Deactivating Active Share

Andrea Frazzini, Ph.D.
Principal

Jacques Friedman
Principal

Lukasz Pomorski, Ph.D.
Vice President

April 2015

We investigate Active Share, a measure meant to determine the level of active management in investment portfolios. We evaluate the claim that the measure predicts investment performance by considering theoretical arguments and via empirical analysis. We do not find strong economic motivations for why Active Share may correlate with performance. We also use the same data set used in the original Active Share studies (Cremers and Petajisto, 2009 and Petajisto, 2013) to evaluate the robustness of the empirical results from those studies. We find that the empirical support for the measure is weak and is entirely driven by the strong correlation between Active Share and the benchmark type. For example, Active Share correlates with benchmark returns, but does not predict actual fund returns; within individual benchmarks, Active Share is as likely to correlate positively with performance as it is to correlate negatively. We conclude that neither theory nor data justify the expectation that Active Share might help investors improve their returns.

AQR Capital Management, LLC
Two Greenwich Plaza
Greenwich, CT 06830

p: +1.203.742.3600
f: +1.203.742.3100
w: aqr.com

Active Share is a metric proposed by Cremers and Petajisto (2009) and Petajisto (2013) (hereafter, C&P) to measure the distance between a given portfolio and its benchmark, and identify where a manager lies in the passive to active spectrum. It ranges from zero, when the portfolio is identical to its benchmark (totally passive), to one, when there is no overlap in names between the benchmark and the portfolio. Technically, Active Share is defined as one half of the sum of the absolute value of active weights:

$$\text{Active Share} = \frac{1}{2}\sum_{j=1}^{N}|w_j|$$

where $w_j = w_{j,fund} - w_{j,benchmark}$ is the active weight of stock j, defined as the difference between the weight of the stock in the portfolio and the weight of the stock in the benchmark index. Using holdings and performance data of actively managed domestic mutual funds (from the Thomson Reuters and CRSP databases, respectively), C&P show that historically high Active Share funds outperform their reported benchmarks and that the benchmark-adjusted return of high Active Share funds is higher than the benchmark-adjusted return of low Active Share funds. They also provide investors with a simple rule of thumb: funds with Active Share below 60% should be avoided as they are closet indexers that charge high fees for merely providing index returns.

Not surprisingly, these results have attracted considerable attention in the investment community. In response, more-active mutual fund and institutional money managers tout their Active Share, several leading investment consultants strongly emphasize the measure, and online tools are now available to allow investors to screen managers based on Active Share.[1]

Institutional investors are more focused on asset managers with a high Active Share, and some have even embedded a high Active Share requirement in their investment guidelines. For example, a large public pension plan has added the following requirement to a recent request for proposals:

"The firm and/or portfolio manager must: (…) Have a high Active Share in the Small-Cap Strategy, preferably greater than 75% in the last three years"; furthermore *"if the Active Share is lower than 75%, please clearly state that in the RFP response and explain why the Active Share is low and why it is beneficial."*

This white paper addresses Active Share from two perspectives. First, we investigate theoretical (ex ante) arguments for why Active Share may predict performance and potential misperceptions of Active Share. Second, we go to the data to evaluate the robustness of the empirical evidence behind this measure.

Overall, our conclusions do not support an emphasis on Active Share. Predicting investment performance is difficult and there do not seem to be any silver bullets. On the theory side, we believe there is little economic intuition that would justify a preference for high Active Share. A plausible economic story would require assumptions that are strong, far from obvious, and rarely made explicit by prior papers discussing the concept.

On the empirical evidence, we use the original data set to closely replicate the findings produced in C&P but we believe that their conclusions are subject to misinterpretation.[2] We have three main results:

---

[1] For example: http://online.wsj.com/public/resources/documents/st_FUNDS20140117.html.

[2] For example, "U.S. mutual funds with higher active share significantly outperformed those with lower active share" (Ely, 2014, p. 4); "empirically higher active share means higher returns" (Allianz, 2014, p. 7); "portfolios

- High Active Share funds and low Active Share funds systematically have different benchmarks. A majority of high Active Share funds are small caps and a majority of low Active Share funds are large caps.

- The authors' results are very sensitive to their choice of comparing funds using benchmark-adjusted returns rather than total returns. Over this sample, small-cap benchmarks had large negative four-factor alphas compared to large-cap benchmarks and this was crucial to the statistical significance of their results.

- Controlling for benchmarks, Active Share has no predictive power for fund returns, predicting higher fund performance within half of the benchmark indexes and lower fund performance within the other half.

We agree with C&P on one point: fees matter, and if you deliver index-like returns, you should charge index-fund-like fees. In general, fees should be commensurate with the active risk funds take. There are many ways beyond Active Share to measure the degree of "activity" in a portfolio, including predicted and realized tracking error and other concentration measures. A prudent investor should use multiple measures to determine if a manager is taking risks commensurate with fees.[3]

Active Share — Theoretical Arguments and Misperceptions

Let's put on our theory hats and examine Active Share. First, this is not so easy because the proponents of Active Share do not have a theory for why it works that we can evaluate directly. The proponents of Active Share have not proposed an economic mechanism for why this measure should predict outperformance. It is not easy to come up with one. Although it is clear that a portfolio that does not deviate from the benchmark (zero Active Share) cannot outperform the benchmark, it is a larger leap to claim that the higher the deviation, the higher the positive alpha. The world is neither continuous nor monotonic, and while a portfolio that strays further away from a benchmark may take on more active risk, why should it be more likely to over- rather than underperform? Even if the extra risk were compensated, there is no reason why relative returns for the risk taken should be larger. Simply put, while it may fit the intuition of some, there is no evidence you're more likely to be right just because you have a high conviction.

Going a step further, let's consider an equilibrium argument. If we make the assumption that the multitrillion-dollar universe of mutual fund managers is a decent proxy for the equity market, we know that the market clears: before fees, every dollar of outperformance must be offset by a dollar of underperformance. C&P and others make the claim that the investment universe is divided between high Active Share managers who outperform the market and closet indexers who only match market returns before fees (and woefully underperform after fees). What is lacking is an economic argument for the source of the high Active Share outperformance – who is underperforming systematically before fees and why? Proponents of Active Share have not offered a hypothesis or any empirical support.

There are some misconceptions about Active Share that pervade the literature. One argument is that large deviations from a benchmark are somehow **necessary** for economically large outperformance.[4] They're not. For a stylized example, consider a long-only, S&P 500-benchmarked manager who can predict which single stock will deliver the lowest returns over the subsequent month. Every month the manager avoids this one stock with the lowest return and, not having any other information, holds the remaining S&P 500 stocks proportionally to their index weights. From January 1990 through October 2014, this manager would have beaten the benchmark by 93bps/year before fees with an average Active Share of only 0.4%. If the manager dropped five stocks with the lowest returns, he would have outperformed by 4.51% per year with the average Active Share of only 2.2%. (Similarly, it is also easy to construct an example in which a high Active Share manager has horrible performance.)

A related misperception is that managers with low Active Share must earn heroic returns on their small "active" holdings to justify their fees (e.g., Chatburn, 2012; Flaherty and Chiu, 2014). This is imprecise, simply because an Active Share of x does not imply that a fund's return is (1-x) times the benchmark return plus x times the return on the "active" holdings. Active Share measures overlap in holdings, not how similar a fund's return is to the benchmark's return. As our example above shows, holdings that overlap with the benchmark may realize a much higher return than that of the benchmark, as long as the manager wisely chooses the stocks he is not investing in.

Finally, Active Share is only one measure of "activity" or concentration in a portfolio. If one argues that Active Share can predict performance, what about other measures of concentration? For example, tracking error captures similar dimensions as Active Share, and yet Cremers and Petajisto (2009) show that high-tracking-error funds do not outperform low-tracking-error funds. Schlanger, Philips, and Peterson LaBarge (2012) look at five different measures of active management and find no evidence that they predict performance.

It might be that Active Share happens to capture some critical feature of what it means to be active and we just do not know what it is. Theory would be helpful here, but there is none. So why is Active Share so special that it is the only measure that seems to predict performance? One explanation is that it may just be a spurious, data-mined result. With this troubling possibility in mind, we next revisit the evidence from the original studies, using the same data and approach as Cremers and Petajisto (2009) and Petajisto (2013).

Active Share and Mutual Fund Performance

We use the same sample as Petajisto (2013) which includes data on Active Share and benchmark assignment on all actively managed U.S. domestic mutual funds from 1980 to 2009. We follow the methodology in Petajisto (2013) closely and focus on performance over the period from 1990 to 2009.[5] Throughout our analysis we use the same data and focus on the same period as

---

[4] For example, Ely (2013) writes about the "difficulty inherent in generating strong relative performance (…) from a portfolio that closely mimics its benchmark"; Chatburn (2012) writes that "not incorporating active share into the evaluation makes identifying an equity strategy that can deliver excess returns even more daunting"; Flaherty and Chiu (2014) claim that "only benchmark-differentiating holdings can generate relative performance," forgetting that stocks managers choose *not* to hold also have an impact; etc.

[5] We thank Antti Petajisto for making the Active Share and tracking error data available through his website, http://petajisto.net/data.html. We complement it with CRSP Mutual Fund database, with academic factor returns from Ken French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html , and with benchmark index returns obtained from eVestment Alliance.

Exhibit 1 — Active Share Statistics by Benchmark. A sort on Active Share is also a sort on benchmark type. For each benchmark, we present the average (dots), 25th and 75th percentile (whiskers) of the Active Share of funds following that benchmark. Benchmarks are sorted on the average Active Share.
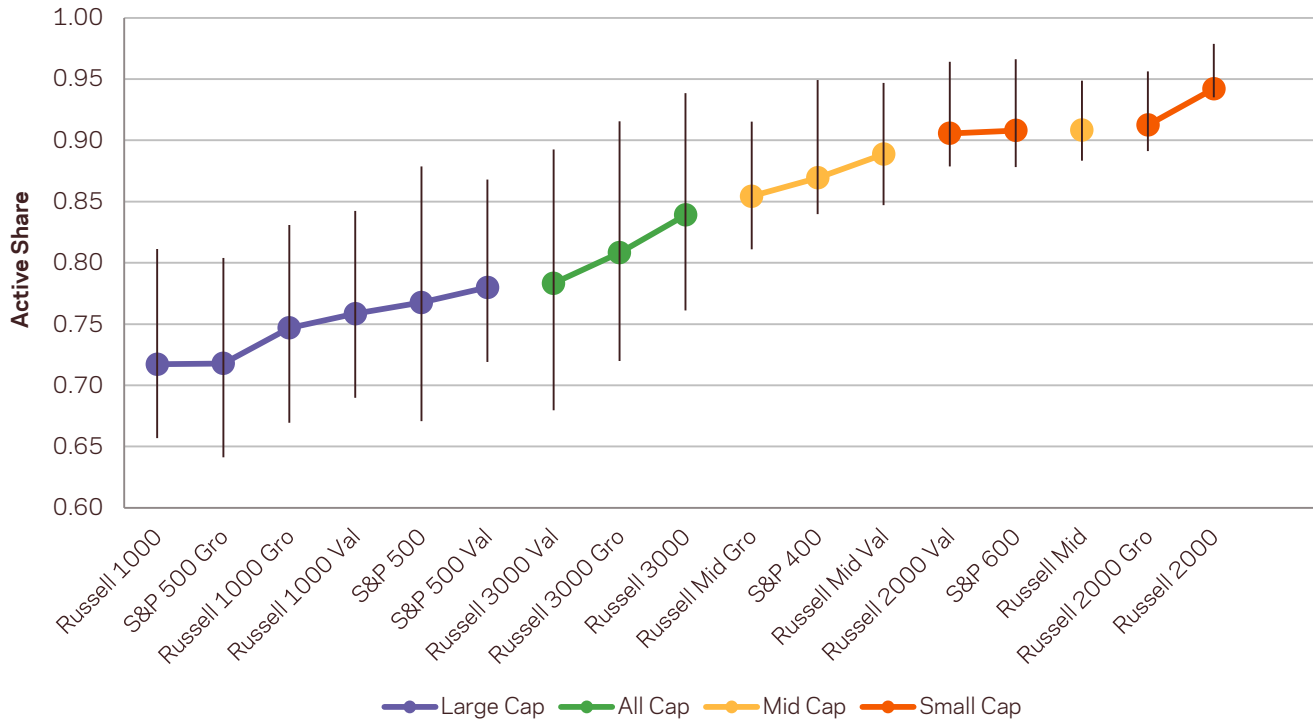
Source: AQR using data from Petajisto (2013) http://www.petajisto.net/data.html.Data is from 1990-2009.

Petajisto (2013), but our conclusions also hold for the shorter sample of Cremers and Petajisto (2009). Before evaluating manager performance, let's take a look at the composition of the manager universe with regard to the Active Share measure.

Our first observation is that a sort on Active Share is equivalent to a sort on the benchmark. Exhibit 1 makes it clear by depicting the average, the 25th, and 75th percentile of Active Share within each benchmark.[6]

Exhibit 1 shows a strong small-cap bias in funds' Active Shares. For example, all large-cap benchmarks are clustered to the left, as funds that follow them have the lowest Active Shares; small-

cap benchmarks are clustered to the right, in line with the highest Active Shares of small-cap funds. In fact, the top quartile of Active Share of large-cap funds is substantially below even the bottom quartile of Active Share of small-cap funds. This presents a clear problem. Papers that sort funds on Active Share (as do C&P) end up sorting funds on their benchmarks. In practice, few investors would evaluate all managers on a particular dimension and then accept whichever benchmark falls out. Instead, they would start with a benchmark and select a manager from within that benchmark. We will do precisely that in our empirical analysis.

A second issue is that various benchmarks realized very different performance over the sample period in the original studies. To compare performance across benchmarks we estimate their four-factor alphas, controlling for each

---

[6] Data is over 1990-2009. Two of the 19 benchmarks used in Cremers and Petajisto (2009) and Petajisto (2013), Wilshire 4500 and Wilshire 5000, only have 2 and 5 funds, respectively, in the average month, so we excluded them from our analysis.

Exhibit 2 — Active Share Correlates With Benchmark Type and Benchmark Alphas. For each benchmark index in Cremers and Petajisto (2009) and Petajisto (2013) we compute that benchmark's four-factor alpha (the intercept in the regression of benchmark returns on market, size, value and momentum factors) and plot it against the average Active Share of all funds that follow that benchmark. Benchmarks are sorted on the average Active Share, as in Exhibit 1.

Average Active Share of funds following each benchmark
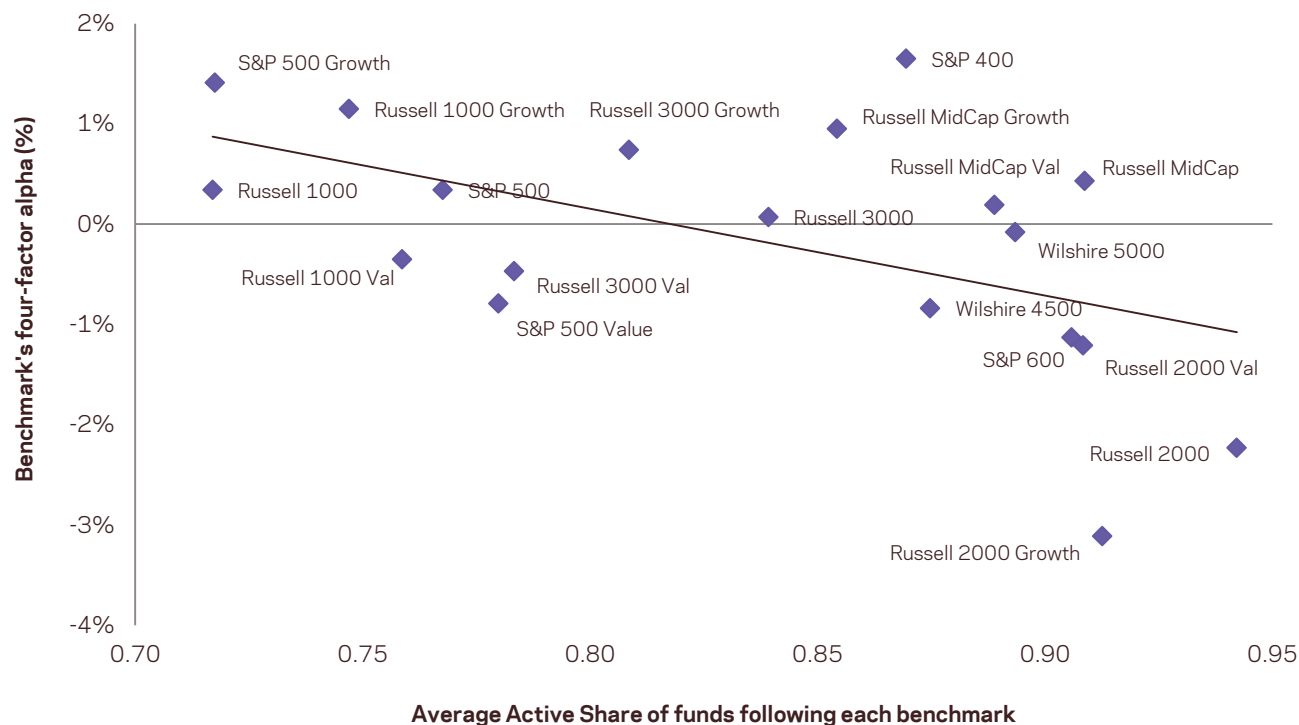
Source: AQR using data from Petajisto (2013) http://www.petajisto.net/data.html. Data is from 1990-2009.

benchmark's market beta and its exposures to size, value and momentum. (This four-factor adjustment is also the preferred performance metric in C&P papers.) Importantly, we do not use any actual fund returns for this analysis, only the returns on benchmark indexes.

Small-cap benchmarks, associated with high Active Share funds, underperform large-cap benchmarks which tend to be associated with low Active Share funds. The differences, estimated over 1990-2009, are substantial, with annualized alphas ranging from -3.35% for Russell 2000 Growth to +1.44% for S&P 500 Growth. The fitted regression line implies about 2% difference between the extremes, and in spite of having only 19 observations the slope is significant at the 1% level with a t-statistic of 2.92. The surprising underperformance of small-cap benchmarks is

also discussed in Cremers, Petajisto and Zitzewitz (2013). One could speculate that in this sample period small-cap benchmarks were easier to beat for investors who could access value, size and momentum as defined in the academic literature. This is consistent with findings of other studies critical of Active Share that have observed that its performance predictability can be explained by a bias towards the small-cap sector.[7]

We now go a step further and use C&P's original data set to analyze their key result on Active Share's ability to distinguish high from low performers.

[7] E.g., Schlanger, Philips and Peterson LaBarge (2013) or Cohen, Leite, Nelson and Browder (2014).

Deconstructing Active Share: Benchmark Performance vs. Fund Performance

Using the C&P methodology and the same data as before, we sort mutual funds into groups based on their Active Share and realized tracking error. The funds are then allocated into portfolios, for example, "Stock Pickers" or "Closet Indexers" (we use the same names as C&P, see for example Exhibit 1 in either of their papers). The "Stock Pickers" group is comprised of the managers who are in the highest quintile of Active Share intersected with all but the highest quintile of tracking error. The "Closet Indexers" are the lowest quintile of Active Share interacted with all but the highest quintile of tracking error. We will not comment on C&P's choice of Active Share groupings, but instead perform analysis that can be compared apples-to-apples with their original studies.

First, we confirm that the benchmark-selection bias we commented on above pervades the analysis in the original C&P papers. In the "Closet Indexer" group of funds, over 91% of data (fund-month observations) comes from large-cap funds in the S&P 500 and Russell 1000 family of benchmarks. Across the "Stock Picker" funds, 56% of data comes from Russell 2000 indexes and 75% of data comes from small- and mid-cap benchmarks. In this light, Active Share's key insight to manager selection seems to be "sell large-cap funds, buy small-cap funds."

Next, we replicate the baseline result of Petajisto (2013) in Table 1. It is not difficult to see why Active Share generates so much interest: Stock Pickers (portfolio P5) outperform Closet Indexers (portfolio P1) by over 2% per year, a figure that is statistically and economically significant.[8] The

result is compelling when comparing both benchmark-adjusted returns and four-factor alphas.

Table 1 — Active Share Performance Results. We replicate Table 5 from Petajisto (2013) and report net of fee annualized performance of the five mutual fund portfolios highlighted in Cremers and Petajisto (2009) and Petajisto (2013) over 1990-2009. The portfolios are based on a two-way sort on Active Share and on the tracking error. As these prior studies, we compute alphas as the intercept in the regression of benchmark-adjusted fund returns on market, size, value and momentum factors.

	Benchmark-adjusted returns	Benchmark-adjusted 4-factor alphas
Closet indexers (P1)	**-0.93***	**-1.05***
	(-3.48)	(-4.66)
Moderately active (P2)	-0.53	**-0.76***
	(-1.19)	(-1.89)
Factor bets (P3)	-1.27	**-2.12***
	(-1.32)	(-3.13)
Concentrated (P4)	-0.49	-1.04
	(-0.32)	(-0.88)
Stock pickers (P5)	1.21*	**1.37**
	(1.81)	(2.04)
P5 minus P1	**2.14***	**2.42***
	(3.33)	(3.81)

Source: AQR. Please see "Category Descriptions" in the Disclosures for a description of the categories used. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Many in the investment community have embraced this result and interpret it as evidence that mutual fund investors are better off selecting high Active Share managers. Note, however, that a key feature of C&P's analysis is the focus on benchmark-adjusted returns to study performance:

$$R_{benchmark-adj} = R_{fund} - R_{benchmark}$$

Specifically, the left column of Table 1 reports the average benchmark-adjusted returns to each Active Share grouping and the right column of Table 1 uses benchmark-adjusted returns on the LHS of the four-factor regression to calculate alphas. Benchmark-adjusted returns surely are important – after all, managers are tasked with outperforming their benchmarks, and the above

---

[8] See Petajisto (2013), Table 5. Our results are within 5bps/year of the performance of the most relevant portfolios, P1 ("Closet indexers") and P5 ("Stock Pickers"), as well as the difference between them. The small differences may be driven for example by CRSP revising historical mutual return data.

Table 2 — Active Share Predicts Benchmark Performance, but Not Fund Performance. We decompose returns and alphas of the five Active Share portfolios of Cremers and Petajisto (2009) and Petajisto (2009) into the contribution from fund returns and the contribution from the benchmark.

Dependent variable	Decomposing benchmark-adj returns:						Decomposing alphas:					
	Fund return minus benchmark		Fund return		Benchmark return		Fund return minus benchmark		Fund return		Benchmark return		
Closet indexers (P1)	**-0.93*****	=	**8.28****	-	**9.21*****		**-1.05*****	=	**-0.75*****	-	0.29		
	(-3.48)		(2.48)		(2.68)		(-4.66)		(-2.62)		(1.03)		
Moderately active (P2)	-0.53	=	**9.20*****	-	**9.74*****		-0.76*	=	-0.74	-	0.02		
	(-1.19)		(2.64)		(2.73)		(-1.89)		(-1.37)		(0.06)		
Factor bets (P3)	-1.27	=	**7.85****	-	**9.12****		**-2.12*****	=	**-1.84****	-	0.28		
	(-1.32)		(2.00)		(2.47)		(-3.13)		(-2.54)		(0.65)		
Concentrated (P4)	-0.49	=	**9.20****	-	**9.66****		-1.04	=	-1.66	-	-0.64		
	(-0.32)		(1.99)		(2.49)		(-0.88)		(-1.36)		(-1.21)		
Stock pickers (P5)	1.21*	=	**10.99*****	-	**9.78****		**1.37****	=	0.18	-	**-1.19****		
	(1.81)		(2.89)		(2.53)		(2.04)		(0.21)		(-2.00)		
P5 minus P1	**2.14*****	=	2.71	-	0.57		**2.42*****	=	0.93	-	**-1.48****		
	(3.33)		(1.62)		(0.34)		(3.81)		(1.08)		(-2.16)		

difference may capture skill better than funds' raw returns. However, benchmark-adjusted returns should not be the only metric one looks at, particularly when comparing funds across various benchmarks. Doing so confounds differences between funds and differences between benchmark indexes (recall the pattern from Exhibit 2). In other words, this measure may look attractive when the fund return, R_{fund}, is high when compared with other funds, but also when the benchmark return, $R_{benchmark}$, is low relative to other benchmarks.

Given the potential benchmark-selection bias, we can decompose both columns in Table 1 to understand the role the benchmarks play in the significance of the results. Table 2 decomposes the average returns and the alphas of the five portfolios into the contribution from fund returns and the contribution from the benchmarks.

In its left panel, Table 2 shows that Stock Pickers have higher raw fund returns than Closet Indexers (10.99% versus 8.28%). The 2.7% difference is economically large, but is now not statistically significant with a 1.62 t-statistic. In the right panel, C&P's strongest result, a

benchmark-adjusted alpha of 2.4% with a 3.81 t-stat for P5 minus P1 has been rendered much weaker with the decomposition: the alpha of the raw fund returns is 0.9% with a t-stat of 1.08, while the alpha from benchmark return is -1.5% with a t-stat of 2.16. That is, the economic significance of the alpha is more than halved and the statistical significance of the alpha is gone. In the right panel, it is not surprising that the benchmark return alpha is significant and negative, given our earlier result on the benchmark-relative bias and the negative alphas of small-cap versus large-cap benchmarks over this time period.

A quick sidebar: statistical robustness is vital in studies like these, because even when the true difference in expected returns is zero, in any given sample a difference in realized returns may arise just by chance. For example, we can use our same data sample to see how much the first letter of a fund's name "influences" performance.[9] It turns out that "K" funds, on average, underperform "Q" funds by 2.3% per year, a difference similar in magnitude and statistical

---

[9] We use fund names as reported in the Thomson Reuters holdings database.

Table 3 — Active Share Performance Results. In the two leftmost columns we replicate Table 5 from Petajisto (2013) and report net-of-fee annualized performance of the five mutual fund portfolios highlighted in Cremers and Petajisto (2009) and Petajisto (2013) over 1990-2009. These portfolios are based on a sort on Active Share across the whole universe of funds. In the two rightmost columns, we present performance of analogous portfolios based on a sort on Active Share within each benchmark separately. We use the same performance evaluation tools as C&P, subtracting benchmark returns from fund returns and reporting the average benchmark-adjusted returns and alphas estimated as the intercept in the regression of benchmark-adjusted fund returns on market, size, value and momentum factors.

Dependent variable	Sorting on Active Share across all benchmarks, as in C&P		Sorting on Active Share separately within each benchmark	
	Bmk-adj returns	Bmk-adj alphas	Bmk-adj returns	Bmk-adj alphas
Closet indexers (P1)	-0.93***	-1.05***	-0.71**	-0.88***
	(-3.48)	(-4.66)	(-2.53)	(-3.76)
Moderately active (P2)	-0.53	-0.76*	-0.41	-0.58
	(-1.19)	(-1.89)	(-0.95)	(-1.46)
Factor bets (P3)	-1.27	-2.12***	-1.15	-1.47***
	(-1.32)	(-3.13)	(-1.48)	(-2.64)
Concentrated (P4)	-0.49	-1.04	-0.71	-1.46
	(-0.32)	(-0.88)	(-0.40)	(-1.25)
Stock pickers (P5)	1.21*	1.37**	0.45	-0.004
	(1.81)	(2.04)	(0.53)	(-0.01)
P5 minus P1	2.14***	2.42***	1.16	0.88
	(3.33)	(3.81)	(1.48)	(1.48)

Source: AQR. Please see "Category Descriptions" in the Disclosures for a description of the categories used. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

insignificance (t-stat = 1.64) to the difference between Stock Pickers and Closet Indexers. Of course, the difference is a mirage driven by statistical noise in returns.

Thus, we have verified that without the benchmark correction there is no statistical difference between returns, or alphas, of Stock Pickers and Closet Indexers. In fact, the original C&P (2009) paper reaches the same conclusion: *"the standard non-benchmark-adjusted Carhart* **alphas show no significant relationship with Active Share.** *The reason behind this is that the benchmark indexes of the highest Active Share funds have large negative Carhart alphas, while the benchmarks of the lowest Active Share funds have large positive alphas"*(emphasis ours).[10]

Controlling for Benchmark, Active Share Does Not Predict Performance

C&P rank funds on Active Share over their pooled universe, which, as we saw in Exhibit 1,

effectively ranks funds by their benchmark. Few investors would compare funds across such a range of different universes. We think it is more realistic to rank funds **separately within each benchmark**. This way we are directly comparing high and low Active Share funds that share the same benchmark universe. With this methodology, we can recalculate returns and alphas for the five Active Share groupings. Table 3 re-states the original C&P results from earlier, side-by-side with our newly calculated returns where all comparisons are within benchmark.

Once we control for benchmarks, the performance difference between Stock Pickers and Closet Indexers (raw, benchmark-adjusted, or alphas), while positive, is not statistically different from zero. Benchmark-adjusted returns are nearly halved from 2.14% to 1.16% with statistical significance dropping from a t-statistic of 3.33 to 1.48. Benchmark-adjusted alphas are cut by nearly two thirds from 2.42% to 0.88% with statistical significance dropping from 3.81 to 1.48. In other words, for a given benchmark, there is

---

[10] Cremers and Petajisto (2009), page 3333. Moreover, Cremers, Petajisto and Zitzewitz (2013) discuss methodological choices that can lead to positive estimated alphas of large-cap benchmarks and large negative alphas of small-cap indexes.

inadequate evidence that high Active Share funds have higher returns than low Active Share funds.

The results are even more striking when we break out the results benchmark-by-benchmark in Exhibit 3.

If Active Share predicted performance, then the estimated Stock Picker minus Closet Indexer alpha should be positive. This happens in eight out of 17 benchmark indexes, and in only one is the relationship statistically significant (we denote significance with a red border). In each of the remaining nine benchmarks, higher Active Share predicts lower performance (in one benchmark significantly so). We do find a large and positive alpha for the most popular benchmark, S&P 500, which we count as a win for Active Share. On the other hand, the second most popular benchmark, Russell 1000 Growth, has a negative alpha. Within each market-cap category we can find both benchmarks where Active Share predicts positive performance and benchmarks in which it does the reverse (for example, outperformance within the S&P 500, but underperformance within the Russell 1000). This

lack of robustness leaves us even more skeptical about the measure.

Conclusion

In this paper, we discuss the potential of Active Share to predict performance. We find no theory to justify the hypothesis that more-active managers should be expected to deliver higher performance. We use the same data as Cremers and Petajisto (2009) and Petajisto (2013) to re-evaluate the empirical evidence of Active Share's return predictability. We find only insignificant statistical evidence that high and low Active Share funds have returns that are different from each other. Moreover, Active Share sorts the manager universe on benchmark choice, which is problematic; controlling for benchmark, there is no evidence that Active Share correlates with fund performance. We conclude that Active Share does not (and should not be expected to) predict performance, and that investors who rely on it to identify skill may reach erroneous conclusions.

Active Share may not be useful for predicting outperformance, but it could be useful for

Exhibit 3 — Annualized Difference in Performance Between High and Low Active Share Funds by Benchmark. Within a given benchmark, Active Share does not reliably predict performance. We present the difference in alpha between Stock Pickers and Closet Indexers estimated separately in each benchmark. The alpha measures outperformance controlling for market, size, value and momentum. Benchmarks are sorted on the average Active Share, as in Exhibits 1 and 2.
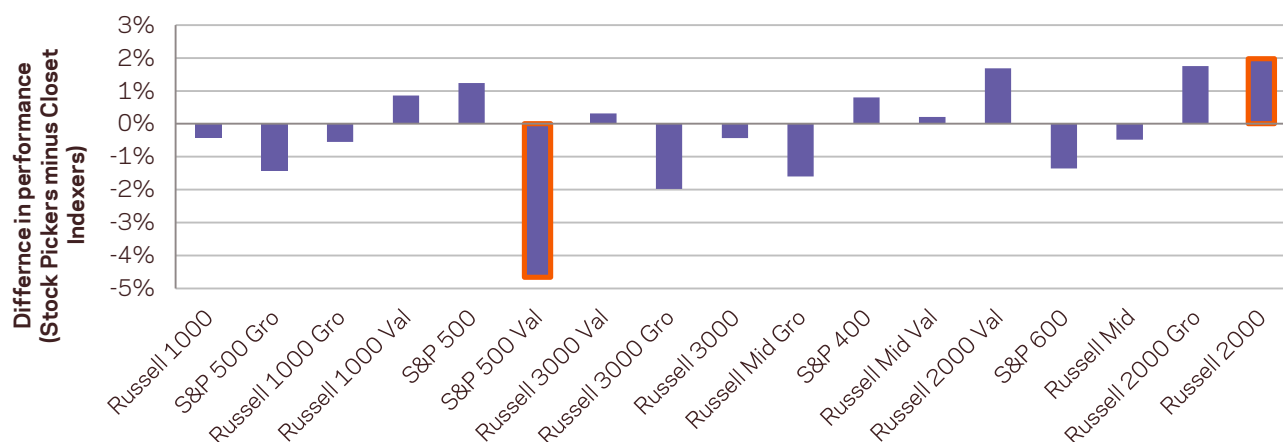
Source: AQR using data from Petajisto's website; CRSP Mutual Fund Database. Data is from 1990-2009.

evaluating costs when used in conjunction with other tools such as tracking error. Fees matter, and we believe they should be in line with the active risk taken. Active share is one measure to assess the degree of active management, but it is just one of many, and it does not capture all relevant dimensions (e.g., it is oblivious to which industries various active bets come from). We recommend using a combination of measures of "activity" to determine if investors are getting enough active risk for the fees they are paying.

Related Studies

Allianz, 2014, "The Changing Nature of Equity Markets and the Need for More Active Management," Allianz Global Investors white paper

Busse, Jeffrey A., Edwin J. Elton and Martin J. Gruber, 2004, "Are Investors Rational? Choices Among Index Funds," *Journal of Finance*, 59 (1)

Chatburn, Sean, 2012, "Get Active! The Importance of Active Share," Mercer Perspectives on Equity Investments, 3 (2), pp. 6-10

Cohen, Tim, Brian Leite, Darby Nelson and Andy Browder, 2012, "Active Share: A Misunderstood Measure in Manager Selection," Fidelity Leadership Series Investment Insights, February 2014

Cremers, Martijn and Antti Petajisto, 2009, "How Active Is Your Fund Manager? A New Measure that Predicts Performance," *Review of Financial Studies*, 22 (9), pp. 3329-3365

Cremers, Martijn, Antti Petajisto, and Eric Zitzewitz, 2013, "Should Benchmark Indices Have Alpha? Revisiting Performance Evaluation," *Critical Finance Review*, 2, pp. 1-48

Ely, Kevin, 2014, "Hallmarks of Successful Active Equity Managers," Cambridge Associates white paper

Flaherty, Joseph C., and Richard Chiu, 2014, "Active Share: A Key to Identifying Stockpickers," MFS white paper

Petajisto, Antti, 2013, "Active Share and Mutual Fund Performance," *Financial Analyst Journal*, 69 (4), pp. 73-93

Schlanger, Todd, Christopher B. Philips and Karin Peterson LaBarge, 2012, "The Search for Outperformance: Evaluating 'Active Share'," Vanguard research, May 2012

Biographies

Andrea Frazzini, Ph.D., Principal

Andrea is a senior member of AQR's Global Stock Selection team, focusing on research and portfolio management of the Firm's Long/Short and Long-Only equity strategies. He has published in top academic journals and won several awards for his research, including Bernstein Fabozzi/Jacobs Levy Award, the Amundi Smith Breeden Award, the Fama-DFA award, the BGI best paper award and the PanAgora Crowell Memorial Prize. Prior to AQR, Andrea was an associate professor of finance at the University of Chicago's Graduate School of Business and a Research Associate at the National Bureau of Economic Research. He also served as a consultant for DKR Capital Partners and JPMorgan Securities. He earned a B.S. in economics from the University of Rome III, an M.S. in economics from the London School of Economics and a Ph.D. in economics from Yale University.

Jacques A. Friedman, Principal

Jacques is the head of AQR's Global Stock Selection team and is involved in all aspects of research, portfolio management and strategy development for the firm's equity products and strategies. Prior to AQR, he developed quantitative stock-selection strategies for the Asset Management division of Goldman, Sachs & Co. Jacques earned a B.S. in applied mathematics from Brown University and an M.S. in applied mathematics from the University of Washington. Before joining Goldman, he was pursuing a Ph.D. in applied mathematics at Washington, where his research interests ranged from mathematical physics to quantitative methods for sports handicapping.

Lukasz Pomorski, Ph.D., Vice President

Lukasz is a senior strategist in AQR's Global Stocks Selection group, where he conducts research on equity markets and engages clients on equity-related issues. Prior to AQR, he was an Assistant Director for Research in the Funds Management and Banking Department of the Bank of Canada and an Assistant Professor of Finance at the University of Toronto. His research has been published in top academic journals and won several awards, including the first prize award at 2010 Chicago Quantitative Alliance Academic Paper Competition, 2011 Toronto CFA Society and Hillsdale Canadian Investment Research Award, and the 2013 Best Paper Award from the Review of Asset Pricing Studies. Lukasz earned a B.A. and M.A. in economics at the Warsaw School of Economics, an M.A. in finance at Tilburg University, and a Ph.D. in finance at the University of Chicago.

Disclosures

Category Descriptions

We follow the process described in details in Petajisto (2013). We focus on all actively managed domestic equity mutual funds over the period 1990-2009. We use the data on funds' Active Share and tracking error that we downloaded from Petajisto's website, http://www.petajisto.net/data.html . Petajisto (2013) and Cremers and Petajisto (2009) computed active share (tracking error) from mutual fund holdings reported in the Thomson Reuters database (from daily mutual fund returns, primarily from the CRSP mutual fund database).

To construct the portfolios, we sort funds first on active share and then on tracking error, into quintiles of these two variables. We follow C&P in our Tables 1 and 2 and sort funds across the whole universe, regardless of benchmark. In our Table 3 we sort funds separately within each benchmark.

The allocation to portfolios is as described in Table 3 of Petajisto (2013). Closet Indexers (P1) are funds in the bottom quintile of Active Share and the four bottom quintiles of tracking error; Moderately Active (P2) are funds in quintiles 2-4 of Active Share and quintiles 1-4 of tracking error; Factor Bets (P3) are funds in quintiles 1-4 of Active Share and the top quintile of tracking error; Concentrated (P4) are funds in the top quintile of Active Share and top quintile of tracking error; Stock Pickers (P5) are funds in the top quintile of Active Share and quintiles 1-4 of tracking error.