# Active Share and Mutual Fund Performance*

Antti Petajisto†

January 15, 2013

**Abstract**

I sort domestic all-equity mutual funds into different categories of active management using Active Share and tracking error. I find that over my sample period until the end of 2009, the most active stock pickers have outperformed their benchmark indices even after fees and transaction costs. In contrast, closet indexers or funds focusing on factor bets have lost to their benchmarks after fees. The same long-term performance patterns held up over the 2008-2009 financial crisis, and they also hold within market cap styles. Closet indexing increases in volatile and bear markets and has become more popular after 2007. Cross-sectional dispersion in stock returns positively predicts average benchmark-adjusted performance by stock pickers.

*JEL classification:* G10, G14, G20, G23
*Keywords:* Active Share, tracking error, closet indexing

* I wish to thank Yakov Amihud, Ned Elton, Marcin Kacperczyk, Lukasz Pomorski, Walter Prahl, and Vesa Puttonen for comments, as well as Dow Jones, Frank Russell Co., Standard and Poor's, and Morningstar for providing data for this study.

† NYU Stern School of Business, 44 W 4th St, Suite 9-190, New York, NY 10012-1126, tel. +1-212-998-0378, http://www.petajisto.net/, antti.petajisto@stern.nyu.edu.

Should a mutual fund investor pay for active fund management? Generally the answer is no: a number of studies have repeatedly come to the conclusion that net of all fees and expenses, the average actively managed fund loses to a low-cost index fund.[1] However, active managers are not all equal: they differ in how active they are and what type of active management they practice. This allows us to distinguish different types of active managers, which turns out to matter a great deal for investment performance.

How should active management be measured? For example, consider the Growth Fund of America, which is currently the largest equity mutual fund in the U.S. The fund's portfolio can be decomposed into two components: the S&P 500 index, which is the passive component, plus all the deviations from the index which comprise the active component. In any stock where the fund is overweight relative to the index, it effectively has an active long position, and in any stock where it is underweight relative to the index, it has an active short position. At the end of 2009, investing $100 in the fund was equivalent to investing $100 in the S&P 500 index together with $54 in the fund's active long positions and $54 in the fund's active short positions. The size of these active positions as a fraction of the portfolio, which is 54% in this case, is what I label the Active Share of the fund. Intuitively, it tells us the percentage of the portfolio that differs from the passive benchmark index. A common alternative measure is tracking error, which measures the time-series standard deviation of the return on those active positions.

I divide active managers into multiple categories based on both Active Share, which measures mostly stock selection, and tracking error, which measures mostly exposure to systematic risk, similarly to Cremers and Petajisto (2009). Active stock pickers take large but diversified positions away from the index. Funds focusing on factor bets generate large volatility with respect to the index even with relatively small active positions. Concentrated funds combine very active stock selection with exposure to systematic risk. Closet indexers do not engage much in any type of active management.

[1] This includes Jensen (1968), Gruber (1996), Wermers (2000), and many others.

A large number of funds in the middle are moderately active without a clearly distinctive style.

In this paper I start by providing examples of different fund types and focus on closet indexing, going into more details on two famous funds. I also investigate general trends in closet indexing over time and the reasons behind them. I then turn to fund performance, testing the performance of each category of funds until 12/2009. I separately explore fund performance during the financial crisis from 1/2008 to 12/2009 to see if historical patterns held up during this highly unusual period. Finally, I try to identify when market conditions are generally most favorable to active stock pickers.

I find that closet indexing has been increasing in popularity in 2007-2009, currently accounting for about one third of all mutual fund assets. Over time, the average level of active management is low when volatility is high, particularly in the cross-section of stocks, and when recent market returns have been low, which also explains the previous peak in closet indexing in 1999-2002.

The average actively managed fund has had weak performance, losing to its benchmark by –0.41%. The performance of closet indexers is predictably poor: they largely just match their benchmark index returns before fees, so after fees they lag behind their benchmarks by approximately the amount of their fees. Funds focusing on factor bets have also lost money for their investors. However, one group has added value to investors: the most active stock pickers, which have beaten their benchmarks by 1.26% per year after fees and expenses. Before fees, their stock picks have even beaten the benchmarks by 2.61%, displaying a nontrivial amount of skill. High Active Share is most strongly related to future returns among small-cap funds, but its predictive power within large-cap funds is also both economically and statistically significant.

The financial crisis hit active funds severely in 2008, leading to broad underperformance in 2008 and a strong recovery in 2009. The general patterns were similar to historical averages: the active stock pickers beat their indices over the crisis period by about 1%, while the closet indexers continued to underperform.

Cross-sectional dispersion in stock returns positively predicts benchmark-adjusted return on the most active stock pickers, suggesting that stock-level dispersion can be used to identify market conditions favorable to stock pickers. Other related measures such as the average correlation with the market index do not predict returns equally well.

This paper is most closely related to Cremers and Petajisto (2009), adding six more years to their sample period and extending their analysis in several ways. A few other papers in the literature have also investigated active management and its impact on fund performance, using such measures as tracking error relative to the S&P 500 (Wermers (2003)), industry concentration of fund positions (Kacperczyk, Sialm, and Zheng (2005)), $R^2$ with respect to a multifactor model (Amihud and Goyenko (2010)), active stock selection and timing efforts inferred from daily return data (Ekholm (2011)), and deviations from a passive benchmark formed on the basis of past analyst recommendations (Kacperczyk and Seru (2007)). Looking at stock returns directly, Cohen, Polk, and Silli (2010) find that the largest active positions of fund managers outperform, suggesting that managers should hold less diversified portfolios. Among hedge funds, Sun, Wang, and Zheng (2009) find that funds aggressively deviating from their peers outperform the more conservative funds.

The paper proceeds as follows. Section I defines and discusses the measures of active management used in the paper and provides examples of each fund category. Section II presents the data and basic empirical methodology. Section III investigates the time series of active management and discusses closet indexing in more detail. Section IV presents the results on fund performance, including the financial crisis. Section V concludes.

# I. Measuring Active Management of Mutual Funds

## *A. Types of Active Management*

An active manager can only add value by deviating from his benchmark index. A manager can do this in two different ways: by stock selection or factor timing. Stock selection involves active bets on individual stocks, for example selecting only one stock from a particular industry. Factor timing, also known as tactical asset allocation, involves time-varying bets on broader factor portfolios, for example overweighting particular sectors of the economy, or having a temporary preference for value stocks, or even choosing to keep some assets in cash rather than invest in equities.

To quantify active management at mutual funds, I follow the methodology of Cremers and Petajisto (2009). First, I use the Active Share of a fund, defined as

$$\text{Active Share} = \frac{1}{2}\sum_{i=1}^{N}\left|w_{fund,i} - w_{index,i}\right|, \tag{1}$$

where $w_{fund,i}$ is the weight of stock $i$ in the fund's portfolio, $w_{index,i}$ is the weight of the same stock in the fund's benchmark index, and the sum is computed over the universe of all assets. Intuitively, Active Share is simply the percentage of the fund's portfolio that differs from the fund's benchmark index. For an all-equity mutual fund that has no leveraged or short positions, the Active Share of the fund will always be between zero and 100%.

The other measure of active management I use is tracking error volatility, often simply called tracking error. I use the common definition

$$\text{Tracking error} = Stdev\left[R_{fund} - R_{index}\right], \tag{2}$$

where I compute the time-series standard deviation of the difference between the fund return $R_{fund}$ and its benchmark index return $R_{index}$. Intuitively, tracking error measures the volatility of the fund that is not explained by movements in the fund's benchmark index.

Conceptually, what is the difference between these two measures of active management? Too see that, let us consider a portfolio with 50 stocks – in other words, a potentially well-diversified portfolio. How active management shows up in these two measures of active management depends on one key question: do the active positions have exposure to systematic risk? For example, if all the overweight positions are in technology stocks which tend to move together, even small active positions will generate a high tracking error. Alternatively, assume there are 50 industries with 20 stocks in each industry, and the fund picks just one stock out of 20 in each industry, while keeping the same industry weights as the benchmark index. The fund is therefore very selective within industries, generating a high Active Share of about 95%, but because it is not taking any positions across industries, most of the risk in its active positions will be diversified away, producing low tracking error.

Hence, Active Share and tracking error emphasize different aspects of active management. Active Share is a reasonable proxy for stock selection, whereas tracking error is a proxy for systematic factor risk. To get a complete picture of active management, we need both measures.

Figure 1 illustrates the two dimensions of active management and how they can be linked to different types of active management. Diversified stock pickers have a high Active Share and low tracking error, while funds focusing on factor bets take the opposite approach. Concentrated funds combine stock selection with factor bets, thus scoring high on both measures. Closet indexers score low on both measures. Later on in Section IV.A, I choose cutoffs for the categories to be able to use them in the performance tests.

Table I shows the actual distribution of Active Share and tracking error across all-equity funds in 2009. Each cell contains the number of funds in that group. There is a clear positive correlation between Active Share and tracking error, but the interesting aspect is that there is substantial independent variation along both dimensions. For example, a fund with 4-6% tracking error can have an Active Share anywhere from under 40% to over 90%, and a fund with an Active Share of 60-70% can have a tracking error anywhere from under 4% to over 14%. In other words, the distribution is wide enough that we can meaningfully distinguish between different active management styles based on the two measures.

### *B. Examples of Funds*

Figure 2 shows some examples of all-equity mutual funds in each category, plotted along the two dimensions of active management. The numbers are from the last date in 2009 when the fund holdings are disclosed in the database (end of September for most funds).

The two funds plotted at the origin and mostly on top of each other are pure index funds: Vanguard 500 and Fidelity Spartan US Equity index fund. Each fund has essentially zero Active Share and tracking error, like we would expect from pure indexers. Their very low expense ratios reflect their passive management approach: they are at 12 basis points (bp) and 9 bp per year, respectively.

The upper left-hand corner includes diversified stock pickers such as T Rowe Price Mid-Cap Value fund, which has a high Active Share of 93%, yet a low tracking error of 5.4% relative to the S&P 400 index. This is only possible if the fund has similar sector weights as the benchmark index, and instead focuses on finding individual underpriced stocks within sectors and industries. Another example is FMI Large Cap fund, which has an Active Share of 95% and tracking error of 5.4% with respect to the S&P 500 index. That fund has only 24 stock positions, but those positions are sufficiently well diversified across industries that the fund's tracking error has remained low; the fund even mentions its low-risk approach in its prospectus.

The lower right-hand corner includes funds focusing on factor bets, which means that they have a relatively high tracking error in spite of a moderately low Active Share. One example is GMO Quality fund with an Active Share of only 65% and yet a tracking error of 12.9%. The fund says that it may time factors such as industries and sectors, size, and value, and it may keep some assets in cash or invest in high-quality debt, instead of trying to minimize its risk relative to the S&P 500. Also the AIM Constellation fund has a relatively high tracking error of 9.7% with a low Active Share of 66%, reflecting the sector bets of the fund as well as its decision to allocate to cash during the financial crisis.

The upper right-hand corner includes concentrated stock pickers that combine active stock selection with factor bets. Sequoia fund has an Active Share of 97% and tracking error of 14.1%, which is not surprising for a fund that takes large positions in individual stocks. It holds 22 stocks in total, sometimes as few as ten, and it has some positions that account for 10% or more of the portfolio. Among small-cap funds, Longleaf Partners Small-Cap fund has only 19 stocks in its portfolio, which has given it an Active Share of 99% and tracking error of 14.4% relative to the Russell 2000.

Finally, the funds in the lower left-hand corner but above index funds have both a low Active Share and low tracking error, indicating that they do not engage much in either stock selection or factor timing. Given that such funds still claim to be actively managed and charge fees for active management, they can be labeled closet indexers. Riversource Disciplined Equity fund has an Active Share of only 44% with a tracking error of 3.1%. The fund also holds 276 stocks, which is more than half of the stocks in its benchmark index. A new entrant to this category is the Growth Fund of America, which is wrestling with $140 billion in assets and has ended up with an Active Share of only 54% and a tracking error of 4.4%.

## II. Empirical Methodology

### *A. Data*

To compute Active Share, we need data on the portfolio composition of mutual funds as well as their benchmark indices. Stock holdings are matched with the CRSP stock return database. The stock holdings of mutual funds are from the Thomson Reuters database which is based on mandatory quarterly filings with the SEC.

As benchmarks for the funds, I include essentially all indices used by the funds themselves over the sample period. I have a total of 19 indices from S&P, Russell, and Dow Jones Wilshire, including their common large-cap, midcap, and small-cap indices as well as their value and growth components. The index holdings data are directly from the index providers.

Monthly returns for mutual funds are from the CRSP mutual fund database. These are net returns, i.e. after fees, expenses, and brokerage commissions but before any front-end or back-end loads. Daily returns for mutual funds are from multiple sources: starting in 9/1998, daily returns are available in the CRSP mutual fund database, and before that period I use the same combined database as Cremers and Petajisto (2009). Both monthly and daily returns for benchmark indices are from S&P, Russell, and Dow Jones, and all of them include dividends. All my databases are free of survivorship bias as they contain both live and dead funds.

### *B. Sample Selection*

I start by merging the CRSP mutual fund database with the Thomson holdings database using MFLINKS. For funds with multiple share classes, I compute the value-weighted averages of all variables such as monthly and daily returns, fees, and turnover across all share classes. To identify domestic all-equity funds, I use four different objective codes in CRSP, one code from Thomson Reuters, and I also require the average stock holdings in CRSP to be at least 70% and the share of matched U.S. stock holdings to be at least 60%. I eliminate all sector funds and funds below $10 million in assets. I distinguish between index funds, enhanced index funds,[2] and active (non-index) funds, and flag each fund accordingly. To compute reasonably accurate estimates of tracking error, I compute it from daily returns using the six months prior to each holdings report date. After the aforementioned screens, my final sample consists of 2,740 funds in the period 1980-2009.

### *C. Differences with Cremers and Petajisto (2009)*

My methodology of identifying funds and putting together the sample follows that of Cremers and Petajisto (2009) with a few exceptions. First, whenever available, I prefer to use the benchmark index self-reported by a manager in the fund prospectus,

[2] Enhanced index funds differ from closet indexers because they openly offer index-like performance with small active bets on top, and their low fees reflect that.

rather than assigning the index that produces the lowest Active Share. I have two snapshots of the "primary benchmark index" as collected by Morningstar from fund prospectuses, one from 1/2007 and another from 3/2010, and I use the earlier snapshot whenever available. If the prospectus benchmark is unavailable, I pick the index that produces the lowest average Active Share over the prior three years. The benefit of the prospectus benchmark is that it is the index the fund manager has publicly committed to beat, so both investors and the manager focus on performance relative to that benchmark. Even if a manager has reported a misleading benchmark, it is not an issue because I control for any remaining beta, size, value, and momentum exposures separately.

Second, I prefer not to backdate benchmark index data, so I only use each index after its inception date. This reflects the set of benchmarks available to a manager at the time he was actually making his portfolio decision, making the comparison more relevant. However, most of the indices were available by the early 1990s, so this has essentially no impact on performance results and only a minor impact on other results in the 1980s.

Third, I compute tracking error as the standard deviation of the benchmark-adjusted return, rather than as the residual volatility from a regression of the fund return on its benchmark index.[3] Since fund performance is commonly compared to the benchmark index, and not beta times the benchmark index, this better captures the risk the manager is taking relative to his benchmark. Specifically, if the manager is timing the equity market by temporarily holding a large amount of cash, this represents meaningful risk that is captured in the traditional tracking error measure but is not captured by the regression residual.

Fourth, I am adding six more years to the sample, extending it from 12/2003 to 12/2009. During this time, the CRSP mutual fund database switched its data provider from Morningstar to Lipper. Both CRSP versions are free of survivorship bias and are

[3] In fact this is also how Cremers and Petajisto (2009) originally computed it in their working paper.

supposed to include all live and dead funds, but each version is still missing some of the funds the other one has. Hence, the fund samples are slightly different, so even with an identical methodology I would not be able to perfectly match their results for the earlier time period.

Fifth, I am mapping the Thomson holdings data with CRSP mutual fund data using MFLINKS, a dedicated product for that purpose. This has become the standard used in the academic literature, but it still suffers from some omissions and errors which I have tried to correct manually.

# III. Closet Indexing: Examples and Trends

## *A. What Is Closet Indexing?*

Closet indexing, loosely defined, is the practice of staying close to the benchmark index while still claiming to be an active manager and usually also charging management fees similar to those of truly active managers. It is hard to define exact cutoffs for the definition, but Active Share can still serve as a useful guide to identify closet indexers.

By construction, about 50% of the value of the index experiences above-average returns and about 50% experiences below-average returns relative to the index itself. Hence, regardless of the beliefs of the manager, he cannot reasonably believe that over 50% of the index will beat the index. If a manager holds more than 50% of the index (i.e., has an Active Share less than 50%), then some of the positions cannot be there because the manager expects them to outperform the index; they exist only because he wants to reduce his risk relative to the index, even when it means including negative-alpha stocks in the portfolio. This is of course the opposite of what investors are paying active managers to do, since investors can always buy a cheap index fund if they want to reduce volatility relative to the index. Hence, an Active Share of 50% is the theoretical minimum that an active manager could possibly have. As in Cremers and Petajisto (2009), I generally set the closet indexer cutoff at an Active Share of 60%. This implies that an active manager should be able to select his investments from what he considers to be the top 40% of all stocks based on their future alphas. Alternatively, it means that an active manager should never fish within what he considers the bottom 60% of stocks, because by definition even the best stocks in this category can just match or barely beat the index. Note that these cutoffs are independent of what the manager's beliefs actually are: two managers can come to a very different conclusion about what stocks are likely to outperform, but each one of them should still actively invest based on his own beliefs.

The problem with closet indexing is not that low Active Share is inherently bad; in fact, a rational investor could well combine a position in a very active fund with a position in an index fund, thus ending up with a low Active Share in his overall portfolio. The problem is that closet indexers are very expensive relative to what they offer. A closet indexer charges active management fees on all the assets in the mutual fund, even when some of the assets are simply invested in the benchmark index. If a fund has an Active Share of 33%, this means that fund-level annual expenses of 1.5% amount to 4.5% as a fraction of the active positions of the fund. Since only the active positions of the fund can possibly outperform the benchmark, in the long run it is very difficult for a closet indexer to overcome such fees and beat its index net of all expenses.

### *B. Fidelity Magellan*

Fidelity Magellan is still famous for its spectacular record under Peter Lynch from 1977 to 1990. In his last ten years as a fund manager, he beat the S&P 500 index by a stunning 150%. Riding on this track record, the fund attracted large inflows and later became the largest mutual fund in the U.S., with over $100 billion in assets in 2000. However, the subsequent performance of the fund has been mixed. During Robert Stansky's tenure as fund manager from 1996 to 2005, performance was weak and the formerly active fund was suspected of being a closet indexer. Such claims were vehemently denied by the fund manager and the issue remained unresolved.[4]

However, one can shed some light on the issue by computing Magellan's Active Share, which is shown in Figure 3 from 1980 to 2009. It indeed started out as a very

[4] "Magellan's Manager Has Regrets," *The Wall Street Journal*, May 28, 2004.

active fund under Peter Lynch, with Active Share over 90%. Active Share did decline toward the end of Lynch's tenure, but then came back up again to almost 80% under Jeffrey Vinik. However, when Stansky took over in June 1996, Active Share suddenly plunged by 30% to less than 40% in just two years, and then kept going down and stayed at about 33-35% for the rest of his tenure. This remarkable shift in the fund's policy represents a conscious decision to become a closet indexer.

Not surprisingly, performance suffered during the closet indexing period: the fund lagged behind the S&P 500 by about 1% per year for ten years. This is not disastrous performance, but it is exactly what you would expect from a closet indexer: essentially the same return as the benchmark index, minus about 1% in fees and expenses for supposedly active management.

Under some pressure to make the fund more active again, Fidelity appointed Harry Lange to replace Stansky on 10/31/2005. Lange was well-known as a bold and active manager, so this was intended to dispel any doubts about closet indexing. Active Share confirms this: in just three months from September to December 2005, Active Share jumped from under 40% to 66%. Subsequently it has increased to as high as 80%, comfortably away from closet indexing. Fund performance has also become more detached from the benchmark index: as of June 2008, Lange was 6% ahead of the index after fees, but then he suffered heavy losses in the fall of 2008.

Even though larger funds tend to be less active in general, asset growth does not explain the patterns in Magellan's Active Share. Magellan's assets grew from $20 billion to $55 billion under Vinik, yet he simultaneously increased the fund's Active Share from 62% to 76%. Under Stansky, the fund's assets did keep growing but only after he had significantly tilted toward the index.

### *C. Growth Fund of America*

Currently by far the largest equity mutual fund in the U.S., the Growth Fund of America had over $140 billion in assets at the end of 2009. In spite of its popularity, it has both low Active Share and low tracking error, placing it solidly in the closet indexer category. Can the fund really be a closet indexer?

Figure 4 shows the Active Share and total assets of the fund from 1981 to 2009. The fund has generally been active, although its Active Share has been declining over time, falling to only 54% at the end of 2009. Simultaneously, the fund's assets have grown from under $40 billion in 2002 to as much as $200 billion in 2007.

The inflows have followed good performance. Interestingly, the fund actually underperformed the S&P 500 index from 1980 to 1998 by almost 0.5% per year, but from 9/1998 to 2/2000, the fund beat the index by a remarkable 56%. From 2/2000 to 12/2009 performance has been much steadier but still over 1% per year after fees. However, the recent fall in Active Share suggests that this good performance is hard to maintain going forward.

Nevertheless, one possibly redeeming feature of the fund is its unusual organizational structure: assets are divided among ten autonomous portfolio managers where each manager has full responsibility for his own subportfolio. Hence, if the fund is effectively a portfolio of ten individual mutual funds, then it is possible that individual managers are much more active, even if some of their bets cancel out when aggregated into the bigger fund. Still, investors should be cautious because for any regularly structured mutual fund, the recent drop in Active Share to closet index territory would signal that the fund's best days are behind it.

### *D. Trends in Closet Indexing*

Are there any general trends in closet indexing? Figure 5 shows the fraction of mutual fund assets in five Active Share categories from 1980 to 2009. The bottom group of funds with Active Share below 20% consists of pure index funds, which have grown from almost nothing in 1980 to one fifth of mutual fund assets at the end of 2009. The next two groups of funds with Active Share between 20% and 60% are the closet indexers. It appears that closet indexing has become even more popular than pure indexing, with the closet indexers accounting for about one third of all mutual fund assets at the end of 2009.

To understand the trends in closet indexing, I investigate how the average level of Active Share across all funds can be explained with other variables. I focus on two potential explanations: market volatility and recent fund returns. High market volatility amplifies any return differences between their portfolio and the benchmark index, and underperforming the benchmark may be particularly painful in a down market when everyone is suffering losses, as opposed to an up market where investors are making money even when they are trailing the benchmark.

Table II shows the monthly time-series regression results. The trailing one-year moving average of the VIX index indeed negatively predicts average Active Share. However, the one-year trailing average of cross-sectional dispersion in stock returns (discussed in more detail in Section IV.F) shows up as an even more significant predictor. This can arise in response to tracking error targets: when cross-sectional volatility increases, tracking error will increase unless a manager reduces the size of his active positions.

Also recent market returns play a role: the trailing three-year average benchmark index return is positively related to average Active Share, confirming that managers collectively tend to be more active when their investors are sitting on capital gains. However, this relationship is insignificant for the average benchmark-adjusted performance of managers.

Closet indexing peaked in 1999-2002, declined until 2006, and then increased again from late 2007 to 2009 toward its prior peak. Consistent with these patterns, the VIX index was high at about 25% throughout 1998-2002, cross-sectional volatility was also high, and the market subsequently fell in 2000-2002. Closet indexing declined in 2003 when the market recovered strongly and volatility came down, and it kept going down until 2006. In 2007, volatility shot back up when the subprime crisis started and substantial economic uncertainty appeared, and in 2008 it was followed by even more extreme market volatility and declines. Simultaneously, closet indexing reared its head again, and by 2009 it had climbed all the way back to its prior peak level.

One initial trigger for closet indexing might also be the SEC's decision in 1998 to require all mutual funds to disclose a benchmark index in their prospectus. Presumably this made both mutual fund investors and managers more aware of benchmarks, which is desirable in itself but may also have increased managers' incentives to minimize risk relative to the benchmark.

## IV. Results on Fund Performance

### *A. Categories of Funds*

Funds can be sorted into a 5x5 grid of Active Share and tracking error to distinguish between different types and degrees of active management. I start with this 5x5 grid, but I want to simplify it and make it economically more meaningful so I create categories of funds based on the grid and label them according to the broad type of active management they engage in. I only include active (non-index) funds in the grid; both index funds and enhanced index funds are eliminated at this stage. Funds are sorted sequentially, first by Active Share and then by tracking error within each quintile.

Table III shows how I form the groups. The lowest Active Share quintile can be labeled "closet indexers," which reflects their mean Active Share of less than 60%. The exception are the funds with the highest tracking error: these funds are generating significant volatility relative to their very small active positions, so those positions must be exposed to systematic factor risk and thus can be labeled "factor bets." In fact, all groups in the highest tracking error quintile can be labeled factor bets as they are all exposed to systematic risk in their active positions. The only exception is the highest Active Share group: these funds are combining high volatility with a high degree of stock selection, so they fall in the "concentrated" group. Non-concentrated funds with high Active Share form the group of more diversified "stock pickers." The rest of the funds can be called "moderately active," as they fall in the middle in terms of both Active

Share and tracking error. Throughout this paper, I will show the performance results for these five groups rather than using the more complicated matrix of 25 portfolios.

Table IV shows some sample statistics for the fund groups. Each month I compute the mean and standard deviation of a variable, and then I compute the time-series averages across all the months. A typical month has 1,124 funds in total, with about 180 funds each in the stock picker, factor bets, and closet indexer groups. Fees are 1.27% on average and comparable across all groups, although concentrated funds are slightly more expensive and closet indexers slightly cheaper. The average fund holds 104 stock positions, with closet indexers holding an average of 161. Stock pickers hold only 66 stocks, which is almost as few as the 59 stocks held by concentrated funds, showing that these two groups indeed differ from each other mostly because of their systematic risk exposure and not because of a different number of positions. The average portfolio turnover is 87%, with factor bets and concentrated funds generating the greatest turnover. Based on turnover and fees, closet indexers actually appear slightly less expensive than other actively managed funds, but they are of course still substantially more expensive per dollar of Active Share or tracking error.

### ***B. Overall Performance Results***

How does fund performance vary across the different categories of actively managed funds? I look at both "net returns," which I define as the investors' returns after all fees and transaction costs, and "gross returns," which I define as the hypothetical returns on the disclosed portfolio holdings. Gross returns help us identify whether any categories of funds have skill in selecting portfolios that outperform their benchmarks, and net returns help us determine whether any such skill survives the fees and transaction costs of those funds. My sample period for the performance results is 1/1990 to 12/2009, thus excluding the 1980s when almost all funds were very active.

Table V shows the equal-weighted returns for the five groups of funds, as well as the average across all groups. Looking at gross returns across all fund groups, I find that the average fund was able to select a portfolio of stocks that beat its benchmark index by 0.96% per year before fees and expenses. If I use the four-factor model of Carhart (1997) to control for any remaining exposure to market, size, value, or momentum, that outperformance falls to 0.31%. Most of the outperformance comes from the stock pickers and concentrated funds, with benchmark-adjusted returns of 2.61% and 1.64%, respectively. Moderately active funds also exhibit slight skill but funds taking factor bets do not. Not surprisingly, closet indexers largely just match their benchmark indices before fees and expenses. The difference in the performance of stock picks between closet indexers and stock pickers is 2.17% ($t$ = 3.31), which is statistically significant.

Looking at net returns after fees and transaction costs, I find that the average fund underperformed its benchmark by about –0.41%. Moderately active funds experienced slight underperformance of –0.52%. Factor bets turned out very poorly for investors, generating a –1.28% benchmark-adjusted return. Closet indexers predictably lost to their indices by –0.91%, which is only slightly less than their fees. Even concentrated funds essentially just matched their benchmarks net of fees. The only group that added value to investors was active stock pickers: they beat their benchmarks by 1.26%, or by 1.39% after controlling for the four-factor model. The stock pickers also beat the closet indexers net of fees by a statistically significant amount of 2.17% ($t$ = 3.48).

Economically, this means that stock selection as indicated by high Active Share is rewarded in the stock market, and the most aggressive stock pickers are able to add value to their investors even net of all expenses. In contrast, factor bets as indicated by high tracking error are not rewarded in the market, and on average those funds have destroyed value for their investors. Cremers and Petajisto (2009) found very similar results for their shorter time period, except for one group: concentrated funds. That group suffered in the 2004-2009 period and especially during the financial crisis, which explains part of the difference in the results.[5]

[5] Another part comes simply from having a different version of the CRSP mutual fund database with a slightly different sample of funds. Since the concentrated stock pickers are a small group and their returns

An alternative approach would be to use the same 5x5 grid as in Table III, but instead of forming quintiles based on absolute levels of Active Share and tracking error, form quintiles based on a fund's ranking relative to funds within its own style group. Hence, I also form the 5x5 grid separately for large-cap, mid-cap, and small-cap funds, and then I form the fund groups within each of the three styles. The results from this analysis (not reported) are broadly similar to the earlier results: Before fees, the best performance is exhibited by stock pickers and concentrated funds which beat their indices by 2.54% and 0.98%, respectively. After fees, only stock pickers have beaten their benchmarks, by 0.89% per year. The performance improvement over closet indexers is still economically and statistically significant; however, since closet indexing is more common in large-cap funds than small-cap funds, this methodology will mitigate the difference between the two active management types. Even if funds are divided into nine styles (as in the 3x3 Morningstar style box) based both on market cap and value dimensions before they are sorted into the five active management types, the results remain similar.

### *C. Fund Size and Performance*

Table VI shows how fund size affects performance net of all expenses within each of the five categories. There is only a very weak relationship between size and performance: the best performers are the smallest funds within the stock picker group, earning 1.84% per year net of fees, but this relationship is not even monotonic for any of the groups. From prior literature, we know that fund size in general hurts performance (e.g., Chen, Hong, Kubik, and Stein (2004)). However, this effect arises not within but across the groups: closet indexers tend to be larger and they perform poorly, while the most active stock pickers tend to be smaller funds. In other words, fund size seems to

are the most volatile of all, including or excluding a few funds can impact the results. The other groups have many more funds and are thus less sensitive to such data issues.

hurt performance because it is correlated with the type of active management, not because it is hurts performance within a type.

### *D. Performance Persistence*

If some fund managers have skill but others do not, we would expect to see persistence in fund performance. To examine this, I sort funds within each group into quintiles based on their benchmark-adjusted net return over the prior calendar year, analogously to Carhart (1997). Table VII shows the subsequent annualized returns on these portfolios net of all expenses.

The benchmark-adjusted returns in Panel A exhibit considerable persistence for the concentrated funds: prior-year winners beat prior-year losers by 10.04% in the following year, with the spread arising equally from both winners and losers. Stock pickers, factor bets, and moderately active funds also display some performance persistence, with the prior-year winners beating prior-year losers by about 3% in the following year. However, statistical significance for concentrated funds ($t$ = 2.28) is not meaningfully higher than for the other groups because it is also the smallest group. Only closet indexers do not exhibit much persistence: all five prior-return quintiles have about equally poor performance going forward.

Panel B shows the results when we control for the momentum factor of Carhart (1997). As in the prior literature, this eliminates a large amount of performance persistence across funds. This indicates that the top-performing funds buy stocks with positive momentum; in fact, Lou (2010) suggests that those funds themselves may even push the value of their current holdings up because of the new inflows they receive and invest in their existing positions. However, concentrated funds exhibit economically significant performance persistence even after controlling for stock-level momentum, with the prior winners beating prior losers by 4.61% per year. In contrast, among the more diversified stock pickers, the prior winners beat prior losers by only 1.00%. Since Cremers and Petajisto (2009) found considerable performance persistence within the highest Active Share quintile, this suggests that it was mostly due to the concentrated rather than diversified stock pickers.

Why do the concentrated funds exhibit so much more performance persistence than the stock pickers? Fund manager performance and skill are of course closely related: skill can even be defined as expected (ex ante) performance before fees, expenses, and price impact. But the persistence results do not necessarily tell us anything about the average level of skill between the two groups; instead, they suggest that the dispersion of skill within each of the two groups is different. If the concentrated funds have both extremely good and extremely bad managers, whereas the stock pickers are good managers in general but do not have much heterogeneity, then the persistence results should look the way they do. For example, some small and unskilled fund managers might be tempted take very large random bets in an attempt to "win the lottery," become a top-performing fund, and attract large inflows (somewhat similarly to the tournament behavior in Brown, Harlow, and Starks (1996)), which would place them in the same fund group with genuinely talented managers who take large high-conviction bets on companies they have thoroughly researched and strongly believe are undervalued. The stock picker category has a much lower tracking error so it does not offer similar gambling incentives for unskilled managers.

### *E. Multivariate Evidence on Performance*

Could it be that fund categories as well as Active Share proxy for other known variables that in turn predict fund returns? Table VIII addresses this question by showing the results of pooled panel regressions where I try to explain fund performance net of expenses with a large number of explanatory variables. I again use both benchmark-adjusted returns (columns 1–3) as well as four-factor alphas of benchmark-adjusted returns (columns 4–6). All explanatory variables are as of the end of year $t-1$, while the fund returns are annual returns in year $t$.[6]

---

[6] A fund-year is included even if it has only 1 month of returns in year $t$ to avoid creating a survivorship bias.

Column 1 shows that Active Share alone predicts fund returns with economic and statistical significance: a 10% increase in Active Share predicts a 74 bp increase in fund return ($t = 2.76$). In contrast, tracking error is slightly negatively related to performance. In column 3, I combine Active Share and tracking error to create fund categories as before, with a dummy variable for each category (except closet indexers which is taken as the benchmark category), and the results are comparable to those in Table V: stock pickers have beaten closet indexers by 2.88% per year ($t = 2.48$) net of fees, while the other fund categories have been much less impressive. Moderately active funds have done better than closet indexers, but they still lag behind market indices.

How does Active Share predict returns within market capitalization groups? Column 2 shows the results from a regression where I add dummy variables for large cap, midcap, and small-cap funds and interact those dummies with Active Share. This actually increases the coefficient on Active Share for all groups, and the coefficients remain statistically significant in spite of the smaller sample size for each. The effect is strongest for small-cap funds, but even within midcap and large-cap stocks, Active Share still predicts future fund performance.

The other variables that predict fund returns are expenses and fund age. For each one dollar in expenses, the fund's net return actually suffers by slightly more than a dollar. Hence, fees are not just direct costs to investors, but they also signal poor fund quality beyond that. Older funds slightly underperform: for every 10 years in existence, a fund's return decreases by 15–17 bp per year. In general, the results are similar between columns 1–3 and 4–6, indicating that the four-factor adjustment does not change any of the conclusions.

### *F. Identifying Stock Pickers' Markets: Stock Return Dispersion*

What if the attractiveness of an active manager's opportunity set varies over time? Anecdotally, managers talk about "stock pickers' markets" where opportunities are rife in individual stocks and active managers are adding value, while at other times returns seem to be driven by macroeconomic issues which may even exacerbate existing mispricings at the level of individual stocks.[7]

One measure of the importance of stock-level news relative to macroeconomic news is the cross-sectional dispersion in stock returns. This can be defined as

$$\sigma_t = \sqrt{\sum_{i=1}^{N} w_{i,t} \left( R_{i,t} - R_{m,t} \right)^2}, \tag{3}$$

where $\sigma_t$ is the cross-sectional dispersion at time $t$, $w_{i,t}$ is the weight of stock $i$ in the market index, $R_{i,t}$ is the return on stock $i$, and $R_{m,t}$ is the return on market index. This follows the definition of the recently introduced Russell-Parametric CrossVol indices. However, the Russell CrossVol data do not start until 7/1996, so I compute the measure myself each month using Russell 3000 index holdings which allows me to start my tests much earlier.

Table IX shows how the average performance of active managers is related to cross-sectional dispersion in stock returns. Columns 1–5 use only funds categorized earlier as stock pickers, and they show the regression results where the dependent variable is monthly benchmark-adjusted net return, and the independent variables are CrossVol index values at various monthly lags. It turns out that dispersion in month $t$ is not significantly related to fund returns in month $t$, but it does predict returns in the following month $t + 1$. In a multivariate regression, future dispersion is not related to fund returns but prior dispersion is up to a lag of three months.

Columns 4–5 distinguish between expected dispersion and unexpected dispersion. The expected dispersion $E_{t-1}\left[\text{CrossVol}\left(t\right)\right]$ in month $t$ is computed based on an AR(3) model using CrossVol values between months $t - 3$ and $t - 1$, and the unexpected dispersion is defined as $\varepsilon_{\text{CrossVol}(t)} = \text{CrossVol}\left(t\right) - E_{t-1}\left[\text{CrossVol}\left(t\right)\right]$. The expected dispersion predicts fund returns slightly better than simply the prior month's dispersion in column 2. However, the unexpected dispersion predicts returns with the opposite sign

[7] E.g., "Macro Forces in Market Confound Stock Pickers," *The Wall Street Journal*, 9/24/2010.

and a slightly greater economic magnitude. In other words, high dispersion is good for stock pickers going forward, particularly if dispersion subsequently falls. Conversely, low dispersion is bad for stock pickers, but increasing dispersion is particularly disastrous for their performance.

Economically, what might explain these patterns? A natural hypothesis would be that during high-dispersion periods, stocks are moved by idiosyncratic news about their fundamentals, and when dispersion falls, it is because many of the idiosyncratic mispricings have been corrected. A manager betting on fundamentals performs best when mispricings start at a high level but subsequently converge to zero. Conversely, increasing dispersion means that mispricings may actually get bigger before they converge again, thus hurting manager performance in the meantime. In fact, managers' own actions may even contribute to this pattern: when dispersion increases, some managers reduce their active positions (as shown in Table II) because the positions just became more risky and the only way to prevent tracking error from increasing is to scale back active positions, but that in turn pushes prices further away from fundamentals; when dispersion falls, the same mechanism works in the opposite direction.

To understand the measure better, we can decompose it into a few separate components. If we use a single-factor model to express the excess return on a single stock as $R_{i,t} = \beta_i R_{m,t} + \varepsilon_{i,t}$, we can write the cross-sectional dispersion at time $t$ as

$$\sigma_t = \sqrt{R_{m,t}^2 \sigma_{\beta,t}^2 + \sigma_{\varepsilon,t}^2}, \tag{4}$$

where $\sigma_{\beta,t}$ is the value-weighted cross-sectional dispersion in betas and $\sigma_{\varepsilon,t}$ is the value-weighted cross-sectional dispersion in idiosyncratic return at time $t$.[8] Hence, the measure

[8] For notational convenience, returns are expressed in excess of the risk-free rate. To derive equation (4), we first start with equation (3) and then write $R_{i,t} - R_{m,t} = \left(\beta_i - 1\right) R_{m,t} + \varepsilon_{i,t}$ and $\left(R_{i,t} - R_{m,t}\right)^2 = \left(\beta_i - 1\right)^2 R_{m,t}^2 + \varepsilon_{i,t}^2 + 2\left(\beta_i - 1\right) R_{m,t}\varepsilon_{i,t}$. The weighted sum of the latter expression is then $\sum_i w_{i,t}\left(R_{i,t} - R_{m,t}\right)^2 = \sum_i w_{i,t}\left(\beta_i - 1\right)^2 R_{m,t}^2 + \sum_i w_{i,t}\varepsilon_{i,t}^2 + 2R_{m,t}\sum_i w_{i,t}\left(\beta_i - 1\right)\varepsilon_{i,t}$, where

will be high if either idiosyncratic risk is high, market returns are large (either positive or negative), or beta dispersion is high. When investors focus on firm-specific fundamentals, idiosyncratic risk should be high as firm-specific news are efficiently incorporated in the prices of individual stocks, but also beta dispersion should be high as investors distinguish between the beta exposures of different firms.

Popular press articles discussing stock pickers' markets usually refer to another metric, the average correlation between stocks. This can mean the average pairwise stock correlation or the average stock correlation with the market index, both of which capture the same effect. To compare this metric with cross-sectional dispersion, I compute it relative to the market index. The average correlation can be expressed as

$$\rho_t = \sum_{i=1}^{N} w_{i,t} corr\left(R_{i,t}, R_{m,t}\right) = \sum_{i=1}^{N} w_{i,t} \frac{\beta_{i,t}\sigma_{m,t}}{\sigma_{i,t}} = \sum_{i=1}^{N} w_{i,t} \frac{\beta_{i,t}\sigma_{m,t}}{\sqrt{\beta_{i,t}^2\sigma_{m,t}^2 + \sigma_{\varepsilon_i,t}^2}}, \tag{5}$$

where $\sigma_{m,t}$ is market volatility and $\sigma_{\varepsilon_i,t}$ is the idiosyncratic time-series volatility of stock $i$. This requires the time-series estimation of betas and volatilities, so I generate monthly values from a market model regression by using daily data within each month.[9]

Table X shows where the return predictability comes from, using simple one-month lagged values of explanatory variables. Among the components of cross-sectional dispersion in equation (4), idiosyncratic dispersion has the highest explanatory power ($R^2$), followed by beta dispersion, but market index volatility does not explain future returns. Since cross-sectional dispersion itself is overwhelmingly driven by idiosyncratic dispersion (regressing the former on the latter produces $R^2$ = 89.8%, versus 90.2% with

---

the first term equals market variance $R_{m,t}^2$ times the (cap-weighted) cross-sectional variance of betas $\sigma_{\beta,t}^2$, the second term is the cross-sectional variance in idiosyncratic returns $\sigma_{\varepsilon,t}^2$, and the third term is zero because idiosyncratic risk and market risk (beta) are uncorrelated by definition.

[9] The estimates for single stocks are somewhat inaccurate as they are based on only about 21 daily data points (non-overlapping) for each month, but the cross-sectional average correlation is more accurate as some of the estimation errors cancel out in the cross-section. I choose the S&P 500 index as my universe for these calculations because using daily data requires all stocks to be very liquid.

the other two variables included), this is also driving the performance predictability result. Idiosyncratic dispersion in the cross-section is also highly correlated with the cross-sectional average of idiosyncratic time-series volatility from a market model, but the two measures are not identical and cross-sectional dispersion has greater predictive power for fund returns.[10]

Perhaps surprisingly, the average correlation with the market index is not a statistically significant predictor of future returns. Compared with cross-sectional dispersion, it is a more complicated function of the underlying variables: beta dispersion and market volatility explain 57% of it, and, surprisingly, idiosyncratic volatility does not empirically explain more than 0.1% of it. Thus the only component of average correlation that also explains fund returns is beta dispersion, and since that component only explains 34% of it, its overall predictive power for returns remains low.

Intuitively, cross-sectional volatility does better than average correlation mainly because the former emphasizes the absolute magnitude of return differences across stocks, which is key to beating the index. In contrast, the average correlation scales everything by total volatility, thus offsetting rises in idiosyncratic volatility with rises in broad market volatility which does not predict fund returns.

Existing literature (e.g., Ankrim and Ding (2002)) has documented the link between the cross-sectional dispersion in fund manager performance and the cross-sectional dispersion in stock returns, which may not be surprising because the two dispersion measures are mechanically linked unless managers consciously and fully offset the effects with their active decisions. In contrast, my test is on the average level of fund returns, which has no mechanical link to cross-sectional dispersion. Most importantly, my results suggest that investors can time their investments in stock-picking mutual funds by using the information in the cross-section of stocks to gauge the opportunity set currently available to active managers.

[10] The fact that CrossVol is a standard deviation whereas the other components are variances does not help the predictive power of CrossVol. On the contrary, squaring CrossVol to get to cross-sectional variance would slightly increase its predictive power.

My results are not driven by extreme dispersion in a few unusual months, as they are not materially affected by removing any monthly dispersion values over 15%. Since benchmark-adjusted average fund returns exhibit some positive autocorrelation, I also computed Newey-West standard errors with 2 and 12 monthly lags and obtained very similar levels of statistical significance. If I use benchmark-adjusted four-factor alpha as the dependent variable, the coefficient estimates drop by about one half, suggesting that the four-factor benchmark returns follow a similar pattern with the performance of individual stock picks. If we expand the test sample from stock pickers to all U.S. equity funds in columns 6–7, the results do become weaker, so dispersion is specifically related to stock picker performance but not the performance of other fund categories such as closet indexers. In fact, funds taking factor bets even perform better when dispersion is increasing, presumably reflecting their focus on predicting broader macro events.

### *G. Performance over the Financial Crisis*

The financial crisis in the fall of 2008 shook virtually all segments of the financial market, causing wild swings in asset prices and large numbers of hedge fund failures. Table XI shows how different categories of mutual funds performed over this period. The table includes both the crisis and the recovery over a two-year period starting in 1/2008 and ending in 12/2009. It shows the annualized benchmark-adjusted net returns after fees and expenses. While the crisis period is of course too short for reliable statistical inference on average performance, it nevertheless provides an interesting real-life stress test for mutual funds.

In spite of the unprecedented turmoil, many of the categories performed similarly to their historical averages. The average active (non-index) mutual fund lost to its benchmark by –0.51% per year net of expenses. Closet indexers lost by –0.83%, moderately active funds were down –0.32%, and factor bets lost by as much as –1.72%. Stock pickers continued to outperform by 0.97% per year. The main exception was concentrated funds: they were hit so hard in 2008 that in spite of their strong comeback of almost 10% over their indices in 2009, they remained down –2.59% per year relative to the indices.

If all fund categories lost to their benchmarks and some of them very significantly in 2008, the recovery in 2009 was equally dramatic. In addition to concentrated funds, stock pickers also beat their indices by an impressive 6.09% net of expenses. Even the average fund beat its benchmark by 2.13% net of fees. The only group that lost to its benchmarks in 2009 was closet indexers who again produced predictably weak performance of –0.66%.

## V. Conclusions

The average actively managed mutual fund has underperformed its benchmark index. However, the degree and type of active management matters considerably for performance. In this paper I use Active Share and tracking error to sort domestic all-equity mutual funds into five categories based on the type of active management they practice. I find that the most active stock pickers have been able to add value to their investors, beating their benchmark indices by about 1.26% per year after all fees and expenses. Factor bets have destroyed value after fees. Closet indexers have essentially just matched their benchmark index performance before fees, which has produced consistent underperformance after fees. The results are similar during the 2008-2009 financial crisis, and they also hold separately within large-cap and small-cap funds.

Economically, this means that there are some inefficiencies in the market that can be exploited by active stock selection. Furthermore, I find that active stock selection is most successful at times of high cross-sectional dispersion in stock returns. However, fund managers are not able to add value by betting on broader factor portfolios, indicating that they are more efficiently priced than individual stocks.

For mutual fund investors, these findings suggest that they need to pay attention to measures of active management. When selecting mutual funds, they should go with only the most active stock pickers, or combine those funds with inexpensive index funds; in other words, they should pick from the two extremes of Active Share, but not invest in any funds in the middle. The funds in the middle are providing only moderate levels of active management, which has not added enough value even to cover their fees. Closet indexers who stay very close to the benchmark index are a particularly bad deal, as they are almost guaranteed to underperform after fees given the small size of their active bets, yet they account for about one third of all mutual fund assets.

## References

Amihud, Yakov, and Ruslan Goyenko, 2010, Mutual fund's $R^2$ as predictor of performance, Working paper, NYU Stern.

Ankrim, Ernest M., and Zhuanxin Ding, 2002, Cross-sectional volatility and return dispersion, *Financial Analysts Journal* 58: 67-73.

Brown, Keith C., W.V. Harlow, and Laura T. Starks, 1996, Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry, *Journal of Finance* 51, 85-110.

Carhart, Mark, 1997, On persistence in mutual fund returns, *Journal of Finance* 52, 57-82.

Chen, J., H. Hong, M. Huang, and J.D. Kubik, 2004, Does fund size erode performance? Organizational diseconomies and active money management, *American Economic Review* 94, 1276-1302.

Cohen, Randolph, Christopher Polk, and Bernhard Silli, 2010, Best ideas, Working paper, London School of Economics.

Cremers, Martijn, and Antti Petajisto, 2009, How active is your fund manager? A new measure that predicts performance, *Review of Financial Studies* 22, 3329-3365.

Ekholm, Anders G., 2011, Portfolio returns and manager activity: How to decompose tracking error into security selection and market timing, Working paper, Hanken School of Economics.

Fama, Eugene F., 1972, Components of investment performance, *Journal of Finance* 27, 551-567.

Gruber, Martin J., 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51, 783-810.

Jensen, Michael C., 1968, The performance of mutual funds in the period 1945-1964, *Journal of Finance* 23, 389-416.

Kacperczyk, Marcin, and Amit Seru, 2007, Fund manager use of public information: New evidence on managerial skills, *Journal of Finance* 60, 1983-2011.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2005, On industry concentration of actively managed equity mutual funds, *Journal of Finance* 60, 1983-2011.

Lou, Dong, 2010, A flow-based explanation for return predictability, Working paper, London School of Economics.

Sun, Zheng, Ashley Wang, and Lu Zheng, 2009, The road less traveled: Strategy distinctiveness and hedge fund performance, Working paper, UC Irvine.

Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses, *Journal of Finance* 55, 1655-1695.

Wermers, Russ, 2003, Are mutual fund shareholders compensated for active management "Bets"? Working paper, University of Maryland.

**Table I. Active Share and Tracking Error in 2009.**

The table shows the number of U.S. all-equity mutual funds in each Active Share and tracking error category. Active Share is defined as the percentage of a fund's portfolio holdings that differ from the benchmark index. Tracking error is defined as the annualized standard deviation of a fund's return in excess of its benchmark index, and it is computed from daily returns over the prior six months. Active Share and tracking error are average values in 2009.

| Active Share | Tracking error (% per year) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| (%) | 0-2 | 2-4 | 4-6 | 6-8 | 8-10 | 10-12 | 12-14 | >14 | All |
| 90-100 | | | 6 | 36 | 66 | 47 | 44 | 87 | 285 |
| 80-90 | | | 35 | 83 | 67 | 55 | 35 | 50 | 326 |
| 70-80 | | 7 | 56 | 62 | 63 | 33 | 17 | 19 | 257 |
| 60-70 | | 22 | 85 | 60 | 25 | 13 | 5 | 6 | 216 |
| 50-60 | | 24 | 49 | 25 | 14 | 4 | 2 | | 120 |
| 40-50 | 2 | 28 | 20 | 6 | 3 | | | | 61 |
| 30-40 | 4 | 14 | 9 | 2 | | | | | 30 |
| 20-30 | | 3 | | | | | | | 5 |
| 10-20 | 5 | 3 | | | | | | | 8 |
| 0-10 | 70 | | | | | | | | 73 |
| All | 82 | 104 | 262 | 275 | 238 | 152 | 103 | 164 | 1,380 |

**Table II. Explaining Average Active Share over Time.**

The dependent variable is the monthly equal-weighted average Active Share across U.S. all-equity mutual funds. VIX is the volatility index and CrossVol is the monthly cross-sectional dispersion for all U.S. equities, both computed as 12-month trailing averages. Index return is the average return on the benchmark indices across all funds and active return is the average fund net return relative to the benchmark, both computed as 36-month trailing averages. The sample period is from 1/1990 to 12/2009. The *t*-statistics (in parentheses) are based on Newey-West standard errors with 36 monthly lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Index funds, sector funds, and funds with less than $10M in assets have been excluded.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VIX | -0.2462** | | | | 0.0973 | |
| | (-2.30) | | | | (0.88) | |
| CrossVol | | -0.8749*** | | | -1.0127*** | -0.8044*** |
| | | (-3.78) | | | (-5.34) | (-3.23) |
| Index return | | | 0.0409*** | | 0.0468** | 0.0345*** |
| | | | (2.85) | | (2.43) | (3.05) |
| Active return | | | | -0.2211 | 0.0895 | |
| | | | | (-1.53) | (0.69) | |
| | | | | | | |
| $N$ | 239 | 239 | 239 | 239 | 239 | 239 |
| $R^2$ | 25.2% | 38.7% | 21.8% | 11.4% | 55.1% | 53.9% |

**Table III. Different Types of Active Management.**

The table shows the cutoffs used in this paper to define different types of active management for U.S. all-equity mutual funds. At the end of each month, all funds are sorted into quintiles first by Active Share and then by tracking error, using the latest values available for each fund. Index funds, sector funds, and funds with less than $10M in assets have been excluded.

| Active Share | Tracking error quintile | | | | |
|---|---|---|---|---|---|
| quintile | Low | 2 | 3 | 4 | High |
| High | 5 | 5 | 5 | 5 | 4 |
| 4 | 2 | 2 | 2 | 2 | 3 |
| 3 | 2 | 2 | 2 | 2 | 3 |
| 2 | 2 | 2 | 2 | 2 | 3 |
| Low | 1 | 1 | 1 | 1 | 3 |

| Group | Label |
|---|---|
| 5 | Stock pickers |
| 4 | Concentrated |
| 3 | Factor bets |
| 2 | Moderately active |
| 1 | Closet indexers |

**Table IV. Sample Statistics for Fund Categories 1990-2009.**

This table shows sample statistics for the fund categories defined in Table III and subsequently used in the performance tables. The equal-weighted mean and standard deviation of each variable are first computed each month over the sample period, and the reported numbers are their time-series averages across all the months.

Panel A: Mean values

| Group | Label | Number of funds | Assets ($M) | Active Share | Tracking error | Turnover | Expense ratio | Number of stocks |
|---|---|---|---|---|---|---|---|---|
| 5 | Stock pickers | 180 | 430 | 97% | 8.5% | 83% | 1.41% | 66 |
| 4 | Concentrated | 45 | 463 | 98% | 15.8% | 122% | 1.60% | 59 |
| 3 | Factor bets | 179 | 1,412 | 79% | 10.4% | 104% | 1.34% | 107 |
| 2 | Moderately active | 541 | 902 | 83% | 5.9% | 84% | 1.25% | 100 |
| 1 | Closet indexers | 180 | 2,009 | 59% | 3.5% | 69% | 1.05% | 161 |
| | All | 1,124 | 1,067 | 81% | 7.1% | 87% | 1.27% | 104 |

Panel B: Standard deviations

| Group | Label | Assets ($M) | Active Share | Tracking error | Turnover | Expense ratio | Number of stocks |
|---|---|---|---|---|---|---|---|
| 5 | Stock pickers | 858 | 1.4% | 1.9% | 78% | 0.40% | 40 |
| 4 | Concentrated | 1,164 | 1.5% | 4.3% | 132% | 0.66% | 48 |
| 3 | Factor bets | 5,174 | 12.2% | 4.2% | 106% | 0.49% | 137 |
| 2 | Moderately active | 2,575 | 7.5% | 1.5% | 74% | 0.40% | 98 |
| 1 | Closet indexers | 6,003 | 9.3% | 0.9% | 54% | 0.39% | 177 |
| | All | 3,846 | 14% | 3.7% | 83% | 0.45% | 119 |

**Table V. Fund Performance 1990-2009.**

The table shows the annualized performance of U.S. all-equity mutual funds for five types of active management. The fund types are defined in Table III. Gross returns are the returns on a fund's stock holdings and do not include any fees or transaction costs. Net returns are the returns to a fund investor after fees and transaction costs. The numbers are expressed in percent per year, followed by $t$-statistics (in parentheses) based on White's standard errors. Index funds, sector funds, and funds with less than $10M in assets have been excluded.

| | | Gross return | | Net return | |
|---|---|---|---|---|---|
| Group | Label | Benchmark-adjusted | Four-factor alpha | Benchmark-adjusted | Four-factor alpha |
| 5 | Stock pickers | 2.61 | 2.10 | 1.26 | 1.39 |
| | | (3.42) | (2.72) | (1.95) | (2.10) |
| 4 | Concentrated | 1.64 | 0.52 | -0.25 | -0.89 |
| | | (0.90) | (0.40) | (-0.17) | (-0.72) |
| 3 | Factor bets | 0.06 | -1.02 | -1.28 | -2.19 |
| | | (0.06) | (-1.47) | (-1.31) | (-3.01) |
| 2 | Moderately active | 0.82 | 0.20 | -0.52 | -0.78 |
| | | (1.63) | (0.39) | (-1.16) | (-1.81) |
| 1 | Closet indexers | 0.44 | 0.13 | -0.91 | -1.07 |
| | | (1.67) | (0.51) | (-3.38) | (-4.46) |
| | All | 0.96 | 0.31 | -0.41 | -0.71 |
| | | (1.70) | (0.61) | (-0.86) | (-1.59) |
| 5 - 1 | Difference | 2.17 | 1.96 | 2.17 | 2.45 |
| | | (3.31) | (3.04) | (3.48) | (4.00) |

**Table VI. Fund Size and Performance.**

The table shows the annualized performance of U.S. all-equity mutual funds for fund size quintiles within five types of active management from 1/1990 to 12/2009. The fund types are defined in Table III. Returns are net returns to a fund investor after fees and transaction costs. The numbers are expressed in percent per year, followed by t-statistics (in parentheses) based on White's standard errors. Index funds, sector funds, and funds with less than $10M in assets have been excluded.

| Group | Label | Fund size quintile | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Low | 2 | 3 | 4 | High | All | High-Low |
| 5 | Stock pickers | 1.84 | 0.89 | 1.05 | 1.16 | 1.38 | 1.26 | -0.46 |
| | | (2.44) | (1.22) | (1.42) | (1.56) | (1.73) | (1.95) | (-0.69) |
| 4 | Concentrated | -1.99 | 0.13 | 0.81 | 0.17 | -0.63 | -0.25 | 1.36 |
| | | (-1.11) | (0.07) | (0.49) | (0.08) | (-0.32) | (-0.17) | (0.73) |
| 3 | Factor bets | -1.73 | -1.11 | -1.04 | -1.61 | -0.97 | -1.29 | 0.75 |
| | | (-1.84) | (-1.20) | (-0.93) | (-1.47) | (-0.83) | (-1.32) | (1.03) |
| 2 | Moderately active | -0.67 | -0.52 | -0.49 | -0.21 | -0.73 | -0.52 | -0.06 |
| | | (-1.41) | (-1.14) | (-1.04) | (-0.41) | (-1.40) | (-1.17) | (-0.15) |
| 1 | Closet indexers | -0.88 | -1.05 | -0.99 | -0.85 | -0.83 | -0.92 | 0.06 |
| | | (-2.98) | (-3.90) | (-3.26) | (-3.04) | (-2.19) | (-3.44) | (0.22) |
| | All | -0.52 | -0.45 | -0.35 | -0.31 | -0.44 | -0.41 | 0.08 |
| | | (-1.20) | (-1.01) | (-0.71) | (-0.57) | (-0.77) | (-0.88) | (0.24) |
| 5 - 1 | Difference | 2.72 | 1.93 | 2.04 | 2.01 | 2.20 | 2.18 | |
| | | (3.44) | (2.64) | (2.92) | (2.84) | (2.88) | (3.49) | |

**Table VII. Performance Persistence.**

The table shows the annualized performance of U.S. all-equity mutual funds for fund size quintiles within five types of active management from 1/1990 to 12/2009. The fund types are defined in Table III. Returns are net returns to a fund investor after fees and transaction costs. Panel A shows the benchmark-adjusted returns, and Panel B shows the Carhart four-factor alphas of benchmark-adjusted returns. The numbers are expressed in percent per year, followed by t-statistics (in parentheses) based on White's standard errors. Index funds, sector funds, and funds with less than $10M in assets have been excluded.

Panel A: Benchmark-adjusted net return

| Group | Label | Prior one-year return quintile | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Low | 2 | 3 | 4 | High | All | High-Low |
| 5 | Stock pickers | -0.26 | 0.78 | 1.22 | 1.39 | 2.93 | 1.22 | 3.20 |
| | | (-0.20) | (0.85) | (1.68) | (1.82) | (2.72) | (1.88) | (1.68) |
| 4 | Concentrated | -5.34 | -2.42 | -1.07 | 1.87 | 4.70 | -0.41 | 10.04 |
| | | (-2.15) | (-1.24) | (-0.63) | (0.94) | (1.56) | (-0.27) | (2.28) |
| 3 | Factor bets | -2.74 | -2.30 | -1.88 | -0.90 | 0.88 | -1.38 | 3.62 |
| | | (-1.96) | (-2.61) | (-1.69) | (-0.63) | (0.45) | (-1.43) | (1.34) |
| 2 | Moderately active | -1.65 | -1.17 | -0.81 | -0.20 | 1.30 | -0.51 | 2.95 |
| | | (-2.09) | (-2.20) | (-1.78) | (-0.38) | (1.50) | (-1.12) | (2.22) |
| 1 | Closet indexers | -1.25 | -1.11 | -0.97 | -0.84 | -0.36 | -0.91 | 0.89 |
| | | (-3.10) | (-3.69) | (-3.48) | (-2.55) | (-0.71) | (-3.32) | (1.31) |
| | All | -1.66 | -1.06 | -0.68 | -0.07 | 1.35 | -0.42 | 3.02 |
| | | (-2.00) | (-1.95) | (-1.47) | (-0.11) | (1.35) | (-0.90) | (1.97) |
| 5 - 1 | Difference | 0.99 | 1.89 | 2.19 | 2.23 | 3.30 | 2.13 | |
| | | (0.90) | (2.20) | (3.08) | (3.14) | (3.79) | (3.38) | |

Panel B: Four-factor alpha of benchmark-adjusted net return

| Group | Label | Prior one-year return quintile | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Low | 2 | 3 | 4 | High | All | High-Low |
| 5 | Stock pickers | 0.87 | 1.50 | 1.39 | 1.01 | 1.87 | 1.34 | 1.00 |
| | | (0.78) | (1.83) | (1.81) | (1.29) | (2.06) | (2.00) | (0.70) |
| 4 | Concentrated | -3.38 | -1.82 | -1.49 | 0.48 | 1.24 | -0.96 | 4.61 |
| | | (-1.72) | (-0.96) | (-0.90) | (0.30) | (0.61) | (-0.76) | (1.54) |
| 3 | Factor bets | -2.02 | -2.18 | -3.08 | -2.62 | -1.73 | -2.32 | 0.29 |
| | | (-1.62) | (-2.65) | (-3.74) | (-2.86) | (-1.46) | (-3.18) | (0.16) |
| 2 | Moderately active | -1.24 | -1.14 | -0.90 | -0.77 | 0.12 | -0.79 | 1.35 |
| | | (-1.69) | (-2.12) | (-2.13) | (-1.65) | (0.19) | (-1.80) | (1.38) |
| 1 | Closet indexers | -1.07 | -1.04 | -1.08 | -1.09 | -1.06 | -1.07 | 0.01 |
| | | (-2.74) | (-3.60) | (-4.21) | (-4.09) | (-2.97) | (-4.44) | (0.01) |
| | All | -1.07 | -0.88 | -0.92 | -0.77 | -0.04 | -0.74 | 1.03 |
| | | (-1.43) | (-1.61) | (-2.08) | (-1.57) | (-0.06) | (-1.63) | (1.00) |
| 5 - 1 | Difference | 1.94 | 2.55 | 2.47 | 2.11 | 2.93 | 2.41 | |
| | | (1.97) | (3.42) | (3.41) | (2.78) | (3.51) | (3.87) | |

**Table VIII. Predictive Regression for Fund Performance 1992-2009.**

The dependent variable in columns 1-3 is the cumulative net return (after all expenses) in excess of the benchmark index return in year *t*, while the independent variables are measured at the end of year $t-1$. The dependent variable in columns 4-6 is the four-factor alpha of benchmark-adjusted return. Large cap, midcap, and small cap are dummy variables interacted with Active Share. Columns 3 and 6 include dummy variables for fund categories. Control variables include returns and flows over the prior 1-3 years, fund size squared, number of stocks, and manager tenure. All specifications include year dummies. The *t*-statistics (in parentheses) are based on standard errors clustered by year. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | Benchmark-adjusted return | | | Four-factor alpha | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Active Share | 0.0739*** | | | 0.0609** | | |
| | (2.76) | | | (2.24) | | |
| Active Share * large cap | | 0.0867** | | | 0.0492** | |
| | | (2.09) | | | (2.01) | |
| Active Share * mid cap | | 0.1023* | | | 0.1288** | |
| | | (1.84) | | | (2.47) | |
| Active Share * small cap | | 0.1635** | | | 0.1446* | |
| | | (2.03) | | | (1.90) | |
| Stock picker | | | 0.0288** | | | 0.0211** |
| | | | (2.48) | | | (2.06) |
| Concentrated | | | 0.0014 | | | 0.0071 |
| | | | (0.07) | | | (0.59) |
| Factor bets | | | -0.0010 | | | -0.0035 |
| | | | (-0.12) | | | (-0.68) |
| Moderately active | | | 0.0090** | | | 0.0041* |
| | | | (2.10) | | | (1.69) |
| Tracking error | -0.0827 | -0.1019 | | -0.0855 | -0.0859 | |
| | (-0.54) | (-0.69) | | (-0.85) | (-0.86) | |
| Turnover | 0.0019 | 0.0030 | 0.0030 | -0.0026 | -0.0018 | -0.0019 |
| | (0.32) | (0.51) | (0.48) | (-0.85) | (-0.58) | (-0.61) |
| Expenses | -1.3423*** | -1.3281*** | -1.1162** | -1.3978*** | -1.4187*** | -1.2686*** |
| | (-3.31) | (-3.45) | (-2.41) | (-7.64) | (-7.88) | (-6.25) |
| $Log_{10}$(TNA) | -0.0040 | 0.0011 | -0.0024 | -0.0001 | 0.0032 | 0.0021 |
| | (-0.36) | (0.10) | (-0.22) | (-0.01) | (0.40) | (0.26) |
| Fund age / 100 | -0.0153** | -0.0170** | -0.0163** | -0.0154** | -0.0148** | -0.0165** |
| | (-2.16) | (-2.43) | (-2.33) | (-2.05) | (-2.15) | (-2.29) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 11,534 | 11,534 | 11,534 | 11,534 | 11,534 | 11,534 |
| $R^2$ | 11.0% | 11.3% | 11.0% | 7.8% | 8.1% | 7.7% |

**Table IX. Fund Performance and Cross-Sectional Dispersion.**

The dependent variable is the cumulative net return (after all expenses) in excess of the benchmark index return in month *t*. The only funds included are stock pickers as defined in Table III. CrossVol is the monthly cross-sectional dispersion for all U.S. equities computed by Russell. The variable $E_{t\text{-}1}[\text{CrossVol}(t)]$ is the predicted value of CrossVol($t$) based on information available at $t$ – 1., whereas $\varepsilon_{\text{CrossVol}(t)}$ is the shock to CrossVol($t$) at time $t$, defined as CrossVol($t$) – $E_{t\text{-}1}[\text{CrossVol}(t)]$. The sample period is 1/1990–12/2009. The $t$-statistics (in parentheses) are based on White's standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | Stock pickers | | | | | All funds | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| CrossVol(t+1) | | | 0.0248 | | | 0.0382 | |
| | | | (0.65) | | | (1.52) | |
| CrossVol(t) | 0.0216 | | -0.1742*** | | | -0.0434 | |
| | (0.53) | | (-3.30) | | | (-1.08) | |
| CrossVol(t-1) | | 0.0970*** | 0.1378*** | | | 0.0040 | |
| | | (3.05) | (2.63) | | | (0.13) | |
| CrossVol(t-2) | | | -0.0242 | | | 0.0302 | |
| | | | (-0.58) | | | (1.09) | |
| CrossVol(t-3) | | | 0.1426*** | | | 0.0325 | |
| | | | (3.27) | | | (1.13) | |
| CrossVol(t-4) | | | -0.0183 | | | -0.0112 | |
| | | | (-0.53) | | | (-0.50) | |
| $E_{t\text{-}1}[\text{CrossVol(t)}]$ | | | | 0.1205*** | 0.1195*** | | 0.0562*** |
| | | | | (3.10) | (3.36) | | (2.66) |
| $\varepsilon_{\text{CrossVol(t)}}$ | | | | | -0.1637*** | | -0.0284 |
| | | | | | (-3.13) | | (-0.78) |
| $N$ | 162 | 161 | 158 | 159 | 159 | 158 | 159 |
| $R^2$ | 0.6% | 12.3% | 29.4% | 12.4% | 24.7% | 8.5% | 6.5% |

**Table X. Fund Performance and Alternative Measures of Cross-Sectional Dispersion.**

The dependent variable is the cumulative net return (after all expenses) in excess of the benchmark index return in month $t$. The only funds included are stock pickers as defined in Table III. CrossVol is the monthly cross-sectional dispersion for all U.S. equities. AvgCorr is the correlation of daily returns between stock $i$ and the market index in month $t$, averaged across all stocks. $\mathrm{Var}(R_{m,t})$ is the return variance of the market index in month $t$. $\mathrm{Var}(\beta_{i,t})$ is the cross-sectional variance of one-month betas across all stocks. $\sigma_{\varepsilon,i}^2$ is the cross-sectional average of one-month idiosyncratic variance. $\sigma_{\varepsilon}^2$ is the cross-sectional variance of realized one-month idiosyncratic returns. AvgVar is the cross-sectional average of one-month total return variance. All one-month time series values like variances are computed from daily returns. All variables are measured in month $t$ – 1 for return prediction in month $t$. The sample period is 1/1990–12/2009. The $t$-statistics (in parentheses) are based on White's standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| CrossVol | 0.0846*** | | | | | | | |
| | (2.77) | | | | | | | |
| AvgCorr | | -0.0074 | | | | | | |
| | | (-1.37) | | | | | | |
| $\mathrm{Var}(R_{m,t})$ | | | 1.7073 | | | | | |
| | | | (0.83) | | | | | |
| $\mathrm{Var}(\beta_{i,t})$ | | | | 0.0064*** | | | 0.0041* | |
| | | | | (3.91) | | | (1.89) | |
| $\sigma_{\varepsilon}^2$ | | | | | 0.5260** | | 0.4218 | |
| | | | | | (2.42) | | (1.63) | |
| $\sigma_{\varepsilon,i}^2$ | | | | | | 6.6273** | | |
| | | | | | | (2.16) | | |
| AvgVar | | | | | | | | 2.3807* |
| | | | | | | | | (1.78) |
| $N$ | 240 | 239 | 239 | 239 | 239 | 239 | 239 | 239 |
| $R^2$ | 0.076 | 0.010 | 0.003 | 0.051 | 0.073 | 0.044 | 0.091 | 0.024 |

**Table XI. Fund Performance over the Financial Crisis.**

The table shows the annualized performance of U.S. all-equity mutual funds for five types of active management during the financial crisis from 1/2008 to 12/2009, and separately during the recovery period from 1/2009 to 12/2009. The fund types are defined in Table III. Returns are benchmark-adjusted net returns to a fund investor after fees and transaction costs. The numbers are expressed in percent per year, followed by t-statistics (in parentheses) based on White's standard errors. Index funds, sector funds, and funds with less than $10M in assets have been excluded

| Group | Label | 2008-2009 | 2009 |
|---|---|---|---|
| 5 | Stock pickers | 0.97 | 6.09 |
| | | (0.42) | (1.84) |
| 4 | Concentrated | -2.59 | 9.41 |
| | | (-0.56) | (2.11) |
| 3 | Factor bets | -1.72 | 2.21 |
| | | (-0.63) | (0.82) |
| 2 | Moderately active | -0.32 | 1.12 |
| | | (-0.24) | (0.54) |
| 1 | Closet indexers | -0.83 | -0.66 |
| | | (-1.09) | (-0.67) |
| | All | -0.51 | 2.13 |
| | | (-0.32) | (1.01) |
| 5 - 1 | Difference | 1.79 | 6.75 |
| | | (0.89) | (2.28) |

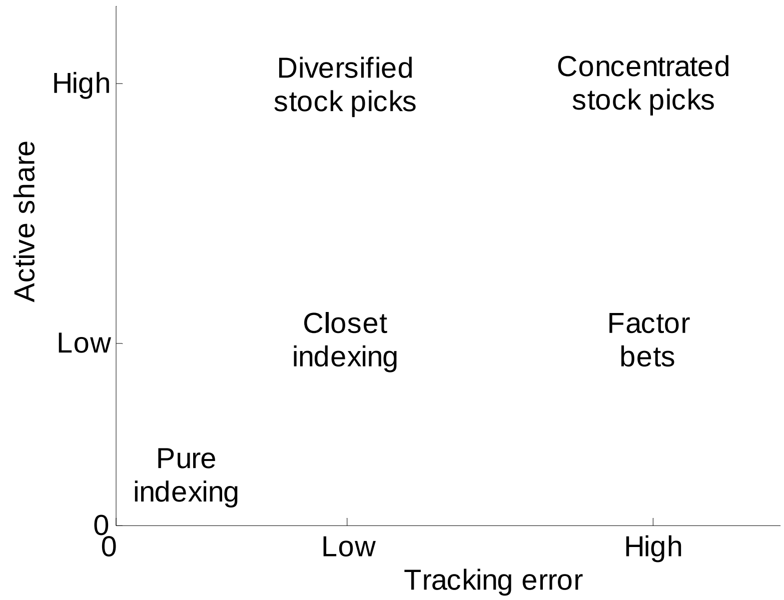


**Figure 1. Different types of active management.**

Active Share represents the fraction of portfolio holdings that differ from the benchmark index, thus emphasizing stock selection. Tracking error is the volatility of fund return in excess of the benchmark, so it emphasizes bets on systematic risk. The figure is from Cremers and Petajisto (2009).

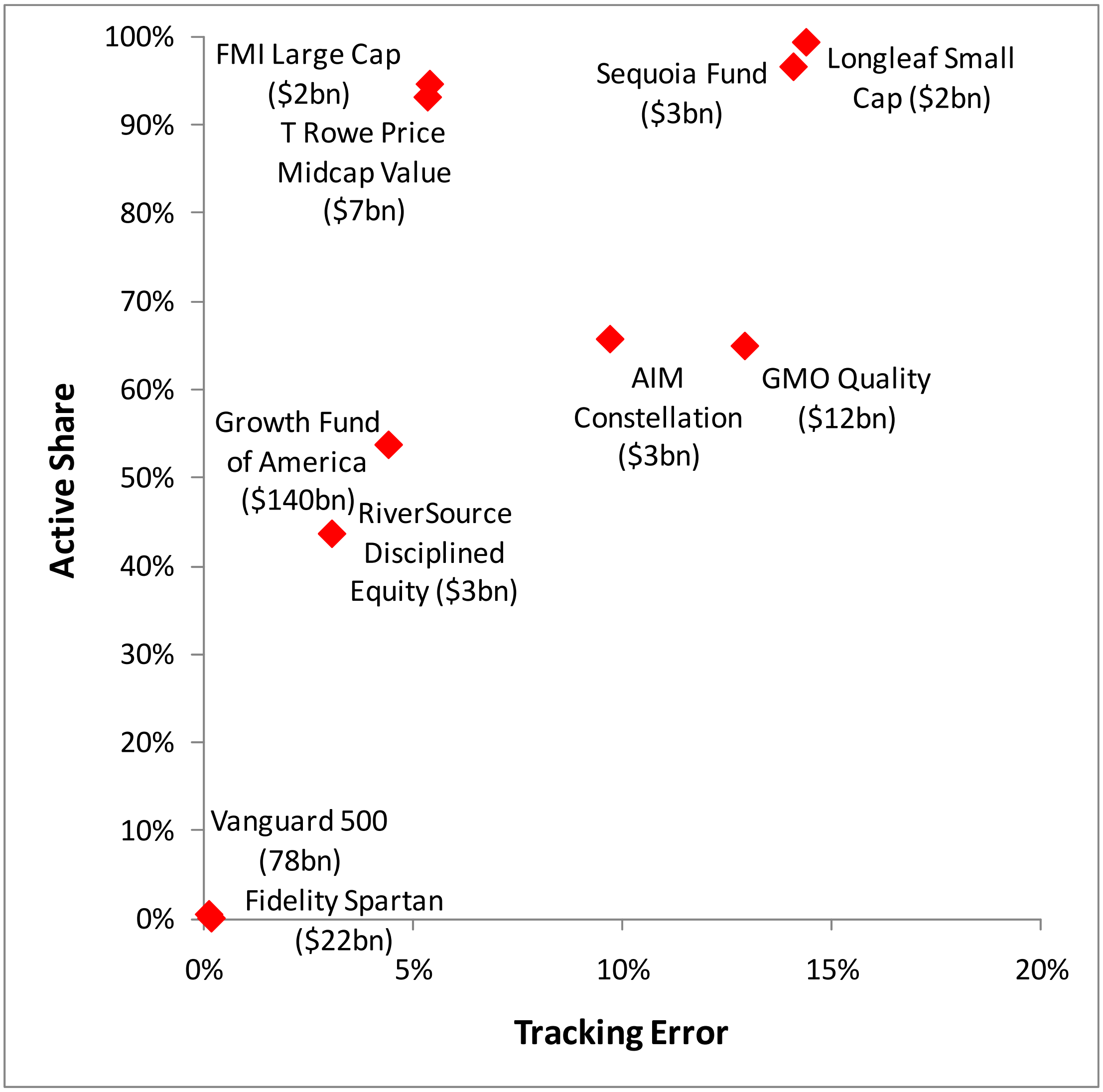


**Figure 2. Examples of funds in each category in 2009.**

For each fund, Active Share and tracking error are current as of the last holdings disclosure date in 2009. Total assets are shown in parentheses.

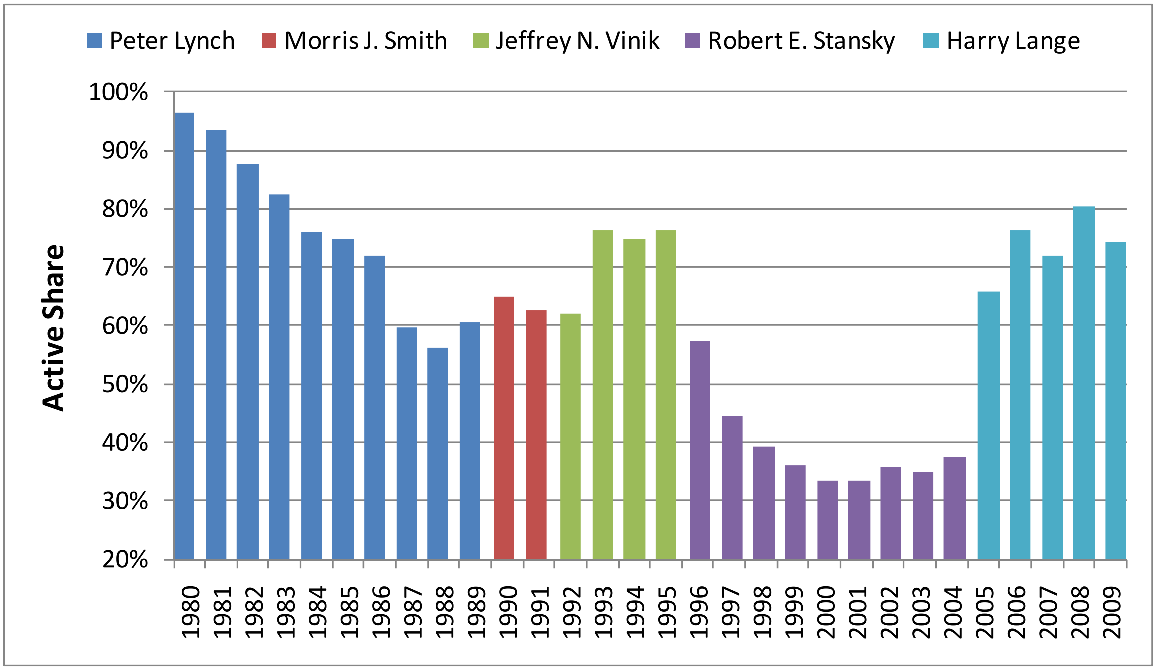


**Figure 3. Fidelity Magellan's Active Share over time.**

Active Share is shown for each manager of the fund at the end of the year.

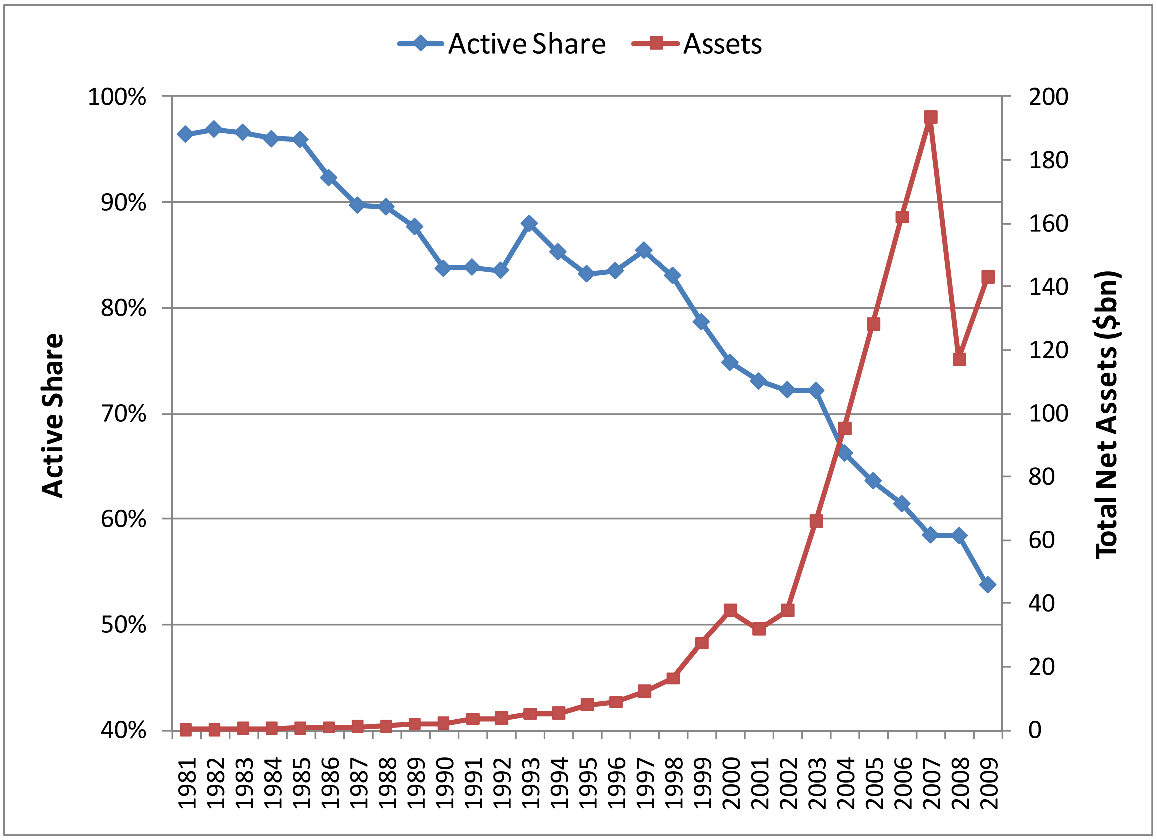


**Figure 4. Active Share and assets of the Growth Fund of America.**
Active Share and total net assets are shown at the end of each year.

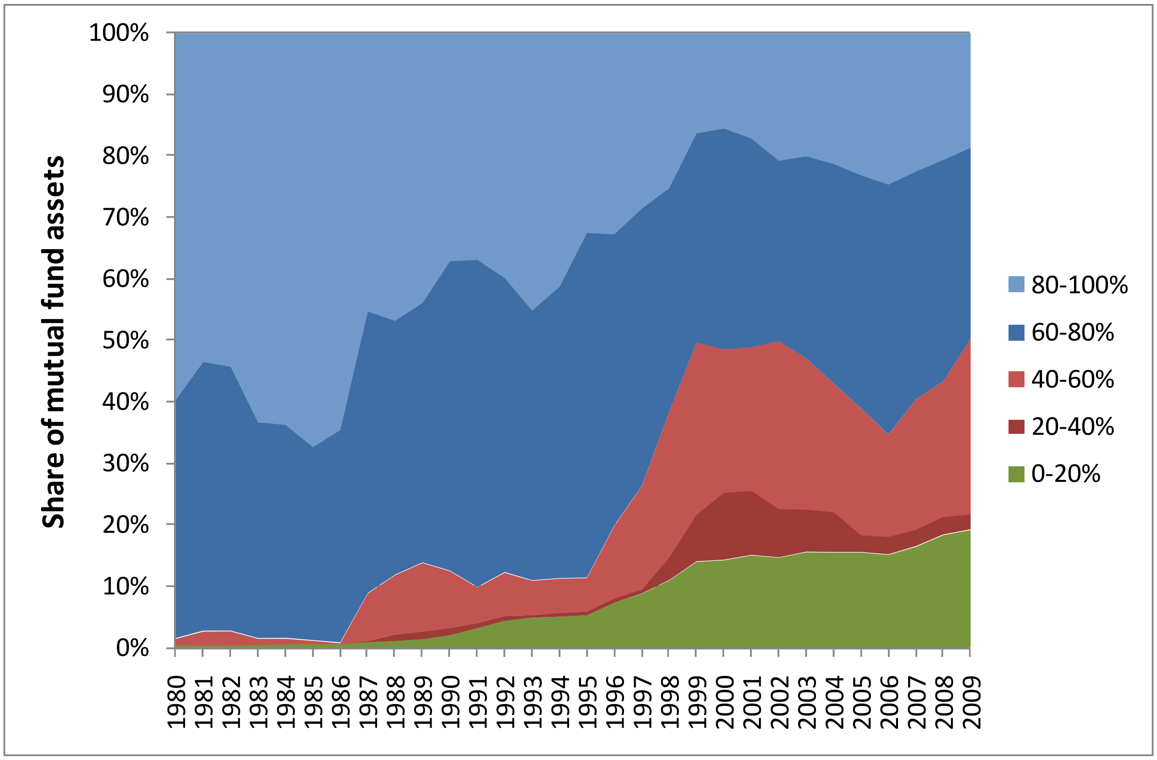


**Figure 5. Evolution of Active Share 1980-2009.**

This figure shows the fraction of assets in U.S. all-equity mutual funds in each Active Share category. The bottom category with Active Share below 20% contains pure index funds, while the next two categories contain the closet indexers.