RFS Advance Access published August 6, 2009

How Active Is Your Fund Manager? A New Measure That Predicts Performance

K. J. Martijn Cremers
International Center for Finance, Yale School of Management

Antti Petajisto
International Center for Finance, Yale School of Management

We introduce a new measure of active portfolio management, Active Share, which represents the share of portfolio holdings that differ from the benchmark index holdings. We compute Active Share for domestic equity mutual funds from 1980 to 2003. We relate Active Share to fund characteristics such as size, expenses, and turnover in the cross-section, and we also examine its evolution over time. Active Share predicts fund performance: funds with the highest Active Share significantly outperform their benchmarks, both before and after expenses, and they exhibit strong performance persistence. Nonindex funds with the lowest Active Share underperform their benchmarks. (*JEL* G10, G14, G20, G23)

An active equity fund manager can attempt to outperform the fund's benchmark only by taking positions that are different from the benchmark. Fund holdings can differ from the benchmark holdings in two general ways: either because of stock selection or factor timing (or both).[1] Stock selection involves picking individual stocks that the manager expects to outperform their peers. Factor timing involves time-varying bets on systematic risk factors such as entire industries, sectors of the economy, or more generally any systematic risk relative to the benchmark index. Because many fund managers favor one approach over the other, it is not clear how to quantify active management across all funds.

We wish to thank Nick Barberis, Jonathan Berk, Lauren Cohen, Roger Edelen, Frank Fabozzi, Andrea Frazzini, Will Goetzmann, John Griffin, Marcin Kacperczyk, Owen Lamont, Juhani Linnainmaa, Ludovic Phalippou, Andrei Shleifer, Clemens Sialm, Matthew Spiegel, Russ Wermers, Lu Zheng, and Eric Zitzewitz for comments, as well as conference and seminar participants at the AFA 2007 Annual Meeting, CFEA 2006, CRSP Forum 2006, EFA 2007 Annual Meeting, FRA 2006 Annual Meeting, NBER Asset Pricing Meeting, NYU Stern Five-Star Conference, AllianceBernstein, Barclays Global Investors, Goldman Sachs Asset Management, Morningstar Investment Conference, Super Bowl of Indexing, Federal Reserve Bank of New York, Securities and Exchange Commission, Amsterdam University, Baruch College, Boston College, Helsinki School of Economics, ISCTE Business School (Lisbon), Tilburg University, University of Chicago, University of Maryland, University of Texas at Austin, University of Vienna, and Yale School of Management. We are also grateful to Barra, Frank Russell Co., Standard & Poor's, and Wilshire Associates for providing data for this study. Send correspondence to Antti Petajisto, Yale School of Management, PO Box 208200, New Haven, CT 06520-8200; telephone: (203) 436-0666. E-mail: antti.petajisto@yale.edu. Web page: http://www.petajisto.net/.

[1] The basic idea has been presented and discussed by Fama (1972); Brinson, Hood, and Beebower (1986); Daniel et al. (1997); and many others.

doi:10.1093/rfs/hhp057

Tracking error volatility (hereafter just "tracking error") is the traditional way to measure active management. It represents the volatility of the difference between a portfolio return and its benchmark index return. However, the two distinct approaches to active management contribute very differently to tracking error, despite the fact that either of them could produce a higher alpha. For example, the T. Rowe Price Small Cap fund is a pure stock picker, which hopes to generate alpha with its stock selection within industries, but it simultaneously aims for high diversification across industries. In contrast, the Morgan Stanley American Opportunities fund is a "sector rotator," which focuses on actively picking entire sectors and industries that outperform the broader market while holding mostly diversified (and thus passive) positions within those sectors. The tracking error of the diversified stock picker is substantially lower than that of the sector rotator, suggesting that the former is much less active. But this would be an incorrect conclusion—its tracking error is lower simply because individual stock picks allow for greater diversification, even while potentially contributing to a positive alpha.

Instead, we can compare the portfolio holdings of a fund to its benchmark index. When a fund overweights a stock relative to the index weight, it has an active long position in it, and when a fund underweights an index stock or does not buy it at all, it implicitly has an active short position in it. In particular, we can decompose any portfolio into a 100% position in its benchmark index plus a zero-net-investment long-short portfolio on top of that (Asness 2004 discusses the same decomposition, albeit from the point of view of tracking error alone). For example, a fund might have 100% in the S&P 500 plus 40% in active long positions and 40% in active short positions.

We propose the size of this active long-short portfolio (40% in the previous example) as a new measure of active management, and we label this measure the Active Share of a portfolio. Since mutual funds almost never take actual short positions, their Active Share will always be between zero and 100%. Active Share can thus be easily interpreted as the "fraction of the portfolio that is different from the benchmark index."

We argue that Active Share is useful for two main reasons. First, it provides information about a fund's potential for beating its benchmark index—after all, an active manager can only add value relative to the index by deviating from it. Some positive level of Active Share is therefore a necessary (albeit not sufficient) condition for outperforming the benchmark.

Second, while Active Share is a convenient stand-alone measure of active management, it can also be used together with tracking error for a more comprehensive picture of active management, allowing us to distinguish between stock selection and factor timing. The main conceptual difference between the measures is that tracking error incorporates the covariance matrix of returns and thus puts significantly more weight on correlated active bets, whereas Active Share puts equal weight on all active bets regardless of diversification. Hence,

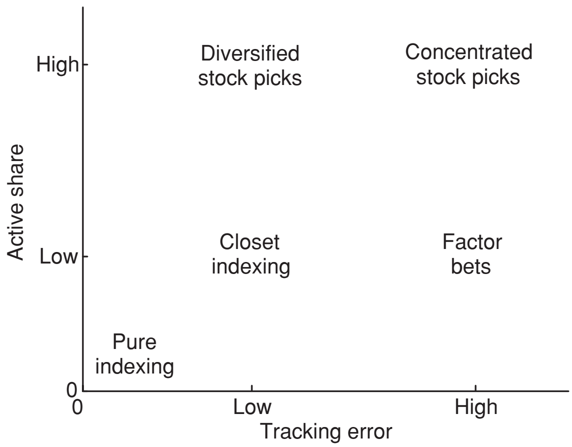

Figure 1
Different types of active and passive management
Active Share represents the fraction of portfolio holdings that differ from the benchmark index, thus emphasizing stock selection. Tracking error is the volatility of fund return in excess of the benchmark, so it emphasizes bets on systematic risk.

we can choose tracking error as a reasonable proxy for factor bets and Active Share for stock selection.[2]

Using these proxies, we illustrate the two dimensions of active management in Figure 1. A diversified stock picker can be very active despite its low tracking error, because its stock selection within industries can still lead to large deviations from the index portfolio. In contrast, a fund betting on systematic factors can generate a large tracking error even without large deviations from index holdings. A concentrated stock picker combines the two approaches, thus taking positions in individual stocks as well as in systematic factors. A "closet indexer" scores low on both dimensions of active management while still claiming to be active.[3] Finally, a pure index fund has almost zero tracking error and Active Share.

In this article, we apply the methodology to characterize active management for all-equity mutual funds in the United States. The passive benchmark is assigned separately for each fund and each point in time by choosing the index that produces the lowest Active Share. First, we determine how much and what type of active management each fund practices, and we test how this is related to other fund characteristics such as size, fees, flows, and prior returns. Second, we examine the time series from 1980 to 2003 to understand the evolution of active management over time. Third, we investigate fund performance to find out whether more active managers have more skill and whether that skill

[2] In principle, either dimension could be measured entirely from portfolio holdings or from returns. For example, we also use industry-level Active Share in this article as a holdings-based proxy for industry bets.

[3] Fidelity Magellan at the end of our sample period is one of the most prominent examples, despite the denials by its manager (e.g., *The Wall Street Journal*, May 28, 2004, "Magellan's Manager Has Regrets").

survives their fees and expenses. Our methodology allows us to focus on the performance of the truly active funds as well as the different types of active funds, complementing the existing mutual fund literature, which has typically not made such distinctions between nonindex funds.

In the cross-section of funds, we find wide dispersion along both dimensions of active management. For example, a tracking error of 4–6% can be associated with an Active Share anywhere between 30% and 100%, thus including both closet indexers as well as very active funds. The Active Share of an individual fund is extremely persistent over time. Consistent with the popular notion, small funds are indeed more active than large funds; however, the effect is economically small, and it only becomes significant after about $1 billion in assets. The expense ratio is much lower for index funds, but for all other funds it exhibits surprisingly little relationship with Active Share, which makes closet indexers disproportionately expensive.

The fraction of pure index funds grew substantially over the 1990s, from about 1% to 15% of mutual fund assets. However, the fraction of closet indexers increased even more significantly: funds with low Active Share (20–60%) had about 30% of all assets in 2003, compared with almost zero in the 1980s. This trend dragged down the average Active Share of nonindex large-cap funds from about 80% to 60% over the same period.

Fund performance in excess of the benchmark is significantly related to active management, as revealed by a two-dimensional sort of nonindex funds by Active Share and tracking error. Funds with the highest Active Share exhibit some skill and pick portfolios that outperform their benchmarks by 1.51–2.40% per year. After fees and transaction costs, this outperformance decreases to 1.13–1.15% per year. In contrast, funds with the lowest Active Share have poor benchmark-adjusted returns and alphas before expenses (between 0.11% and −0.63%) and do even worse after expenses, underperforming by −1.42% to −1.83% per year. The differences in performance across the top and bottom Active Share groups are also statistically significant.

Interestingly, tracking error by itself is not related to fund returns. Hence, not all dimensions of active management are rewarded in the market, but the dimension captured by Active Share is. Economically, these results suggest that the most active stock pickers have enough skill to outperform their benchmarks even after fees and transaction costs. In contrast, funds focusing on factor bets seem to have zero-to-negative skill, which leads to particularly bad performance after fees. Hence, it appears that there are some mispricings in individual stocks that active managers can exploit, but broader factor portfolios may either be too efficiently priced or too difficult for the managers to predict. Closet indexers, unsurprisingly, exhibit zero skill but underperform because of their expenses.

Active Share is very significantly related to benchmark-adjusted performance within the smallest 60% of funds, producing a spread in returns of 2.5–3.8%. A weaker but still positive relationship exists for the largest 40% of funds, where the return spread varies from 1% to 2% per year.

Among the highest Active Share quintile, there is significant persistence in benchmark-adjusted fund performance even after controlling for momentum. The funds in the highest Active Share and highest prior-year return quintiles continue to outperform their benchmarks by 5.10% per year ($t = 3.67$) after expenses, or 3.50% per year ($t = 3.29$) under the four-factor model of Carhart (1997).

While our results using benchmark-adjusted returns are robust to the four-factor Carhart model, the standard non-benchmark-adjusted Carhart alphas show no significant relationship with Active Share. The reason behind this is that the benchmark indexes of the highest Active Share funds have large negative Carhart alphas, while the benchmarks of the lowest Active Share funds have large positive alphas, even though these benchmark indexes are passive, well-diversified, and widely followed. This may not matter for investors who tend to care about performance relative to the official benchmark index rather than relative to a long-short Carhart benchmark, but the result does suggest a misspecification in the four-factor Carhart model (see Cremers, Petajisto, and Zitzewitz 2008).

The current mutual fund literature has done little to investigate active management per se. Instead, a large volume of research has focused on fund performance directly.[4] For example, a comprehensive study by Wermers (2000) computes mutual fund returns before and after expenses; our work refines those performance results by dividing funds into various active management categories. Even more closely related, Wermers (2003) investigates active management and fund performance but uses only the S&P 500 tracking error as a measure of active management; we add the Active Share dimension, which turns out to be crucial for fund returns, and we use a variety of actual stock market indexes rather than only the S&P 500.

Kacperczyk, Sialm, and Zheng (2005) ask a related question about whether industry concentration of mutual funds explains fund performance. This amounts to testing whether funds with concentrated stock picks or large factor bets in industries perform better than other funds. Our performance results address the broader question about whether any active stock picks are reflected in fees and alphas, and whether any type of factor bet, including those unrelated to specific industries, is similarly reflected in performance.

Another important feature separating our article from many others in the literature is the data. First, we have holdings data for the most common benchmark indexes used in the industry over the sample period: the S&P 500, S&P 400, S&P 600, S&P 500/Barra Value, S&P 500/Barra Growth, Russell 1000, Russell 2000, Russell 3000, Russell Midcap, the value and growth components of the four Russell indexes (i.e., eight Russell style indexes), Wilshire 5000,

[4] Various performance measures have been developed and applied by Jensen (1968); Grinblatt and Titman (1989, 1993); Gruber (1996); Daniel et al. (1997); Wermers (2000); Pastor and Stambaugh (2002); Cohen, Coval, and Pastor (2005); and many others. Studies focusing on performance persistence include, for example, Brown and Goetzmann (1995); Carhart (1997); Bollen and Busse (2004); and Mamaysky, Spiegel, and Zhang (2007).

and Wilshire 4500, for a total of nineteen indexes. This allows us to compute Active Share relative to a fund's realistic benchmark index as opposed to picking the same market index for all funds. Second, we use daily data on mutual fund returns. This is important for the accurate calculation of tracking error, especially when funds do not keep their styles constant over the years or when funds have only short return histories.

The article proceeds as follows. Section 1 examines our definition and measures of active management. Section 2 describes the data sources and sample selection criteria. The empirical results for active management are presented in Section 3 and for fund performance in Section 4. Section 5 concludes.

1. Definition and Measures of Active Management

"Passive management" of a portfolio is easy to define: it consists of replicating the return on an index with a strategy of buying and holding all (or almost all) index stocks in the official index proportions.

"Active management" can then be defined as any deviation from passive management. Measuring it involves measuring the "degree of deviation" from passive management. However, there are different types of active management, and this is where the difficulties arise: how to measure the deviation depends on what aspect of active management we want to capture.

1.1 Tracking error

Tracking error (or more formally, tracking error volatility) is commonly defined (e.g., Grinold and Kahn 1999) as the time-series standard deviation of the difference between a fund return ($R_{\text{fund},t}$) and its benchmark index return ($R_{\text{index},t}$):

$$\text{Tracking error} = Stdev[R_{\text{fund},t} - R_{\text{index},t}].$$

A typical active manager aims for an expected return higher than the benchmark index, but at the same time he wants to have a low tracking error (volatility) to minimize the risk of significantly underperforming the index. Mean-variance analysis in this excess-return framework is a standard tool of active managers (e.g., Roll 1992; or Jorion 2003).

The common definition of tracking error effectively assumes a beta equal to 1 with respect to the benchmark index, and thus any deviation from a beta of 1 will generate tracking error. In this article, we adopt a slightly modified definition of tracking error, obtained by regressing excess fund returns on excess index returns:

$$\begin{aligned} R_{\text{fund},t} - R_{f,t} &= \alpha_{\text{fund}} + \beta_{\text{fund}}(R_{\text{index},t} - R_{f,t}) + \varepsilon_{\text{fund},t} \\ \text{Tracking error} &= Stdev[\varepsilon_{\text{fund},t}]. \end{aligned}$$

Following from this definition, any persistent allocation to cash or to high-beta or low-beta stocks will not contribute to our measure of tracking error.

1.2 Active Share

Our new intuitive and simple way to quantify active management is to compare the holdings of a mutual fund with the holdings of its benchmark index. We label this measure the Active Share of a fund, and we define it as

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

where $w_{\text{fund},i}$ and $w_{\text{index},i}$ are the portfolio weights of asset i in the fund and in the index, and the sum is taken over the universe of all assets.[5]

Active Share has an intuitive economic interpretation. We can decompose a mutual fund portfolio into a 100% position in the benchmark index, plus a zero-net-investment long-short portfolio. The long-short portfolio represents all the active bets the fund has taken. Active Share measures the size of that long-short portfolio as a fraction of the total portfolio of the fund. We divide the sum of portfolio weight differences by 2 so that a fund that has 0 overlap with its benchmark index gets a 100% Active Share (i.e., we do not count the long side and the short side of the positions separately).

As an illustration, let us consider a fund with a $100 million portfolio benchmarked against the S&P 500. Imagine that the manager starts by investing $100 million in the index, thus having a pure index fund with five hundred stocks. Assume that the manager only likes half of the stocks, so he eliminates the other half from his portfolio, generating $50 million in cash, and then he invests that $50 million in those stocks he likes. This produces an Active Share of 50% (i.e., 50% overlap with the index). If he invests in only fifty stocks out of five hundred (assuming no size bias), his Active Share will be 90% (i.e., 10% overlap with the index). According to this measure, it is equally active to pick fifty stocks out of a relevant investment universe of five hundred or ten stocks out of hundred—in either case you choose to exclude 90% of the candidate stocks from your portfolio.

For a mutual fund that never shorts a stock and never buys on margin, Active Share will always be between 0 and 100%. In other words, the short side of the long-short portfolio never exceeds the long index position. In contrast, the Active Share of a hedge fund can significantly exceed 100% due to its leverage and net short positions in individual stocks.

[5] We compute the sum across stock positions only, as we apply the measure exclusively to all-equity portfolios. However, in general one should sum up across all positions, including cash and bonds, which may also be part of the portfolio (or part of the index).

If a portfolio contains derivatives, Active Share becomes a more complex but still feasible concept. Then we would have to decompose the derivatives into implied positions in the underlying securities (e.g., stock index futures would be expressed as positions in stocks and cash) and compute Active Share across those underlying securities. Because mutual funds tend to have negligible derivative positions, this is not a concern for us.

1.3 Combining Active Share with tracking error

Why do we need to know the Active Share of a fund if we already know its tracking error? The main limitation of using tracking error alone is that different types of active management will contribute to it differently; active management is not a one-dimensional concept and thus it cannot be completely characterized by a one-dimensional measure.

There are two basic ways an active fund manager can hope to outperform his benchmark index: by stock selection or factor timing. Fama (1972) was an early advocate of this return decomposition, which has spawned a large body of research, including, for example, the performance attribution methodologies of Brinson, Hood, and Beebower (1986) and Daniel et al. (1997). Stock selection means attempting to pick outperforming stocks relative to a benchmark portfolio with similar exposure to systematic risk. This may include controlling for market beta, book-to-market ratio, market capitalization, or industry. Factor timing (also known as "tactical asset allocation" or in some contexts "market timing" or "sector rotation"), in contrast, involves taking time-varying positions in broader factor portfolios according to the manager's views of their future returns.

While the prior literature has largely focused on ex post returns and performance attribution, we focus on quantifying an active manager's ex ante attempt to engage in stock selection or factor timing. To capture a manager's efforts in the two dimensions, we need two separate measures. We suggest using Active Share and tracking error together to span these two dimensions of active management.

The main conceptual difference between Active Share and tracking error is that tracking error includes the covariance matrix of returns. As a result, tracking error puts significantly more weight on correlated active bets—in other words, bets on systematic factors. This makes tracking error a reasonable proxy for factor timing. In contrast, Active Share puts equal weight on all active bets (relative to the index), regardless of whether the risk in such bets is largely diversified away in a portfolio. Thus it serves as a reasonable proxy for stock selection.

Figure 1 illustrates the economics behind the two-dimensional classification of funds. A diversified stock picker may take large stock-specific active positions within industries, producing a high Active Share. If the fund simultaneously diversifies its active positions across all industries and does not bear any systematic risk relative to the benchmark index, it will have a low tracking error just like closet indexers. Yet its high Active Share is far from irrelevant: a manager can only outperform the benchmark index by deviating from it, so this is a direct indication of the fund's active efforts to outperform. Conversely, a fund that is exclusively timing broad factor portfolios but not attempting to choose stocks within such portfolios would have high tracking error and (relatively) low Active Share.

In principle, we could measure either dimension of active management entirely from portfolio holdings or from portfolio returns. Factor timing could be measured either with tracking error, which emphasizes bets on systematic risk, or with Active Share computed over broad factor portfolios (such as the industry-level Active Share in Section 3.1.4, which is closely related to the Industry Concentration Index of Kacperczyk, Sialm, and Zheng 2005). Stock selection could be measured either with Active Share (or an intraindustry measure of Active Share), or with residual volatility from a multifactor regression of fund return on a number of systematic factor portfolios (intended to capture all exposure to systematic risk).

The choice of tracking error and Active Share as proxies for the two dimensions of active management has the following main benefits: tracking error allows us to measure factor timing without assuming anything about how fund managers define factor portfolios at each point in time, whereas a holdings-based approach would require such assumptions. Tracking error is also by far the most commonly used measure of active management in practice. Active Share similarly does not require any assumptions about the relevant factor portfolios, and it is an extremely simple and intuitive measure with a convenient economic interpretation.

2. Empirical Methodology

2.1 Data on holdings

In order to compute Active Share, we need data on the portfolio composition of mutual funds as well as their benchmark indexes. All stock holdings, for both funds and benchmark indexes, are matched with the CRSP stock-return database. The stock holdings of mutual funds are from the CDA/Spectrum mutual fund holdings database maintained by Thomson Financial. The database is compiled from mandatory SEC filings as well as voluntary disclosures by mutual funds. Starting in 1980, it reports most mutual fund holdings quarterly. Wermers (1999) describes the database in more detail.

As benchmarks for the funds, we include essentially all indexes used by the funds themselves over the sample period. We have a total of nineteen indexes from three index families: S&P/Barra, Russell, and Wilshire.

The S&P/Barra indexes we pick are the S&P 500, S&P 500/Barra Growth, S&P 500/Barra Value, S&P MidCap 400, and S&P SmallCap 600. The S&P 500 is the most common large-cap benchmark index, consisting of approximately the largest five hundred stocks. It is further divided into a growth and value style, with equal market capitalization in each style, and this forms the Barra Growth and Value indexes. The S&P 400 and S&P 600 consist of four hundred mid-cap and six hundred small-cap stocks, respectively. The index constituent data for the S&P/Barra indexes are directly from Standard & Poor's and Barra. We have month-end constituents for the large-cap style indexes starting in

September 1992; the S&P 400 holdings data start in July 1991 and the S&P 600 data start in December 1994. The S&P 500 data cover the sample since January 1980.

From the Russell family, we have twelve indexes: the Russell 1000, Russell 2000, Russell 3000, and Russell Midcap indexes, plus the value and growth components of each. The Russell 3000 covers the largest three thousand stocks in the United States and the Russell 1000 covers the largest thousand stocks. The Russell 2000 is the most common small-cap benchmark, consisting of the smallest two thousand stocks in the Russell 3000. The Russell Midcap index contains the smallest eight hundred stocks in the Russell 1000. The index constituent data are from Frank Russell Co. and start in December 1978.

Finally, we include the two most popular Wilshire indexes (now owned by Dow Jones), namely the Wilshire 5000 and Wilshire 4500. The Wilshire 5000 covers essentially the entire U.S. equity market, with about 5,000 stocks in 2004 and peaking at over 7,500 stocks in 1998. The Wilshire 4500 is equal to the Wilshire 5000 minus the five hundred stocks in the S&P 500 index, which makes it a mid-cap to small-cap index. The Wilshire index constituent data are from Wilshire Associates and start in January 1979.

In order to cover all basic investment styles over our full time period and to keep the set of benchmarks as constant as possible, we use all the data we have, even if they include constituent data backdated to a time before the inception of an index. This means that we backdated the benchmark index holdings ourselves (Wilshire 4500 before 1983) or inferred intermediate month-end holdings from officially backdated quarter-end holdings (Russell indexes before 1987). This has an effect on our results in the 1980s, but it has no effect on our performance results that start in January 1990.

2.2 Data on returns

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. Monthly returns for benchmark indexes are from S&P, Russell, and Ibbotson Associates, and all of them include dividends. Daily returns for mutual funds are from multiple sources. Our main source is Standard & Poor's, which maintains a comprehensive database of live mutual funds (also known as the Micropal mutual fund data). We use their "Worths" package, which contains daily per-share net asset values (assuming reinvested dividends) starting from January 1980. Because the S&P data do not contain dead funds, we supplement them with two other data sources. The first one is the CRSP mutual fund database, which also contains daily returns for live and dead funds starting in January 2001. The second one is a database used by Goetzmann, Ivkovic, and Rouwenhorst (2001) and obtained from the Wall Street Web. It is free of survivorship bias and contains daily returns (assuming reinvested dividends) from January 1968 to January 2001, so we use it to match dead funds earlier in our sample. Whenever available, we use the S&P data because they appear slightly cleaner than the latter two sources. Finally, daily returns for benchmark indexes are from a few different sources. The S&P 500 (total return) is from CRSP, while the rest of the S&P, Russell, and Wilshire index returns are directly from the index providers.

2.3 Sample selection

We start by merging the CRSP mutual fund database with the CDA/Spectrum holdings database. The mapping is a combined version of the hand mapping used in Cohen, Coval, and Pastor (2005) and the algorithmic mapping used in Frazzini (2006), where we manually resolve any conflicting matches. For funds with multiple share classes in CRSP, we compute the sum of total net assets in each share class to arrive at the total net assets in the fund. For the expense ratio, loads, turnover, and the percentage of stocks in the portfolio, we compute the value-weighted average across the share classes. For all other variables such as fund name, we pick the variables from the share class with the highest total net assets.

We want to focus on all-equity funds, so we look at investment objective codes from Wiesenberg, ICDI, and Spectrum, and we require each objective code for each fund to be aggressive growth, growth, growth and income, equity income, growth with current income, income, long-term growth, maximum capital gains, small capitalization growth, unclassified, or missing. We also look at the percentage of stocks in the portfolio as reported by CRSP, compute its time-series average for each fund, and select the funds where this average is at least 80% or missing. Because this value is missing or zero for many legitimate all-equity funds, we also separately compute the value of the stock holdings from Spectrum and their share of the total net assets of the fund; since we can only include the stock holdings that we can match with the CRSP stock file, we set the threshold here to 67% of reported total net assets. These criteria most notably exclude any bond funds, balanced and asset allocation funds, international funds, precious metals, and sector funds.

To compute Active Share, the report date of fund holdings has to match the date of index holdings. For virtually all of our sample, this is not a problem as both index holdings and fund holdings are month-end, and we drop the remaining few exceptions from the sample. To compute tracking error, we require at least a hundred trading days of daily return data for each fund in the six months immediately preceding its holdings report date. This is necessary for reasonably accurate estimates of tracking error, but it does decrease the number of funds in our sample by 5.4%, mostly in the 1980s. Evans (2004) discusses an incubation bias in fund returns, which we address by eliminating observations before the starting year reported by CRSP as well as the observations with a missing fund name in CRSP. Finally, we only include funds with equity holdings greater than $10 million.

After the aforementioned screens, our final sample consists of 2,647 funds in the period 1980–2003. For each year and each fund, the stock holdings are reported for an average of three separate report dates (rdate); the total number of such fund-rdate observations in the sample is 48,354.

2.4 Selection of the benchmark index

Determining the benchmark index for a large sample of funds is not a trivial task. Our solution is to estimate proper benchmark assignment from the stock holdings of mutual funds for the full time period from 1980 to 2003.[6] We compute the Active Share of a fund with respect to all nineteen indexes and assign the index with the lowest Active Share as that fund's benchmark. By construction, this index has the greatest amount of overlap with the stock holdings of the fund across the set of nineteen indexes.

Besides being intuitive, our methodology has a few distinct advantages. It cannot be completely off—if it assigns an incorrect benchmark, it happens only because the fund's portfolio actually does resemble that index more than any other index. It also requires no return history and can be determined at any point in time as long as we know the portfolio holdings. Thus we can use it to track a fund's style changes over time, or even from one quarter to the next when a fund manager is replaced.

3. Results: Active Management

In this section, we present the empirical results for active management. We start with a cross-sectional analysis of fund characteristics for various types of funds, using the two dimensions of Active Share and tracking error. We then proceed to investigate the determinants of Active Share in a more general multivariate case. Finally, we discuss the time-series evolution of active management.

3.1 Two-dimensional distribution of funds

We first compile the distribution of all funds in our sample along the two dimensions of Active Share and tracking error, and then investigate how various fund characteristics are related to this distribution. The most recent year for which we have complete data is 2002, so we start our analysis with a snapshot of the cross-section of all funds that year. Panel A of Table 1 presents the number of funds as bivariate distributions and also as univariate marginal distributions along the Active Share and tracking error dimensions.

The distribution of funds clearly reveals a positive correlation between the two measures of active management. Yet within most categories of Active Share

[6] Since 1998, the SEC has required each fund to report a benchmark index in its prospectus; however, this information is not part of any publicly available mutual fund database, and prior to 1998, it does not exist for all funds. These self-declared benchmarks might even lead to a bias: some funds could intentionally pick a misleading benchmark to increase their chances of beating the benchmark by a large margin, as discussed in Sensoy (2009).

Typically mutual funds have just one benchmark index, but in some cases a fund's objective may justify a split benchmark between two indexes. We do not consider that extension in this article.

Table 1
All-equity mutual funds in the United States in 2002, sorted by the two dimensions of active management

	Tracking error (% per year)								
Active Share (%)	0–2	2–4	4–6	6–8	8–10	10–12	12–14	>14	All
				Panel A: Number of mutual funds					
90–100			66	125	77	41	22	26	358
80–90		17	100	120	54	24	10	10	336
70–80		26	124	83	27	5	7	10	281
60–70		75	115	41	12		1		247
50–60	3	102	55	15	3				179
40–50	9	66	20						98
30–40	15	27	3						47
20–30	11	4							14
10–20	8								10
0–10	104	4							109
All	150	323	482	388	174	73	41	48	1678
				Panel B: Median net asset value ($M)					
90–100			174	127	97	95	93	51	115
80–90		264	263	177	109	128	206	43	183
70–80		264	163	149	185	237	96	26	156
60–70		379	256	208	180				259
50–60		262	256	257					251
40–50	151	304	281						275
30–40	535	269							267
20–30	200								196
10–20	58								58
0–10	480								480
All	395	303	220	162	110	110	92	48	190

Active Share is defined as the percentage of a fund's portfolio holdings that differ from the fund's benchmark index. It is computed based on Spectrum mutual fund holdings data and index composition data for nineteen common benchmark indexes from S&P, Russell, and Wilshire. Tracking error is defined as the annualized standard deviation of the error term when the excess return on a fund is regressed on the excess return on its benchmark index. It is computed based on daily fund returns and daily index returns over a six-month period before the corresponding portfolio holdings are reported. To include only all-equity funds, every fund classified by CRSP as balanced or asset allocation has been removed from the sample. Also sector funds have been eliminated. In panel A, if a cell has less than five observations (fund-dates), it is shown as empty. In panel B, a statistic must be based on at least five funds to be reported.

or tracking error, there is still a considerable variation in the other measure. For example, a tracking error of 4–6% can be associated with an Active Share anywhere between 30% and 100%, and an Active Share of 70–80% can go with a tracking error ranging from 2% to over 14%. This confirms that distinguishing between the two dimensions of active management is also empirically important if we want to understand how much each fund engages in stock selection and factor timing.[7]

Funds with an Active Share less than 20% consist of pure index funds. When we refer to "closet indexers," we generally mean nonindex funds with relatively

[7] While the Active Share numbers are based on reported fund holdings at the end of a quarter, it is unlikely that any potential "window dressing" by funds would systematically distort their Active Share. For example, to increase Active Share by 10% at the end of each quarter and to decrease it by the same 10% a few days later would require an 80% annual portfolio turnover. A fund with an average portfolio turnover of 80% would therefore double its turnover to 160%, incurring large trading costs in the process, all in an effort merely to increase its Active Share by 10%. This seems rather implausible.

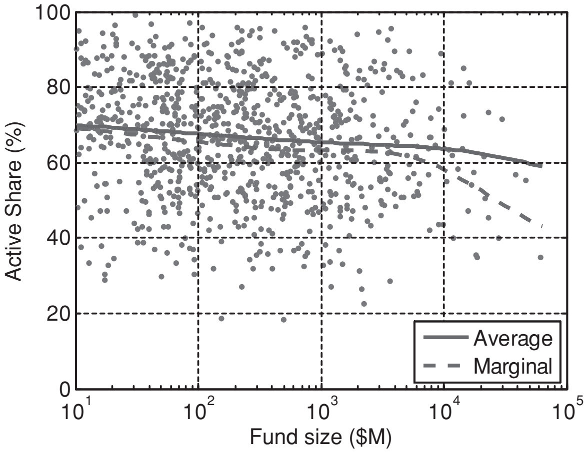

Figure 2
Average Active Share and the Active Share of a marginal dollar
The sample includes U.S. large-cap all-equity mutual funds in 2002. Fund size is total net assets expressed in millions of dollars. We exclude all index funds and funds with less than $10 million in stock holdings. The average Active Share is estimated from a nonparametric kernel regression with a Gaussian kernel and bandwidth equal to 0.5.

low Active Share, sometimes specifically referring to the funds with an Active Share of only 20–60%.[8]

3.1.1 Are smaller funds more active? Funds with high Active Share indeed tend to be small while funds with low Active Share tend to be larger. Panel B in Table 1 shows that the median fund size varies from less than $200 million for high Active Share funds to $250 million and above for low Active Share funds. The relationship is almost monotonic when going from the most active funds to closet indexers: fund size is indeed negatively correlated with active management. Figure 2 shows a scatter plot of Active Share as a function of fund size for all nonindex funds with large-cap benchmarks in 2002. It also shows the average Active Share and the Active Share of a marginal dollar added to a fund's portfolio, both computed from a nonparametric kernel regression of Active Share on log fund size.[9]

The Active Share of that marginal dollar stays constant at roughly 70% for all the way from a $10 million fund to a $1 billion fund, meaning that these small-to-medium-sized active large-cap funds tend to index approximately 30% of their assets. Above $1 billion in assets Active Share starts to fall more rapidly, first to 60% at $10 billion and then to about 50% for the largest funds,

8 It is very hard to see how an active fund could justify investing in more than half of all stocks, because regardless of the managers' beliefs on individual stocks, he must know that no more than half of all stocks can beat the market. Thus a fund with an Active Share less than 50% is always a hybrid between a purely active and purely passive portfolio.

9 We use the Nadaraya-Watson kernel estimator with a Gaussian kernel and a bandwidth equal to 0.5. Other reasonable bandwidths give similar results.

implying that the largest large-cap funds index about one-half of their new assets. However, we should be somewhat cautious when interpreting these results for an individual fund. There is substantial dispersion in Active Share for all fund sizes, so while the mean is descriptive of the entire population, many individual funds still deviate from it significantly in either direction.

Finally, our calculations for Active Share put us in a unique position by allowing us to test one of the assumptions of a prominent theoretical model by Berk and Green (2004), who predict a strong relationship between fund size and active management. In the model, an active manager typically starts with the ability to generate a positive alpha, but he also faces a linear price impact (in turn generating a quadratic dollar cost) which reduces his initial alpha. The manager then optimally chooses the size of his active portfolio to maximize his dollar alpha, implying that all the remaining assets in the fund will be indexed. In other words, once a fund has reached some minimum size, the active share of a marginal dollar should be zero.

Figure 2 shows that marginal Active Share is instead almost equal to the average Active Share, about 70% for most large-cap funds. The regression evidence in Section 3.2 further shows that recent inflows of assets do not have any economically meaningful impact on the Active Share of a fund. Qualitatively, it is still true that Active Share decreases with fund size, but quantitatively, it is very hard to reconcile this result with the zero marginal Active Share implied by the model.

In fact, Figure 2 suggests an alternative story: when a fund receives inflows, instead of indexing all the new assets, it simply scales up its existing positions. This too is a simplification, but it would match the data on active positions much better. It is also supported by Pollet and Wilson (2008), who find that "funds overwhelmingly respond to asset growth by increasing their [existing] ownership shares rather than by increasing the number of investments in their portfolio."

3.1.2 Fees and active management. Panel A of Table 2 shows the equal-weighted expense ratio of all funds across Active Share and tracking error in 2002. The equal-weighted expense ratio across all funds in the sample is 1.24% per year, while the value-weighted expense ratio (unreported) is lower at 0.89%. Index funds clearly have the lowest expense ratios: the equal-weighted average of the lowest Active Share and tracking error group is 0.47% per year, while the value-weighted average is only 0.22%.

The funds with the highest Active Share charge an average expense ratio of 1.42%. The other active fund groups exhibit slightly lower fees for lower Active Shares, but the differences are economically small for these intermediate ranges of Active Share. For example, the average expense ratio for funds with Active Share between 30% and 40% is about 1.08% per year, which is closer to the 1.23% of the group with Active Share between 60% and 70% than the 0.47% of the pure index funds.

Table 2
Expense ratios and annual portfolio turnover for all-equity mutual funds in 2002

	Tracking error (% per year)								
Active Share (%)	0–2	2–4	4–6	6–8	8–10	10–12	12–14	>14	All
				Panel A: Equal-weighted total expense ratio (%)					
90–100			1.33	1.37	1.51	1.47	1.49	1.50	1.42
80–90		1.30	1.30	1.43	1.44	1.43	1.37	2.11	1.41
70–80		1.19	1.29	1.37	1.33	1.40	1.85	1.34	1.33
60–70		1.10	1.24	1.35	1.37				1.23
50–60		1.04	1.21	1.43					1.14
40–50	1.12	1.08	1.07						1.08
30–40	1.03	1.06							1.08
20–30	0.92								0.88
10–20	0.71								0.75
0–10	0.47								0.47
All	0.62	1.08	1.27	1.39	1.44	1.45	1.54	1.59	1.24
				Panel B: Equal-weighted turnover (%)					
90–100			71.2	101.7	107.8	118.2	140.0	198.5	108.8
80–90		93.5	101.9	133.5	124.5	134.1	210.2	147.5	123.5
70–80		69.3	91.7	98.6	133.8	80.7	74.2	123.9	96.1
60–70		69.0	93.9	107.5	108.0				89.2
50–60		65.5	92.0	87.4					76.8
40–50	57.1	69.7	61.6						67.3
30–40	72.9	117.4							97.8
20–30	141.7								148.9
10–20	60.0								66.1
0–10	18.1								18.4
All	38.2	73.9	89.9	111.1	116.5	119.1	145.3	170.0	94.8

Funds are sorted by the two dimensions of active management. The measures of active management are computed as before. Turnover is defined by CRSP as the maximum of annual stock purchases and annual stock sales, divided by the fund's total net assets. To include only all-equity funds, every fund classified by CRSP as balanced or asset allocation has been removed from the sample. Also sector funds have been eliminated. To be reported in the table, a statistic must be based on at least five funds.

3.1.3 Portfolio turnover. Portfolio turnover for the average mutual fund is 95% per year (Table 2, panel B). Average turnover for fund groups varies from 18% for index funds to 210% for one of the highest Active Share groups.

The correlation of turnover with Active Share is surprisingly weak at 18% (Spearman's rank correlation at 17%). Table 2 reveals that almost all nonindex fund groups have roughly comparable turnover averages, while the index funds clearly stand out with their lower turnover. This would be consistent with closet indexers (perhaps unwittingly) masking their passive strategies with portfolio turnover, i.e., a relatively high frequency of trading their rather small active positions. Tracking error turns out to predict turnover better than Active Share, implying that the strategies generating a high tracking error also involve more frequent trading.

3.1.4 Industry concentration and industry-level Active Share. So far we have computed Active Share at the level of individual stocks. If we compute Active Share at the level of industry portfolios, the resulting "industry-level Active Share" indicates the magnitude of active positions in entire industries or sectors of the economy. If we contrast this measure with Active Share, we can see how much each fund takes industry bets relative to its bets on individual stocks. We assign each stock to one of ten industry portfolios. The industries are defined as in Kacperczyk, Sialm, and Zheng (2005).

When we generate a similar two-dimensional table for industry-level Active Share (table available upon request), we find that industry-level Active Share is relatively constant within a tracking error group, even as stock-level Active Share varies from 50% to 100%. Within Active Share groups, industry-level Active Share increases significantly with tracking error. This confirms our earlier conjecture that a high tracking error often arises from active bets on industries, whereas active stock selection without industry exposure allows tracking error to remain relatively low.

3.2 Explaining Active Share

To complement the nonparametric univariate results, we run a panel regression of Active Share on a variety of explanatory variables (Table 3). Since some variables are reported only annually, observations are at the fund-year level; when a fund has multiple report dates for holdings during the year, we choose the last one.

We use tracking error, turnover, expense ratio, and the number of stocks as explanatory variables, as they are all under the fund manager's control and thus clearly endogenous, as well as fund size, fund age, manager tenure, prior inflows, prior benchmark returns, and prior benchmark-adjusted returns, which are beyond the manager's direct control. We also include year dummies to capture any fixed effect within the year. Because both Active Share and many of the independent variables are persistent over time, we cluster standard errors by fund.

We find that tracking error is by far the most closely related to Active Share: it explains about 13% of the variance in Active Share (the year dummies explain about 10%). Economically, its coefficient of 1.8 (column 2 of Table 3) means that a 5% increase in the annualized tracking error increases Active Share by about 9%. This is significant, but it still leaves a great deal of unexplained variance in Active Share. Fund size is related to Active Share, although this relationship is nonlinear and economically not strong. The expense ratio is statistically significant, but the effect is also economically small: a (large) 1% increase in the expense ratio increases Active Share by only about 4.4%. Turnover has neither statistical nor economic significance. Interestingly, fund age and manager tenure act in opposite directions, where long manager tenure is associated with higher Active Share.

Fund inflows over the prior one to three years do not matter for Active Share. This may appear surprising, but it only means that when managers get inflows, they quickly reach their target Active Share, and thus prior fund flows add no explanatory power beyond current fund size. This result is not affected by the presence of control variables (such as prior returns) in the regression.

Table 3
Determinants of Active Share for all-equity mutual funds in 1992–2003

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tracking error	1.4015	1.8111	1.7002	1.5965	1.5210	1.4439	
	(19.16)	(18.15)	(17.40)	(16.09)	(12.81)	(12.17)	
Turnover				−0.0016		−0.0021	
				(0.65)		(0.66)	
Expenses				4.4359	4.6230	4.6267	7.7859
				(6.33)	(5.28)	(5.33)	(9.72)
lg(TNA)			0.0554	0.0601	0.0451	0.0614	0.0389
			(2.96)	(3.16)	(2.02)	(2.87)	(1.62)
$(\lg(\text{TNA}))^2$			−0.0177	−0.0171	−0.0150	−0.0177	−0.0166
			(4.85)	(4.58)	(3.56)	(4.36)	(3.65)
Number of stocks						−0.0001	
						(2.04)	
Fund age						−0.0005	−0.0003
						(2.26)	(1.06)
Manager tenure						0.0036	0.0041
						(6.72)	(7.00)
Inflow, $t-1$ to t						0.0052	0.0045
						(1.30)	(1.04)
Inflow, $t-3$ to $t-1$						0.0010	0.0019
						(0.94)	(1.53)
Return over index, $t-1$ to t					0.1068	0.0996	0.1189
					(8.12)	(7.45)	(8.21)
Return over index, $t-3$ to $t-1$					0.1103	0.1089	0.1478
					(9.39)	(9.17)	(13.00)
Index return, $t-1$ to t						0.0655	0.0756
						(5.28)	(6.02)
Index return, $t-3$ to $t-1$					−0.0619	−0.0570	−0.0469
					(7.87)	(6.93)	(5.19)
Year dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
N	11,726	11,726	11,726	11,554	8,417	8,320	8,374
R^2	0.1316	0.2373	0.2642	0.2781	0.2984	0.3235	0.2037

The dependent variable is Active Share for each fund-year observation. All the variables are computed as before. Turnover and expense ratio are annualized values. Fund age and fund manager tenure are measured in years. Fund inflows and returns are all cumulative percentages. Index return represents the benchmark assigned to each fund, and return over the index represents a fund's net return (after all expenses) in excess of its benchmark index. Index funds are excluded from the sample. Since the expense ratio and manager tenure are missing before 1992, we limit all specifications to the same time period. Year fixed-effects are included in all specifications. The t-statistics (in parentheses) are based on standard errors clustered by fund.

Benchmark-adjusted returns over the prior three years are significantly related to Active Share, meaning that fund managers who were successful in the past choose a higher Active Share. Funds are most active when their benchmark index has underperformed other indexes for a few years but has outperformed in the previous year. The regression includes year dummies, so the effect is truly cross-sectional and not explained by an overall market reaction.[10]

At a more general level, the regression results reveal that Active Share is not easy to explain with other variables—even the broadest specification produces an R^2 of only 32%. Hence, it is indeed a new dimension of active management

[10] In fact, the t-statistics on the benchmark index returns are likely to be somewhat overstated because the benchmark index returns (common to all funds with the same benchmark) will also capture some benchmark-specific differences in Active Share.

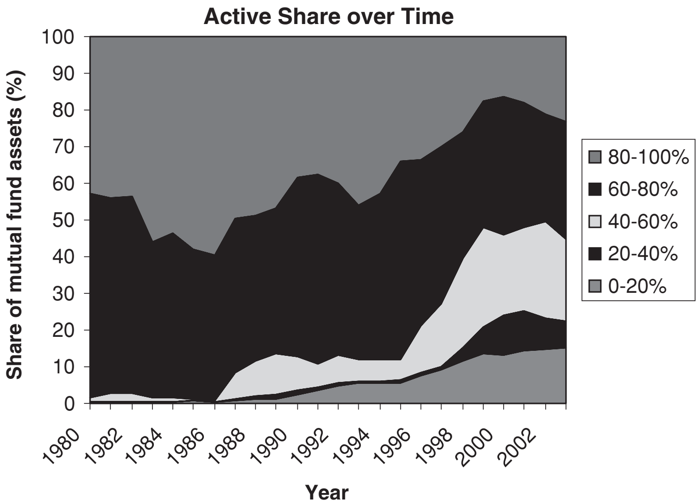

Figure 3
The share of US all-equity mutual fund assets in each Active Share category in 1980–2003

that should be measured separately and cannot be conveniently subsumed by other variables.

3.3 Active management over time

3.3.1 Active Share. Figure 3 shows the time-series evolution of active management from 1980 to 2003, as measured by Active Share. There is a clear time trend toward lower Active Share. For example, the percentage of assets under management with Active Share less than 60% went up from 1.5% in 1980 to 44.8% in 2003. Correspondingly, the percentage of fund assets with Active Share greater than 80% went down from 42.8% in 1980 to 23.3% in 2003. The fraction of index funds before 1990 tends to be less than 1% of funds and of their total assets but grows rapidly after that to 15.3% in 2003. Similarly, there are very few nonindex funds with Active Share below 60% until about 1987, but since then we see a rapid increase in such funds throughout the 1990s, reaching about 18% of funds and about 30% of their assets in 2000–2001. This suggests that closet indexing has only been an issue since the 1990s—before that, almost all mutual funds are truly active. The number of funds in the sample grew from 126 in 1980 to 340 in 1990 and to 2,026 in 2003, while the amount of assets under management grew from $25 billion in 1980 to $119 billion in 1990 and to $1,954 billion in 2003.

3.3.2 Fund-level Active Share versus aggregate Active Share. Active Share can also be computed for the entire mutual fund sector rather than only for individual funds. This aggregate Active Share indicates whether the entire mutual fund sector can act as a marginal investor, buying underpriced

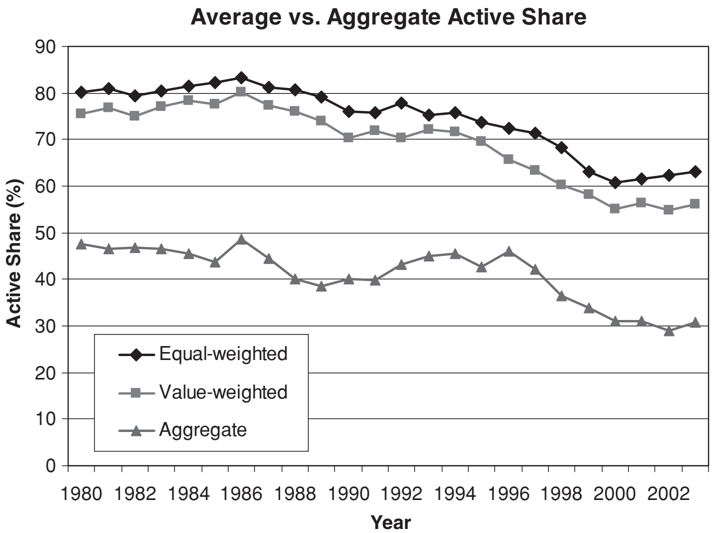

Figure 4
Aggregate-level and fund-level Active Share
We only include active funds that have the S&P 500 as their benchmark index. Each year we compute the equal-weighted and value-weighted (by fund size) Active Share across the funds. We also aggregate the funds' portfolios into one aggregate portfolio and compute its Active Share. Index funds are excluded from the sample.

stocks and selling overpriced ones, thus helping to make the cross-section of stock prices more efficient. Furthermore, just like Active Share for individual funds, aggregate Active Share is direct evidence of the potential of the entire mutual fund sector to outperform its benchmarks and add value to its investors.

Figure 4 shows the aggregate Active Share for nonindex funds, together with the equal-weighted and the value-weighted averages at the individual fund level. To compute aggregate Active Share, we sum up all stock positions across individual funds into one large aggregate fund and then compute the Active Share of that aggregate portfolio. To keep the aggregation meaningful, we do not mix funds with different benchmark indexes; we only use funds benchmarked to the S&P 500 (the most common index) for all three time series.

If funds never take active positions against each other, the value-weighted average Active Share should equal the aggregate Active Share. If instead they trade only against each other, e.g., if these funds were the only investors in the market, the aggregate Active Share should sum up to zero. The figure shows that about one-half of those active positions actually cancel out each other: in the 1980s, the aggregate Active Share falls to about 45% from a value-weighted average of 75–80%, while in the most recent years, the aggregate value has been about 30% out of a fund-level average of 55–60%.

This means that the mutual fund sector as a whole gives investors an Active Share of no more than 30%. The remaining active bets are just noise between funds, which will not contribute to an average alpha; any benefit from such bets for one fund must come at the expense of other funds. This helps us understand why the average mutual fund underperforms net of fees: given their low aggregate Active Share, they would have to display considerable skill in their aggregate active bets to fully overcome their fees and expenses.

However, given the large size of the mutual fund sector, their aggregate active bets are still significant in absolute terms, giving mutual funds the potential to bring prices closer to fundamental values. Their performance seems consistent with this, with most empirical evidence in the literature finding slight outperformance (before expenses) for mutual fund portfolios.[11]

3.3.3 Persistence of fund-level Active Share. Active Share tends to be highly persistent. Each year we rank all funds into Active Share deciles. For all the stocks in each decile, we compute the average decile rank one to five years later. The decile ranking does not change much from year to year: the top decile ranking falls from 10 to 9.67 and the bottom decile rises from 1 to 1.27. Even over five years, the top decile rank falls only to 8.88 from 10 while the bottom decile rank rises to 2.08 from 1. A decile transition matrix over one year tells a similar story, with the diagonal elements ranging from about 40% to 75%. Hence, Active Share this year is a very good predictor of Active Share next year and thereafter. Tracking error ranks are also persistent but somewhat less so: five years later the top decile has fallen from 10 to 7.52, and the bottom decile has risen from 1 to 2.24.

4. Results: Fund Performance

This section analyzes how active management is related to benchmark-adjusted fund returns. We look at both "net returns," which we define as the investors' returns after all fees and transaction costs, and "gross returns," which we define as the hypothetical returns on the disclosed portfolio holdings, as in Wermers (2000). The gross returns help us identify whether any categories of funds have skill in selecting portfolios that outperform their benchmarks, and the net returns help us determine whether any such skill survives the fees and transaction costs of those funds.

Prior studies show that the average fund slightly outperforms the market before expenses and underperforms after expenses. Since outperformance can only arise from active management, we hypothesize that there are cross-sectional differences in fund performance: the more active the fund, the higher its average gross return. However, a priori it is not clear how this performance relationship shows up across the two dimensions of active management (i.e., whether Active Share matters more than tracking error) or whether the relationship is linear. For net returns, the relationship is even more ambiguous

[11] Equilibrium asset pricing implications due to the presence of financial institutions such as mutual funds have been explored in a theoretical model by Petajisto (2009). Our empirical estimate for aggregate Active Share can also be used to calibrate that model and to confirm its parameter selection as reasonable.

a priori because we do not know how fees and transaction costs are related to the two dimensions of active management.

We pick 1990–2003 as our sample period. This is motivated by Figure 3, which confirms that almost all funds were very active in the 1980s. In contrast, starting around 1990 we begin to see some heterogeneity in the distribution, with a meaningful mass of active (nonindex) funds having a modest Active Share of 60% or less. It is this cross-sectional dispersion in active management that we conjecture will show up as dispersion in fund performance. Because pure index funds are conceptually different from active funds, we conduct the entire performance analysis only for active (nonindex) funds.[12]

4.1 Fund performance: Active Share versus tracking error

The sample consists of monthly returns for each fund. A fund is included in the sample in a given month if it has reported its holdings in the previous twelve months. Each month we sort funds first into Active Share quintiles and then further into tracking error quintiles. We compute the equal-weighted benchmark-adjusted return within each of the twenty-five fund portfolios and then take the time-series average of these returns over the entire sample period.

Panel A in Table 4 shows the average benchmark-adjusted net returns on these fund portfolios. When we regress the monthly benchmark-adjusted returns on the four-factor model of Carhart (1997), thus controlling for exposure to the market, size, value, and momentum, we obtain the alphas shown in panel B.

The average fund loses to its benchmark index by 0.43% per year, and the loss increases to 1.14% under the four-factor model. Tracking error does not help us much when picking funds: the marginal distribution across all tracking error quintiles shows consistently negative benchmark-adjusted returns and alphas. Going from a low to high tracking error may even hurt performance, which is statistically significant for the lowest Active Share groups.

In contrast, Active Share does improve fund performance relative to the benchmark. The difference in benchmark-adjusted return between the highest and lowest Active Share quintiles is 2.55% per year ($t = 3.47$), which further increases to 2.98% ($t = 4.51$) with the four-factor model. The difference in abnormal returns is positive and economically significant within all tracking error quintiles. An investor should clearly avoid the lowest three Active Share quintiles and instead pick from the highest Active Share quintile. Funds in the highest Active Share quintile beat their benchmarks by 1.13% ($t = 1.60$), or 1.15% ($t = 1.86$) with the four-factor model.

Panels A and B in Table 5 report the corresponding results for gross returns. The high Active Share funds again outperform the low Active Share funds with both economical and statistical significance. The benchmark-adjusted returns indicate that the lowest Active Share funds essentially match their benchmark

[12] Index funds are identified by two methods: sorting all funds by Active Share as well as searching for the words "index" or "idx" in the CRSP fund name.

Table 4
Net equal-weighted alphas for all-equity mutual funds in 1990–2003

Active Share quintile	Tracking error quintile						
	Low	2	3	4	High	All	High-Low
	Panel A: Benchmark-adjusted return						
High	0.09	0.39	1.34	2.76	1.05	1.13	0.97
	(0.09)	(0.41)	(1.52)	(2.86)	(0.62)	(1.60)	(0.44)
4	−0.43	−0.15	0.56	0.50	0.76	0.25	1.20
	(−0.61)	(−0.19)	(0.64)	(0.42)	(0.36)	(0.31)	(0.48)
3	−1.42	−0.98	−0.25	−0.49	−0.60	−0.75	0.82
	(−2.06)	(−1.34)	(−0.29)	(−0.45)	(−0.35)	(−0.95)	(0.43)
2	−1.89	−1.14	−1.13	−1.01	−1.66	−1.37	0.23
	(−3.20)	(−1.55)	(−1.53)	(−1.08)	(−1.22)	(−1.99)	(0.16)
Low	−1.35	−1.32	−1.28	−1.51	−1.63	−1.42	−0.28
	(−4.95)	(−3.68)	(−2.77)	(−2.76)	(−2.13)	(−3.53)	(−0.39)
All	−1.00	−0.64	−0.15	0.05	−0.42	−0.43	0.58
	(−1.92)	(−1.24)	(−0.24)	(0.06)	(−0.30)	(−0.76)	(0.36)
High-Low	1.44	1.71	2.62	4.26	2.68	2.55	
	(1.50)	(1.71)	(2.97)	(4.36)	(1.80)	(3.47)	
	Panel B: Four-factor alpha of benchmark-adjusted return						
High	1.44	0.79	0.48	2.72	0.29	1.15	−1.15
	(1.79)	(1.02)	(0.68)	(3.17)	(0.22)	(1.86)	(−0.74)
4	−0.11	−0.91	−0.88	−1.52	−1.64	−1.02	−1.53
	(−0.22)	(−1.17)	(−1.23)	(−1.63)	(−1.33)	(−1.63)	(−1.08)
3	−1.05	−1.41	−1.58	−2.25	−2.86	−1.83	−1.81
	(−1.97)	(−2.15)	(−2.34)	(−2.23)	(−2.51)	(−2.84)	(−1.59)
2	−1.46	−1.47	−1.82	−2.67	−3.43	−2.18	−1.97
	(−3.31)	(−2.29)	(−2.99)	(−3.31)	(−3.61)	(−4.00)	(−2.17)
Low	−1.29	−1.36	−1.66	−2.26	−2.57	−1.83	−1.28
	(−4.80)	(−4.80)	(−4.33)	(−4.43)	(−3.73)	(−5.01)	(−2.13)
All	−0.50	−0.87	−1.09	−1.20	−2.05	−1.14	−1.55
	(−1.45)	(−2.13)	(−2.58)	(−1.81)	(−2.28)	(−2.53)	(−1.68)
High-Low	2.73	2.16	2.13	4.99	2.86	2.98	
	(3.33)	(2.52)	(2.61)	(5.60)	(2.26)	(4.51)	

Funds are sorted by the two dimensions of active management. The measures of active management are computed as before. Net fund returns are the returns to a fund investor after fees and transaction costs. Index funds are excluded from the sample. The table shows annualized returns, followed by t-statistics (in parentheses) based on White's standard errors.

returns while the highest Active Share funds beat their benchmarks by 2.40% per year ($t = 2.80$). The four-factor model reduces the performance of all fund portfolios but does not change the difference in returns across Active Share and still leaves an economically significant 1.51% outperformance for the highest Active Share funds ($t = 2.23$). Tracking error again exhibits a zero to negative (but statistically insignificant) relationship with fund performance.

The evidence in these two panels suggests that the funds with low Active Share and high tracking error tend to do worst, both in terms of net and gross returns, which implies that factor bets tend to destroy value for fund investors. Closet indexers (low Active Share, low tracking error) also exhibit no ability and tend to lose money after fees and transaction costs. The best performers are concentrated stock pickers (high Active Share, high tracking error), followed by diversified stock pickers (high Active Share, low tracking error). Both groups appear to have a stock-picking ability, and even after fees and transaction costs, the most active of them beat their benchmarks. If we reverse the order of sorting,

Table 5
Gross equal-weighted alphas for all-equity mutual funds in 1990–2003

Active Share quintile	Tracking error quintile: Low	2	3	4	High	All	High-Low
	Panel A: Benchmark-adjusted return						
High	1.34	1.56	3.01	3.34	2.72	2.40	1.38
	(1.61)	(1.67)	(3.30)	(2.70)	(1.29)	(2.80)	(0.60)
4	1.02	1.32	1.35	1.39	1.58	1.33	0.56
	(1.56)	(1.59)	(1.28)	(0.97)	(0.64)	(1.28)	(0.20)
3	0.09	0.78	0.97	1.19	1.06	0.81	0.97
	(0.16)	(1.03)	(1.10)	(1.00)	(0.54)	(0.94)	(0.46)
2	−0.24	0.13	0.68	0.59	0.02	0.24	0.26
	(−0.54)	(0.23)	(0.93)	(0.59)	(0.01)	(0.34)	(0.17)
Low	0.00	0.37	0.06	0.22	−0.08	0.11	−0.08
	(−0.02)	(1.24)	(0.14)	(0.40)	(−0.10)	(0.29)	(−0.10)
All	0.44	0.83	1.22	1.35	1.05	0.98	0.61
	(1.04)	(1.56)	(1.82)	(1.42)	(0.63)	(1.41)	(0.34)
High-Low	1.35	1.19	2.95	3.13	2.81	2.29	
	(1.68)	(1.27)	(3.47)	(2.79)	(1.70)	(3.05)	
	Panel B: Four-factor alpha of benchmark-adjusted return						
High	1.39	0.86	1.38	2.50	1.37	1.51	−0.02
	(1.80)	(1.00)	(1.76)	(2.54)	(1.02)	(2.23)	(−0.02)
4	0.42	−0.23	−0.92	−1.28	−1.08	−0.63	−1.50
	(0.76)	(−0.27)	(−1.07)	(−1.12)	(−0.78)	(−0.81)	(−1.01)
3	−0.33	−0.38	−0.88	−1.24	−1.58	−0.89	−1.26
	(−0.55)	(−0.52)	(−1.15)	(−1.19)	(−1.40)	(−1.28)	(−1.08)
2	−0.59	−0.83	−0.60	−1.58	−2.21	−1.17	−1.63
	(−1.42)	(−1.59)	(−0.98)	(−1.93)	(−2.32)	(−2.14)	(−1.73)
Low	−0.30	−0.13	−0.67	−0.72	−1.31	−0.63	−1.01
	(−1.18)	(−0.47)	(−1.62)	(−1.41)	(−1.98)	(−1.73)	(−1.69)
All	0.12	−0.14	−0.34	−0.46	−0.97	−0.36	−1.09
	(0.32)	(−0.28)	(−0.63)	(−0.62)	(−1.06)	(−0.69)	(−1.18)
High-Low	1.69	0.99	2.05	3.22	2.68	2.13	
	(2.15)	(1.12)	(2.57)	(3.41)	(2.21)	(3.29)	

Funds are sorted by the two dimensions of active management. The measures of active management are computed as before. Gross fund returns are the returns on a fund's portfolio and do not include any fees or transaction costs. Index funds are excluded from the sample. The table shows annualized returns, followed by t-statistics (in parentheses) based on White's standard errors.

the results are similar: Active Share is related to returns even within tracking error quintiles, while tracking error does not have such predictive power. If we estimate tracking error from monthly returns rather than daily returns, it similarly fails to predict fund returns. A separate subperiod analysis of 1990–1996 and 1997–2003 produces very similar point estimates for both seven-year periods, so the results seem consistent over the entire sample period.

Our general results about the profitability of stock selection and factor timing agree with Daniel et al. (1997), who find that managers can add value with their stock selection but not with their factor timing. Because we develop explicit measures of active management, we can refine their results by distinguishing between funds based on their degree and type of active management, thus establishing the best- and worst-performing subsets of funds.

We also complement the work of Kacperczyk, Sialm, and Zheng (2005), who find that mutual funds with concentrated industry bets tend to outperform. Their Industry Concentration Index is highest among the concentrated stock pickers and lowest among the closet indexers, with the diversified stock picks and factor bets in the middle. As our article adds a second dimension of active management, we can further distinguish between these middle groups of funds. This is important for performance because the diversified stock picks outperform and factor bets underperform; consequently, Active Share turns out to be the dimension of active management that best predicts performance. We discuss the comparison in more detail in Section 4.6.

Part of the difference in net return between the high and low Active Share funds arises from a difference in the "return gap" of Kacperczyk, Sialm, and Zheng (2008). This accounts for 0.64% of the 2.55% spread in benchmark-adjusted net return and 1.22% of the 2.98% spread in four-factor alphas. Hence, if the high Active Share funds have higher trading costs, this is more than offset by the funds' short-term trading ability and their other unobserved actions. Yet most of the net return difference between the high and low Active Share funds still comes from the long-term performance of their stock holdings.

The four-factor betas across all funds when their benchmark-adjusted returns are regressed on the market excess return, SMB, HML, and UMD are small on average (−0.01, 0.11, 0.05, and 0.02, respectively), which means that funds collectively do not exhibit a tilt toward any of the four sources of systematic risk. Across Active Share groups, there is no pattern in any of the betas. Across tracking error groups there is more variation in systematic risk: funds with a high tracking error tend to be more exposed to market beta and small stocks, with slight preferences for growth stocks and momentum. This exposure seems natural because systematic risk is precisely what produces a high tracking error for a fund.

4.2 Fund size and Active Share

Since fund size is related to both active management and fund returns, we next investigate how size interacts with Active Share when predicting fund returns. We sort funds into quintiles first by fund size and then by Active Share. The results are reported in Table 6. The median fund sizes for the size quintiles across the sample period are \$28 million, \$77 million, \$184 million, \$455 million, and \$1,600 million. In the twenty-five basic portfolios sorted on Active Share and tracking error, median fund size varies from about \$100 million to \$400 million.

Controlling for size, Active Share again predicts fund performance. Within the smallest fund size quintile, the difference between net benchmark-adjusted returns for the top versus the bottom Active Share quintiles equals 2.92% per year and 3.78% after adjusting for the four-factor model (only the four-factor alphas are reported in Table 6). Even within the next two size quintiles, the difference in net performance varies from 2.53% to 3.20% and maintains its statistical significance. For the second-largest fund quintile, the difference is slightly lower, ranging from 1.72% to 1.83% per year, and is still statistically significant. For the largest fund quintile, the difference is lower still at about

Table 6
Net equal-weighted alphas for all-equity mutual funds in 1990–2003

Active Share quintile	Fund size quintile: Low	2	3	4	High	All	High-Low
	Four-factor alpha of benchmark-adjusted return						
High	1.71	1.39	1.15	0.19	−0.67	0.75	−2.39
	(1.97)	(1.58)	(1.61)	(0.25)	(−1.01)	(1.26)	(−2.60)
4	0.87	−0.24	−0.02	−1.55	−1.90	−0.57	−2.78
	(1.09)	(−0.28)	(−0.02)	(−1.72)	(−2.61)	(−0.82)	(−3.74)
3	−1.47	−1.60	−2.11	−2.58	−1.54	−1.86	−0.07
	(−2.21)	(−2.13)	(−2.97)	(−3.71)	(−2.36)	(−3.09)	(−0.12)
2	−1.95	−2.52	−2.79	−1.56	−2.16	−2.20	−0.21
	(−3.24)	(−4.27)	(−4.56)	(−2.04)	(−3.88)	(−4.02)	(−0.43)
Low	−2.06	−1.81	−1.90	−1.64	−1.69	−1.82	0.38
	(−3.97)	(−4.04)	(−4.61)	(−3.89)	(−5.30)	(−4.81)	(1.03)
All	−0.59	−0.96	−1.14	−1.43	−1.60	−1.14	−1.01
	(−1.34)	(−1.93)	(−2.41)	(−2.58)	(−3.41)	(−2.53)	(−3.05)
High-Low	3.78	3.20	3.05	1.83	1.01	2.57	
	(3.74)	(3.22)	(3.75)	(2.51)	(1.43)	(3.87)	

Funds are sorted by fund size and Active Share (sequentially and in that order). Active Share is computed as before. Net fund returns are the returns to a fund investor after fees and transaction costs. Index funds are excluded from the sample. The table shows annualized returns, followed by t-statistics (in parentheses) based on White's standard errors.

1.01% per year and is no longer statistically significant. Therefore, it is especially for the smaller funds (i.e., excluding the largest 40% of funds) that the highest Active Share funds exhibit economically significant stock-picking ability: their stock picks outperform their benchmarks by about 2.5–3.8% per year, net of fees and transaction costs.

Fund size alone is also negatively related to fund performance: the difference between the smallest versus the largest size quintile in benchmark-adjusted net alphas is 1.01% ($t = 3.05$). This is consistent with the findings of Chen et al. (2004). However, fund size is helpful mostly in identifying the funds that underperform (the largest funds); even the smallest funds on average still do not create value for their investors. To identify funds that actually outperform, we also need to look at Active Share.

4.3 Active Share and performance persistence

If some managers have skill to beat their benchmark, we would expect persistence in their performance. This persistence should be strongest among the most active funds. To investigate this, we sort funds into quintiles first by Active Share and then by each fund's benchmark-adjusted gross return over the prior one year. We report the results in Table 7 (only the four-factor alphas are shown).

The benchmark-adjusted net returns of the most active funds show remarkable persistence: the spread between the prior-year winners and losers is 6.81% per year ($t = 3.35$). In contrast, the least active funds have a spread of only 1.69% per year ($t = 1.91$). Most interestingly, controlling for the four-factor model that includes momentum, the spread between prior-year winners and

Table 7
Net equal-weighted alphas for all-equity mutual funds in 1990–2003

Active Share quintile	Prior one-year return quintile						
	Low	2	3	4	High	All	High-Low
	Four-factor alpha of benchmark-adjusted return						
High	−0.98	0.39	0.89	1.04	3.50	0.96	4.48
	(−1.01)	(0.46)	(1.25)	(1.27)	(3.29)	(1.56)	(3.06)
4	−2.28	−1.83	−1.90	−0.44	0.46	−1.19	2.74
	(−2.26)	(−2.14)	(−2.84)	(−0.59)	(0.41)	(−1.90)	(1.72)
3	−2.48	−2.65	−2.08	−1.78	−0.99	−2.00	1.49
	(−2.39)	(−3.24)	(−2.67)	(−2.50)	(−1.04)	(−3.10)	(1.00)
2	−2.55	−2.16	−2.41	−1.77	−1.80	−2.14	0.75
	(−2.47)	(−3.21)	(−4.60)	(−3.14)	(−2.30)	(−3.90)	(0.59)
Low	−2.05	−2.26	−1.78	−1.52	−1.58	−1.84	0.47
	(−3.41)	(−5.85)	(−4.97)	(−3.42)	(−3.14)	(−5.01)	(0.70)
All	−2.07	−1.72	−1.47	−0.90	−0.11	−1.26	1.96
	(−2.69)	(−3.08)	(−3.30)	(−1.99)	(−0.15)	(−2.76)	(1.74)
High-Low	1.07	2.65	2.67	2.56	5.08	2.80	
	(1.15)	(3.14)	(3.45)	(2.67)	(4.91)	(4.33)	

Funds are sorted by Active Share and prior one-year return (sequentially and in that order). The prior return on a fund is measured as its benchmark-adjusted gross return over the previous twelve months. Only funds with at least nine months of such returns are included. Active Share is computed as before. Net fund returns are the returns to a fund investor after fees and transaction costs. Index funds are excluded from the sample. The table shows annualized returns, followed by t-statistics (in parentheses) based on White's standard errors.

losers for the most active funds decreases but remains economically and statistically very significant at 4.48% per year ($t = 3.06$). In contrast, the spread between prior-year winners and losers for the least active funds decreases to 0.47% per year and is no longer significant, which is consistent with the results of Carhart (1997).

From an investor's point of view, the prior one-year winners within the highest Active Share quintile seem very attractive, with a benchmark-adjusted 5.10% ($t = 3.67$) annual net return and a 3.50% ($t = 3.29$) annualized alpha with respect to the four-factor model. The performance of this subset of funds is also clearly statistically significant, supporting the existence of persistent managerial skill. If we run the same analysis only for below-median-sized funds, the top managers emerge as even more impressive: their benchmark-adjusted net returns are 6.49% ($t = 4.40$) or 4.84% ($t = 4.04$) after controlling for the four-factor model. This suggests that investors should pick active funds based on all three measures: Active Share, fund size, and prior one-year return.

4.4 Benchmark performance and Active Share

One benefit of Active Share is that it provides a relatively accurate estimate of each fund's official benchmark index. This allows us to directly compare the performance of each fund to that of its benchmark index; after all, that benchmark through a low-cost index fund is the most direct investment alternative for a mutual fund investor. To control for any remaining exposure to systematic risk, we compute the four-factor alphas of benchmark-adjusted returns. However, we can also choose to ignore the official benchmark indexes of the funds and instead apply the four-factor model to the funds' returns in excess of the

Table 8
Equal-weighted Carhart alphas of mutual funds and their benchmark indexes in 1990–2003

Active Share quintile	Tracking error quintile: Low	2	3	4	High	All	High-Low
	Panel A: Four-factor alpha of excess return on funds						
High	0.08	0.13	−0.93	0.72	−1.29	−0.25	−1.37
	(0.06)	(0.10)	(−0.69)	(0.55)	(−0.73)	(−0.21)	(−0.80)
4	−1.40	−0.33	−1.37	−2.34	−1.13	−1.31	0.26
	(−1.41)	(−0.28)	(−1.37)	(−1.83)	(−0.76)	(−1.32)	(0.15)
3	−1.28	−0.24	−0.90	−1.77	−1.17	−1.08	0.11
	(−1.37)	(−0.27)	(−1.09)	(−1.64)	(−0.97)	(−1.35)	(0.07)
2	−1.29	−0.35	−0.62	−1.22	−1.65	−1.03	−0.36
	(−2.11)	(−0.49)	(−1.08)	(−1.64)	(−1.77)	(−2.05)	(−0.32)
Low	−0.65	−0.16	−0.30	−0.41	−0.88	−0.47	−0.23
	(−1.76)	(−0.41)	(−0.60)	(−0.78)	(−1.38)	(−1.24)	(−0.35)
All	−0.91	−0.19	−0.82	−1.00	−1.22	−0.83	−0.32
	(−1.25)	(−0.25)	(−1.18)	(−1.17)	(−1.18)	(−1.19)	(−0.27)
High-Low	0.73	0.29	−0.63	1.13	−0.41	0.23	
	(0.67)	(0.24)	(−0.51)	(0.91)	(−0.25)	(0.21)	
	Panel B: Four-factor alpha of excess return on benchmark indexes						
High	−1.36	−0.66	−1.40	−2.00	−1.58	−1.40	−0.22
	(−1.07)	(−0.54)	(−1.16)	(−2.01)	(−1.64)	(−1.36)	(−0.20)
4	−1.28	0.57	−0.49	−0.82	0.51	−0.29	1.79
	(−1.26)	(0.67)	(−0.61)	(−0.99)	(0.67)	(−0.43)	(1.53)
3	−0.23	1.17	0.68	0.48	1.69	0.76	1.92
	(−0.31)	(1.99)	(1.16)	(0.77)	(2.33)	(1.70)	(1.61)
2	0.17	1.12	1.20	1.45	1.79	1.15	1.61
	(0.33)	(2.28)	(2.19)	(2.54)	(2.62)	(2.83)	(1.72)
Low	0.64	1.20	1.36	1.86	1.69	1.35	1.05
	(1.70)	(2.91)	(2.75)	(2.93)	(2.57)	(3.05)	(1.69)
All	−0.41	0.68	0.27	0.20	0.82	0.31	1.23
	(−0.60)	(1.19)	(0.51)	(0.36)	(1.45)	(0.66)	(1.43)
High-Low	−2.00	−1.86	−2.76	−3.85	−3.27	−2.75	
	(−1.72)	(−1.55)	(−2.22)	(−3.36)	(−2.69)	(−2.53)	

Funds are sorted by the two dimensions of active management. The measures of active management are computed as before. Panel A shows the four-factor alphas of net fund returns in excess of the risk-free rate. Index funds are excluded from the sample. Panel B shows the four-factor alphas of returns on the official benchmark indexes of the funds in panel A. The table shows annualized returns, followed by t-statistics (in parentheses) based on White's standard errors.

risk-free rate. This gives us the standard Carhart alphas shown in panel A of Table 8.

In stark contrast to our benchmark-adjusted returns, the Carhart alphas show no significant relationship between Active Share and performance. The reason behind this is that the benchmark indexes of the highest Active Share funds have a large negative Carhart alpha, and the benchmark indexes of the lowest Active Share funds have a large positive alpha, producing a spread of 2.75% ($t = 2.53$) in benchmark alphas (panel B). For example, individual indexes such as the S&P 500 and Russell 2000 have economically and statistically significant annual four-factor alphas of 1.08% ($t = 2.72$) and −2.73% ($t = -2.58$), respectively, during our sample period. Yet it would be inappropriate to attribute the 1.08% alpha to the "skill" of a purely mechanical S&P 500 index fund. Instead, these numbers suggest a misspecification in the four-factor model (see Cremers, Petajisto, and Zitzewitz 2008 for a detailed analysis).

Adjusting fund returns for the benchmark index return effectively recalibrates the alpha of the benchmark to zero. This seems reasonable, as a passive benchmark index such as the S&P 500 should almost by definition have a zero alpha. If we look at raw returns instead of Carhart alphas, the performance spread across the benchmarks of high and low Active Share funds is actually reversed, which casts further doubt on the four-factor alphas.

We prefer to focus on the benchmark-adjusted performance measures for the following reasons: first, mutual funds are legally required to declare a benchmark index, and the purpose of an active manager is to beat that benchmark. Both fund investors and fund managers care about performance relative to this benchmark; they do not (or, arguably, should not) care about unadjusted Carhart alphas, nor are most investors even aware of them. Second, the benchmark indexes are easily tradable portfolios—there are a number of products such as ETFs, index mutual funds, and various derivative contracts that allow investors to tailor their exposure to a particular index at a low cost. This tradability also puts benchmark indexes in direct competition with active managers in terms of attracting assets. In contrast, the Carhart factors are not directly tradable, and they would be very costly if not impossible for mutual fund investors to replicate due to, for example, the short positions they require in small- and micro-cap stocks.

Furthermore, the benchmark adjustment alone (with our set of nineteen benchmarks) already accounts for most of the style differences across funds. The benchmark-adjusted returns have factor betas that are generally close to zero, and the differences in betas between the top and bottom Active Share quintiles for market excess return, SMB, HML, and UMD are only −0.02, 0.00, 0.00, and −0.03, respectively (all statistically insignificant). Consequently, using the four-factor model makes relatively little difference for benchmark-adjusted returns across Active Share groups, although it does matter slightly more across tracking error groups. Hence, our main result of predicting fund returns using Active Share is very robust to whether or not returns are adjusted for the Carhart model.

4.5 Fund performance in a multivariate regression

To directly isolate the effect of different fund characteristics on fund performance, we run pooled panel regressions of fund performance on all the explanatory variables (Table 9). The values for the independent variables are chosen at the end of each year, while the dependent variable is performance over the following year. We use three different performance metrics: four-factor alphas of benchmark-adjusted returns, four-factor alphas of excess returns (relative to the risk-free rate), and the Characteristic Selectivity (CS) measure of Daniel et al. (1997). The first two metrics are calculated using net returns whereas the CS measure is based on gross returns.

The list of explanatory variables includes Active Share, tracking error, turnover, expense ratio, the number of stocks, fund size, fund age, manager

Table 9
Predictive regression for fund performance in 1992–2003

	Benchmark-adjusted alphas		Excess return (over risk-free rate) alphas		Characteristic selectivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Active Share	0.0722	0.0666	0.0496	0.0450	0.0200	0.0154
	(2.53)	(2.42)	(1.89)	(1.75)	(1.66)	(1.31)
Active Share		0.0139		0.0133		0.0136
(below median size)		(2.36)		(2.55)		(5.07)
Tracking error	−0.1454	−0.1459	−0.1006	−0.1022	−0.0567	−0.0578
	(1.76)	(1.75)	(1.71)	(1.72)	(0.66)	(0.68)
Turnover	−0.0041	−0.0041	−0.0033	−0.0033	0.0003	0.0003
	(0.84)	(0.84)	(0.78)	(0.78)	(0.10)	(0.10)
Expenses	−1.3117	−1.3024	−1.3447	−1.3348	−0.2797	−0.2694
	(6.00)	(5.99)	(5.10)	(5.06)	(0.75)	(0.73)
$\log_{10}$(TNA)	−0.0187	−0.0013	−0.0127	0.0040	−0.0019	0.0155
	(3.06)	(0.14)	(2.22)	(0.43)	(0.31)	(2.39)
$(\log_{10}(\text{TNA}))^2$	0.0025	0.0003	0.0015	−0.0005	0.0003	−0.0019
	(2.12)	(0.22)	(1.46)	(0.40)	(0.23)	(1.60)
Number of stocks/100	0.0043	0.0043	0.0027	0.0028	0.0014	0.0015
	(3.81)	(3.82)	(2.90)	(2.97)	(3.59)	(3.70)
Fund age/100	−0.0213	−0.0214	−0.0129	−0.0130	−0.0088	−0.0089
	(3.45)	(3.44)	(3.67)	(3.59)	(1.80)	(1.80)
Manager tenure/100	0.0245	0.0250	0.0199	0.0201	0.0452	0.0453
	(0.85)	(0.87)	(0.75)	(0.77)	(2.50)	(2.50)
Inflow, $t-1$ to t	0.0025	0.0024	−0.0018	−0.0019	0.0033	0.0033
	(0.77)	(0.74)	(0.53)	(0.56)	(0.88)	(0.85)
Inflow, $t-3$ to $t-1$	0.0010	0.0010	0.0011	0.0012	0.0012	0.0012
	(1.00)	(1.05)	(1.05)	(1.09)	(1.39)	(1.44)
Return over index, $t-1$ to t	0.0745	0.0739	0.0757	0.0753	0.0572	0.0566
	(1.36)	(1.35)	(1.51)	(1.50)	(1.52)	(1.51)
Return over index, $t-3$ to $t-1$	−0.0353	−0.0350	−0.0378	−0.0374	−0.0749	−0.0746
	(1.72)	(1.68)	(1.59)	(1.56)	(3.23)	(3.18)
Index return, $t-1$ to t	0.0369	0.0371	0.0010	0.0011	0.0325	0.0327
	(1.40)	(1.42)	(0.12)	(0.13)	(3.31)	(3.24)
Index return, $t-3$ to $t-1$	−0.0233	−0.0228	−0.0563	−0.0560	−0.0559	−0.0556
	(0.65)	(0.64)	(2.80)	(2.82)	(5.45)	(5.42)
N	8,232	8,232	8,232	8,232	6,615	6,615
R^2	0.0376	0.0395	0.1768	0.1778	0.168	0.1694

The dependent variable in columns 1–4 is based on the cumulative net return (after all expenses) over calendar year t, while the independent variables are measured at the end of year $t-1$. Alphas are computed with respect to the four-factor model. All explanatory variables are computed as before in Table 3. Index funds are excluded from the sample. Since the expense ratio and manager tenure are missing before 1992, we limit all specifications to the same time period. All specifications include year dummies, and columns 3–6 also include benchmark dummies. The t-statistics (in parentheses) are based on standard errors clustered by year.

tenure, prior inflows, prior benchmark returns, and prior benchmark-adjusted returns. As Active Share was shown earlier to be more strongly related to fund performance for smaller funds, we also include the interaction of Active Share with a dummy variable indicating below-median fund size for that year. Since the pooled panel regressions exhibit significant residual correlations within a year, we also include year dummies and cluster standard errors by year in each regression.

Active Share comes up as a highly significant predictor of future benchmark-adjusted net alphas (column 1 in Table 9), with a coefficient of 0.0722 and a t-statistic of 2.42. This means that, controlling for the other variables, a 30%

increase in Active Share is associated with an increase of 2.17% in benchmark-adjusted alpha over the following year. Rather than being subsumed by other variables, the predictive power of Active Share actually goes up when those other variables are added.

Unlike Active Share, tracking error produces a small negative effect on future performance, which is marginally statistically significant. Size and expenses emerge as the most significant other predictors of returns. Size enters in a nonlinear but economically and statistically significant way, showing that larger funds in our sample tend to underperform. Column 2 in Table 9 confirms that the relation between Active Share and performance is stronger for smaller funds, as the interaction of Active Share and a dummy for below-median fund size has a positive and significant coefficient. Overall, for below-median-sized funds, a 30% increase in Active Share is associated with an increase in benchmark-adjusted alphas of 2.41% per year.

In columns 3 and 4 of Table 9, our performance measure is the four-factor alpha over net excess fund returns over the risk-free rate, thus without the benchmark adjustment. As discussed in the previous section, it is important to control both for the nonzero alphas of the benchmarks themselves and for differences in benchmarks across Active Share levels. We aim to account for both by adding dummy variables for all nineteen benchmarks. The main result is that the predictive ability of Active Share decreases but remains economically and statistically significant at the 10% level. As a final robustness check, we use a fund's CS measure of performance in columns 5 and 6. We again add benchmark dummies to control for nonzero CS of the benchmarks and for differences in benchmarks across Active Share levels. For below-median-sized funds, there is a positive and significant coefficient, indicating that a 30% increase in Active Share is associated with an increase in next year's CS of 0.87%. For above-median-sized funds, the predictive ability is about half that but no longer statistically significant.

4.6 Comparison of all measures of active management

Table 10 shows a comparison of Active Share with other measures of active management. We compare Active Share with tracking error, industry-level Active Share, Industry Concentration Index, stock concentration index, and turnover.[13] Industry-level Active Share is computed similarly to Active Share, except that it replaces individual stocks with ten industry portfolios (as in Section 3.1.4). The Industry Concentration Index is computed as in Kacperczyk, Sialm, and Zheng (2005) (see also the Appendix of this article), except that the benchmark index is selected following the methodology of our article. The stock concentration index is analogous to the Industry Concentration Index, except that it uses individual stocks rather than industry portfolios. Standard

[13] The Pearson correlations of Active Share with these other measures are 45%, 62%, 36%, 49%, and 18%, respectively, and the Spearman rank correlations are 56%, 60%, 60%, 60%, and 17%.

Table 10
Predicting returns with different measures of active management in 1992–2003

	Benchmark-adjusted alphas								Excess return (over risk-free rate) alphas	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Active Share	0.0560						0.0751	0.0612	0.0067	0.0172
	(2.70)						(2.39)	(2.11)	(0.32)	(0.73)
Active Share							0.0115	0.0141	0.0123	0.0130
(below median size)							(2.26)	(2.40)	(3.07)	(2.52)
Tracking error		−0.0604					−0.2017	−0.1463	−0.1870	−0.1181
		(0.62)					(1.76)	(1.77)	(2.06)	(1.88)
Industry-level Active Share			0.0396				−0.0283	0.0464	0.0303	0.0845
			(1.82)				(0.56)	(0.93)	(0.60)	(1.83)
Industry Concentration Index				0.0816			0.1321	−0.0755	0.0606	−0.1243
				(2.74)			(1.84)	(1.13)	(0.84)	(2.61)
Stock concentration index					0.0388		−0.3070	−0.0503	0.0763	0.1434
					(0.18)		(1.18)	(0.18)	(0.31)	(0.58)
Turnover						−0.0019	−0.0021	−0.0039	−0.0007	−0.0029
						(0.35)	(0.43)	(0.78)	(0.14)	(0.69)
Control variables	No	No	No	No	No	No	No	Yes	No	Yes
N	11,480	11,480	11,480	11,480	11,481	11,351	11,351	8,232	11,351	8,232
R^2	0.0098	0.0004	0.0032	0.0031	0.0002	0.0007	0.0184	0.0397	0.1381	0.1791

The dependent variable is the benchmark-adjusted cumulative net return (after all expenses) over calendar year t, while the independent variables are measured at the end of year t-1. Active Share and tracking error are computed as before. Industry-level Active Share is computed similarly to Active Share, except that it replaces individual stocks with ten industry portfolios. The Industry Concentration Index is computed as in Kacperczyk, Sialm, and Zheng (2005), except that the benchmark index is selected by following the same methodology as elsewhere in this article. The stock concentration index is computed just like the Industry Concentration Index, except that it uses individual stocks rather than industry portfolios. Turnover is an annualized value. The control variables include all the remaining variables in Table 9. Index funds are excluded from the sample. Since the expense ratio and manager tenure are missing before 1992, we limit all specifications to the same time period. All specifications include year dummies, and columns 9–10 also include benchmark dummies. The t-statistics (in parentheses) are based on standard errors clustered by year.

errors are clustered by year to be conservative, and all regressions include year dummies.

We first consider each measure's ability to predict performance measured as next year's benchmark-adjusted four-factor alpha from net returns (columns 1–8 in Table 10). In the univariate regressions without control variables, Active Share, industry-level Active Share, and Industry Concentration Index all come up as significant, while tracking error, stock concentration index, and turnover are not significant. When all the variables are included in the same regression (column 7), Active Share dominates the other variables, especially after we add the control variables already used in Table 9 (column 8 in Table 10). In fact, Active Share is the only variable that is clearly significant and remains so in all of these regression specifications. Tracking error has a negative sign that is marginally significant, and the (marginal) predictive ability of the Industry Concentration Index disappears after adding the controls.

Finally, columns 9 and 10 in Table 10 use four-factor alphas from excess net fund returns over the risk-free rate, again also adding benchmark dummies. Active Share now predicts performance only for below-median-sized funds.[14]

5. Conclusions

Traditionally, the degree of active management is quantified along just one dimension: tracking error relative to a benchmark index. Yet this fails to capture the two different dimensions of active management: stock selection and factor timing.

This article points out that active management can be measured in two dimensions with Active Share and tracking error as convenient empirical proxies. Tracking error measures the volatility of portfolio return around a benchmark index, thus emphasizing correlated active bets such as exposure to systematic factor risk. Active Share measures the deviation of portfolio holdings from the holdings of the benchmark index, placing equal weight on all active bets regardless of diversification and thus emphasizing stock selection. This new methodology also allows us to empirically identify different types of active management: diversified stock picks, concentrated stock picks, factor bets, closet indexing, and pure indexing.

We apply this methodology to all-equity mutual funds, assigning a passive benchmark index for each fund based on what index produces the lowest Active Share for the fund. We find significant dispersion along both dimensions of active management. We also find evidence for the popular belief that small funds are more active, while a significant fraction of the largest funds are closet indexers. However, this pattern emerges only gradually after $1 billion

[14] The positive and significant coefficient for industry-level Active Share in column 10 should be interpreted with caution. Industry-level Active Share has a high (85%) correlation with the Industry Concentration Index, so this may be driven by multicollinearity. If either of these two is excluded (unreported result), then the other is not significant.

in assets—before that, fund size does not matter much for the fraction of active positions in the portfolio.

There has been a significant shift from active to passive fund management over the 1990s. Part of this is due to index funds, but an even larger part is due to closet indexers and a general tendency of funds to mimic the holdings of benchmark indexes more closely. Furthermore, about half of all active positions at the fund level cancel out within the mutual fund sector, thus making the aggregate mutual fund positions even less active.

Active management, as measured by Active Share, significantly predicts fund performance relative to the benchmark. Funds with the highest Active Share outperform their benchmarks both before and after expenses, while funds with the lowest Active Share underperform after expenses. In contrast, active management as measured by tracking error does not predict higher returns.

The relationship between Active Share and benchmark-adjusted fund returns exists for all fund sizes but it is stronger within the bottom three fund size quintiles than within the top two quintiles. We also find strong evidence for performance persistence for the funds with the highest Active Share, even after controlling for momentum. From an investor's point of view, funds with the highest Active Share, smallest assets, and best one-year performance seem very attractive, outperforming their benchmarks by 6.5% per year net of fees and expenses.

The main advantage of our methodology is that it allows us to distinguish between different types of active funds as well as to focus on the ones that are truly active. This could also help other researchers refine and potentially improve their existing results. Furthermore, our approach will allow researchers to investigate the risk-taking and incentives of mutual fund managers from a new and economically meaningful perspective.

Appendix: Other Measures of Active Management

A.1 Industry Concentration Index

Kacperczyk, Sialm, and Zheng (2005) investigate a related question about the industry concentration of mutual funds. They call their measure the Industry Concentration Index, which they define as

$$\text{Industry Concentration Index} = \sum_{i=1}^{I}(w_{\text{fund},i} - w_{\text{index},i})^2,$$

where $w_{\text{fund},i}$ and $w_{\text{index},i}$ are the weights of industry i in the fund and in the index, and they sum up across I industry portfolios (instead of N individual stocks). They also use the CRSP value-weighted index as their only benchmark. A more fundamental difference between Active Share and the Industry Concentration Index arises from the fact that the latter uses squared weights. For our study, we prefer to use Active Share for three reasons.

First, Active Share has a convenient economic interpretation: it immediately tells us the percentage of a fund that is different from the benchmark index. If the weights are squared, the numerical value loses this interpretation, and its main purpose is then just to rank funds relative to each other.

Second, different funds have different benchmark indexes, yet Active Share can still be easily applied when comparing any two funds: a 90% Active Share means essentially the same thing whether the benchmark is the S&P 500 (with five hundred stocks) or the Russell 2000 (with two thousand stocks). If we square the weights, we lose the ability to make such easy comparisons across indexes because the number of stocks begins to matter. For example, if a fund with the Russell 2000 as a benchmark is likely to have more stocks in its portfolio than a fund with the S&P 500 as a benchmark because the Russell 2000 investment universe contains four times as many stocks, then the typical active weight in a stock will be smaller and thus the sum of squares will be smaller.

Third, the squared weights make the Industry Concentration Index something of a hybrid between Active Share and tracking error.[15] However, to get a more complete picture of active management, we need to quantify it along two separate dimensions. We therefore pick two measures that are as different from each other as possible, and here Active Share and tracking error seem to satisfy that objective.

A.2 Turnover

Portfolio turnover has also been suggested as a measure of active management. For our purposes, it has some significant shortcomings and plays only a minor role in our tests.

Although portfolio turnover implies an action (i.e., trading) by the fund manager, turnover per se cannot add value to a portfolio—only holding a position does. Turnover just measures the frequency of revisions in the manager's active bets (i.e., positions), but it does not measure the activeness of the bets themselves. These are two different kinds of activeness: either "being busy" with the portfolio, or holding positions that differ significantly from the benchmark and thus have a chance to outperform or underperform. This article focuses on the latter definition.[16]

Fund inflows and outflows can also generate additional turnover, which does not tell us anything about the active management of the fund. Furthermore, if turnover is widely used as a measure of active management, less active funds may have an incentive to generate unnecessary trades to appear more active.

References

Asness, C. 2004. An Alternative Future. *Journal of Portfolio Management* 30:94–103.

Berk, J. B., and R. C. Green. 2004. Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy* 112(6):1269–95.

Bollen, N. P. B., and J. A. Busse. 2004. Short-Term Persistence in Mutual Fund Performance. *Review of Financial Studies* 18(2):569–97.

Brinson, G. P., L. R. Hood, and G. L. Beebower. 1986. Determinants of Portfolio Performance. *Financial Analysts Journal* 42(4):39–44.

[15] Assume that a fund has no systematic risk except for an index beta of 1. Its tracking error is then given by

$$\sigma(R_{\text{fund}} - R_{\text{index}}) = \sigma\left(\sum_{i=1}^{N}(w_{\text{fund},i} - w_{\text{index},i})R_i\right) = \sqrt{\sum_{i=1}^{N}(w_{\text{fund},i} - w_{\text{index},i})^2\sigma^2_{\varepsilon_i}}.$$

If the stocks (or industry portfolios) have a similar idiosyncratic volatility $\sigma^2_{\varepsilon_i}$, then tracking error will be approximately proportional to the square root of the Industry Concentration Index.

[16] To illustrate this, let us consider the famous Legg Mason Value Trust, which beat the S&P 500 index fifteen years in a row: in 2003 it had an Active Share of 86%, holding only thirty stocks in the portfolio, yet it had a turnover of only 25%. The same year, iShares Russell 2000 index fund had a turnover of 30% because of turnover in the underlying index. The low turnover of Legg Mason Value Trust simply indicates the long investment horizon of its stock picks rather than any adherence to a benchmark index.

Brown, S. J., and W. N. Goetzmann. 1995. Performance Persistence. *Journal of Finance* 50(2):679–98.

Carhart, M. 1997. On Persistence in Mutual Fund Returns. *Journal of Finance* 52(1):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(5):1276–302.

Cohen, R. B., J. D. Coval, and L. Pastor. 2005. Judging Fund Managers by the Company They Keep. *Journal of Finance* 60(3):1057–96.

Cremers, K. J. M., A. Petajisto, and E. Zitzewitz. 2008. Should Benchmark Indices Have Alpha? Revisiting Performance Evaluation. Working Paper, Yale University.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. *Journal of Finance* 52(3):1035–58.

Evans, R. B. 2004. Does Alpha Really Matter? Evidence from Mutual Fund Incubation, Termination, and Manager Change. Working Paper, University of Pennsylvania.

Fama, E. F. 1972. Components of Investment Performance. *Journal of Finance* 27(3):551–67.

Frazzini, A. 2006. The Disposition Effect and Underreaction to News. *Journal of Finance* 61(4):2017–46.

Goetzmann, W. N., Z. Ivkovic, and K. G. Rouwenhorst. 2001. Day Trading International Mutual Funds: Evidence and Policy Solutions. *Journal of Financial and Quantitative Analysis* 36(3):287–309.

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

Grinblatt, M., and S. Titman. 1993. Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns. *Journal of Business* 66(1):47–68.

Grinold, R. C., and R. N. Kahn. 1999. *Active Portfolio Management*, 2nd ed. New York: McGraw-Hill.

Gruber, M. J. 1996. Another Puzzle: The Growth in Actively Managed Mutual Funds. *Journal of Finance* 51(3):783–810.

Jensen, M. C. 1968. The Performance of Mutual Funds in the Period 1945–1964. *Journal of Finance* 23(2):389–416.

Jorion, P. 2003. Portfolio Optimization with Tracking-Error Constraints. *Financial Analysts Journal* 59(5):70–82.

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

Kacperczyk, M. T., C. Sialm, and L. Zheng. 2008. Unobserved Actions of Mutual Funds. *Review of Financial Studies* 21(6):2379–416.

Mamaysky, H., M. Spiegel, and H. Zhang. 2007. Improved Forecasting of Mutual Fund Alphas and Betas. *Review of Finance* 11(3):359–400.

Pastor, L., and R. F. Stambaugh. 2002. Mutual Fund Performance and Seemingly Unrelated Assets. *Journal of Financial Economics* 63:315–49.

Petajisto, A. 2009. Why Do Demand Curves for Stocks Slope Down? *Journal of Financial and Quantitative Analysis* 44(3).

Pollet, J. M., and M. Wilson. 2008. How Does Size Affect Mutual Fund Behavior? *Journal of Finance* 63(6):2941–69.

Roll, R. 1992. A Mean/Variance Analysis of Tracking Error. *Journal of Portfolio Management* 18(4):13–22.

Sensoy, B. A. 2009. Incentives and Mutual Fund Benchmarks. *Journal of Financial Economics* 92(1):25–39.

Wermers, R. 1999. Mutual Fund Herding and the Impact on Stock Prices. *Journal of Finance* 54(2):581–622.

Wermers, R. 2000. Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses. *Journal of Finance* 55(4):1655–95.

Wermers, R. 2003. Are Mutual Fund Shareholders Compensated for Active Management Bets? Working Paper, University of Maryland.