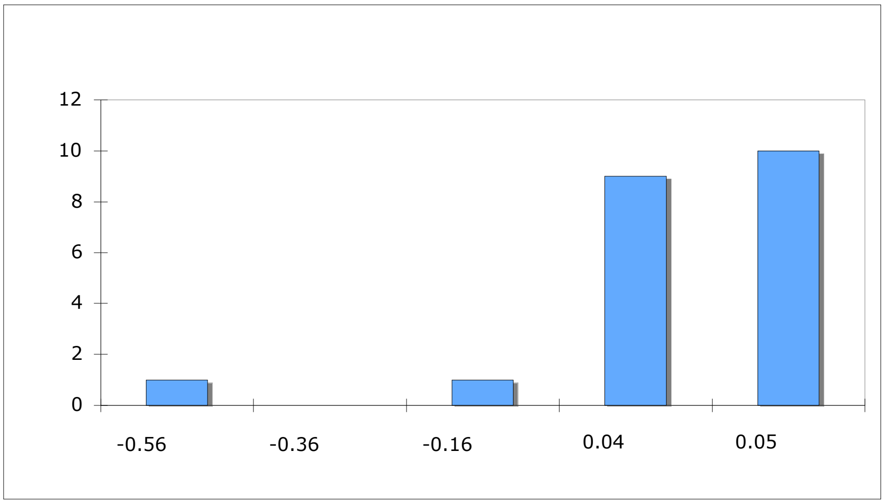
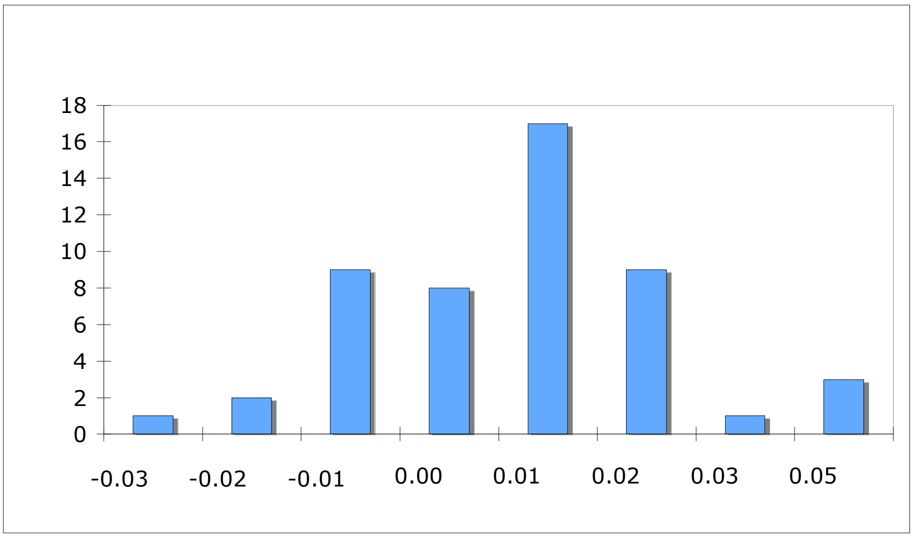


Exhibit 11: Residuals of Median Performing Fund



Notes: Exhibit 9, 10 and 11 display the residuals of the best, worst and median funds respectively.

Exhibit 12: Bootstrap Results of REMF Performance using Kosowski et al. Method

	Min	5%	10%	20%	Median	20%	10%	5%	Max
Ex-post Alpha	-0.0251	-0.0158	-0.0110	-0.0092	-0.0049	-0.0022	-0.0006	0.0009	0.0099
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
@ 1%	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	GOOD SKILL	GOOD SKILL

Notes: Exhibit 12 presents the summary bootstrap results for the unconditional model using the Kosowski et al. (2006) methodology, which estimates the distribution of luck for each individual fund.

Exhibit 13: Bootstrap Results of REMF Performance by Sub-period

Panel A: January 1995-March 2000									
	Min	**5%**	**10%**	**20%**	**Median**	**20%**	**10%**	**5%**	**Max**
Ex-post Alpha	-0.0076	-0.0075	-0.0037	-0.0030	-0.0017	0.0004	0.0016	0.0042	0.0164
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0009
@ 1%	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	GOOD SKILL
Panel B: April 2000-December 2006									
	Min	**5%**	**10%**	**20%**	**Median**	**20%**	**10%**	**5%**	**Max**
Ex-post Alpha	-0.0180	-0.0139	-0.0103	-0.0031	-0.0018	0.0010	0.0024	0.0049	0.0083
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
@ 1%	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL	POOR SKILL

Notes: Exhibit 13 presents the summary bootstrap results for two sub-periods.

Appendix

Exhibit 1A: Descriptive Statistics for the 80 REMFs and Benchmarks

	Months Traded	Mean Return	St. Dev.	Sharpe Ratio
Panel A: Fund Results				
Fund 1	87	0.45	6.65	0.07
Fund 2	24	1.74	3.06	0.57
Fund 3	77	0.91	5.13	0.18
Fund 4	46	0.75	6.15	0.12
Fund 5	87	1.01	4.34	0.23
Fund 6	158	0.96	6.09	0.16
Fund 7	47	0.70	4.87	0.14
Fund 8	81	0.80	5.52	0.15
Fund 9	99	0.65	6.21	0.11
Fund 10	102	0.07	6.61	0.01
Fund 11	30	0.76	3.29	0.23
Fund 12	160	1.28	5.91	0.22
Fund 13	95	0.86	4.97	0.17
Fund 14	160	0.89	4.67	0.19
Fund 15	160	0.62	5.18	0.12
Fund 16	51	0.46	3.98	0.12
Fund 17	58	0.16	3.80	0.04
Fund 18	160	0.87	4.37	0.20
Fund 19	138	0.51	5.58	0.09
Fund 20	57	0.05	7.47	0.01
Fund 21	160	1.05	4.23	0.25
Fund 22	40	-0.43	7.07	-0.06
Fund 23	94	0.98	4.88	0.20
Fund 24	23	0.37	6.22	0.06
Fund 25	113	0.05	7.90	0.01
Fund 26	123	0.58	4.13	0.14
Fund 27	67	1.22	4.74	0.26
Fund 28	62	0.19	1.77	0.11
Fund 29	134	0.78	4.59	0.17
Fund 30	141	0.64	4.66	0.14
Fund 31	111	0.94	4.97	0.19
Fund 32	135	0.15	5.60	0.03
Fund 33	16	-1.12	7.49	-0.15
Fund 34	128	0.77	4.70	0.16
Fund 35	27	0.16	6.08	0.03
Fund 36	15	-1.15	6.32	-0.18
Fund 37	26	0.17	2.75	0.06
Fund 38	81	0.28	4.16	0.07
Fund 39	52	0.86	5.36	0.16
Fund 40	30	-0.59	10.50	-0.06
Fund 41	110	0.56	6.30	0.09
Fund 42	122	0.83	4.77	0.17
Fund 43	63	1.01	5.25	0.19
Fund 44	95	0.60	4.89	0.12
Fund 45	39	-0.17	8.01	-0.02
Fund 46	16	-1.50	7.30	-0.21
Fund 47	27	1.77	4.40	0.40
Fund 48	21	0.55	3.57	0.15
Fund 49	21	1.11	4.68	0.24
Fund 50	88	0.73	5.20	0.14
Fund 51	155	0.39	6.94	0.06
Fund 52	135	0.50	4.86	0.10
Fund 53	71	0.54	5.87	0.09
Fund 54	154	0.27	7.38	0.04
Fund 55	54	1.23	5.36	0.23
Fund 56	19	0.26	5.92	0.04
Fund 57	104	1.27	4.43	0.29
Fund 58	160	0.91	4.48	0.20
Fund 59	40	0.69	5.33	0.13
Fund 60	34	0.07	6.14	0.01
Fund 61	104	1.18	6.15	0.19

Table 1A: Descriptive Statistics for the 80 REMFs and Benchmarks (Continued)

Fund 62	93	1.12	6.45	0.17
Fund 63	59	0.15	4.72	0.03
Fund 64	38	0.57	6.03	0.09
Fund 65	127	0.66	4.83	0.14
Fund 66	34	0.43	4.85	0.09
Fund 67	52	0.19	4.37	0.04
Fund 68	22	-0.10	3.82	-0.03
Fund 69	86	2.40	19.34	0.12
Fund 70	55	0.32	6.14	0.05
Fund 71	66	0.87	4.66	0.19
Fund 72	119	0.81	4.93	0.16
Fund 73	122	1.00	4.36	0.23
Fund 74	99	1.13	3.65	0.31
Fund 75	34	0.76	5.14	-0.02
Fund 76	67	0.73	5.37	0.14
Fund 77	160	0.61	4.63	-1.77
Fund 78	21	-2.91	16.94	-0.17
Fund 79	82	0.77	3.61	0.21
Fund 80	46	2.07	4.03	0.51
Average Across Funds	**82**	**0.56**	**5.59**	**0.10**
Panel B: Index Results				
EW Portfolio 80 REMFs	160	0.76	4.23	0.18
S&P500	160	0.93	3.99	0.23
NAREIT All REITs	160	1.11	4.02	0.28
NAREIT US Listed R.E	160	1.26	4.18	0.30
Wilshire All REITs	160	1.19	4.15	0.29

Endnotes:

[1] A recent paper by Barras et al. (2010) adopts a different approach in the examination of 'luck'. They consider the 'False Discovery Rate' which effectively considers the proportion of funds classified as outperforming, in terms of a significant alpha, that can be deemed truly successful. A disadvantage with the Barras et al. (2010) approach is that is not possible to identify which specific funds are actually outperforming, merely the proportion.

[2] The investment style of the fund used in the Kosowski et al. (2006) paper is that specified in the fund's investment objective, rather than an empirically estimated definition using a technique such as Style Analysis.

[3] Our sample does differ from that used by Hartzell et al. (2010). We obtain our data from Thomson Reuters Datastream and Morningstar, whereas Hartzell et al. (2010) use the CRSP mutual fund database. Furthermore, the restrictions we impose detailed in the text with respect to international investment and tracker funds may also lead to a reduction in our sample in comparison with Hartzell et al. (2010). The sample used in Derwell et al. (2009) is substantially higher than that utilized in either the Hartzell et al. (2010) paper or the current study at 282 funds. While both Hartzell et al. (2010) and our paper only consider unique funds the high number of funds utilized by Derwell et al. (2009) would suggest that they include replications of the same funds.

[4] Hartzell et al. (2010) differ in their approach in that they use real estate security specific factors, rather than the more general stock market variables commonly used and also utilised in the current study.

[5] Gallo et al's (2000) finding of sector-weighting impacting fund performance studied a time period when the REIT market was less homogenous.

[6] To some degree the fact that the standard single index model is selected is advantageous in the sense that this is the specification generally used and quoted by funds.

[7] The fact that our findings do not report any significant outperformance overcomes a possible bias noted by Fama & French (2009). They argue that in comparison to their bootstrapping approach, the failure to account for the joint distribution of fund and explanatory variable returns may produce a bias towards positive performance.