# Measuring Managerial Skill in the Mutual Fund Industry*

August 28, 2012

**Abstract**

Using the dollar-value a mutual fund manager adds as the measure of skill, we find that not only does skill exist (the average mutual fund manager adds about $2 million per year), but this skill is persistent, as far out as 10 years. We further document that investors recognize this skill and reward it by investing more capital with skilled managers. Higher skilled managers are paid more and there is a strong positive correlation between current managerial compensation and future performance.

*We could not have conducted this research without the help of the following research assistants for which we are grateful: Ashraf El Gamal, Maxine Holland, Christine Kang, Fon Kulalert, Ian Linford, Binying Liu, Jin Ngai, Michael Nolop, William Vijverberg and Christina Zhu. We thank George Chacko, Rick Green, Ralph Koijen, David Musto, Paul Pfleiderer, Anamaria Pieschacon, Robert Stambaugh and seminar participants at Robeco, Stockholm School of Economics, Stanford, University of Chicago, University of Toronto, Vanderbilt, Wharton, the NBER summer institute, and the Stanford Berkeley joint seminar for helpful comments and suggestions.

An important principle of economics is that agents earn economic rents if and only if they have a skill in short supply. As central as this principle is to microeconomics, surprisingly little empirical work has addressed the question of whether or not talent is actually rewarded, or, perhaps more interestingly, whether people without talent can earn rents. One notable exception is the research on mutual fund managers. There, an extensive literature in financial economics has been amassed that has focused on the question of whether stock picking or market timing talent exists. The overall conclusion of that literature is that it does not. Considering that mutual fund managers are amongst the highest paid members of society, this conclusion appears to represent a challenge to the economic principle relating skill to rents. It implies that it is possible to make economic rents without possessing a skill in short supply.

Given the importance of the question, the objective of this paper is to re-examine whether or not mutual fund managers do earn economic rents without possessing skill. In contrast to the existing literature, we find that the average mutual fund manager uses his talents to add about $2 million a year. As to be expected, this skill is persistent. We show that it is possible to predict long-term outperformance as far out as 10 years into the future. We find that the distribution of managerial talent is consistent with the predictions of Lucas (1978) — higher skilled managers manage larger funds and reap higher rewards. One of our most surprising results is that investors appear to be able identify talent and compensate it. We demonstrate that there is a tight relationship between compensation and value added. In addition, current compensation predicts future performance.

Our methodology for measuring the value managers add differs from prior work in a number of important respects. First we use all actively managed mutual funds thereby greatly increasing the power of our tests. Prior work has used shorter time periods and focused attention exclusively on funds that hold only U.S. stocks. Second, we use a tradable benchmark to evaluate managers — all available Vanguard index funds (including balanced funds and funds that hold non-U.S. stocks). Prior work has used benchmarks that not only are not traded (and so ignore transactions costs) but were also not necessarily known or marketed at the time.

Finally, most prior studies use the net alpha to investors, i.e., the average abnormal return *net* of fees and expenses, as the measure of managerial skill. However, as Berk and Green (2004) argue, if managerial skill is in short supply, the net return is determined in equilibrium by competition between investors, and not by the skill of managers. One might hypothesize, based on this insight, that the *gross* alpha (the average abnormal return before fees) would be the correct measure of managerial skill, but this hypothesis is also flawed. The gross alpha is a *return* measure, not a *value* measure. That is, a manager who adds a gross alpha of 1% on a $10 billion fund adds more value than a manager who adds a gross alpha of 10% on a $1 million fund. Thus the correct measure of managerial skill is the expected value the manager adds, i.e., the product of the manager's abnormal return (his return before fees minus the benchmark return) and assets under management. This measure consists of two pieces: the amount of money the manager takes home for himself (his fee multiplied by the assets-under-management) plus the amount he takes from or gives to investors (the overall dollar under- or over-performance relative to the benchmark).

The primary objective of this paper is to measure the skill of mutual fund managers. Our perspective is therefore different from most papers in the mutual fund literature that are primarily concerned with the abnormal return investors earn in the fund. However we do provide new insight on that question as well. Once we evaluate managers against a tradable benchmark we no longer find evidence of underperformance. Over the time period in our sample, the equally weighted net alpha is 3 b.p./month and the value weighted net alpha is -1 b.p./month. Neither estimate is statistically significantly different from zero.

The rest of the paper is organized as follows. In the next section we briefly review the literature. In Section 2 we derive our measure of skill and in the following section explain how we estimate it. We describe the data in Section 4. Section 5 demonstrates that skill exists. We then analyze how this skill is rewarded in Section 6. Section 7 investigates what portion of managerial skill is attributable to diversification services rather than other sources such as stock picking or market timing and the following section shows the importance of using the full sample of active funds rather than the subset most researchers have used in the past. Section 9 concludes the paper.

## 1 Background

The idea that active mutual fund managers lack skill has its roots in the very early days of modern financial economics (Jensen (1968)). Indeed, the original papers that introduced the Efficient Market Hypothesis (Fama (1965, 1970)) cite the evidence that, as a group, investors in active mutual funds underperform the market, and, more importantly, mutual fund performance is unpredictable. Although an extensive review of this literature is beyond the scope of this paper, the conclusion of the literature is that, as investment vehicles, active funds underperform passive ones, and, on average, mutual fund returns before fees show no evidence of outperformance. As we have already mentioned, this evidence is taken to imply that active managers do not have the skills required to beat the market, and so in Burton Malkiel's words: the "study of mutual funds does not provide any reason to abandon a belief that securities markets are remarkably efficient." (Malkiel, 1995, p. 571)

In a recent paper on the subject, Fama and French (2010) re-examine the evidence and conclude that the average manager lacks skill. They do find some evidence of talent in the upper tail of the distribution of managers. However based on their estimate of skill (gross alpha) they conclude that this skill is economically small. In this paper we argue that the economic magnitude of skill can only be assessed by measuring the total dollar value added not the abnormal return generated. As we will see, when the economic value added is calculated by multiplying the abnormal return by assets under management, a completely different picture emerges in our dataset — the top 10% of managers are able to use their skill to add about $24 million a year, on average.

Researchers have also studied persistence in mutual fund performance. Using the return the fund makes for its investors, a number of papers (see Gruber (1996), Carhart (1997), Zheng (1999) and Bollen and Busse (2001)) have documented that performance is largely unpredictable, leading researchers to conclude that outperformance is driven by luck rather than talent.[1] In contrast, we show that the value added of a manager is persistent.

Despite the widespread belief that managers lack skill, there is in fact a literature in financial economics that does find evidence of skill. One of the earliest papers is Grinblatt and Titman (1989), which documents positive gross alphas for small funds and growth funds. In a followup paper (Grinblatt and Titman (1993)) these authors show that at least for a subset of mutual fund managers, stocks perform better when they are held by the managers than when they are not. Wermers (2000) finds that the stocks mutual funds hold outperform broad market indices, and Chen, Jegadeesh, and Wermers (2000) find that the stocks managers buy outperform the stocks that they sell. Kosowski, Timmermann, Wermers, and White (2006) use a bootstrap analysis and find evidence, using gross and net alphas, suggesting that 10% of managers have skill. Kacperczyk, Sialm, and Zheng (2008) compare the actual performance of funds to the performance of the funds' beginning of quarter holdings and find that for the average fund, performance is indistinguishable, suggesting superior performance gross of fees and thus implying that the average manager adds value during the quarter. Cremers and Petajisto (2009) show that the amount a fund deviates from its benchmark is associated with better performance, and that this superior performance is persistent. Finally, Cohen, Polk, and Silli (2010) and Jiang, Verbeek, and Wang (2011) show that this performance results from overweighing stocks that subsequently outperform the stocks that are underweighted.

There is also evidence suggesting where this skill comes from. Coval and Moskowitz (2001) find that geography is important — funds that invest a greater proportion of their assets locally do better. Kacperczyk, Sialm, and Zheng (2005) find that funds that concentrate in industries do better than funds that do not. Baker, Litov, Wachter, and Wurgler (2010) show that, around earnings announcement dates, stocks that active managers purchase outperform stocks they sell and Shumway, Szefler, and Yuan (2009) produce evidence that superior performance is associated with beliefs that more closely predict future performance. Cohen, Frazzini, and Malloy (2007) find that portfolio managers place larger bets on firms they are connected to

[1] Some evidence of persistence does exist in low liquidity sectors or at shorter horizons, see, for example, Bollen and Busse (2005), Mamaysky, Spiegel, and Zhang (2008) or Berk and Tonks (2007).

through their social network, and perform significantly better on these holdings relative to their non-connected holdings. These studies suggest that the superior performance documented in other studies in this literature is likely due to specialized knowledge and information.

Yet many researchers in financial economics remain unconvinced that mutual fund managers have skill. This reticence to accept the above evidence is at least partly attributable to the lack of any convincing evidence of the value added that results from this talent. Our objective is to provide this evidence.

## 2 Theory and Definitions

Let $R_{it}^n$ denote the excess return (that is, the return in excess of the risk free rate) earned by investors in the $i$'th fund at time $t$. This return can be split up into the return of the investor's next best alternative investment opportunity $R_{it}^B$, which we will call the manager's *benchmark*, and a deviation from the benchmark $\varepsilon_{it}$:

$$R_{it}^n = R_{it}^B + \varepsilon_{it}, \tag{1}$$

The most commonly used measure of skill in the literature is the mean of $\varepsilon_{it}$, or the *net alpha*, denoted by $\alpha_i^n$. Assuming that the benchmark return is observed (we relax this assumption later), the net alpha can be consistently estimated by:

$$\hat{\alpha}_i^n = \frac{1}{T_i}\sum_{t=1}^{T_i}\left(R_{it}^n - R_{it}^B\right) = \frac{1}{T_i}\sum_{t=1}^{T_i}\varepsilon_{it}. \tag{2}$$

where $T_i$ is the number of periods that fund $i$ appears in the database.

As we pointed out in the introduction, the net alpha is a measure of the abnormal return earned by investors, not the skill of the manager. To understand why, recall the intuition that Eugene Fama used to motivate the Efficient Market Hypothesis — just as the expected return of a firm does not reflect the quality of its management, neither does the expected return of a mutual fund. Instead, what the net alpha measures is the rationality and competitiveness of capital markets. A zero net alpha indicates that markets are competitive and investors rational. A positive net alpha implies that capital markets are not competitive, that the supply of capital is insufficient to compete away the abnormal return. A negative net alpha implies that investors are committing too much capital to active management — it is evidence of sub-optimality on the part of at least some investors.[2]

Some have argued that the gross alpha, $\alpha_i^g$, the abnormal return earned by fund $i$ before

[2]For a formal model that relates this underperformance to decreasing returns to scale at the industry level, see Pastor and Stambaugh (2010).

management expenses are deducted, should be used to measure managerial skill. Let $R_{it}^g$ denote the *gross* excess return, or the excess return the manager makes before he takes out his fee $f_{it}$:

$$R_{i,t}^g \equiv R_{it}^n + f_{i,t} = R_{it}^B + \varepsilon_{it} + f_{i,t} \tag{3}$$

The gross alpha can then be consistently estimated as:

$$\hat{\alpha}_i^g = \frac{1}{T_i}\sum_{t=1}^{T_i}\left(R_{it}^g - R_{it}^B\right) = \frac{1}{T_i}\sum_{t=1}^{T_i}\left(f_{i,t} + \varepsilon_{it}\right). \tag{4}$$

Unfortunately, gross alpha does not measure the skill of a manager either. Just as the internal rate of return cannot be used to measure the value of an investment opportunity (it is the net present value that does), the gross alpha cannot be used to measure the value of a manager. It measures the return the manager makes, not the value she adds.

To correctly measure the skill of the manager, one has to measure the dollar value of what the manager adds over the benchmark. To compute this measure, we multiply the benchmark adjusted realized gross return, $R_{it}^g - R_{it}^B$, by the real size of the fund (assets under management adjusted by inflation) at the end of the previous period, $q_{i,t-1}$, to obtain the realized value added between times $t-1$ and $t$:

$$V_{it} \equiv q_{i,t-1}\left(R_{it}^g - R_{it}^B\right) = q_{i,t-1}f_{i,t} + q_{i,t-1}\varepsilon_{it}, \tag{5}$$

where the second equality follows from (3). This estimate of value added consists of two parts — the part the manager takes home with him as compensation (the dollar value of all fees charged), which is necessarily positive, plus any value he provides (or extracts from) investors, which can be either positive or negative. Our measure of skill is the (time series) expectation of (5):

$$S_i \equiv E[V_{it}]. \tag{6}$$

For a fund that exists for $T_i$ periods this estimated value added is given by:

$$\hat{S}_i = \sum_{t=1}^{T_i}\frac{V_{it}}{T_i}. \tag{7}$$

The average value added can be estimated in one of two ways. If we are interested in the mean of the distribution managers are drawn from, what we term the *ex-ante* distribution, then a consistent estimate of average value added is given by:

$$\bar{S} = \frac{1}{N}\sum_{i=1}^{N}\hat{S}_i, \tag{8}$$

where $N$ is the number of mutual funds in our database. Alternatively we might be interested in the mean of surviving funds, what we term the *ex-post* distribution. In this case the average value added is estimated by weighting each fund by the number of periods that it appears in the database:

$$\bar{S}_W = \frac{\sum_{i=1}^{N} T_i \hat{S}_i}{\sum_{i=1}^{N} T_i}. \tag{9}$$

Before we turn to how we actually compute $V_{it}$ and therefore $S_i$, it is worth first considering what the main hypotheses in the literature imply about this measure of skill.

**Unskilled managers, irrational investors**

A widely accepted hypothesis and the one considered in Fama and French (2010) is that no manager has skill. We call this the *strong form* no-skill hypothesis, originally put forward by Eugene Fama in his Efficient Market papers. Because managers are unskilled and yet charge fees, these fees can only come out of irrational investors' pockets. These managers can either invest in the index, in which case they do not destroy value, or worse than that, follow the classic example of "monkey investing" by throwing darts and incurring unnecessary transaction costs. So under this hypothesis:

$$S_i \leq 0, \text{ for every } i, \tag{10}$$

$$\alpha_i^n \leq -\mathrm{E}\left(f_{it}\right), \text{ for every } i. \tag{11}$$

Because no individual manager has skill, the average manager does not have skill either. Thus this hypothesis also implies that we should expect to find

$$\bar{S} = \frac{1}{N}\sum_{i=1}^{N}\hat{S}_i \leq 0. \tag{12}$$

The latter equation can also be tested in isolation. We term this the *weak form* no-skill hypothesis. This weak-form hypothesis states that even though some individual managers may have skill, the average manager does not, implying that at least as much value is destroyed by active mutual fund managers as is created. We will take this two part hypothesis as the Null Hypothesis in this paper.

**Skilled managers, rational investors**

The second hypothesis we consider is motivated by Berk and Green (2004) and states that managers have skill that is in short supply. Because of competition in capital markets, investors do not benefit from this skill. Instead, managers derive the full benefit of the economic rents they generate from their skill. If investors are fully rational then these assumptions imply that the net return investors expect to make is equal to the benchmark return. That is:

$$\alpha_i^n = 0, \text{ for every } i. \tag{13}$$

Because fees are positive, the expected value-added is positive for every manager:

$$S_i > 0, \text{ for every } i. \tag{14}$$

When investors cannot observe skill perfectly, the extent to which an individual manager actually adds value depends on the ability of investors to differentiate talented managers from charlatans. If we recognize that managerial skill is difficult to measure, then one would expect unskilled managers to take advantage of this uncertainty. In this case we would expect to observe the presence of charlatans — managers who charge a fee but have no skill. Thus when skill cannot be perfectly observed, it is possible that for some managers $S_i \leq 0$. However, even when skill is not perfectly observable, because investors are rational, every manager must still add value in expectation. Hence, under this hypothesis, the average manager must generate value and hence we would expect to find:

$$\bar{S} > 0. \tag{15}$$

We will take this hypothesis as the Alternative Hypothesis in this paper.

Some have claimed, based on Sharpe (1991), that in a general equilibrium it is impossible for the average manager to add value. In fact this argument has two flaws. To understand the flaws, it is worth quickly reviewing Sharpe's original argument. Sharpe divided all investors into two sets: people who hold the market portfolio, who he called "passive" investors and the rest, who he called "active" investors. Because market clearing requires that the sum of active and passive investors' portfolios is the market portfolio, the sum of just active investors' portfolios must also be the market portfolio. This observation immediately implies that the abnormal return of the average active investor must be zero. As convincing as the argument appears to be, it cannot be used to conclude that the average active mutual fund manager cannot add value. In his definition of "active" investors, Sharpe includes *any* investor not holding the market, not just active mutual fund managers. If active individual investors exist, then as a group active mutual fund managers could provide a positive abnormal return by making trading profits from individual investors who make a negative abnormal return. Of course, as a group individual active investors are better off investing in the market, which leaves open the question of why these individuals are actively trading.

Perhaps more surprisingly to some, Sharpe's argument does not rule out the possibility that the average active manager can earn a higher return than the market return even if all investors, including individual investors, are assumed to be fully rational. What Sharpe's argument ignores is that even a passive investor must trade at least twice, once to get into the passive position and once to get out of the position. If we assume that active investors are better informed than passive, then whenever these liquidity trades are made with an active investor, in expectation, the passive investor must lose and the active must gain. Hence, the expected return to active investors must exceed the return to passive investors, that is, active investors earn a liquidity premium.

## 3 Choice of Benchmarks and Estimation

To measure the value the mutual fund manager either gives or takes from investors, her performance must be compared to the performance of the next best investment opportunity available to investors at that time, what we have termed the benchmark. Thus far we have assumed that this benchmark return is known. In reality it is not known, so in this section we describe two methods we use to identify the benchmark.

The standard practice in financial economics is to not actually construct the alternative investment opportunity itself, but rather simply adjust for risk using a factor model. In recent years the extent to which factor models accurately correct for risk has been subject to extensive debate. In response to this, mutual fund researchers have opted to construct the alternative investment opportunity directly instead of using factor models to adjust for risk. That is, they have interpreted the factors in the factor models as investment opportunities available to investors, rather than risk factors.[3] The problem with this interpretation is that these factor portfolios were (and in some cases are) not actually available to investors.

There are two reasons investors cannot invest in the factor portfolios. The first is straightforward: these portfolios do not take transaction costs into account. For example, the momentum strategy requires high turnover, which not only incurs high transaction costs, but also requires time and effort to implement. Consequently momentum index funds do not exist. The second is more subtle. Many of these factor portfolios were discovered well after the typical starting date of mutual fund databases. For example, when the first active mutual funds started offering size and value-based strategies, the alternative investment opportunity set was limited to investments in individual stocks and well-diversified index funds. That is, these active managers were being rewarded for the skill of finding a high return strategy that was not widely known. It has taken a considerable amount of time for most investors to discover these strategies, and so using portfolios that can only be constructed with the benefit of hindsight ignores the skill required to uncover these strategies in real time.

[3]See, for example, Fama and French (2010). Note that interpreting the benchmarks as alternative investment opportunities is not the same argument as the one made by Pastor and Stambaugh (2002) for using benchmarks.

For these reasons we take two approaches to measuring skill in this paper. First, we follow the recent literature by adopting a *benchmark approach* and taking a stand on the alternative investment opportunity set. Where we depart from the literature, however, is that we ensure that this alternative investment opportunity was marketed and tradable at the time. Because Vanguard mutual funds are widely regarded as the least costly method to hold a well diversified portfolio, we take the set of passively managed index funds offered by Vanguard as the alternative investment opportunity set.[4] We then define the benchmark as the closest portfolio in that set to the mutual fund. If $R_t^j$ is the excess return earned by investors in the $j$'th Vanguard index fund at time $t$, then the benchmark return for fund $i$ is given by:

$$R_{it}^B = \sum_{j=1}^{n(t)} \beta_i^j R_t^j, \tag{16}$$

where $n(t)$ is the total number of index funds offered by Vanguard at time $t$ and $\beta_i^j$ is obtained from the appropriate linear projection of the $i$'th active mutual fund onto the set of Vanguard index funds. By using Vanguard index funds as benchmarks, we can be certain that investors had the opportunity to invest in the funds at the time and that the returns of these funds necessarily include transaction costs and reflect the dynamic evolution of active strategies.[5]

Second, we use the traditional *risk-based approach.* The standard in the literature implicitly assumes the riskiness of the manager's portfolio can be measured using the factors identified by Fama and French (1995) and Carhart (1997), hereafter, the Fama-French-Carhart (FFC) factor specification. In this case the benchmark return is the return of a portfolio of equivalent riskiness constructed from the FFC factor portfolios:

$$R_{it}^B = \beta_i^{mkt}\text{MKT}_t + \beta_i^{sml}\text{SML}_t + \beta_i^{hml}\text{HML}_t + \beta_i^{umd}\text{UMD}_t$$

where $\text{MKT}_t, \text{SML}_t, \text{HML}_t$ and $\text{UMD}_t$ are the realizations of the four factor portfolios and $\beta_i^{\cdot}$ are risk exposures of the $i$'th mutual fund, which can be estimated by regressing the fund's return onto the factors. Although standard practice, this approach has the drawback that no theoretical argument exists justifying why these factors measure systematic risk in the economy. Fama and French (2010) recognize this limitation but argue that one can interpret the factors as simply alternative (passive) investment opportunities. As we point out above, such an interpretation is

[4]The ownership structure of Vanguard — it is owned by the investors in its funds — also makes it attractive as a benchmark because there is no conflict of interest between the investors in the fund and the fund owners. Bogle (1997) provides a brief history of Vanguard's index fund business.

[5]Notice, also, that if we used this benchmark to evaluate the manager of one of the Vanguard index funds themselves, we would get that this manager adds value equal to the dollar value of the fees he charges. Vanguard managers add value because they provide investors with the lowest cost means to diversification. By using net returns on Vanguard index funds we are explicitly accounting for the value added of diversification services. Because active managers also provide diversification services our measure credits them with this value added as well. We separate the value added from diversification and other skills in Section 7.

only valid when the factors are tradable portfolios.

| Fund Name | Ticker | Asset Class | Inception Date |
|---|---|---|---|
| S&P 500 Index | VFINX | Large-Cap Blend | 08/31/1976 |
| Extended Market Index | VEXMX | Mid-Cap Blend | 12/21/1987 |
| Small-Cap Index | NAESX | Small-Cap Blend | 01/01/1990* |
| European Stock Index | VEURX | International | 06/18/1990 |
| Pacific Stock Index | VPACX | International | 06/18/1990 |
| Value Index | VVIAX | Large-Cap Value | 11/02/1992 |
| Balanced Index | VBINX | Balanced | 11/02/1992 |
| Emerging Markets Stock Index | VEIEX | International | 05/04/1994 |
| Mid-Cap Index | VIMSX | Mid-Cap Blend | 05/21/1998 |
| Small-Cap Growth Index | VISGX | Small-Cap Growth | 05/21/1998 |
| Small-Cap Value Index | VISVX | Small-Cap Value | 05/21/1998 |

Table 1: **Benchmark Vanguard Index Funds:** This table lists the set of Vanguard Index Funds used to calculate the Vanguard benchmark. The listed ticker is for the Investor class shares which we use until Vanguard introduced an Admiral class for the fund, and thereafter we use the return on the Admiral class shares (Admiral class shares have lower fees but require a higher minimum investment.)

*NAESX was introduced earlier but was originally not an index fund. It was converted to an index fund in late 1989, so the date in the table reflects the first date we included the fund in the benchmark set.

We picked eleven Vanguard index funds to use as benchmark funds – see Table 1. We arrived at this set by excluding all bond or real estate index funds and any fund that was already spanned by existing funds.[6] Because the eleven funds do not exist throughout our sample period, we first arrange the funds in order of how long they have been in existence. We then construct an orthogonal basis set out of these funds by projecting the $n^{th}$ fund onto the orthogonal basis produced by the first $n-1$ funds over the time period when the $n^{th}$ fund exists. The mean plus residual of this projection is the $n^{th}$ fund in the orthogonal basis. In the time periods in which the $n^{th}$ basis fund does not exist, we insert zero. We then construct an augmented basis by replacing the zero in the time periods when the basis fund does not exist with the mean return of the basis fund when it does exist. We show in the appendix that value added can be consistently estimated by first computing the projection coefficients ($\beta_i^j$ in (16)) using the augmented basis and then calculating the benchmark return using (16) and the basis where missing returns are replaced with zeros.

To quantify the advantages of using Vanguard funds rather than the FFC factor mimicking portfolios as benchmark funds, Table 2 shows the results of regressing each FFC factor mimicking

[6] The complete list of all Vanguard's Index funds can be found here: https://personal.vanguard.com/us/funds/vanguard/all?reset=true&mgmt=i.

portfolio on the basis set of passively managed index funds offered by Vanguard. Only the market portfolio does not have a statistically significant positive alpha. Clearly, the FFC factor mimicking portfolios were better investment opportunities than what was actually available to investors at the time. In addition, the $R^2$ of the regressions are informative. The value/growth strategy became available as an index fund after size, so it is not surprising that the $R^2$ of the SMB portfolio is higher than the HML portfolio. Furthermore, the momentum strategy involves a large amount of active trading, so it is unlikely to be fully captured by passive portfolios, which accounts for the fact that the UMD portfolio has the lowest $R^2$ and the highest alpha.

| | MKT | SMB | HML | UMD |
|---|---|---|---|---|
| Alpha (b.p./month) | 2 | 22 | 35 | 70 |
| $t$-Statistic | 0.83 | 2.80 | 3.37 | 3.38 |
| Adjusted $R^2$ | 99% | 74% | 52% | 15% |

Table 2: **Net Alpha of FFC Portfolios:** We regress each FFC factor portfolio on the Vanguard Benchmark portfolios. The table lists the estimate (in b.p./month) and $t$-statistic of the constant term (Alpha) of each regression, as well as the $R^2$ of each regression.

Given that the alpha of the FFC factor mimicking portfolios are positive, and that they do not represent actual investable alternatives, they cannot be interpreted as benchmark portfolios. Of course the FFC factor specification might still be a valid measure of risk. For completeness, we will report our results using both methods to calculate the fund's alpha, but we will always interpret the Vanguard funds as benchmark portfolios and the FFC factor specification as an adjustment for risk.

# 4 Data

Our main source of data is the CRSP survivorship bias free database of mutual fund data first compiled in Carhart (1997). The data set spans the period from January 1962 to March 2011. Although this data set has been used extensively, it still has a number of important shortcomings that we needed to address in order to complete our study. As a result we undertook an extensive data project to address these shortcomings, the details of which are described in a 17 page online appendix to this paper. The main outcome of this project is reported below.

Even a casual perusal of the returns on CRSP is enough to reveal that some of the reported returns are suspect. Because part of our objective is to identify highly skilled managers, misreported returns, even if random, are of concern. Hence we procured additional data from Morningstar. Each month, Morningstar sends a complete updated database to its clients. The monthly update is intended to completely replace the previous update. We purchased every update from January 1995 through March 2011, and constructed a single database by combining all the updates. One major advantage of this database is that it is guaranteed to be free of survivorship bias. Morningstar adds a new fund or removes an old fund in each new monthly update. By definition, it cannot change an old update because its clients already have that data. So we are guaranteed that in each month whatever data we have was the actual data available to Morningstar's clients at that time.

We then compared the returns reported on CRSP to what was reported on Morningstar. Somewhat surprisingly, 3.3% of return observations differed. Even if we restrict attention to returns that differ by more than 10 b.p., 1.3% of the data is inconsistent. An example of this is when a 10% return is accidentally reported as "10.0" instead of "0.10". To determine which database is correct we used dividend and net asset value (NAV) information reported on the two databases to compute the return. In cases in which in one database the reported return is inconsistent with the computed return, but the other database was consistent, we used the consistent database return. If both databases were internally consistent, but differed from each other, but within 6 months one data base was internally inconsistent, we used the database that was internally consistent throughout. Finally, we manually checked all remaining unresolved discrepancies that differed by more than 20 b.p. by comparing the return to that reported on Bloomberg. All told, we were able to correct about two thirds of the inconsistent returns. In all remaining cases we used the return reported on CRSP.

Unfortunately, there are even more discrepancies between what Morningstar and CRSP report for total assets under management (AUM). Even allowing for rounding errors, fully 16% of the data differs across the two databases. Casual observation reveals that much of this discrepancy appears to derive from Morningstar often lagging CRSP in updating AUM. Consequently, when both database report numbers we use the numbers reported on CRSP with one important exception. If the number reported on CRSP changed by more than $8\times$ (we observed a number of cases where the CRSP number is off by a fixed number of decimal places) and within a few months the change was reversed by the same order of magnitude, and, in addition, this change was not observed on Morningstar, we used the value reported on Morningstar. Unfortunately both databases contained significant numbers of missing AUM observations. Even after we used both databases as a source of information, 17.2% of the data was missing. In these cases we filled any missing observation by the most recent observation in the past. Finally we adjusted all AUM numbers by inflation by expressing all numbers in January 1, 2000 dollars.

The amount of missing expense ratio data posed a major problem.[7] To compute the gross return, expense ratios are needed and over 40% of expense ratios are missing on the CRSP

[7]Because fees from an important part of our skill measure, we chose not to follow Fama and French (2010) by filling in the missing expense ratios with the average expense ratios of funds with similar AUM.

database. Because expense ratios are actually reported annually by funds, we were able to fill in about 70% of these missing values by extending any reported observation during a year to the entire fiscal year of the fund and combining the information reported on Morningstar and CRSP. We then went to the SEC website and manually looked up the remaining missing values on EDGAR. At the end of this process we were missing only 1.6% of the observations, which we elected to drop.

Both databases report data for active and passively managed funds. CRSP does not provide any way to discriminate between the funds. Morningstar provides this information, but the accuracy of their classification is suspect. In addition we only have this information after 1995 when the Morningstar database begins. We therefore augmented the Morningstar classification by using the following algorithm to identify passively managed funds. We first generate a list of common phrases that appear in fund names identified by Morningstar as index funds. We then compile a list of funds with these common phrases that were not labeled as index funds by Morningstar and compile a second list of common phrases from these funds' names. We then manually checked the original prospectuses of any fund that contained a word from the first list but was not identified as an index fund at any point in its life by Morningstar or was identified as an index fund at some point in its life by Morningstar but nevertheless contained a phrase in the second list. Funds that were not tracked by Morningstar (e.g., only existed prior to 1995) that contained a word from the first list were also manually checked. Finally, we also manually checked cases in which fund names satisfied any of these criteria in some periods but not in others even when the Morningstar classification was consistent with our name classification to verify that indeed the fund had switched from active to passive or vice versa. We reclassified 14 funds using this algorithm.

It is important to identify subclasses of mutual funds because both databases report subclasses as separate funds. In most cases the only difference amongst subclasses is the amount of expenses charged to investors, so simply including them as separate funds would artificially increase the statistical significance of any identified effect. For funds that appear in the CRSP data base, identifying subclasses is a relatively easy process — CRSP provides a separator in the fund name (either a ":" or a "/"). Information after the separator denotes a subclass. Unfortunately, Morningstar does not provide this information, so for mutual funds that only appear on the Morningstar database we used the last word in the fund name to identify the subclass (the details of how we did this are in the online appendix). Once identified we aggregated all subclasses into a single fund.

We dropped all index funds, bond funds and money market funds[8] and any fund observations before the fund's (inflation adjusted) AUM reached \$5 million. We also dropped funds with less

[8] We classed a fund as a bond fund if it held, on average, less than 50% of assets in stocks and identified a money market fund as a fund that on average held more than 20% of assets in cash.

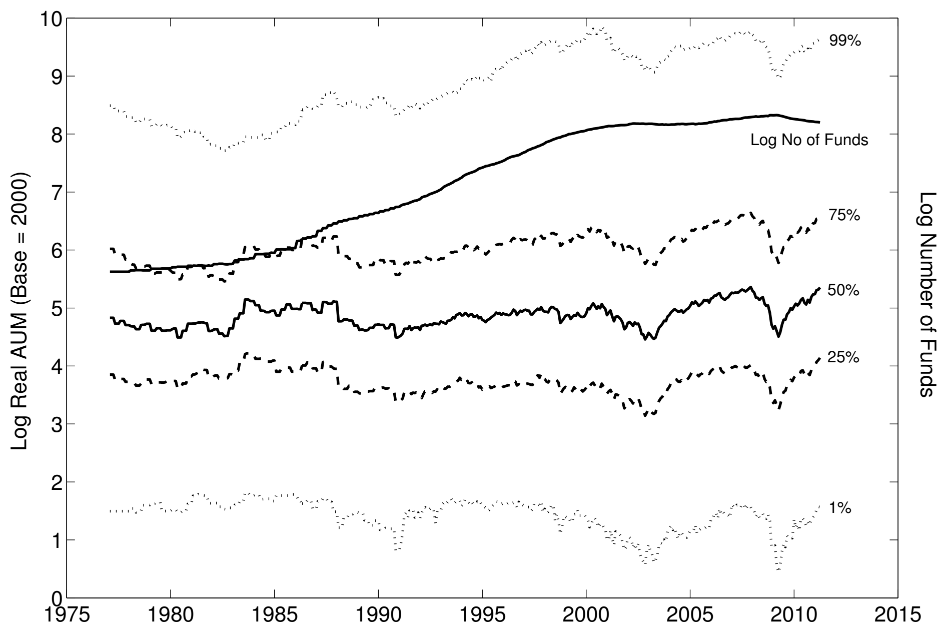



Figure 1: **Fund Size Distribution**
The graph displays the evolution of the distribution of the logarithm of real assets under management in $ millions (base year is 2000) by plotting the 1st, 25th, 50th, 75th and 99th percentiles of the distribution at each point in time. The solid black line is the logarithm of the total number of funds.

than 2 years of data. In the end we were left with 6054 equity funds. This sample is considerably larger than comparable samples used by other researchers. There are a number of reasons for this. Firstly, we do not restrict attention to funds that hold only U.S. equity. Clearly, managerial skill, if it exists, could potentially be used to pick non-U.S. stocks. More importantly, by eliminating any fund that at any point holds a *single* non-U.S. or bond, researchers have been eliminating managers who might have had the skill to market time by opportunistically moving capital either in and out of bonds or to and from the U.S.[9] Second, the Morningstar database contains funds not reported on CRSP. Third, we use the longest possible sample length available.

When we use the Vanguard benchmark to compute alpha we chose to begin the sample in the period just after Vanguard introduced its S&P 500 index fund — January, 1977. Because few funds dropped out of the database prior to that date, the loss in data is minimal — we are still left with 5974 funds.

[9]It is important to appreciate that most of the additional funds still hold mainly U.S. stocks, it is just that they also hold some non-U.S. stocks. As we will discuss in Section 7 expanding the sample to all equity funds is not innocuous — not only is the statistical power of our tests greatly increased but, more importantly, we will show that managerial skill is correlated to the fraction of capital in non-U.S. stocks.

# 5 Results

We begin by measuring managerial skill and then show that the skill we measure is persistent.

## 5.1 Measuring Skill

We begin by first estimating $S_i$ for every fund in our sample. Because $S_i$ is the product of the abnormal return and fund size, one may have concerns about whether the product is stationary. Figure 1 allays such concerns — median fund size has remained roughly the same over our sample period. As the black solid line in the figure makes clear, growth in the industry's assets under management is driven by increases in the number of funds rather than increases in fund size.

Table 3 provides the distribution of $S_i$ in our sample. The average manager adds an economically significant \$140,000 per month (in Y2000 dollars). The standard error of this average is just \$30,000, implying at $t$-statistic of 4.57. There is also large variation across funds. The least skilled manager amongst the top 1% of managers generated \$7.82 million per month. Even the least skilled manager amongst the top 10% of managers generated \$750,000 a month on average. The median manager lost an average of \$20,000/month and only 43% of managers had positive estimated value added. In summary, most funds destroyed value but because most of the capital is controlled by skilled managers, on average, active mutual funds added value.

Thus far we have ignored survivorship bias, that is, successful funds are more likely to survive than unsuccessful funds. Equivalently, one can think of the above statistics as estimates of the *ex-ante* distribution of talent. We can instead take account of the survivorship bias and compute the time-weighted mean given by (9). In this case we get an estimate of the *ex-post* distribution of talent. Not surprisingly this estimate is higher. The average manager added \$270,000/month. When we use the FFC factor specification to correct for risk, we obtain very similar results.[10]

It is tempting, based on the magnitude of our $t$-statistics to conclude that the Null (in both weak and strong form) can be rejected. However, caution is in order. There two reasons to believe that our $t$-statistics are overstated. First, there is likely to be correlation in value added across funds. Second, the value added distribution features excess kurtosis. Even though our panel includes 6000 funds and 411 months, the sample might not be large enough to ensure that the $t$-statistic is $t$-distributed. However, a central tenant of the literature on skill in mutual fund management is that if indeed managers have skill, then their skill should be persistent. Consequently, if the value added identified in Table 3 results from managerial skill rather than just luck, we must also see evidence that this measure of value added is persistent — managers that added value in the past should continue to add value in the future.

[10] For the reasons pointed out in Lillainmaa (2012) our measures of value added underestimates the true skill of managers.

| | Vanguard Benchmark | FFC Risk Measure |
|---|---|---|
| Cross-Sectional Mean | 0.14 | 0.10 |
| Standard Error of the Mean | 0.03 | 0.03 |
| $t$-Statistic | 4.57 | 3.43 |
| 1st Percentile | -3.60 | -3.93 |
| 5th Percentile | -1.15 | -1.43 |
| 10th Percentile | -0.59 | -0.77 |
| 50th Percentile | -0.02 | -0.03 |
| 90th Percentile | 0.75 | 0.70 |
| 95th Percentile | 1.80 | 1.98 |
| 99th Percentile | 7.82 | 6.76 |
| Percent with less than zero | 57.01% | 59.70% |
| Cross-Sectional Weighted Mean | 0.27 | 0.25 |
| Standard Error of the Weighted Mean | 0.05 | 0.06 |
| $t$-Statistic | 5.74 | 3.94 |
| No. of Funds | 5974 | 6054 |

Table 3: **Value Added ($\hat{S}_i$):** For every fund in our database we estimate the monthly value added, $\hat{S}_i$. The *Cross-Sectional* mean, standard error, $t$-statistic and percentiles are the statistical properties of this distribution. *Percent with less than zero* is the fraction of the distribution that has value added estimates less than zero. The *Cross-Sectional Weighted* mean, standard error and $t$-statistic are computed by weighting by the number of periods the fund exists, that is, they are the statistical properties of $\bar{S}_W$ defined by (9). The numbers are reported in Y2000 \$ millions per month.

To test for persistence we follow the existing literature and sort funds into deciles based on our inference of managerial skill. To infer skill at time $\tau$, we construct what we will term, the *Skill Ratio*, defined as:

$$SKR_i^\tau \equiv \frac{\hat{S}_i^\tau}{\sigma(\hat{S}^\tau)}, \tag{17}$$

where $\hat{S}_i^\tau = \sum_{t=1}^{\tau} \frac{V_{it}}{\tau}$ and $\sigma(\hat{S}_i) = \frac{\sqrt{\sum_{t=1}^{\tau}(V_{it}-S_i)^2}}{\tau}$. The skill ratio at any point in time is essentially the $t$-static of the value added estimate measured over the entire history of the fund until that time.[11] We term the time period from the beginning of the fund to $\tau$ the *sorting period*. That is, the funds in the 10th (top) decile are the funds where we have the most confidence that

[11] For ease of exposition, we have assumed that the fund that starts at time 1. For a fund that starts later, the start date in the skill ratio is adjusted to reflect this.

the actual value added over the sorting period is positive. Similarly, funds in the 1st (bottom) decile are funds where we have the most confidence that the actual value added in the sorting period is negative. We then measure the average value added of funds in each decile over a specified future time horizon, hereafter the *measurement horizon*.[12]

The main difficulty with implementing this strategy is uncertainty in the estimate of the fund's betas. When estimation error in the sorting period is positively correlated to the error in the measurement horizon, a researcher could falsely conclude that evidence of persistence exists when there is no persistence. To avoid this bias we do not use information from the sorting period to estimate the betas in the measurement horizon. This means that we require a measurement horizon of sufficient length to produce reliable beta estimates, so the shortest measurement horizon we consider is 3 years.

At the beginning of each time horizon, we use all the information until that point in time to sort firms into 10 deciles based on the skill ratio. As before we require a fund to have at least 2 years of data to be included in the sort. For each fund in each decile, we then calculate the value added, $\hat{S}_{i,\tau+m\rightarrow\tau+h}$, over different measurement horizons, $h$, varying between 36 to 120 months using only the information in the measurement horizon. Because we need a minimum number of months, $m$, to estimate the fund's betas in the measurement horizon, we drop all funds with less data than $m$. To remove the obvious selection bias, for the remaining funds we drop the first $m$ value added observations as well. Because the Vanguard Benchmark has at most 11 factors plus the constant, we use $m = 18$. We use $m = 6$ when we adjust for risk using the FFC factor specification. We then average over funds in each decile in each month, that is, we compute, for each decile, a monthly average value added. At the end of the horizon, funds are again sorted into deciles based on the skill ratio at that time and the process is repeated as many times as the data allows.[13] At the end of the process, in each decile, we have a time series of monthly estimates for average value added. For each decile, we then compute the mean of this time series and its standard error. Figure 2 plots this mean as well as the two standard error bounds for each decile and time horizon.

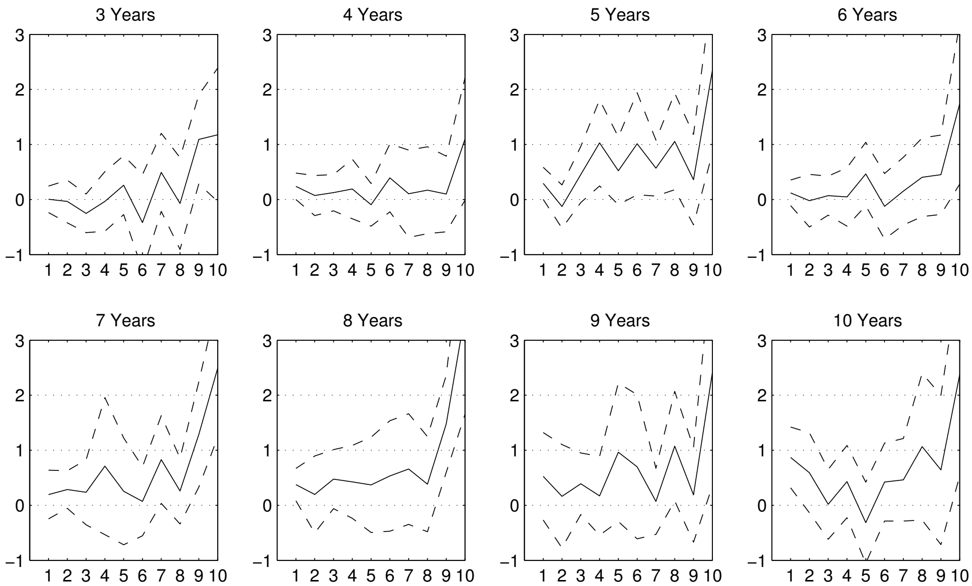
From Figure 2 it appears that there is evidence of persistence as far out as 10 years. The point estimate of the average value added of 10th decile managers is positive at every horizon and is always the best preforming decile. The value added estimates are economically large. Although clearly noisy, the average tenth decile manager adds around \$2 million/month. Table 4 formally tests the Null Hypothesis that the value added of 10th decile is zero or less, under the usual asymptotic assumptions. The Null is rejected at every horizon at the 95% confidence interval, however, as we have noted above we have concerns about the validity of the $t$-test.[14]

[12]Similar results obtain if we use the value added estimate itself to sort funds.

[13]We choose the starting point to ensure that the last month is always included in the sample.

[14]The earlier concerns are less important in this case because in each month we average over funds so the $t$-statistic is calculated using time series observations of the decile mean, thereby substantially reducing the effect

**Panel A:** Vanguard Benchmark




**Panel B:** FFC Risk Adjustment

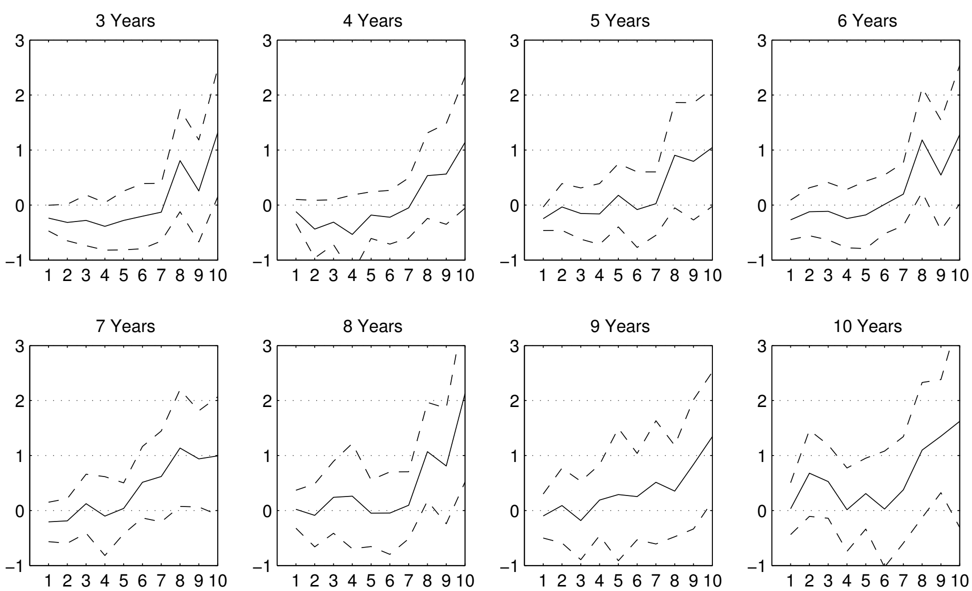



Figure 2: **Out of Sample Value Added**
Each graph displays average out of sample value added, $\hat{S}_i$ (in Y2000 \$ million/month), of funds sorted into deciles on the Skill Ratio, over the future horizon indicated. The solid line indicates the performance of each decile and the dashed lines indicated the two standard error bounds. Panel A shows the results when value added is computed using Vanguard index funds as benchmark portfolios and Panel B shows the results using the FFC risk adjustment.

| Horizon | Value Added | | Top Outperforms Bottom | | Top in Top Half | | Fraction of Total |
|---|---|---|---|---|---|---|---|
| Years | $ Mil | $p$-value (%) | Freq. (%) | $p$-value (%) | Freq. (%) | $p$-value (%) | **AUM** (%) |
| | | | Panel A: Vanguard Benchmark | | | | |
| 3 | 1.19 | 2.51 | 56.32 | 4.75 | 56.32 | 4.75 | 24.82 |
| 4 | 1.10 | 2.49 | 57.14 | 2.07 | 59.45 | 0.32 | 25.56 |
| 5 | 2.32 | 0.11 | 55.81 | 3.54 | 56.98 | 1.46 | 24.34 |
| 6 | 1.72 | 0.95 | 57.09 | 1.09 | 57.46 | 0.79 | 25.30 |
| 7 | 2.47 | 0.00 | 61.57 | 0.01 | 64.55 | 0.00 | 22.57 |
| 8 | 3.44 | 0.01 | 58.23 | 0.67 | 58.65 | 0.46 | 25.65 |
| 9 | 2.42 | 1.00 | 54.21 | 9.15 | 55.31 | 4.50 | 24.94 |
| 10 | 2.38 | 0.52 | 54.69 | 5.55 | 57.93 | 0.31 | 24.95 |
| | | | Panel B: FCC Risk Adjustment | | | | |
| 3 | 1.30 | 1.33 | 56.13 | 0.47 | 57.63 | 0.06 | 17.93 |
| 4 | 1.13 | 3.01 | 58.14 | 0.02 | 57.72 | 0.05 | 19.50 |
| 5 | 1.03 | 2.68 | 59.60 | 0.00 | 58.79 | 0.01 | 17.88 |
| 6 | 1.27 | 2.22 | 58.85 | 0.01 | 56.50 | 0.28 | 19.38 |
| 7 | 0.98 | 3.37 | 59.71 | 0.00 | 56.12 | 0.44 | 17.91 |
| 8 | 2.13 | 0.42 | 59.12 | 0.01 | 57.14 | 0.13 | 19.01 |
| 9 | 1.35 | 1.12 | 56.51 | 0.18 | 55.15 | 1.09 | 16.10 |
| 10 | 1.62 | 4.67 | 58.91 | 0.01 | 56.74 | 0.22 | 21.83 |

Table 4: **Out-of-sample Performance of the Top Decile:** The two columns labeled "Value Added" report the average value added of the top decile at each horizon and the associated $p$-value. The next two columns report the fraction of the time and associate $p$-value the top decile has a higher value added realization than the bottom decile. The columns labeled "Top in Top Half" report the fraction of time the realized value added of the top decile is in the top half and the final column reports the average fraction of total AUM in the top decile. All $p$-values are one tailed, that is, the probability, under the Null of the observed value or greater.

If managers are skilled, and there are cross-sectional differences in the amount of skill, then relative performance will be persistent. Hence we can use relative performance comparisons to construct a more powerful test of the Null hypothesis (that skill does not exist) by counting the number of times the 10th decile outperforms the 1st, and the number of times the 10th decile is in the top half.[15] As is evident from Table 4, the Null Hypothesis can be rejected at the 95% confidence level at almost all horizons. The FFC factor specification produces much more definitive results — with the sole exception of the 9 year horizon, the Null can be rejected at the 99% confidence level. Finally, note from the final column of Table 4 the disproportionate share of capital controlled by 10th decile managers. Investors clearly reward skilled managers

of cross fund correlation and excess kurtosis.

[15]Because the volatility of the deciles varies, we restrict attention to tests where the probability under the Null is not a function of the volatility of the decile.

| | Vanguard Benchmark | FFC Risk Measure |
|---|---|---|
| Equally Weighted | 2.74 | -3.88 |
| $t$-statistic | 0.73 | -1.40 |
| Value Weighted | -0.95 | -5.88 |
| $t$-statistic | -0.31 | -2.35 |

Table 5: **Net Alpha (in b.p./month):** The table reports the net alpha of two investment strategies: Investing \$1 every month by equally weighting over all existing funds (*Equally Weighted*) and investing \$1 every month by value weighting (based on AUM) over all existing funds (*Value Weighted*).

by providing them with more capital.

It might be tempting, based on our sorts, to conclude that all the skill is concentrated in 10th decile managers, that is, at most 10% of managers actually have skill. But caution is in order here. Our sorts are unlikely to separate skill perfectly. Although the estimates of value added in the other deciles are not significantly different from zero, they are almost all positive. Since we know that many managers destroyed value over the sample period, these positive point estimates imply that enough skilled managers are distributed throughout the other deciles to overcome the significant fraction of managers that destroy value.

### 5.2 Returns to Investors

Given the evidence of skill, a natural question to ask is who benefits from this skill? That is, do mutual fund managers (companies) capture all the rents from their skill, or are these rents shared with investors? Table 5 provides summary evidence. The average net alpha across all funds is not significantly different from zero, so there is no evidence that investors share in the fruits of this skill.

Slightly lower net alpha estimates are produced when the FFC factors are used as a measure of risk. But, as we have noted, relying on these estimates requires the additional assumption that this model correctly measures risk.

## 6 Skill and Labor Market Efficiency

To see how realized value added is cross-sectionally distributed in the sample, we sorted funds into deciles based on the Skill Ratio calculated over the whole sample. The first row of Table 6 gives the average value added in each decile. There is clearly large variation in the data. The worst decile destroyed almost \$800,000 (Y2000) per month while the largest decile added about

| | Deciles Sorted on Skill Ratio | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High |
| | Panel A: Vanguard Benchmark | | | | | | | | | |
| Value Added | -0.76 | -0.68 | -0.54 | -0.39 | -0.22 | -0.05 | 0.24 | 0.54 | 1.19 | 2.03 |
| Realized Net Alpha | -28 | -9 | -10 | -7 | -2 | 0 | 7 | 7 | 14 | 25 |
| AUM | 234 | 358 | 348 | 399 | 421 | 441 | 489 | 495 | 616 | 760 |
| Age | 141 | 220 | 198 | 217 | 209 | 238 | 247 | 242 | 240 | 234 |
| Compensation | 0.16 | 0.27 | 0.29 | 0.34 | 0.35 | 0.39 | 0.44 | 0.43 | 0.52 | 0.62 |
| Fees | 1.14 | 1.26 | 1.30 | 1.29 | 1.32 | 1.32 | 1.35 | 1.32 | 1.31 | 1.25 |
| | Panel B: FCC Risk Adjustment | | | | | | | | | |
| Value Added | -0.91 | -0.67 | -0.53 | -0.52 | -0.33 | -0.12 | 0.15 | 0.53 | 1.35 | 2.08 |
| Realized Net Alpha | -35 | -19 | -14 | -5 | -2 | 1 | 7 | 10 | 17 | 24 |
| AUM | 193 | 263 | 261 | 402 | 413 | 472 | 446 | 505 | 700 | 727 |
| Age | 196 | 245 | 208 | 265 | 230 | 231 | 233 | 243 | 241 | 276 |
| Compensation | 0.19 | 0.21 | 0.22 | 0.33 | 0.34 | 0.39 | 0.38 | 0.43 | 0.57 | 0.60 |
| Fees | 1.38 | 1.28 | 1.28 | 1.25 | 1.23 | 1.24 | 1.30 | 1.32 | 1.27 | 1.24 |

Table 6: **Characteristics of Deciles Sorted on the Skill Ratio:** *Value Added* is the within decile average $\hat{S}_i$ in Y2000 \$ millions/month, *Compensation* is the within decile average of $\sum q_{it} f_{it}/T_i$, (in Y2000 \$ millions/month), *Fees* (in %/annum) is the within decile average $\sum f_{it}/T_i$, *Realized Net Alpha* (in b.p./month) is the realized (*ex-post*) abnormal return to investors, AUM is average assets under management (in Y2000 \$ millions) and *Age* is the average number of monthly observations in the decile.

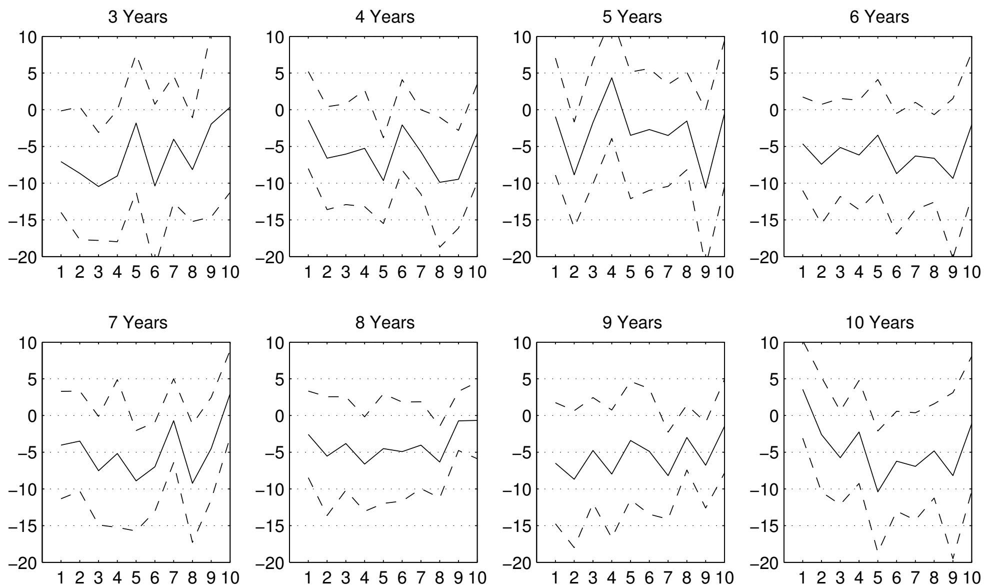
\$2 million. Only the top 4 deciles added value, but managers in these deciles controled 52% of the capital under management. Realized net-alpha increases over the deciles. Interestingly, the realized net alpha is greater than zero for all the deciles that added value and is less than zero in all deciles that destroyed value. At least *ex-post*, managers that added value also gave up some of this value to their investors.

What about *ex-ante*? That is, would an investor who identified a skilled manager based on passed data have expected a positive net alpha? To investigate this possibility, we calculate the average net alpha of investing in the out-of-sample sorts. That is, in each decile, for each fund and at each point in time we calculate the net abnormal return,

$$\varepsilon_{it} = R_{it}^n - R_{it}^B$$

over measurement horizons of 3 to 10 years. As before, we drop the first $m$ observations in the measurement horizon, where $m = 18$ or 6 months for the Vanguard Benchmark and the FFC factor specification respectively. We then compute, at each point in time, the weighted average net abnormal return of each decile. At the end of the process, in each decile, we have a time

**Panel A:** Vanguard Benchmark




**Panel B:** FFC Risk Adjustment

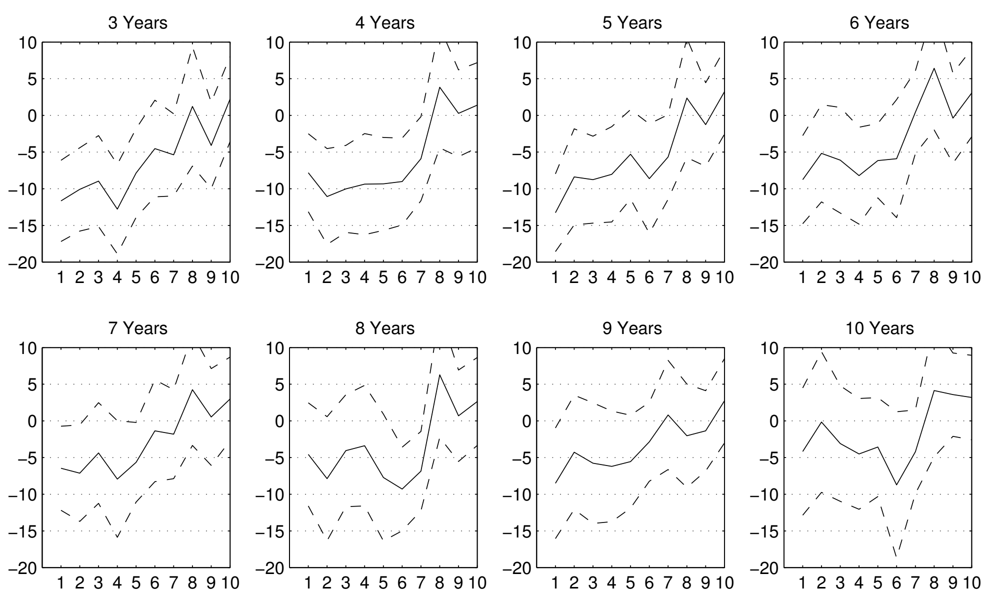



Figure 3: **Out of Sample Net Alpha**
Each graph displays the out of sample performance (in b.p./month) of funds sorted into deciles on the Skill Ratio, $\hat{S}_i$, over the horizon indicated. The solid line indicates the performance of each decile and the dashed lines indicated the 95% confidence bands (two standard errors from the estimate). Panel A shows the results when net alpha is computed using Vanguard index funds as benchmark portfolios and Panel B shows the results using he FFC risk adjustment.

| Horizon | Net-Alpha | | Top Outperforms Bottom | | Top in Top Half | |
|---|---|---|---|---|---|---|
| Years | b.p. | $t$-stat. | Freq. (%) | $p$-value (%) | Freq. (%) | $p$-value (%) |
| | | | Panel A: Vanguard Benchmark | | | |
| 3 | 0 | 0.06 | 54.21 | 13.82 | 58.42 | 1.21 |
| 4 | -3 | -0.95 | 55.76 | 5.15 | 57.14 | 2.07 |
| 5 | -1 | -0.11 | 52.33 | 24.68 | 52.33 | 24.68 |
| 6 | -2 | -0.43 | 54.91 | 5.84 | 55.27 | 4.56 |
| 7 | 3 | 0.99 | 58.58 | 0.29 | 60.08 | 0.06 |
| 8 | -1 | -0.29 | 53.17 | 18.16 | 56.54 | 2.56 |
| 9 | -1 | -0.46 | 53.11 | 16.64 | 56.41 | 1.97 |
| 10 | -1 | -0.24 | 47.90 | 78.71 | 52.10 | 24.74 |
| | | | Panel B: FCC Risk Adjustment | | | |
| 3 | 2 | 0.76 | 59.14 | 0.00 | 60.43 | 0.00 |
| 4 | 1 | 0.47 | 54.97 | 1.72 | 57.72 | 0.05 |
| 5 | 3 | 1.11 | 60.40 | 0.00 | 59.19 | 0.00 |
| 6 | 3 | 1.02 | 58.21 | 0.02 | 57.78 | 0.04 |
| 7 | 3 | 1.04 | 56.12 | 0.44 | 56.12 | 0.44 |
| 8 | 3 | 0.88 | 59.34 | 0.00 | 57.36 | 0.10 |
| 9 | 3 | 0.96 | 57.28 | 0.05 | 54.95 | 1.37 |
| 10 | 3 | 1.10 | 56.09 | 0.51 | 55.44 | 1.11 |

Table 7: **Out-of-sample Net-Alpha of the Top Decile:** The columns labeled "Net-Alpha" report the weighted average net alpha (in b.p./month) of the top decile at each horizon and the associated $p$-value. The next two columns report the fraction of the time and associate $p$-value the top decile has a net alpha realization greater than the bottom decile. The columns labeled "Top in Top Half" report the fraction of time the realized net alpha of the top decile is in the top half. All $p$-values are one tailed, that is, the probability, under the Null of the observed value or greater.

series of monthly estimates for the weighted average net alpha of each decile. The time series represents the strategy of investing $1 in each month in a value weighted portfolio of funds in the decile. That is, the strategy represents the return of an extra marginal dollar invested in each decile. To get the average net alpha of this strategy, we compute the mean of this time series and its standard error. Figure 3 plots this mean as well as the two standard error bounds for each decile and time horizon.

Almost all net alpha estimates are not statistically significantly different from zero. As we show in Table 7, the point estimates of the tenth decile are very close to zero and mostly negative. The order statistics in Table 7 confirm the overall impression from Figure 3, there is weak evidence of predictability in net alpha. Of the 16 order statistics, 7 of them have a one tailed $p$-value below 5% and only two are below 1%. So, at best, there is weak evidence that by picking the best managers, investors can get better returns than by picking the worst managers.

The evidence appears more consistent with the idea that competition in capital markets drives net alphas close to zero.

In this case there is a striking difference when we use the FFC factor specification as a risk adjustment — there is strong, statistically significant evidence of relative performance differences across the deciles (all but 3 of the order statistics are below 1% in this case). Both Figure 3 and Table 7 provide convincing out of sample evidence that investors could have done better by picking managers based on the Skill Ratio. These out of sample net alpha results are intriguing because they imply that either investors are leaving money on the table (not enough funds are flowing to the best managers resulting in positive net alphas), or investors do not care about the net alpha relative to the FFC factor specification, raising the possibility that the FFC factor specification does not measure risk investors care about.

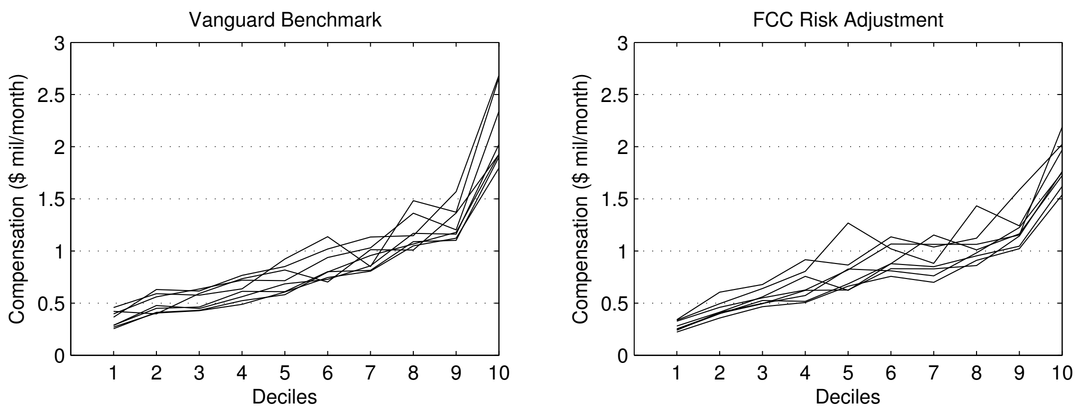



Figure 4: **Out of Sample Compensation**
The plots display the average out of sample monthly compensation of each decile sorted on the Skill Ratio using the Vanguard Benchmark and the FFC risk adjustment. Each line in the plots represents a different horizon, which varies between 3 and 10 years. For ease of comparison the data sample (time period) is the same for both plots.

The evidence actually paints a picture of remarkable labor market efficiency. First note, from Table 6, that the percentage fee is relatively constant across the deciles. However, average compensation across the deciles is close to monotonically increasing, especially in the extreme deciles where we have the most confidence of our estimates of value added. *Ex-post* there is a tight relationship between measured skill and compensation. What about *ex-ante* — once managers reveal their skill by adding value, do investors reward them with higher subsequent compensation? Figure 4 plots out-of-sample compensation and demonstrates that they do. Not only is compensation increasing in the deciles, but the average 10th decile manager earns considerably more than managers in the other deciles. Because the average fee does not differ by much across deciles, by choosing to allocate their capital to skilled managers, it is *investors* that determine these compensation differences, confirming a central insight in Berk and Green (2004).

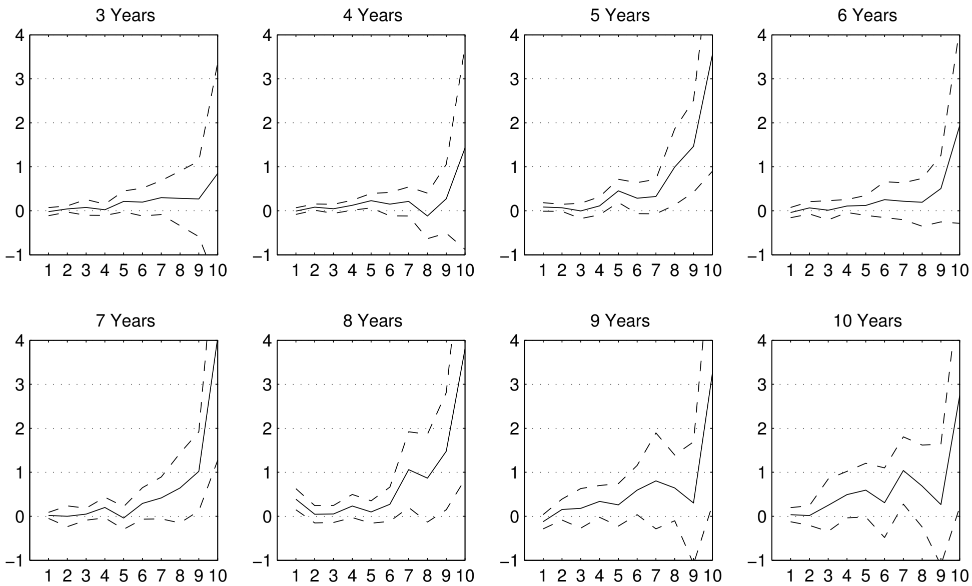
Figure 4 illustrates, again, that using the FFC risk adjustment makes a material difference. Compensation is still increasing in the deciles, but the differences are smaller than when the Vanguard benchmark is used.

If investors reward better managers with higher compensation, then they must be able to identify better managers *ex ante*. Thus, compensation should predict performance. To test this inference, we repeated the previous sorting procedure, except we use total compensation rather than the Skill Ratio to sort funds. That is, at the beginning of each time horizon, we use the product of the current AUM and fee to sort funds into the deciles and then follow the identical procedure we used before. Figure 5, summarizes the results — current compensation does predict future performance. When managers are sorted into deciles by their total compensation the relative difference in performance across the deciles is slightly larger than when the Skill Ratio is used.

One striking difference between when the sorts are based on compensation rather than the Skill Ratio (i.e., Figure 5 vs. Figure 2) is the increased monotonicity when the sorts are based on compensation. To formally document this difference we count the number of times each decile outperforms the next lowest decile (in terms of value added). Table 8 reports the $p$-value of observing the reported numbers under the Null hypothesis that there is no skill (so the probability is 1/2). The table confirms what the pictures imply. While the Skill Ratio can identify extreme performers, it does not differentiate the rest of managers very well. In contrast, investors appear to do a much better job correctly differentiating between managers at all skill levels. We again see a difference when the FFC factor specification is used to adjust for risk. In this case investors do not appear to differentiate as well, consistent with the prior evidence that compensation is not as highly correlated with subsequent performance. Again, the evidence is consistent with the idea that investors do not seem to care about outperformance relative to the FFC risk specification.

For many years now researchers have characterized the behavior of investors in the mutual fund sector as suboptimal — dumb investors chasing past returns. This evidence relating compensation to performance suggests quite the opposite conclusion. Investors appear able to differentiate good managers from bad, and compensate them accordingly. Notice from Figure 1 that real compensation for the top managers has increased over time — fund size has increased while fees have remained constant. On the other hand, for median managers real compensation has remained constant, suggesting that overall increases in compensation, in at least this sector of the financial services industry, are rewards for skill.

**Panel A:** Vanguard Benchmark




**Panel B:** FFC Risk Adjustment

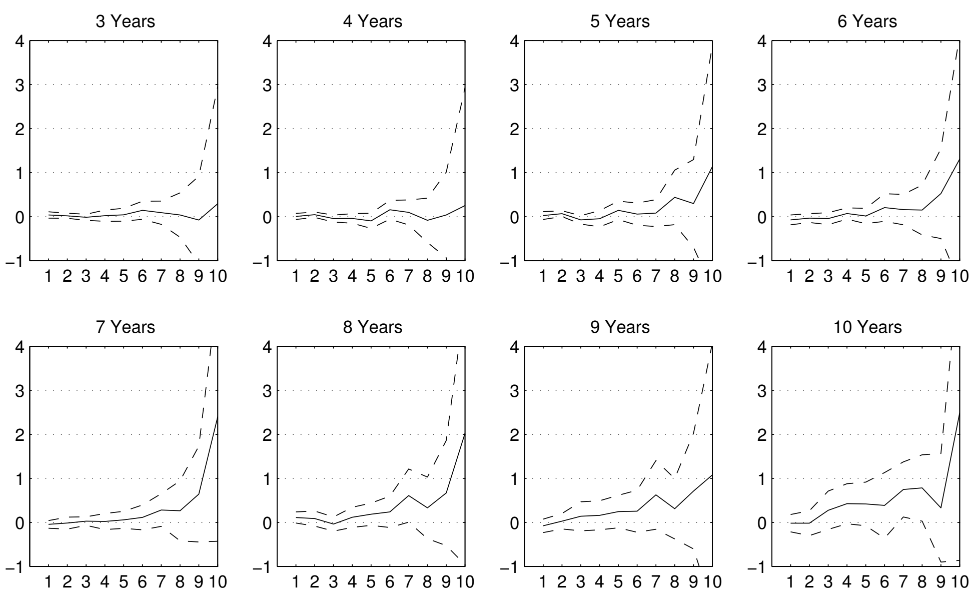



Figure 5: **Value Added Sorted on Compensation**
Each graph displays average out of sample value added, $\hat{S}_i$ (in Y2000 \$ million/month), of funds sorted into deciles based on total compensation (fees $\times$ AUM). The solid line indicates the performance of each decile and the dashed lines indicated the 95% confidence bands (two standard errors from the estimate). Panel A shows the results when value added is computed using Vanguard index funds as benchmark portfolios and Panel B shows the results using the FFC risk adjustment.

| | Vanguard Benchmark | | FFC Risk Adjustment | |
|---|---|---|---|---|
| Horizon | Skill Ratio | Compensation | Skill Ratio | Compensation |
| 3 | 18.55 | 9.17 | 2.76 | 72.15 |
| 4 | 3.51 | 1.87 | 12.20 | 4.89 |
| 5 | 18.61 | 0.02 | 8.40 | 48.81 |
| 6 | 4.57 | 9.23 | 0.58 | 3.24 |
| 7 | 15.92 | 5.85 | 0.53 | 17.52 |
| 8 | 4.16 | 3.79 | 4.88 | 25.58 |
| 9 | 28.61 | 14.71 | 5.97 | 3.90 |
| 10 | 53.02 | 0.25 | 16.38 | 4.82 |

Table 8: **Out-of-sample Monotinicity:** At each horizon we calculate the number of times each decile outperforms the next lowest decile. The table shows the $p$-value (in percent) of the observed frequency under the Null Hypothesis that skill does not exist, i.e., that for a sample length of N months, the probability of the event is Binomial$(9N, 1/2)$.

## 7 Analyzing Skill

The Vanguard benchmarks are constructed from net returns while the funds' value added numbers are constructed using gross returns. Because Vanguard index funds provide diversification services, this means our value-added measure includes both the diversification benefits as well as other skills and services managers provide. Therefore, if an active manager chooses to do nothing other than exactly replicate a Vanguard benchmark fund, we would compute a positive value added for that manager equal to the diversification benefits he provides (i.e., the fees charged by Vanguard times the size of the fund). So a natural question to ask is what fraction of value added is compensation for providing diversification and what fraction can be attributed to other skills.

We answer this question by recomputing value-added using the *gross* returns (including fees) of the Vanguard funds as the benchmark and comparing that to our earlier measures. The first two columns of Table 9 demonstrate that about half the value added is due to diversification benefits ($70,000 per month) and half ($70,000 per month) is due to other types of skill such as stock picking and/or market timing. The non-diversification skills are also persistent. As the bottom panel in Table 9 demonstrates, when funds are sorted on the Skill Ratio computed using gross returns, the top decile consistently outperforms the bottom decile.[16] So the evidence suggests that active managers provide more than just diversification benefits. Similar results obtain when we use the *ex-post* distribution of skill (i.e., equation 9) — slightly less than half the value added can be attributed to diversification benefits.

An alternative way to estimate how much diversification benefits mutual funds provide is to calculate the average value added of all the index funds in our database using Vanguard *net*

[16]The other order statistics also support persistence and are available on request.

| | **Active Funds** | | **Index Funds** | |
|---|---|---|---|---|
| | Vanguard Gross | Vanguard Net | Vanguard Gross | Vanguard Net |
| Number of funds | 5974 | 5974 | 644 | 644 |
| In Sample VA | | | | |
| Mean ($mil/mon) | 0.07 | 0.14 | -0.05 | 0.03 |
| $t$-statistic | 2.49 | 4.57 | -0.49 | 0.37 |
| Weighted Mean ($mil/mon) | 0.16 | 0.27 | -0.02 | 0.11 |
| $t$-statistic | 3.46 | 5.74 | -0.20 | 0.94 |
| 1st percentile | -3.83 | -3.60 | -6.18 | -5.98 |
| 5th percentile | -1.27 | -1.15 | -1.20 | -1.15 |
| 10th percentile | -0.64 | -0.59 | -0.53 | -0.47 |
| 50th percentile | -0.02 | -0.02 | -0.01 | 0.00 |
| 90th percentile | 0.61 | 0.75 | 0.50 | 0.76 |
| 95th percentile | 1.55 | 1.80 | 1.56 | 1.82 |
| 99th percentile | 7.56 | 7.82 | 4.83 | 4.83 |
| In Sample Net Alpha | | | | |
| Equally Weighted (b.p./mon) | - | 2.7 | - | -1.9 |
| $t$-statistic | - | 0.73 | - | -0.41 |
| Value Weighted (b.p./mon) | - | -1.0 | - | 1.3 |
| $t$-statistic | - | -0.31 | - | 0.65 |
| Persistence ($p$-value (%) of the top decile outperforming the bottom decile at each horizon) | | | | |
| 3 year horizon | 4.31 | 4.75 | - | - |
| 4 year horizon | 18.59 | 2.07 | - | - |
| 5 year horizon | 0.90 | 3.54 | - | - |
| 6 year horizon | 2.12 | 1.09 | - | - |
| 7 year horizon | 0.00 | 0.01 | - | - |
| 8 year horizon | 0.05 | 0.67 | - | - |
| 9 year horizon | 4.88 | 9.15 | - | - |
| 10 year horizon | 4.32 | 5.55 | - | - |

Table 9: **Performance of Active Funds and Index Funds:** The table computes the value-added, net alpha numbers and the $p$-value of the persistence order statistic that counts the number of times the top decile outperforms the bottom decile for the set of active mutual funds, and compares it the set of index funds (including the Vanguard index funds themselves). To separate the value added coming from diversification benefits vrs. stock picking/market timing, we use two different benchmarks: (1) Vanguard index funds gross returns and (2) Vanguard index funds net returns, labelled "Vanguard Gross" and "Vanguard Net" in the table.

returns as the benchmark. The fourth column of Table 9 provides the results of this exercise — index funds add approximately $30,000/month in diversification benefits. This estimate of the diversification benefits is lower than before because Vanguard is more efficient at providing diversification services than the average index fund — when value added of the average index fund is computed using Vanguard gross returns as the benchmark (third column of the table), the estimates are negative. This inefficiency is also reflected in the funds' net alphas — investors in Vanguard funds get the diversification benefits more cheaply than investors in other index funds.

# 8 Sample Selection

Because we do not exclude funds that invest internationally, the set of funds in our study is considerably larger than the set previously studied in the literature. One may therefore wonder to what extent the ability to invest in international stocks affects our value added numbers. We explore this question in Table 10 by forming subsamples of active and index funds based on their average portfolio weight in international stocks. We find that active funds that invested more in international stocks added more value. Indeed, funds that restricted themselves to only investing in U.S. stocks (on average, less than 10% in non-U.S. stocks) added no value on average.

One worry is that our Vanguard benchmark funds do not appropriately define the alternative investment opportunity set for international stocks, even though we include all the international index funds that Vanguard offers. If this explanation is right, it implies that index funds that invest more internationally will add more value. Table 10 shows that this is not the case. We find that index funds that invested more in international stocks added less value. Therefore, the *ex post* selection of active funds that have invested more or less in international funds appears to be correlated with skill. By excluding mutual funds that invest in international stocks, researchers may unknowingly introduced a selection bias into their results.

# 9 Conclusion

In this paper we provide evidence of the existence of rents that can be attributable to managerial skill. We show that the average mutual fund manager uses his skills to generate value — about $2 million/year. This value added cannot easily be attributable to luck alone because it is persistent. Managers sorted on this measure of skill continue to add value, in some cases for as long as 10 years into the future.

Perhaps our most surprising result is that investors appear to be able to identify and correctly reward this skill. Not only do better managers earn higher compensation, but compensation itself is a better predictor of future value added than past value added.

**Active Funds**

| | | Vanguard BM Net | | Vanguard BM Gross | |
|---|---|---|---|---|---|
| Frac. int. | No of funds | Mean VA | Mean VA TW | Mean VA | Mean VA TW |
| <10 | 3740 | 0 | 0.013 | -0.045 | -0.073 |
| <30 | 4617 | 0.055 | 0.126 | -0.002 | 0.025 |
| <50 | 4817 | 0.074 | 0.159 | 0.016 | 0.056 |
| <70 | 5002 | 0.106 | 0.219 | 0.045 | 0.113 |
| <90 | 5236 | 0.133 | 0.266 | 0.073 | 0.158 |
| $\leq$ 100 | 5974 | 0.135 | 0.269 | 0.072 | 0.162 |

**Index Funds**

| | | Vanguard BM Net | | Vanguard BM Gross | |
|---|---|---|---|---|---|
| Frac. int. | No of funds | Mean VA | Mean VA TW | Mean VA | Mean VA TW |
| <10 | 462 | 0.102 | 0.175 | 0.034 | 0.032 |
| <30 | 485 | 0.094 | 0.167 | 0.028 | 0.021 |
| <50 | 494 | 0.123 | 0.178 | 0.042 | 0.056 |
| <70 | 509 | 0.121 | 0.177 | 0.041 | 0.051 |
| <90 | 521 | 0.070 | 0.163 | 0.026 | -0.003 |
| $\leq$ 100 | 644 | 0.034 | 0.114 | -0.025 | -0.046 |

Table 10: **Fraction in International Funds and the Performance of Active Funds vs Index Funds:** The table computes value-added numbers for funds with varying degrees of international stock exposure. We compute the numbers for active as well as passive funds. We use two different benchmarks: (1) Vanguard index funds net returns and (2) Vanguard index funds gross returns.

Our results are consistent with the main predictions of Berk and Green (2004). Investors appear to be able to identify skilled managers and determine their compensation through the flow–performance relation. That model also assumes that because rational investors compete in capital markets, the net alpha to investors is zero, that is, managers are able to capture all economic rents themselves. In this paper we find that the average abnormal return to investors is close to zero. Further, we find little evidence that investors can generate a positive net alpha by investing with the best managers.

# Appendix

## A Benchmarks Funds with Unequal Lives

In this appendix we explain how we construct our set of benchmarks. We show how to evaluate a fund relative to two benchmarks that exist over different periods of time. The general case with $N$ benchmark funds is a straightforward generalization and is left to the reader.

Let $R_{it}^g$ denote the gross excess return of active fund $i$ at time $t$, which is stacked in the vector $R_i^g$ :

$$R_i^g = \begin{bmatrix} R_{i1}^g \\ \vdots \\ R_{iT}^g \end{bmatrix}$$

and let $R_{1t}^B$ denote the return on the first benchmark fund and $R_{2t}^B$ the return on the second benchmark fund, which, over the time period in which they both exist, form the matrix $R_t^B$:

$$R_t^B = \begin{bmatrix} R_{1t}^B & R_{2t}^B \end{bmatrix}.$$

Assume that the first benchmark fund is available to investors over the whole sample period, while the second benchmark fund is only available over a subset of the sample, say the second half.

Let $\beta$ denote the projection coefficient of $R_{it}^g$ on the first benchmark fund's return, $R_{1t}^B$, and let

$$\gamma \equiv \begin{bmatrix} \gamma_1 \\ \gamma_2 \end{bmatrix}.$$

denote the projection coefficients of $R_{it}^g$ on both benchmark funds, $R_{1t}^B$ and $R_{2t}^B$. Thus, during the time period when only the first benchmark exists, the value added of the fund at time $t$ is:

$$V_{it} = q_{i,t-1} \left( R_{it}^g - \beta R_{1t}^B \right). \tag{18}$$

When both benchmark funds are offered, the value-added in period $t$ is:

$$V_{it} = q_{i,t-1} \left( R_{it}^g - R_t^B \gamma \right). \tag{19}$$

Let there be $T$ time periods and suppose that the second benchmark fund starts in period $S+1$.

The matrix of benchmark return observations is given by:

$$X = \begin{bmatrix} 1 & R_{11}^B & \cdot \\ \vdots & \vdots & \cdot \\ 1 & R_{1S}^B & \cdot \\ 1 & R_{1,S+1}^B & R_{2,S+1}^B \\ \vdots & \vdots & \vdots \\ 1 & R_{1T}^B & R_{2T}^B \end{bmatrix}$$

where $\cdot$ indicates a missing value. Let $X^O$ denote the following orthogonal matrix:

$$X^O = \begin{bmatrix} 1 & R_{11}^B & \bar{R}_2^{BO} \\ \vdots & \vdots & \vdots \\ 1 & R_{1S}^B & \bar{R}_2^{BO} \\ 1 & R_{1,S+1}^B & R_{2,S+1}^{BO} \\ \vdots & \vdots & \vdots \\ 1 & R_{1T}^B & R_{2,T}^{BO} \end{bmatrix}$$

where:

$$\bar{R}_2^{BO} = \frac{\sum\limits_{t=S+1}^{T} R_{2t}^{BO}}{T-S}.$$

and where $R_{2,S+1}^{BO}, ..., R_{2,T}^{BO}$ are obtained by projecting $R_{2t}^B$ onto $R_{1t}^B$:

$$R_{2t}^{BO} = R_{2t}^B - \theta R_{1t}^B \text{ for } t = S+1, ..., T$$

where,

$$\theta = \frac{cov\left(R_{2t}^B, R_{1t}^B\right)}{var\left(R_{1t}^B\right)}.$$

Finally, define:

$$\hat{X}^O = \begin{bmatrix} 1 & R_{11}^B & 0 \\ \vdots & \vdots & \vdots \\ 1 & R_{1S}^B & 0 \\ 1 & R_{1,S+1}^B & R_{2,S+1}^{BO} \\ \vdots & \vdots & \vdots \\ 1 & R_{1T}^B & R_{2,T}^{BO} \end{bmatrix}.$$

**Proposition 1** *The value-added of the firm at any time $t$ can be estimated as follows:*

$$V_{it} = q_{i,t-1}\left(R_{it}^{g} - \zeta_2 \hat{X}_{2t}^{O} - \zeta_3 \hat{X}_{3t}^{O}\right) \tag{20}$$

*using a single OLS regression to estimate $\zeta$:*

$$\zeta = \left(X^{O\prime} X^{O}\right)^{-1} X^{O\prime} R_i^g.$$

**Proof:** The second and the third column of $X^O$ are orthogonal to each other, both over the full sample as well as over the two subsamples. Because of this orthogonility and $X_{2t}^O = R_{1t}^B$, the regression coefficient $\zeta_2$ is given by:

$$\zeta_2 = \frac{cov\left(R_{it}^g, R_{1t}^B\right)}{var\left(R_{1t}^B\right)} = \beta.$$

So for any $t \leq S$, (20) reduces to (18) and so this estimate of value added is consistent over the first subsample. Using the orthogonality of $X^O$,

$$\zeta_3 = \frac{cov\left(R_{it}^g, X_{3t}^O\right)}{var\left(X_{3t}^O\right)} = \frac{cov\left(R_{it}^g, R_{2t}^{BO}\right)}{var\left(R_{2t}^{BO}\right)},$$

rewiting

$$\gamma_1 R_{1t}^B + \gamma_2 R_{2t}^B = \gamma_1 R_{1t}^B + \gamma_2\left(\theta R_{1t}^B + R_{2t}^{BO}\right) = \left(\gamma_1 + \theta\gamma_2\right) R_{1t}^B + \gamma_2 R_{2t}^{BO}$$

and using the fact that linear projections are unique implies

$$\zeta_2 = \beta = \gamma_1 + \theta\gamma_2$$

and

$$\zeta_3 = \gamma_2.$$

So for $t > S$,

$$\begin{aligned} V_{it} &= q_{i,t-1}\left(R_{it}^{g} - \zeta_2 \hat{X}_{2t}^{O} - \zeta_3 \hat{X}_{3t}^{O}\right) \\ &= q_{i,t-1}\left(R_{it}^{g} - \left(\gamma_1 + \theta\gamma_2\right) R_{1t}^B - \gamma_2 R_{2t}^{BO}\right) \\ &= q_{i,t-1}\left(R_{it}^{g} - \gamma_1 R_{1t}^B - \gamma_2 R_{2t}^B\right) \end{aligned}$$

which is (19) and so the estimate is also consistent over the second subsample.

# B Robustness

Table 11 reports the results of conducting our study within different subsamples of our data. We select the samples based on the time period and whether managers invest internationally. Even when we consider active funds that invest in U.S. equity only, we always use all 11 Vanguard index funds at the benchmark.

| | **All Equity** | | | **U.S. Equity Only** | | |
|---|---|---|---|---|---|---|
| | Beg-3/11 | 1/84-9/06 | 1/90-3/11 | Beg-3/11 | 1/84-9/06 | 1/90-3/11 |
| Panel A: Vanguard Benchmark | | | | | | |
| In Sample VA | | | | | | |
| Mean ($mil/mon) | 0.14** | 0.28** | 0.14** | -0.01 | 0.01 | -0.02 |
| Weighted Mean ($mil/mon) | 0.27** | 0.42** | 0.29** | -0.00 | -0.05 | 0.00 |
| In Sample Net Alpha | | | | | | |
| Equally Weighted (b.p./mon) | 3 | -7* | -5* | -1 | -11** | -6** |
| Value Weighted (b.p./mon) | -1 | -7* | -5* | -5 | -12** | -8** |
| Total Number of Funds | 5974 | 4599 | 5943 | 2731 | 2218 | 2700 |
| Panel B: FCC Risk Adjustment | | | | | | |
| In Sample VA | | | | | | |
| Mean ($mil/mon) | 0.10** | 0.15** | 0.16** | -0.07 | -0.03 | -0.05* |
| Weighted Mean ($mil/mon) | 0.25** | 0.37** | 0.29** | -0.05 | -0.02 | 0.00 |
| In Sample Net Alpha | | | | | | |
| Equally Weighted (b.p./mon) | -4 | -9* | -8* | -7** | -9** | -7* |
| Value Weighted (b.p./mon) | -6** | -7* | -5 | -8** | -10** | -8* |
| Total Number of Funds | 6054 | 4599 | 5943 | 2811 | 2218 | 2700 |

Table 11: **Subsample Analysis:** *Beg* is the beginning date of our sample, 1/77 for Vanguard Benchmark and 1/62 for FFC Risk Adjustment. * – $t$-statistic greater (in absolute value) than 1.96. **– $t$-statistic greater (in absolute value) than 2.54.

## References


Baker, M., L. Litov, J. A. Wachter, and J. Wurgler (2010): "Can Mutual Fund Managers Pick Stocks? Evidence from Their Trades Prior to Earnings Announcements," *Journal of Financial and Quantitative Analysis*, 45(05), 1111–1131.

Berk, J. B., and R. C. Green (2004): "Mutual Fund Flows and Performance in Rational Markets," *Journal of Political Economy*, 112(6), 1269–1295.

Berk, J. B., and I. Tonks (2007): "Return Persistence and Fund Flows in the Worst Performing Mutual Funds," Working Paper 13042, National Bureau of Economic Research.

Bogle, J. C. (1997): "The First Index Mutual Fund: A History of Vanguard Index Trust and the Vanguard Index Strategy," Discussion paper, The Vanguard Group.

Bollen, N. P. B., and J. A. Busse (2001): "On the Timing Ability of Mutual Fund Managers," *The Journal of Finance*, 56(3), 1075–1094.

——— (2005): "Short-Term Persistence in Mutual Fund Performance," *Review of Financial Studies*, 18(2), 569–597.

Carhart, M. M. (1997): "On Persistence in Mutual Fund Performance," *Journal of Finance*, 52, 57–82.

Chen, H.-L., N. Jegadeesh, and R. Wermers (2000): "The Value of Active Mutual Fund Management: An Examination of the Stockholdings and Trades of Fund Managers," *Journal of Financial and Quantitative Analysis*, 35, 343–368.

Cohen, L., A. Frazzini, and C. Malloy (2007): "The Small World of Investing: Board Connections and Mutual Fund Returns," Working Paper 13121, National Bureau of Economic Research.

Cohen, R. B., C. K. Polk, and B. Silli (2010): "Best Ideas," *SSRN eLibrary*.

Coval, J. D., and T. J. Moskowitz (2001): "The Geography of Investment: Informed Trading and Asset Prices," *The Journal of Political Economy*, 109(4), pp. 811–841.

Cremers, K. J. M., and A. Petajisto (2009): "How Active Is Your Fund Manager? A New Measure That Predicts Performance," *Review of Financial Studies*, 22(9), 3329–3365.

Fama, E. F. (1965): "The Behavior of Stock-Market Prices," *Journal of Business*, 38(1), 34–105.

——— (1970): "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance*, 25(2), 383–417.

Fama, E. F., and K. R. French (1995): "Size and Book-to-Market Factors in Earnings and Returns," *Journal of Finance*, 50, 131–155.

——— (2010): "Luck versus Skill in the Cross-Section of Mutual Fund Returns," *The Journal of Finance*, 65(5), 1915–1947.

Grinblatt, M., and S. Titman (1989): "Mutual Fund Performance: An Analysis of Quarterly Portfolio Holdings," *The Journal of Business*, 62(3), pp. 393–416.

——— (1993): "Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns," *The Journal of Business*, 66(1), pp. 47–68.

Gruber, M. J. (1996): "Another Puzzle: The Growth in Actively Managed Mutual Funds," *Journal of Finance*, 51, 783–810.

Jensen, M. C. (1968): "The Performance of Mutual Funds in the Period 1945–1964," *Journal of Finance*, 23, 389–416.

Jiang, H., M. Verbeek, and Y. Wang (2011): "Information Content When Mutual Funds Deviate from Benchmarks," *SSRN eLibrary*.

Kacperczyk, M., C. Sialm, and L. Zheng (2005): "On the Industry Concentration of Actively Managed Equity Mutual Funds," *The Journal of Finance*, 60(4), pp. 1983–2011.

——— (2008): "Unobserved Actions of Mutual Funds," *Review of Financial Studies*, 21(6), 2379–2416.

Kosowski, R., A. Timmermann, R. Wermers, and H. White (2006): "Can Mutual Fund 'Stars' Really Pick Stocks? New Evidence from a Bootstrap Analysis.," *Journal of Finance*, 61(6), 2551 – 2595.

Lillainmaa, J. T. (2012): "Reverse Survivorship Bias," *Journal of Finance*, forthcoming.

Lucas, Robert E., J. (1978): "On the Size Distribution of Business Firms," *The Bell Journal of Economics*, 9(2), pp. 508–523.

Malkiel, B. G. (1995): "Returns from Investing in Equity Mutual Funds 1971 to 1991," *The Journal of Finance*, 50(2), pp. 549–572.

Mamaysky, H., M. Spiegel, and H. Zhang (2008): "Estimating the Dynamics of Mutual Fund Alphas and Betas," *Review of Financial Studies*, 21(1), 233–264.

Pastor, L., and R. F. Stambaugh (2002): "Mutual fund performance and seemingly unrelated assets," *Journal of Financial Economics*, 63(3), 315 – 349.

——— (2010): "On the Size of the Active Management Industry," Working Paper 15646, National Bureau of Economic Research.

Sharpe, W. F. (1991): "The Arithmetic of Active Management," *Financial Analysts Journal*, 47(1), pp. 7–9.

Shumway, T., M. B. Szefler, and K. Yuan (2009): "The Information Content of Revealed Beliefs in Portfolio Holdings," .

Wermers, R. (2000): "Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses," *The Journal of Finance*, 55(4), 1655–1703.

Zheng, J. X. (1999): "Testing Heteroskedasticity in Nonlinear and Nonparametric Regressions with an Application to Interest Rate Volatility," Working paper, University of Texas at Austin.