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Active Share and Mutual Fund Performance

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Using Active Share and tracking error, the author sorted all-equity mutual funds into various categories of active management. The most active stock pickers outperformed their benchmark indices even after fees, whereas closet indexers underperformed. These patterns held during the 2008–09 financial crisis and within market-cap styles. Closet indexing has increased in both volatile and bear markets since 2007. Cross-sectional dispersion in stock returns positively predicts performance by stock pickers.

Should a mutual fund investor pay for active fund management? Generally, the answer is no. A number of studies have concluded that the average actively managed fund loses to a low-cost index fund, net of all fees and expenses.[1] However, active managers are not all equal: They differ in how active they are and what type of active management they practice. These distinctions allow 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, currently the largest equity mutual fund in the United States. The fund's portfolio can be broken down into two components: the S&P 500 Index, which is the passive component, and all the deviations from the index, which constitute the active component. If the fund is overweight in a particular stock relative to the index, it effectively has an active long position in that stock; if the fund is underweight in a particular stock relative to the index, it has an active short position in that stock. At the end of 2009, investing \$100 in the fund was equivalent to investing \$100 in the S&P 500, 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—54% in this case—is what I call 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 metric is tracking error, which measures the time-series standard deviation of the return on the active positions.

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Author's Note: This article was written when the author was a finance professor at the NYU Stern School of Business.

In my study, following Cremers and Petajisto (2009), I divided active managers into several categories on the basis of both Active Share, which measures mostly stock selection, and tracking error, which measures mostly exposure to systematic risk. Active stock pickers take large but diversified positions away from the index. Funds that focus 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. A large number of funds in the middle are moderately active without a clearly distinctive style.

I started by looking at examples of different types of funds and then examined two famous funds in detail. I also investigated general trends in closet indexing over time and the reasons behind them. I then turned to fund performance, testing the performance of each category of funds through December 2009. I separately explored fund performance in the financial crisis of January 2008–December 2009 to see whether historical patterns held up during this highly unusual period. Finally, I tried to identify when market conditions are generally most favorable to active stock pickers.

Discussion of findings. I found that closet indexing has been increasing in popularity since 2007, 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 has been predictably poor: They largely just match their benchmark index returns before fees, and so after fees, they lag behind their benchmarks by approximately the amount of their fees. Funds that focus on factor bets have also lost money for their investors. However, one group has added value for investors: the most active stock pickers, who have beaten their benchmarks by 1.26% a 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 followed by 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%, whereas the closet indexers continued to underperform.

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

My study is most closely related to Cremers and Petajisto (2009); I added six more years to their sample period and extended their analysis in several ways. A few other studies 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) found that the largest active positions of fund managers outperformed, suggesting that managers should hold less diversified portfolios. Sun, Wang, and Zheng (2009) found that hedge funds that deviated aggressively from their peers outperformed more conservative funds.

Measuring Active Management of Mutual Funds

In this section, I define and discuss the measures of active management that I used in my study and offer examples of each fund category.

Types of Active Management. An active manager can add value only by deviating from his benchmark index in one of two ways: 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, having a temporary preference for value stocks, and even choosing to keep some assets in cash rather than invest in equities.

To quantify active management of mutual funds, I followed the methodology of Cremers and Petajisto (2009). First, I used 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 0% and 100%.

Tracking-error volatility, often simply called tracking error, is the other measure of active management that I used—specifically, the common definition

$$\text{Tracking error} = \text{stdev}\left(R_{fund} - R_{index}\right), \tag{2}$$

where I computed 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? To see the difference, 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: Are the active positions exposed 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, let us assume there are 50 industries with 20 stocks in each industry and the fund picks just 1 stock out of 20 in each industry while keeping the same industry weights as the benchmark index. The fund is thus 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 a 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 a low tracking error, whereas funds that focus 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 in my study, I chose cutoffs for the categories in order to use them in the performance tests.

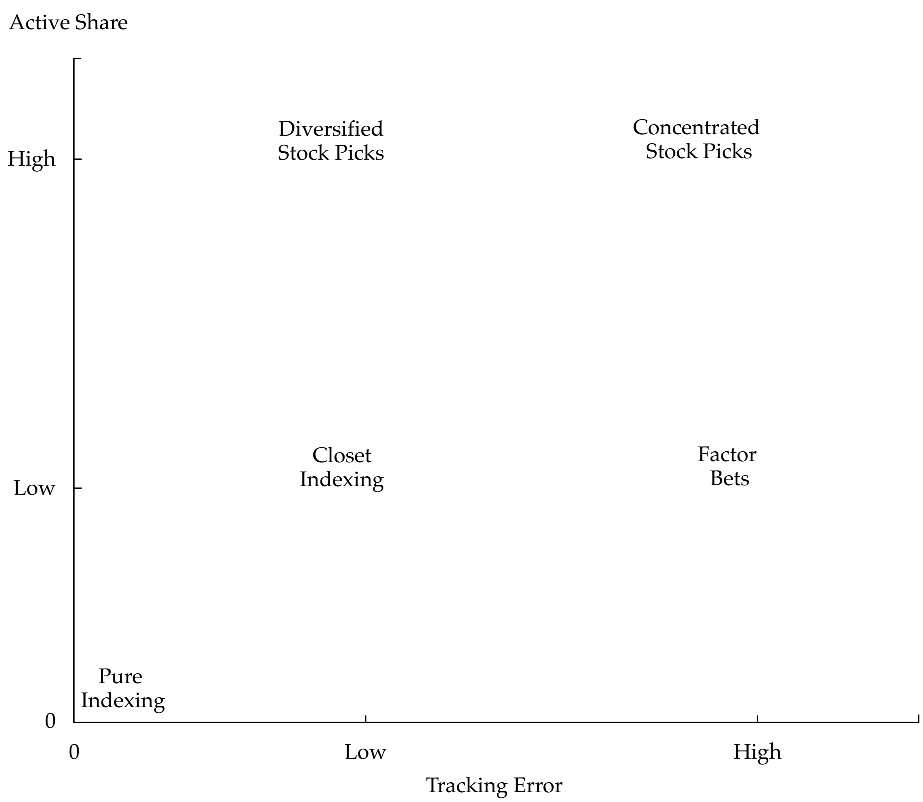
Table 1 shows the actual distribution of Active Share and tracking error across all-equity funds in 2009. Each cell contains the number of funds in that group. A clear, positive correlation exists between Active Share and tracking error, but the interesting aspect is the substantial independent variation along both dimensions. For example, a fund with a 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 on the basis of the two measures.

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 were reported in the database (the end of September for most funds).

The two funds plotted at the origin and mostly on top of each other are pure index funds: the Vanguard 500 Index Fund and the Fidelity Spartan U.S. Equity Index Fund. Each fund has essentially zero Active Share and tracking error, as we would expect from pure indexers. Their very low expense ratios—12 bps and 9 bps a year, respectively—reflect their passive management approach.

The upper left-hand corner includes such diversified stock pickers as the T. Rowe Price Mid-Cap Value Fund, which has a high Active Share of 93%

Figure 1. Different Types of Active Management



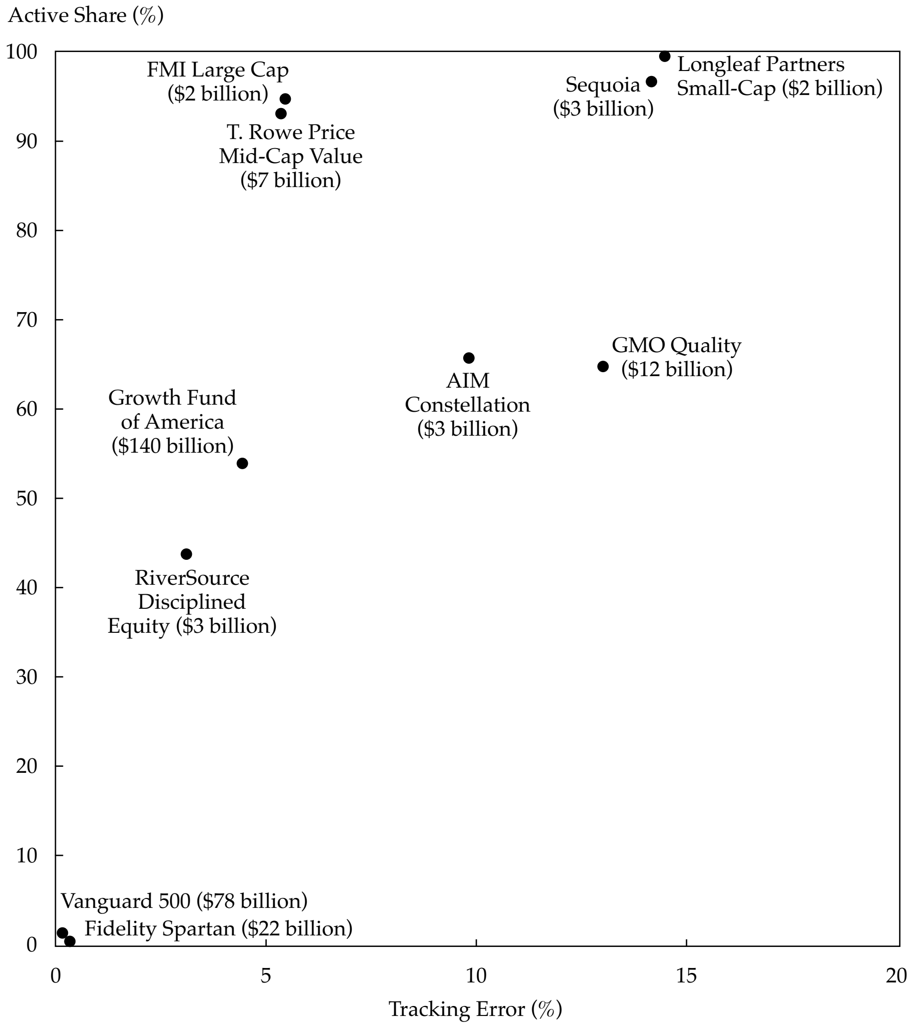
Source: Cremers and Petajisto (2009).

Table 1. Distribution of Mutual Funds across Active Share and Tracking-Error Ranges, 2009

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

Notes: This table shows the number of U.S. all-equity mutual funds in each Active Share and tracking-error category. Tracking error is computed from daily returns over the previous six months.

Figure 2. Examples of Funds in Each Category, 2009



Note: Total assets are shown in parentheses.

yet a low tracking error of 5.4% relative to the S&P 400 Index. This outcome is possible only if the fund's sector weights are similar to those of the benchmark index and the fund focuses instead on finding individual underpriced stocks within sectors and industries. Another example is the FMI Large Cap Fund, which has an Active Share of 95% and a tracking error of 5.4% with respect to the S&P 500. The fund has only 24 stock positions, but those positions are sufficiently well diversified across industries that its tracking error has remained low; the fund even mentions its low-risk approach in its prospectus.

Among the nonindex funds, the lower right-hand side includes funds that focus on factor bets, which means that they have a relatively high tracking error in spite of a moderately low Active Share. One example is the GMO Quality Fund, with an Active Share of only 65% but a tracking error of 12.9%. The fund states that it may time such factors as industries, sectors, size, and value and that 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. In addition, the AIM Constellation Fund has a relatively high tracking error of 9.7% and 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. The Sequoia Fund has an Active Share of 97% and a 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 10, and has some positions that account for 10% or more of the portfolio. Among small-cap funds, the Longleaf Partners Small-Cap Fund has only 19 stocks in its portfolio, which gives it an Active Share of 99% and a tracking error of 14.4% relative to the Russell 2000 Index.

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

Data and Empirical Methodology

This section presents the data and basic empirical methodology that I used in my study.

Data. To compute Active Share, I needed data on the portfolio composition of mutual funds as well as their benchmark indices. I matched stock holdings with the CRSP stock return database. I obtained data on the stock holdings of mutual funds from the Thomson Reuters database, which is based on mandatory quarterly filings with the U.S. SEC.

For the funds' benchmarks, I included essentially all indices used by the funds themselves over the sample period—a total of 19 indices from Standard & Poor's (S&P), Russell Investments, and Dow Jones/Wilshire Associates, including their common large-cap, mid-cap, and small-cap indices as well as their value and growth components. I obtained the index holdings data directly from the index providers.

I obtained data on monthly returns for mutual funds 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). I obtained data on daily returns for mutual funds from multiple sources. Daily returns are available in the CRSP mutual fund database from September 1998 on; before that period, I used the same combined database as in Cremers and Petajisto (2009). I obtained data on both monthly and daily returns for benchmark indices from S&P, Russell Investments, and Dow Jones, and all of those returns included dividends. All my databases were free of survivorship bias because they contained both live and dead funds.

Sample Selection. Using MFLINKS, I started by merging the CRSP mutual fund database with the Thomson Reuters holdings database. For funds with multiple share classes, I computed the value-weighted averages of all variables—including monthly and daily returns, fees, and turnover—across all share classes. To identify domestic all-equity funds, I used four different objective codes from CRSP and one code from Thomson Reuters; I also required 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 eliminated all sector funds and funds below $10 million in assets. I distinguished between index funds, enhanced index funds,[2] and active (nonindex) funds and flagged each fund accordingly. To obtain reasonably accurate estimates of tracking error, I computed it by using data on daily returns from the six months preceding each holdings report date. After applying these screens, I ended up with a final sample of 2,740 funds over 1980–2009.

Differences from Cremers and Petajisto (2009). My methodology of identifying funds and putting the sample together followed that of Cremers and Petajisto (2009), with a few exceptions. First, I preferred to use the benchmark index self-reported by a manager in the fund prospectus whenever possible rather than assigning the index that produced the lowest Active Share. I had two snapshots of the "primary benchmark index" as collected by Morningstar from fund prospectuses—one from January 2007 and the other from March 2010—and I used the earlier snapshot whenever possible. If the prospectus benchmark was unavailable, I picked the index that produced the lowest average Active Share over the previous three years. The benefit of using the prospectus benchmark is that it is the index that the fund manager has publicly committed to beat, and thus, both investor and manager focus on performance relative to that benchmark. Even if a manager had reported a misleading benchmark, it was not an issue because I controlled for any remaining beta, size, value, and momentum exposures separately.

Second, I preferred not to backdate benchmark index data; therefore, I used each index only after its inception date. This approach reflected the set of benchmarks available to a manager at the time of actually making the portfolio decision, rendering the comparison more relevant. However, because most of the indices were available by the early 1990s, this approach had essentially no impact on performance results and only a minor impact on other results in the 1980s.

Third, I computed 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] Fund performance is commonly compared with the benchmark index—not beta times the benchmark index—which better captures the risk the manager is taking relative to the benchmark. Specifically, if the manager is timing the equity market by temporarily holding a large amount of cash, this action represents meaningful risk that is captured in the traditional tracking-error measure but not in the regression residual.

Fourth, I added six more years to the sample, extending it from December 2003 to December 2009. During that time, the CRSP mutual fund database switched its data provider from Morningstar to Lipper. Both CRSP versions are free of survivorship bias and are supposed to include all live and dead funds, but each version still lacks some of the funds the other one has. Hence, my fund samples were slightly different, and even with an identical methodology, I would have been unable to perfectly match their results for the earlier period.

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

Closet Indexing: Examples and Trends

I next examined closet indexing in more detail and investigated time trends in active management.

What Is Closet Indexing? Loosely defined, closet indexing is the practice of staying close to the benchmark index while 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 term, but Active Share can serve as a useful guide for identifying closet indexers.

About 50% of the value of the index will always experience above-average returns and about 50% will always experience below-average returns relative to the index itself. Thus, if a manager holds more than 50% of the index (i.e., has an Active Share of less than 50%), then some of the positions cannot exist 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 that means including negative-alpha stocks in the portfolio. This approach is generally the opposite of what investors pay active managers to do. In fact, Treynor and Black (1973) showed that when investors can allocate to both an active fund and a passive index fund, they can achieve the highest possible Sharpe ratio when the active fund maximizes its information ratio (defined as alpha per unit of tracking error).

Therefore, an Active Share of 50% is the theoretical minimum that a pure active manager could have—anything below that is essentially a combination of an active fund and an index fund.[4] As in Cremers and Petajisto (2009), I generally set the closet indexer cutoff at an Active Share of 60%, which implies that an active manager should be able to select her investments from what she considers the top 40% of all stocks on the basis of their future alphas. Alternatively, it means that an active manager should never fish within what she 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 the manager's actual beliefs: Two managers can come to very different conclusions about which stocks are likely to outperform, but each manager should still actively invest on the basis of his own beliefs.

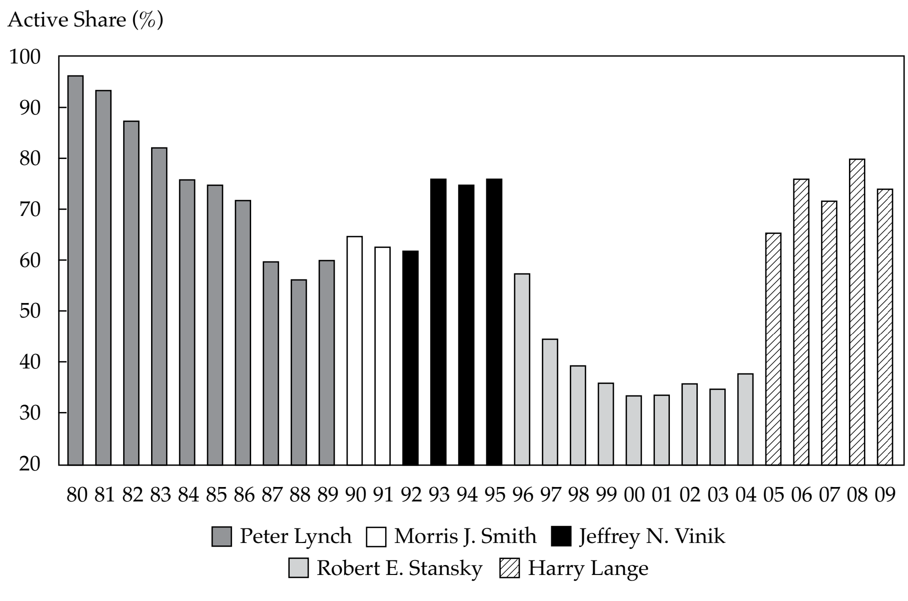
The problem with closet indexing is not that a low Active Share is inherently bad; in fact, a rational investor could well combine a position in a very active fund with a position in an index fund, thus ending up with a low Active Share in his overall portfolio. The problem is that closet indexers are 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%, then fund-level annual expenses of 1.5% amount to 4.5% of the active positions of the fund. Because only the active positions of the fund can possibly outperform the benchmark, it is very difficult in the long run for a closet indexer to overcome such fees and beat its index net of all expenses.

Fidelity Magellan. Fidelity Magellan is still famous for its spectacular record under Peter Lynch from 1977 to 1990. In his last 10 years as fund manager, Lynch beat the S&P 500 by a stunning 150%. Riding on this track record, the fund attracted large inflows and later became the largest mutual fund in the United States, with more than $100 billion in assets in 2000. The fund's subsequent performance, however, 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.[5] Nevertheless, one can shed some light on the issue by computing Fidelity Magellan's Active Share, which is shown in **Figure 3** over 1980–2009. Fidelity Magellan did indeed start out as a very active fund under Peter Lynch, with an Active Share over 90%. Its Active Share declined toward the end of Lynch's tenure but then came back up again to almost 80% under Jeffrey Vinik. After Stansky took over in June 1996, however, Active Share plunged more than 30 percentage points (pps) to 40% in just two years, and it then kept going down until stabilizing at 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% a year for 10 years. Although not a disastrous performance, 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 pressure to make the fund more active again, Fidelity appointed Harry Lange to replace Stansky on 31 October 2005. Lange was well known as a bold and active manager, and thus his appointment was intended to dispel any suspicions about closet indexing, which the fund's Active Share confirms: In the three months from September to December 2005, its Active Share jumped from less than 40% to 66%. It has subsequently increased to as high as 80%, comfortably

Figure 3. Fidelity Magellan's Active Share, 1980–2009



Note: Active Share is shown for each fund manager at year-end.

away from closet indexing. The fund's performance has also become more detached from the benchmark index; as of June 2008, Lange was 6% ahead of the index after fees, but he suffered heavy losses in the fall of 2008.

Even though large funds generally tend to be less active than small funds, asset growth does not explain the patterns in Fidelity Magellan's Active Share. Its 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.

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

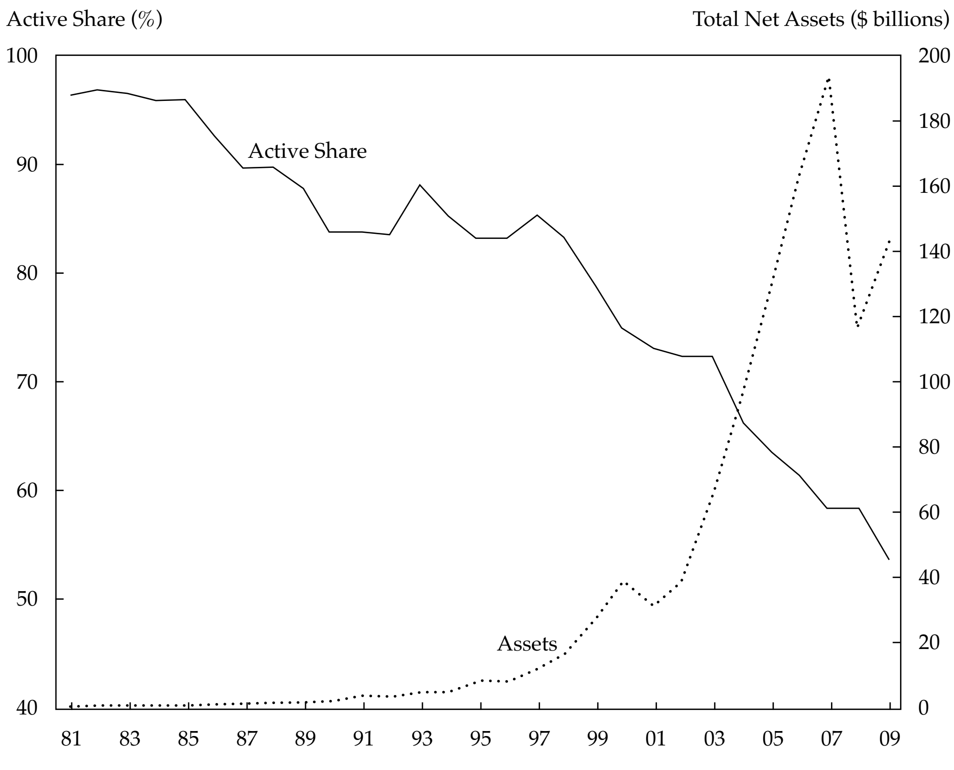
Figure 4 shows the fund's Active Share and total assets over 1981–2009. Although the fund has generally been active, its Active Share has been declining over time, falling to only 54% at the end of 2009. Simultaneously, the fund's assets have grown from under $40 billion in 2002 to as much as $200 billion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

The inflows have followed good performance. Interestingly, the fund underperformed the S&P 500 over 1980–1998 by almost 0.5% a year, but it beat the index by a remarkable 56% over September 1998–February 2000. From February 2000 to December 2009, its performance was much steadier but still more than 1% a year after fees. However, its recent fall in Active Share suggests that this good performance will be hard to maintain.

Nevertheless, one possibly redeeming feature of the fund is its unusual organizational structure. Its assets are divided among 10 autonomous portfolio managers, whereby each manager has full responsibility for his own subportfolio. Thus, if the fund is effectively a portfolio of 10 individual mutual funds, it is possible that individual managers are very 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, a drop in Active Share to closet indexing territory would be a signal that its best days are behind it.

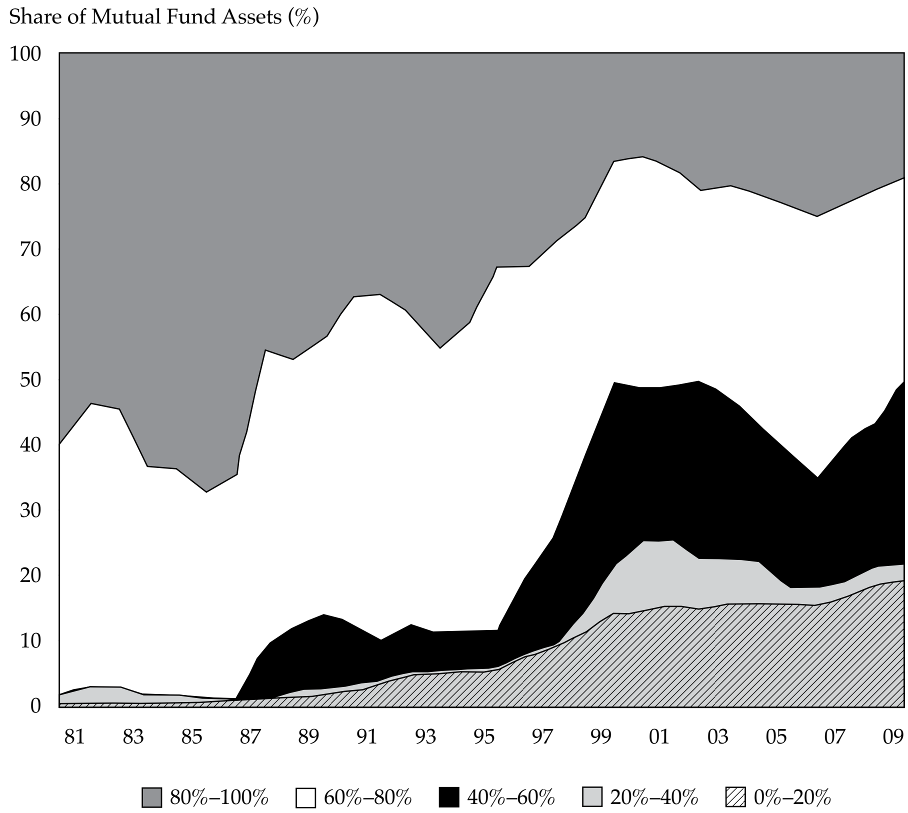
Trends in Closet Indexing. Are there any general trends in closet indexing? **Figure 5** shows the fraction of U.S. mutual fund assets in five Active Share categories over 1980–2009. The bottom group of funds, with Active Share below 20%, consists of pure index funds, which grew from almost nothing

Figure 4. Growth Fund of America's Active Share and Assets, 1981–2009



Note: Active Share and total net assets are shown at year-end.

Figure 5. Evolution of Active Share, 1980–2009



Notes: 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; the next two categories contain the closet indexers.

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

Table 2 shows the monthly time-series regression results. The trailing one-year moving average of the CBOE Volatility Index (VIX) negatively predicts average Active Share. However, the trailing one-year average of cross-sectional dispersion in stock returns (discussed in more detail later in the article) shows up as an even more significant predictor. This outcome can arise in response to tracking-error targets: When cross-sectional volatility increases, tracking error will increase unless a manager reduces the size of her active positions.

Recent market returns also 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 was high at about 25% throughout 1998–2002, cross-sectional volatility was also high, and the market fell dramatically 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, followed by even more extreme market volatility and

Table 2. Explaining Average Active Share, January 1990–December 2009 (*t*-statistics in parentheses)

	(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%

Notes: 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 are 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 are computed as 36-month trailing averages. The *t*-statistics are based on Newey–West standard errors with 36 monthly lags. Index funds, sector funds, and funds with less than $10 million in assets were excluded.

**Significant at the 5% level.

***Significant at the 1% level.

declines in 2008. Simultaneously, closet indexing reared its head again, climbing all the way back to its previous peak by 2009.

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 prospectuses. Presumably, this requirement made both 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.

Results on Fund Performance

Investigating the type and degree of active management can help us understand the inputs of a fund's portfolio. But how do these inputs translate into outputs—or, more specifically, fund performance—across the different types of actively managed funds and over a long period?

Categories of Funds. Funds can be sorted into a 5 × 5 grid of Active Share and tracking error to distinguish between different types and degrees of active management. Because I wanted to simplify this 5 × 5 grid and make it economically more meaningful, I created categories of funds on the basis of the grid and labeled them according to the broad type of active management they engaged in. I included only active (nonindex) funds in the grid; both index funds and enhanced index funds were eliminated at this stage. I sorted funds sequentially, first by Active Share and then by tracking error, within each quintile.

Table 3 shows how I formed the groups. I labeled the lowest–Active Share quintile "closet indexers," reflecting their mean Active Share of less than 60%. The exception is the funds with the highest tracking error. These funds generate significant volatility relative to their very small active positions, and because those positions must be exposed to systematic factor

Table 3. Different Types of Active Management

	Tracking-Error Quintile						
Active Share Quintile	1 (Low)	2	3	4	5 (High)	Group	Label
5 (high)	5	5	5	5	4	5	Stock pickers
4	2	2	2	2	3	4	Concentrated
3	2	2	2	2	3	3	Factor bets
2	2	2	2	2	3	2	Moderately active
1 (low)	1	1	1	1	3	1	Closet indexers

Notes: This table shows the cutoffs I used to define different types of active management for U.S. all-equity mutual funds. I sorted all funds into quintiles, first by Active Share and then by tracking error, using the latest values available for each fund at the end of each month. Index funds, sector funds, and funds with less than $10 million in assets were excluded.

risk, I labeled them "factor bets." In fact, all groups in the highest-tracking-error quintile can be labeled factor bets because they are all exposed to systematic risk in their active positions. The only exception is the highest–Active Share group. These funds combine high volatility with a high degree of stock selection and thus fall into the "concentrated" group. Nonconcentrated funds with high Active Share form the group of more diversified "stock pickers." The rest of the funds can be called "moderately active" because they fall in the middle in terms of both Active Share and tracking error. For purposes of my study, I focused on the performance results for these five groups rather than using the more complicated matrix of 25 portfolios.

Table 4 shows some sample statistics for the fund groups. For each month, I computed the mean and standard deviation of a variable and then computed the time-series averages across all the months. A typical month has a total of 1,124 funds, with about 180 funds each in the stock picker, factor bet, and closet indexer groups. Average fees are 1.27% and are 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 do 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. With respect to turnover and fees, closet indexers appear slightly less expensive than other actively managed funds, but they are, of course, still substantially more expensive per unit of Active Share or tracking error.

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

Table 5 shows the equal-weighted returns for the five groups of funds, as well as the averages across all groups. Looking at gross returns across all fund groups, I found that the average fund was able to select a portfolio of stocks that beat its benchmark index by 0.96% a year before fees and expenses. When I used the four-factor model of Carhart (1997) to control for any remaining exposure to market, size, value, or momentum, that outperformance fell to 0.31%. Most of the outperformance came from the stock pickers and concentrated funds, with benchmark-adjusted returns of 2.61% and 1.64%, respectively. Moderately active funds also exhibited

Table 4. Sample Statistics for Fund Categories, 1990–2009

Group	Label	No. of Funds	Assets (millions)	Active Share	Tracking Error	Turnover	Expense Ratio	No. of Stocks
A. Mean values								
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
B. Standard deviations								
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	14.0%	3.7%	83%	0.45%	119

Notes: This table shows sample statistics for the fund categories defined in Table 3 and subsequently used in the performance tables. The equal-weighted mean and standard deviation of each variable are first computed for each month over the sample period, and the reported numbers are their time-series averages across all the months.

Table 5. Fund Performance, January 1990–December 2009 (*t*-statistics in parentheses)

		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)

Notes: This table shows the annualized equal-weighted performance of U.S. all-equity mutual funds for five types of active management (defined in Table 3). Gross returns are returns on a fund's stock holdings and do not include any fees or transaction costs. Net returns are returns to a fund investor after fees and transaction costs. The numbers are expressed in percent per year, followed by *t*-statistics based on White's standard errors. Index funds, sector funds, and funds with less than $10 million in assets were excluded.

slight skill, but funds taking factor bets did not. Not surprisingly, closet indexers largely just matched 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 found that the average fund underperformed its benchmark by about –0.41%. Moderately active funds experienced a 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 was only slightly less than their fees. Even concentrated funds essentially just matched their benchmarks net of fees. The only group that added value for investors was active stock pickers; they beat their benchmarks by 1.26%, or by 1.39% for the four-factor model. The stock pickers also beat the closet indexers net of fees by a statistically significant 2.17% (t = 3.48).

Economically, these results mean 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 for their investors even net of all expenses. In contrast, factor bets, as indicated by high tracking error, are not rewarded in the market; on average, those funds have destroyed value for their investors. Cremers and Petajisto (2009) found very similar results for their shorter period, except for one group: concentrated funds. That group suffered over 2004–2009 and especially during the financial crisis, which explains part of the difference in the results.[6]

An alternative approach would be to use the same 5 × 5 grid as in Table 3 but, instead of forming quintiles on the basis of absolute levels of Active Share and tracking error, form quintiles on the basis of a fund's ranking relative to funds within its own style group. Thus, I also formed the 5 × 5 grid separately for large-cap, mid-cap, and small-cap funds and then formed the fund groups within each of the three styles. The results from this analysis (unreported) 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 beat their benchmarks, by 0.89% a year. The performance improvement over closet indexers is still economically and statistically significant; however, because closet indexing is more common in large-cap funds than in 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 3 × 3 Morningstar Style Box) on the basis of both market-cap and value dimensions before being sorted into the five active management types, the results remain similar.

Fund Size and Performance. All performance numbers throughout this article are equal-weighted averages across funds so that individual fund categories would not be dominated by one or two very large funds. However, **Table 6** shows how fund size affects performance net of all expenses within each of the five categories. The relationship between size and performance is very weak. The best performers are the smallest funds within the stock picker group, earning 1.84% a 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 (see, e.g., Chen, Hong, Huang, and Kubik 2004). However, this effect arises not within but, rather, across the groups. Closet indexers tend to be larger and to perform poorly, whereas the most active stock pickers tend to be smaller funds. In other words, fund size seems to hurt performance because it is correlated with the type of active management, not because it hurts performance within a type.

Performance Persistence. If some fund managers have skill but others do not, we would expect to see persistence in fund performance. To examine this notion, I sorted funds within each group into quintiles on the basis of their benchmark-adjusted net returns over the prior calendar year (see Carhart 1997). **Table 7** 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 controlling for the momentum factor of Carhart (1997). As in the prior literature, this approach eliminates a large amount of performance persistence across funds and indicates that the top-performing funds buy stocks with positive momentum. In fact, Lou (2010) suggested that the 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 the prior losers by 4.61% a year. In contrast, among the more

Table 6. Fund Size and Performance, January 1990–December 2009 (*t*-statistics in parentheses)

		Fund Size Quintile						
Group	Label	1 (Low)	2	3	4	5 (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)	

Notes: This table shows the annualized equal-weighted performance of U.S. all-equity mutual funds for fund size quintiles within five types of active management (defined in Table 3). 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 based on White's standard errors. Index funds, sector funds, and funds with less than $10 million in assets were excluded.

Table 7. Performance Persistence, January 1990–December 2009 (*t*-statistics in parentheses)

		Prior One-Year Return Quintile						
Group	Label	1 (Low)	2	3	4	5 (High)	All	High – Low
A. Benchmark-adjusted net return								
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)	
B. Four-factor alpha of benchmark-adjusted net return								
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)	

Notes: This table shows the annualized equal-weighted performance of U.S. all-equity mutual funds for prior one-year return quintiles within five types of active management (defined in Table 3). 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 based on White's standard errors. Index funds, sector funds, and funds with less than $10 million in assets were excluded.

diversified stock pickers, the prior winners beat the prior losers by only 1.00%. The finding by Cremers and Petajisto (2009) of considerable performance persistence within the highest–Active Share quintile thus appears to have been mostly due to the concentrated rather than the 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 generally good managers 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 to take very large random bets in an attempt to "win the lottery," become a top-performing fund, and attract large inflows (somewhat similar to the tournament behavior in Brown, Harlow, and Starks 1996), which would place them in the same fund group as 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, and so it does not offer similar gambling incentives for unskilled managers.

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 8** addresses this question by showing the results of pooled panel regressions in which I tried to explain fund performance net of expenses

Table 8. Predictive Regressions for Fund Performance, 1992–2009 (*t*-statistics in parentheses)

	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 pickers			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%

Notes: 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; 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 the benchmark-adjusted return. Large-cap, mid-cap, 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 previous one to three years, fund size squared, number of stocks, and manager tenure. All specifications include year dummies. Log_{10}(TNA) is the base-10 logarithm of total net assets. The t-statistics are based on standard errors clustered by year.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

with a large number of explanatory variables. I again used both benchmark-adjusted returns (columns 1–3) and four-factor alphas of benchmark-adjusted returns (columns 4–6). All explanatory variables are as of the end of year t – 1; the fund returns are annual returns in year t.[7]

Column 1 shows that Active Share alone predicts fund returns with economic and statistical significance. A 10 pp 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 combined Active Share and tracking error to create fund categories as before, with a dummy variable for each category (except closet indexers, the benchmark category), and the results are comparable to those in Table 5: Stock pickers beat closet indexers by 2.88% a year (t = 2.48) net of fees, but the other fund categories are much less impressive. Moderately active funds did better than closet indexers, but they still lagged behind market indices.

How does Active Share predict returns within market-capitalization groups? Column 2 shows the results from a regression in which I added dummy variables for large-cap, mid-cap, and small-cap funds and interacted those dummies with Active Share. This approach increases the coefficients 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 mid-cap 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 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; they also signal poor fund quality. Older funds slightly underperform: For every 10 years in existence, a fund's return decreases by 15–17 bps a 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.

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 but where returns sometimes seem driven by macroeconomic issues that may even exacerbate existing mispricings at the level of individual stocks.[8]

One measure of the importance of stock-level news relative to macroeconomic news is the cross-sectional dispersion in stock returns, which 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

σ_t = the cross-sectional dispersion at time t

$w_{i,t}$ = the weight of stock i in the market index

$R_{i,t}$ = the return on stock i

$R_{m,t}$ = the return on the market index

This definition follows the definition of the recently introduced Russell-Parametric Cross-Sectional Volatility (CrossVol) indices. However, the Russell CrossVol data do not start until July 1996, and so I computed the measure myself for each month, using Russell 3000 Index holdings, which allowed me to start my tests much earlier.

Table 9 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 results from regressions in which the dependent variable is the 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 in month t, E_{t-1}[CrossVol(t)], is computed on the basis of an AR(3) model using CrossVol values between months t – 3 and t – 1, and the unexpected dispersion is defined as $\varepsilon_{CrossVol(t)}$ = CrossVol(t) – E_{t-1}[CrossVol(t)]. The expected dispersion predicts fund returns slightly better than the prior month's dispersion in Column 2. However, the unexpected dispersion predicts returns with the opposite sign 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.

What economic effect 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

Table 9. Fund Performance and Cross-Sectional Dispersion, January 1990–December 2009 (*t*-statistics in parentheses)

	Stock Pickers					All Funds	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CrossVol(t + 1)			0.0073			0.0274	
			(0.20)			(1.08)	
CrossVol(t)	0.0169		–0.1604***			–0.0468	
	(0.44)		(–3.06)			(–1.24)	
CrossVol(t – 1)		0.0846***	0.1313**			0.0157	
		(2.77)	(2.55)			(0.55)	
CrossVol(t – 2)			–0.0040			0.0327	
			(–0.10)			(1.25)	
CrossVol(t – 3)			0.1125**			0.0192	
			(2.55)			(0.69)	
CrossVol(t – 4)			–0.0139			–0.0083	
			(–0.39)			(–0.37)	
E_{t-1}[CrossVol(t)]				0.1040***	0.1071***		0.0478**
				(2.78)	(3.18)		(2.35)
$\varepsilon_{CrossVol(t)}$					–0.1582***		–0.0356
					(–3.08)		(–1.01)
N	240	240	240	240	240	240	240
R^2	0.3%	7.6%	18.0%	7.4%	16.1%	4.4%	3.7%

Notes: The dependent variable is the cumulative equal-weighted net return (after all expenses) in excess of the benchmark index return in month t. The only funds included are stock pickers (defined in Table 3). CrossVol is the monthly cross-sectional dispersion for all U.S. equities computed by Russell Investments. E_{t-1}[CrossVol(t)] is the predicted value of CrossVol(t) based on information available at t – 1, whereas $\varepsilon_{CrossVol(t)}$ is the shock to CrossVol(t) at time t, defined as CrossVol(t) – E_{t-1}[CrossVol(t)]. The t-statistics are based on White's standard errors.

**Significant at the 5% level.

***Significant at the 1% level.

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 contribute to this pattern: When dispersion increases, some managers reduce their active positions (as shown in Table 2) because those positions just became more risky and the only way to prevent tracking error from increasing is to scale back active positions, but that action, 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 break it down 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

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

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 returns at time t.[9] Hence, the measure will be high if idiosyncratic risk is high, market returns are large (either positive or negative), or beta dispersion is high. When investors focus on company-specific fundamentals, idiosyncratic risk should be high because company-specific news is efficiently incorporated in the prices of individual stocks, but beta dispersion should also be high because investors distinguish between the beta exposures of different companies.

Popular press articles discussing stock pickers' markets usually refer to another metric, the average correlation between stocks. This metric 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 computed it relative to the market index. The average correlation can be expressed as

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

where $\sigma_{m,t}$ is market volatility and $\sigma_{\varepsilon_i,t}$ is the idiosyncratic time-series volatility of stock i. This computation requires the time-series estimation of betas and volatilities, so I generated monthly values from a market model regression by using daily data within each month.[10]

Using simple one-month lagged values of explanatory variables, **Table 10** shows where the return predictability comes from. 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. Cross-sectional dispersion itself is overwhelmingly driven by idiosyncratic dispersion (regressing the former on the latter produces an R^2 of 89.8%, versus 90.2% with the other two variables included), which also drives 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.[11]

Perhaps surprisingly, the average correlation with the market index is not a statistically significant predictor of future returns. Compared with cross-sectional dispersion, average correlation is a more complicated function of the underlying variables: Beta dispersion and market volatility explain 57% of average correlation; 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 because that component

Table 10. Fund Performance and Alternative Measures of Cross-Sectional Dispersion, January 1990–December 2009
(*t*-statistics in parentheses)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CrossVol	0.0846***							
	(2.77)							
AvgCorr		–0.0074						
		(–1.37)						
var($R_{m,t}$)			1.7073					
			(0.83)					
var($\beta_{i,t}$)				0.0064***			0.0041*	
				(3.91)			(1.89)	
σ_ε^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	7.6%	1.0%	0.3%	5.1%	7.3%	4.4%	9.1%	2.4%

Notes: The dependent variable is the cumulative equal-weighted net return (after all expenses) in excess of the benchmark index return in month t. The only funds included are stock pickers (defined in Table 3). 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; var($R_{m,t}$) is the return variance of the market index in month t; var($\beta_{i,t}$) is the cross-sectional variance of one-month betas across all stocks; σ_ε^2 is the cross-sectional variance of realized one-month idiosyncratic returns; $\sigma_{\varepsilon,i}^2$ is the cross-sectional average of one-month idiosyncratic variance. 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 t-statistics are based on White's standard errors.

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

explains only 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.

Earlier studies (see, e.g., Ankrim and Ding 2002) have 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 was 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.

My results are not driven by extreme dispersion in a few unusual months because they are not materially affected by removing any monthly dispersion values over 15%. Because 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. With the 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 pattern similar to the performance of individual stock picks. If we expand the test sample from stock pickers to all U.S. equity funds (columns 6–7), the results do become weaker, and thus dispersion is specifically related to stock picker performance but not the performance of other fund categories, such as closet indexers. In fact, funds that take factor bets even perform better when dispersion is increasing, presumably reflecting their focus on predicting broader macroeconomic events.

Performance during 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 11** 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 January 2008 and ending in December 2009. It shows the annualized benchmark-adjusted net returns after fees and

Table 11. Fund Performance during the Financial Crisis, January 2008–December 2009
(*t*-statistics in parentheses)

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)

Notes: This table shows the annualized equal-weighted performance of U.S. all-equity mutual funds for five types of active management during the entire financial crisis (January 2008–December 2009) and the recovery period only (January–December 2009). 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 based on White's standard errors. Index funds, sector funds, and funds with less than $10 million in assets were excluded.

expenses. Although 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 (nonindex) mutual fund lost to its benchmark by –0.51% a 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% a year. The main exception was concentrated funds, which 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% a year relative to the indices.

If all fund categories lost to their benchmarks—and some of them did so 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 a predictably weak performance of –0.66%.

Conclusion

Although the average actively managed mutual fund has underperformed its benchmark index, both the type and the degree of active management matter considerably for performance. In my study, I used Active Share and tracking error to sort domestic all-equity mutual funds into five categories on the basis of the type of active management they practice. I found that the most active stock pickers have been able to add value for their investors, beating their benchmark indices by about 1.26% a 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 over the 2008–09 financial crisis, and they also hold separately within large-cap and small-cap funds.

Economically, these results mean that there are some inefficiencies in the market that can be exploited by active stock selection. Furthermore, I found that active stock selection is most successful at times of high cross-sectional dispersion in stock returns. However, equity fund managers are unable 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. In contrast, high tracking error is not desirable because funds that focus on factor bets underperform and even concentrated managers who combine active stock selection with factor bets have not outperformed. Closet indexers who stay very close to the benchmark index are a particularly bad deal because 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.

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This article qualifies for 1 CE credit.

Notes

1. See, among many others, Jensen (1968); Gruber (1996); Wermers (2000).
2. Enhanced index funds differ from closet indexers in that the former openly offer index-like performance with small active bets on top—and their low fees reflect that.
3. In fact, Cremers and Petajisto (2009) also took this approach in computing tracking error in earlier versions of their study.
4. Actually, even this combination can be fine but *only* if fees are low enough to reflect this "enhanced indexing" approach.
5. See "Magellan's Manager Has Regrets," *Wall Street Journal* (28 May 2004).
6. Another part of the difference comes simply from having a different version of the CRSP mutual fund database with a slightly different sample of funds. Because the concentrated stock pickers are a small group and their returns are the most volatile of all, including or excluding a few funds can affect the results. The other groups have many more funds and are thus less sensitive to such data issues.
7. To avoid creating a survivorship bias, I included a fund year even if it had only one month of returns in year t.
8. See, for example, "Macro Forces in Market Confound Stock Pickers," *Wall Street Journal* (24 September 2010).
9. 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 $R_{i,t} - R_{m,t} = (\beta_i - 1)R_{m,t} + \varepsilon_{i,t}$ and $\left(R_{i,t} - R_{m,t}\right)^2 = (\beta_i - 1)^2 R_{m,t}^2 \varepsilon_{i,t}^2 + 2(\beta_i - 1)R_{m,t}\varepsilon_{i,t}$. The weighted sum of the latter expression is then

$$\sum_i w_{i,t}\left(R_{i,t} - R_{m,t}\right)^2 = \sum_i w_{i,t}(\beta_i - 1)^2 R_{m,t}^2 + \sum_i w_{i,t}\varepsilon_{i,t}^2 + 2R_{m,t}\sum_i w_{i,t}(\beta_i - 1)\varepsilon_{i,t},$$

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

10. The estimates for single stocks are somewhat inaccurate because they are based on only about 21 daily (nonoverlapping) data points for each month, but the cross-sectional average correlation is more accurate because some of the estimation errors cancel out in the cross-section. I chose the S&P 500 as my universe for these calculations because using daily data requires that all stocks be very liquid.
11. 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.

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