Managerial Activeness and Mutual Fund Performance

Hitesh Doshi
University of Houston

Redouane Elkamhi
University of Toronto

Mikhail Simutin
University of Toronto

A closet indexer is more likely to meet a value-weighted investment benchmark by value weighting the portfolio. Following this intuition, we introduce a simple measure of active management, the absolute difference between the value weights and actual weights held by a fund, summed across its holdings. This proxy captures managerial skill: active funds outperform passive ones by 2.5% annually. Compared with known measures of skill, our proxy robustly predicts fund flows, asset growth, factor-adjusted performance, and value added. Its predictive ability is orthogonal to that of other measures and is robust to controlling for volatility timing, past performance, and style. (*JEL* G10, G12, G14, G20, G23)

An important long-standing question in financial economics is whether active mutual fund managers possess skills to beat their benchmarks. The answer to this question is crucial for steering the asset allocation decisions of investors, guiding investment strategies of money managers, and evaluating market efficiency. The resounding evidence that an average actively managed equity mutual fund underperforms the benchmark[1] and the declining costs of passive investments have contributed to the ongoing shift by investors into

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[1] The idea that active mutual fund managers lack skill dates back to Jensen (1968) and Fama (1970) and is supported in later research by Malkiel (1995), Gruber (1996), Carhart (1997), Zheng (1999), Bollen and Busse (2001), Fama and French (2010), and others. Several papers find that managers select stocks that outperform benchmarks before, but not after, expenses, for example, see Grinblatt and Titman (1989, 1993), Daniel et al. (1997), and Wermers (2000). Other authors showing evidence of some skill, even at the average fund level, include Chen, Jegadeesh, and Wermers (2000), Alexander, Cici, and Gibson (2007), Cohen, Polk, and Silli (2010), Kacperczyk, van Nieuwerburgh, and Veldkamp (2014), and Berk and van Binsbergen (forthcoming).

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index funds.[2] Nonetheless, total assets in active equity funds continue to grow, jumping from \$5.9 to \$7.7 trillion during 2013 alone, and these funds continue to be the primary vehicle for households. Ninety-six million individual U.S. investors held money in mutual funds at the end of 2013, most of it in actively managed funds.

The average actively managed fund may underperform, but it is possible some managers possess true skill. Taking this premise to heart, a developing line of literature attempts to identify such managers. This research proposes measures of managerial "activeness" and shows that they predict fund performance.[3] An econometrician using these proxies of skill faces several challenges. She needs to correctly identify funds' investment benchmarks or peer groups, specify asset pricing models, and rely on a long time-series for calculations, hence implicitly assuming that fund attributes and management teams remain stable (see Amihud and Goyenko 2013 for further discussion of these shortcomings).

In this paper, we propose a simple new measure of managerial activeness: the absolute difference between the value weights and the actual weights held by a fund, summed across its holdings. This measure, which we term active weight, robustly predicts fund performance even after controlling for existing proxies of managerial activeness. Importantly, it does not necessitate identifying investment benchmarks and their holdings or using historical return data. It only requires the readily available knowledge of a fund's holdings and their market capitalizations. The empirical simplicity of active weight allows an econometrician to easily capture managerial activeness not only in the commonly studied samples of U.S. equity funds but also in a variety of settings in which relying on other measures may be challenging. For example, pension, endowment, hedge, and other funds that need not disclose returns frequently and that may change their benchmarks periodically, international funds for which imputing benchmarks or selecting asset pricing models is particularly difficult, and young funds with short return histories.

Why is active weight a promising measure of managerial activeness? Every mutual fund manager must make two important decisions when creating a portfolio: (1) they must select assets from the universe of suitable investments given a fund's investment objective and benchmark, and (2) they must assign weights to each selected asset. Clearly, managerial skill can play an important role in both decisions. However, inferring the skill from the first decision is empirically challenging as doing so requires knowledge not only of the universe of suitable investments but also of the actual rather than the stated

[2] The proportion of assets under management invested in equity index funds has been growing rapidly, from 11.4% in 2003 to about 18.4% in 2013. The statistics in this paragraph are from the 2014 Investment Company Factbook.

[3] See Kacperczyk, Sialm, and Zheng (2005, 2008), Brands, Brown, and Gallagher (2005), Kacperczyk and Seru (2007), Cremers and Petajisto (2009), Busse and Tong (2012), and Amihud and Goyenko (2013).

benchmark, both of which are not accurately observable by investors or econometricians. For example, Sensoy (2009, 25) shows that "almost one-third of actively managed, diversified U.S. equity mutual funds specify a size and value/growth benchmark index in the fund prospectus that does not match the fund's actual style." By contrast, we propose inferring managerial activeness from the second decision, which is not subject to the same complications as the first decision. Intuitively, active managers are expected to use their research and talents to overweight some securities and underweight others. As a result, a high active weight is a promising proxy for active management.

A low active weight is likely to be symptomatic of a passive investment approach. To see this, consider how a closet indexer will weigh stocks in the portfolio. Almost certainly, this manager would value weight the positions, leading to a low active weight. Two main ideas support this conjecture. First, and most important, market indices, exchange-traded funds, and the benchmarks used by mutual funds are almost exclusively value weighted (e.g., all of the nineteen indices used by Cremers and Petajisto 2009). Therefore, to minimize the risk of trailing the benchmark, a closet indexer is better off value weighting the portfolio. Second, Bhattacharya and Galpin (2011) show that value weighting is increasingly dominating mutual fund investing in developed markets. Hence, to outperform peers, an active manager is more likely to deviate from a value-weighted strategy, and our measure captures this deviation.

We base our analysis on 2,790 actively managed U.S. equity funds during a thirty-four-year period. We provide strong evidence for the existence of managerial skill by documenting predictability in fund returns. We find that the decile of funds with high active weight outperforms the low decile by 2.6% annually.[4] This result is robust to adjusting for factor exposure using conditional Ferson and Schadt (1996) and unconditional Carhart (1997) models, studying gross and net returns, controlling for differences in allocations to small capitalization stocks, and accounting for volatility timing as suggested by Ferson and Mo (2015). Decomposing fund performance as in Daniel et al. (1997), we find that close to one-half of the outperformance of high-active weight managers is due to their superior stock-selection ability.

What distinguishes active weight from the plethora of measures of managerial skill proposed in the recent literature? Indeed, at first glance, active weight appears to be closely related to proxies such as industry concentration ratio, active share, and R-squared (Kacperczyk, Sialm, and Zheng 2005; Cremers and Petajisto 2009; Amihud and Goyenko 2013, respectively). Like active weight, these measures strive to capture the extent of deviation of a fund's portfolio from some benchmark and suggest that more active

[4] We provide detailed SAS code to replicate this result on the authors' Web page (www-2.rotman.utoronto.ca/simutin).

funds outperform. However, the close link with these and similar proxies stops here.

We run regressions of different measures of future fund performance on both active weight and other skill proxies. In all specifications, our measure retains significance. We also regress active weight on each of the other measures in the cross-section and show that the residual, the component of active weight that is orthogonal to other skill proxies, robustly predicts fund performance.

Another set of findings adds to the evidence that active weight is distinct from the existing measures and successfully captures managerial activeness. Managerial skill is defined not only by the ability to generate alpha but also by how much money the manager attracts to the fund (i.e., flows) and by how much the fund's assets grow. If active weight truly captures managerial activeness, then it should forecast fund flows and asset growth. Consistent with this intuition, we find that active weight performs remarkably well in forecasting these two proxies of fund performance. We also show that active weight predicts the Berk and van Binsbergen (forthcoming) value-added performance proxy. Overall, active weight is the only measure successful in delivering predictability along several dimensions of performance.

Active weight is most closely related—even in name—to active share. The latter is a very thoughtful measure that aims to capture managerial skills from both of the decisions described earlier, that is, (1) selecting assets from the universe of suitable investments given a fund's investment objective and benchmark, and (2) assigning weights to each selected asset. By contrast, active weight aims to identify skilled managers from the second decision alone. Given the empirical challenges associated with identifying the benchmarks, determining whether active share or active weight is more informative about managerial skill is ultimately an empirical question. Consistent with Cremers and Petajisto's (2009) results, we find that active share does not predict factor-adjusted returns (see their Table 10). By contrast, active weight significantly predicts not only factor-adjusted returns but also all other dimensions of performance examined.

Our results suggest that funds with high active weight have higher factor-adjusted return and load positively on the SMB factor. This positive relation raises a potential concern that exposure to small capitalization stocks drives our results. To alleviate this concern, we perform several robustness tests. Specifically, we show that the factor-adjusted returns of the high-low active weight portfolio are significant even when we augment the four-factor model with the component of the CRSP equally weighted portfolio that is orthogonal to the other factors (market, SMB, HML, and momentum). This is important since the CRSP equally weighted portfolio has significant alpha with respect to the four-factor model during our sample, suggesting that the SMB factor may not capture the size effect properly during our sample. We also show that the results are robust to dropping stocks in a fund's portfolio that are in the bottom NYSE size quintile. Additionally, our results are robust to controlling for the lagged SMB loadings of the fund, where we first sort on the lagged SMB loadings and then sort on the active weight. Finally, we examine the performance of the active weight portfolios during months with negative SMB returns. The high-low active weight portfolio continues to generate significant factor-adjusted returns in months with negative SMB returns.

Overall, our results suggest that active weight captures a new dimension of active management. Active weight intuitively measures managerial activeness and is simple to compute, requiring only knowledge of a fund's holdings and their market capitalizations. Hence, it overcomes empirical challenges of other measures. We show that active weight predicts fund performance, fund flows, growth in fund assets, and value added, even after controlling for other measures of managerial activeness and volatility timing. We conclude that fund performance is positively affected by managerial activeness.

1. Data and Sample Selection

We obtain fund returns, expenses, total net assets (TNA), investment objectives, and other fund characteristics from the Center for Research in Security Prices (CRSP) Survivor Bias-Free Mutual Fund Database. Our analysis requires fund holdings, which we obtain by linking this database to the Thomson Financial Mutual Fund Holdings using MFLINKS files from the Wharton Research Data Services. The holdings database contains stock identifiers, allowing us to link positions of each fund to CRSP equity files to obtain market capitalization of each stock on the reported portfolio date.

Most funds have multiple share classes, which typically differ only in the fee structure and the target clientele. We combine such classes into a single fund. In particular, we calculate the TNA of each fund as the sum of TNAs of its share classes and calculate fund age as the age of its oldest share class. For all other fund characteristics, we use the TNA-weighted average over the share classes.

We restrict the analysis to diversified domestic actively managed equity mutual funds. CRSP has recently introduced a new variable to describe funds' investment objectives, crsp_obj_cd, which we use to define our sample and funds' style categories.[5] We screen styles and fund names to exclude international, balanced, sector, bond, money market, and index funds. We also exclude funds with TNA of less than $15 million, as Elton, Gruber, and Blake (2001) show that the returns on such small funds tend to be biased

[5] In untabulated results we confirm that the final sample defined using crsp_obj_cd is nearly identical to the one obtained when including funds with AGG, GMC, GRI, GRO, ING, and SCG Strategic Insight codes, EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE Lipper codes, and G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG Wiesenberger codes.

upward in the CRSP database. To reduce the effect of incubator bias documented by Evans (2010), we additionally remove the first eighteen months of returns on each fund. Since the reported fund objectives do not always accurately characterize a fund, following Kacperczyk, Sialm, and Zheng (2008), we exclude funds that during their life hold on average less than 80% of net assets in equity.[6] We follow Cremers and Petajisto (2009) and Amihud and Goyenko (2013) and delete funds with missing names in CRSP. Finally, we eliminate all observations with ten or fewer stock holdings in order to compute a meaningful measure of active weight. Our final sample extends from 1980 to 2013 and contains 343,964 fund-month observations covering 2,790 distinct funds. Table 1 provides summary statistics for fund characteristics. The average fund in our sample is 8.9 years old, manages $699 million of assets, charges 1.16% in expenses, generates turnover of 86%, and holds 98 stocks.

2. Active Weight

Our measure of managerial activeness is very simple to compute. It only requires data on fund holdings and market capitalization of each stock held. Specifically, we define active weight of fund i at time t as

$$\text{Active weight}_{it} = \frac{1}{2}\ \Sigma_j |w_{it}^{j} - w_{it}^{jm}|, \tag{1}$$

where w_{it}^{j} is the weight of stock j in fund i's equity portfolio at time t and w_{it}^{jm} is the weight that this stock would have been assigned had the manager market cap-weighted the equity portfolio. The active weight is thus the absolute difference between the value weights and the actual weights held by a fund, summed across its holdings. For a long-only portfolio, it is in the [0,1) range. A manager who value weights the holdings has an active weight of zero. The more the manager deviates from a market cap-weighted portfolio, the closer the active weight moves to one.

The definition of active weight is similar in spirit to the definition of active share, with the key difference being that we compare a fund's portfolio weights with a market-cap weighted portfolio of a fund's holdings, whereas Cremers and Petajisto (2009) use a broad benchmark index. Active share is an attractive measure, but several issues can give rise to complications when using it empirically, for example, determining the correct benchmark. We direct the reader to Amihud and Goyenko's (2013) section 6.1 for an in-depth overview of such limitations.

[6] See also Glode (2011) and Sialm and Starks (2012). Imposing this restriction introduces a potential lookahead bias. We verify in Table IA8 of the Internet Appendix that applying this filter on the basis of only past data does not meaningfully impact our results.

Table 1
Summary statistics
This table reports summary statistics for fund characteristics. AR is the first-order autocorrelation at the annual horizon. The last column shows correlations with active weight. All statistics are computed annually for all funds and then averaged over time. The active weight of fund i at time t is defined as $\frac{1}{2}\sum_j |w_{it}^j - w_{it}^{jm}|$, where w_{it}^j is the equity portfolio weight of stock j held by fund i and w_{it}^{jm} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio. Industry concentration index is defined following Kacperczyk, Sialm, and Zheng (2005) as the sum of squared differences between the fund's holdings weights in ten industries, defined by Kacperczyk, Sialm, and Zheng (2005), and the weights of these industries in the market portfolio. Return gap is calculated following Kacperczyk, Sialm, and Zheng (2008) as the difference between a fund's monthly returns and returns on its most recently reported holdings, averaged over the most recent twelve months. Active share is from Antti Petajisto's Web site, computed as in Cremers and Petajisto (2009). R-squared is calculated following Amihud and Goyenko (2013) as R-squared from Carhart (1997) four-factor regressions using monthly returns covering the most recent twenty-four months. The sample period is from 1980–2013

Variable	Mean	Median	SD	10th pctl	90th pctl	AR	Corr
Active weight, percent	42.0	41.5	10.4	29.2	55.5	0.471	1.000
Total net assets, million	699	173	2532	29.0	1410	0.976	−0.007
Expense ratio, percent	1.16	1.14	0.49	0.60	1.73	0.573	0.104
Turnover ratio, percent	86.1	66.4	81.9	18.9	172	0.710	0.051
Number of stocks	98	68.6	113	34.8	178	0.861	−0.073
Fund age, years	8.91	8.52	6.26	3.27	11.9	0.883	0.027
Industry concentration ratio, percent	5.48	4.16	5.05	1.33	10.8	0.687	0.079
Annual return gap, percent	−0.33	−0.32	6.11	−4.38	3.90	0.185	−0.004
Active share, percent	82.5	85.1	13.5	63.9	97.3	0.364	0.185
R-squared, percent	91.5	93.0	6.3	84.6	97.0	0.297	−0.173
12-month fund return runup, percent	12.8	12.5	10.7	1.00	25.4	0.065	0.002

Even when the benchmark is known with certainty, active share faces an additional challenge. Consider a manager who lacks any skill and whose benchmark is the S&P 500 index. To minimize the risk of trailing the index, and to appear "active," unskilled managers using the S&P 500 index benchmark may choose to hold a representative subset of stocks in the benchmark. One potential strategy would be to sort stocks in the S&P 500 index by market capitalization and choose one stock randomly from the five largest stocks, another stock randomly from the next five largest stocks, etc. The resultant value-weighted portfolio would contain 100 stocks that can be expected to track the S&P 500 index closely on average. The average active share of this portfolio would be 0.80, the average for all actively managed funds (see Table 1), and hence the manager would appear "active," when in fact she is a closet indexer.

Our measure of managerial activeness overcomes many of the challenges faced by active share. Most importantly, our computations do not require knowledge of a fund's benchmark and benchmark holdings. Despite their differences, active share and active weight are similar in the sense that they both measure the extent of deviation of a fund's holdings from some reference portfolio. Thus, it is not surprising that the two measures have a positive correlation of 18.5% (see Table 1). Importantly, this correlation is considerably lower than the correlation of active share with other measures.

For example, Amihud and Goyenko (2013) report that the correlation of their measure of activeness with active share is more than double this value.

No measure of managerial activeness is perfect. Thus, it is prudent to discuss the limitations of active weight. An important caveat with the measure is that it almost certainly understates the degree of total managerial activeness. This happens because it captures managerial abilities by analyzing the weights that a manager assigns to the assets in the portfolio and ignores the skills that a manager displays when selecting the assets from the universe of suitable investments. For example, a manager who forms a value-weighted portfolio of "outstanding" stocks is more skilled than active weight would suggest. Consequently, active weight may only provide a lower bound of mutual fund managerial activeness.

Figure 1 shows the time series of cross-sectional averages of active weight for the funds in our sample. For comparison, we also plot the values for passive index funds. Two observations from this figure are noteworthy. First, active weights of index funds are very close to zero, highlighting the effectiveness of the measure in identifying passive investments. Second, there is a clear time trend toward lower active weight, from a high of 50% in the early 1980s to a low of 36% in 2013, suggesting that closet indexing has grown increasingly prevalent.

If managerial skill is persistent, and active weight captures skill, then we would expect active weight to be highly persistent. Figure 2 examines the persistence of active weight. We assign funds into active weight quintiles each quarter and examine their active weight ranks five years before and after assignment. The average quintile ranks before and after portfolio assignment are highly persistent, suggesting that high active weight funds continue to stay in the high active weight quintiles.

2.1 Analysis of active weight

To understand the characteristics of the funds with different active weights, and to verify that our proposed measure is a new dimension of active management, we run panel regressions of active weight on the contemporaneous fund characteristics, including the commonly considered measures of active management.[7] Table 2 summarizes the results of this analysis.

In specification (1), as explanatory variables, we include the most widely studied measures of active management proposed in the prior literature: industry concentration index, return gap, active share, and R-squared.[8] Out of

7 Our results here and in subsequent tables are robust to using annual Fama-MacBeth (1973) regressions instead of panel regressions.

8 We follow Kacperczyk, Sialm, and Zheng (2005, 2008) in calculating industry concentration and return gap. Active share data are from Antti Petajisto's Web site (www.petajisto.net). The data cover the 1980–2009 period, and so the analysis that uses the data is restricted to the same time frame. R-squared is calculated following Amihud and Goyenko (2013) from Carhart (1997) four-factor regressions on past twenty-four months of monthly data.

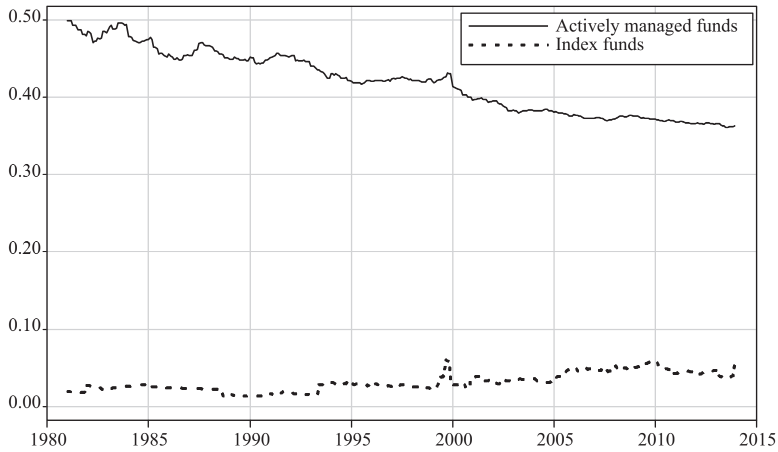

Figure 1
Active weight of actively managed and index funds
This figure plots the average active weight for a sample of U.S. actively managed and index equity funds. The active weight of fund i at time t is defined as $\frac{1}{2}\sum_j |w_{it}^j - w_{it}^{jm}|$, where w_{it}^j is the equity portfolio weight of stock j held by fund i and w_{it}^{jm} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio.

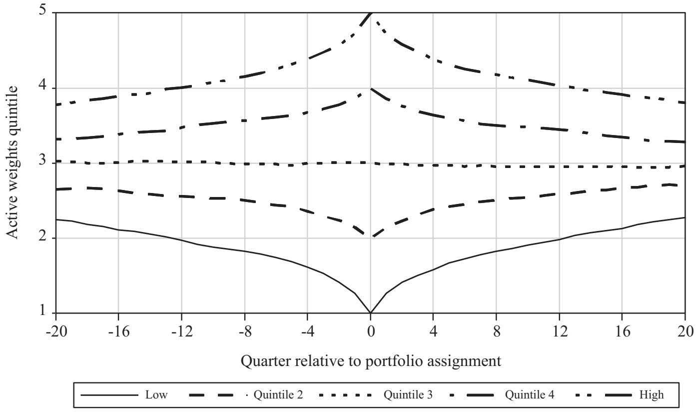

Figure 2
Persistence of active weight
Funds are assigned into active weight quintiles in quarter 0, and their active weight ranks are calculated five years before and after that time. This figure plots the resultant average quintile ranks. The active weight of fund i at time t is defined as $\frac{1}{2}\sum_j |w_{it}^j - w_{it}^{jm}|$, where w_{it}^j is the equity portfolio weight of stock j held by fund i and w_{it}^{jm} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio. The sample period is from 1980–2013.

the four measures, active weight is significantly related only to active share and R-squared. Importantly, the four measures explain only 9% of the variation in active weight. This provides the first strong indication that active weight is distinct from previously proposed measures of managerial activeness, a finding we confirm in Section 5.

Table 2
Analysis of active weight
This table reports the results of panel regressions of active weight on contemporaneous fund characteristics. The active weight of fund i in month t is defined as $\frac{1}{2}\sum_j |w_{it}^j - w_{it}^{jm}|$, where w_{it}^j is the equity portfolio weight of stock j held by fund i and w_{it}^{jm} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio. Industry concentration index is defined following Kacperczyk, Sialm, and Zheng (2005) as the sum of squared differences between the fund's holdings weights in ten industries, defined by Kacperczyk, Sialm, and Zheng (2005), and the weights of these industries in the market portfolio. Return gap is calculated following Kacperczyk, Sialm, and Zheng (2008) as the difference between a fund's monthly returns and returns on its most recently reported holdings, averaged over the most recent twelve months. Active share is from Antti Petajisto's Web site, computed as in Cremers and Petajisto (2009). R-squared is calculated following Amihud and Goyenko (2013) as R-squared from Carhart (1997) four-factor regressions using monthly returns covering the most recent twenty-four months. Regressions use yearly data. Reported are coefficients, t-statistics based on standard errors clustered by fund and month, and the adjusted R^2 values. The sample period is from 1980–2013, except in regressions including active share, where data unavailability limits the period from 1980–2009

Variable	(1)	(2)	(3)
Industry concentration index	0.095		0.151
	[1.89]		[3.03]
Return gap, percent	−0.003		0.005
	[−0.72]		[1.88]
Active share	0.134		0.314
	[3.60]		[6.57]
R-squared	−0.160		−0.112
	[−3.05]		[−3.66]
Log total net assets, million		−0.013	−0.005
		[−2.47]	[−1.09]
Squared log total net assets, million		0.001	0.000
		[1.30]	[0.97]
Log number of stocks		−0.012	0.019
		[−3.86]	[3.66]
Expense ratio		2.582	2.239
		[3.35]	[3.32]
Turnover ratio		0.009	0.003
		[2.60]	[1.79]
Fund age		−0.003	0.003
		[−0.68]	[0.81]
Past 12-month fund return		0.000	0.000
		[2.59]	[0.69]
Micro cap dummy		−0.116	−0.210
		[−2.87]	[−3.38]
Mid cap dummy		−0.078	−0.123
		[−3.36]	[−4.52]
Small cap dummy		−0.086	−0.172
		[−3.74]	[−5.05]
Growth and income dummy		−0.013	0.005
		[−1.96]	[0.85]
Growth dummy		−0.005	0.000
		[−0.79]	[0.08]
Adjusted R^2, percent	9.45	17.67	36.71

Specification (2) suggests that active weight is significantly related to a fund's investment style and several other fund characteristics, including the expense ratio. Interestingly, funds with size objectives (e.g., small-cap funds) are more likely to value weight their holdings and have lower active weights. In untabulated results, we find that flows out of such funds appear to be more sensitive to poor lagged performance than the flows of other funds. For example, funds with micro-, mid-, and small-cap objectives that fall in the bottom decile in terms of the fund performance during a year suffer on average 12% outflows during the following year. For funds with other benchmarks, the corresponding figure is only 9%. Following superior performance, the funds with size-related objectives do not attract as high of inflows as do the other funds. These results suggest that funds with size-related objectives have substantial outflows when their performance is poor and enjoy limited gains when their performance is good. Consequently, managers running such funds may have limited incentives to actively deviate from a value-weighted benchmark compared with managers of other funds.[9]

Combining the explanatory variables from the first two regressions in specification (3) explains approximately one-third of the cross-sectional variation in active weight. Therefore, active weight appears to be a new dimension of active mutual fund management that needs to be considered separately from the measures studied in the prior literature.

3. Future Performance of Funds Sorted by Lagged Active Weight

To study the relation between active weight and future performance, at the end of every month t, we sort funds into deciles on the basis of active weight of their most recently disclosed portfolio. We sort funds into deciles within each investment style and then aggregate funds across styles to obtain ten style-neutral portfolios.[10] Only funds that reported their holdings within twelve months ending in month t are included in the portfolios.

We then compute TNA-weighted returns of each decile portfolio in month $t+1$. We study fund performance both before and after deducting fund expenses. Investors are mainly concerned about the performance net of expenses, but examining performance before expenses allows for a better assessment of differences in managerial abilities if skilled managers extract rents by charging higher expenses (cf. Berk and Green 2004).

3.1 Raw returns and Daniel et al. (1997) decomposition

The first two columns of Table 3 show average returns that funds in active weight-sorted portfolios generate before and after expenses. The returns after expenses are the reported fund returns realized by investors, and the

[9] Trading costs offer another possible explanation of the higher propensity of funds with size-related objectives to value-weight their holdings. For such funds, assigning a high weight to smaller stocks is unattractive because transaction costs tend to be higher for such stocks (e.g., Keim and Madhavan 1997). Assigning a higher weight to a larger stock may be unattractive because doing so will tilt the fund away from its size objective, while tilting into larger stocks that tend to have lower returns.

[10] Sorting within styles is motivated by the results of Table 2, which show that style is an important determinant of active weight. Assigning funds into groups without conditioning on style may lead to portfolios being primarily composed of funds of a particular style. Later in the paper and in the Internet Appendix, we show robustness to portfolio assignment without conditioning on style.

Table 3

Average returns and performance attribution analysis of portfolios sorted by active weight

This table reports annualized moments of returns of portfolios created by assigning funds into deciles at the end of every month t on the basis of their most recently available active weight and holding the resultant total net assets-weighted portfolios during month $t+1$. The active weight of fund i in month t is defined as $\frac{1}{2}\sum_j |w_{it}^j - w_{it}^{jm}|$, where w_{it}^j is the equity portfolio weight of stock j held by fund i and w_{it}^{jm} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio. To be included in a portfolio at the end of month t, a fund must report holdings within the previous twelve months. The first two columns show actual average returns before and after deducting expenses. The last three columns decompose the performance of gross returns of a hypothetical portfolio containing a fund's stock holdings into three components following Daniel et al. (1997): characteristic selectivity is $CS_t = \sum_j w_{t-1}^j (R_{j,t} - BR_{j,t}^{t-1})$; characteristic timing is $CT_t = \sum_j (w_{t-1}^j BR_{j,t}^{t-1} - w_{t-13}^j BR_{j,t}^{t-13})$; and average style is $AS_t = \sum_j w_{t-13}^j BR_{j,t}^{t-13}$, where w_{t-k}^j is the weight of stock j in the fund equity portfolio at the end of month $t-k$, $R_{j,t}$ is the return on stock j in month t, and $BR_{j,t}^{t-k}$ is the return in period t on the benchmark portfolio to which stock j was assigned in month $t-k$ on the basis of its size, value, and momentum characteristics. The rows labeled "High-low" and "t-stat" show the moments and corresponding t-statistics for the portfolio that longs the high active weight group and shorts the low group. The bottom row shows the p-values from a bootstrap exercise described in the Appendix. The sample period is from 1980–2013

Active weight portfolio	Gross return	Net return	Characteristic selectivity	Characteristic timing	Average style
Low	11.9	10.8	0.08	−0.17	10.8
Decile 2	12.7	11.6	0.17	0.08	11.0
Decile 3	13.0	11.9	0.36	−0.16	11.5
Decile 4	12.7	11.6	0.39	0.15	11.2
Decile 5	13.1	11.9	0.52	−0.01	11.6
Decile 6	13.5	12.4	0.65	0.03	11.6
Decile 7	13.5	12.3	0.88	0.14	11.6
Decile 8	13.6	12.4	0.81	0.16	11.6
Decile 9	13.5	12.5	0.80	0.16	11.7
High	14.5	13.2	1.04	0.08	12.2
High-low	2.63	2.43	0.95	0.25	1.33
t-stat	[4.21]	[3.89]	[2.75]	[1.08]	[1.88]
Bootstrap p-value	(0.00)	(0.00)	(0.02)	(0.24)	(0.11)

returns before expenses are computed by adding the expense ratio to the reported fund returns. A clear pattern emerges: funds with high active weights perform better in the future than do those with low active weights. High-active weight funds outperform low-active weight funds by more than 2.6% annually before deducting expenses.[11] This difference in returns is not only statistically significant (t-statistic of 4.2) but is also economically large.

To get an early indication of the driving forces behind the positive relation, we compute characteristic selectivity, characteristic timing, and average style measures for every decile portfolio, as in Daniel et al. (1997). The three components are

[11] Mutual funds cannot be shorted, so the return difference should not be interpreted as a return an investor can generate by buying one set of funds and selling another. The correct interpretation of the difference is the relatively higher return an investor would generate by buying the high decile portfolio instead of the low decile portfolio.

$$
\begin{aligned}
CS_t &= \Sigma_j w_{j,t-1}\left(R_{j,t} - BR_{j,t}^{t-1}\right),\\
CT_t &= \Sigma_j\left(w_{j,t-1}BR_{j,t}^{t-1} - w_{j,t-13}BR_{j,t}^{t-13}\right), \text{ and} \qquad (2)\\
AS_t &= \Sigma_j w_{j,t-13}BR_{j,t}^{t-13},
\end{aligned}
$$

where $w_{j,t-k}$ is the weight of stock j in a fund's equity portfolio at the end of month t-k, $R_{j,t}$ is the return on stock j in month t, and $BR_{j,t}^{t-k}$ is the return in period t on the benchmark portfolio to which stock j was assigned during period t-k on the basis of its size, value, and momentum characteristics.[12] The sum of the three components equals the gross performance of a hypothetical portfolio containing a fund's stock holdings.

We perform the decomposition for each fund in a given decile portfolio and compute the TNA-weighted average of each of the measures in a given decile portfolio. Table 3 reports the results of the decomposition for each decile portfolio. We find that characteristic selectivity is increasing with active weight, suggesting that more active managers exhibit better stock-selection skills. The difference in the selectivity measures of the top and bottom deciles reaches nearly 1% per year with a t-statistic of 2.75. Note that even though active weight does not capture the skill involved in the initial screening of stocks, it captures managerial abilities associated with the decision about how to weight the stocks in the portfolio. Our results about selectivity come from this assignment of weights within a fund's portfolio.[13]

To further evaluate the statistical significance of the relation between active weight and future performance, we perform a bootstrap exercise and report the corresponding p-values in the bottom row of Table 3.[14] Our objective is to examine the relation between active weight and future returns or characteristic selectivity after removing the actual active decision of the fund manager to choose specific weights. For each fund and each stock, we model the weights with a first-order autoregressive process. We keep the intercept and slope as parameters and retain the residuals. We then randomly assign the residuals, building up the weights recursively, starting from a randomly chosen value for the first period. We provide complete details of the methodology in the Appendix. We then compute active weights of the resultant "funds" and evaluate their future performance. The gross returns of each

[12] We direct the reader to Daniel et al. (1997) for calculation details. The decomposition has been used by, among others, Wermers (2000), Kacperczyk, Sialm, and Zheng (2005, 2008), Kacperczyk and Seru (2007), Cremers and Petajisto (2009), Amihud and Goyenko (2013), Wang (2014), and Ferson and Mo (2015).

[13] Put differently, characteristic selectivity is higher for funds that select stocks that outperform their benchmark and is higher if the weight that the manager puts on the stock is higher. Our measure captures selectivity through the second channel, where the manager tilts her portfolio within the universe of stocks selected toward the ones that outperform their benchmark.

[14] The cross-sectionally bootstrapped p-values are computed following Kosowski et al. (2006).

fund for the bootstrap exercise are computed using the actual returns of the stocks and the weights assigned to each stock. We repeat the exercise 10,000 times. Table 3 shows that the resultant p-values of the net and gross returns, as well as the characteristic selectivity measures are all below 0.05.[15]

3.2 Factor-adjusted returns

Although the performance is stronger for funds with high active weights, these funds may be generating superior returns because of greater exposure to factors that generate higher returns. It is therefore important to account for the differences in factor loadings across active weight portfolios. We use two widely applied models to compute factor-adjusted returns of the portfolios. First, we consider the Carhart (1997) four-factor model:

$$R_{it} = \alpha_i^U + \beta_i^M R_{Mt} + \beta_i^{HML} R_{HMLt} + \beta_i^{SMB} R_{SMBt} + \beta_i^{UMD} R_{UMDt} + \varepsilon_{it}, \tag{3}$$

where R_{it} is the excess return in month t of a portfolio of funds that belong to active weight decile i, and R_{Mt}, R_{HMLt}, R_{SMBt}, and R_{UMDt} are the market, value, size, and momentum factors, respectively. The intercept from this regression is the unconditional four-factor alpha.

Second, we use the Ferson and Schadt (1996) conditional performance measure to account for the possibility that market betas are time varying. The Ferson-Schadt model uses a predetermined set of conditioning variables:

$$R_{it} = \alpha_i^C + \beta_i^M R_{Mt} + \beta_i^{HML} R_{HMLt} + \beta_i^{SMB} R_{SMBt} + \beta_i^{UMD} R_{UMDt} + \Sigma_Z \beta_i^Z Z_{t-1} R_{Mt} + \nu_{it}, \tag{4}$$

where Z_{t-1} is the demeaned value of macroeconomic variable Z in month t - 1. Following the literature (Kacperczyk, Sialm, and Zheng 2005), we include the dividend yield of the S&P 500 index, term spread (the difference between the rates on a ten-year Treasury note and a three-month Treasury bill), default spread (the difference between the rates on AAA and BAA bonds), and the three-month Treasury-bill rate as the macroeconomic variables.[16] The intercept from this regression is the Ferson-Schadt conditional performance measure.

[15] We thank the editor and the referee for suggesting this approach. We also perform an alternative simulation exercise in which we assign random weights drawn from a uniform distribution to the stocks in a fund's portfolio instead of randomizing its actual weights. However, this exercise suffers from the criticism that in large number of simulations, the average portfolio would resemble an equal-weighted portfolio. We thank the editor for pointing this out. Nevertheless, the p-values from this exercise confirm the statistical significance of the relation between active weight and future fund performance.

[16] Dividend yield is computed following Fama and French (1988). Data on the Treasury and corporate bond rates are from the Federal Reserve (http://research.stlouisfed.org/fred2). Data on the factors and the risk-free rate are from Ken French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). We follow Wermers (2003), Kacperczyk, Sialm, and Zheng (2005), and Kosowski et al. (2006) in allowing time variation only for the market beta. We show in Table IA9 of the Internet Appendix that allowing all four betas to vary over time does not affect our results.

Table 4 summarizes the factor-adjusted performance measures from the two models. As with simple returns above, we evaluate fund performance both before and after deducting expenses. No hypothetical holdings-based returns are used in this analysis. Columns 2 to 5 of the table show that future fund performance, both before and after expenses, relates positively to active weight. This result holds true for both conditional and unconditional alphas. For example, the top active weight group generates a significantly positive conditional (unconditional) alpha of 1.88% (1.98%) per year before expenses, while the corresponding value for the bottom group is negative at −0.76% (−0.57%). The difference in the performance of the two groups is 2.64% (2.55%) annually using the conditional (unconditional) model; the difference is both economically and statistically significant.

The last four columns of Table 4 summarize the unconditional betas of the active weight decile portfolios. The unconditional loadings are computed using the returns net of expenses. The unconditional factor loadings are similar across active weight deciles, except in the case of the size factor, which is larger for portfolios with high active weights.

3.3 Factor-adjusted returns: Controlling for exposure to size

The higher SMB loadings of portfolios with higher active weights warrant additional discussion because they raise a potential concern that our results are driven by exposure to small capitalization stocks. More specifically, it is possible that funds that allocate more than value weights to small stocks have simultaneously higher active weights and higher returns due to greater exposure to the size factor. The results in Table 4 show that this is unlikely to be the case: funds with higher active weight achieve superior future performance even after accounting for loadings on the size factor. We now conduct several tests to further alleviate concerns that the relation between active weight and future fund performance may be driven by exposure to small capitalization stocks.

In panel A of Table 5, we include a fifth factor into the regressions: the component of the CRSP equal-weighted index that is orthogonal to the other four factors.[17] We do this because the SMB factor by itself may be insufficient to account for size tilts of portfolios. For example, the equal-weighted market index has a four-factor alpha that is significant at the 10% level during our sample period, and hence the proposed fifth factor can help to better control for size-related exposure. The results show that the high-active weight portfolios continue to significantly outperform the low-active weight portfolios even after this change in the methodology.

In panel B of Table 5 we compute active weight for every fund after excluding all stocks from each fund's holdings that fall below the 20th

[17] For brevity, Table 5 reports results only for the high-low portfolio. The results for all deciles are available in the Internet Appendix.

Table 4

Future alphas and loadings of portfolios sorted by active weight

This table reports portfolio alphas, in percent per year, from the Carhart's (1997) unconditional four-factor model and from the Ferson and Schadt (1996) conditional model. The factor-adjusted returns are calculated before and after subtracting expenses (gross and net returns). The returns after expenses are the reported returns realized by fund investors. The last four columns summarize the factor loadings from unconditional Carhart (1997) four-factor model regressions using net-of-expenses returns. Funds are assigned into deciles at the end of every month t on the basis of their most recently available active weight, and portfolio returns in month $t+1$ are used in performance regressions. The active weight of fund i in month t is defined as $\frac{1}{2}\sum_j |w^j_{it} - w^{jm}_{it}|$, where w^j_{it} is the equity portfolio weight of stock j held by fund i and w^{jm}_{it} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio. To be included in a portfolio at the end of month t, a fund must report holdings within the previous twelve months. The bottom two rows show the alphas, factor loadings, and corresponding t-statistics for the portfolio that longs the high-active weight group and shorts the low group. The sample period is from 1980–2013

Active weight portfolio	Carhart alphas		Ferson-Schadt alphas		Unconditional loadings			
	Gross	Net	Gross	Net	MKT	HML	SMB	UMD
Low	−0.57	−1.67	−0.76	−1.87	1.01	−0.10	0.16	0.02
Decile 2	0.20	−0.90	0.08	−1.02	1.00	−0.09	0.17	0.03
Decile 3	0.05	−1.08	−0.09	−1.23	1.03	−0.05	0.17	0.04
Decile 4	0.01	−1.13	−0.20	−1.34	1.00	−0.05	0.18	0.04
Decile 5	0.14	−1.00	0.15	−1.02	0.97	−0.08	0.13	0.01
Decile 6	0.59	−0.58	0.50	−0.67	0.98	−0.04	0.18	0.02
Decile 7	0.74	−0.44	0.58	−0.60	1.00	−0.01	0.21	0.02
Decile 8	0.71	−0.48	0.55	−0.64	1.00	0.00	0.24	0.02
Decile 9	1.04	−0.01	0.89	−0.17	0.98	0.00	0.24	−0.01
High	1.98	0.68	1.88	0.58	0.98	−0.02	0.34	−0.01
High-low	2.55	2.35	2.64	2.45	−0.04	0.08	0.18	−0.03
	[4.49]	[4.14]	[4.71]	[4.36]	[−1.36]	[3.98]	[11.4]	[−3.28]

NYSE market capitalization percentile. We make no other changes to the methodology. This approach allows us to evaluate whether the relation between active weight and subsequent fund performance is due to allocations to small stocks. The results show that the difference in returns between the high- and low-active weight portfolios remains economically large and statistically significant. Importantly, this approach proves effective in reducing the differences in exposures to small capitalizations stocks across active weight portfolios. The difference in loadings on the size factor of the high- and low-active weight deciles reduces dramatically, from 0.18 with a t-ratio of 11.4 (Table 4) to 0.04 with a t-ratio of 2.05 (panel B of Table 5).

We also repeat the analysis of Table 4, except that we first sort funds into quintiles based on their lagged SMB loadings and then assign the quintiles into active weight deciles within each SMB quintile.[18] Grouping all funds based on a given active weight decile results in ten portfolios with approximately similar SMB exposure and hence minimizes the confounding effects of exposure to small-cap stocks. The results, summarized in panel C of Table 5, show that SMB factor loadings are indeed economically similar across active

[18] Consistent with other analysis in the paper and also in line with Amihud and Goyenko (2013), we estimate lagged SMB loadings as of the end of month t from four-factor regressions on monthly data spanning $t-23$ to t.

Table 5

Future alphas and loadings of portfolios sorted by active weight: Robustness

This table reports portfolio alphas, in percent per year, from the Carhart (1997) unconditional four-factor model and from the Ferson and Schadt (1996) conditional model. The factor-adjusted returns are calculated before and after subtracting expenses (gross and net returns). The returns after expenses are the reported returns realized by fund investors. The right set of columns summarizes factor loadings from unconditional regressions using net-of-expenses returns. Unless specified otherwise, funds are assigned into deciles at the end of every month t on the basis of their most recently available active weight, and total net asset-weighted portfolio returns in month $t+1$ are used in performance regressions. The active weight of fund i in month t is defined as $\frac{1}{2}\sum_j |w_{it}^j - w_{it}^{jm}|$, where w_{it}^j is the equity portfolio weight of stock j held by fund i and w_{it}^{jm} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio. To be included in a portfolio at the end of month t, a fund must report holdings within the previous twelve months. In panel A, the regressions include an additional factor: the component of the equal-weighted market factor (MKT^{EW}) orthogonal to the value weighted market factor as well as size, value, and momentum factors. For the purposes of calculating active weight in panel B, all stocks that fall below 20th NYSE market capitalization percentile are excluded from funds' portfolios. In panel C, funds are first assigned into quintiles on the basis of their SMB loadings from four-factor regressions using monthly returns spanning the prior two years. Within each SMB loading group, funds are then grouped into deciles on the basis of their active weight. Panel D restricts the sample to months with negative SMB factor returns. In panel E, funds in each active weight decile are equally weighted. Unlike in the main sample, in panel F, funds are assigned into active weight groups not within each style but unconditionally. In panel G, the active weight is computed relative to an equal-weighted benchmark, that is, $w_{it}^{jm} = 1/N_{it}$, where N_{it} is the number of stocks held by the fund. Shown are the alphas, factor loadings, and corresponding t-statistics for the portfolio that longs the high-active weight decile and shorts the low decile. The sample period is from 1980–2013

	Carhart alphas		Ferson-Schadt alphas		Unconditional loadings				
Active weight portfolio	Gross	Net	Gross	Net	MKT^{EW}	MKT	HML	SMB	UMD
Panel A: Controlling for equal-weighted market factor orthogonal to the other four									
High-low	2.54	2.35	2.64	2.44	−0.02	−0.04	0.08	0.19	−0.04
t-statistic	[4.48]	[4.13]	[4.70]	[4.35]	[−0.58]	[−2.94]	[5.00]	[9.25]	[−3.20]
Panel B: Active weight computed excluding stocks below 20th NYSE size breakpoint									
High-low	2.04	2.01	2.17	2.12		−0.02	−0.01	0.04	−0.01
t-statistic	[2.85]	[2.77]	[3.21]	[3.13]		[−2.42]	[−0.65]	[2.05]	[−0.95]
Panel C: Conditional sort on lagged SMB loadings and active weight									
High-low	2.01	1.99	2.13	2.19		−0.05	0.08	0.05	−0.06
t-statistic	[3.08]	[3.09]	[3.37]	[3.30]		[−1.66]	[5.51]	[3.61]	[−6.20]
Panel D: Negative SMB factor returns									
High-low	3.53	3.37	3.53	3.37		−0.04	0.09	0.20	−0.06
t-statistic	[3.40]	[3.23]	[3.41]	[3.24]		[−3.10]	[4.62]	[6.41]	[−4.07]
Panel E: Equal-weighted active weight portfolios									
High-low	2.50	2.32	2.86	2.68		−0.02	0.12	0.19	−0.04
t-statistic	[3.97]	[3.76]	[4.04]	[3.91]		[−1.39]	[4.83]	[8.45]	[−2.76]
Panel F: Active weight computed without controlling for fund style									
High-low	2.61	2.46	2.78	2.63		−0.06	0.02	0.02	−0.02
t-statistic	[4.08]	[3.85]	[4.37]	[4.14]		[−1.62]	[1.30]	[0.93]	[−1.59]
Panel G: Active weight computed based on deviations from an equal-weighted benchmark									
High-low	0.97	1.14	1.43	1.60		−0.03	−0.09	0.04	−0.03
t-statistic	[1.81]	[2.12]	[3.01]	[3.37]		[−3.21]	[−5.53]	[2.63]	[−3.14]

weight portfolios. As with the other tests above, using this approach effectively reduces the differences in size exposure of the low- and high-active weight portfolios. The difference in future returns of the two portfolios remains economically large and significant, while the SMB loading of the high-low portfolio is smaller (0.05) relative to 0.18 in Table 4.

Finally, we conduct an additional test to determine whether tilts to small capitalization stocks drive our findings: we examine the performance of active weight portfolios in months with negative SMB factor returns. The results, shown in panel D of Table 5, point to a strong positive relation between active weight and future fund performance even when SMB realizations are negative. These results provide another piece of evidence that the findings are unlikely to be due to differences in allocations to small stocks.

Overall, the results presented in panels A through D of Table 5 strongly suggest that the ability of active weight to predict fund performance is not driven by exposure to small stocks.

3.4 Factor-adjusted returns: Additional robustness tests

We now consider three additional tests for evaluating the robustness of our findings related to the empirical choices made when obtaining the base-case results reported in Table 4. First, we form equal-weighted, rather than total net assets-weighted, portfolios. Panel E of Table 5 shows that this change in methodology has a negligible impact on our results.

Second, we evaluate the sensitivity of the results to conditioning on fund style when creating active weight-sorted portfolios. Given that fund style is related to active weight (see Table 2), grouping funds within each style, as we do in our base-case analysis, helps to distinguish the role of active weight from the role of style. Yet, this method admittedly detracts from the simplicity of our measure. We therefore consider assigning funds into active weight portfolios unconditionally. Panel F of Table 5 shows that doing so widens the difference in future performance of the high- and low-active weight portfolios. For example, Ferson and Schadt's (1996) alphas, using gross returns with and without controlling for fund style, are 2.64% and 2.78% per year, respectively. Notably, the SMB factor loadings of the high- and low- active weight portfolios are similar without controlling for fund style. This happens because funds with small-cap objectives have simultaneously lower active weights and higher SMB loadings. As a result, when funds are assigned into active weight portfolios unconditionally, the bottom decile has disproportionately more funds with small-cap objectives and hence a high SMB loading. Assigning funds into active weight groups without controlling for fund style thus provides another way to mitigate differences in exposure of the high- and low-active weight portfolios to small-cap stocks. Again, the positive relation between active weight and future returns remains robust.

Finally, we redefine active weight as the absolute difference between the equal weights and the actual weights held by a fund, summed across its holdings. This redefined measure can also plausibly identify skilled managers by capturing their propensity to underweight or overweight securities. Moreover, DeMiguel, Garlappi, and Uppal (2009) show the attractiveness of the 1/N benchmark for portfolio allocation policy. While an equal-weighted benchmark may be attractive, it is important to emphasize that we focus on the value-weighted benchmarks because market indices, exchange-traded funds, and the benchmarks used by mutual funds are almost exclusively value weighted. As a result, a closet indexer is better off value weighting the portfolio, and choosing equal weights is unattractive because it increases the possibility of deviating from the benchmark, something a closet indexer wants to avoid. Also, the value-weighted benchmark naturally results in an active weight of zero for passive index funds, which does not happen for an equal-weighted benchmark.[19]

Trading costs are also higher for smaller stocks (e.g., Keim and Madhavan 1997), so forming an equal-weighted portfolio of a set of stocks is on average more costly than creating a value-weighted portfolio of these stocks. Maintaining equal weights is also costly. As some stocks in a portfolio go up and down in value, the weights move away from equal weights, requiring the manager to rebalance the portfolio frequently. By contrast, weights of stocks in an initially value-weighted portfolio change with market capitalizations of the stocks, and the portfolio does not require any significant rebalancing to maintain value weights (except for any minor rebalancing due to dividend payments, for example). This difference in trading costs of maintaining an equal- vs. value-weighted positions gives an "unskilled" manager another reason for preferring value weighting.

Consistent with the value-weighted benchmark being the more appropriate one, active weight computed relative to the equal-weighted benchmark has limited ability to predict fund performance, as shown in panel G, Table 5.

3.5 Ferson and Mo (2015) decomposition

In a recent paper, Ferson and Mo (2015) propose a new holdings-based performance measurement methodology that accounts not only for market timing but also for volatility timing. Their results suggest that, with only one exception (R-squared of Amihud and Goyenko 2013), the commonly considered predictors of fund performance relate insignificantly to future alphas when controlling for both sources of timing. Ferson and Mo (2015) thus set a very high bar for predicting fund performance.

We follow their methodology and use the generalized method of moments of Hansen (1982) to decompose the total alpha of active weight portfolios into three components: level timing, volatility timing, and selectivity. Decomposition is performed using the hypothetical returns computed based on a fund's stock holdings and hence allows us to evaluate robustness relative to the results obtained using reported fund returns in Table 4. We perform

[19] Figure 1 shows that active weight, as we define it, correctly characterizes index fund as funds with low levels of activeness. For comparison, active weight of the S&P 500 index relative to the equal-weighted benchmark is 0.44 at the end of 2013, a magnitude that would place the S&P 500 index in the top decile of actively managed equity funds. Using such a benchmark thus has the potential to misclassify closet indexers as active managers.

decomposition for each fund in a given decile portfolio and compute the TNA-weighted average of each of the three components for each decile portfolio. The results, summarized in Table 6, show that even after accounting for volatility timing, active weight relates positively to future fund performance. Funds with high active weights outperform funds with low measures by more than 2% per year, with three quarters of the performance difference attributable to superior selectivity skills of high-active weight funds. Differences in both the selectivity measures and the total alphas of high- and low-active weight funds are statistically significant.

To summarize, Tables 3 through 6 show that active weight has significant predictive power for fund performance. The difference in performance of the high- and low-active weight funds is economically large and statistically significant, both net and gross of expenses, both before and after adjusting for common factors, and based on both conditional and unconditional asset pricing models. The superior performance of high-active weight managers appears to be in large part attributable to their better selectivity skills.

4. Predicting Fund Performance with Active Weight: Evidence from Panel Regressions

In this section, we examine whether active weight can predict future fund performance in a multivariate setting. Unlike the univariate analysis presented in the previous section, the multivariate regressions allow us to control for multiple fund characteristics that may be related to fund performance and to ensure that the ability of active weight to predict performance is not due to such characteristics. The panel regressions we consider are

$$\begin{aligned} Performance_{i,t} = {} & \gamma_1 Active\ \ weight_{i,t-1} + \gamma_2 log\left(TNA_{i,t-1}\right) \\ & + \gamma_3 log\left(Number\ \ of\ \ stocks_{i,t-1}\right) \\ & + \gamma_4 Expense_{i,t-1} + \gamma_5 Turnover_{i,t-1} + \gamma_6 Fund\ \ age_{i,t-1} \\ & + \gamma_7 Past\ \ return_{i,t-1} \\ & + \Sigma_s \delta_s Style\ \ dummy_{i,s,t-1} + \eta_{i,t}, \end{aligned} \tag{5}$$

where i indexes funds, t indexes months, and styles are defined by CRSP and include micro-cap, mid-cap, small cap, growth and income, growth, and income. The independent variables that we choose are commonly considered in the literature and can be expected to relate to fund performance. We cluster standard errors by fund and time.

A manager can add value to the fund not only by generating a high alpha but also by other means, such as growing total assets under management. Hence, we consider several measures of performance in addition to alpha: characteristic selectivity, growth of assets under management, fund flows, and

Table 6

Future performance of portfolios sorted by active weight: Ferson-Mo decomposition

This table reports results of Ferson and Mo (2015) decomposition of fund alpha into market timing, volatility timing, and selectivity components for portfolios sorted by active weight. The Carhart (1997) four factors define the benchmark. The model in Ferson and Mo is estimated using the generalized method of moments (Hansen 1982) with a Newey-West (1987) covariance matrix with three lags. Decomposition is performed using the hypothetical returns computed based on a fund's stock holdings. The bottom row shows the *t*-statistics for the High-Low portfolio. The sample period is from 1980–2013

Active weight portfolio	Level timing	Volatility timing	Combined timing	Selectivity	Total alpha
Low	−0.26	−0.80	−1.06	0.06	−1.00
Decile 2	−0.82	−0.60	−1.42	0.70	−0.72
Decile 3	0.49	−0.77	−0.28	1.18	0.90
Decile 4	−0.50	−0.41	−0.90	0.45	−0.45
Decile 5	−0.24	−0.70	−0.94	0.83	−0.11
Decile 6	0.11	−0.74	−0.62	0.48	−0.14
Decile 7	−0.09	−0.62	−0.71	0.77	0.06
Decile 8	−0.66	−0.44	−1.10	1.43	0.33
Decile 9	−0.23	−0.72	−0.95	1.38	0.43
High	0.01	−0.59	−0.59	1.65	1.06
High-low	0.27	0.21	0.47	1.59	2.06
	[0.46]	[0.48]	[0.73]	[2.23]	[2.06]

the value-added variable proposed by Berk and van Binsbergen (forthcoming). If active weight captures managerial abilities, then it should predict all these measures. Our hypothesis is that $\gamma_1 > 0$ for each measure of fund performance.

The first measure of fund performance we consider is the four-factor alpha. Following Amihud and Goyenko (2013), we calculate alpha as the difference between the fund's excess return in month t and the fund's predicted return, calculated by multiplying the factor realizations in month t by the loadings from Carhart (1997) four-factor model regressions on monthly data covering $t-24$ to $t-1$.

Specification (1) of Table 7 shows that active weight significantly predicts fund alpha (*t*-statistic of 2.76). To evaluate the economic significance of the coefficient, consider two funds that are identical, except that one fund has an active weight of 0.29 (10th percentile, see Table 1) and the other fund has an active weight of 0.56 (90th percentile). The coefficient $\gamma_1 = 4.201$ suggests that the difference in alphas of the two funds is around 1.13% per year.

The results summarized in Tables 3 and 6 suggest that managers with higher active weights make better stock selection decisions. Specification (2) of Table 7 confirms this result in a multivariate setting: active weight relates positively to future characteristic selectivity. The results discussed in the previous section suggest that selectivity appears to account for between one-half (Table 3) and three-fourths (Table 6) of total fund alpha. The results of Table 7 are consistent with this finding. The slope coefficient on active weight in the regression predicting selectivity is one-half of the corresponding coefficient in the regression predicting fund alpha.

Table 7

Effect of active weight on measures of future fund performance

This table reports the results of panel regressions of measures of fund performance in month t on variables measured at the end of month $t-1$. Four-factor alpha is the difference between the fund's excess return in month t and its predicted return, calculated by multiplying the factor realizations in month t by the loadings from Carhart's (1997) four-factor model regressions using monthly returns covering $t-24$ to $t-1$. Characteristic selectivity is measured following Daniel et al. (1997). Asset growth is the growth in a fund's total net assets between months $t-1$ and t. Fund flows are calculated for month t. Value added is the product of the four-factor alpha in month t and fund size at the end of month $t-1$. Fund returns are net of expenses. Independent variables calculated using fund holdings are measured based on the most recently (prior to month t but after month $t-12$) disclosed fund holdings. Alphas, characteristic selectivity, asset growth, and fund flows are in percent per year. The active weight of fund i in month t is defined as $\frac{1}{2}\sum_j |w_{it}^j - w_{it}^{jm}|$, where w_{it}^j is the equity portfolio weight of stock j held by fund i and w_{it}^{jm} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio. Reported are coefficients, t-statistics based on standard errors clustered by fund and month, and the adjusted R^2 values. The sample period is from 1980–2013

	Regressions using as dependent variable:				
Independent variable	Four-factor alpha (1)	Characteristic selectivity (2)	Asset growth (3)	Fund flows (4)	Value added (5)
Active weight	4.201	2.086	11.656	7.079	4.453
	[2.76]	[2.53]	[3.12]	[2.74]	[2.65]
Log total net assets, million	−0.226	−0.041	−1.813	−1.022	−0.994
	[−1.54]	[−0.47]	[−4.88]	[−3.18]	[−2.29]
Log number of stocks	0.340	0.139	2.836	2.007	0.284
	[1.56]	[0.62]	[4.20]	[4.04]	[1.15]
Expense ratio	−1.383	0.111	3.305	2.407	−0.591
	[−3.78]	[0.42]	[1.58]	[1.50]	[−2.82]
Turnover ratio	0.061	0.180	−1.133	−2.408	−0.192
	[0.26]	[1.25]	[−1.46]	[−3.26]	[−1.49]
Fund age	0.001	−0.003	−0.021	−0.019	−0.002
	[0.49]	[−1.52]	[−2.71]	[−3.60]	[−0.84]
Past 12-month fund return	0.125	0.098	2.125	1.758	0.040
	[4.14]	[3.93]	[8.77]	[8.36]	[1.93]
Adjusted R^2, percent	9.115	8.816	14.114	12.787	8.426

A manager's compensation in large part depends on assets under management. Total assets are affected by the returns generated by the fund and flows into and out of the fund. It is natural to expect that managerial abilities relate positively to asset growth: a skilled manager should generate higher returns and attract higher inflows of new money than an unskilled manager. Hence, active weight, as a measure of managerial abilities, should relate positively to future growth in fund assets and to future fund flows. Specifications (3) and (4) of Table 7 show that this is indeed the case. The coefficient on active weight is statistically significant and economically important in both regressions. The difference in the rate of asset growth of a fund in the 90th percentile of active weight, and the one in the 10th percentile is almost 3.15% per year, while the difference in the future flows of the two funds is 1.91% annually.

Berk and van Binsbergen (forthcoming) suggest using a dollar-value measure to capture fund performance. They posit that skilled managers should be able to extract a higher dollar amount from the financial markets and suggest that the product of lagged assets under management and fund alpha captures this "value-added" amount. Following their logic, we define Value Added in month t as the product of fund assets at the end of month $t-1$ and fund alpha in month t. Specification (5) of Table 7 shows that active weight significantly relates to future value added.

Overall, the results of Table 7 provide strong evidence that active weight positively and significantly predicts future fund performance. This holds true for each of the performance proxies we consider. We now evaluate the robustness of this result in controlling for other measures of managerial activeness proposed in the literature.

5. Comparison with Other Predictors of Fund Performance

During recent years, several proxies for managerial activeness have been linked to future fund performance. In this section, we show that active weight is distinct from the four widely considered measures proposed in the prior literature: industry concentration index of Kacperczyk, Sialm, and Zheng (2005), return gap of Kacperczyk, Sialm, and Zheng (2008), active share of Cremers and Petajisto (2009), and R-squared of Amihud and Goyenko (2013). First, we consider portfolios sorted by the residual from the cross-sectional regressions of active weight on each of the other proxies. This residual captures the component of active weight that is orthogonal to other measures and allows us to study whether our findings are driven by information contained in active weight or by information captured in other proxies. Second, we ask how including each performance measure as an additional control in Equation (5) affects the ability of active weight to predict fund performance.[20] We also study predictability of long-term performance and find that our measure is uniquely successful at predicting fund returns over a variety of horizons.

5.1 Portfolio sorts

The ability of active weight to predict performance can plausibly arise because it contains the same information captured in other measures already known to forecast fund performance. Table 1 provides the first evidence that this is unlikely: it shows that although the average cross-sectional correlation of active weight with other measures is positive, it is low. To investigate this hypothesis further, we form portfolios using the component of active weight that is orthogonal to each of the other proxies of skill instead of using active weight directly. Specifically, at the end of each month t, we run univariate cross-sectional regressions of active weight on alternative proxies of skill and assign funds into deciles on the basis of the residual from this regression. As before, we then evaluate returns of the resulting portfolios

[20] We compare our measure with other measures individually because the correlation among the measures is high, and including them simultaneously results in multicollinearity. Nevertheless, in untabulated results, we have confirmed that including the measures simultaneously yields qualitatively similar findings.

in month $t+1$. The construction of the portfolios is identical to the method used in Table 4, except that we use orthogonal component of active weight instead of actual active weight.

Table 8 summarizes the results of this analysis, where the decile portfolios are constructed using the component of active weight that is orthogonal to industry concentration, return gap, active share, or R-square. For brevity, we report the factor-adjusted returns of the high-low difference portfolios only. The results clearly show that the component of active weight orthogonal to any of the four widely used alternative proxies of skill robustly predicts future performance. This finding is robust to using net or gross returns and considering unconditional and conditional asset pricing models.

5.2 Panel regressions

In the next set of tests aimed at distinguishing active weight from other measures, we add each of the performance measures as controls to Equation (5). Tables IA10 through IA13 of the Internet Appendix show that active weight retains its significance in all regressions and for all measures of fund performance, even after controlling for industry concentration, return gap, active share, and R-squared. The magnitudes of the coefficients on active weight are very similar to those reported in Table 7. Active weight thus displays a significant ability to predict mutual fund performance, in addition to predicting abilities of the other proxies.

5.3 Predictability of long-horizon fund performance

Most studies of the predictability of fund performance focus on predictability only at short horizons. For example, Kacperczyk, Sialm, and Zheng (2005) evaluate predictability at a three-month horizon. Kacperczyk, Sialm, and Zheng (2008) show that return gap predicts one-month performance three months after the time of the return gap calculation. Cremers and Petajisto (2009) include a fund in an investment portfolio if it reports holdings within the last twelve months. Since most funds report quarterly, their performance forecasting horizon ranges primarily between one and three months. Amihud and Goyenko (2013) focus their analysis on one-month-ahead predictability, and in a robustness test they study predictability at a six-month horizon.

The results documented thus far for active weight have followed the literature and focused on short-horizon predictability. If active weight captures managerial skill, and skill itself is persistent, we should expect active weight to persist over time. We therefore should expect active weight to predict performance at long horizons.

We show in Figure 2 that active weight is highly persistent. We now examine the ability of active weight to predict long-horizon performance. Figure 3 shows that the difference in performance of funds with distinct levels of active weight persists for as long as five years. Table 9 documents

Table 8

Future alphas and loadings of portfolios sorted by active weight: Orthogonalization to other proxies

This table reports portfolio alphas, in percent per year, from the Carhart (1997) unconditional four-factor model and the Ferson and Schadt (1996) conditional model. The factor-adjusted returns are calculated before and after subtracting expenses (Gross and Net returns). The returns after expenses are the reported returns realized by fund investors. The last four columns summarize the factor loadings from unconditional Carhart (1997) four-factor model regressions using net-of-expenses returns. Funds are assigned into deciles at the end of every month t on the basis of their most recently available residual active weight, and portfolio returns in month $t+1$ are used in performance regressions. The residual active weight is calculated as the residual from the month t cross-sectional regression of the active weight on industry concentration ratio, return gap, active share, or R-squared. The active weight of fund i in month t is defined as $\frac{1}{2}\sum_j |w_{it}^j - w_{it}^{jm}|$, where w_{it}^j is the equity portfolio weight of stock j held by fund i and w_{it}^{jm} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio. To be included in a portfolio at the end of month t, a fund must report holdings within the previous twelve months. The table reports the statistics for the portfolio that is long the high active weight decile and short the low active weight decile. The sample period is from 1980–2013

Active weight portfolio	Carhart alphas		Ferson-Schadt alphas		Unconditional loadings			
	Gross	Net	Gross	Net	MKT	HML	SMB	UMD
Panel A: Sorts by component of active weight orthogonal to industry concentration								
High-low	2.58	2.45	3.05	2.91	−0.07	0.09	0.15	−0.04
t-statistic	[3.14]	[2.98]	[3.85]	[3.67]	[−4.14]	[3.78]	[6.50]	[−2.67]
Panel B: Sorts by component of active weight orthogonal to return gap								
High-low	2.56	2.43	3.10	2.96	−0.05	0.05	0.19	−0.03
t-statistic	[3.00]	[2.84]	[3.74]	[3.57]	[−2.77]	[1.81]	[7.80]	[−1.99]
Panel C: Sorts by component of active weight orthogonal to active share								
High-low	3.21	3.18	3.53	3.50	−0.06	0.06	−0.04	−0.04
t-statistic	[3.21]	[3.17]	[3.49]	[3.46]	[−2.81]	[2.21]	[−1.46]	[−2.19]
Panel D: Sorts by component of active weight orthogonal to R-square								
High-low	2.62	2.52	3.08	2.97	−0.04	0.06	0.16	−0.04
t-statistic	[3.03]	[2.91]	[3.78]	[3.65]	[−2.17]	[2.30]	[6.55]	[−2.37]

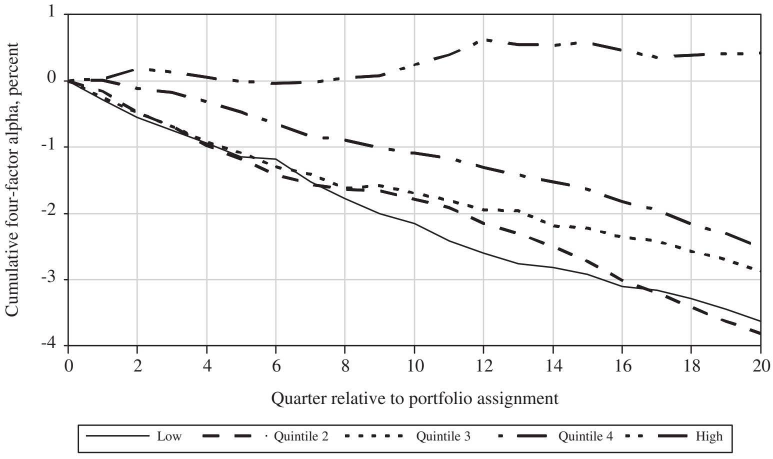

Figure 3

Long-term performance of portfolios sorted by active weight

This figure plots the cumulative Carhart (1997) four-factor alphas of portfolios formed by assigning funds into quintiles on the basis of active weight. Portfolio performance is shown five years following portfolio assignment date. The active weight of fund i at time t is defined as $\frac{1}{2}\sum_j |w_{it}^j - w_{it}^{jm}|$, where w_{it}^j is the equity portfolio weight of stock j held by fund i and w_{it}^{jm} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio. Net-of-expenses returns are used. The sample period is from 1980–2013.

Table 9

Long-term performance of portfolios sorted on measures of managerial activeness

This table reports the differences in Carhart (1997) four-factor alphas of portfolio of funds with high and low measures of managerial activeness. At the end of every calendar quarter, funds are sorted into either deciles, quintiles, or halves (panels A through C, respectively) on the basis of their most recently available measures of managerial activeness shown in the first column. The resultant total net assets-weighted portfolios are held without rebalancing for the horizon shown. The difference in average returns of the high and low portfolios is regressed on the Carhart four factors, and the resultant alphas (in percent per year) and the corresponding t-statistics are reported in the table. The active weight of fund i in month t is defined as $\frac{1}{2}\sum_j |w_{it}^j - w_{it}^{jm}|$, where w_{it}^j is the equity portfolio weight of stock j held by fund i and w_{it}^{jm} is the weight that the stock would have been assigned had the manager value weighted the equity portfolio. Industry concentration index is defined following Kacperczyk, Sialm, and Zheng (2005) as the sum of squared differences between the fund's holdings weights in ten industries, defined by Kacperczyk, Sialm, and Zheng (2005), and the weights of these industries in the market portfolio. Return gap is calculated following Kacperczyk, Sialm, and Zheng (2008) as the difference between a fund's monthly returns and returns on its most recently reported holdings, averaged over the most recent twelve months. Active share is from Antti Petajisto's Web site, computed as in Cremers and Petajisto (2009). R-squared is calculated following Amihud and Goyenko (2013) as R-squared from Carhart (1997) four-factor regressions using monthly returns covering the most recent twenty-four months. The sample period is from 1980–2013, except for active share, where data unavailability limits the sample from 1980–2009

	Holding horizon											
Activeness measure	6 months		1 year		2 years		3 years		4 years		5 years	
Panel A: Difference in four factor alphas of high and low decile portfolios												
Active weight	1.61	[1.99]	1.63	[2.12]	1.33	[1.95]	1.31	[1.88]	1.26	[2.17]	1.21	[2.12]
Industry concentration	−0.30	[−0.39]	−0.52	[−0.72]	−0.36	[−0.55]	−0.17	[−0.27]	0.05	[0.08]	0.21	[0.37]
Return gap	0.58	[1.42]	0.61	[1.04]	0.32	[0.71]	0.43	[1.10]	0.45	[1.18]	0.31	[0.82]
Active share	−0.08	[−0.08]	0.46	[0.47]	−0.08	[−0.08]	0.50	[0.51]	1.05	[1.13]	1.06	[1.20]
R-squared	−0.51	[−1.25]	−0.46	[−0.59]	−0.89	[−1.39]	−0.76	[−1.34]	−0.72	[−1.34]	−0.62	[−1.19]
Panel B: Difference in four factor alphas of high and low quintile portfolios												
Active weight	1.31	[2.29]	1.03	[2.11]	0.98	[1.91]	0.92	[1.98]	1.01	[2.27]	1.01	[2.30]
Industry concentration	−0.15	[−0.24]	−0.24	[−0.41]	0.03	[0.06]	0.19	[0.36]	0.39	[0.80]	0.40	[0.86]
Return gap	0.43	[0.80]	0.43	[0.94]	0.36	[0.97]	0.59	[1.93]	0.66	[2.30]	0.51	[1.87]
Active share	0.08	[0.08]	0.60	[0.66]	0.34	[0.37]	0.81	[0.92]	0.98	[1.20]	0.95	[1.24]
R-squared	−0.10	[−0.15]	−0.16	[−0.27]	−0.35	[−0.73]	−0.42	[−0.98]	−0.42	[−1.01]	−0.37	[−0.90]
Panel C: Difference in four factor alphas of high and low half portfolios												
Active weight	0.96	[2.95]	0.80	[2.65]	0.61	[2.17]	0.67	[2.50]	0.60	[2.35]	0.56	[2.18]
Industry concentration	−0.11	[−0.29]	−0.11	[−0.31]	−0.05	[−0.17]	0.09	[0.31]	0.19	[0.69]	0.21	[0.79]
Return gap	0.17	[0.52]	0.13	[0.47]	0.24	[1.05]	0.38	[2.00]	0.36	[2.16]	0.25	[1.63]
Active share	0.12	[0.22]	0.39	[0.78]	0.10	[0.21]	0.30	[0.63]	0.40	[0.92]	0.42	[1.03]
R-squared	−0.12	[−0.31]	−0.13	[−0.39]	−0.18	[−0.66]	−0.20	[−0.83]	−0.18	[−0.78]	−0.19	[−0.83]

this result more robustly. At the end of every calendar quarter, we sort funds into deciles, quintiles, or halves on the basis of their most recently available active weight. The resultant portfolios are held without rebalancing for horizons from six months to five years. We then regress the difference in average returns of the high- and low-active weight portfolios on the Carhart four-factors. Alphas from these regressions are large and statistically significant at every horizon. This holds true regardless of whether we assign funds into deciles, quintiles, or halves.

For comparison, Table 9 also summarizes the ability of other measures of managerial activeness to predict fund performance at long horizons. While the results of Tables IA10 through IA13 of the Internet Appendix are consistent with the ability of these measures to predict performance at short horizons, other managerial activeness proxies generally do not do as well at long horizons. Active weight excels both at different horizons and in application to different portfolio formation methodologies.

6. Conclusion

We offer a new and empirically convenient way to measure active portfolio management and predict mutual fund performance using only the fund's holdings and their market capitalizations. Our measure, which we term active weight, is the absolute difference between the value weights and the actual weights held by a fund, summed across its holdings. We show that active weight captures a new dimension of active management and is distinct from previously proposed measures.

Funds in the high-active weight portfolio outperform the low-active weight funds by 2.63% per year in the future. This result is robust to adjusting for exposure to common factors, using gross and net returns, and controlling for volatility timing as suggested by Ferson and Mo (2015). Confirming that active weight captures managerial abilities, we show that it predicts fund flows, growth in fund assets, and the Berk and van Binsbergen (forthcoming) proxy for value added. Our results are robust after controlling for other measures of active management, fund characteristics, past performance, and style.

Appendix

In this Appendix, we describe the details of the bootstrap exercise used to compute *p*-values reported in Table 3. For each fund and each stock, we model the quarterly weights with a first-order autoregressive process. We keep the intercept and slope as parameters and retain the residuals. We require at least five quarters of observations for estimating the parameters. For stocks with fewer observations, we use the intercept and slope estimated using the panel of fund-level observations, that is, in this case we estimate the first-order autoregressive process parameters by pooling all stocks in a fund's portfolio. Most mutual funds disclose their holdings quarterly throughout our sample. For funds that disclose semiannually, we infer their quarterly holdings by linearly interpolating the split-adjusted number of shares.

For the first time a fund appears in our sample, we use the actual stock positions it disclosed at that time and randomly assign to them actual weights of that fund. For subsequent periods, we recursively build up these randomly chosen initial weights by summing the intercept parameter, the slope parameter multiplied by the stock's lagged weight, and a randomly assigned rescaled residual. We rescale residuals for every fund and every quarter so that weights sum to one. When a stock is dropped from the portfolio, we set its weight to zero. When a new stock is added to the portfolio in quarter t, we set its weight to a randomly chosen value from the set of weights of all actual stock positions a fund disclosed at time t. We repeat this process for every fund in our sample.

We then compute active weights of the resulting "funds" and evaluate their future performance. The gross returns of each fund for the bootstrap exercise are computed using the actual returns of the stocks and the random weights assigned to each stock. We repeat the exercise 10,000 times.

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