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WHAT DRIVES ACTIVE SHARE? ACTIVE STOCK SELECTION OR ACTIVE STOCK WEIGHTS*

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Active Share is a popular measure of active management. However, it is not clear what drives Active Share. To improve our understanding, we decompose Active Share into Active Stock Selection (ASE) and Active Stock Weights (ASW). ASE captures portfolio weights in stocks outside the portfolio benchmark and correlates positively (88%) with Active Share. ASW captures portfolio weight deviations from market capitalization weights and correlates negatively (−55%). Furthermore, we find some evidence that ASE positively predicts performance, while ASW negatively predicts performance. Our results suggest that the benefits of Active Share stem from the selection decision rather than from the weighting decision.

1 Introduction

Active Share is gaining popularity among professional investors since its introduction by Cremers and Petajisto (2009). A recent survey by the Office of the New York Attorney General (NYOAG) finds that all of the 14 major U.S. mutual fund firms use Active Share extensively in managing their investment portfolios.[1] Despite its simplicity and popularity, we know little about what drives Active Share. In fact, the deviation from the benchmark portfolio can stem from several sources, including out-of-benchmark stock selections and drifts from market capitalization (market-cap) weights. The main objective of our paper is to examine these deviations and improve our understanding of Active Share.

To achieve this objective, we investigate the deviations of fund portfolios from their benchmarks by decomposing Active Share into two components: Active Stock Weights (ASW) and Active Stock Selection (ASE). ASW captures differences between funds' actual weights and weights based on market capitalization. ASW compares two

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portfolios with similar sets of stocks but different weights. Next, ASE captures differences between funds' value weights (i.e., should the fund have adopted market-cap weights for its holdings) and benchmark weights. This compares two portfolios with similar weighting schemes, i.e., market-cap weights, but with different set of stocks. Armed with ASW and ASE, we test how these components relate to Active Share and affect future fund performance.

Using a large panel of 3,495 actively managed U.S. equity funds over the period from 1991 to 2017, we find that ASW and ASE display stark differences in their relationship with Active Share. While ASW relates negatively to Active Share (correlation equal to −55%), ASE displays a positive and stronger relationship with Active Share (correlation equal to 88%). Furthermore, Active Share does not split equally into ASW and ASE. In fact, ASE accounts for about 85% of the Active Share value. Therefore, in gauging a fund's deviation from to its benchmark, the selection of stocks is more important than the stock-weighting decision. These results confirm that Active Share is primarily a stock selectivity measure.

We also examine whether ASW and ASE predict future fund performance. Using the seven-factor model of Cremers (2017), we find that ASW and ASE predict risk-adjusted fund performance, both at short and long horizons. However, ASW and ASE have opposite impact on future performance. While funds with high ASE exhibit significantly higher risk-adjusted returns, funds with high ASW exhibit significantly lower risk-adjusted returns. In contrast, using the Carhart's and Fama–French (1995) models, we find weaker evidence of performance predictability compared to the seven-factor model of Cremers (2017).

We also look at determinants of ASW and ASE individually. We begin the study by examining existing measures of activeness as important determinants. We find that ASW and ASE display substantial differences in their relationships with existing activeness measures. For example, we find ASW correlates positively with Active Weight. This is not surprising, given that both these measures capture deviations in the holding weights relative to the market-cap weights. Similarly, we find ASE correlates positively with other well-known stock selectivity measures such as the Industry Concentration Index (ICI), one minus *R*-squared, and the Return Gap, consistent with the idea that these measures capture deviations from the benchmark holdings.

Lastly, we investigate how our Active Share-derived measures relate to factor-timing ability. Using three different measures of factor timing, namely the Characteristics Timing (CT) proposed by Daniel *et al.* (1997), a timing measure of Elton *et al.* (2011), and the return-based timing skill measure of Angelidis *et al.* (2013), we find mixed evidence. Two out of the three timing measures relate negatively to Active Share and ASE and positively to ASW. Since Active Share and ASE relate negatively to some factor-timing measures but positively to risk-adjusted performance, this suggests that portfolio managers possess stock-picking skills but not factor-timing skills.

Our paper makes two contributions to the active management literature. First, it offers new insights into understanding Active Share and its relation to managerial skill. By breaking the Active Share down into Active Stock Selection and Active Stock Weights components, our paper links fund activeness and managerial skill. Consistent with the intuition of Cremers and Petajisto (2009) and Petajisto (2013), our analysis clearly identifies stock selection as the driver of outperformance for high-Active Share funds. Second, our paper bridges an important gap between two popular activeness measures—Active Share

(Cremers and Petajisto, 2009) and Active Weight (Doshi *et al.*, 2015)—missing from the extant literature. Both measures relate to activeness but they capture *different* dimensions of managerial skill.

It is important to note that the performance predictability of Active Share is not the focus of our paper.[2] Our aim is to (i) investigate the sources of Active Share by decomposing it into Active Stock Weights and Active Stock Selection; and (ii) examine how each of these components relates to future performance. To date, only Fulkerson and Riley (2015) have explored this research avenue. They deconstruct Active Share into four separate quantities—include, exclude, overweight, and underweight—and find that the inclusion component explains about two-thirds of Active Share's outperformance.

Our Active Share-derived measures have important practical implications. Our decomposition allows investors to accurately gauge managerial skill with respect to stock selectivity and stock allocation. This is particularly important for investors who prefer a particular investment strategy—stock selection or allocation—based on their investment goals. Another important implication relates to fund fees. Our decomposition helps investors examine whether high-Active Share funds that charge higher management fees add value. Using ASW and ASE, fee-conscious investors can clearly identify funds with high stock selection ability that add value and choose to pay more for these funds compared to funds with high-Active Stock Weights. Lastly, fund managers may increase out-of-benchmark stock holdings to achieve high Active Share. This can potentially lead to unwanted risk exposure as well as to inconsistency with the fund's mandate. Investors can use our Active Share-derived measures for monitoring the underlying portfolio risk as well as mandate adherence. Overall, understanding the source of Active Share helps investors make informed investment decisions with respect to managerial skill, costs, and risks.

2 Decomposing Active Share: Active Shock Selection and Active Stock Weights

This section describes in detail our variable construction approach. We decompose Active Share in the following way:

$$
\begin{aligned}
\text{Active Share}
&= \frac{1}{2}\sum_{i=1}^{\mathrm{N}} |\omega_{i,t}^{\text{fund}} - \omega_{i,t}^{\text{index}}| \\
&= \frac{1}{2}\sum_{i=1}^{N} (\omega_{i,t}^{\text{fund}} - \omega_{i,t}^{\text{index}}) * \mathrm{I}_{\omega_{i,t}^{\text{fund}} > \omega_{i,t}^{\text{index}}} \\
&\quad - \frac{1}{2}\sum_{i=1}^{N} (\omega_{i,t}^{\text{fund}} - \omega_{i,t}^{\text{index}}) * \mathrm{I}_{\omega_{i,t}}^{\text{fund}} \le \omega_{i,t}^{\text{index}} \\
&= \underbrace{\sum_{i=1}^{N} (\omega_{i,t}^{\text{fund}} - \omega_{i,t}^{M}) * I_{\omega_{i,t}^{\text{fund}} > \omega_{i,t}^{\text{index}}}}_{\text{Active Stock Weights}} \\
&\quad + \underbrace{\sum_{i=1}^{N} (\omega_{i,t}^{M} - \omega_{i,t}^{\text{index}}) * I_{\omega_{i,t}^{\text{fund}} > \omega_{i,t}^{\text{index}}}}_{\text{Active Stock Selection}} \\
&= \sum_{i=1}^{N} (\omega_{i,t}^{\text{fund}} - \omega_{i,t}^{\text{index}}) * I_{\omega_{i,t}}^{\text{fund}} > \omega_{i,t}^{\text{index}} \\
&= \underbrace{- \sum_{i=1}^{N} (\omega_{i,t}^{\text{fund}} - \omega_{i,t}^{\text{index}}) * I_{\omega_{i,t}}^{\text{fund}} \le \omega_{i,t}^{\text{index}}}_{\text{Active Stock Weights}} \\
&\quad \underbrace{- \sum_{i=1}^{N} (\omega_{i,t}^{M} - \omega_{i,t}^{\text{index}}) * I_{\omega_{i,t}}^{\text{fund}} \le \omega_{i,t}^{\text{index}}}_{\text{Active Stock Selection}}
\end{aligned}
\tag{1}
$$

where $\omega_{i,t}^{\text{fund}}$ and $\omega_{i,t}^{\text{index}}$ are the actual weights of stock i at quarter t in the fund and benchmark index portfolio, respectively. $\omega_{i,t}^{M}$ is the market-cap-based weight of stock i at quarter t, following Doshi *et al.* (2015). N is the stock universe (i.e., the universe of all stocks available) and I is an indicator variable. To move from line two to line three in Equation (1), we rely on the simple logic that, if the sum of weights in the fund and in the benchmark index portfolios is equal to 100%, then the sum of the overweights of the fund with respect to the benchmark index is equal to the sum of the underweights.[3] Thus, we can either focus on the overweight or underweight side, as these deviations are perfectly symmetric. Doing this, we get rid of the absolute value and decompose the Active Share into Active Stock Weights (ASW) and Active Stock Selection (ASE) measures. The same logic allows us to move from line three to line five.

The first component in Equation (1), which we name Active Stock Weights (ASW), captures the differences between the fund's actual weights and the market-cap (or value) weights. Intuitively, ASW compares two portfolios with similar sets of stocks but different distributions of weights. The remaining part of Equation (1), which we name Active Stock Selection (ASE), captures differences between the fund's value weights (i.e., if the fund had adopted market-cap weights) and the benchmark weights. Hence, this second comparison is between two portfolios with similar weighting approaches but different selections of stocks.

Equation (1) offers a number of straightforward interpretations. A fund that mimics the composition of the benchmark index should have Active Share and its two components equal to 0. A fund that invests in a different set of stocks but nonetheless with a value-weighted allocation strategy should have ASW equal to 0 and ASE different from 0. Appendixes 2 and 3 illustrate numerical examples to highlight the decomposition mechanism of Active Share into ASW and ASE.

In theory, both ASW and ASE could be either positive or negative, yet their sum lies between 0 and 1. However, empirically we find that the overwhelming majority of observations are positive (97% of the observations for ASW and 100% of the observations for ASE) and both quantities are significantly different from zero. Thus, both components are likely to reflect activeness of the portfolio.

Furthermore, it is important to note that, in Equation (1), the two components do not systematically capture deviations as they do not contain absolute values, but they capture the portion each component contributes to Active Share. Indeed, computing the sum of the absolute values of the two quantities would yield a measure higher than Active Share.[4] This is an important distinction and is in line with the objective of this paper. We aim to break Active Share into two components and understand how each drives Active Share.

Equation (1) decomposes Active Share into ASW and ASE. At the stock level, every stock can contribute positively or negatively to ASW and ASE. The sum of all stocks in the fund portfolio determines the contribution of ASW and ASE to the Active Share of that portfolio. Hence, negative deviations may actually decrease Active Share through reducing either ASW or ASE. However, the sum of ASW and ASE must be non-negative and equal to Active Share, by definition.

In order to achieve a high and positive contribution of the first component, a fund can either overweight, with respect to the market capitalization, the stocks whose fund weights are larger than those of the benchmark index, or underweight with respect to the market capitalization the stocks whose fund's weights are smaller than those of the benchmark index. If we reverse these scenarios, we can negatively impact the Active Share measure.

Similarly, for the second component, the market-cap portfolio should have larger weights (relative to the benchmark index) in the stocks whose fund weights are larger than those of the benchmark index, and smaller weights (relative to the benchmark index) in the stocks whose fund weights are smaller than those of the benchmark index. In situations where the market-cap portfolio has smaller weights in the stocks whose fund weights are larger than those of the benchmark index or larger weights in the stocks whose fund weights are smaller than those of the benchmark index, ASE will likely reduce Active Share.

3 Data

3.1 Sample selection

The sample consists of U.S. domestic equity funds and covers the period from January 1991 to December 2017. We select U.S. equity mutual funds based on four style classification variables (Strategic Insight Objective Codes, Lipper Classifications, Wiescat Codes, and Wiesenberger Codes) and exclude index funds, international funds, balanced funds and sector funds. We retrieve monthly returns, total net assets (TNA), annual expense ratios, and turnover ratios from the Center for Research in Security Prices (CRSP) mutual fund database. We obtain fund holdings from the Thomson Financial CDA/Spectrum database. We then merge the two datasets using the MFLINK file and we aggregate share classes at the portfolio level. The final sample comprises 3,495 funds. In selecting our sample, we eliminate funds that are smaller than $15 million in size, hold fewer than 10 stocks in their portfolio, or invest less than 80% of their total assets in equity.

We collect holdings and returns data for the following 17 benchmarks: 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, and the value and growth components of the four Russell indices (i.e., eight Russell-style indexes). The weights of the S&P indexes are from Compustat and CRSP by matching historical index constituents with stock market capitalizations. Weights for the Russell indexes are directly from the Russell Company but are available over the period 1996–2014. Monthly returns on all these indexes are from Morningstar Direct.[5]

Monthly stock returns and prices are from the CRSP stock database and merged with fund holdings using CUSIP as a common identifier. Fama–French (1993) and momentum factors are from Kenneth French's website. The seven factors of the Cremers (2017) model are as follows: S5RF is the excess return of the S&P 500 index, RMS5 is the Russell Midcap minus S&P 500, R2RM is the Russell 2000 minus Russell Midcap, S5VS5G is the S&P 500 Value minus S&P 500 Growth, RMVRMG is the Russell Midcap Value minus Russell Midcap Growth, R2VR2G is the Russell 2000 Value minus Russell 2000 Growth and the Momentum factor (MOM). Monthly returns of all these indexes are extracted from Morningstar Direct. Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) characteristic-based benchmarks are from Russ Wermers' website.

Using these data, we compute Active Share for all funds at a quarterly frequency. To validate our computation steps, we examine the correlation between our Active Share (self-constructed) measure and the one reported by Cremers and Petajisto (2009) on Anti Petajisto's website. We find the Pearson correlation coefficient of 94.93% with an insignificant difference in means between the two measures.

We choose benchmarks in the following way. Between 1991 and 2009, we rely on the data provided by Cremers and Petajisto (2009) to select the corresponding benchmark. However, we have no data on Russell indices between 1991 and 1995 or Wilshire indices over any of the period. Thus, those observations are missing, but they represent only 10.48% of the total observations. From 2009 to 2017, we determine our own benchmark, i.e., the one that minimizes Active Share among a set of 17 indexes (S&P and Russell indexes). In doing so, we are able to compute the Active Share at a quarterly frequency up to December 2017.

Although our benchmark choices closely follow the Cremers and Petajisto (2009) methodology, it is not immune from caveats. Therefore, we also consider alternative definition based on the fund's self-declared benchmark. The correlation between the Active Share based on the self-declared benchmark and that based on the Active Share minimization equals to 98.52%. Therefore,

Table 1 Descriptive statistics for Active Share, Active Stock Weights and Active Stock Selection and other activeness measures.

Panel A: Descriptive statistics

Variable	Mean	Median	Std.	Min.	Max.
Activeness measures					
Active share	79.8	82.1	13.1	36.3	98.8
Active Stock Weights (ASW)	12.7	9.45	12.4	−1.83	49.2
Active Stock Selection (ASE)	67.1	69.1	22.5	13.96	98.8
ICI	5.44	4.06	4.91	0.23	38.5
Active Weight	39.4	38.6	9.97	16.3	70.0
R-squared	90.9	92.4	6.09	60.4	99.0
Return gap	−0.45	−0.42	3.41	−17.4	14.6

Panel B: Correlation matrix of activeness measures

	AS	ASW	ASE	ICI	AW	*R*-squared	Return gap
AS	1.00						
ASW	−0.55**	1.00					
ASE	0.88**	−0.87**	1.00				
ICI	0.41**	−0.25**	0.37**	−1.00			
AW	0.14**	0.41**	−0.15**	0.12**	1.00		
R-squared	−0.44**	0.22**	−0.38**	−0.37**	−0.19**	1.00	
Return gap	0.01**	−0.02**	0.02**	0.01**	−0.04**	0.06**	1.00

Panel A displays descriptive statistics (mean, median, standard deviation, minimum, and maximum) for our set of activeness measures in percentage: Active Share (AS), Active Stock Weights (ASW), Active Stock Selection (ASE), Industry Concentration Index (ICI), Active Weight, the *R*-squared of Amihud and Goyenko (2013), and Return Gap. All the statistics are first computed cross-sectionally and then averaged across all months. Panel B reports the Pearson correlation coefficients for the activeness measures. All the correlations are computed cross-sectionally for each month and then averaged across all months. ** and * indicate significance at the 1% and 5% levels, respectively. All the variables are winsorized at 0.5% and 99.5%.

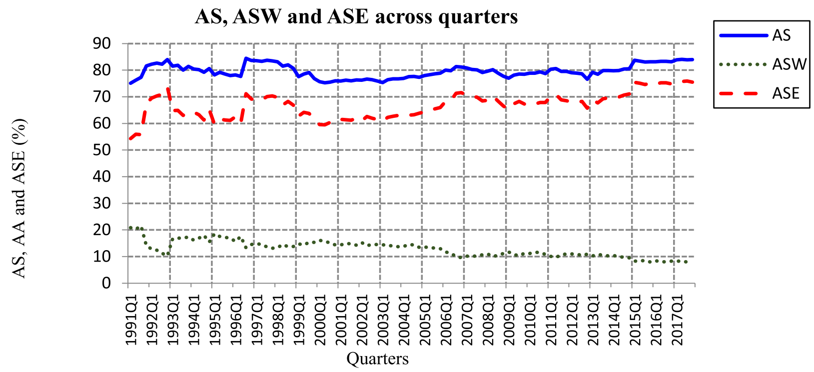
the choice of definition has little impact on results.

3.2 Other activeness measures

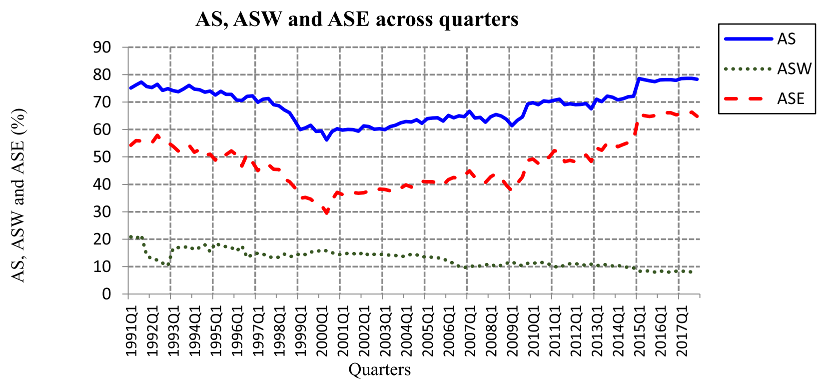
The mutual fund literature documents a strong relationship between activeness measures and future fund performance. To make sure our results are robust to using different activeness measures, we include four in our analyses: the Industry Concentration Index (ICI), Active Weight (AW), *R*-squared (*R*-sq), and Return Gap (RG).[9,10] Appendix 1 reports detailed definitions of these activeness measures.

3.3 Descriptive statistics and determinants of Active Stock Selection and Active Stock Weights

Panel A of Table 1 reports descriptive statistics for our measures of activeness, i.e., Active Stock Weights (ASW) and Active Stock Selection (ASE), as well as other measures of activeness: Active Share, ICI, Active Weight, *R*-square, and Return Gap. The table shows that Active Share splits unequally between ASW and ASE. The average Active Share is equal to 79.8%, the average ASW is equal to 12.7%, and the average ASE is equal to 67.1%. Hence, ASE accounts for



Panel A: All benchmarks



(b) Panel B: Funds with the S&P 500 as a benchmark

Figure 1 Average Active Share, Active Stock Weights, and Active Stock Selection across quarters.

This figure depicts, for each quarter, the cross-sectional mean of Active Share (AS), Active Stock Weights (ASW), and Active Stock Selection (ASE), in percentage, for the mutual funds in our sample during the 1991 Q1 to 2017 Q4. AS, ASW, and ASE are reported on the *y*-axis and quarters are reported on the *x*-axis. Panel A reports the results for the full sample and Panel B reports those for funds that have the S&P 500 as a benchmark.

about 85% of the Active Share value. Moreover, ASE displays higher cross-sectional dispersion (as measured by standard deviation) than Active Share and ASW.

Figure 1 depicts, for each quarter, the means of Active Share, ASW and ASE for mutual funds in our sample during the 1991 Q1to 2017 Q4 period. Panel A shows relatively small variation of Active Share across quarters. Panel B, which reports the results for funds that have the S&P 500 as a benchmark, depicts a comparable result, with, however, a marked decrease in Active Share and ASE around the year 2000.

Panel B of Table 1 reports the correlations between the three main measures of activeness. We find that Active Share negatively relates to ASW but positively and more strongly relates to ASE. The correlations of Active Share with respect to ASW and ASE are equal to −55% and 88%, respectively. This is in line with Cremers and Petajisto (2009), who emphasize the selectivity dimension of Active Share. Interestingly, we find that ASW and ASE are negatively correlated. This suggests that funds that deviate from the market-cap weights are likely to invest in stocks included in the benchmark index. Therefore, funds either tend to invest outside the benchmark index but with weights close to market-cap weights, or invest within the benchmark index stock universe but deviate from market-cap weights.

Table 2 Determinants of Active Share (AS), Active Stock Weights (ASW), and Active Stock Selection (ASE).

Independent variable	AS	AS	ASW	ASE
Activeness measures				
Active Stock Weights (ASW)	−0.298**			
	(−24.57)			
Active Stock Selection (ASE)		0.444**		
		(79.81)		
ICI	0.094**	0.008	−0.159**	0.300**
	(3.44)	(0.56)	(−5.18)	(5.40)
Active weight	0.532**	0.410**	0.412**	−0.003
	(29.62)	(35.08)	(23.50)	(−0.12)
R-squared	−0.212**	−0.073**	0.162**	−0.422**
	(−12.75)	(−7.44)	(8.24)	(−12.44)
Return Gap	0.040*	0.011	−0.041*	0.093**
	(2.31)	(1.06)	(−2.11)	(2.84)
Intercept	1.053**	0.489**	−0.346**	1.503**
	(39.33)	(27.72)	(−10.63)	(27.56)
N	60628	60628	60628	60628
adj. R-sq.	0.752	0.894	0.568	0.699
Fund characteristics	Yes	Yes	Yes	Yes

The table reports the results of the quarterly panel regression of Active Share (AS), Active Stock Weights (ASW), and Active Stock Selection (ASE) on activeness measures (as defined in Table 1) and fund characteristics. Regressions include time (i.e., quarter) and style dummies and standard deviations are clustered by fund for all columns. Coefficients are displayed in the first line and t-statistics are shown in parentheses in the second line. ** and * indicate significance at the 1% and 5% levels, respectively. For brevity, we do not report the coefficients of fund characteristics.

In addition, the correlation results confirm that the ASE component captures selectivity. ASE correlates positively with the other known selectivity measures: the ICI measure (37%) and one minus R-square (38%). On the other hand, ASW is linked to Active Weight (41%). The Return Gap displays negative and positive correlations with ASW and ASE, respectively. It is worth mentioning that the correlations of ASE with all fund activeness measures concur with those of Active Share (i.e., display the same sign), except for the correlations with Active Weight.

Table 2 reports the results of the determinants of Active Share, ASW and ASE after controlling for fund style and time effects. First, in line with the correlation analysis, ASE strongly and positively relates to Active Share, while ASW displays a negative regression coefficient. Second, ASE is significantly related to Active Share, ICI and R-squared, and therefore belongs to the family of selectivity measures. ASW is significantly and positively related to Active Weight.

4 Predicting Performance using Active Stock Weights and Active Stock Selection

4.1 *Simple sorts*

To examine how ASW and ASE impact future performance, we rank funds into quintiles each quarter based on their Active Share, ASW and ASE respectively and save the returns over the next three months. Then, we compute equally weighted portfolio returns of each quintile over the entire period and thereby obtain time series of monthly returns. Next, we compute the seven-factor model (Cremers, 2017) alphas and in each case save the factor loadings. Our primary motivation to choose the seven-factor model is to make sure our results are comparable to those of Cremers (2017).

Furthermore, we report the results using both gross and net returns. Net returns are investors' returns after all fees and transaction costs. Gross returns are managers' portfolio returns, i.e., returns before any management fees, commission

Table 3 Simple sort on Active Share (AS), Active Stock Weights (ASW), and Active Stock Selection (ASE).

	Simple sort on AS		Simple sort on ASW		Simple sort on ASE	
	Gross	Net	Gross	Net	Gross	Net
Low	−0.37	−1.40**	0.87*	−0.43	−0.32	−1.37**
2	−0.40	−1.51**	0.77	−0.47	−0.42	−1.55**
3	−0.07	−1.23**	−0.58	−1.73**	−0.34	−1.50**
4	0.24	−1.01**	−0.64*	−1.74**	0.58	−0.66
High	1.05*	−0.29	0.02	−1.10**	0.93*	−0.40
High–Low	1.43**	1.11*	−0.84*	−0.67	1.25**	0.97*
t-Statistic	(2.86)	(2.23)	(−2.07)	(−1.65)	(2.63)	(2.05)

The table reports the seven-factor alphas (annualized and in percentages), using net returns and gross of fees returns, for fund quintiles sorted by Active Share (AS), Active Stock Weights (ASW), and Active Stock Selection (ASE). Gross returns are based on a fund's stock holdings and with no fees or transaction costs deducted. Net returns are investors' returns after fees and transaction costs. Quintile 1 includes the funds with, respectively, the smallest AS, ASW, and ASE, and quintile 5 includes those with the largest. Each quarter, funds are assigned to one of five portfolios according to their AS, ASW, and ASE and then the fund's return over the next three months is saved. Next, we form the equally-weighted returns of these portfolios and run monthly regressions of excess returns on the seven factors (Cremers, 2017). The bottom two rows display the difference in alphas between the top and bottom quintiles and the t-statistic for this difference. ** and * indicate significance at the 1% and 5% levels, respectively.

or transaction costs. As Petajisto (2013, p. 83) pointed out, "*Gross returns help identify whether any categories of funds have skill in selecting portfolios that outperform their benchmarks, and net returns help determine whether any such skill survives the fees and transaction costs of those funds.*"

Table 3 reports the empirical results of our simple sort analysis. Confirming the Cremers and Petajisto (2009) results, we find that, using the seven-factor alphas, the difference between the top and bottom Active Share-sorted quintiles is positive, and statistically significant. The difference between the top and bottom quintiles is equal to 1.43% using gross returns and 1.11% using net returns. Thus, the relationship between Active Share and performance is positive.

When we sort funds on ASW, the seven-factor alphas show a negative and significant difference between the high and low quintiles using both gross and net returns. The differences between the top and bottom quintiles are equal to −0.84% and −0.67% using gross and net returns, respectively. Hence, high ASW is associated with underperformance.

The sort on ASE reveals the opposite results to those found using ASW. The difference in risk-adjusted performance as measured by the seven-factor alphas offers positive and significant differences between the top and bottom quintiles that are equal to 1.25% and 0.97% using gross and net returns, respectively. Hence, the relationship between ASE and fund performance is positive.

4.2 *Cross-sectional regressions*

To investigate the relationship between ASW, ASE, and fund performance, we use the same procedure as in Amihud and Goyenko (2013) and Doshi *et al.* (2015). Our monthly performance measure is the alpha based on the Cremer's seven-factor model. We obtain seven-factor loadings from a 36-month rolling window regression of fund excess returns on these seven factors. After that, we compute the next month's predicted returns by multiplying the factor loadings by the next month's factor returns. We then subtract predicted returns from the observed excess returns to get the seven-factor alphas. We use the following monthly Fama–Macbeth regression:

$$\begin{aligned}
\text{Performance}_{j,t+1} &= a_0 + a_1 \textit{Activeness Measure}_{j,t} \\
&\quad + a_2 \textit{ICI}_{j,t} + a_3 \textit{Active Weight}_{j,t} \\
&\quad + a_4 \textit{R-squared}_{j,t} + a_5 \textit{Return Gap}_{j,t} \\
&\quad + a_6 \textit{returns_12m}_{j,t} + a_7 \textit{volatility_12m}_{j,t} \\
&\quad + a_8 \textit{flows}_{j,t} + a_9 \ln(\textit{TNA}_{j,t}) \\
&\quad + a_{10} \ln(\textit{number of stocks}_{j,t}) \\
&\quad + a_{11} \textit{expense ratio}_{j,t} + a_{12} \textit{fund age}_{j,t} \\
&\quad + \sum_{s=1}^{7} b_s \textit{style dummy}_{j,s,t} + \varepsilon_{j,t} \qquad (2)
\end{aligned}$$

where *Activeness Measure* will successively be Active Share, Active Stock Weights (ASW) and Active Stock Selection (ASE). Performance is the alphas (annualized and as a percentage) of fund j in month $t + 1$. The other independent variables are defined in Appendix 1.

Table 4 reports the Fama–Macbeth regression results for Equation (2) and shows that Active Share displays positive and significant relationships with the next month's alpha. An increase of 10% (per quarter) in the fund's Active Share increases the risk-adjusted performance by 93 bps per year, which is economically significant. ASW displays a negative relationship with the seven-factor alphas. An increase of 10% (per quarter) in the fund's ASW decreases the risk-adjusted

Table 4 Cross-sectional regressions and subsample analysis.

Seven-factor alpha	Full sample		1991–1999	2000–2008	2009–2017
AS	9.395**	4.640*	11.263**	4.247*	2.282
	(3.85)	(2.57)	(3.15)	(2.19)	(1.64)
ASW	−4.211**	−2.872**	−5.169**	−1.489	−1.714
	(−3.28)	(−3.44)	(−2.98)	(−1.36)	(−1.70)
ASE	6.515**	2.239**	7.029**	2.956*	1.738*
	(4.29)	(2.90)	(3.81)	(2.42)	(2.18)
Fund characteristics	Yes	Yes	Yes	Yes	Yes
Activeness measures	No	Yes	No	No	No

The table reports the Fama–Macbeth regression results of the monthly risk-adjusted gross returns (i.e., annualized alpha and in percentages) regressed on the one-month-lagged fund activeness measures: Active Share (AS), Active Stock Weights (ASW), and Active Stock Selection (ASE) and fund characteristics. Monthly risk-adjusted returns are computed as the difference between the observed fund returns and predicted returns. The latter are computed using the estimates of the seven-factor model over the last 36 months. However, for brevity's sake, we report only the AS, ASW, and ASE coefficients. Coefficients are displayed in the first line and t-statistics between parentheses in the second line. ** and * indicate significance at the 1% and 5% levels, respectively.

performance by 42 bps per year, which is economically significant. ASE displays a positive relationship with the seven-factor alphas. An increase of 10% (per quarter) in the fund's ASE increases the risk-adjusted performance (as measured by the seven-factor alpha) by 65 bps per year, which is economically significant.

When we further control for other activeness measures suggested by the mutual fund literature (i.e., Industry Concentration Index (ICI), Active Weight, the R-squared of Amihud and Goyenko (2013) and Return Gap) the results remain very similar, as reported in column 2 of Table 4.

Furthermore, to conduct subsample analysis, we split the sample into three equal subperiods: 1991–1999, 2000–2008, and 2009–2017. The last three columns of Table 4 report these results. We find AS and ASE significantly predict cross-sectional fund alpha in at least two of the three subsamples. In fact, ASE positively predicts fund alpha across all subsamples, even though the economic magnitude diminishes slightly after 2009. This result is in line with Cremers (2017). Likewise, the relationship between ASW and fund alpha is negative in each of the three subsamples, albeit weaker over the period 2000–2008.

Taken together, these results show that ASE positively predicts performance while ASW negatively predicts performance. Hence, investing in stocks not included in the benchmark index seems to add value to a fund's performance while deviating from market-cap weights seems to be a value-destroying strategy. The sum of the two effects, as captured by Active Share, remains largely positive though.[14]

4.3 *Active share, active stock weights, active stock selection and long-term performance*

We investigate the long-term relationship between Active Share, ASW, ASE, and fund performance. For this purpose, we repeat the simple sort analysis of Table 3, but for longer horizons (six months to five years instead of three months). Table 5 reports the alphas of the differences between the top and bottom quintile portfolios for various horizons. Our results show that ASW continues

Table 5 Active Share (AS), Active Stock Weights (ASW), Active Stock Selection (ASE), and long-term performance.

	AS	ASW	ASE
Horizon	High–Low	High–Low	High–Low
Six months	1.31**	−0.95**	1.55**
	(2.70)	(−2.38)	(3.77)
One year	1.38**	−1.02**	1.22**
	(2.87)	(−2.65)	(2.64)
Three years	1.66**	−1.13**	1.53**
	(3.72)	(−3.02)	(3.48)
Five years	1.55**	−1.07**	1.50**
	(3.77)	(−3.02)	(3.60)

Table 5 reports the risk-adjusted alphas (annualized and in percentages) using gross returns and computed for a horizon h from six months to five years following the Active Share (AS), Active Stock Weights (ASW), and Active Stock Selection (ASE) computations. Each quarter, each fund is assigned to one of five quintiles according to its Active Share (AS), Active Stock Weights (ASW), or Active Stock Selection (ASE) respectively, and then we keep that fund for the next h months. Next, we regress the equally weighted excess returns of these portfolios over the seven factors of Cremers (2017). For each horizon, we report two rows: the difference between the largest (i.e., High) and smallest (i.e., Low) quintiles and between parentheses the t-statistic of the difference. ** and * indicate significance at the 1% and 5% levels, respectively.

to be negatively related to performance and ASE to be positively related to performance for horizons equal to or higher than six months and up to five years.

5 Predicting Timing Ability Using Active Stock Weights and Active Stock Selection

Although Active Share and its components are not directly linked to factor-timing ability, we investigate this relationship. In doing so, we rely on three measures of timing skill: (i) characteristic timing (CT) suggested by Daniel *et al.* (1997), (ii) a timing measure suggested by Elton *et al.* (2011), which we refer to as Timing_EGB, and (iii) Timing skill, which is a return-based measure suggested by Angelidis *et al.* (2013).

We use the regression model of Equation (2) in which timing skill is now the dependent variable (i.e., the performance measure). Panel 8 reports the regression results for Active Share, ASE and ASW and for our three different measures of timing (i.e., CT, timing_EGB, and timing skill). For brevity's sake, we report only the coefficient of interest, i.e., that of Active Share, ASE or ASW, respectively. The results offer mixed evidence as to whether more active funds, as measured by Active Share, display timing skills. CT is positively related to Active Share while both Timing_EGB and Timing skill display a negative relationship with it. Looking at the Active Share components, i.e., ASE and ASW, we find that ASE displays similar coefficient signs to Active Share, while ASW displays the opposite results.

Taken together, the results of this section do not show that Active Share or its components are unequivocally linked to factor timing. This further reinforces the notion that Active Share is mainly about the selection of stocks. The fact that Active Share is negatively linked to some factor timing measures may be interpreted, however, as

Table 6 Multivariate regressions: predicting timing ability with Active Share (AS), Active Stock Weights (ASW), and Active Stock Selection (ASE).

Dependent variable t+1	CT	Timing EGB	Timing skill
AS	3.889**	−1.819**	−1.263**
	(6.91)	(−4.04)	(−3.80)
ASW	−1.731**	1.807**	2.058**
	(−3.71)	(4.28)	(7.16)
ASE	2.006**	−1.288**	−1.199**
	(6.38)	(−4.92)	(−6.37)
Fund characteristics	Yes	Yes	Yes
Activeness measures	Yes	Yes	Yes

The table reports the monthly regression results of various timing-ability measures (annualized and in percentages) Characteristic Timing (CT, Daniel *et al.*, 1997), Timing_EGB (Elton *et al.*, 2011) and Timing Skill (Angelidis *et al.*, 2013) regressed on the one-month-lagged fund activeness measures: Active Share (AS), Active Stock Weights (ASW), or Active Stock Selection (ASE), respectively. All regressions include fund activeness measures (i.e., ICI, Active Weight, R-squared, and Return Gap), fund characteristics, time (month) and style dummies. For brevity, we only report the coefficients of interest (i.e., AS, ASW, or ASE, respectively). Coefficients are displayed in the first line and t-statistics between parentheses in the second line. ** and * indicate significance at the 1% and 5% levels, respectively.

evidence of portfolio managers not being able to cumulate timing and selection skills at the same time.

6 Conclusion

Cremers and Petajisto (2009) made an important contribution to the literature on mutual fund performance by providing a holdings-based measure that gauges the deviation of a fund's holdings from its benchmark. We build on their work to further investigate the sources of this deviation. We deconstruct the Active Share measure into *Active Stock Weights* and *Active Stock Selection*. Active Stock Weights captures deviations from market-cap weights and Active Stock Selection captures investment in stocks outside the benchmark.

Using data on U.S. equity mutual funds from 1991 to 2017, we find three important results. First, we find that the main driver of Active Share is the stock selection decision and not the weighting decision. Active Stock Selection accounts for about 85% of Active Share. Active Share is positively correlated with Active Stock Selection (88%) and negatively correlated with Active Stock Weights (−55%).

Second, we examine the performance predictability of our activeness measures. Using the Cremers (2017) model, we find that Active Stock Selection positively predicts risk-adjusted performance, while Active Stock Weights negatively predicts risk-adjusted performance. The comparison between the highest and lowest quintiles, as sorted based on Active Stock Weights and Active Stock Selection, respectively, reveals differences of −0.84% and 1.25% in the annual risk-adjusted seven-factor alpha. Therefore, investment skill is more pronounced among managers that hold portfolio weights close to market-cap weights and select stocks outside the benchmark. Furthermore, since Active Stock Selection, unlike Active Stock Weights, is not benchmark-free, a corollary of our results is that the component that drives the positive performance of Active Share correlates with the benchmark. This is consistent with Frazzini *et al.* (2016) that show the positive performance of Active Share is dependent on the benchmark choice.

Third, we investigate the determinants of Active Stock Weights and Active Stock Selection. We find that Active Stock Selection positively relates to traditional measures of selectivity (e.g., Return Gap, Industry Concentration Index, one minus R-square) while Active Stock Weights displays positive correlation only with Active Weight.

Our Active Share-derived measures offer a number of practical implications for investors. First, Active Stock Weights and Active Stock Selection allow investors to distinguish between funds that deviate from market-cap weights and funds that hold stocks outside the benchmark. Second, by investing in funds with high Active Stock Selection and low Active Stock Weights, investors are more likely to select outperforming funds. Third, we show that high-Active Share funds display high Active Stock Selection as these funds hold stocks that are outside the benchmark. Lastly, the information embedded in Active Stock Selection and Active Stock Weights persists over several quarters in the future.

Our measures are not without limitations. Not surprisingly, these measures inherit all the limitations of Active Share. For example, like Active Share, Active Stock Weights, and Active Stock Selection measures are sensitive to the choice of performance evaluation model. The relation between the Active Share-derived measures and fund performance measured by Carhart and Fama–French five-factor alphas is weak compared to Cremers (2017) seven-factor alphas. Furthermore, similar to Active Share, the predictability ability of these measures has seen a decline in recent times.

In summary, knowing the sources of Active Share is important for investors because it will help them evaluate managerial skill accurately and avoid unexpected exposure to risk. Future research can focus on understanding the various dimensions embedded in other measures of activeness including Active Share.

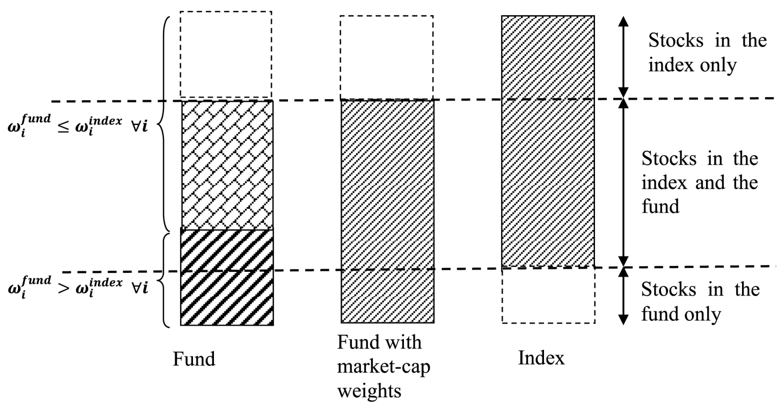
Appendix I: Definitions of Variables

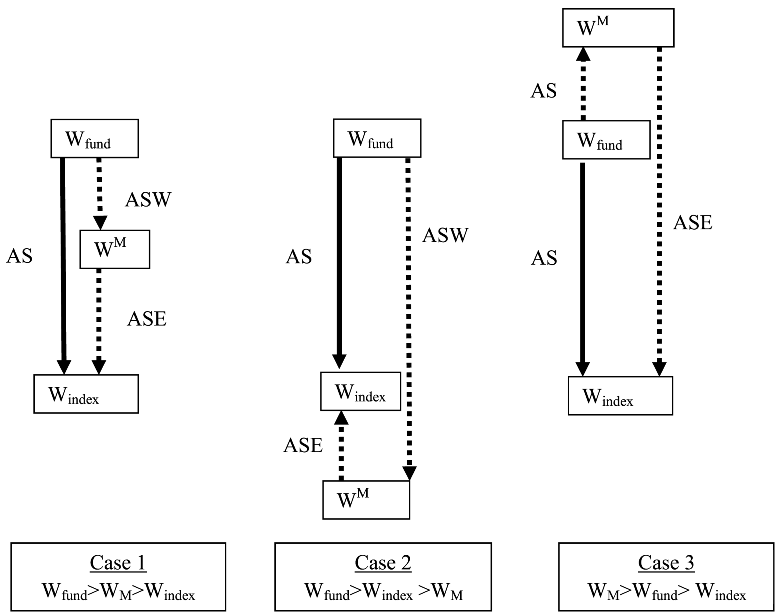
Variable	Definition
Active Share (AS)	Equal to half of the sum of the absolute differences between the fund weights and the corresponding benchmark weights as defined in Cremers and Petajisto (2009).
Active Stock Weights (ASW)	Equal to the difference between the fund's actual weights and market-value weights on the portion of the portfolio where fund's actual weights exceed benchmark index weights.
Active Stock Selection (ASE)	Equal to the difference between the fund's weights if using market-value weights and benchmark index weights on the portion of the portfolio where fund weights exceed benchmark index weights.
Industry Concentration Index (ICI)	The sum of squared differences in industry weights between the mutual fund and the total market portfolio as defined in Kacperczyk *et al*. (2005).

Continued

Variable	Definition
Active Weight (AW)	Equal to half of the sum of the absolute differences between the actual weights and the theoretical market-value weights of the portfolio as defined in Doshi *et al*. (2015).
R-square	*R*-square of Amihud and Goyenko (2013) that is obtained from regressing the fund excess returns on the Carhart factors using a rolling window of 24 months.
Return Gap	The average Return Gap (RG) over the last 12 months as defined in Kacperczyk *et al.* (2008) and is equal to the difference between the net investor return and net holdings return.
Return_12m	The trailing 12-month cumulative return.
Volatility_12m	The annualized return volatility computed over the last 12 months.
Flows	The quarterly net flows: $[TNA_t - TNA_{t-1}(1 + R_t)]/TNA_{t-1}$
Total net assets (TNA)	Total net assets (TNA) in millions of \$.
Number of stocks	Number of stocks included in the portfolio.
Expense ratio	Ratio of total net assets that shareholders pay for the fund's operating expenses, which include 12b-1 fees.
Turnover	Minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month total net assets of the fund.
Fund age	Age of the fund in years since its inception.
Style dummy	A dummy variable that equals 1 if the fund belongs to style *s* and 0 otherwise.

Appendix 2: Explaining the Active Share decomposition





At the stock level, and for every stock that has $\omega_i^{fund} > \omega_i^{index} \forall\, i$, the stock-level deviation is equal to

$$\mathrm{AS}_i = \underbrace{(\omega_{i,t}^{fund} - \omega_{i,t}^{index})}_{\text{active share}}$$
$$= \underbrace{(\omega_{i,t}^{fund} - \omega_{i,t}^{M})}_{\text{active stock weights}} + \underbrace{(\omega_{i,t}^{M} - \omega_{i,t}^{index})}_{\text{active stock selection}}$$

Since $\mathrm{AS}_i > 0$, we then have three cases:

Appendix 3: Illustrative Examples of the Active Share Decomposition

To better understand the decomposition reported in Equation (1), the current section provides several numerical scenarios that allow the reader to grasp the mechanism of the distribution of the Active Share between Active Allocation and Active Selection.

The stock universe is made of four stocks A, B, C, and D. At time t, the stock prices of A equals to \$10, that of B equals \$20, that of C is \$30, that of D is \$40 and that of E equals \$50.

The equity index (i.e., the benchmark) is invested in three stocks A, B, and C. The market capitalization of the index is then equal to \$60.

We then vary the weights of the fund in the different stocks A, B, C, and D. To simplify our computations, we suppose that the number of outstanding shares in the market of A, B, C and D is equal.

Scenario 1 Same set of stocks and same allocation, i.e., replicating the benchmark index

In this, case the fund is invested in the same set of stocks (A, B, and C) and in the same weights.

Active Share is equal to $\frac{1}{2}(|\frac{10}{60} - \frac{10}{60}| + |\frac{20}{60} - \frac{20}{60}| + |\frac{30}{60} - \frac{30}{60}|) = 0$

Active Allocation is equal to 0 (there are no $W_{fund} > W_{index}$)

Active Selection is equal to 0 (there are no $W_{fund} > W_{index}$)

Scenario 2 A different set of stocks but using a market cap allocation

Table A.1 Panel regressions: predicting risk-adjusted performance with Active Share (AS), Active Stock Weights (ASW), and Active Stock Selection (ASE).

Seven-factor alpha	Gross returns		Net returns	
AS	5.042**	3.926**	4.361**	3.130**
	(9.46)	(5.39)	(9.40)	(5.06)
ASW	−1.468**	−2.575**	−1.529**	−1.993**
	(−2.83)	(−4.02)	(−2.91)	(−3.15)
ASE	2.731**	2.362**	2.353**	1.786**
	(7.43)	(5.63)	(7.27)	(4.77)
Fund characteristics	Yes	Yes	Yes	Yes
Activeness measures	No	Yes	No	Yes

The table reports the monthly regression results for various risk-adjusted measures of performance (annualized and in percentages) regressed on the one-month-lagged fund activeness measures: Active Share (AS), Active Stock Weights (ASW) and Active Stock Selection (ASE), and fund characteristics. The dependent variable is the monthly risk-adjusted returns that are computed as the difference between the observed fund returns and predicted returns. The latter are computed using the estimates of the seven-factor model over the last 36 months and both gross and net of fees returns. All regressions include fund characteristics, time (month) and style dummies. However, for brevity's sake, we do not report these coefficients. Coefficients are displayed in the first line and t-statistics between parentheses in the second line. ** and * indicate significance at the 1% and 5% levels, respectively.

The fund is invested only in stocks A and B with relative market capitalization as relative weights.

In this case:

Active Share is equal to $\frac{1}{2}(|\frac{10}{30} - \frac{10}{60}| + |\frac{20}{30} - \frac{20}{60}| + |\frac{0}{30} - \frac{30}{60}|) = 50\%$

Active Allocation is equal to $((\frac{10}{30} - \frac{10}{30}) \times 1 + (\frac{20}{30} - \frac{20}{30}) \times 1) = 0\%$

Active Selection is equal to $((\frac{10}{30} - \frac{10}{60}) \times 1 + (\frac{20}{30} - \frac{20}{60}) \times 1 + (\frac{0}{30} - \frac{30}{60}) \times 0) = 50\%$

Scenario 3 Same set of stocks but different allocation (i.e., not market-cap)

Suppose the fund is invested in A, B and C, but has 0.5 quantity in A, 0.5 quantity in B and 1 quantity in C. In this scenario, the portfolio value is equal to $0.5 * 10 + 0.5 * 20 + 1 * 30 = \$45$

Active Share is equal to $\frac{1}{2}(|\frac{5}{45} - \frac{10}{60}| + |\frac{10}{45} - \frac{20}{60}| + |\frac{30}{45} - \frac{30}{60}|) = 16.67\%$

Active Allocation is equal to $((\frac{5}{45} - \frac{10}{60}) \times 0 + (\frac{10}{45} - \frac{20}{60}) \times 0 + (\frac{30}{45} - \frac{30}{60}) \times 1) = 16.67\%$

Active selection is equal to $((\frac{10}{60} - \frac{10}{60}) \times 0 + (\frac{20}{60} - \frac{20}{60}) \times 0 + (\frac{30}{60} - \frac{30}{60}) \times 1) = 0\%$

Scenario 4 No overlap between the fund and the benchmark index

The fund is invested in only one stock D.

Active Share is equal to $\frac{1}{2}(|\frac{0}{40} - \frac{10}{60}| + |\frac{0}{40} - \frac{20}{60}| + |\frac{0}{40} - \frac{30}{60}| + |\frac{40}{40} - \frac{0}{60}|) = 100\%$

Active Allocation is equal to $((\frac{0}{40} - \frac{0}{40}) \times 0 + (\frac{0}{40} - \frac{0}{40}) \times 0 + (\frac{0}{40} - \frac{0}{40}) \times 0 + (\frac{40}{40} - \frac{40}{40}) \times 1) = 0\%$

Active Selection is equal to $((\frac{0}{40} - \frac{10}{60}) \times 0 + (\frac{0}{40} - \frac{20}{60}) \times 0 + (\frac{0}{40} - \frac{30}{60}) \times 0 + (\frac{40}{40} - \frac{0}{60}) \times 1) = 100\%$

Scenario 5 Different set of stocks and different allocation

The fund is invested in one share of A and two shares of D, total portfolio value is equal to $10 + 2 * 40 = \$90$

Active Share is equal to $\frac{1}{2}(|\frac{10}{90} - \frac{10}{60}| + |\frac{0}{90} - \frac{20}{60}| + |\frac{0}{90} - \frac{30}{60}| + |\frac{80}{90} - \frac{0}{60}|) = 88.88\%$

Active Allocation is equal to $((\frac{10}{90} - \frac{10}{50}) \times 0 + (\frac{0}{90} - \frac{0}{50}) \times 0 + (\frac{0}{90} - \frac{0}{50}) \times 0 + (\frac{80}{90} - \frac{40}{50}) \times 1) = 8.88\%$

Active selection is equal to $((\frac{10}{50} - \frac{10}{60}) \times 0 + (\frac{0}{50} - \frac{20}{60}) \times 0 + (\frac{0}{50} - \frac{30}{60}) \times 0 + (\frac{40}{50} - \frac{0}{60}) \times 1) = 80.00\%$

Notes

1 NYOAG Report, https://ag.ny.gov/sites/default/files/ny_ag_report_on_mutual_fund_fees_and_active_share.pdf.

2 There is significant debate in the literature about the predictive power of Active Share with respect to future fund performance. While some studies show that it successfully predicts future fund performance (e.g., Cremers and Petajisto, 2009; Petajisto, 2013, 2016), others question this evidence (e.g., Schlanger *et al.*, 2012; Frazzini *et al.*, 2016).

3 The formula for Active Share expressed in line 3 (or line 5) of Equation (1) is relevant for readers interested in computing it. Indeed, it requires a smaller number of stocks, which is at most equal to the number of stocks included in the fund's portfolio. The original formula in line 1 requires the computation of the weight differences over the benchmark's and the fund's universes, which necessitates a consideration of all of the stocks in the benchmark index and in the fund (i.e., the sum of both stock sets). Hence, the formula in line 3 (or line 5) is even simpler (in terms of computational demand) than the one recently suggested by Cremers (2017) which uses all the stocks included in the fund. Thanks to lines 3 and 5, one can compute Active Share by either focusing solely on the overweights (i.e., $\omega_{i,t}^{\text{fund}} > \omega_{i,t}^{\text{index}}$) or the underweights (i.e., $\omega_{i,t}^{\text{fund}} \leq \omega_{i,t}^{\text{index}}$).

4 We compute the unconditional absolute version of ASE (i.e.. the sum of the absolute differences between the fund's value weights and the benchmark weights) and find a correlation of 92% with ASE and 96% with Active Share. The unconditional absolute version of ASW is the Active Weight measure suggested by Doshi *et al.* (2015) and correlates with ASW at 41% and with Active Share at only 14% (as reported in Table 2). Therefore, even when using absolute differences, ASE remains the main driver of Active Share.

5 We would like to thank the Russell Company for providing us with data on Russell index constituents.

6 http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

7 We thank Anti Petajisto and Martijn Cremers for making the Active Share data available. The Active Share data are available via http://www.petajisto.net/data.html. A description of these data can be found in Petajisto (2013).

8 Frazzini *et al.* (2016) argue that performance predictability of Active Share may be sensitive to the choice of the benchmark.

9 ASW is similar to the Active Weight measure of Doshi *et al.* (2015) as both capture deviation with respect to the market-cap portfolio. However, while Active Weight captures all deviations, ASW captures only net deviations, as the sign matters. A fund may deviate from a market-cap allocation, but ASE may capture this deviation. For example, if a fund invests in two stocks that are not part of the benchmark, then Active Weight may be substantial, depending on how the weights differ from the market-cap allocation. However, these weights will have no impact on Active Share as it will still equal 100%.

10 We thank Mikhail Simutin for making the SAS code for the Active Weight measure available on his website. We follow Kacperczyk *et al.* (2005, 2008) to compute the ICI and Return Gap and Amihud and Goyenko (2013) to compute the R-square of the Carhart model.

11 Cremers (2017, p. 65) offers a thorough discussion on the advantages of the seven-factor model in comparison with the four-factor model.

12 In unreported results, we also conducted a simple sort analysis using raw returns, the Carhart (1997) alpha and the Fama–French (2015) alpha. Consistent with Cremers (2017), these results are insignificant.

13 Table A.1 of Appendix 3 reports panel regressions results using Equation (2). The results are in line with the Fama–Macbeth regression results. In unreported results, we also conducted Fama–Macbeth regressions using the following performance measures as a dependent variable: excess returns, the Carhart (1997) alpha, the Fama–French (2015) alpha, and the characteristic selectivity (CS) of DGTW (1997). The results are, however, weakly significant.

[14] We also conduct a double sort analysis on ASW and ASE and find that it only marginally improves the performance difference obtained using simple sorts.

[15] Characteristic timing (CT) is by Daniel *et al.* (1997) and is equal to $\sum_{j=1}^{N}(w_{j,t-1}R_t^{b_{j,t-1}} - w_{j,t-13}R_t^{b_{j,t-13}})$, where $w_{j,t-1}$ and $w_{j,t-13}$ are the weights of stock j at month $t-1$ and $t-13$, and $R_t^{bj,t-1}$ and $R_t^{bj,t-13}$ are the month t return of the characteristic-based benchmark portfolio that is matched to stock j during $t-1$ and $t-13$, respectively. We compute CT at a monthly frequency using quarterly fund holdings. The Elton *et al.* (2011) timing measure equals $\frac{1}{T}\sum_{t=1}^{T}(\beta_{Pjt} - \beta^*_{Pjt}) \times I_{jt+1}$, where β_{Pjt} is the sensitivity of fund P to factor j in month $t$and β^*_{Pjt} is the target beta, i.e., the average beta for the portfolio over the entire period and T is the number of months of data available and I_{jt+1} is the excess return or differential return for factor j for the month t+1. We compute EGB measure using three years of monthly instead of weekly returns to compute stock betas and quarterly instead of monthly fund holdings. Finally, the timing skill measure of Angelidis *et al.* (2013) equals $\hat{\beta}^*_{i1}(\overline{R_m - R_f}) + \hat{\beta}^*_{i2}\overline{SMB} + \hat{\beta}^*_{i3}\overline{HML} + \hat{\beta}^*_{i4}\overline{MOM}$, where $\hat{\beta}^*_{i1}$, $\hat{\beta}^*_{i2}$, $\hat{\beta}^*_{i3}$ and $\hat{\beta}^*_{i4}$ are the factor loadings of the Carhart (1997) model. We compute fund betas using rolling-windows of fund returns over 36 months instead of daily returns over one month.

References

Angelidis, T., Giamouridis, D., and Tessaromatis, N. (2013). "Revisiting Mutual Fund Performance Evaluation," *Journal of Banking & Finance* **37**, 1759–1776.

Amihud, Y. and Goyenko R. (2013). "Mutual Fund's R^2 as Predictor of Performance," *Review of Financial Studies* **26**, 667–694.

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

Cremers, M. (2017). "Active Share and the Three Pillars of Active Management: Skill, Conviction, and Opportunity," *Financial Analysts Journal*, **73**, 61–79.

Cremers, M. and Pareek, A. (2016). "Patient Capital Outperformance: The Investment Skill of High Active Share Managers Who Trade Infrequently," *Journal of Financial Economics* **122**, 288–306.

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

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. (1997). "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks," *Journal of Finance* **52**, 1035–1058.

Doshi, H., Elkamhi, R., and Simutin, M. (2015). "Managerial Activeness and Mutual Fund Performance," *Review of Asset Pricing Studies* **5**, 156–184.

Elton, E., Gruber, M., and Christopher R. (2011). "An Examination of Mutual Fund Timing Ability Using Monthly Holdings Data," *Review of Finance* **16**, 619–645.

Fama, E. and French, K. (1993). "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* **33**, 3–56.

Fama, E. and French, K. (2015). "A Five-Factor Asset Pricing Model," *Journal of Financial Economics* **116**, 1–22.

Fama, E. and MacBeth, J. (1973). "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy* **81**, 607–636.

Frazzini, A., Friedman, J. and Pomorski, L. (2016). "Deactivating Active Share," *Financial Analysts Journal*, **72**, 14–21.

Fulkerson, J. and Riley, T. (2015). "Deconstructing Active Share," *Loyola University Maryland and U.S. Securities and Exchange Commission*, Working paper.

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

Kacperczyk, M., Sialm, C. and Zheng, L. (2008). "Unobserved Actions of Mutual Funds," *Review of Financial Studies* **21**, 2379–2416.

Petajisto, A. (2013). "Active Share and Mutual Fund Performance," *Financial Analysts Journal* **69**, 73–93.

Petajisto, A. (2016). "Author Response to 'Deactivating Active Share," *Financial Analysts Journal* **72**, 11–12.

Schlanger, T., Philips, C., and LaBarge, K. (2012). "The Search for Outperformance: Evaluating Active Share," Vanguard.

Wermers, R. (2000). "Mutual Fund Performance: An Empirical Decomposition into Stock-picking Talent, Style, Transactions Costs, and Expenses," *Journal of Finance* **55**, 1655–1695.

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JEL Classification: G11, G12, G14