Luck versus Skill in Evaluating Hedge Fund Managers' Performance

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Abstract

Purpose – *The purpose of this paper is to examine if excess returns produced by hedge fund managers are due to luck or skill.*

Method – *False Discovery Rate (FDR) method addresses the question of how manager skill, as opposed to luck, affects abnormal risk-adjusted return performance of actively-managed funds. This study uses the FDR method to separate hedge fund managers into one of three groups: a) Skilled; b) Unskilled; and c) Zero-alpha (i.e., neutral). After identifying skillful hedge fund managers, the Fung-Hsieh benchmark model is used to understand the source of excess returns.*

Findings – *After analyzing hedge fund monthly returns from 1999 to 2012 using the FDR method, only 2.68% of managers of hedge funds are found to be truly skilled, 33.20% are unskilled, and the rest are managers of zero-alpha funds. There is evidence to suggest that skillful fund managers are better at using emerging markets, foreign exchange, and commodities compared to unskilled managers.*

Limitations – *This study is restricted to hedge funds. Further studies may include participants from other alternative investments (i.e., private equity, real estate) to see if skill exists in other alternative asset classes.*

Implications – *Investors pay a significantly higher fee to hedge fund managers, hoping that the manager has skill in producing higher risk-adjusted returns. Therefore, investors (such as public pension funds) need to know if a manager is producing any excess returns due to luck or skill.*

Originality – *Luck versus skill debate has raged on for over three decades in the mutual fund segment. This paper extends this debate to the hedge fund segment. Besides, this paper applies the FDR method, initially intended for use in Biological Sciences, to evaluate hedge fund performance.*

Keywords: hedge fund, false *discovery* rate, FDR, performance evaluation, luck, skill.

JEL classification: G14, G18.

Reference to this paper should be made as follows: Malladi, R. (2020). Luck versus skill in evaluating hedge fund managers' performance. *Journal of Business and Management, 26*(1), March, 22-39. DOI: 10.6347/JBM.202003_26(1).0002.

Introduction

The march of passive investing has been one of the defining themes of asset management over the past decade. The active vs. passive debate is upending the investment industry (Ptak, 2014). The exodus from active funds has sent manager fees inexorably lower, led to the loss of thousands of jobs, and forced large-scale consolidation among firms (Waite et al., 2008). According to the 2019 Investment Company Fact Book, passive (index) funds have doubled as a share of the fund market between 2008 and 2018. By year-end 2018, total net assets in these passive funds grew to \$6.6 trillion USD – index-based mutual funds and ETFs together accounted for 36 percent of assets in long-term funds, up from 18 percent a decade earlier. Though shrinking in market share, actively-managed funds continue to be a dominant segment, with 64 percent of the fund assets market share in 2018 (ICI, 2019).

Of all actively-managed funds, hedge funds tend to be the most active since they charge a significantly higher fee compared to mutual funds and deploy various active investment strategies. Hedge funds are considered by some to be the epitome of active management (Fung et al., 2008). By year-end 2018, \$2.87 trillion USD was invested in the global hedge fund industry (BarclayHedge, 2019), or 104% growth since 2011. In contrast, \$17.71 trillion USD is invested in the global mutual funds registered in the U.S. during the same period (Szmigiera, 2019), or 52% growth since 2011. So, it appears that despite all the merits of passive investing, and the availability of investable passive ETFs since 1993, active funds are experiencing significant growth from a dominant market share position. Therefore, it is essential to understand if the returns produced by active fund managers are due to skill level or simple luck.

This paper is organized in the following sections: Literature Review, Data, False Discovery Rate (FDR) description, FDR Bootstrap Method that separates skill from luck. Fund Performance Model that decomposes returns, Discussion of Results, Conclusion, and Managerial Implications.

Literature Review

Do active fund managers who actively trade different assets add value? Academics have debated this issue since the seminal paper of Jensen (1968), who found that on average active mutual funds were not able to predict security prices well enough to outperform the passive strategy of buy-the-market-and-hold. Though it is well documented by Wermers (2000) that the average U.S. equity mutual fund underperforms its benchmark, Kosowski et al. (2007) found that the cross-sectional standard deviation of the alphas for individual funds is high, indicating the possibility that some funds are performing very well and others very poorly. However, the majority of this excess performance in a mutual fund universe is attributed to luck rather than skill by several authors, most notably Fama and French (2010), Barras et al. (2010), and Berk (2005).

Numerous papers have been written on the value creation of active mutual fund managers, starting with Jensen (1968), Ferson and Schadt (1996), Carhart (1997), Daniel et al. (1997), Wermers (2000), P´astor and Stambaugh (2002), Cohen et al. (2005), Kacperczyk et al. (2005), Kosowski et al. (2006), Barras et al. (2010), and Fama and French (2010), etc. A survey of the literature by Jones and Wermers (2011) on the value of active management shows that the average active managers do not outperform, but a significant minority of active managers do add value. Berk and Van Binsbergen (2015) find that the average mutual fund has used the skill to generate about $3.2 million USD per year. Since the late 1990s, the empirical properties of hedge fund performance have been documented by many authors such as Brown et al. (1999), Agarwal and Naik (2000), and Agarwal and Naik (2004). For a review of hedge fund performance literature, refer to Getmansky et al. (2015). Unlike the literature on mutual fund performance, several hedge fund performance studies document positive risk-adjusted returns in the hedge fund industry, starting with Brown et al. (1999), Ackermann et al. (1999), Agarwal and Naik (2000), Fung and Hsieh (2004), Kosowski et al. (2007), and Fung et al. (2008), etc.

However, the source of these positive risk-adjusted returns can be due to either the manager's luck or skill. A very useful technique called False Discovery Rate was developed by Storey (2002), Storey and Tibshirani (2003), and Storey (2011) to control for false discoveries in Biological Science. This FDR technique was later applied to a mutual fund setting by Barras et al. (2010), referred to as BSW method in this paper, to estimate the proportion of skilled funds (those with a positive alpha, net of trading costs and expenses), zero-alpha funds, and unskilled funds (those with a negative alpha) in the entire population. This paper extends the BSW method to evaluate hedge fund manager performance, to attribute any excess performance to either luck or skill, and to identify underlying fund strategies that can explain any excess performance. The luck versus skill debate has been extended from the U.S. mutual fund market to the U.K. mutual fund market by Cuthbertson et al. (2008), to the Chinese mutual fund market by Yang and Liu (2017), to the Australian managed funds by Kim et al. (2014), and to large-cap value funds by Cornell (2009). Besides, Malladi and Fabozzi (2017) quantified manager skill by creating metrics based on returns of 'confidential holdings' of U.S. hedge fund managers. In this paper, an attempt is made to extend the luck versus skill debate using the FDR method to hedge funds.

Data

Monthly global hedge fund returns (including fund of funds) are obtained from the TASS database (TASS, 2012) for all 6,392 hedge funds (including fund of funds) between March 1999 to January 2012. A total of 420,432 hedge fund monthly returns are analyzed in this paper. These funds include both active and inactive (i.e., closed, liquidated, or stopped reporting for any reason). Data beyond 2012 could not be obtained though it would have been helpful. The window of analysis includes both the dot-com and the financial crisis periods. The trend line showing the number of funds, as well as the average monthly returns of all funds are provided in Figure 1 and Table 1. Fund performance calculations are performed based on Fung and Hsieh (2001) with data obtained from their website (Hsieh, 2012).

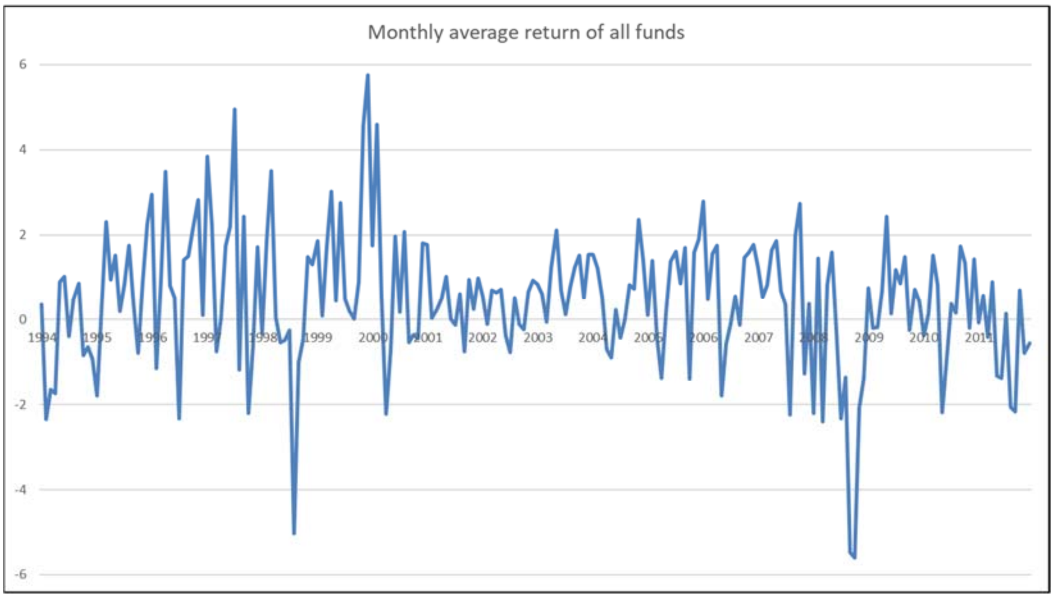

Figure 1: Average monthly return of the 6,392 hedge funds from 03/1999 to 01/2012.

Table 1: Descriptive statistics of hedge fund monthly returns (from 03/1999 to 01/2012).

Descriptive Statistics of Monthly Returns (in %)	
Number of hedge funds	6,392
Number of Monthly Returns	420,432
Mean	0.46
Standard Error	0.11
Median	0.52
Standard Deviation	1.56
Kurtosis	2.52
Skewness	-0.36

Range	11.34
Minimum	-5.59
Maximum	5.75

False Discovery Rate (FDR)

A seemingly reasonable way to estimate the prevalence of skilled fund managers is to count the number of funds with sufficiently high estimated alphas, $\hat{\alpha}$. In implementing such a procedure, one is conducting a multiple hypothesis test because all funds are being examined rather than just one fund. However, a simple count of significant-alpha funds does not properly adjust for luck in such a multiple test setting —many of the funds will have significant estimated alphas by luck alone (i.e., their true alphas are zero).

Three different performance categories are defined as follows (note the difference between actual (or true) alpha α, and estimated alpha $\hat{\alpha}$.

(1) Unskilled funds: Funds that have managers with stock-picking skills insufficient to recover their trading costs and expenses, creating an alpha shortfall: $\alpha < 0$. The proportion of the unskilled funds in the population is denoted by π_A^-.

(2) Zero-alpha funds: Funds that have managers with stock-picking skills sufficient to recover trading costs and expenses, $\alpha = 0$. The proportion of the zero-alpha funds in the population is denoted by π_0.

(3) Skilled funds: Funds that have managers with stock-picking skills sufficient to provide an alpha surplus beyond simply recovering trading costs and expenses, creating an alpha surplus, $\alpha > 0$. The proportion of the skilled funds in the population is denoted by π_A^+. The sum of π_A^-, π_0, and π_A^+ is 100%.

To illustrate, consider a population of funds with skills just sufficient to cover trading costs and expenses (truly zero-alpha funds). With a significance level of 5%, one should expect that 5% of these zero-alpha funds will have significant estimated alphas. Some of them will be unlucky (significant with $\hat{\alpha} < 0$). Others will be lucky (significant with $\hat{\alpha} > 0$), but all will be *false discoveries*: funds with significant estimated alphas $\hat{\alpha} > 0$, but zero true alphas α. The BSW approach much more precisely estimates the proportions of unskilled and skilled funds in the population (those with truly negative and positive alphas, respectively), and their respective locations in the left and right tails of the cross-sectional estimated alpha (or estimated alpha *t*-statistic) distribution.

One main virtue of this approach is its simplicity: to determine the frequency of false discoveries, the only parameter needed is the proportion of zero-alpha funds in the population, π_0. Rather than arbitrarily impose a prior assumption on π_0, this approach estimates it with a straightforward computation that uses the p-values of individual fund estimated alphas—no further econometric tests are necessary. A second advantage is its accuracy over the standard approach that assumes a null hypothesis that all funds have an alpha of zero to control for luck.

How does one measure the frequency of false discoveries in the tails of the cross-sectional (alpha) t-distribution? The null hypothesis, H_0, is that fund i has no abnormal performance, and the alternative hypothesis, H_A, being that the fund delivers either positive or negative performance:

$$H_0 : \alpha_i = 0,\ H_A : \alpha_i > 0 \text{ or } \alpha_i < 0 \qquad (1)$$

At a given significance level, γ, it is clear that the probability that a zero-alpha fund exhibits luck equals $\gamma/2$. If the proportion of zero-alpha funds in the population is π_0, the expected proportion of false positives, or "lucky funds", or zero-alpha funds with positive and significant t-statistics is

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

Suppose that one chooses a significance level, γ, of 10%. Of course, one cannot observe the true alphas of each fund in the population. So, how does one best infer the prevalence of each of the above skill groups from performance estimates for individual funds? First, use the t-statistic, $\hat{t}_i = \hat{\alpha}_i/\hat{\sigma}_{\hat{\alpha}_i}$, as the performance measure in which the numerator is the estimated alpha for fund i, and the denominator is the estimated standard deviation. Kosowski et al. (2007) show that a t-statistic has superior statistical properties relative to the alpha because alpha estimates have differing precision across funds with varying lives and portfolio volatilities.

Since $E(F_\gamma^+)$ is the expected proportion of false positives, or lucky funds, and $E(S^+)$ is the significant positive alpha funds, or expected proportion of lucky and skilled funds, calculate the expected proportion of truly skilled funds, $E(T^+)$. The following denotations are used: $\widehat{T_\gamma^+}$ for truly skilled funds, $\widehat{S_\gamma^+}$ for significant alpha funds, and $\widehat{F_\gamma^+}$ for false discoveries (i.e., lucky funds). They can be decomposed as follows.

$$\widehat{T_\gamma^+} = \widehat{S_\gamma^+} - \widehat{F_\gamma^+} = \widehat{S_\gamma^+} - \hat{\pi}_0\gamma/2 \qquad (3)$$

$$E(T_\gamma^+) = E(S_\gamma^+) - E(F_\gamma^+) = E(S_\gamma^+) - \pi_0\gamma/2 \qquad (4)$$

By the same token, the proportion of funds with a negative and significant t-statistic, $E(S_\gamma^-)$, overestimates the proportion of unskilled funds because it includes some unlucky zero-alpha funds. Because the probability of a zero-alpha fund being unlucky is also equal to $\gamma/2$, the expected proportion of unskilled funds is

$$E(T_\gamma^-) = E(S_\gamma^-) - E(F_\gamma^-) = E(S_\gamma^-) - \pi_0\gamma/2 \qquad (5)$$

The FDR among the statistically significant positive-alpha funds, or expected proportion of lucky funds in the portfolio at the significance level γ, is

$$FDR_\gamma^+ = E\left(F_\gamma^+\right)/E\left(S_\gamma^+\right) = \pi_0\gamma/2E(S_\gamma^+) \qquad (6)$$

Now one can estimate the proportions of unskilled and skilled funds in the entire population π_A^- and π_A^+, simply by choosing an appropriately large value for γ. Ultimately, as γ increases, $E\left(T_\gamma^-\right)$ and $E\left(T_\gamma^\mp\right)$ converge to π_A^- and π_A^+, thus minimizing Type II error (failing to locate truly unskilled or skilled funds).

FDR Bootstrap Method

The next key step is to estimate π_0, the proportion of zero-alpha funds, using the fund returns data. The FDR bootstrap procedure proposed by Storey (2002) and Storey et al. (2004) is used to estimate π_0. The FDR approach is very straightforward, as its sole inputs are the (two-sided) p-values associated with the (alpha) t-statistics of each of the M funds. In our case M = number of hedge funds (including fund of funds) = 6,392. For any given fund i (i=1,..., M), the estimated *p-value* is compared with a conventional significance level γ (5%, 10%, or Type I error). The null hypothesis of no performance is rejected if the p-value is smaller than γ, implying that fund i has a significant estimated alpha. Fund i is called significant if its p-value is smaller than γ.

By definition, zero-alpha funds satisfy the null hypothesis, $H_{0,i}: \alpha_i = 0$, and therefore have p-values that are uniformly distributed over the interval [0, 1]. In contrast, p-values of unskilled and skilled funds tend to be very small because their estimated t-statistics tend to be far from zero. This information is used to estimate π_0 without knowing the exact distribution of the p-values of the unskilled and skilled funds. The estimated proportion of zero-alpha funds, $\hat{\pi}_0(\lambda^*)$ where λ^* is a threshold value computed from the data so that a vast majority of fund's p-values larger than the threshold value λ^*. λ^* is chosen such that the mean square error (MSE) of $\hat{\pi}_0(\lambda)$, defined as $E(\hat{\pi}_0(\lambda) - \pi_0)^2$, is minimized. This means that

$$\lambda^* = argmin_\lambda \, \widehat{MSE}(\lambda) \qquad (7)$$

$$\widehat{\pi_0}(\lambda^*) = \frac{\widehat{W}(\lambda^*)}{M}\frac{1}{(1-\lambda^*)} \qquad (8)$$

First compute $\hat{\pi}_0(\lambda^*)$ using Equation (8) across a range of λ values (λ = 0.01, 0.05, 0.10, 0.20. . . 0.90, 0.95, and 0.99). In this Equation, $\widehat{W}(\lambda^*)$ is the number of funds with p-values exceeding λ^* and $\frac{\widehat{W}(\lambda^*)}{M}$ is the area covered by the bars to the right of λ, as plotted in Figure 2, based on the estimated p-values computed from the hedge funds return data. Second, the effect of changing λ^* on $\hat{\pi}_0(\lambda^*)$ is characterized using Equation (8). From this graph, one can see that the proportion of zero-alpha funds in the population, π_0, attains a minimum value, denoted as $\hat{\pi}_{min0}(\lambda)$. Third, for each possible value of λ, 1,000 bootstrap replications are created for $\hat{\pi}_0(\lambda)$ by drawing with replacement from a M x 1 vector of fund p-values. These are denoted by $\hat{\pi}_0^b(\lambda)$, where b=1, 2,..., 1000. Finally, λ^* is selected such that Equation (7) is satisfied, where

$$\widehat{MSE}(\lambda) = \frac{1}{1{,}000}\sum_{b=1}^{1{,}000}\left[\hat{\pi}_0^b(\lambda) - \hat{\pi}_{min0}(\lambda)\right]^2 \qquad (9)$$

Likewise, the unskilled fund returns have the least statistically significant relationship with the MSCI benchmark, whereas the skilled funds have the most significant relationship.

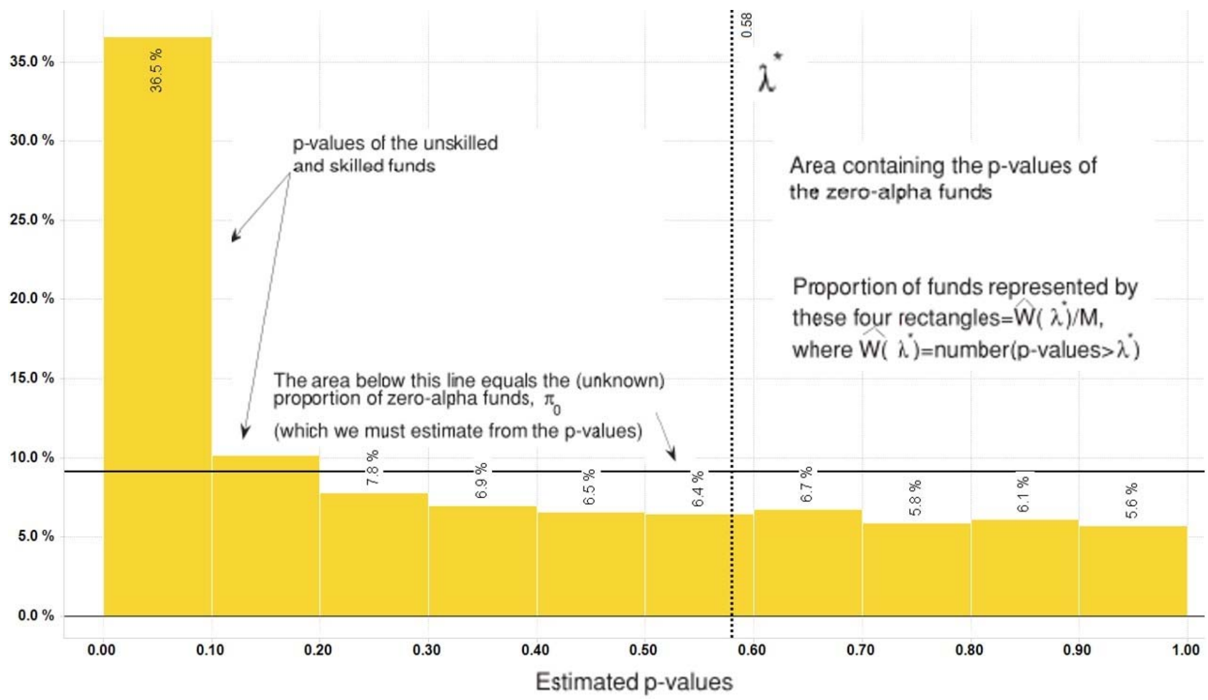

Figure 2: Histogram of fund p-values for M=6,392 funds.

The diagram in Figure 2 is used to estimate the proportion of zero-alpha funds, $\hat{\pi}_0(\lambda^*)$ where λ^* is a threshold value computed from the data such that a vast majority of fund's p-values larger than the threshold value λ^* come from zero-alpha funds. λ^* is computed as 0.58 such that the mean square error (MSE) of $\hat{\pi}_0(\lambda^*)$, defined as $E(\hat{\pi}_0(\lambda) - \pi_0)^2$, is minimized. The area under bars to the right of $\lambda^* = \frac{\widehat{W}(\lambda^*)}{M} = 6.39\%/5 + 6.68\% + 5.82\% + 6.05\% + 5.63\% = 25.47\%$. By substituting these values in Equation (8), $\hat{\pi}_0(\lambda^*) = 60.57\%$. This figure is formatted very similar to the one in Barras et al. (2010) for comparison purposes.

Although the main advantage of this procedure is that it is entirely data-driven, $\hat{\pi}_0(\lambda^*)$ is not overly sensitive to the choice of λ^*. For instance, a simple approach that fixes the value of λ^* to intermediate levels (such as 0.5 or 0.6) produces estimates similar to the MSE approach. By solving for λ in Equation (7), one can compute that λ^* is 0.58. From this value, the proportion of zero-alpha funds in the population, $\hat{\pi}_0(\lambda^*)$ can be computed as 60.57%. The proportion of skilled funds in the population, π_A^+ is 2.94% (188 out of M = 6,392). The rest are unskilled funds with a proportion, π_A^-, of 36.49%. The proportion of lucky funds is computed as 3.02% using Equation (2) for a given significance level γ of 10%.

After choosing a significance level, γ (e.g., 10%), observe whether $\hat{t}_i$ lies outside the thresholds implied by γ (denoted by t_γ^- and t_γ^+) and label it significant if it is such an outlier. When γ is 10%, t_γ^- is -1.65 and t_γ^+ is 1.65. The probability that the observed t-statistic is greater than t_γ^+ = 1.65 equals 5% for a zero-alpha fund and 91% for a skilled fund. Multiplying these two probabilities by the respective proportions represented by their categories (π_0 and π_A^+) yields 5.70%, or 5.70% of funds have a positive and significant t-statistic. This proportion is denoted by $E(S_\gamma^+)$ and includes both lucky and skilled funds, out of which the proportion of truly skilled funds, $E(T_\gamma^+)$, is computed using Equation (4) as 0.0570 - 0.03029 = 0.0268, or 2.68%. Similarly multiplying the two probabilities by the respective proportions represented by their categories (π_0 and π_A^-) yields 36.23%, meaning 36.23% of funds have a negative and significant t-statistic. This proportion is denoted by $E(S_\gamma^-)$ and includes both unlucky and skilled funds, out of which the proportion of truly unskilled funds, $E(T_\gamma^-)$, is computed using Equation (5) as 0.3623 - 0.03029 = 0.3320, or 33.20%. This implies that the $FDR_\gamma^+ = \pi_0\gamma/2E(S_\gamma^+) =$ (0.6057*0.1)/(2*0.057) = 53.13%, according to Equation (6). So, it can be concluded conclude from the data that only 2.68% of the 6,392 evaluated hedge funds are truly skilled, 33.20% are unskilled, and the remaining 64.13% are zero-alpha funds.

Fund Performance Model

To compute fund performance, the Fung-Hsieh benchmark model from Fung and Hsieh (2001) is used in this paper. Hedge fund strategies typically generate option-like returns. Linear-factor models using benchmark asset indices have difficulty explaining them. Fung-Hsieh model describes how to model hedge fund returns by focusing on the popular "trend-following" strategy, in addition to the equity and fixed-income oriented risk factors. In Hsieh (2012) model described in Equation (10), the first three factors are related to equity, next two for fixed-income, and the last three for trends of bonds, currencies, and commodities. These trend following factors capture nonlinear exposures to bonds, currencies, and commodities. All these eight factors are shown in Figure 3.

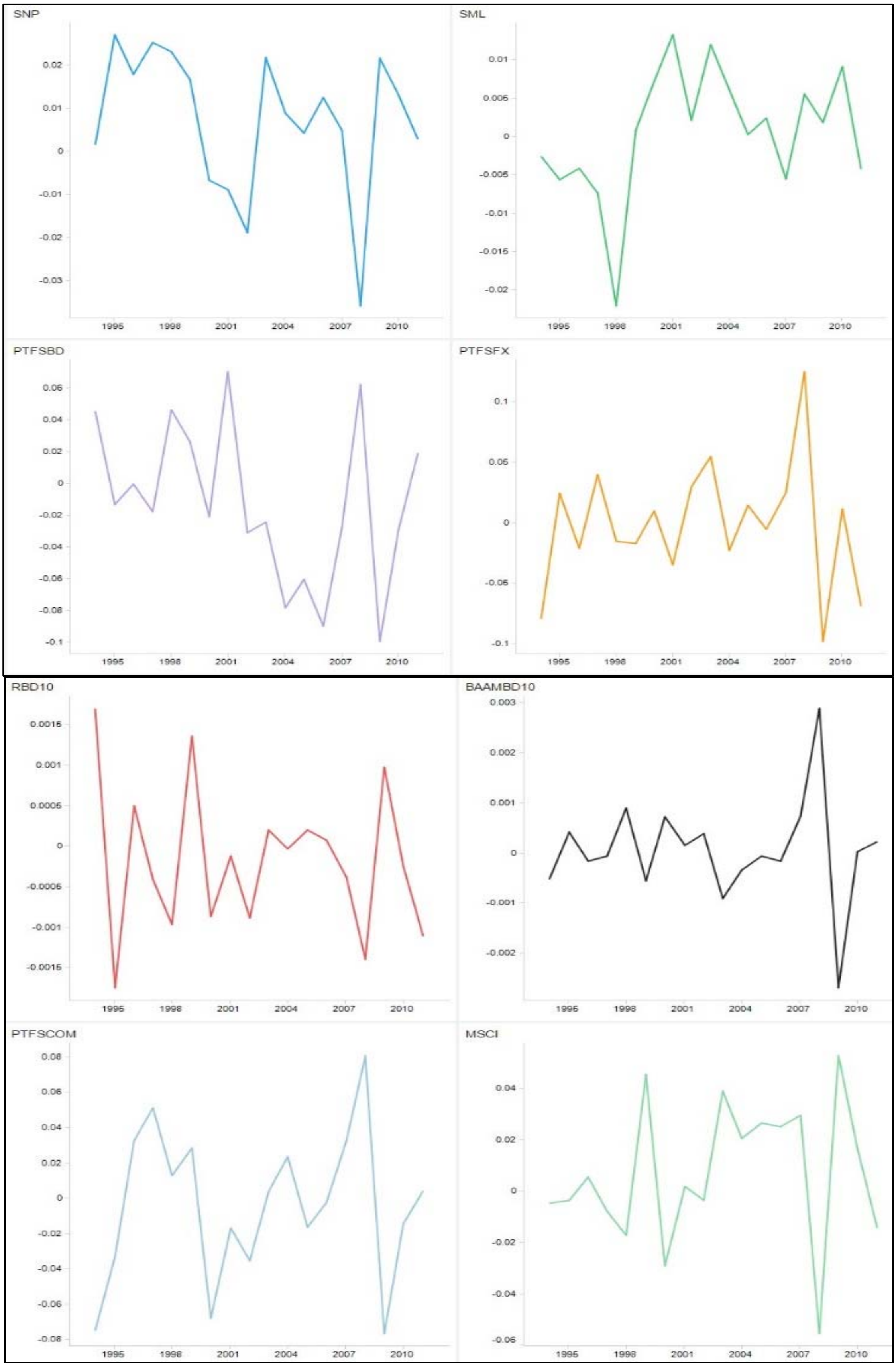

Figure 3: Eight underlying factors from 1999 to 2012, as shown in Equation (10).

$$r_{exc_{i,t}} = \alpha_i + \beta_i^1 SNP_{exc_t} + \beta_i^2 SML_t + \beta_i^3 MSCI_{em_t} + \beta_i^4 RBD10_t + \beta_i^5 BAAMBD10_t + \beta_i^6 PTFSBD_t + \beta_i^7 PTFSFX_t + \beta_i^8 PTFSCOM_t + \varepsilon_{i,t} \quad (10)$$

where, $r_{exc_{i,t}}$: excess returns of the hedge fund i in month t,
SNP_{exc_t}: monthly return on the S&P500 minus the 1-month T-bill return,
SML_t: Russell 2000 index monthly return minus S&P500 monthly return,
$MSCI_{em_t}$: monthly return on the MSCI Emerging Markets index,
$RBD10_t$: change in constant maturity yield 10-year T-note,
$BAAMBD10_t$: change in the spread between Moody's BAA bonds and 10-year T-note,
$PTFSBD_t, PTFSFX_t, PTFSCOM_t$: returns on Primitive Trend Following Strategies ($PTFS$) for bonds(BD), currency(FX), and commodities (COM).

Discussion

The results of the FDR analysis of hedge funds can be summarized in three ways. First, hedge fund manager's monthly returns are analyzed to understand if a hedge fund manager is producing superior returns, and how much of that return can be attributed to pure luck versus skill defined by the false discovery rate approach. Using the FDR bootstrap method as described in the FDR Bootstrap Method section, computations in this paper uncover that only 2.68% of the 6,392 evaluated hedge funds are truly skilled, 33.20% are unskilled, and the remaining 64.13% are zero-alpha funds.

Even though this paper focuses on hedge funds and previous papers focused on mutual funds, findings in this paper are broadly similar to the previous findings of other researchers. As reported by Fama and French (2010), only 2.3% of the mutual fund managers have an alpha of more than 2.5% per year. Similarly, Barras et al. (2010) have found that out of the 2,076 actively managed U.S. open-end, domestic equity mutual funds that existed between 1975 and 2006, 75.4% were zero-alpha funds, 24.0% were unskilled, while only 0.6% were skilled. Cuthbertson et al. (2008) have found that in aggregate, U.S. and U.K. mutual funds are made of 75.0% zero-alpha, 20.0% unskilled, and only 0.5% skilled. The results from these papers are summarized in Table 2. The skill level of hedge fund managers shows a similar pattern to the skill level of mutual fund managers (i.e., both groups have a very low proportion of skill and a high proportion of zero-alpha). However, as a group, hedge fund managers appear to be at least four times more skillful than mutual fund managers, supporting a body of evidence to back Berk and Green (2004) model of active portfolio management.

Table 2: Comparison of results from three papers.

	U.S. mutual funds (Barras et al., 2010)	U.K. mutual funds (Cuthbertson et al., 2008)	Global hedge funds (This Paper)
Unskilled	24.0%	20.0%	33.20%
Skilled	0.6%	0.5%	2.68%
Zero-alpha	75.4%	75.0%	64.13%

Second, the underlying portfolio characteristics of skilled and unskilled hedge fund managers are studied using the Fung and Hsieh (2001) model described in the Fund Performance Model section. Using the aggregate alpha at the fund level for a given month, multiple regression is conducted with the excess return of the hedge fund as the dependent variable and the eight factors as the independent variables. The monthly fund returns are analyzed at the aggregate level, and by the type of fund manager (unskilled, skilled, and zero-alpha), as measured by the FDR technique. The results are summarized in Table 3.

Most hedge funds track different benchmarks, such as the ones listed in Hedge Fund Research Indices (HFRI, 2012). Databases do not accurately report the underlying benchmark for a given hedge fund. So, the excess return of a hedge fund is computed as the difference between the fund return and the S&P500 return. The unskilled fund returns have the most statistically significant relationship (*p*-value of 0.02) with the underlying benchmark (S&P500), possibly due to index hugging (i.e., keeping investment weights very similar to the underlying index). Whereas, the skilled funds have the least significant relationship (*p*-value of 0.52) with the S&P500. As one would guess, the zero-alpha fund's *p*-value of 0.27 falls in between that of the unskilled and skilled funds. Likewise, the coefficients show that skilled-fund return (with a coefficient of 1.83) is less dependent on the S&P500 return than the unskilled-fund return (which has a coefficient of 5.21).

Finally, it can be observed in Table 3 that the skilled hedge funds use MSCI emerging market stocks, bonds, currencies, and commodities more effectively than the unskilled hedge funds – skilled fund returns show lower *p*-values and higher coefficients when compared to those of the unskilled funds. Since investing in these five categories of assets (i.e., emerging market stocks, bonds, currencies, and commodities) requires a sufficient amount of skill compared to the plain-vanilla S&P500 stocks, it can be interpreted that skilled hedge funds are adept at investing in complex asset categories across the globe and deploy a range of strategies (CFA Institute, 2019).

Table 3: Fund performance using Fung and Hsieh (2001) benchmark model.

Unskilled funds					Zero-alpha funds				
Multiple R	0.712				Multiple R	0.76			
R Square	0.506				R Square	0.57			
Adjusted R Square	0.487		N	2122	Adjusted R Square	0.55		N	4099
Standard Error	0.966				Standard Error	1.08			
	Coefficients	*Standard Error*	*t Stat*	*P-value*		*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Intercept	0.522	0.067	7.777	0.000	Intercept	(0.28)	0.08	(3.73)	0.00
SNP	5.212	2.231	2.336	0.020	SNP	(2.75)	2.50	(1.10)	0.27
SML	4.908	2.053	2.390	0.018	SML	(3.90)	2.30	(1.69)	0.09
MSCI	8.274	1.491	5.549	0.000	MSCI	(13.55)	1.67	(8.11)	0.00
RBD	(52.116)	32.484	(1.604)	0.110	RBD	41.30	36.41	1.13	0.26
BAAMBD	(159.471)	41.495	(3.843)	0.000	BAAMBD	185.28	46.50	3.98	0.00
PTFSBD	(0.655)	0.462	(1.420)	0.157	PTFSBD	0.20	0.52	0.39	0.70
PTFSFX	0.864	0.378	2.287	0.023	PTFSFX	(1.04)	0.42	(2.46)	0.01
PTFSCOM	0.983	0.526	1.869	0.063	PTFSCOM	(1.34)	0.59	(2.28)	0.02
Skilled funds					**All funds together**				
Multiple R	0.77				Multiple R	0.75			
R Square	0.59				R Square	0.56			
Adjusted R Square	0.58		N	171	Adjusted R Square	0.55		N	6392
Standard Error	1.22				Standard Error	1.05			
	Coefficients	*Standard Error*	*t Stat*	*P-value*		*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Intercept	0.11	0.08	1.30	0.20	Intercept	0.351	0.073	4.836	0.000
SNP	1.83	2.82	0.65	0.52	SNP	4.151	2.421	1.715	0.088
SML	3.03	2.59	1.17	0.24	SML	4.061	2.225	1.825	0.069
MSCI	16.85	1.88	8.94	0.00	MSCI	11.693	1.613	7.248	0.000
RBD	(36.68)	41.04	(0.89)	0.37	RBD	(44.921)	35.205	(1.276)	0.203
BAAMBD	(227.56)	52.43	(4.34)	0.00	BAAMBD	(199.289)	44.719	(4.456)	0.000
PTFSBD	0.05	0.58	0.09	0.93	PTFSBD	(0.394)	0.500	(0.788)	0.432
PTFSFX	1.13	0.48	2.37	0.02	PTFSFX	0.951	0.409	2.324	0.021
PTFSCOM	1.55	0.66	2.32	0.02	PTFSCOM	1.198	0.570	2.101	0.037

Conclusion

Using the FDR method, it is found that only 2.68% of the hedge funds are genuinely skilled, 33.20% are unskilled, and 64.12% are zero-alpha funds. There is evidence to suggest that unskilled funds may engage in index hugging. Whereas, skilled hedge funds use MSCI emerging market stocks, bonds, currencies, and commodities more effectively than the unskilled hedge funds. The skill level of hedge fund managers shows a similar pattern to the skill level of mutual fund managers (i.e., both groups have a very low proportion of skill and a high proportion of zero-alpha). However, as a group, hedge fund managers appear to be at least four times more skillful than mutual fund managers.

Managerial Implications

In the U.S., several public pension funds face unfunded liabilities (i.e., pension funds will not have sufficient assets to pay future retirees in full). These unfunded liabilities impact millions of current and future retirees. As of 2018, unfunded public pension liabilities top $6 trillion USD, amounting to $18,676 USD of unfunded liabilities for every U.S. resident. Lack of proper funding and artificially high estimates of future returns have prodded many pension funds into chasing higher returns. For instance, managers have shifted from fixed-income instruments (such as treasury bonds and high-grade corporate bonds) to publicly traded equity and also to alternative investments. This alternatives class of investments (including private equity, real estate, and hedge funds) is particularly problematic — Although an opportunity for outsized gains may exist, these investments are often riskier, more challenging to value, and less liquid (Powers et al., 2017). The fees charged by hedge funds, traditionally 2 percent of assets plus 20 percent of any profits, can be hundreds of times higher than those of the lowest-cost mutual funds (Weinberg, 2018). Investors pay a significantly higher fee to hedge fund managers hoping that the manager has skill in producing higher risk-adjusted returns. Therefore, investors (such as public pension funds) need to know if a manager is producing any excess returns due to luck or skill.

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Acknowledgment

I thank Professor Rene Garcia for his help in evaluating results and providing data, and Pallavi Malladi for providing statistical research and editorial support. I particularly acknowledge Dr. Eldon Y. Li, editor of the Journal of Business Management, for his helpful comments during the review and publication process.

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