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Abstract

This paper is concerned with differences in the performance-flow relationship (PFR) between standard and specialist market segments of the mutual fund industry. We expect differences in this relationship because investor characteristics might vary across different segments. Our results show that the PFR is more convex in standard segments as compared to specialist segments. Furthermore, investors in standard segments are less risk-averse and invest more in high-load funds than investors in specialist segments. Our findings are consistent with investors in standard segments being less sophisticated than investors in specialist segments and to rely more heavily on the advice of financial brokers, which is compensated for by load fees.

1 Introduction

Mutual funds are offered in a wide variety of market segments. This paper is concerned with determinants of mutual funds' growth in these different segments. Specifically, we examine the relationship between a mutual fund's performance and its subsequent growth due to net-inflows. The contribution of our paper is to investigate differences of this performance flow relationship (PFR) across different segments of the industry. Such differences with respect to the PFR and with respect to other determinants of fund inflows like past return risk and fees have not been systematically examined in the literature so far.

Although there are several papers that examine the PFR [see, e.g., IPPOLITO (1992), CHEVALIER/ELLISON (1997), and SIRRI/TUFANO (1998)], all of them look at the large standard segments of the mutual fund industry like Growth or Growth & Income or at more specialized segments only in isolation. They report that the PFR is positive and convex.

There is evidence that investor characteristics as well as search costs to find a specific fund influence the convexity of the PFR [see, e.g., SIRRI/TUFANO (1998), DELGUERCIO/TKAC (2002), and HUANG/WEI/YAN (2004)]. We argue that investor characteristics and search costs vary across segments. Therefore, these differences should be reflected in differences in the convexity of the PFR.

Our empirical study covers the whole US equity mutual fund market for the time period 1993 to 2001. Our main result is that the PFR in large segments (which we label as 'standard') is significantly more convex than the PFR in the usually more exotic small segments (which we label as 'specialist').

Furthermore, our study provides two interesting additional insights: first, the average investor in standard segments tends to invest in high load fee funds, whereas the average investor in small segments is averse to fees. Second, investors' reaction to risk differs between large and small segments. Our results indicate that investors in large segments seem to prefer high-risk funds whereas investors in small segments do not.

The option-like characteristics of a convex PFR gives rise to risk-taking incentives for the managers of individual funds, because they get paid dependent on their assets under management [KHORANA (1996)].[1] BROWN/HARLOW/STARKS (1996), CHEVALIER/ELLISON (1997), ELTON/GRUBER/BLAKE (2000) and KEMPF/RUENZI (2004a) all present empirical evidence that fund managers strongly react to these incentives. According to option theory the strength of these incentives positively depends on the strength of the convexity of the PFR. CHEVALIER/ELLISON (1997) confirm this theoretical prediction by showing empirically that fund managers react stronger to these incentives the more convex the PFR is. Our main result of a more convex PFR in standard segments leads to, ceteris paribus, stronger risk taking incentives for fund managers. These incentives are even reinforced by the fact that fund growth in standard segments positively depends on past return risk.

The schedule of this paper is as follows: Section 2 describes how search costs and investors' characteristics influence the PFR. Furthermore, we explain how these characteristics vary between different segments and what consequences this has for the PFR. In Section 3, we present the empirical model and describe the data. The differences in the PFR are examined in Section 4, where we also conduct several robustness checks. Section 5 concludes and provides possible directions for future research.

2 Search Costs, Investor Characteristics, and the PFR

The PFR has two main characteristics. The first characteristic is that it is positive. A positive PFR can be rationalized by the fact that there is some - albeit only weak – evidence for persistence in mutual fund performance [see, e.g., BROWN/GOETZMANN (1995), ELTON/GRUBER/BLAKE (1996), and BOLLEN/BUSSE (2001)]. Therefore, it is a sensible strategy for fund investors to base their purchase decisions on past performance.

The second striking characteristic of the PFR is its pronounced convexity [see, e.g., IPPOLITO (1992), SIRRI/TUFANO (1998), CHEVALIER/ELLISON (1997), and KEMPF/RUENZI (2004b)]. The extreme growth of top-funds and the lack of outflows from badly performing funds are harder to explain in the context of a rational model. Why should an investor stick with a bad fund? An argument can be made, that investors who picked a bad fund in the past have learned that they are not very good at picking funds. However, even if these investor might not be able to pick a star fund, they are still better off switching to any other fund if transaction costs are not too high.[2] Therefore, the strong reluctance to sell losers still presents a puzzle, given that strong persistence is mainly documented for badly performing funds [see, e.g., BROWN/GOETZMANN (1995)]. Overall, investors seem to have problems to correctly assess future performance prospects of funds.

There are two possible explanations for a convex PFR. First, fund investors base their purchase decisions on past performance, but later do not sell funds that show a bad performance [see, e.g., GOETZMANN/PELES (1997)]. This averseness to sell losers can be explained by investors being subject to a disposition effect [SHEFRIN/STATMAN (1985)]. Second, top-performing funds are more visible than bad or mediocre funds for several reasons. For example, the financial press often reports about star performers. Furthermore, such top-funds also show up high in the performance rankings. Finally, fund families place ads for their best funds [JAIN/WU (2000)]. Therefore, even uninformed investors will be familiar with these top-funds. They are consequently more likely to be bought. This leads to the observed disproportional high inflows into top-performing funds. The combination of investors being subject to a disposition effect and their familiarity with past top performers can explain the observed convex PFR.

The strength of the disposition effect as well as the visibility of funds are likely to differ between different market segments for at least three possible reasons:

- First, the share of first-time investors is likely to vary across segments. We argue that such rather inexperienced investors are more likely to be prone to behavioral biases like the disposition effect.[3] It is reasonable to assume, that these investors usually turn to one of the well-known funds from the large standard segments first.

- Second, the share of wealthy investors is also likely to vary across segments. Wealthy fund investors hold a portfolio of funds from different standard and specialist segments, while less wealthy investors will be forced to concentrate on a small number of funds due to cost considerations. Therefore, the latter will usually concentrate on some large, well-diversified funds from the large standard segments, in order to still achieve a sufficiently diversified portfolio. This leads us to suppose that the share of wealthy investors is higher in specialist segments than in standard segments. As these wealthy investors are usually more experienced, they should also be less prone to behavioral biases.

- Third, fund families mainly advertise their large flagship funds, which usually belong to one of the large standard segments [JAIN/WU (2000)]. Furthermore, the popular press mainly focuses on standard segments and the performance rankings for these segments are most widely observed. Therefore, top-funds from these segments are more visible to investors than funds from other segments.

Because of all of these reasons, we would expect a more pronounced convexity of the PFR in standard segments than in smaller and often more exotic specialist segments. The results we present below support this view.

3 Methodology and Data Source

3.1 Empirical Model

We use pooled OLS regressions to examine the relationship between a fund's growth and its previous performance as well as other variables that might influence fund growth.[4] 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. $Rank_{i,t}$ denotes the relative return rank of fund i in year t within its market segment. Rank numbers are evenly distributed between 0 and 1. The best fund gets assigned the rank number 1. As a stability test, we will later use ranks based on various risk-adjusted performance measures. Our main results do not hinge on the choice of the performance measure (see Section 4.4).

Note, that the ranking system we use ensures that funds from segments with different numbers of funds can be easily compared. However, this ranking system might also give rise to another phenomenon: Assume that the rankings in the popular press always show the, e.g., Top-10 funds in a segment. According to our ranking system, the 10^{th} best fund in a large segment will be ranked lower than the 10^{th} best fund in a smaller segment, although both funds would have the same visibility to potential investors due to their appearance in the Top-10 listing. To control for such potential effects, in regressions not reported we include a dummy variable that takes on the value one, if a fund belongs to the Top-10, Top-5 and Top-3 in its segment, respectively, and zero otherwise. The results we report below are not affected, if we include such an additional dummy.[5]

To account for the supposed non-linearity of the PFR we apply the specification suggested in 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.[6] A positive influence of the squared segment rank indicates a convex PFR. We will also apply a piecewise-linear regression approach as suggested by SIRRI/TUFANO (1998) (see Section 4.4).

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. The significance of the dummy-interacted terms indicates the significance of the *difference* in the influence of the respective independent variable between standard and specialist segments. 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. It captures the *additional* convexity in standard segments. Our regression model reads:

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

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 examine funds from different segments, we also include the growth of the segment the fund belongs to as control variable. Thereby, we control for other factors that drive the growth of all funds in a specific segment. For example, it is possible that a specific segment becomes fashionable and the funds in this segment experience large growth rates. We allow for a nonlinear influence of the growth of the segment a fund belongs to by adding the squared growth rate of the segment in addition to the growth rate of the segment itself.

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 linearly dependent.

3.2 Data

We use data on all US equity mutual funds from the CRSP Survivorship Bias Free Mutual Fund Database.[7] This database contains all necessary information to conduct our study. Specifically, the database lists the Strategic Insight (SI) objective classification for each fund. This classification defines the market segments. As the SI-objectives are available from 1993 on, our study starts in this year. It covers the years until 2001. We exclude all fund year observations with extreme growth rates of more than 500% as these are usually due to a very small asset base of the fund at the beginning of the year and as data in these cases often seems questionable.[8] 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 their fee structure and other characteristics, they are separate investment alternatives from the point of view of the fund investors. Therefore, we include all share classes of the funds as individual observations. Our main results do not hinge on this. They also hold, if we aggregate all share classes of a fund (see Section 4.3). However, looking at share classes individually allows us to examine the influence of the fee structure on fund growth in detail. Overall, our final sample consists of 15.172 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'. 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. Although the cutoff for standard segments is somewhat 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) are not affected.

4 Results

4.1 The PFR in the Whole Sample

We start by estimating the PFR from model (1), but leave aside the dummy-interaction terms for the moment. This allows us to examine the convexity of the PFR in the whole market, without distinguishing between standard and specialist segments, and to compare our results to the literature. Results for the whole sample period 1993-2001 are presented in Column (A) of Table 2.

Please Insert Table 2

We find strong evidence of a convex PFR. The coefficient for the influence of the squared segment rank is significantly positive. This result confirms the results reported in the literature [see, e.g., CHEVALIER/ELLISON (1997), and SIRRI/TUFANO (1998)].

With respect to the control variables, we find no significant influence of $std_{i,t-1}$. This result suggests that the average mutual fund investor does not care about risk very much.[9] This surprising result is consistent with the results of earlier studies like SIRRI/TUFANO (1998), who also find no significant influence of past return standard deviation on money inflows. The fund's age, size and fees all have a significantly negative influence on fund growth. Funds with a higher turnover rate in the previous year tend to grow faster. The influence of the fund's previous year growth is significantly positive. Furthermore, the growth of a fund depends on the growth of the segment a fund belongs to in a concave manner. Overall, the estimates for the control variables confirm the findings of earlier studies. The R^2 is over 18%, which is similar to the R^2s reported in the literature. For example, SIRRI/TUFANO (1998) report a R^2 of about 14%. The R^2 of a similar regression in ELTON/GRUBER/BLAKE (2000) is 17.9%.

4.2 Differences in the Convexity of the PFR

We now turn to the examination of differences in the convexity of the PFR between standard and specialist segments. Results of our estimation of the complete model (1) are presented in Column (B) of Table 2. They indicate that the PFR in specialist as well as standard segments is clearly convex. More importantly, we find strong evidence for a difference in the convexity of the PFR. There is a positive and highly significant influence of $Rank^2_{i,t-1}D$ on fund growth. This coefficient denotes the *additional* convexity, which is due to the fact that a fund belongs to a standard segment rather than to a specialist segment. This result strongly supports our main hypothesis that the convexity of the PFR is more pronounced in standard segments than in specialist segments. As a robustness check, in Column (C) we report results of an estimation of model (1), where we aggregate all share classes of a fund. Results are very similar. In the following we will treat each share class as single observation again, as this allows us to take a closer look at the influence of the fee structure on fund growth (see Section 4.3).

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. However, these stronger incentives might be neutralized. For example, it is possible that popular funds from the standard segments are more closely followed by the press and rating agencies. If they report negatively about the excessive risk-taking of these funds, this might have a negative impact on their growth. Furthermore, it is possible that fund investors in standard segments are more risk-averse than investors in specialist segments. We turn to a detailed examination of the influence of risk in the following section.

4.3 Differences in the Influence of Risk and Fees

If investor characteristics and search costs differ between standard and specialist segments, this should also be reflected in differences in the influence of other variables. For example, we expect inexperienced investors to be less fee-sensitive, as they are more reliant on financial advice that regularly is compensated for by higher load fees. This should result in fund growth being less negatively (or even positively) dependent on fees in standard segments than in specialist segments. Furthermore, SHILLER (1984) argues that investors are not able to correctly assess risk. This problem should be more severe with inexperienced investors. Therefore, investors in standard segments should be less sensitive to differences in funds' risk and fees.

To examine differences in the influence of past risk and fees 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 model. Again, D takes on the value 1 if the fund belongs to a standard segment and zero otherwise:

$$\begin{aligned} g_{i,t} &= \beta_1 Rank_{i,t-1} + \beta_2 Rank_{i,t-1}^2 + \beta_{1L} Rank_{i,t-1} D + \beta_{2L} Rank_{i,t-1}^2 D \\ &\quad \beta_3 std_{i,t-1} + \beta_{3L} std_{i,t-1} D + \beta_4 Fees_{i,t-1} + \beta_{4L} Fees_{i,t-1} D + \ldots \end{aligned} \tag{2}$$

Similar as above, the influence of the interacted terms denotes the *additional* influence of the respective variable if a fund belongs to a standard segment as compared to a specialist segment. This approach allows us to explicitly test for statistical differences in the influence of risk and fees between standard and specialist segments. Results are presented in Column (D) of Table 2.

Our result of a stronger convexity in standard segments remains unaffected by the inclusion 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. However, in standard segments there is a positive impact, as indicated by the positive influence of $std_{i,t-1}D$. Therefore, the stronger risk-taking incentives of fund managers in standard segments due to the more pronounced convexity of the PFR there as compared to specialist segments are even reinforced.

Looking at the influence of fees we also find a striking difference. 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. This is consistent with the view that many of them are reliant on professional advice, which is compensated for by high load fees. Furthermore, such inexperienced investors are more likely to be driven to funds that spend a lot of money on distribution and marketing. These funds usually charge higher load fees, too. In contrast, investors in specialist segments seem to be very fee-sensitive and strongly prefer low-fee funds.

To get a more detailed picture of the influence of fees on fund growth, we split up our fees variable, $Fees_{i,t-1}$, into the load fees a fund levies, $Load_{i,t-1}$, and the total expense ratio of the fund, $TER_{i,t-1}$.[10] Both fee variables are interacted with the standard-segment dummy, D. Whereas expenses are usually levied to cover the cost of running the fund and compensating the fund manager, load fees are used to compensate brokers and to cover marketing expenditures. If our conjecture that investors in standard segments are more reliant on professional advice is true, then we should, on the one hand, see a stronger positive influence of load fees in these segments as compared to specialist segments. On the other hand, expenses directly hurt performance, as they are deducted from the asset base of the fund. Therefore, we expect a negative influence of the total expense ratio in standard as well as in specialist segments.

The results presented in Column (E) of Table 2 confirm our arguments. We find a significantly positive influence of load fees on fund growth in standard segments, but not in specialist segments. This might also be due to the fact, that these investors are usually wealthier and rely on fee-based advisors rather than brokers, that have to be compensated via loads.

In contrast, the influence of the total expense ratio is strongly negative in specialist as well as in standard segments. There is no systematic difference across segments, as indicated by the insignificant influence of $TER_{i,t-1}D$.

4.4 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. Next, we report results from estimations, where we base segment ranks on different performance measures other than returns and take a look at the temporal stability of our results. Finally, we explore whether our results are driven by funds with specific individual characteristics.

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 to 4th quintile together.[11] 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:

$$\begin{aligned} g_{i,t} &= \beta_{low} LOW_{i,t-1} + \beta^{L}_{low} LOW_{i,t-1} D + \beta_{mid} MID_{i,t-1} + \beta^{L}_{mid} MID_{i,t-1} D \\ &\quad + \beta_{high} HIGH_{i,t-1} + \beta^{L}_{high} HIGH_{i,t-1} D + \gamma\, Controls + \sum_{j=1993}^{2001} \alpha_j D_j + \varepsilon_{i,t} \end{aligned} \qquad (3)$$

The estimation results of model (3) 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), (C) and (D) 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. Thereby, our results from Table 2 are confirmed. The difference in the convexity is driven by the much stronger performance sensitivity in the top-quintile. This is consistent with the argument that the additional convexity in standard segments is driven by a higher visibility of top-funds there than in specialist segments. Furthermore, our earlier results with respect to the differences in the influence of fees and risk are also confirmed (see Columns (C) and (D)).[12]

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)). Furthermore, the R^2 of the regressions based on risk-adjusted measures are never as high as those of the respective regressions using returns (see Table 2). This agrees to the findings of PATEL/ZECKHAUSER/HENDRICKS (1994). 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. 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 1993-1995, 1996-1998, and 1999-2001. We report results for segment ranks based on returns.

Please insert Table 5

Our main result of a more convex PFR in standard segments is very stable over time. The influence of $Rank^2_{i,t-1}D$ is significantly positive in all subperiods. Furthermore, investors in specialist segments are never significantly less risk-averse than investors in standard segments. However, the results with respect to the influence of fees slightly differ between the subperiods. The influence of the expense ratio is usually negative except of in the period 1993-1995, where it is only significantly negative in standard segments. Regarding load fees, we find no significant influence in specialist segments in the later two subperiods, and a weakly negative influence in the first period. In standard segments, we find a significantly positive influence of loads as compared to the influence of loads in specialist segments in the first two subperiods, but not in the 1999-2001 period. In this period, the influence of loads in specialist segments is not significantly different from zero and the difference in the influence of loads between standard and specialist segments is insignificant, too.[13]

Results (not reported here) do not change if we base ranks on one of the 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.

Influence of Individual Fund Characteristics

Funds from standard segments are larger and older than funds from specialist segments. The median fund according to size in standard segments has a TNA of 275.25 million USD, while the median fund in specialist segments has a TNA of only 167.6 million USD. The median age of funds from standard as well as specialist segments is 6 years. However, the mean age is 11.31 years in standard segments, but only 8.43 years in specialist segments.

Therefore, if the convexity of the PFR for larger or older funds is greater than for smaller or younger funds, respectively, this could also drive our results. To examine this possibility, we interact the slope coefficients of model (1) not only with a dummy D indicating whether a fund belongs to a standard or specialist segment, but also with a dummy D_{big} and D_{old}, respectively. D_{big} equals one, if a fund's size is above the median TNA and zero otherwise. Accordingly, D_{old} equals one, if a fund's age is above the median age and zero otherwise.[14] We estimate two models where we only include dummy-interactions with either the big-fund or the old-fund dummy, respectively, and one model where we include dummy interactions with the standard-segment dummy, the big-fund dummy and the old-fund dummy in one model. Estimation results of these extended models are presented in Table 6.

Please insert Table 6

Our results show that the convexity of the PFR is actually less pronounced for large (old) funds, as indicated by the significantly negative influence of $Rank^2_{i,t-1}D_{big}$ ($Rank^2_{i,t-1}D_{old}$) in Column (A) (Column (B)) and Column (C). This result also confirms the result of CHEVALIER/ELLISON (1997), who report a less convex PFR for older funds. Overall, our results show that the difference in age and size of funds from specialist and standard segments does not drive our result. In contrast, solely based on the differences in age and size, we would expect a stronger convexity of the PFR in specialist segments as compared to standard segments.

We also conduct the same examination using the piecewise-linear regression methodology described above. Results (not reported here) again indicate that the convexity of the PFR is less pronounced for older and larger funds. Similarly, we examine the influence of the load status on the convexity of the PFR. Our results (not reported) indicate, that the convexity of the PFR does not differ between load and no-load funds.

5 Conclusion

This paper investigates how the PFR varies between different market segments of the equity mutual fund industry. Differences in search costs for funds and in investor wealth and investor characteristics between these segments can cause such differences. Our main result is that the convexity of the PFR is more pronounced in standard segments than in specialist segments. Furthermore, we find that load fees have a positive impact on fund growth in standard segments, but not in specialist segments. Finally, our results indicate that investors in standard segments buy relatively risky funds, whereas investors in specialist segments prefer funds with relatively low risk. Our main results are very stable over time as well as with respect to different methodological approaches. They are also robust against the influence of individual fund characteristics like age, size, and load status that might influence the convexity of the PFR.

Identifying differences in the convexity of the PFR has important implications for fund managers. A convex PFR leads to risk-taking incentives for fund managers [BROWN/HARLOW/STARKS (1996), KEMPF/RUENZI (2004a)]. The strength of these incentives positively depends on the convexity of the PFR. Therefore, our results indicate that risk-taking incentives for fund managers in standard segments are stronger than for managers in specialist segments. These stronger incentives are even reinforced by a positive influence of risk on fund growth in standard segments. Whether fund managers do actually engage more heavily in risk taking activities in standard segments than in specialist segments is an open empirical question left for future research.

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 (2004b)
$TNA_{i,t}$	Total net assets under management in million USD of fund i in year t	e.g. SIRRI/TUFANO (1998)
$Load_{i,t}$	Sum of all front and back-end load fees of fund i in year t.	e.g. BARBER/ODEAN/ZHENG (2004)
$TER_{i,t}$	Total expense ratio of fund i in year t	e.g. BARBER/ODEAN/ZHENG (2004)
$Fees_{i,t}$	1/7th of the total load fee plus the TER of fund i in year t	e.g. SIRRI/TUFANO (1998)
$Turnover_{i,t}$	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)	(D)	(E)
$Rank_{i,t-1}$	-0.0673	0.0520	0.1250	0.1540**	0.1233*
$Rank^2_{i,t-1}$	0.6260***	0.4273***	0.3348***	0.3411***	0.3660***
$Rank_{i,t-1}D$		-0.1993***	-0.2819**	-0.3818***	-0.3444***
$Rank^2_{i,t-1}D$		0.3396***	0.4468***	0.4938***	0.4621***
$std_{i,t-1}$	-0.0523	-0.0453	-0.0338	-0.0638	-0.0427
$std_{i,t-1}$ D				0.1729***	0.1688***
$g_{i,t-1}$	0.1449***	0.1453***	0.0235***	0.1447***	0.1447***
$lnTNA_{i,t-1}$	-0.0329***	-0.0330***	-0.0291***	-0.0335***	-0.0359***
$lnAge_{i,t-1}$	-0.0437***	-0.0435***	-0.0665*	-0.0439***	-0.0522***
$Fees_{i,t-1}$	-0.7572	-0.6006	0.0738	-1.6194**	
$Fees_{i,t-1}D$				1.8728**	
$Load_{i,t-1}$					0.0017
$Load_{i,t-1}D$					0.0093***
$TER_{i,t-1}$					-3.4849***
$TER_{i,t-1}D$					0.2067
$Turnover_{i,t-1}$	0.0146**	0.0148**	0.0143*	0.0145**	0.0162***
$g(Seg)_{i,t-1}$	0.2873***	0.2851***	0.5743***	0.2845***	0.2852***
$g(Seg)^2_{i,t-1}$	-0.0463***	-0.0457***	-0.0391***	-0.0456***	-0.0457***
N	15,348	15,348	6,681	15,348	15,348
R^2	19.46%	19.63%	17.46%	19.71%	19,84%

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. Column (C) contains results from a regression where all share classes of a fund are aggregated into the largest share class. In Column (D) an interaction term between a standard-segment dummy, D, and fees and risk, respectively, is added. In Column (E) the fee measure is split up in load fees, $Load_{i,t-1}$, and the expense ratio, $TER_{i,t-1}$. Both measures are also interacted with a large-segment dummy. 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 fees and past return risk.

Table 3: The PFR estimated using piecewise-linear regressions
Period: 1993-2001

	(A)	(B)	(C)	(D)
$LOW_{i,t-1}$	0.3086***	0.3138***	0.4242***	0.3672***
$MID_{i,t-1}$	0.4148***	0.4337***	0.4265***	0.4291***
$HIGH_{i,t-1}$	1.9879***	1.1398***	1.1505***	1.1441***
$LOW_{i,t-1}D$		-0.0096	-0.2181	-0.1355
$MID_{i,t-1}D$		-0.0286	-0.0137	-0.0241
$HIGH_{i,t-1}D$		1.4347***	1.4095***	1.4393***
$std_{i,t-1}$	-0.0506	-0.0425	-0.0629	-0.0412
$std_{i,t-1}$ D			0.1731***	0.1678***
$g_{i,t-1}$	0.1432***	0.1438***	0.1433***	0.1432***
$lnTNA_{i,t-1}$	-0.0328***	-0.0331***	-0.0335***	-0.0360***
$lnAge_{i,t-1}$	-0.0439***	-0.0436***	-0.0440***	-0.0527***
$Fees_{i,t-1}$	-0.7300	-0.6376	-1.3905*	
$Fees_{i,t-1}D$			1.3430*	
$Load_{i,t-1}$				0.0021
$Load_{i,t-1}D$				0.0090**
$TER_{i,t-1}$				-3.2022***
$TER_{i,t-1}D$				-1.0708
$Turnover_{i,t-1}$	0.0146**	0.0144**	0.0141**	0.0158***
$g(Seg)_{i,t-1}$	0.2863***	0.2836***	0.2834***	0.2840***
$g(Seg)^2_{i,t-1}$	-0.0459***	-0.0451***	-0.0452***	-0.0453***
R^2	19.80%	20.09%	20.15%	20.29%

This table shows regression results from model (3) as described in the main text. In Columns (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. In Column (D) the fee measure is split up in load fees, $Load_{i,t-1}$, and the expense ratio, $TER_{i,t-1}$. Both measures are also interacted with a large-segment dummy. The number of observations in all regressions is 15,348. 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 fees and past return risk.

Table 4: Ranks based on Sharpe-Ratios, 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)
$Rank_{i,t-1}$	0.0756	0.1407**	0.2205***	0.1816***	0.3217***	0.4208***	0.1888***	0.3090***	0.3781***
$Rank^2_{i,t-1}$	0.4409***	0.3060***	0.2397***	0.1674***	-0.0628	-0.1460*	0.1446**	-0.0626	-0.1201
$Rank_{i,t-1}D$		-0.1343**	-0.3059***		-0.2803***	-0.4711***		-0.2420***	-0.3865***
$Rank^2_{i,t-1}D$		0.2665***	0.4113***		0.4489***	0.6066***		0.4049***	0.5236***
$std_{i,t-1}$	-0.0289	-0.0130	-0.0105	-0.1700***	-0.1751***	-0.1650***	-0.1684***	-0.1699***	-0.1616***
$std_{i,t-1}$ D			0.1834***			0.1473**			0.1451**
$g_{i,t-1}$	0.1476***	0.1476***	0.1468***	0.1577***	0.1580***	0.1574***	0.1584***	0.1588***	0.1582***
$lnTNA_{i,t-1}$	-0.0340***	-0.0342***	-0.0372***	-0.0305***	-0.0307***	-0.0336***	-0.0301***	-0.0302***	-0.0331***
$lnAge_{i,t-1}$	-0.0427***	-0.0430***	-0.0523***	-0.0442***	-0.0449***	-0.0542***	-0.0437***	-0.0444***	-0.0538***
$Fees_{i,t-1}$	-1.1448**	-0.8304		-1.3091**	-1.2034**		-1.2917**	-1.1004*	
$Load_{i,t-1}$			0.0012			0.0012			0.0016
$Load_{i,t-1}D$			0.0103***			0.0096***			0.0092**
$TER_{i,t-1}$			-3.9614***			-4.7268***			-4.2717***
$TER_{i,t-1}D$			0.0538			0.6624			0.0400
$Turnover_{i,t-1}$	0.0150**	0.0153***	0.0168***	0.0148**	0.0141**	0.0156***	0.0189***	0.0184***	0.0198***
$g(Seg)_{i,t-1}$	0.2887***	0.2850***	0.2852***	0.2934***	0.2910***	0.2909***	0.2931***	0.2902***	0.2902***
$g(Seg)^2_{i,t-1}$	-0.0470***	-0.0462***	-0.0463***	-0.0482***	-0.0478***	-0.0478***	-0.0482***	-0.0476***	-0.0476***
R^2	18.52%	18.70%	18.94%	14.66%	14.93%	15.17%	14.38%	14.63%	14.84%

This table shows regression results from regression model (2) using the same methodology as described in Table 2. 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 number of observations in all regressions is 15,384. 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 fees and past return risk.

Table 5: Temporal Stability of Results

	Segment Ranks Based on Return Ranks		
	1993-1995	1996-1998	1999-2001
$Rank_{i,t-1}$	0.3436	-0.0472	0.1970**
$Rank^2_{i,t-1}$	0.0147	0.4561***	0.3394***
$Rank_{i,t-1}D$	-0.5113*	-0.3399**	-0.3748***
$Rank^2_{i,t-1}D$	0.8246**	0.6095***	0.4005***
$std_{i,t-1}$	-0.3339	-0.3253**	-0.0095
$std_{i,t-1}D$	0.0512	0.0171	0.2114***
$Load_{i,t-1}$	-0.0175*	0.0003	0.0056
$Load_{i,t-1}D$	0.0270**	0.0152**	0.0049
$TER_{i,t-1}$	2.2620	-3.4517*	-5.4310***
$TER_{i,t-1}D$	-10.2228**	-1.4789	1.7282
...	...	...	...
N	1,471	4.100	9,777
R^2	24.62%	24.77%	17.43%

This table shows regression results from the same model as in Column (E) 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 fees and past return risk. Dots represent the other control variables not reported in this table. They are the same as in Tables 2-4.

Table 6: Influence of Other Fund Characteristics

	Segment Ranks Based on Return Ranks		
	(A): Large vs. Small	(B): Old vs. Young	(C): Complete Model
$Rank_{i,t-1}$	-0.7664***	-0.1584	-0.6061***
$Rank^2_{i,t-1}$	1.0108***	0.8477***	0.8935***
$Rank_{i,t-1}D_{big}$	1.5959***		1.5031***
$Rank^2_{i,t-1}D_{big}$	-0.9887***		-0.8528***
$Rank_{i,t-1}D_{old}$		0.2425*	0.1903
$Rank^2_{i,t-1}D_{old}$		-0.4498***	-0.4621***
$Rank_{i,t-1}D$			-0.3236***
$Rank^2_{i,t-1}D$			0.4312***
...	...	...	...
R^2	20.81%	15.96%	21.25%

This table shows regression results from an extension of model (2) from the main text. Performance coefficients are interacted with dummies indicating whether the fund's age is above the median age (dummy-interaction D_{old}), whether the fund's size is above the median size (dummy-interaction D_{big}) or whether the fund is in a standard segment (dummy-interaction D), respectively, or not. Segment ranks are based on returns. All share classes are aggregated. The number of observations in all regressions is 6,681. The R^2 of the regressions is shown in the last row. ***, **, and * denotes statistical significance at the 1%, 5% and 10%-level, respectively. Dots represent the other independent variables not reported in this table. They are the same as in Tables 2-4.

FOOTNOTES

[1] Although there are also a lot of complicated bonus packages based on, e.g., average three-year performance, the main part of fund managers' salary is usually related to assets under management [KHORANA (1996)].

[2] This is often the case, as many families offer their investors the possibility to switch between its funds for free.

[3] Evidence along similar lines is presented by 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. These markets are dominated by professional investors. The PFR in those markets is less convex than in the retail mutual fund market. These papers argue that the less convex PFR they find can be explained by professional investors being better-informed and less prone to behavioral biases than their retail counterparts. However, there is also some interesting experimental evidence indicating that professional traders are not less prone to behavioral biases than lay people [see, e.g., GLASER/LANGER/WEBER (2003)].

[4] SIRRI/TUFANO (1998) apply FAMA/MACBETH (1973) regressions instead of pooled regressions to examine the PFR. We repeat our analysis using FAMA/MACBETH (1973) regressions, too, and obtain very similar results to those using the pooled regression approach.

[5] All results not reported here for the sake of brevity are available from the author on request.

[6] We assume, that investors mainly care about previous year performance. Our results (not reported in tables) are very similar, if we use the performance over the past three years instead of just the last year.

[7] 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).

[8] 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.

[9] In principle, it would also be interesting to examine the influence of tracking error in order to gain a better understanding of the reaction of fund investors to active risk. However, as the calculation of active risk requires the definition of a benchmark for each fund and it is very hard to define an appropriate benchmark index even at the segment level, we refrain from such an examination.

[10] The loads investors actually pay are often lower than the loads officially reported in the CRSP database. For example, brokers often offer discounts to their clients. Nevertheless, the maximum load reported in the database is still the best proxy for the actual load burden and is regularly used in the literature [e.g., BARBER/ODEAN/ZHENG (2004)].

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

[12] Results are very similar if we include a Top-10, Top-5 or Top-3 fund dummy as described above.

[13] However, looking at the (not reported) results for separate estimations for subsamples of funds from specialist and standard segments, we find a significantly positive influence of loads in the latter, but not in the first.

[14] For these stability test we aggregate all classes of a fund into the first class and use the median of the aggregate TNAs of all classes to define our dummy. The age of a fund is given by the age of its oldest share class. Results are very similar if we do not aggregate, but treat each fund class as individual observation. Results also do not change if we use means instead of medians to define our dummies.

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