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THE DIMINISHING ROLE OF ACTIVE MUTUAL FUNDS: FLOWS AND RETURNS

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U.S. active equity mutual funds have experienced net outflows since around 2006. The AUM-weighted performance remains similar over time, but equal-weighted performance (which emphasizes small AUM active funds) has deteriorated. Inflows/outflows contribute to the over/underperformance of individual active funds. We estimate that the flow-impact on annualized alpha for aggregated active funds industry was a positive 0.33% between 1/1991 and 12/2005, but it was a negative −0.10% between 1/2006 and 9/2021. If the current flow trend continues, the AUM of active mutual funds will drop to 17% of the total AUM of equity funds after 15 years.

1 Introduction

The U.S. active equity mutual fund industry has undergone dramatic change during the last 30 years, with persistent underperformance and net outflows, accompanied by decreasing expense ratios. Decreases in expense ratios did not seem to meaningfully improve *net* returns for investors and did not halt the net outflow trend. We study how both the *performance* and *flows* of U.S. active equity mutual funds have evolved over the last 30 years and extrapolate from the past to forecast the continuing diminishing role of active equity mutual funds.

The *great migration* from active mutual funds into passive funds started around 2006. Since then, we calculate that the cumulative net outflows for U.S. active equity mutual funds were about 2.20 trillion dollars. In contrast, index equity mutual funds and exchange-traded funds (ETFs) together have enjoyed 1.48 trillion dollars of cumulative net inflows during the same period.[1]

Bad relative after-fee performance likely contributed to the net outflows. Consistent with the "arithmetic of active management" (Sharpe, 1991), Fama and French (2010) find that in aggregate, active mutual funds realize net returns

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that underperform CAPM, three-factor, and four-factor benchmarks by expense ratios from 1984 to 2006. The reported analyses on net returns suggest that very few fund managers have enough skill to cover costs.

On a more positive note for active mutual funds, the literature supports the idea that active managers help to eliminate market anomalies and inefficiencies created by the misbehavior of investors (such as noise traders; e.g., Wermers, 2021). The diminishing market share of active mutual funds relative to passive funds might suggest that the market may become less efficient, and thus create opportunities for active managers. We want to emphasize that much of this paper focuses on "active mutual funds," which is only one form of "active management." It is important not to conflate the diminishing role of active equity mutual funds with a diminishing role of active management.

The great migration from active to passive and corresponding fund flows may in fact impact the performance of active mutual funds. Lou (2012) presents the *flow-induced-price-pressure-hypothesis* (or flow-driven-return-effect) and shows that flow-induced-trading has little to do with stock-picking ability, but can cause significant price pressure. This flow-driven-return-effect can fully account for fund performance persistence and partially explain stock price momentum. Using daily returns data, Staer (2017) finds that ETF flows exhibit a statistically significant and cross-sectionally consistent positive association with contemporaneous underlying index returns, supporting the flow-driven-return-effect. Zhu and Woltering (2021) document that the performance of individual mutual funds is positively affected by spillover effects from fund flows to connected mutual funds through overlapping portfolio holdings. More recently, Gabaix and Koijen (2022) develop the *Inelastic Markets Hypothesis*—flows in and out of the stock market have large impacts on prices when the price elasticity of demand of the aggregate stock market is small.

The flow-driven-return-effect implies that flows influence fund returns. Since flows also *chase* outperforming funds, positive (negative) returns can result in *future* inflows (outflows). The flow-driven-return-effect is more on the relation between *contemporaneous* flows and returns, instead of returns and *future* flows.

In this paper, we quantify the impact of flow on the performance of active equity mutual funds. We break the 30-year period into two 15-year periods mainly because aggregated active funds experienced net inflows prior to 2006 and net outflows starting in 2006. Along the way, we update parts of the Fama and French's (2010) results with the latest 15+ years of data (from 2006 to 2021).[2]

We address four questions. First, what is the performance (gross and net alphas) for active and passive funds in the most recent 15+ year period? Second, how does small AUM active mutual funds' performance compare to large AUM active mutual funds' in these two periods?[3] Third, how does the fund flow influence performance for active mutual funds? Fourth, what is the future of active mutual funds? The first three answers are empirical in nature, while the fourth involves extrapolating from the empirical observations into the future.

2 Description of Data

Our study focuses on U.S. domestic equity funds and most of our analyses are on active mutual funds. The universe of U.S. domestic equity funds includes 4,638 active mutual funds, 350 index mutual funds, and 528 passive exchange-traded funds (ETFs) with valid data.[4] The monthly Morningstar assigned benchmarks, *gross* and *net* returns, and fund sizes or assets under managements (AUMs) for these funds (both live and defunct), are all collected from Morningstar Direct from January 1991 to September 2021.[5] Each unique fund's AUM is *aggregated* from all of its share classes. Gross and net returns from the oldest share class are used for each fund.[6] The data for ETFs start in January 2000. New funds (inception date January 2019 or more recently) with a history of shorter than two years and nine months are excluded.

We limit our analyses to funds that have AUM of \$5 million as of January 2006 dollars to mitigate the incubation bias. AUM minimums in other months are inflation adjusted by using the US CPI-U Index. The corresponding AUM minimum is \$3.4 million in January 1991, and \$6.9 million in September 2021. Monthly percentage flows for each fund are restricted between −50% and 100% to avoid outliers and potentially incorrect data. Monthly percentage flows are positively skewed.

Figure 1 shows the fund size, or AUM distribution, for active mutual funds at the beginning, middle, and ending month of our data coverage. Note that the horizontal axis is in log-scale. The AUM distributions for the three snapshots in time appear to be approximately lognormally distributed. The median AUM grows from \$71 million in January 1991 to \$213 million in January 2006, and to \$587 million in September 2021.

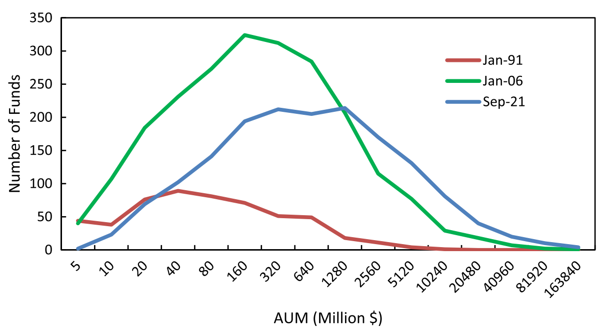

Figure 1 The AUM distribution of active mutual funds as of January 1991, January 2006, and September 2021 (x-axis is in log scale).

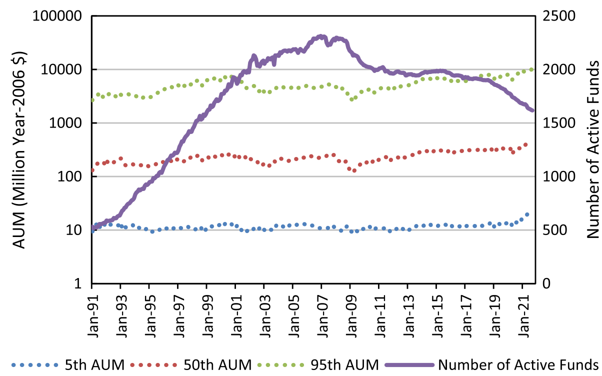

Figure 2 Number of active mutual funds and inflation-adjusted AUMs (as of Year-2006 \$) at selected percentiles over time.

Figure 2 shows the number of active mutual funds in our universe (right y-axis) and the inflation-adjusted AUMs (left y-axis in log scale based on Year-2006 dollars) at selected percentiles (5th, 50th, and 95th) over time. The number of funds increases dramatically from 533 as of January 1991 to 2,211 as of December 2005. The number of funds peaks at 2,313 as of December 2006, and then shrinks to 1,618 as of September 2021, in which the decrease in funds is arguably attributed to the persistent fund outflows in the second period. In each month, we sort the active fund AUMs into percentiles and show the 5th, 50th, and 95th percentiles' AUMs in Figure 2. The inflation-adjusted AUMs at the three selected percentiles have increased 115%, 230%, and 284% over the 30-year period, respectively, even though they all appear flat in log scale. The inflation-adjusted growth of the median active fund size has been relatively small compared to the inflation-adjusted growth of about 530% for the U.S. stock market cap over the same period. This suggests that the distribution of fund sizes is relatively stable over the last 30 years.

3 The Performance of Active Mutual Funds and Passive Funds

The performances for the three fund universes (active mutual funds, index mutual funds, and ETFs) are summarized in Table 1. Gross or Net returns are *aggregated* (either asset-weighted or equal-weighted) for each of the three fund universes in each month. Asset-weighted is simply weighted on asset-under-management (AUM) or AUM-weighted. The top panel (Panel A) covers the 30-year period from January 1991 to September 2021, the mid panel (Panel B) contains the January 1991 to December 2005 (the first period) results, and the bottom panel (Panel C) contains the January 2006 to September 2021 (the second period) results. Panel B and C compare the two periods, while Panel A is presented for a full picture. ETFs only have performance results in the second period. Each of the three panels is then subdivided with the top section containing the results based on gross returns and the bottom section containing results based on net returns. All numbers in Table 1 are annualized.[7]

Annualized alphas are shown in the last four columns in Table 1. We use four methods to estimate alphas (see Appendix for details):

(1) Simple Alpha, defined as fund's return over its Morningstar assigned benchmark return (such as Russell 1000 Growth Index return).
(2) FFC Alpha, defined from the Fama—French and Carhart Four-Factor Model (Carhart, 1997).
(3) IDX4 Alpha, defined from a less biased FFC Model—The Index-Based Four-Factor Model as documented in Cremers *et al.* (2013).
(4) IDX3 Alpha, defined from the Index-Based Three-Factor Model. It is formed by removing the Momentum factor from the IDX4 model.

The performance of active mutual funds is comparable to index funds on *asset-weighted gross* returns for both time periods. Active mutual funds outperformed index funds by annualized 23 bps and 7 bps on *geometric means* (G.M.) during

Table 1 Summary statistics for aggregated active mutual funds, index mutual funds and ETFs for gross and net returns.[a]

A. Both periods (1/1991–9/2021)

1/1991–9/2021	*Gross*	G.M.	St. Dev.	Simple alpha	IDX3 alpha	IDX4 alpha	FFC alpha
Gross returns							
Asset-weighted	Active	11.30%	15.01%	0.16%	0.30%	0.15%	−0.10%
	Index	11.16%	14.81%	−0.06%	0.04%	0.04%	0.08%
Equal-weighted	Active	11.93%	15.49%	0.45%	**0.82**%	**0.71**%	0.17%
	Index	11.47%	15.26%	0.06%	0.20%	0.30%	0.05%
Net returns							
1/1991–9/2021	*Net*						
Asset-weighted	Active	10.35%	15.04%	−**0.68**%	−0.57%	−**0.71**%	−**0.97**%
	Index	10.92%	14.80%	−**0.26**%	−0.18%	−0.17%	−0.13%
Equal-weighted	Active	10.66%	15.47%	−**0.70**%	−0.33%	−0.42%	−**0.96**%
	Index	10.89%	15.26%	−**0.43**%	−0.32%	−0.21%	−0.48%

Table 1 (*Continued*)

B. First period (1/1991–12/2005)

1/1991–12/2005	*Gross*	G.M.	St. Dev.	Simple alpha	IDX3 alpha	IDX4 alpha	FFC alpha
Gross returns							
Asset-weighted	Active	12.07%	14.25%	0.44%	0.39%	−0.16%	−0.44%
	Index	11.84%	14.08%	−0.16%	**0.21**%	0.11%	0.48%
Equal-weighted	Active	13.60%	14.54%	**1.05**%	**1.48**%	**1.06**%	0.31%
	Index	12.47%	14.27%	0.01%	0.41%	0.43%	0.27%
Net returns							
1/1991–12/2005	*Net*						
Asset-weighted	Active	11.03%	14.34%	−0.47%	−0.49%	**−1.05**%	**−1.31**%
	Index	11.55%	14.07%	−0.40%	−0.05%	−0.15%	0.23%
Equal-weighted	Active	12.20%	14.52%	−0.20%	0.23%	−0.18%	−0.90%
	Index	11.84%	14.30%	**−0.47**%	−0.16%	−0.12%	−0.30%

C. Second period (1/2006–9/2021)

1/2006–9/2021	*Gross*	G.M.	St. Dev.	Simple alpha	IDX3 alpha	IDX4 alpha	FFC alpha
Gross returns							
Asset-weighted	Active	10.58%	15.73%	−0.10%	−0.17%	−0.16%	−0.33%
	Index	10.51%	15.51%	0.04%	0.01%	0.02%	−0.17%
	ETFs	10.39%	15.54%	0.03%	0.03%	0.03%	−0.21%
Equal-weighted	Active	10.36%	16.37%	−0.12%	−0.01%	0.00%	−0.42%
	Index	10.53%	16.19%	0.10%	0.21%	0.22%	−0.12%
	ETFs	10.11%	16.39%	0.05%	0.32%	0.34%	−0.18%
Net returns							
1/2006–9/2021	*Net*						
Asset-weighted	Active	9.72%	15.73%	**−0.89**%	**−0.96**%	**−0.95**%	**−1.12**%
	Index	10.32%	15.50%	−0.13%	−0.15%	−0.15%	**−0.34**%
	ETFs	10.23%	15.55%	−0.12%	−0.13%	−0.13%	−0.36%
Equal-weighted	Active	9.22%	16.36%	**−1.17**%	**−1.05**%	**−1.04**%	**−1.46**%
	Index	9.98%	16.18%	**−0.39**%	−0.28%	−0.27%	**−0.61**%
	ETFs	9.77%	16.40%	−0.28%	−0.01%	0.02%	−0.52%

[a]Alphas in bold numbers are significant at the 5% level.

the first (1991–2005) and second period (2006–2021), respectively. However, *equal-weighted* active fund gross returns showed significant deterioration in the second period. Continuing with *gross geometric mean* returns, active mutual funds outperformed index funds by annualized 113 bps during the first period, but they underperformed index funds by annualized 17 bps during the second period.

The four measures of alphas show largely consistent performance results across Table 1 despite some small inconsistencies:

(1) Asset-weighted *gross* alphas for both active mutual funds and index funds are statistically insignificant from zero for both periods except the IDX3 alpha for index funds in the first period.
(2) Comparisons between estimated IDX3 and IDX4 alphas show that IDX3 alpha tends to be higher than IDX4 alpha for active mutual funds in the first period; however, they are nearly the same in the second period. A positive momentum factor loading and positive momentum premium can explain the higher IDX3 alpha in the first period.
(3) The FFC estimated alpha is lower than simple alpha and IDX4 estimated alpha for aggregated active mutual funds in both periods. It is consistent with the findings of Cremers *et al.* (2013) because active mutual funds in aggregate tend to have a higher SMB factor loading than index funds, which suppresses the FFC alpha of active mutual funds.
(4) Equal-weighted *gross* alpha for active mutual funds is higher than that for index funds in the first period, but not in the second period. Moreover, equal-weighted simple *gross* alpha, IDX3 *gross* alpha and IDX4 *gross* alpha for active mutual funds are significantly positive in the first period.

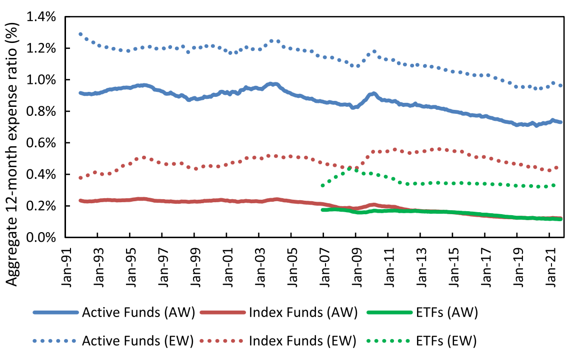

Figure 3 Asset-weighted (AW) and equal-weighted (EW) expense ratios for active mutual funds, index mutual funds, and ETFs through time.

The expense ratios can largely explain the differences between gross and net returns for both active and index funds. Figure 2 shows the asset-weighted and equal-weighted expense ratios for active mutual funds, index funds, and ETFs. On average, the asset-weighted expense ratios for active mutual funds are about 70 bps higher than index funds. Also, the asset-weighted expense ratios have slightly decreased over time for active mutual funds, index funds, and ETFs.

Based on *net* returns, active mutual funds underperformed index funds in most of the comparisons in both periods, with the exception that they outperformed index funds in equal-weighted geometric means during the first period. This is not surprising given that: (1) active mutual funds have higher expense ratios than index funds, and (2) the equal-weighted performance of active mutual funds has deteriorated in the second period.

Finally, based on geometric means, ETFs slightly underperformed index funds by 0.12% and 0.09% in the second period for *asset-weighted* gross and net returns, respectively. ETFs underperformed index funds by 0.42% and 0.21% in the second period for *equal-weighted* gross and net returns, respectively. However, the differences in alphas between ETFs and index funds are smaller than the differences in geometric means.

The results for the first period in Panel A of Table 1 are consistent with those reported in the literature, especially Fama and French (2010). In contrast with both the results of Panel A and those of Fama and French (2010) results, Panel B of Table 1 shows that the equal-weighted performance for active mutual funds in the second period is worse than the first period. In other words, small AUM active funds tend to outperform large AUM active funds in the first period, but not in the second period.

4 The Performance of Active Mutual Funds in Bad Markets

An interesting question is "Can active mutual funds add more value in bad markets?" Looking at an earlier time period, Moskowitz (2000) reports some evidence that active funds perform better during recessions (1975–1994). Kosowski (2006) suggests that traditional unconditional performance measures understate the value added by active funds (1962–2005) in recessions. In contrast, Pastor and Vorsatz (2020) find that most active funds underperform passive benchmarks during the more recent COVID crisis, suggesting that the equal-weighted outperformance of active funds in bad markets might have declined.

Table 2 shows annualized gross alphas during three crisis periods and the bad markets in the two periods for equal-weighted active and index funds. Alphas for these selected periods are calculated as average excess returns or factor-adjusted returns, i.e., $(\alpha + e_t)$ in Equation (A.1) shown in Appendix. The three crisis periods are the Internet Bubble Burst (1/2000–12/2002), the Global Financial Crisis (GFC, 9/2008–3/2009), and the COVID Crisis (2/2020–3/2020). The bad markets are defined as when S&P 500 returns are one standard deviation below its mean (standard deviation and mean are measured over the full 30-year period).

Table 2 shows that active funds outperformed index funds on equal-weighted gross alphas during the Internet Bubble Burst and the GFC, but underperformed index funds during the COVID crisis using all four alpha measures except for IDX3 alpha during GFC. Active funds outperformed index funds in equal-weighted gross alphas during bad markets in the first period, but the outperformance diminishes during bad

Table 2 Annualized gross alphas under three crisis periods and bad markets for equal-weighted active and index funds.

		Internet bubble burst	GFC	COVID crisis	Bad markets in first period	Bad markets in second period
Simple alpha	Active	3.22%	3.87%	−3.01%	5.64%	0.91%
	Index	0.49%	1.52%	−0.95%	−0.60%	0.16%
IDX3 alpha	Active	3.18%	1.03%	−9.04%	3.27%	0.07%
	Index	1.20%	1.25%	−4.81%	1.43%	0.37%
IDX4 alpha	Active	2.99%	1.44%	−8.68%	3.05%	0.27%
	Index	1.40%	0.84%	−5.17%	1.65%	0.17%
FFC alpha	Active	2.90%	−0.08%	−10.67%	2.92%	−0.99%
	Index	1.63%	−0.76%	−4.57%	1.27%	−0.94%

markets in the second period. For IDX4 gross alpha, the equal-weighted outperformance of active funds over index funds decreases from 1.35% (= 3.05% − 1.65%) in bad markets of the first period to 0.10% (= 0.27% − 0.17%) in bad markets of the second period. All the observations in Table 2 are consistent with the related literature and Table 1.

5 The Distribution of Alphas for Individual Active Mutual Funds

Table 1 shows that the equal-weighted performance of active mutual funds has worsened for the second period at the aggregated level, moving from outperformance to underperformance. We now investigate the distribution of individual alphas for all active mutual funds in the two periods. The results are similar for all four measures of alphas. Thus, to save space, we only report results for the IDX4 alphas from now on. The IDX4 alphas are highlighted because they fall somewhere between simple alphas and FFC alphas on asset-weighted performance shown in Table 1.

Once a fund passes $5 million in AUM (in 1/2006 dollars) all returns after that month are included in subsequent tests (even if the AUM subsequently drops below the threshold). In each period, funds are required to have at least 12 months of data. We focus on $t(\alpha)$ – the t-statistic of α– rather than estimates of α, to control for differences in precision due to differences in residual variance and in the number of months. Many funds do not have a full history for the 15-year period so that alphas cannot be compared on the same footing.

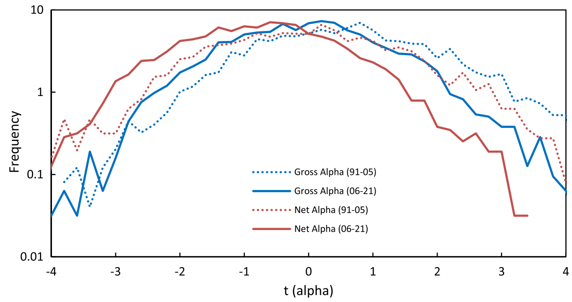

Figure 4 Distributions for t-statistics of gross and net alphas for two periods for active mutual funds.

The loadings to the four IDX4 factors are estimated for each fund and for each 15-year period. Figure 4 shows the distribution of $t(\alpha)$ for the IDX4 alphas for the two periods in log scale so that the tails of the distribution can be seen more clearly. For both gross and net alphas, the entire $t(\alpha)$ distribution curve is shifted to the left from the first period to the second period, which is consistent with the underperformance of active mutual funds on equal-weighted basis in the second period shown in Table 1.

Table 3 shows the percentage of funds that have significant positive ($t(\alpha) \geq 2$, superior funds) or negative ($t(\alpha) \leq -2$, inferior funds) performance. With gross returns, the number of superior funds (17.19%) is much more than the number of inferior funds (3.32%) in the first period, but the number of superior funds (6.00%) is nearly the same as the number of inferior funds (5.69%) in the second period. With net returns, the number of inferior funds (9.55%) is about the same as the number of superior funds (9.39%) in the first period. In contrast, the number of inferior funds

Table 3 Percentage of funds with significant negative or positive alphas.

	$t(\alpha) \leq -2$, Inferior funds		$t(\alpha) \geq 2$, Superior funds	
	1/1991–12/2005	1/2006–9/2021	1/1991–12/2005	1/2006–9/2021
Gross alphas	3.32%	5.69%	17.19%	6.00%
Net alphas	9.55%	17.25%	9.39%	1.74%

(17.25%) is much more than the number of superior funds (1.74%) in the second period, which is not good news for more recent active investors. Overall, it was more difficult to select a superior active mutual fund in the second period.

6 The Flow Trend for Active Mutual Funds

It is well documented that fund flows respond to past performance. For example, Barber *et al.* (2016) find that CAPM alphas are the best predictor of flows among competing performance evaluation methods. In the absence of adequate skill, higher fees make it inevitable that aggregate net returns will be worse, thus outflows would seem nearly unavoidable.

Figure 5 shows the active market share over the last 30 years, where active market share is defined as the ratio of active AUM to total (active + passive) AUM. We combine index funds and ETFs into passive funds even though some cautions are in order.[8] We plot the active market share in Figure 5.

At the far left of Figure 5, back in 1991 active AUM represented 97% of the total U.S. fund market. Interestingly and perhaps ironically, Sharpe's "arithmetic of active management," which makes it very clear that after fees and in aggregate active management is losing proposition, was published in 1991.[9] As shown in Figure 5, the percentage

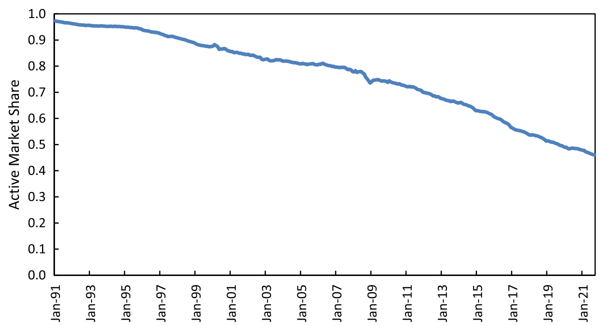

Figure 5 The great migration | ratio of total active AUM to total active + passive AUM.

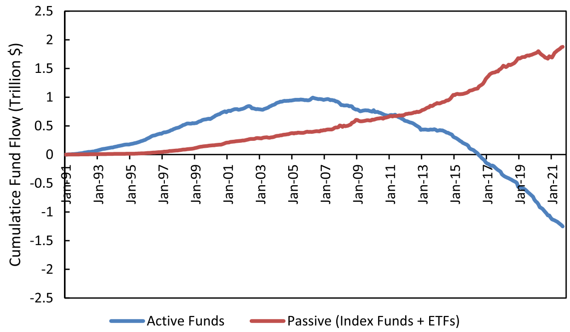

Figure 6 Cumulative net dollar flows into active and passive funds.

of total AUM in active mutual funds has been in steady decline, dropping to 46% as of September 2021. A simple linear fit of the trend over the complete time period suggests that the active mutual funds will almost disappear relative to passive funds in approximately 30 years or 2051. We forecast the active share by using more information in the final section.

Figure 6 shows that the cumulative dollar flows into active mutual funds, index funds, and ETFs. The fund dollar flow into a fund ($Flow_t$) is calculated from three quantities: last month's AUM (A_{t-1}), this month's AUM (A_t), and fund net return (r_t) via Equation (1):

$$Flow_t = A_t - A_{t-1}(1 + r_t) \tag{1}$$

Equation (1) assumes that *dollar* flows occur at the end of month t. *Percentage* flow is simply dollar flow divided by last month's AUM (A_{t-1}). The flows for active mutual funds have been negative since around 2006, while the flows for index funds and ETFs have been positive for most of the time. As mentioned earlier, the cumulative net *outflows* for active mutual funds were 2.20 trillion dollars from January 2006 to September 2021. In contrast, the cumulative net *inflows* during the same period for index mutual funds and exchange traded funds (ETFs) are 0.38 and 1.10 trillion dollars, respectively.

Looking at percentage flows, the arithmetic average monthly flow for active mutual funds is 0.65% (net inflow) from January 1991 to December 2005 and drops to −0.33% (net outflow) from January 2006 to September 2021. In contrast, the arithmetic average monthly net flow for index funds and ETFs are 0.28% and 0.73% from January 2006 to September 2021, respectively.

Further analysis shows that net outflows in active mutual funds have largely been offset by net inflows into ETFs alone. The correlation between dollar flows into the active mutual and index mutual funds is 23%, while the correlation between active mutual funds and ETF dollar flows is −30%, from January 2006 to September 2021.

7 The Performance of Small AUM Active Mutual Funds

To better understand the inconsistent performance of small AUM active mutual funds over the two periods, we conduct a cross-sectional analysis on alphas sorted by fund AUM size for each month. More specifically, starting in January 1991 and using the gross returns to calculate the IDX4 gross alpha, active mutual funds are sorted from lowest to highest AUMs as of December 1990, and they are assigned to one of the five quintiles so that each quintile has nearly the same number of funds. Note that this single-month alpha is $(\alpha + e_t)$ in Equation (A.1) shown in Appendix, which is the excess return or factor-adjusted return for month-t. The corresponding alphas are averaged with equal weights for each quintile. This process is repeated in each month and then averaged from 1/1991 to 9/2021 for both periods, and then from 1/1991 to 12/2005 for the first period, and finally from 1/2006 to 9/2021 for the second period.

The average *annualized* alphas sorted on fund sizes for active mutual funds for the entire 30-year period, and the two separate 15-year periods are shown in Table 4. The results for the 30-year period are roughly the average results of the two 15-year periods. The second to last column in Table 4 is the difference in average alphas

Table 4 The average annualized gross alphas sorted on active mutual fund size.

	Small AUM funds (Q1)	(Q2)	(Q3)	(Q4)	Large AUM funds (Q5)	Small–large	t-Statistic
1/1991–9/2021 (Both Periods)							
Avg. AUM (million $)	22	89	255	727	5717	N/A	N/A
Alpha	1.37%	0.91%	0.66%	0.35%	0.25%	1.13%	5.40
1/1991–12/2005 (First period)							
Avg. AUM (million $)	17	65	174	481	4002	N/A	N/A
Alpha	2.70%	1.77%	1.24%	0.63%	0.33%	2.36%	7.18
1/2006–9/2021 (Second period)							
Avg. AUM (million $)	27	112	333	961	7349	N/A	N/A
Alpha	0.13%	0.10%	0.11%	0.09%	0.17%	–0.04%	–0.17

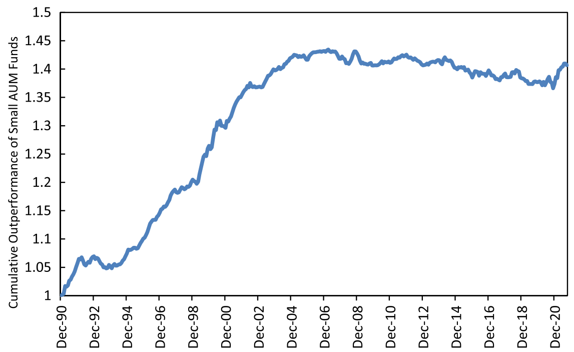

Figure 7 The cumulative excess gross alpha of the small AUM quintile over the large AUM quintile active mutual funds.

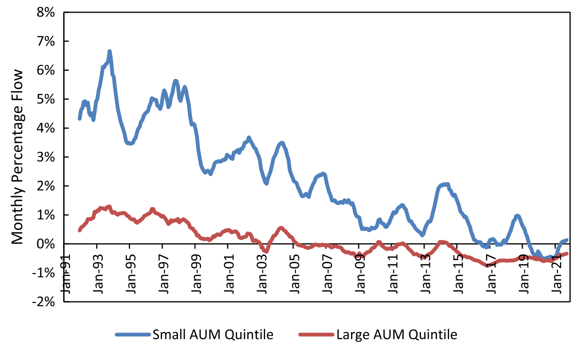

Figure 8 Rolling average 12-month average percentage flows into small AUM and large AUM quintile active mutual funds.

between small AUM and large AUM funds. The last column of Table 4 shows t-statistics for the difference in average alphas. The alpha difference between small AUM funds and large AUM funds is 2.36% which is statistically significant for the first period, but insignificant at -0.04% for the second period.[10]

The cumulative alpha differences between the small AUM and large AUM active mutual funds are plotted in Figure 7. Small AUM funds outperformed large AUM funds in the first period, but they slightly underperformed in the second period. Clearly, the excess performance that small AUM funds enjoyed over the first period disappeared over the second period.

Figure 8 shows the rolling 12-month average percentage flows for the small AUM and large AUM active mutual funds over the 30-year period. It shows negative trend for both fund AUM groups. The slope of the percentage flow for small AUM funds is about 2.5 times the slope for the large AUM funds, indicating a much faster drop of percentage flow for small AUM funds. Small AUM funds have higher average percentage flows (3.75%) than large AUM funds (0.54%) in the first period. In contrast, the average percentage flow for small AUM funds (0.74%) is not far away from that for large AUM funds (-0.33%) in the second period. Large AUM funds are much larger than small AUM funds, so they tend to have smaller magnitudes of percentage flows.

Figure 7 raises an interesting question: why has the performance of small AUM funds deteriorated in the second period? Our data includes defunct funds so that survivorship bias is not a main factor. Figures 7 and 8 suggest that consistently reduced flows are associated with deteriorated performance of the small AUM funds.

We argue that the *flow-driven-return-effect*, documented in Lou (2012), can be one of the factors that drive small AUM funds to outperform large AUM funds in the first period. Flow-driven-return-effect means that flows in and out of funds influence performance. It has little to do with skill, and it is more related to liquidity and trading costs. Extrapolating from Lou (2012), when funds experience immediate large outflows, liquidity is low and trading costs can be high, which can drag down the performance or alphas. Conversely, funds experiencing large inflows can create price pressure in the stocks held in common by these funds, helping them to earn abnormal returns (see Coval and Stafford, 2007). Therefore, steady inflows can lift performance, while steady outflows can drag down performance for active mutual funds. We quantify this impact next.

8 The Impact of Flow on Active Mutual Fund Performance

In this section, we focus on *gross* returns and study the impact of contemporaneous flow on performance for active mutual funds while controlling for fund size using two methods: (1) a time-series of cross-sectional regressions in the spirit of Fama–MacBeth (1973) for statistical significance; and (2) building 25 composite portfolios that are double-sorted on fund sizes and fund flows for economic significance.

Method 1: *Time-Series of Cross-Sectional Regressions*

For the first method, the dependent variable is the fund's factor-adjusted return or IDX4 alpha in month t: Alpha_t. Independent variables are fund's contemporaneous monthly percentage flow: Flow_t; fund's last month percentage flow: Flow_{t-1}; fund's last month alpha: Alpha_{t-1}; and the log of fund's AUM at the end of month $t-1$: FSize_{t-1}.

The regression equation for IDX4 alphas is:

$$\begin{aligned} Alpha_t = a &+ \text{b}_1 \cdot \text{Flow}_t \\ &+ \text{b}_2 \cdot \text{Flow}_{t-1} \\ &+ \text{b}_3 \cdot \text{Alpha}_{t-1} \\ &+ \text{b}_4 \cdot \text{FSize}_{t-1} + e_t \end{aligned} \tag{2}$$

Table 5 shows the regression results of alphas on contemporaneous fund flows while controlling for lagged fund sizes, lagged flows, and lagged alphas for all active mutual funds. All regression coefficients for the 30-year period are roughly equal to the average values of the corresponding coefficients for the two 15-year periods. The coefficient on contemporaneous flows is significantly positive in both periods, but it is nearly cut by half in the second period. It means that a monthly percentage inflow of 1% will increase annualized alpha by 0.171% in the first period, and by 0.089% in the second period.

The flow impact is mechanically related to the price impact of underlying fund holdings when funds trade. Our estimates show that the average Amihud illiquidity measure (Amihud, 2002) for all U.S. stocks is cut by nearly half from the first period to the second period, suggesting that the price impact of stock market is cut by half over the two periods. In turn, higher liquidity or lower price impact in the stock market can reduce the flow impact in the second period.

The coefficient on lagged alpha is significantly positive (0.068) in the first period, but insignificant (0.023) in the second period. This is the fund performance persistence well documented in the literature (e.g., Carhart, 1997). It is interesting to note that the performance persistence is no longer significant in the second period. The coefficient on fund size is significantly negative in the first period, but insignificantly positive in the second period, which is consistent with Table 4 and Figure 7 in which small AUM funds outperformed large AUM funds in the first period, but not in the second period.

Method 2: *Double sorts on fund size and fund flows*

Second, a double sort is conducted on fund sizes and fund flows. Once again, flows and alphas are contemporaneous. For each month, we first sort the active fund universe into five quintiles based on fund size (Small AUM S1 through Large AUM S5). Then, within each size quintile, we sort the funds into five quintiles based on monthly percentage flow (Low Flow F1 through High Flow F5). Thus, we have 25 composites (i.e., five S1 composites, five S2 composites, and so on). We then calculate equal-weighted alphas for each 1 of the 25 composites in each month, and then take average over the two 15-year periods. Panel A of

Table 5 Regression of alphas on flows and fund sizes for active mutual funds.[a]

	Intercept	$Flow_t$	$Flow_{t-1}$	$Alpha_{t-1}$	$Fsize_{t-1}$
1/1991–9/2021 (Both periods)					
$Alpha_t$	0.030	0.129	0.011	0.045	−0.001
t-Stat	3.86	14.92	1.58	4.48	−3.59
1/1991–12/2005 (First period)					
$Alpha_t$	0.066	0.171	0.021	0.068	−0.003
t-Stat	5.08	12.38	1.92	4.69	−4.86
1/2006–9/2021 (Second period)					
$Alpha_t$	−0.004	0.089	0.002	0.023	0.0003
t-Stat	−0.49	9.12	0.20	1.67	0.63

[a]Percentage flows are monthly and IDX4 alphas are annualized.

Table 6 reports the double sort results for the 30-year period, while Panel B and Panel C report the double sort results for the first and second periods, respectively. Our interest is more on Panels B and C, and Panel A is approximately the average of Panels B and C. Within each panel, the top five rows report the average percentage flows, and the bottom five rows report the average IDX4 alphas for the 25 composites.

Table 6 Panel B shows two monotonic relations: (1) between fund size and alpha, and (2) between fund flow and alpha within each size quintile. By taking average along each column of the bottom five rows, one recovers the mid panel of Table 4 in which fund size is monotonically associated with performance or alpha. Within each column or each fund size quintile, the IDX4 alphas monotonically increase with increased fund flows. The

Table 6 Double sorts on size and flow for gross alphas for all active mutual munds.[a]

	Small AUM (S1)	S2	S3	S4	Large AUM (S5)
Panel A. Both periods (1/1991–9/2021)					
Flow					
Low flow (F1)	−5.21%	−5.20%	−4.56%	−4.05%	−2.89%
F2	−0.74%	−1.09%	−1.12%	−1.08%	−0.86%
F3	0.39%	−0.07%	−0.21%	−0.26%	−0.19%
F4	2.23%	1.35%	1.02%	0.82%	0.63%
High flow (F5)	14.20%	9.45%	7.42%	5.85%	3.73%
IDX4 alpha					
Low flow (F1)	0.37%	−0.36%	−0.38%	−0.89%	−0.93%
F2	0.28%	0.08%	−0.14%	−0.33%	−0.46%
F3	0.96%	0.37%	0.49%	0.25%	0.18%
F4	1.60%	1.41%	0.84%	0.61%	0.73%
High flow (F5)	3.67%	3.04%	2.48%	2.12%	1.73%

[a]Percentage flows are monthly and IDX4 alphas are annualized.

Table 6 (*Continued*)

	Small AUM (S1)	S2	S3	S4	Large AUM (S5)
Panel B. First period (1/1991–12/2005)					
Flow					
Low flow (F1)	−4.80%	−5.03%	−4.27%	−3.87%	−2.64%
F2	−0.37%	−0.78%	−0.85%	−0.86%	−0.62%
F3	0.98%	0.41%	0.24%	0.12%	0.12%
F4	3.66%	2.38%	1.87%	1.47%	1.10%
High flow (F5)	18.98%	12.63%	9.82%	7.64%	4.65%
IDX4 alpha					
Low flow (F1)	1.43%	0.06%	−0.44%	−1.42%	−1.42%
F2	0.94%	0.48%	−0.01%	−0.50%	−0.84%
F3	2.16%	0.88%	0.94%	0.59%	0.32%
F4	3.01%	2.51%	1.57%	1.08%	1.40%
High flow (F5)	5.98%	4.92%	4.13%	3.43%	2.23%
Panel C. Second period (1/2006–9/2021)					
Flow					
Low flow (F1)	−5.61%	−5.36%	−4.84%	−4.23%	−3.14%
F2	−1.09%	−1.38%	−1.37%	−1.29%	−1.09%
F3	−0.18%	−0.53%	−0.64%	−0.62%	−0.50%
F4	0.86%	0.37%	0.20%	0.19%	0.18%
High flow (F5)	9.66%	6.42%	5.14%	4.15%	2.86%
IDX4 alpha					
Low flow (F1)	−0.62%	−0.75%	−0.32%	−0.38%	−0.46%
F2	−0.34%	−0.31%	−0.27%	−0.17%	−0.09%
F3	−0.18%	−0.11%	0.06%	−0.07%	0.04%
F4	0.28%	0.37%	0.15%	0.16%	0.10%
High flow (F5)	1.51%	1.28%	0.93%	0.89%	1.25%

only exception is that the average alpha for the lowest flow quintile (1.43%) is higher than that for the second-lowest flow quintile (0.94%) for small AUM funds.

Panel B of Table 6 shows that contemporaneous flows can have strong impact on performance. For example, the highest flow quintile (with monthly percentage flow of 18.98%) for the smallest AUM quintile is associated with 5.98% alpha. A fund experienced high inflows can boost its performance due to flow impact which has nothing to do with skills.

We estimate the flow impact using Table 6 (Panels B and C). The first column of Panel B in Table 6 shows that the spread in monthly percentage flows and the spread in annualized alphas are 23.78% (= 18.98% + 4.80%) and 4.55% (= 5.98% − 1.43%), respectively, across the five flow quintiles for small AUM funds in the *first* period. It suggests a flow impact of 0.19 (= 4.55/23.78) which is comparable to the flow coefficient of 0.171 shown in Table 5[11]. Likewise, the spread in monthly percentage flows and the spread in annualized alphas are 15.27% and 2.13%, respectively, for small AUM funds in the *second* period (Panel C). It suggests a flow impact of 0.14 which is comparable to the flow coefficient of 0.089 shown in Table 5.

On the other side, for large AUM funds, the flow impact is more than doubled at 0.50 and 0.29 for the first and second periods, respectively. Note that the average AUM for large AUM funds is about 200 times more than that for small AUM funds (Table 4). The dollar flows will be more than 200 times higher for large AUM funds given the same percentage flows, which can lead to a higher flow impact. In other words, net new inflows (or outflows) of 200 million dollars will have higher flow impact than net new inflows (or outflows) of 1 million dollars.

Figure 9 shows the impact of percentage flows on alphas for small AUM and large AUM funds for the two periods with the data taken from Table 6 (Panels B and C). There are at least two factors that contribute to the outperformance of small AUM active mutual funds in the first period:

(1) The average monthly percentage flow for small AUM funds (3.75%) is higher than that for large AUM funds (0.54%) in the first period. Given the above-mentioned flow impact of 0.19 and 0.50 for small AUM and large AUM funds, respectively, the flow impact on annualized alpha is 0.71% and 0.27% for small and large AUM funds, respectively.[12] In other words, flow impact helped small AUM funds to outperform large AUM funds by 0.44% (= 0.71% − 0.27%). This is relatively small compared to the 2.36% outperformance of small AUM funds shown in Table 4. Thus, other factors played a residual positive role of 1.92% (= 2.36% − 0.44%).[13]

(2) The slopes for most of the flow quintiles on the two dashed lines (the first period) are larger than the slopes for most of the flow quintiles on the two solid lines (the second period). It indicates that the average flow impact is higher in the first period as discussed earlier.

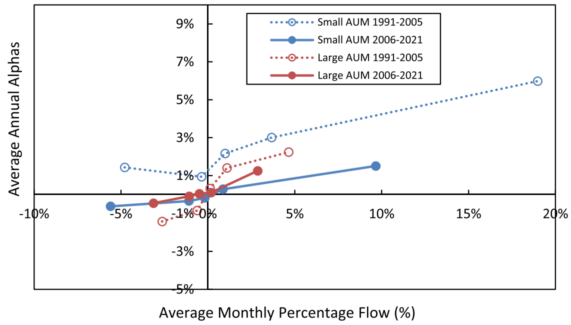

Figure 9 The impact of percentage flows on alphas for small and large AUM funds for the two periods.

It is interesting to note that there are three lines that cross the origin point (large AUM funds in both periods, and small AUM funds in the second period), except the dashed blue line (small AUM funds in the first period). Crossing the origin point is consistent with the flow-driven-return-effect: inflows lift performance and outflows drag down performance.[14] Thus, Figure 9 provides evidence to support the flow-driven-return-effect for large AUM funds in both periods, and for small AUM funds in the second period.

The two most negative flow quintiles for small AUM funds in the first period are associated with positive alphas, which is at odds with the flow-driven-return-effect. It suggests that, in addition to the flow-driven-return-effect, other factors have also contributed to increase the average alpha for small AUM funds in the first period as mentioned above.

During the second period, both percentage flow and flow impact have been lowered significantly for small AUM funds. The flow impact on alpha is 0.10% ($= 0.74\% * 0.14$) for small AUM funds and -0.10% ($= -0.33\% * 0.29$) for large AUM funds, so that the flow impact helped small AUM funds to outperform large AUM funds by 0.20%. However, Table 4 shows that small AUM funds underperform large AUM funds by 0.04%. Therefore, other factors have played a negative role of -0.24% in the second period, in contrast to a positive role in the first period. All these lead to deteriorated performance for small AUM funds in the second period.

Table 6 and Figure 9 show that flows have meaningful and important impact on performance for different flow quintiles. We now estimate the flow impact on the *aggregated* level for the active mutual funds industry. As mentioned earlier, the average monthly percentage flow for aggregated active mutual funds is 0.65% (net inflow) in the first period and drops to -0.33% (net outflow) in the second period. Given the above-mentioned flow impact of 0.50 (first period) and 0.29 (second period) for large AUM funds, the flow impact on annualized alpha is positive 0.33% for the first period and negative -0.10% for the second period, which leads to a change of -0.43% alpha across the two periods.[15] In other words, the negative flow trend has impacted the performance for the active fund industry by negative 0.43% over the last 30 years. This 0.43% is economically meaningful and is comparable to the expensive ratio difference ($\sim$0.70%) between active and index funds. The negative flow impact of -0.10% alpha in the second period is expected to continue in the future, and it is probably large enough to exert negative feedback on the active fund industry: bad net performance → outflows → additional negative performance due to flow impact → more outflows.

9 Robustness Tests

Most of our analyses are conducted by using the IDX4 alphas in previous sections. In unreported results, we repeated all the analyses by using the other three alpha measures: simple alphas, IDX3 alphas, and FFC alphas. All conclusions remain qualitatively the same.

We followed Fama and French (2010) to limit the sample to funds that are greater than \$5 million in AUM. Raising fund AUM threshold from \$5 million to \$100 million is approximately equivalent to removing the smallest AUM quintile, which does not change the conclusions for the rest four quintiles in Tables 4 and 6. The equal-weighted IDX4 gross alpha for active funds in Table 1 in the first period decreases from 1.06% to 0.53% when funds with AUM less than \$100 million are excluded, confirming that relatively smaller AUM funds did better in the first period.

Equation (1) is used to calculate dollar flows for all the analyses so far. Another more direct way is to use fund reported new sales and redemptions that measure the cash involved in share purchases (dollar inflows), and the cash resulting from share redemptions (dollar outflows), respectively. We repeated all analyses with sales and redemptions for the second period, and the results are similar.[16]

The flow impact on alpha is 0.72 and 0.60 in bad markets for the first and second periods, respectively, which are much larger than the corresponding values (0.50 and 0.29) for the full sample of the first and second periods, respectively. This is expected as liquidity is lower and price impact is greater in bad markets.

10 Forecasting Active Market Share

Given the net outflows of aggregated active mutual funds during the more recent 15+ years, is the active mutual fund industry likely to remain large in the future? To forecast the active market share for the next 180 months or 15 years, we simply use information on returns from the second period in Table 1 and flow information in the second period from Figure 6.[17] More specifically, the monthly *geometric* mean net returns are 0.78%, 0.82%, and 0.82% for active funds, index funds, and ETFs, respectively. The monthly *geometric* mean percentage flows are −0.33% (negative), 0.28%, and 0.70% for active funds, index funds, and ETFs, respectively. The equation to calculate AUM at the end of Month-180 for active or passive funds is:

$$AUM = AUM_0(1 + r + f)^{180} \qquad (3)$$

where r and f are the monthly geometric mean return and monthly geometric mean flow, respectively.

Figure 10 shows the forecasted active market share, or the ratio of active AUM to total AUM. The active market share is forecasted to drop to 17% after 15-years. The assumption for future market returns do not change much the active share forecast because it has the same impact on both active funds and passive funds.

The diminishing role of the active fund industry shown in Figure 10 may have a meaningful impact on capital markets and asset pricing. While

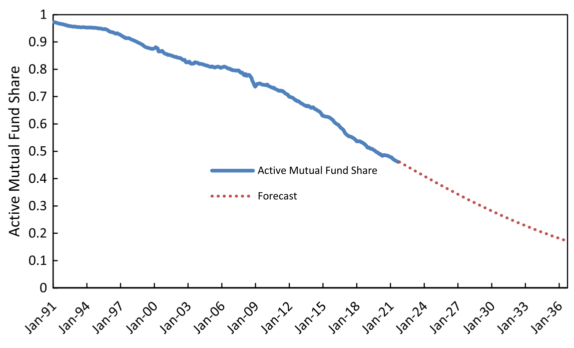

Figure 10 Forecasted ratio of active mutual fund AUM to total AUM.

index investing, via index funds or exchange-traded funds (ETFs), has enjoyed spectacular growth since the late 1990s, a few recent academic studies have highlighted certain unintended consequences that ETFs have on the underlying securities. For example, ETFs distort stock prices and risk–return tradeoffs (Wurgler, 2010), and increase the volatility of the underlying securities (Ben-David *et al.*, 2018).

Are active mutual funds going to disappear? Of course, we do not believe that they will disappear completely. Active mutual funds will likely remain prevalent in 401(k) plans for the foreseeable future because 401(k) recordkeepers struggle to handle ETFs (Rekenthaler, 2021). It has been argued that at some point as the ratio of active AUM to total AUM drops, the market will become less efficient, leading to exploitable alpha opportunities, and encourage money to flow to active managers. This argument will be tested soon.

11 Conclusions

The year 2006 marks a significant landscaping change for the U.S. active equity mutual funds industry. Starting around 2006, active mutual funds have experienced continuous net outflows, while index funds and ETFs have experienced continuous net inflows. This is the "great migration" from active to passive management.

The asset-weighted performance of active mutual funds remains similar over time, but the equal-weighted performance has deteriorated during the last 15 years. Prior to 2006, small AUM active mutual funds have outperformed large AUM active mutual funds. In contrast, since around 2006 small AUM active mutual funds have slightly underperformed large AUM active mutual funds. The documented extra outperformance of active mutual funds in crisis periods or bad markets also diminishes.

Flows impact the performance of individual active mutual funds. There are at least two factors that contribute to the outperformance of small AUM funds in the first period: (1) higher percentage inflows and (2) higher flow impact. These two factors helped small AUM funds to outperform large AUM funds by 0.44% in the first period. However, both factors played less role in the second period.

At the aggregated level for active funds industry, the flow impact on annualized alpha is 0.33% for the first period and −0.10% for the second period, which leads to a negative change of 0.43% in alphas across the two periods. The negative flow-induced impact of −0.10% on alpha in the second period is expected to continue in the future, and it is probably large enough to exert negative feedback on the active mutual funds industry.

Finally, the fee difference of about 70 bps between active and index funds may shrink, but is not expected to disappear, continuing to drag down the net performance and drive the persistent outflows from active mutual funds. If the flows for active mutual funds, index funds and ETFs for the next 15 years are the same as last 15 years, active market share will likely drop to 17%.

Acknowledgments

The authors thank John Rekenthaler and the anonymous referee for their helpful comments.

Appendix. Alpha Measures

The simple gross or net alpha is calculated as a fund's gross or net return over its Morningstar assigned benchmark return. Morningstar periodically updates assigned benchmarks as fund styles change over time, and we use these historically updated benchmarks in calculating simple alphas. One drawback is that benchmarks do not account for some funds whose investment strategies are not constrained to a single asset class or investment category. Another minor issue is that most active mutual funds hold small amount of required cash but Morningstar assigned benchmarks are 100% equities. Nonetheless, it is straightforward to many investors and essentially free of regression-based estimation errors.

The FFC Alpha has been widely adopted in academic research for asset pricing and performance evaluation purposes as shown in Equation (A.1).[18]

$$\begin{aligned} R_{i,t} - R_{ft} = \alpha_i + b_i(R_{M,t} - R_{ft}) \\ + s_i SMB_t + h_i HML_t \\ + m_i MOM_t + e_{i,t} \end{aligned} \tag{A.1}$$

where the intercept α is the alpha, and regression coefficients b, s, h, and m are loadings to the four factors. $(\alpha + e_t)$ is the factor-adjusted return in month t, and we also call it alpha (for a month) in the cross-sectional analyses for convenience.

One concern with the FFC model is the FFC factors are long–short portfolios whose returns cannot be achieved by mutual fund managers with no cost. In addition, the FFC model suffers from biases. Cremers *et al.* (2013) show that these biases cause the benchmarks provided by the FFC model to be tough to beat for small-cap managers (who have a positive beta on SMB) and easy to beat for large-cap managers (who have a negative beta on SMB). To mitigate these biases, they proposed an index-based model (IDX4) that explains average returns well, producing alphas close to zero for all fund groups. The IDX4 model simply replaces the three Fama–French factors with index-based returns, while the MOM factor remains the same:

R_M → S&P 500 Index returns
SMB → Russell 2000 Index – S&P 500 Index
HML → Russell 3000 Value – Russell 3000 Growth

One can argue that the MOM factor requires a lot of turnover and thus it is a kind of active strategy. We also test the IDX3 model, which is formed by removing the MOM factor from the IDX4 model.

Endnotes

1 As we will show later, estimates are based on fund data from Morningstar Direct. New mutual funds and ETFs since 1/2019 are excluded because of the short history. Mutual funds and ETFs that are smaller than $5 million dollars (as of Year-2006) are excluded. Cumulative net inflows from new ETFs alone are nearly $0.4 trillion from 1/2019 to 9/2021. The net outflows from active mutual funds industry are nearly offset by the combined inflows into index mutual funds and ETFs from 1/2006 to 9/2021 when new funds and new ETFs are included.

2 It happens that serendipitously the Fama and French (2010) analysis also ended in September 2006, which seemed to correspond to a turning point for the active fund industry—active mutual funds have suffered steady outflows as well as relatively poor performance since then.

3 Note that small AUM funds are not necessarily small-cap-stock funds, although small AUM funds tend to hold small-cap stocks. Small AUM funds can hold large-cap stocks. Likewise, large AUM funds are not large-cap-stock funds, although they tend to hold large-cap stocks. Large AUM funds can hold small-cap stocks.

4 Morningstar Direct has a flag "Index Fund" for ETFs ("Yes" for passive ETFs, and "No" for active ETFs). Majority of the ETFs are passive. Active ETFs are excluded because they constitute only a small portion of the ETF space, and their history is short.

5 Morningstar assigns benchmarks based on the nine size–valuation squares that constitute the nine-style box representing the U.S. equity universe, the three valuation-based columns from the style box (blend, growth, and value), the three size-based rows from the style box (large, mid, and small). The benchmark returns for the nine styles are represented by the nine Russell index total returns: Russell 1000, Russell 1000 Growth, Russell 1000 Value, Russell Mid Cap, Russell Mid Cap Growth, Russell Mid Cap Value, Russell 2000, Russell 2000 Growth, and Russell 2000 Value.

6 Gross returns for different share classes for each unique fund are the same. Most of our analyses are on gross returns. Net returns are slightly different for different share classes. The net returns for the oldest share class are very close to the share-class-weighted net returns because AUM for the oldest share class on average accounts for more than 70% of the aggregated AUM from all share classes.

7 Alphas are annualized as monthly alphas multiplied by 12. Standard deviations are annualized as monthly standard deviations multiplied by square root of 12.

8 Cautions are in order when ETFs are treated as passive funds. First, some ETFs attempt to replicate the performance of what is essentially an active strategy structured as index; thus, shifting the active management component to index construction. Wermers (2021) argues that some rules-based ETFs can be considered as "quasi-active" strategies. Next, the short average holding period of ETFs and their large trading volumes suggest that investors are using them to practice a form of active management.

9 Pedersen (2018) argues that Sharpe's implicit assumption that the market portfolio never changes does not hold in the real world because new shares are issued, others are repurchased, and indexes are reconstituted—so even "passive" investors must regularly trade. Wermers (2021) suggests that the benefits of active management are amplified in small- and mid-cap U.S. stocks.

10 Note that the average alpha across the five size quintiles in Table 4 is slightly greater than the corresponding IDX4 alpha in Table 1 in both periods. The difference is primarily because the number of funds is different over time. The alpha or excess return for each fund in Table 4 is estimated by regressions of the fund's available data (often with a history less than the full period), while the alpha in Table 1 is estimated by regressions of the aggregate returns. If all funds had data for the entire period, the average alpha in both tables would be the same. For Simple Alpha, the average alpha in both tables is the same because it does not require regressions.

11 Regressions tend to be dominated by small AUM funds because they tend to have large absolute values of percentage flows. The flow coefficient is higher for large AUM funds.

12 The flow impact of 0.19 for small AUM funds is underestimated because other factors played a positive role. Assuming that other factors play no or less of a role in the second period, we can use the flow impact ratio between small AUM funds and large AUM funds in the second period to disentangle the role of other factors and infer the flow impact for small AUM funds in the first period. The flow impact for small AUM funds (0.14) is about half of the flow impact for large AUM funds (0.29) in the second period. Using the same ratio of 0.48

$(= 0.14/0.29)$, the flow impact would be increased from 0.19 to 0.24 $(= 0.48 * 0.50)$ for small AUM funds in the first period, and the flow impact on alpha would increase from 0.71% to 0.90% $(= 3.75\% * 0.24)$. In other words, flow impact may have contributed approximately 0.90% alpha to small AUM funds prior to 2006.

[13] Other factors played a positive role of 1.27% and 1.25% for simple alpha and FFC alpha, respectively. Therefore, the role played by other factors depends on alpha models. In addition, the literature suggests a few potential other factors: (1) Prior to 2006, active mutual funds exhibited some evidence of stock-picking skills (e.g., see Daniel *et al.*, 1997; Wermers, 2000; Kosowski *et al.*, 2006); and (2) von Reibnitz (2015) shows that active strategies have the greatest impact on returns during periods of high dispersion, when alpha produced by the most active mutual funds significantly exceeds than that produced in other months. We found that higher cross-sectional stock return dispersion in the first period is positively associated with the outperformance of small AUM funds.

[14] This flow-driven-return-effect is consistent with Figure 5 of Gabaix and Koijen (2022), in which the aggregate flow into the stock market has a linear relation with the return on the aggregate stock market, and the relation approximately crosses the origin point.

[15] The flow impact for large AUM funds is used because active mutual funds in aggregate are dominated by large AUM funds.

[16] Unfortunately, historical sales and redemption data only starts from 1999 in Morningstar Direct, so that we can only test the second period.

[17] Bootstrap simulations that draw flows and returns from the second period yield close results at the 50th percentile.

[18] $R_{i,t}$ is the return on fund i for month t, R_{ft} is the risk-free rate (the 1-month U.S. Treasury bill rate), R_{Mt} is the market return (the return on an asset-weighted portfolio of NYSE, Amex, and NASDAQ stocks), SMB_t and HML_t are the size and value-growth returns of Fama and French (1993), MOM_t is Carhart's (1997) momentum return. All the monthly factor returns are downloaded from the French Data Library.

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