MUTUAL FUND GROWTH IN STANDARD AND SPECIALIST MARKET SEGMENTS

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ABSTRACT

We examine differences in the performance flow relationship (PFR) between different segments of the fund industry. Such differences can be caused by distinct mutual fund investors' characteristics in different segments. In our empirical study of the US equity mutual fund industry in 1993-2001, we find a much more convex PFR in standard segments than in specialist segments. Furthermore, our results suggest that investors in the latter are more fee- and risk-aware than investors in standard segments. Overall, these results hint at investors in specialist segments being more sophisticated than investors in standard segments. Our results should have serious implications for the management of investment companies and for the behavior of fund managers.

Keywords: Mutual Funds, Performance Flow Relationship

JEL-Classifcation: G23

1 Introduction

The relationship between a mutual fund's performance and its subsequent external growth due to net-inflows is positive [see, e.g., SPITZ (1970) and SMITH (1978)]. Furthermore, this performance-flow relationship (PFR) is not linear, but clearly convex [see, e.g., IPPOLITO (1992), SIRRI/TUFANO (1998), CHEVALIER/ELLISON (1997), and KEMPF/RUENZI (2004a)]. Top funds attract large inflows, whereas bad funds do not suffer from large outflows to the same extent.

One possible explanation for this convexity is that fund investors base their purchase decisions on publicly available performance information, but later do not sell funds that did not live up to the expectations by showing a bad performance. This averseness to sell losers is consistent with investors being subject to a disposition effect [SHEFRIN/STATMAN (1985)].[1] One expects that sophisticated investors are less likely to be subject to such a behavioral bias. This should lead to a less pronounced convexity of the PFR in markets where many sophisticated investors are doing business. This hypothesis is supported by the results reported in SAWICKI (2000) and (2001), DELGUERCIO/TKAC (2002) and KAPLAN/SCHOAR (2003). They examine the PFR in the Australian wholesale mutual fund market, the pension fund market and the private equity fund market, respectively, which are dominated by professional investors. They all find a less convex PFR in those markets as compared to the retail mutual fund market.[2]

Whereas these studies look at the PFR in different markets, ours is the first paper that compares the convexity of the PFR between different segments within the mutual fund market. We argue that it is quite likely that investor sophistication also varies between different mutual fund market segments. Therefore, we expect to find a difference in the convexity of the PFR between different segments. However, it is not clear ex ante in which segments investors are more sophisticated. On the one hand, one can expect unexperienced first-time investors to flock to the standard segments (e.g. "Growth" or "Growth and Income"). If they become more experienced they turn to more exotic and specialist segments (e.g. "Health Sector" or "Chinese Equity"). On the other hand, it is also reasonable to assume that unexperienced investors are more likely to follow fads like the internet boom. In this case we would expect them to mainly invest in exotic and specialist segments, whereas sophisticated investors rather opt for large, well-diversified and cheaper standard-funds.

The main contribution of this paper is to examine differences in the convexity of the PFR between standard and specialist mutual fund segments. Our study of the US equity mutual fund market from 1993-2001 provides convincing evidence for a more pronounced convexity of the PFR in standard as compared to specialist segments. Such differences in the PFR have important implications for fund managers as well as for the management of investment companies:

(1) As fund managers get paid dependent on their assets under management [KHORANA (1996)], the option-like characteristics of a convex PFR gives rise to risk-taking incentives [see, e.g., BROWN/HARLOW/STARKS (1996), CHEVALIER/ELLISON (1997), and KEMPF/RUENZI (2004b)]. Option theory suggests that the strength of these incentives positively depends on the convexity of the PFR. Based on our results, we would therefore predict risk taking incentives of fund managers to be stronger in standard segments. This calls for tight risk taking guidelines for the managers in these segments.

(2) Investment companies are able to selectively push the performance of specific funds at the expense of the company's other funds [GUEDJ/PAPASTAIKOUDI (2004), GASPAR/MASSA/MATOS (2004)]. For example, REUTER (2003) and LÖFFLER (2003) show that investment companies are able to allocate favourable IPO allocations towards certain funds. The expected additional inflows due to such a push in performance is the larger the more convex the PFR is. Our results suggest that the investment company should push the performance of funds in standard segments.

The schedule of this paper is as follows: In Section 2 we present the empirical model and describe the data. The differences in the PFR are examined in Section 3, where we also conduct several robustness checks. Section 4 concludes and provides possible directions for future research.

2 Methodology and Data Source

2.1 Empirical Model

We use pooled OLS regressions to examine the relationship between a funds growth and its previous performance as well as other variables that might influence fund growth.[3] Our dependent variable is the growth, $g_{i,t}$, of fund i in year t due to new inflows. As there are no data on net inflows available in our database, we follow the literature [e.g. SIRRI/TUFANO (1998)] and compute $g_{i,t}$ by subtracting the rate of return earned on the assets under management from the growth rate of the total net assets (TNA) the fund has under management.

PATEL/ZECKHAUSER/HENDRICKS (1994) show that ordinal performance measures based on raw returns are able to explain fund growth better than cardinal measures. They also show that ranks based on returns can explain fund growth better than ranks based on risk-adjusted performance measures. Therefore, we use segment ranks based on returns as independent variables in our regressions.[4] $Rank_{i,t}$ denotes the relative rank of fund i in year t within its segment. Rank numbers are evenly distributed between 0 and 1. The best fund gets assigned the rank number 1.

To account for the supposed non-linearity in the PFR we apply the specification suggested by BARBER/ODEAN/ZHENG (2004). They use the segment rank, $Rank_{i,t-1}$, and the squared segment rank, $Rank^2_{i,t-1}$, as independent variables. A positive influence of the squared segment rank indicates a convex PFR.[5]

To examine possible differences between the convexity of the PFR in standard and specialist segments, we add interaction-terms between a dummy variable D and the performance variables $Rank_{i,t-1}$ and $Rank^2_{i,t-1}$. D takes on the value one, if a fund belongs to the standard segments, and zero otherwise. A positive estimate for the influence of $Rank^2_{i,t-1}D$ is evidence for a stronger convexity of the PFR in the standard segments than in the rest of the market. Our regression model reads:

$$g_{i,t} = \beta_1 Rank_{i,t-1} + \beta_2 Rank_{i,t-1}^2 + \beta_{1L} Rank_{i,t-1} D + \beta_{2L} Rank_{i,t-1}^2 D + \gamma\, Controls + \sum_{j=1993}^{2001} \alpha_j D_j + \varepsilon_{i,t} \quad (1)$$

Controls denotes a vector of control variables. They are described in Table 1. These variables are examined as potential determinants of fund growth in previous studies. We include all variables whose realizations are not known to investors at the beginning of the year with their previous year realization and follow the literature by using the natural logarithm of Age and Size [see, e.g., BARBER/ODEAN/ZHENG (2004)].

Please Insert Table 1

As we use observations from all years in one pooled regression, we have to control for year-specific influences on fund growth. Therefore, we add a dummy, D_j, for each year of our sample. Each yearly dummy takes on the value 1, if the observation is from the respective year, and zero otherwise. We will not report estimation results for the influence of the yearly dummies for the sake of brevity. As we use one dummy variable for each year, we do not add a constant term in our regressions, as this would make the regressors linearily dependent.

2.2 Data

We use data on all US equity mutual funds from the CRSP Survivorship Bias Free Mutual Fund Database.[6] This database contains all the neccessary information to conduct our study. Specifically, the database lists the Strategic Insight (SI) objective classification for each fund. This classification defines our market segments. As the SI-objectives are available from 1993 on, our study starts in 1993. It covers the years until 2001. We exclude all fund year observations with extreme growth rates of more than 500% and funds from very small investment companies with less than 10 funds, as data in these cases often seems questionable.[7] We also exclude all fund year observations for which not all information used in our regressions is available. Some funds offer different share classes. As these classes differ substantially with respect to fee structure and other characteristics, they are separate investment alternatives from the view of investors. Therefore, we include all share classes of the funds as individual observations. This leaves us with a sample of 13.539 fund year observations.

We classify the SI market segments contained in the database as either ‘specialist’ or ‘standard’ segments. We define the five largest segments according to the number of funds offered as ‘standard’, and the rest as ‘specialist’.[9] Our classification allows us to examine systematic differences between these two groups of segments. Standard segments are the SI-objective segments ‘Growth’, ‘Growth & Income’, ‘Small Company Growth’, ‘Balanced’ and ‘International Growth’. The specialist segments include segments like ‘Chinese Equity Funds’ or ‘Health Sector Funds’. This split-up leads to 8,577 observations from standard segments and 6,595 observations from specialist segments.

3 Results

3.1 The PFR in the Whole Sample

In this mainly reproductive section we estimate the PFR from model (1), but leave aside the dummy-interaction terms for the moment. Results for the whole sample period 1993-2001 are presented in Column (A) of Table 2.

Please Insert Table 2

We find strong evidence for a convex PFR. The coefficient for the influence of the squared segment rank is significantly positive. This result confirms the results of earlier studies like CHEVALIER/ELLISION (1997) and others.

With respect to the control variables, we find an insignificant influence of $std_{i,t-1}$. The fund’s age, size and fees all have a significantly negative influence on fund growth. Funds with a higher turnover rate tend to grow faster. The influence of the growth of the segment the fund belongs to and of the fund's previous year growth are significantly positive. Overall, the estimates for the control variables confirm the findings of earlier studies. The R^2 is over 18%.

3.2 Differences in the Convexity of the PFR

To get a first graphical impression of the difference of the PFR in standard and specialist segments, we plot the estimated PFR from the fully specified model (1) for standard and specialist segments.

Please insert Figure 1

It can clearly be seen, that the PFR in standard segments as well as in specialist segments is positive and convex. Furthermore, the convexity of the PFR in standard segments is more pronounced than in specialist segments.

We now turn to the estimation results of model (1), that are presented in Column (B) of Table 2. They confirm the graphical intuition: the PFR in specialist as well as standard segments is clearly convex. More importantly, we find strong evidence for a statistically significant difference in the convexity of the PFR between the two segments. There is a positive and highly significant influence of $Rank^2_{i,t-1}D$ on fund growth. This coefficient denotes the additional convexity coming from the fact that a fund belongs to a standard segment rather than to a specialist segment.

As risk-taking incentives for fund managers positively depend on the convexity of the PFR, our results suggest stronger risk-taking incentives for fund managers in standard than in specialist segments. Such risk-taking behavior can lead to inefficient portfolio allocations from the investors point of view. Therefore, fund investors should monitor the risk-taking behavior of fund managers from standard segements very closely.

Our results also have important consequences for the management of investment companies. They suggest that investment companies should push the performance of funds from standard segments rather than of funds from specialist segments. The following example illustrates our result. Suppose an investment company has one fund in a standard segment and one fund in a specialist segment with otherwise equal characteristics that both would reach a segment rank of 0.8 by the end of the year. This company is assumed to be able to push the performance of one of these funds, so that it reaches a rank of 0.9 in its segment. Given our results from Column (B) in Table 2, such a push will boost the growth of the standard fund by 11.44%, whereas the growth of the specialist fund will only increase 7.78% in absolute terms. Therefore, the investment company should, ceteris paribus, foster the fund from the standard segment.

In short, our results are consistent with the view that investors in standard segments are rather unsophisticated as compared to investors in specialist segments. This can be exploited by fund managers and investment companies.

3.3 Differences in the Influence of Risk and Fees

If standard segment investors are less sophisticated, this should also be reflected in differences in the influence of other variables. For example, we expect unsophisticated investors to be less fee-sensitive, as they are more reliant on financial advice which regularly is compensated for by higher load fees. This should result in fund growth being less dependent on fees in standard segments than in specialist segments. Furthermore, SHILLER (1984) argues that investors are not able to correctly asses risk. This problem should be more severe with unsophisticated investors. Therefore, investors in standard segments should be less aware of differences in funds' risk and fees.

To examine differences in the influence of past risk on fund growth between standard and specialist segments, we add an interaction term between $std_{i,t-1}$ and D as well as between $Fees_{i,t-1}$ and D in our regression models. D takes on the value 1 if the fund belongs to a standard segment and zero otherwise. This allows us to explicitly test for statistical differences in the influence of risk and fees. Results of this extended model are presented in Column (C) of Table 2.

First note, that our result of a stronger convexity in standard segments remains unaffected by the introduction of the two additional interaction terms. With respect to the influence of risk, we now find an interesting difference. Risk has a negative, but insignificant influence on fund growth in specialist segments. We would have expected a stronger negative influence. However, in standard segments there is even a significantly positive impact, as indicated by the positive influence of $std_{i,t-1}D$, which is significant at the 1%-level. This supports our conjecture that investors in standard segments are less risk conscious than investors in specialist segments. Our results indicate that they even prefer riskier funds. Therefore, the stronger risk-taking incentives of fund managers in standard segments as compared to specialist segments are even re-inforced.

Looking at the influence of fees we also find a striking difference which agrees with our conjecture of investors in standard segments being less sophisticated. Fees have a strong negative impact on fund growth in specialist segments. In standard segments, this negative influence is neutralized, as indicated by the significantly positive influence of $Fees_{i,t-1}D$, which is larger (in absolute terms) than the negative influence of $Fees_{i,t-1}D$. Investors in standard segments do not seem to be fee-averse, consistent with the view that they are more reliant on professional advise which is compensated for by higher load fees. Furthermore, unsophisticated investors might be driven to funds that spend a lot of money on distribution and marketing. These funds usually charge higher fees. In contrast, investors in specialist segments seem to be very fee-sensitive and to prefer low-fee funds.

3.4 Stability of Results

In this section we examine the robustness of our results. We start by reporting results using an alternative methodology to capture the convexity of the PFR. Then we report the results from estimations, where we base segment ranks on different performance measures other than returns. Finally, we take a look at the temporal stability of our results.

Piecewise Linear Regression Approach

Instead of using squared ranks to account for the non-linearity of the PFR, we apply a piecewise linear regression approach. This methodology allows us to separately determine the sensitivity of growth to performance in each performance quintile. We follow SIRRI/TUFANO (1998) and group the 2nd-4th quintile together.[8] Ranks are decomposed in the following way: the lowest quintile as $LOW_{i,t-1}=\min(Rank_{i,t-1};0,2)$, the three middle quintiles as $MID_{i,t-1}=\min(Rank_{i,t-1}-LOW_{i,t-1};0,6)$, and the top quintile as $HIGH_{i,t-1}=Rank_{i,t-1}-(LOW_{i,t-1}+MID_{i,t-1})$. The coefficients on these rank decomposition represent the slope of the PFR in the respective quintile(s). Our regression model then reads:

$$
\begin{aligned}
g_{i,t} &= \beta_{low} LOW_{i,t-1} + \beta_{low}^{L} LOW_{i,t-1} D + \beta_{mid} MID_{i,t-1} + \beta_{mid}^{L} MID_{i,t-1} D \\
&\quad + \beta_{high} HIGH_{i,t-1} + \beta_{high}^{L} HIGH_{i,t-1} D + \gamma\, Controls + \sum_{j=1993}^{2001} \alpha_j D_j + \varepsilon_{i,t}
\end{aligned}
\qquad (2)
$$

The estimation results of model (2) are presented in Table 3.

Please insert Table 3

All of our results remain qualitatively unchanged. Results from Column (A) confirm the strong convexity of the PFR in the whole sample. In Columns (B) and (C) we observe a significant influence of $HIGH_{i,t-1}D$, but not of $LOW_{i,t-1}D$ and $MID_{i,t-1}D$. This indicates a stronger convexity of the PFR in standard than in specialist segments and thereby confirms the results from Table 2. Furthermore, our results with respect to the differences in the influence of fees and risk are also confirmed (see Column (C)). The estimated coefficients for the other control variables remain very similar, too.

Alternative Performance Measures

In the examinations above we base our segment ranks on raw returns. As a stability check, we re-do all regressions using segment ranks based on Sharpe-Ratios, FAMA/FRENCH (1993) 3-factor alphas and CARHART (1997) 4-factor alphas. We report results for the BARBER/ODEAN/ZHENG (2004) squared rank specification (1) in Table 4.

Please insert Table 4

We still find a convex PFR in the whole sample (Columns (A), (D), and (G)) and a more pronounced convexity in standard than in specialist segments (Columns (B)-(C), (E)-(F), (H)-(I)). Furthermore, our results with respect to the influence of risk and fees are not affected by the change of the performance measure (Columns (C), (F) and (I)). Results (not reported here) using the SIRRI/TUFANO (1998) piecewise-linear regression methodology and ranks based on the risk-adjusted performance measures are very similar.

Temporal Stability

It is possible that the influence of the various determinants of fund growth changes over time. For example, the difference in the convexity of the PFR reported above might change due to a change in the relative level of investor sophistication in standard segments as compared to specialist segments.

We start again by giving a graphical illustration. In Figure 2, we plot the PFR in standard and specialist segments for the subperiods 1993-1995, 1996-1998, and 1999-2001 as estimated by the squared rank methodology [model (1)].

Please insert Figure 2

Our result of a more pronounced convexity in standard segment than in specialist segments is stable over time. In Table 5 we present the estimation results from the extended version (with interaction terms for fees and risk) of model (1) for the three subperiods. We report results for segment ranks based on returns.

Please insert Table 5

The difference in the convexity of the PFR is very stable over time, as indicated by the significant influence of $Rank^2_{i,t-1}D$ in all subperiods. Furthermore, investors in specialist segments are never significantly less risk- and fee-averse than investors in standard segments. Results (not reported here) do not change if we base ranks on risk-adjusted measures instead of returns. Our results are also very similar, if we use the piecewise-linear regression approach suggested by SIRRI/TUFANO (1998) instead of the squared rank specification.

4 Conclusion

This article investigates how the PFR varies between the different segments of the mutual fund market. We find a more convex PFR in standard segments than in specialist segments. The convexity of the PFR can be explained by investors showing a disposition effect. Unexperienced investors are less sophisticated and more likely to be prone to the disposition effect. Therefore, our results suggest that investors in standard segments are less sophisticated than investors in specialist segments. This conjecture is also supported by our finding of investors in specialist segments being more risk- and fee-aware than investors in specialist segments. All our results are very stable over time as well as with respect to different methodological approaches.

There are some important implications of our results: a convex PFR leads to risk-taking incentives for fund managers [BROWN/HARLOW/STARKS (1996), KEMPF/RUENZI (2004b)]. According to option theory, these incentives positively depend on the convexity of the PFR. Therefore, risk-taking incentives for fund managers in standard segments should be stronger than in specialist segments. These stronger incentives are even reinforced by a positive influence of risk on fund growth in standard segments. Fund investors should be aware of this and closely monitor the risk-taking behavior of fund managers in standard segments. Furthermore, our results indicate, that investment companies should try to push the performance of funds in standard segments rather than in specialist segments. For example, the additional growth that can be expected from pushing an investment company's fund up from the third to the second best performance decile is by an economically meaningful 3.66% larger in standard than in specialist segments.

Our results also give rise to some new hypothesis that call for an empirical examination: First, we would expect fund managers in standard segments to react stronger than those in specialist segments to the implicit incentives stemming from the more convex PFR. Furthermore, JAMES/ISAAC (2000) report that such risk-taking behavior of fund managers leads to irrational price formation in asset markets. Our results suggest more irrational share prices in those segments of the stock market where funds from standard segments are mainly investing than in other segments of the stock market. Finally, based on our results we expect investment companies to push the performance of standard funds at the expense of specialist funds.

Figure 1: The PFR in Standard and Specialist Segments

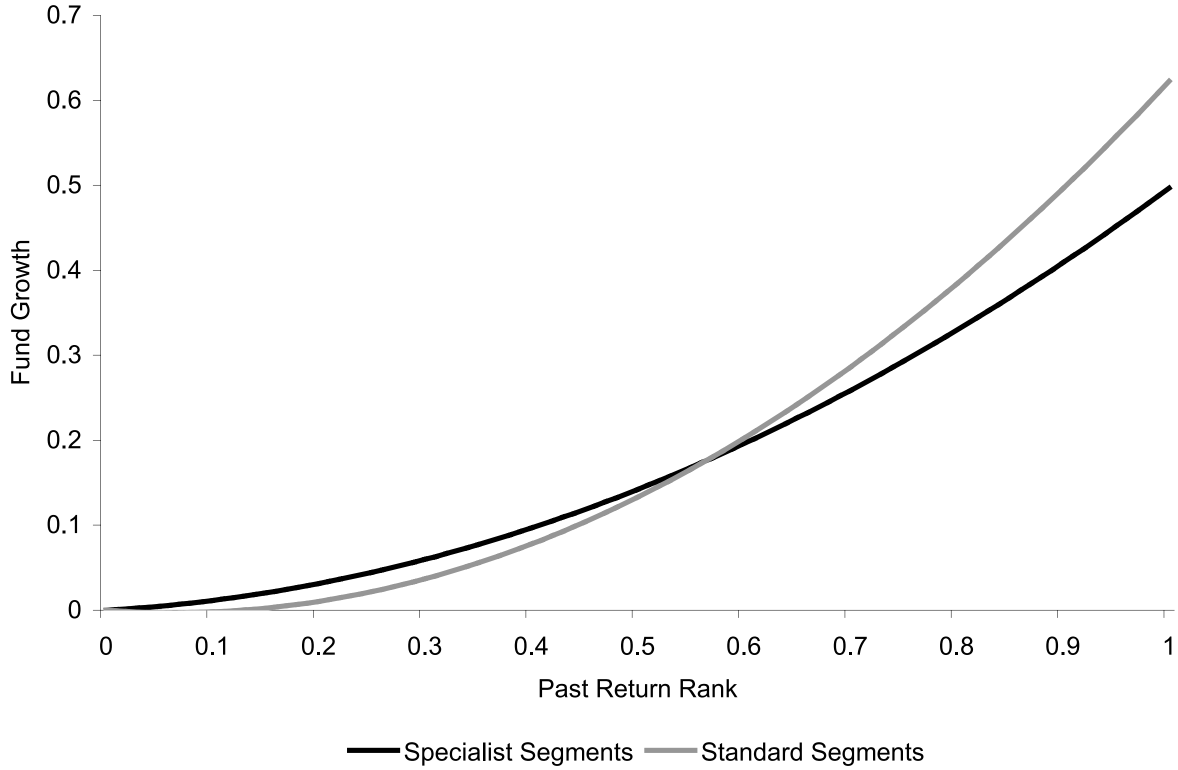

Figure 2: Stability of the PFR in Standard and Specialist Segments Over Time

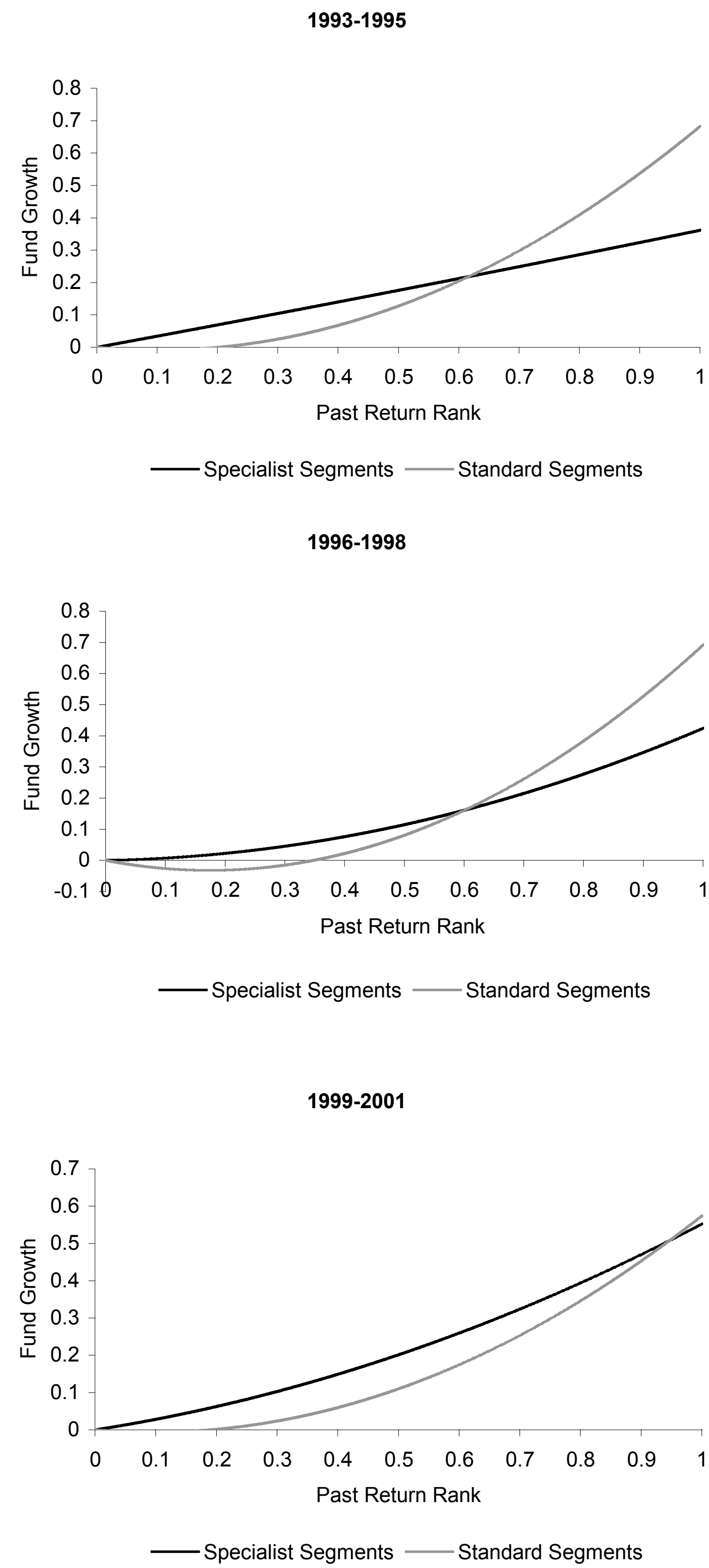

Table 1: Independent Variables in Empirical Study

Variable	Description	Examined in
$std_{i,t}$	Monthly return standard deviation of fund i in year t	e.g. SIRRI/TUFANO (1998)
$g_{i,t-1}$	Growth of fund i in the previous year	e.g. JAIN/WU (2000) and KEMPF/RUENZI (2004c)
$Age_{i,t}$	Age in years of fund i in year t	e.g. KEMPF/RUENZI (2004a)
$TNA_{i,t}$	Total net assets under management in million USD of fund i in year t	e.g. SIRRI/TUFANO (1998)
$Fees_{i,t}$	1/7th of the total load fee plus the expense ratio of fund i in year t	e.g. BARBER/ODEAN/ZHENG (2004)
$Turnover_{i,t}$	Turnover ratio of fund i in year t	e.g. BERGSTRESSER/POTERBA (2002)
$g(Seg)_{i,t}$	Growth rate of fund i's segment in year t	e.g. FANT/O'NEAL (2000)

Table 2: The Performance Flow Relationship

Period: 1993-2001

	(A)	(B)	(C)
$Rank_{i,t-1}$	-0.0377	0.0648	0.1834**
$Rank^2_{i,t-1}$	0.6054***	0.4196***	0.3191***
$Rank_{i,t-1}D$		-0.1660***	-0.3733***
$Rank^2_{i,t-1}D$		0.3131***	0.4886***
$std_{i,t-1}$	-0.0295	-0.0187	-0.0362
$std_{i,t-1}$ D			0.1664***
$g_{i,t-1}$	0.1414***	0.1419***	0.1413***
$lnTNA_{i,t-1}$	-0.0323***	-0.0325***	-0.0330***
$lnAge_{i,t-1}$	-0.0431***	-0.0430***	-0.0435***
$Fees_{i,t-1}$	-1.0604*	-0.7946	-2.0101***
$Fees_{i,t-1}D$			2.2104***
$Turnover_{i,t-1}$	0.0157***	0.0161***	0.0159***
$g(Seg)_{i,t-1}$	0.0951***	0.0949***	0.0946***
N	15,172	15,172	15,172
R^2	18.34%	18.53%	18.62%

Column (A) shows regression results from model (1) as described in the main text, where we leave aside the interaction terms. Column (B) contains results from an estimation of the fully specified model. In Column (C) an interaction term between a standard-segment dummy, D, and fees and risk, respectively, is added. The next to last row contains the number of observations. The R^2 of the regressions is shown in the last row. ***, **, and * denotes statistical significance at the 1%, 5% and 10%-level, respectively. The shaded areas denote the coefficients indicating differences in the shape of the performance flow relationship and in the influence of the fee burden and the past return risk.

Table 3: The PFR estimated using piecewise-linear regressions

Period: 1993-2001

	(A)	(B)	(C)
$LOW_{i,t-1}$	0.3747***	0.3376***	0.4588***
$MID_{i,t-1}$	0.4181***	0.4503***	0.4422***
$HIGH_{i,t-1}$	1.9857***	1.0793***	1.0901***
$LOW_{i,t-1}D$		0.0691	-0.1518
$MID_{i,t-1}D$		-0.0513	-0.0351
$HIGH_{i,t-1}D$		1.5281***	1.5023***
$std_{i,t-1}$	-0.0275	-0.0153	-0.0349
$std_{i,t-1}$ D			0.1652***
$g_{i,t-1}$	0.1398***	0.1404***	0.1398***
$lnTNA_{i,t-1}$	-0.0321***	-0.0326***	-0.0330***
$lnAge_{i,t-1}$	-0.0433***	-0.0432***	-0.0436***
$Fees_{i,t-1}$	-1.0329*	-0.8239	-1.6588**
$Fees_{i,t-1}D$			1.4731*
$Turnover_{i,t-1}$	0.0158***	0.0158***	0.0155***
$g(Seg)_{i,t-1}$	0.0954***	0.0960***	0.0955***
N	15,172	15,172	15,172
R^2	18.69%	19.03%	19.09%

This table shows regression results from model (2) as described in the main text. In Column (B) and (C) the performance variables are interacted with a dummy D for standard segments. In Column (C) the lagged standard deviation and fee burden are also interacted with this dummy. The next to last row contains the number of observations and the R^2 of the regressions is shown in the last row. ***, **, and * denotes statistical significance at the 1%, 5% and 10%-level, respectively. The shaded areas denote the coefficients indicating differences in the shape of the performance flow relationship and in the influence of the fee burden and the past return risk.

Table 4: Ranks based on Three- and Four-Factor Alphas
Period: 1993-2001

	Segment Ranks Based on								
	Sharpe-Ratios			3-Factor Alphas			4-Factor Alphas		
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
$Rank_{i,t-1}$	0.0747	0.1110	0.2369***	0.1875***	0.3107***	0.4528***	0.1966***	0.3006***	0.4160***
$Rank^2_{i,t-1}$	0.4537***	0.3498***	0.2453***	0.1688***	-0.0470	-0.1648**	0.1442**	-0.0493	-0.1447*
$Rank_{i,t-1}D$		-0.0767	-0.3005***		-0.2399***	-0.4848***		-0.2030***	-0.4050***
$Rank^2_{i,t-1}D$		0.2034***	0.3916***		0.4105***	0.6131***		0.3683***	0.5353***
$std_{i,t-1}$	-0.0057	0.0135	-0.0077	-0.1513***	-0.1526***	-0.1660***	-0.1491***	-0.1472***	-0.1624***
$std_{i,t-1}$ D			0.1813***			0.1457**			0.1435**
$g_{i,t-1}$	0.1439***	0.1439***	0.1432***	0.1541***	0.1545***	0.1539***	0.1550***	0.1554***	0.1548***
$lnTNA_{i,t-1}$	-0.0335***	-0.0337***	-0.0343***	-0.0299***	-0.0301***	-0.0306***	-0.0295***	-0.0297***	-0.0301***
$lnAge_{i,t-1}$	-0.0424***	-0.0428***	-0.0433***	-0.0439***	-0.0446***	-0.0453***	-0.0433***	-0.0440***	-0.0447***
$Fees_{i,t-1}$	-1.4444**	-1.0258*	-2.3398***	-1.6328***	-1.4250**	-2.9899***	-1.6125***	-1.3203**	-2.5729***
$Fees_{i,t-1}D$			2.3737***			2.8591***			2.2847***
$Turnover_{i,t-1}$	0.0159***	0.0164***	0.0162***	0.0156**	0.0152**	0.0149**	0.0199***	0.0197***	0.0194***
$g(Seg)_{i,t-1}$	0.0932***	0.0926***	0.0923***	0.0930***	0.0921***	0.0918***	0.0932***	0.0924***	0.0921***
N	15,172	15,172	15,172	15,172	15,172	15,172	15,172	15,172	15,172
R^2	17.45%	17.63%	17.73%	13.43%	13.69%	13.80%	13.14%	13.39%	13.48%

This table shows regression results from a regression model using the same methodology as described in Table 3. In Columns (A) to (C) ranks are based on Sharpe-Ratios. In Columns (D) to (F) they are based on FAMA/FRENCH (1993) 3-factor alphas and in Columns (G) to (I) they are based on CARHART (1997) 4-factor alphas. The next to last row contains the number of observations and the R^2 of the regressions is shown in the last row. ***, **, and * denotes statistical significance at the 1%, 5% and 10%-level, respectively. The shaded areas denote the coefficients indicating differences in the shape of the performance flow relationship and in the influence of the fee burden and the past return risk.

Table 5: Temporal Stability of Results

	Segment Ranks Based on Return Ranks		
	1993-1995	1996-1998	1999-2001
$Rank_{i,t-1}$	0.3426	0.0350	0.2523**
$Rank^2_{i,t-1}$	0.0189	0.3894***	0.2993***
$Rank_{i,t-1}D$	-0.5147	-0.4035**	-0.3870***
$Rank^2_{i,t-1}D$	0.8358**	0.6716***	0.4088***
$std_{i,t-1}$	-0.1757	-0.4423***	-0.0034
$std_{i,t-1}D$	-0.0948	0.0731	0.2061***
$Fees_{i,t-1}$	-1.6274	-1.0808	-2.3548**
$Fees_{i,t-1}D$	-0.4098	2.8205*	2.8263***
...	...	...	...
N	1,380	4.044	9,748
R^2	21.98%	23.68%	16.29%

This table shows regression results from the same model as in Column (C) of Table 2 for different time periods. Segment ranks are based on returns. The next to last row contains the number of observations and the R^2 of the regressions is shown in the last row. ***, **, and * denotes statistical significance at the 1%, 5% and 10%-level, respectively. The shaded areas denote the coefficients indicating differences in the shape of the performance flow relationship and in the influence of the fee burden and the past return risk. Dots represent the other control variables not reported in this table. They are the same as in Tables 2-4.

FOOTNOTES

[1] The disposition effect could be due to cognitive dissonance, which makes investors overestimate the past performance of their funds [GOETZMANN/PELES (1997)]. They are then more reluctant to sell bad performers which eventually leads to a convex PFR.

[2] KAPLAN/SCHOAR (2003) even report a concave relationship.

[3] SIRRI/TUFANO (1998) report that significance levels are more conservative if they calculate t-values as suggested in FAMA/MACBETH (1973). We repeat our analysis using FAMA/MACBETH (1973) regressions and obtain very similar results to those using the pooled regression approach.

[4] As a stability test, we also examine ranks based on various risk-adjusted performance measures. Our main results do not hinge on the choice of the performance measure (see Section 3.4).

[5] We also do all examinations using the piecewise-linear regression methodology suggested by SIRRI/TUFANO (1998). Results are very similar (see Section 3.4).

[6] Source: CRSP™, Center for Research in Security Prices. Graduate School of Business, The University of Chicago. Used with permission. All rights reserved. crsp.uchicago.edu. Further information on the CRSP database is available in CARHART (1997).

[7] Instead of excluding observations with extreme growth rates, we also winsorize them or use a growth rate of 1000% percent as cutoff. Our main results do not change.

[8] Although this cutoff is ad-hoc, we chose this way of classifying segments as any other methodology would have to rely on a subjective classification of the individual segments. We also examine our models defining the three and six largest segments, respectively, as standard segments. Our results (not reported here) indicate that our main conclusions are not affected. All results not reported here for the sake of brevity are available from the author on request.

[9] We also apply the piecewise linear regression approach using different slope coefficients for all five quintiles. Our main results are not affected.

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