2008

# Flow-Performance Relationship and Tournament Behavior in the Mutual Fund Industry

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SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN ECONOMICS

SINGAPORE MANAGEMENT UNIVERSITY

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**in the Mutual Fund Industry**

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## Abstract

In this paper, we interpret the flow-performance relationship as an incentive scheme implicitly given to mutual fund managers by mutual fund investors. We show that the flow-performance relationship varies not only with economic activity but also across fund attributes. We provide evidence that the degree of convexity of the flow-performance relationship has a positive effect on the magnitude of tournament behavior. Different from the conventional tournament hypothesis, we show that although the convexity of the flow-performance relationship does produce implicit incentives for fund managers to modify risk-taking behavior as a function of their prior performance, whether or not the mid-year losers increase the risk of their portfolios highly depends on the convexity degree of the flow-performance relationship.

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## Acknowledgements

I am deeply grateful to my teachers, friends and family in continually supporting me during the process of the thesis writing. Their assistance and encouragement make the completion of the thesis possible.

First and foremost, I would like to express my sincerest appreciation to my advisor, Prof. Anthony S Tay, for his valuable guidance and impressive patience. Throughout the study, Prof. Tay made invaluable efforts to help and offer me detailed suggestions to improve my thesis. I am also indebted to my examiner, Prof. Tomoki Fujii, whose comments and suggestions helped strengthen my thesis. My appreciation also extends to all my teachers who have helped me to develop the fundamental and essential academic competence. I would also like to thank Ms. Li Sun for helping me with the techniques of SAS.

Many thanks go to all my classmates, especially Gregorio, Jing, Leming, Xiaojun and Gurmeet, for their everlasting accompany and support. My thanks also go to my friends in China for their understanding and encouragement. Last but not least, thanks go to my dearest parents and my elder brother for being the strongest mental support whenever I was frustrated. Finally, I would like to dedicate this study to my parents who always say that they feel so proud of me.

## I Introduction

During the last two decades, the mutual fund industry experienced tremendous growth both in the number of funds and amount of assets under management. It is not surprising that this industry has attracted a lot of attention both from the academic and professional communities. Since Ippolito (1992) and Sirri and Tufano (1998), there have been extensive studies on the relationship between investment flows and past performance demonstrating that consumers react strongly and asymmetrically to historical returns.

Brown, Harlow and Starks (1996) put forward the tournament hypothesis for the mutual fund industry, that is, given that the compensation for mutual fund managers is often structured as a flat fee plus a percentage of the level of assets under management, and given that the profession currently assesses and reports fund performance on an annual basis, the convex flow-performance relationship provides implicit incentives for managers to alter the risk of their portfolios.

This topic has attracted a lot of attention and empirical verification from studies such as Chevalier and Ellison (1997), Koski and Pontiff (1999), Li and Tiwari (2005), etc. However, recent studies are less supportive of this conjecture. Busse (2001) challenges the evidence in Brown, Harlow and Starks (1996) by showing that monthly results consistent with tournament hypothesis disappear with daily data and pointed out that the puzzle arises from biases in the monthly volatility estimates attributable to daily return autocorrelation. Goriaev, Nijma and Werker (2005) complement this methodological problem by showing that the source of spurious evidence is not from temporal correlation in returns but cross-correlation between idiosyncratic fund returns. Some researchers have tried to reconcile these seemingly contradictory empirical findings in mutual fund tournament behavior. Chevalier and Ellison (1999) and Qiu (2003) point out that the importance of termination risk on risk-taking behavior by fund managers. Hu et al. (2006) suggest a U-shaped tournament behavior. Olivier and Tay (2008) put forward the “Conditional Tournament Hypothesis”, that is, mid-year underperformers increase the risk of their portfolio only when economic activity is strong.

In this paper, we are primarily interested in exploring what types of incentives the convexity of flow-performance relationship creates for funds to manipulate the risk of their portfolios. Since these incentives are affected by the strength and the convexity of the flow-performance relationship, we begin with an attempt to analyze how the convexity of the flow-performance relationship varies both over time along the business cycle and cross-sectionally with fund attributes. On the one hand, we explore the time-series factor which could affect the convexity of flow-performance relationship. We predict that economic activity measured by real GDP growth rate could affect the sensitivity of investor flows to previous performance. On the other hand, we explore the cross-sectional factors which could affect the convexity. We mainly consider fund attributes, such as fund age, total fees and family size, which have already been shown in previous literature but without consistent views of their effects on the investor flows.

Testing these conjectures with monthly return data for more than 2000 actively managed US domestic equity funds, we find that the convexity of the flow-performance relationship is an increasing function of economic activity. We also find that the convexity of the fund flow-performance relationship increases with fund's age and family size, while it decreases with the fund's total fees. This evidence provides reasonable explanation why the convexity degree of the flow-performance relationship varies from sample to sample and implicates varying implicit incentives for the tournament behavior.

Since the risk-shifting incentives are affected by the strength and the convexity of the flow-performance relationship, we investigate the link between the sources of the convexity in the flow-performance relationship and the inter-temporal risk-shifting behavior of mutual fund managers. We find evidence supporting our predictions both in time-series and in cross-sectional perspectives. In particular, from the time-series perspective, we find that economic activity has a significantly positive effect on the magnitude of tournament behavior. This fact is consistent with the conclusion that the convexity of flow-performance relationship is an increasing function of economic activity of Olivier and Tay (2008). From the cross-sectional perspective, we find that fund age and family size have a significantly positive effect on the magnitude of tournament behavior, while fund total fees have a significantly negative effect on the magnitude of tournament behavior. Hence, our results strongly suggest that risk-shifting behavior of fund managers is consistent with the implicit incentives generated from the flow-performance relationship.

Unlike the conventional tournament hypothesis: mid-year loser funds, those with below-median performance, tend to increase portfolio's volatility in the latter part of the year more than mid-year winner funds. Based on our results, we conclude that the convexity of the flow-performance relationship in the mutual fund industry does produce positive implicit incentives for fund managers to modify risk-taking behavior as a function of their prior performance. However, whether or not the mid-year losers increase the risk of their portfolios highly depends on the convexity degree of the flow-performance relationship.

This paper is closely related to Olivier and Tay (2008) who explore the time-varying incentives along the business cycle and the implication for the tournament puzzle. They show that the convexity of the flow-performance relationship varies with economic activity and provide evidence supporting a conditional tournament hypothesis, that is, poor mid-year performers increase the risk of their portfolio only when economic activity is strong. Our main contribution is to carry this intuition further by investigating not only the effect of economic activity on the flow-performance relationship, but also the effects of fund attributes on the flow-performance relationship, and then to explore comprehensively how the implicit incentives created from the varying flow-performance relationship shape the tournament behavior.

Several previous studies examine the asymmetric flow-performance relationship. Sirri and Tufano (1998) find that search cost is an important determinant of fund flows. Using three proxies, they show that funds with higher fees experience a higher sensitivity of fund flows to previous performance. And fund flows are also directly related to fund family size and current media attention which lower the search costs. Huang, Wei and Yan (2007) carry this intuition further by constructing a model to examine how the participation costs affect fund flows and show that funds with lower participation costs are characterized by a less convex flow-performance relationship. They provide evidence that funds with high marketing fees, and affiliated with larger family complexes experience less convexity in the flow-performance relationship. Another branch of the literature focuses on the termination risk. Hu et al. (2006) provide evidence that funds with younger managers, who face greater employment risk, have more convex U-shaped relative risk-prior performance relations.

Our work differs from these studies in several aspects: firstly, we consider not only fund characteristics as potential factors affecting flow-sensitivity to previous performance but also the dynamic feature of flow-performance relationship along the business cycle, as in Kosowski (2006) and Olivier and Tay (2008). All these differences make our work currently the most comprehensive one in exploring the convexity of flow-performance relationship. Secondly, we investigate the link between the factors affecting the convexity of the flow-performance relationship and the inter-temporal risk-shifting behavior of fund managers. We find evidence that the convexity degree of the flow-performance relationship has a positive impact on the magnitude of tournament behavior. Finally, our conclusion provides a fresh perspective on the literature of the tournament hypothesis and gives reasonable explanation of the previous contradictory empirical findings in mutual fund tournament hypothesis.

The rest of the paper is organized as follows: in the next section we review related literature, with a particular focus on the factors affecting the convexity of flow-performance relationship and debates of the tournament hypothesis in the mutual fund industry, and then motivate our testable hypotheses. Section III describes the data and methodology we employ in our empirical analysis, while section IV and V detail the findings of regression tests we run to support our conclusions. In the final section, we summarize the results and put forward some concluding remarks.

## II Literature Review

Many recent studies analyze the determinants of the behavior of mutual fund investors, concentrating on the relation between net flows to mutual fund and their past performance. Ippolito (1992) and Gruber (1996) document a clear positive impact of risk-adjusted as well as raw past performance on subsequent net fund flows. Since Chevalier and Ellison (1997) and Sirri and Tufano (1998) showed that the flow-performance relationship appears to be convex, there have been extensive and convincing empirical evidences on the convexity of the flow-performance relationship. That is, investors respond asymmetrically to the past performance: the mutual funds that performed worse than the competitors do not experience as significant an outflow of invested capital.

Now there is a large literature examining the determinants of the convexity of the flow-performance relationship, especially the effects of fund attributes such as fund size, age, expense ratio, family size, etc. However, there is no consensus about the determinants of the convexity of the flow-performance relationship. Chevalier and Ellison (1997) apply a semi-parametric model to examine the flow-performance relationship and find that younger funds' flows are more sensitive to recent performance but older funds suffer more convex flow-performance relationship. Their results illustrate that compared to the pattern of younger funds, outflows of older funds do not increase dramatically at the worst performance levels. However, flows do increase sharply for the best-performing funds as the case of younger funds. Sirri and Tufano (1998) focus on search costs as one important determinant of fund flows and predict that investors would purchase those funds that are easier or less costly for them to identify. Using three measures of search costs (i.e., complex size, marketing and distribution expenditures, and media coverage), they find that funds with high marketing expense enjoy a much stronger flow-performance relationship. Funds affiliated with larger families will receive greater inflows, and the flow-performance relationship will be stronger for larger complexes. Contrary to Sirri and Tufano (1998), Hu et al. (2006) find that the degree of the convexity of flow-performance relationship decreases with the fund's expense ratio. However, the fund manager's experience (measured by age) does not have a significant effect on the convexity of the flow-performance relationship. Huang, Wei, and Yan (2007) provide evidence that funds with lower participation costs have a higher flow-sensitivity to medium performance and a lower flow-sensitivity to high performance than higher-cost funds, that is, funds with lower participation costs are characterized by a less convex flow-performance relationship. Using several proxies for participation costs, they find that funds with high marketing fees, and affiliated with larger family complexes experience less convexity in the flow-performance relationship.

However, literature has seldom explored the dynamic feature of the flow-performance relationship. Kosowski (2006) examines the evolution of mutual fund performance and flow across the business cycle and shows that the mutual funds' performance is negative on average but becomes positive during recessions. Cederburg (2008) explores the mutual fund investor behavior across the business cycle and provides evidence that investors chase returns when the economy is in expansion but this return-chasing behavior disappears when the economy is in recession. Olivier and Tay (2008) investigate the impact of economic activity on the convexity of the flow-performance relationship and find that even moderate fluctuations in economic activity can have a large impact on the sensitivity of flow to performance.

A topic that has been of considerable recent interest within both the academic and professional communities is how portfolio managers adapt their investment behavior to the economic incentives they are provided. Brown, Harlow, and Starks (1996) for the first time in the literature put forward the tournament hypothesis, given the convexity of the flow-performance relationship, the nature of the fee structure (and therefore, the compensation of mutual fund managers), and the profession's current system of assessing and reporting fund performance on an annual basis. According to their tournament behavior hypothesis, mid-year loser funds, those with below-median performance, tend to increase portfolio's volatility in the latter part of the year more than midyear winner funds.

However, there is not a consensus on the shape of the relationship between interim performance and inter-temporal risk-shifting behavior. Brown, Harlow and Starks (1996) use contingency table methodology applied to monthly data of 334 growth-oriented mutual funds during 1976-1991 and find evidence in favor of the tournament hypothesis. However, the results are highly sensitive to the sample period with the most recent sub-period providing the greatest support for the tournament hypothesis, a possible explanation given is that the tournament incentive effects become more pronounced with the growth in mutual fund. Koski and Pontiff (1999) use regression analysis and find a negative relation between interim performance and subsequent change in risk, which provide evidence of the tournament hypothesis. Li and Tiwari (2005) present empirical evidence consistent with the tournament hypothesis.

Busse (2001) challenges the evidence in Brown et al. (1996) by maintaining that tournament behavior's tests employing monthly data are miss-specified. In fact, standard deviations estimated with monthly data are biased by the daily autocorrelation in returns. Furthermore, when using tests based on daily data, the author finds no evidence of mid-year losers increasing the end-of-year risk level more than winners. If anything, the results indicate the opposite. Moreover, when correcting the statistical tests with empirical p-values, the actual monthly data produce results consistent with the absence of tournament behavior. Goriaev, Nijman and Werker

(2005) complement the methodological issues raised by Busse (2001). They also report that, depending on the sample period, the evidence in their sample as often supports the tournament hypothesis as it does the opposite result, namely, that poor half-year performers decrease the level of risk of their portfolio relative to that of strong half-year performers.

Some researches have tried to reconcile these contradictory empirical findings in mutual fund tournament behavior. Taylor (2003) models an investment tournament where two funds with different mid-year performance compete to attract end-of-year cash flows, and are subject to a convex compensation schedule. On the one hand, when a manager competes against an exogenous benchmark winner funds invest in the index, whereas loser funds will tend to deviate from the index, thus “gambling”. On the other hand, when both managers are active and interact strategically, the winning manager is more likely to deviate from the index and the losing manager is more likely to choose a “safe” strategy. Olivier and Tay (2008) put forward “conditional tournament hypothesis”, that is, the change in risk by mid-year underperformers should be positively correlated with economic activity.

In this paper, we explore how the flow-performance relationship varies both over time as economic activity changes and cross-sectionally with fund attributes, what types of incentives this creates for fund managers to modify the risk of their portfolios in response to their interim performance, and how the incentives and the resulting tournament behavior are affected by the strength and the convexity of the flow-performance relationship.

## III Data and Methodology

### (A) Sample Description

We obtain fund flow, return, and other fund characteristics data from the CRSP Survivor-Bias-Free US Mutual Fund Database for the period January 1975 – December 2006. Apart from mutual fund data, we use the risk-free rate, market return, Fama and French (1993) SMB and HML factors, and Carhart (1997) momentum factor, which were obtained from the CRSP Mutual Fund Monthly Returns and Fama-French Factors files. Data on real GDP growth rate is downloaded from EconStats[1].

In line with prior studies, we focus on the sample of US domestic equity mutual funds classified as aggressive growth (AG), growth and income (GI), and long-term growth (LG) funds. We restrict our sample to growth-oriented funds since they are evidenced by the attention they receive from both the financial press and direct investor involvement, and they are most widely followed and often-ranked class of publicly traded funds. We exclude funds closed to investors, index funds, and funds of funds. CRSP reports funds' data at the class share level. The different share classes of the same fund only differ with respect to their fee structure or their minimum investment requirements, but are backed by the same portfolio of assets. So for funds with multiple share classes, we only keep one representative class with the largest TNA. We also eliminated funds that merged with other funds during the fund-year and two groups of funds for which the flow data are exceptionally noisy: funds with less than 2 full years of return history and funds whose total net assets never reached $15 million during their existence. Our final sample consists of 2065 funds. For each fund, we select the largest contiguous sample period for which we have no missing observations for TNA or returns. This leaves us with a total of 15083 observations for the regressions. The summary statistics of the sample are presented in Table 1.

(B) Variable Definitions

We consider dollar flows because they directly determine the manager's compensation. This is calculated as:

$$Flow_{i,t} = TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1},$$

[1] http://www.econstats.com/gdp/gdp__a1.htm.

where $TNA_{i,t}$ is fund $i$'s total net assets in year $t$, and $r_{i,t}$ is the fund's return over the prior year.

Fund performance can be measured in many ways. Here we adopt three most commonly used measures of performance in the literature on the flow-performance relationship:

(1) Excess return, obtained as the fund's return less the value-weighted market portfolio return.

(2) One-factor alpha, obtained as the fund excess return less the product of excess market return and beta. Each month we estimate beta of one-factor model by regressing the excess fund returns on the excess market returns using data from the previous 24 months.

$$r_{it} = \alpha_{it} + \beta_{it} MKTRF_t + e_{it},$$

where $r_{it}$ is the return on a portfolio in excess of the one-month T-bill return; $MKTRF_t$ is the excess return on the CRSP value-weighted portfolio of all NYSE, Amex, and Nasdaq stocks; the residual $e_{it}$ reflects the idiosyncratic risk.

(3) Four-factor alpha, obtained as the fund excess return less the sum of the products of each of the four factor realizations and the corresponding factor loadings. Each month we estimate factor loadings of a four-factor model by regressing the excess fund returns on the excess market return, the SMB, HML, and momentum factors using data from the previous 24 months.

$$r_{it} = \alpha_{it} + b_{it} MKTRF_t + s_{it} SMB_t + h_{it} HML_t + p_{it} UMD_t + e_{it},$$

where MKTRF is the excess return on a value-weighted aggregate market proxy; and SMB, HML, and UMD are returns on value-weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns.

For each performance measure, we use each fund's performance ranking relative to other funds in the same period, which is commonly reported in consumer periodicals. A fund's fractional rank represents its percentile performance relative to other funds in the same period, and ranges from 0 to 1. For convenience of comparison, we follow the convention in the literature to break the funds' fractional ranks down into three subgroups by their relative performance in the same period: isolating the top 20 percent and bottom 20 percent quintiles from the middle 60 percent of funds[2]. Following Sirri and Tufano (1998), we restrict this piecewise linear relationship to be continuous by defining:

$$Bottom_{i,t-1} = \min(Rank_{i,t\text{-}1},\ 0.2);$$

$$Middle_{i,t-1} = \min(Rank_{i,t\text{-}1} - Bottom_{i,t-1},\ 0.6);$$

$$Top_{i,t-1} = \min(Rank_{i,t\text{-}1} - Bottom_{i,t-1} - Middle_{i,t-1},\ 0.2);$$

where $Rank_{i,t\text{-}1}$ denotes the rank of fund $i$ in year $t\text{-}1$.

We employ a number of control variables in the various regression specifications, which can be viewed as two types: one is time-series variable, which we interact with performance variables to capture the time-variation of flow-performance relationship and the effect on tournament behavior; the other is cross-sectional variables, which are funds' attributes that have been found by the existing literature to have an impact on flows from investor. More importantly, we also interact these variables with performance variables to explore the impacts of these variables on the convexity of flow-performance relationship and the tournament behavior. The time-series variable we use is the real GDP growth rate, which is computed as 100 times the difference of the log of annual GDP measured in billions of chained 2000 dollars.

[2] Though not reported here, we also run regressions by breaking the performance rank down into five equal subgroups of 20 percent each. The results points in the same direction and with similar economic and statistical significances.

For the cross-sectional variables, we include expenses expressed in percentages, the age of the fund in years, funds' prior relative size, funds' prior volatility, and funds' family size. Investors pay many different types of fees to buy and hold mutual funds, including up-front fees (loads or sales commissions) and ongoing fees (reflected in the fund's expense ratio). Since we focus on exploring the flow-performance relationship, in this paper we are interested in the total fees charged to investors rather than the individual components of fees. Thus, following Sirri and Tufano (1998) we adopt the total fees as a measure of marketing expenses. Total fees are computed as the summation of the annual expense ratio and one-seventh of total load fees because the average holding period of funds is seven years. The initial relative size is defined as $TNA_{i,t-1} / \sum_i TNA_{i,t-1}$ .

The time-variation of potential factors affecting the flow-performance relationship is reported in Figure 1. The time-variation of real GDP growth rate, average age, average total fees and average family size are shown in Panel A, B, C and D respectively. From these panels, we can see that variation in all four factors is substantial in the sample period. The fact intensifies the meaning of exploring the effects of these factors on the flow-performance relationship and tournament behavior.

To examine the tournament hypothesis, we divide each calendar year in the sample period into two equal sub-periods of six months each. We compute the idiosyncratic risk of the fund for each sub-period of the year as the standard deviation of the estimated monthly fund residual using the market model for a particular sub-period. Specifically, the idiosyncratic risk for fund $i$ for sub-period $s$ ($s$ =1, 2) of year $t$, denoted by $\sigma(\varepsilon_{i,t}^s)$, is given by the standard deviation of the monthly residual $\varepsilon_{i,t}^s$. The fund residual is estimated as:

$$\varepsilon_{i,t}^s = \{r_{i,t} - (\hat{\alpha}_{i,t} + \hat{\beta}_{i,t} r_{m,t})\}_{t \in \Gamma(s)},$$

where $\Gamma(s) = \{1,...,6\}$ for $s = 1$; and $\Gamma(s) = \{7,...,12\}$ for $s = 2$.

In the above equation, $r_{i,t}$ denotes the return in excess of the one month US T-bill return for fund $i$ during month $t$, and $r_{m,t}$ denotes the excess return on the CRSP value-weighted market portfolio for month $t$. We obtain the parameters estimates $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ using monthly fund returns for the 24 months immediately preceding year t. We estimated the change in idiosyncratic risk of fund $i$ for year $t$ as $\Delta\sigma_{i,t} = \sigma(\varepsilon_{i,t}^2) - \sigma(\varepsilon_{i,t}^1)$.

(C) Methodology

We follow Sirri and Tufano (1998) to run piecewise regressions on performance to explore the convexity of flow-performance relationship. Since Oliver and Tay (2008) provide evidence that the sensitivity of flow to performance varies at business cycle frequencies, which contradicts the Fama-MacBeth assumptions and could lead to misleading conclusions, we run an unbalanced panel, allowing for time fixed effects via a full set of year dummy variables and controlling for fund-specific effects by using standard errors clustered by funds. The basic model would be:

$$\begin{aligned} Flow_{i,t} &= (Year\ dummies) + (Controls) + \alpha_1 Top_{i,t-1} + \alpha_2 Middle_{i,t-1} + \alpha_3 Bottom_{i,t-1} \\ &+ \beta_1 Top_{i,t-1} * Cvx_{i,t-1} + \beta_2 Middle_{i,t-1} * Cvx_{i,t-1} + \beta_3 Bottom_{i,t-1} * Cvx_{i,t-1} \end{aligned} \quad (1)$$

where $Cvx_{i,t}$ is the general term that indicates the factors inducing the convexity of the flow-performance relationship.

The basic model for exploring the tournament hypothesis[3] is:

$$\Delta\sigma_{i,t} = (Year\ dummies) + (Controls) + \alpha\sigma(\varepsilon_{i,t}^1) + \beta Rank_{i,t}^1 + \gamma Rank_{i,t}^1 * Cvx_{i,t-1} \quad (2)$$

[3] As a robust check we repeat our regressions by using the total risk and systematic risk as risk measures. Though not reported here for brevity, the results are weaker than that using idiosyncratic risk as risk measure. It is reasonable since that underperformers want to catch up by generating "spurious alphas" which is achieved by raising the idiosyncratic risk.

## IV Flow-Performance Relationship

Previous research on the relationship between investment flows and past performance has demonstrated that consumers react strongly and asymmetrically to historical returns. We are primarily interested in exploring what types of incentives this creates for fund managers to modify the risk of their portfolios, and how these incentives vary both over business cycle and cross-sectionally with fund attributes. These incentives are affected by the strength and the convexity of the flow-performance relationship. Hence, in this section we begin with an attempt to explore the flow-performance relationship, and more importantly, how the sensitivity of investor flows to previous performance varies both over time with economic activity and cross-sectionally with fund attributes.

### (A) The Shape of Flow-Performance Relationship

In this subsection, we try to estimate the effects of past performance and other characteristics on the flow of investments into a fund. A number of early papers report a positive linear relationship between asset growth and the performance of individual funds. Since the seminal work by Ippolito (1992), especially after Sirri and Tufano (1998), a large and active literature has confirmed the existence of a convex relationship between flows and past performance, which means that mutual fund investors respond asymmetrically to the past performance: the mutual funds that performed worse than the competitors do not experience as significant an outflow of invested capital.

To examine the flow-performance relationship, we run the following piecewise linear regression:

$$Flow_{i,t} = (Year\ dummies) + (Controls) + \alpha_1 Top_{i,t-1} + \alpha_2 Middle_{i,t-1} + \alpha_3 Bottom_{i,t-1} \quad (3)$$

As we are interested in asymmetric responses to top and bottom performance, we structure the analysis using piecewise linear regression, which allows us to separately calculate the sensitivity of flow to performance in each of three performance quintile. The coefficients on these piecewise decompositions of fractional ranks represent the slope of the flow-performance relationship over their range of sensitivity.

The regression results are presented in Table 2 with three specifications I - III, each representing for one performance measure. For all specifications, there is a significantly negative effect between flows and fund age, and a significantly positive relation between flows and fund family size. That is, the younger the fund is and/or the larger the fund family size is, the more dollar flows attracted by this fund. In line with the existing literature, we find that there is a significantly positive relation between flow and relative performance both for top quintile and middle quintile but there is no significant relation for bottom quintile, which suggests a convex flow-performance relationship. To explore the convexity, we perform a one-sided t-test for all the three specifications with the null hypothesis $H_0$ that the estimated coefficient for Top quintile ($\alpha_1$) is smaller than the estimated coefficient for Bottom quintile ($\alpha_3$). From the one-sided t-test results, we can see that the convexity of flow-performance relationship is robust to all the performance measures. And the convexity is statistically significant at 1% level of confidence for specifications based on excess return and one-factor alpha, at 5% level of confidence for specification based on four-factor alpha.

Overall, our findings are consistent with the existing literature. The flow-performance relationship is positive and convex, that is, mutual fund investors chase returns, flocking to funds with the highest previous returns, but failing to flee from poor performers.

(B) Effect of Economic Activity on the Flow-Performance Relationship

We have already seen that investor flows react asymmetrically to previous performance. Our objective in this subsection is to examine the dynamic feature of the flow-performance relationship. To explore the sensitivity of investor flows to previous performance along the business cycle, we construct interaction term by multiplying the fractional rank with the proxy, $egdp_{i,t}$, for economic activity in the following regression:

$$\begin{aligned} Flow_{i,t} &= (Year\ dummies) + (Controls) + \alpha_1 Top_{i,t-1} + \alpha_2 Middle_{i,t-1} + \alpha_3 Bottom_{i,t-1} \\ &+ \beta_1 Top_{i,t-1} * egdp_{i,t} + \beta_2 Middle_{i,t-1} * egdp_{i,t} + \beta_3 Bottom_{i,t-1} * egdp_{i,t} \end{aligned} \quad (4)$$

where $egdp = g_{GDP} - \overline{g}_{GDP}$, and $g_{GDP}$ denotes the real GDP growth rate in year $t$.

For the above regression, we can decompose the total effect of a change in performance on investor flows in the following way:

$$\frac{dFlow_{i,t}}{dPerformance_{i,t-1}} = \frac{\partial Flow_{i,t}}{\partial Performance_{i,t-1}} + egdp_{i,t} \frac{\partial Flow_{i,t}}{\partial (Performance_{i,t-1} * egdp_{i,t})} \quad (5)$$

The effects can be interpreted as follows: Under average economic activity, that is when the GDP growth rate is equal to its sample mean, the second term in the RHS of (5) is equal to 0. In that case, the total effect of past performance on flows is just given by the partial derivative of flows on performance. Therefore, the coefficient of flows on previous performance can be interpreted as the sensitivity of flows to performance under average economic activity. Otherwise, when economic activity is strong (weak), that is when the GDP growth rate is larger (smaller) than its sample mean, the total effect of previous performance on flows is equal to the partial derivative of flows on previous performance plus the product of economic activity and the partial derivative of flows on the interaction item. Therefore, the sensitivity of flows to previous performance is an increasing function of economic activity if and only if the coefficient on the interaction item is positive.

Table 3 reports the results of our analysis with specifications I - III. The results can be interpreted as follows: The convexity of the flow-performance relationship is an increasing function of economic activity if and only if the coefficient of $Top_{i,t-1} * egdp_{i,t}$ is strictly larger than the coefficient of $Bottom_{i,t-1} * egdp_{i,t}$. We can observe that investor flows react more to funds in the top quintile during years with strong economic activity. From the one-sided t-test results, we can see that the effect is statistically significant at 5% level of confidence for the specifications with rank based on excess return and one-factor alpha. However, the effect is not statistically significant for the specification based on four-factor alpha. In the case of Oliver and Tay (2008), the results based on four-factor alpha are also weaker than that based on excess return and one-factor alpha. We conjecture that this is because the four-factor alpha excludes the momentum effect.

It is important to note that the coefficients for the top performance and the top interaction item are of the same magnitude, which implies that even small fluctuations of the economic activity have a large impact on the convexity degree of the flow-performance relationship. For example, if the GDP growth rate increases by 2%, the slope for the top quintile would be twice as large as that under the average economic activity but there is no big change for the slope of the bottom quintile. This would largely increase the sensitivity of the fund flows to previous performance. Taking consideration of the real GDP growth rate's fluctuations illustrated in Panel A of Figure 1, it is not surprising that the convexity degree of flow-performance relationship is highly sensitive to the sample period.

The result reinforces the empirical results of Oliver and Tay (2008)[4]. Recalling that we set no constraints on the fund front load and rear load in our sample, the result suggests that the effect of economic activity on the flow-performance relationship is robust to fund load type.

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[4] As a robust check we repeat our regressions on the sample restricted to no-load funds, that is, we exclude funds with front loads and funds with rear loads strictly larger than 1% from our sample. Though not reported here for the sake of brevity, our results are qualitatively unchanged for this alternative sample.

(C) Effects of Fund Attributes on the Flow-Performance Relationship

In last subsection, we have already explored how the sensitivity of investor flows to previous performance varies over time. In this subsection, we would extensively examine the effects of fund attributes on the convexity degree of the fund flow-performance relationship. Following the literature investigating factors affecting the convexity of the flow-performance relationship, here we concentrate on three factors, namely fund age, total fees and family size.

Similarly with the method adopted in subsection (B), we explore the effects of fund attributes by including interaction variables, which are constructed as the products of performance rank and fund attributes. Specifically, we multiply previous performance rank with the deviation of log of fund age from its sample mean, deviation of prior total fees from its sample mean and prior relative family size. We adopt the real values of interaction terms instead of using dummy variables to split the sample so as to achieve continuous effects. The regressions exploring the effects of fund age, total fees, family size and the cross-sectional variables on flow-performance relationship are presented in Panel A, B, C and D of Table 4 respectively.

$$\frac{dFlow_{i,t}}{dPerformance_{i,t-1}} = \frac{\partial Flow_{i,t}}{\partial Performance_{i,t-1}} + Cvx_{i,t-1}\frac{\partial Flow_{i,t}}{\partial (Performance_{i,t-1} * Cvx_{i,t-1})} \qquad (6)$$

Similarly, the results can be interpreted as follows: The convexity of the flow-performance relationship is an increasing function of $Cvx_{i,t-1}$ if and only if the coefficient of $Top_{i,t-1} * Cvx_{i,t-1}$ is strictly larger than the coefficient of $Bottom_{i,t-1} * Cvx_{i,t-1}$. Note that here the $Cvx_{i,t-1}$ denote fund attributes, namely fund age, total fees and family size.

Panel A of Table 4 provides evidence that fund age has a significantly positive effect on the degree of convexity of the flow-performance relationship, that is, older funds suffer a more convex flow-performance relationship. The effect is statistically significant at 1% level of confidence for all the three specifications. The most striking feature of this panel is that the effect of age on the convexity comes mainly from its impact on the bottom quintile. This should not come as a surprise since older funds have longer history, the flows they experienced should be less sensitive to their most recent performance. When older funds perform badly, they would not experience as much outflow as younger funds. There is no big difference between older funds and younger funds when they outperform and experience inflows. This point verifies the empirical results illustrated by Figure 1 and Figure 2 of Chevalier and Ellison (1999).

From Panel B of Table 4, we can find that the convexity of flow-performance relationship is a decreasing function of total fees. This is consistent with Hu et al. (2006) and Huang et al. (2007). It's important to note that our one-sided t-test null hypothesis $H_0$ is that the estimated coefficient for Top quintile is smaller than the estimated coefficient for Bottom quintile. The alternative hypothesis $H_1$ would be that the estimated coefficient for Top quintile is not smaller than the estimated coefficient for Bottom quintile. Since the p-values of one-sided t-tests for these three specifications are 0.994, 0.997, and 0.986 respectively, the corresponding p-values of the alternative one-sided t-tests should be 0.006, 0.003, and 0.014 respectively. Therefore, the negative effect of total fees on the convexity is statistically significant at 5% level of confidence for all these three specifications.

Panel C of Table 4 shows that the convexity of flow-performance relationship increases with fund's family size, that is, fund belonging to a larger family is inclined to have a more convex flow-performance relationship. Similar with the case of fund age effect, the effect of family size on the convexity also comes mainly from its impact on the bottom quintile. The intuition behind this evidence is that funds affiliated with larger family size have better market reputation. Investors would flock to these funds when they rank in top quintile as usual, but failing to flee from these funds even if they rank in bottom quintile. It is important to note that for convenience we adopt prior relative family size as proxy rather than deviation from its sample mean since family size has larger magnitude than other variables. So the understanding of coefficients a1 to a3 becomes: the effect of previous performance on flows when the prior relative family size is equal to 0. Since the prior relative family size is always bigger than 0, the shape of flow-performance relationship is mainly determined by the interaction items. The insignificant one-sided t-test results of (a1-a3) do not affect the convexity of the flow-performance relationship.

Panel D of Table 4 reports the joint effects of fund attributes on the flow-performance relationship. We can see that the effects of these variables on the flow-performance are consistent with their separate effects as explored in above panels. Overall, the relationship between fund flows and performance is convex, and the degree of convexity of the flow-performance relationship increases with fund age and family size, while decreasing with total fees.

(D) The Joint Effects on the Flow-Performance Relationship

Table 5 presents the joint effects of economic activity and fund attributes on the flow-performance relationship. The effects retain in the same direction and with similar economic and statistical significances. The results of this section can be summarized as follows:

(i) Generally, the flow-performance relationship of our sample is positive and convex.

(ii) The convexity of the flow-performance relationship positively varies with the economic activity.

(iii) The convexity of the flow-performance relationship varies with fund attributes. Specifically, fund age and family size have significantly positive effects on the degree of the convexity; while total fees have a significantly negative effect on the degree of the convexity.

(iv) The effects of economic activity and fund attributes remain unchanged even when we pool them together.

(v) Given the large fluctuations of these factors as illustrated in Figure 1, the results provide reasonable explanation why the convexity degree of the flow-performance relationship varies from sample to sample.

## V Tournament Behavior

In this section, we come to the question that most interests us: investigating how mutual fund managers adjust the risk of their portfolios in response to the incentives created by the flow-performance relationship. These incentives are affected by the strength and the convexity of the flow-performance relationship. And we have already shown that the convexity of the flow-performance relationship varies not only along business cycle but also cross-sectionally with fund attributes. Therefore, our objective in this section is to explore how these incentives and the resulting inter-temporal risk-shifting behavior of mutual fund managers vary with economic activity and fund attributes.

$$\Delta\sigma_{i,t} = (Year\ dummies) + (Controls) + \alpha\sigma(\varepsilon^{1}_{i,t}) + \beta Rank^{1}_{i,t} + \gamma Rank^{1}_{i,t} * Cvx_{i,t-1} \qquad (2)$$

From the regression model shown in equation (2) and the chain rule, we can decompose the total effect of a change in performance rank on the risk-shifting behavior as follows:

$$\frac{d\Delta\sigma_{i,t}}{dRank^{1}_{i,t}} = \frac{\partial\Delta\sigma_{i,t}}{\partial Rank^{1}_{i,t}} + Cvx_{i,t-1}\frac{\partial\Delta\sigma_{i,t}}{\partial(Rank^{1}_{i,t} * Cvx_{i,t-1})} \qquad (7)$$

The effects can be interpreted as follows: $Cvx_{i,t-1}$ would strengthen the tournament behavior if and only if the coefficient for $Rank^{1}_{i,t} * Cvx_{i,t-1}$ is negative;

$Cvx_{i,t-1}$ would weaken the tournament behavior if and only if the coefficient for $Rank^{1}_{i,t} * Cvx_{i,t-1}$ is positive.

Table 6 reports the effect of economic activity on the tournament behavior. We can find that the coefficients for the interaction terms are negative for specifications with performance rank based on excess return and one-factor alpha. This indicates that when economic activity is strong, the fund managers do adjust their risk in the direction of the incentive we analyzed and the magnitude of the response is larger when the economic activity is stronger. Recall from subsection A of Section IV that the convexity of the flow-performance relationship is an increasing function of economic activity. The positive effect of economic activity on the magnitude of tournament behavior strongly suggests that the risk-shifting behavior of fund managers does react to the implicit incentive created by the time-varying flow-performance relationship. Note that the coefficients for the performance rank and interaction item is -0.131 and 0.045 respectively for the specification based on four-factor alpha. This is consistent with the results in Table 3, namely, the flow-performance relationship is convex under average economic activity but the effect of economic activity is not statistically significant, which we conjecture is due to the exclusion of momentum effect in four-factor alpha.

Table 7 presents the effects of fund attributes on the tournament behavior. From Panel A of Table 7, we can observe that the coefficients for the interaction terms, $Rank^{1}_{i,t} * e\ln age$, are negative for all the three specifications. The effect is statistically significant at the 1% level of confidence for all the three specifications. It is consistent with the effect of fund age on the flow-performance relationship as we explored in Panel A of Table 4. Therefore, fund age has a significantly positive effect on the tournament behavior.

From Panel B of Table 7, we can find that the coefficients for the interaction terms, $Rank_{i,t}^{1} * elfee$, are positive for all the three specifications. The effect is statistically significant at the 1% level of confidence for all the three specifications, which is consistent with the effect of total fees on the flow-performance relationship as we explored in Panel B of Table 4. Hence, total fees have a significantly negative effect on the tournament behavior.

From Panel C of Table 7, we can find that the coefficients for the interaction terms, $Rank_{i,t}^{1} * lrfsize$, are negative for all the three specifications, that is, family size has a positive effect on the tournament behavior. The effect is statistically significant at the 10% level of confidence for specifications with performance rank based on excess return and one-factor alpha. The effect is somewhat weaker for the specification with performance rank based on four-factor alpha. This is consistent with the effect of family size on the flow-performance relationship as we explored in last section. Panel D of Table 7 presents the cross-sectional joint effects on the tournament behavior. We can see that the separate effects of these factors remain unchanged even when we pool them together.

Table 8 reports the joint effects of all these factors on the tournament behavior. We can see that the effects of these factors remain in the same direction and with similar economic and statistical significances even when we pool them together. Consistent with the direction suggested in last section, we can find that the economic activity, fund age, and family size have significantly positive effects on the magnitude of the tournament behavior, while total fees have a significantly negative effect on the magnitude of the tournament behavior.

So far, we have examined how the sources of implicit incentives generated from the varying flow-performance relationship shape the tournament behavior. As shown in last section, economic activity, fund age and family size have significantly positive effects on the convexity degree of flow-performance relationship and total fees have a significantly negative effect on the convexity degree of the flow-performance relationship; and now we provide evidence that the economic activity, fund age and family size strengthen the magnitude of the tournament behavior and total fees weaken the magnitude of the tournament behavior. This fact strongly indicates that the convexity degree of the flow-performance relationship has a significantly positive effect on the magnitude of the tournament behavior. Taking consideration of the substantial fluctuations of these factors as illustrated in Figure 1, it is reasonable to find that the empirical results of the tournament hypothesis highly depends on the sample chosen.

## VI Conclusion

In this paper, we interpret the flow-performance relationship as an incentive scheme implicitly given to mutual fund managers by mutual fund investors. We show that the flow-performance relationship varies not only along business cycle but also across fund attributes. Specifically, the convexity of the flow-performance relationship is an increasing function of economic activity, fund age and family size; and the convexity of the flow-performance relationship is a decreasing function of total fees. All these make our work currently the most comprehensive one in exploring the convexity of flow-performance relationship.

In succession, we investigate the link between the factors affecting the convexity of the flow-performance relationship and the inter-temporal risk-shifting behavior of fund managers. We provide evidence that mutual fund managers respond to this incentive scheme: funds alter their portfolios between June and December in a manner consistent with the implicit risk-shifting incentive generated from the flow-performance relationship. That is, economic activity, fund age and family size have significantly positive effects on the magnitude of the tournament behavior, and total fees have a significantly negative effect on the magnitude of the tournament behavior. The evidence strongly indicates that the higher the convexity degree of the flow-performance relationship is, the higher the magnitude of tournament behavior is.

These findings provide a fresh perspective on the literature of the tournament hypothesis and give a reasonable explanation of the previous contradictory empirical findings of the tournament hypothesis in mutual fund industry.

Different from the conventional tournament hypothesis: mid-year loser funds, those with below-median performance, tend to increase portfolio's volatility in the latter part of the year more than mid-year winner funds, based on our results we conclude that although the convexity of the flow-performance relationship in the mutual fund industry does produce implicit incentives for fund managers to modify risk-taking behavior as a function of their prior performance, whether or not the mid-year losers increase the risk of their portfolios highly depends on the convexity degree of the flow-performance relationship.

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**Figure 1: Time-Variation of Factors**

This figure plots the time-variation of factors which affect the flow-performance relationship during our sample period: 1975-2006. The time-variation of real GDP growth rate, average age, average total fees and average family size are shown in Panel A, B, C and D respectively. Real GDP growth rate is computed as 100 times the difference of the log of annual GDP measured in billions of chained 2000 dollars. Each year, average age is computed as the mean of fund age (years) in the year; average total fees is computed as the mean of total fees (%) in the year; average family size is computed as the mean of family size ($m) in the year.

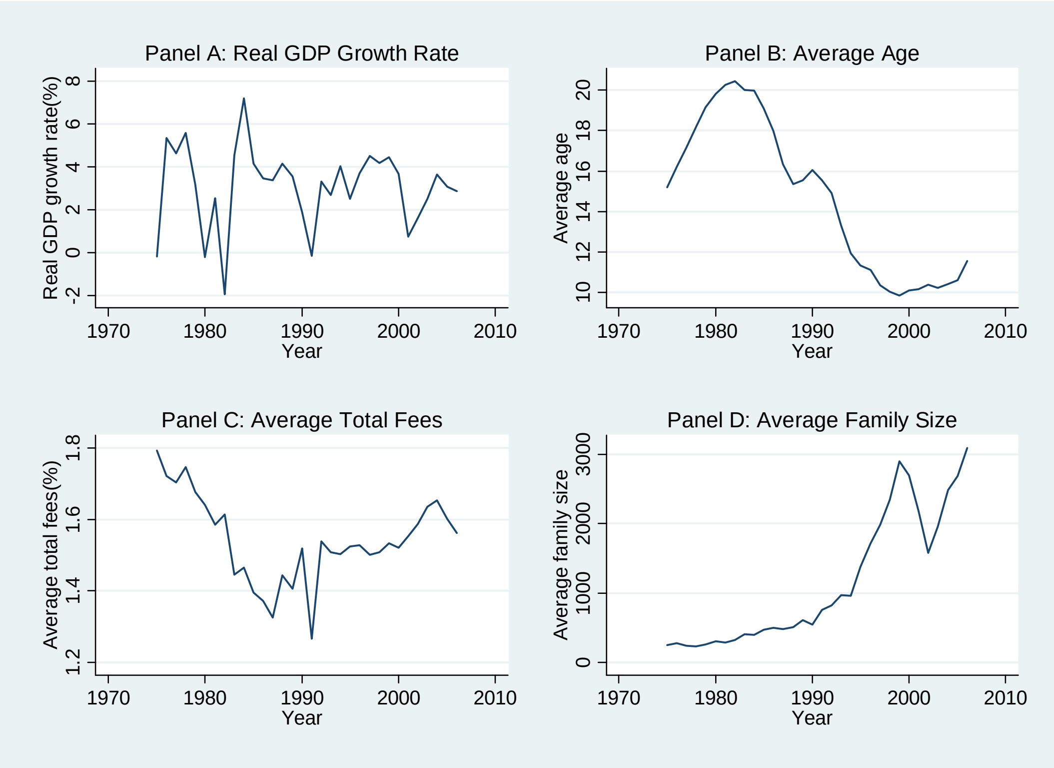

**Table 1: Summary Statistics**

This table presents the summary statistics for the fund flow, performance and control variables. The sample includes US domestic equity funds that have records in the CRSP Survivor-Bias free U.S. Mutual Fund database from 1975 to 2006. By restricting the sample to growth-oriented funds and eliminating other noisy factors, only 2065 funds are left in the sample with 15083 observations. Fund flow is defined as: $Flow_{i,t} = TNA_{i,t} - (1+r_{i,t})TNA_{i,t-1}$, where $TNA_{i,t}$ is fund $i$ 's total net assets at time $t$, and $r_{i,t}$ is the fund's return over the prior year. Size is defined as $TNA_{i,t} / \sum_i TNA_{i,t-1}$. Excess return is obtained as the fund's return less the value-weighted market portfolio return. Each month we estimate factor loadings of a one-factor/four-factor model using data from the previous 24 months. And the one-factor/four-factor alpha is obtained as the fund excess return less the sum of the products of each of the factor realizations and the corresponding factor loadings.

| Variables | Mean | Standard Deviation |
|---|---|---|
| Flow | 15.74 | 392.5 |
| Excess return | 0.001 | 0.12 |
| 1-factor alpha | -0.005 | 0.11 |
| 4-factor alpha | -0.010 | 0.09 |
| Size (%) | 0.20 | 0.66 |
| Age (years) | 13.4 | 12.2 |
| Expense ratio (%) | 1.23 | 0.52 |
| Total fees (%) | 1.55 | 0.71 |
| Family size ($m) | 7480 | 20812 |
| Turn ratio | 1.01 | 1.71 |
| Volatility | 0.05 | 0.02 |
| Real GDP Growth Rate (%) | 3.07 | 0.02 |

**Table 2: Flow-Performance Relationship**

This table examines the flow-performance relationship. For each specification (I-III), we run an unbalanced panel, allowing for time fixed effects via a full set of year dummy variables and control for fund-specific effects by using standard errors clustered by funds. Note that coefficients for the year dummies are not reported for brevity. For each regression, the dependent variable, $Flow_{i,t}$, is defined as: $Flow_{i,t} = TNA_{i,t} - (1+r_{i,t})TNA_{i,t-1}$, where $TNA_{i,t}$ is fund $i$'s total net assets at time $t$, and $r_{i,t}$ is the fund's return over the prior year. Each year, funds are ranked between 0 and 1 based on their previous year performance which is measured by excess return, one-factor alpha, or four-factor alpha. We report below each triplet of rank variables the difference between the coefficient of the top quintile and that of the corresponding bottom quintile and p-value resulting from the one-sided t-test.

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| $Size_{i,t-1}$ | 22.17 | 0.467 | 20.85 | 0.495 | 20.37 | 0.498 |
| $Age_{i,t}$ | -1.95 | 0.005 | -1.99 | 0.004 | -2.14 | 0.002 |
| $Expense_{i,t-1}$ | -3.92 | 0.613 | -2.09 | 0.788 | 0.22 | 0.978 |
| $Lnfsize_{i,t-1}$ | 5.41 | 0.026 | 6.34 | 0.010 | 6.46 | 0.009 |
| $Volatility_{i,t-1}$ | 333.7 | 0.066 | 199.2 | 0.246 | 188.1 | 0.259 |
| $Turnover_{i,t-1}$ | -2.66 | 0.066 | -0.76 | 0.585 | -0.05 | 0.965 |
| $a_1$: $Top_{i,t-1}$ | 505.5 | 0.002 | 496.8 | 0.000 | 320.7 | 0.012 |
| $a_2$: $Middle_{i,t-1}$ | 293.9 | 0.000 | 277.3 | 0.000 | 212.7 | 0.000 |
| $a_3$: $Bottom_{i,t-1}$ | -51.1 | 0.481 | -106.3 | 0.210 | 29.45 | 0.737 |
| $a_1$-$a_3$ | 556.6 | 0.000 | 603.1 | 0.000 | 291.2 | 0.016 |

**Table 3: Effect of Economic Activity on the Flow-Performance Relationship**

This table examines the economic activity effect on the flow-performance relationship. For each specification (I-III), we run an unbalanced panel, allowing for time fixed effects via a full set of year dummy variables and control for fund-specific effects by using standard errors clustered by funds. Note that coefficients for the year dummies are not reported for brevity. For each regression, the dependent variable, $Flow_{i,t}$, is defined as: $Flow_{i,t} = TNA_{i,t} - (1+r_{i,t})TNA_{i,t-1}$. Each year, funds are ranked between 0 and 1 based on their previous year performance which is measured by excess return, one-factor alpha, or four-factor alpha. $egdp$ measures deviations in percentage of the US real GDP growth rate from its sample mean. We report below each triplet of rank variables the difference between the coefficient of the top quintile and that of the corresponding bottom quintile and p-value resulting from the one-sided t-test.

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| $Size_{i,t-1}$ | 21.89 | 0.473 | 20.38 | 0.506 | 20.50 | 0.495 |
| $Age_{i,t}$ | -1.96 | 0.004 | -2.00 | 0.004 | -2.15 | 0.002 |
| $Expense_{i,t-1}$ | -3.88 | 0.615 | -1.59 | 0.838 | 0.18 | 0.982 |
| $Lnfsize_{i,t-1}$ | 5.14 | 0.033 | 6.30 | 0.010 | 6.47 | 0.009 |
| $Volatility_{i,t-1}$ | 146.5 | 0.432 | 231.8 | 0.183 | 211.9 | 0.208 |
| $Turnover_{i,t-1}$ | -2.99 | 0.042 | -0.93 | 0.505 | -0.20 | 0.873 |
| $a_1$: $Top_{i,t-1}$ | 574.2 | 0.001 | 533.3 | 0.000 | 336.4 | 0.013 |
| $a_2$: $Middle_{i,t-1}$ | 297.9 | 0.000 | 280.7 | 0.000 | 215.6 | 0.000 |
| $a_3$: $Bottom_{i,t-1}$ | -74.3 | 0.304 | -109.1 | 0.204 | 43.43 | 0.632 |
| $a_1$-$a_3$ | 648.5 | 0.000 | 642.4 | 0.000 | 292.9 | 0.021 |
| $a_4$: Top*egdp | 275.3 | 0.029 | 265.2 | 0.010 | 114.4 | 0.154 |
| $a_5$: Middle*egdp | 33.39 | 0.062 | 24.49 | 0.119 | 21.59 | 0.129 |
| $a_6$: Bottom*egdp | -59.42 | 0.174 | -40.99 | 0.400 | 78.83 | 0.203 |
| $a_4$-$a_6$ | 334.7 | 0.006 | 306.2 | 0.003 | 35.57 | 0.350 |

**Table 4: Effects of Fund Attributes on the Flow-Performance Relationship**

This table examines the fund attributes' effect on the flow-performance relationship. The separate effects of fund age, total fees, and family size on the flow-performance relationship are reported in Panel A, B, and C respectively. Panel D presents the cross-sectional joint effects. Each year, $e\ln age$ measures the deviations of the log(age) from its sample mean; *elfee* measures the deviations of prior total fees from its sample mean; *lrfsize* measures the prior relative family size. We report below each triplet of rank variables the difference between the coefficient of the top quintile and that of the corresponding bottom quintile and p-value resulting from the one-sided t-test.

**Panel A: Fund Age**

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| $Size_{i,t-1}$ | 19.84 | 0.511 | 17.65 | 0.558 | 18.58 | 0.529 |
| $Expense_{i,t-1}$ | -2.88 | 0.71 | -0.75 | 0.923 | 1.25 | 0.875 |
| $Lnfsize_{i,t-1}$ | 5.67 | 0.019 | 6.61 | 0.007 | 6.63 | 0.007 |
| $Volatility_{i,t-1}$ | 377.6 | 0.034 | 231.8 | 0.168 | 199.7 | 0.223 |
| $Turnover_{i,t-1}$ | -1.78 | 0.194 | -0.63 | 0.630 | -0.21 | 0.868 |
| $a_1$: $Top_{i,t-1}$ | 562.9 | 0.000 | 520.8 | 0.000 | 408.3 | 0.001 |
| $a_2$: $Middle_{i,t-1}$ | 179.2 | 0.000 | 169.7 | 0.000 | 124.8 | 0.000 |
| $a_3$: $Bottom_{i,t-1}$ | 207.8 | 0.003 | 158.4 | 0.046 | 237.1 | 0.003 |
| $a_1$-$a_3$ | 355.2 | 0.008 | 362.4 | 0.003 | 171.2 | 0.106 |
| $a_4$: Top*elnage | 323.1 | 0.289 | 375.7 | 0.222 | -113.6 | 0.636 |
| $a_5$: Middle*elnage | 361.4 | 0.000 | 321.1 | 0.000 | 273.6 | 0.001 |
| $a_6$: Bottom*elnage | -818.2 | 0.000 | -779.7 | 0.000 | -680.9 | 0.000 |
| $a_4$-$a_6$ | 1141.3 | 0.000 | 1155.4 | 0.000 | 567.3 | 0.008 |

**Panel B: Total Fees**

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| $Size_{i,t-1}$ | 22.95 | 0.453 | 21.48 | 0.482 | 21.29 | 0.479 |
| $Age_{i,t}$ | -1.94 | 0.004 | -2.01 | 0.003 | -2.16 | 0.002 |
| $Lnfsize_{i,t-1}$ | 5.31 | 0.028 | 6.22 | 0.010 | 6.25 | 0.011 |
| $Volatility_{i,t-1}$ | 338.6 | 0.062 | 204.9 | 0.232 | 192.8 | 0.243 |
| $Turnover_{i,t-1}$ | -2.45 | 0.082 | -0.83 | 0.542 | -0.08 | 0.949 |
| $a_1$: $Top_{i,t-1}$ | 546.8 | 0.001 | 530.3 | 0.000 | 360.8 | 0.008 |
| $a_2$: $Middle_{i,t-1}$ | 289.8 | 0.000 | 273.0 | 0.000 | 210.3 | 0.000 |
| $a_3$: $Bottom_{i,t-1}$ | -25.02 | 0.726 | -78.33 | 0.348 | 40.43 | 0.643 |
| $a_1$-$a_3$ | 571.8 | 0.000 | 608.6 | 0.000 | 320.4 | 0.013 |
| $a_4$: Top*elfee | -218.9 | 0.222 | -293.4 | 0.101 | -147.2 | 0.326 |
| $a_5$: Middle*elfee | -151.5 | 0.002 | -128.4 | 0.002 | -97.2 | 0.013 |
| $a_6$: Bottom*elfee | 274.4 | 0.001 | 261.5 | 0.001 | 197.1 | 0.004 |
| $a_4$-$a_6$ | -493.3 | 0.994 | -554.9 | 0.997 | -344.3 | 0.986 |

**Panel C: Family Size**

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| $Size_{i,t-1}$ | 6.95 | 0.782 | 0.62 | 0.981 | 1.93 | 0.936 |
| $Age_{i,t}$ | -1.98 | 0.001 | -2.09 | 0.001 | -2.30 | 0.000 |
| $Expense_{i,t-1}$ | 7.61 | 0.358 | 8.25 | 0.322 | 8.21 | 0.336 |
| $Volatility_{i,t-1}$ | 199.4 | 0.245 | 186.8 | 0.263 | 187.2 | 0.236 |
| $Turnover_{i,t-1}$ | -2.26 | 0.093 | -1.15 | 0.364 | -0.19 | 0.875 |
| $a_1$: $Top_{i,t-1}$ | 312.3 | 0.035 | 252.4 | 0.045 | 257.8 | 0.022 |
| $a_2$: $Middle_{i,t-1}$ | 104.9 | 0.000 | 103.7 | 0.000 | 52.48 | 0.021 |
| $a_3$: $Bottom_{i,t-1}$ | 220.6 | 0.004 | 174.0 | 0.020 | 265.7 | 0.000 |
| $a_1$-$a_3$ | 91.7 | 0.280 | 78.38 | 0.298 | -7.89 | 0.524 |
| $a_4$: Top*lrfsize | 263.7 | 0.208 | 283.4 | 0.117 | 158.1 | 0.325 |
| $a_5$: Middle*lrfsize | 158.9 | 0.000 | 145.6 | 0.000 | 130.3 | 0.000 |
| $a_6$: Bottom*lrfsize | -199.9 | 0.000 | -184.1 | 0.000 | -154.4 | 0.003 |
| $a_4$-$a_6$ | 463.7 | 0.011 | 467.4 | 0.005 | 312.6 | 0.016 |

**Panel D: The Cross-Sectional Effects**

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| $Size_{i,t-1}$ | 4.33 | 0.861 | -2.37 | 0.925 | 0.67 | 0.978 |
| $Volatility_{i,t-1}$ | 254.5 | 0.135 | 218.6 | 0.182 | 210.1 | 0.175 |
| $Turnover_{i,t-1}$ | -1.63 | 0.230 | -1.18 | 0.351 | -0.37 | 0.759 |
| $a_1$: $Top_{i,t-1}$ | 363.3 | 0.022 | 292.3 | 0.045 | 319.6 | 0.013 |
| $a_2$: $Middle_{i,t-1}$ | 34.30 | 0.210 | 33.8 | 0.230 | 4.15 | 0.886 |
| $a_3$: $Bottom_{i,t-1}$ | 402.8 | 0.000 | 363.2 | 0.000 | 403.8 | 0.000 |
| $a_1$-$a_3$ | -39.5 | 0.593 | -70.8 | 0.669 | -84.24 | 0.725 |
| $a_4$: Top*elnage | 247.6 | 0.351 | 215.9 | 0.402 | -92.30 | 0.659 |
| $a_5$: Middle*elnage | 259.5 | 0.000 | 239.3 | 0.000 | 178.6 | 0.002 |
| $a_6$: Bottom*elnage | -660.4 | 0.000 | -648.7 | 0.000 | -549.0 | 0.000 |
| $a_4$-$a_6$ | 907.9 | 0.001 | 864.6 | 0.001 | 456.7 | 0.015 |
| $a_7$: Top*elfee | -83.34 | 0.610 | -105.0 | 0.525 | -100.9 | 0.456 |
| $a_8$: Middle*elfee | -45.65 | 0.203 | -35.85 | 0.271 | -20.2 | 0.555 |
| $a_9$: Bottom*elfee | 129.02 | 0.027 | 130.1 | 0.020 | 90.9 | 0.062 |
| $a_7$-$a_8$ | -212.4 | 0.882 | -235.2 | 0.902 | -191.7 | 0.923 |
| $a_{10}$: Top*lrfsize | 263.1 | 0.211 | 279.6 | 0.125 | 164.3 | 0.307 |
| $a_{11}$: Middle*lrfsize | 146.9 | 0.000 | 135.5 | 0.000 | 122.5 | 0.000 |
| $a_{12}$: Bottom*lrfsize | -177.9 | 0.000 | -164.9 | 0.001 | -141.7 | 0.005 |
| $a_{11}$-$a_{12}$ | 440.9 | 0.015 | 444.5 | 0.007 | 306.0 | 0.018 |

**Table 5: The Joint Effects on the Flow-Performance Relationship**

This table examines the joint effects on the flow-performance relationship. *egdp* measures deviations in percentage of the US real GDP growth rate from its sample mean. Each year, $e\ln age$ measures the deviations of the log(age) from its sample mean; *elfee* measures the deviations of prior total fees from its sample mean; *lrfsize* measures the prior relative family size. We report below each triplet of rank variables the difference between the coefficient of the top quintile and that of the corresponding bottom quintile and p-value resulting from the one-sided t-test.

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| $Size_{i,t-1}$ | 4.03 | 0.871 | -2.56 | 0.919 | 0.91 | 0.969 |
| $Volatility_{i,t-1}$ | 108.8 | 0.536 | 237.6 | 0.155 | 226.8 | 0.148 |
| $Turnover_{i,t-1}$ | -1.92 | 0.159 | -1.31 | 0.299 | -0.53 | 0.661 |
| $a_1$: $Top_{i,t-1}$ | 438.4 | 0.007 | 335.4 | 0.024 | 342.7 | 0.011 |
| $a_2$: $Middle_{i,t-1}$ | 36.0 | 0.199 | 35.9 | 0.209 | 5.97 | 0.840 |
| $a_3$: $Bottom_{i,t-1}$ | 388.9 | 0.000 | 359.4 | 0.000 | 420.4 | 0.000 |
| $a_1$-$a_3$ | 49.53 | 0.385 | -24.01 | 0.559 | -77.73 | 0.703 |
| $a_4$: Top*egdp | 254.6 | 0.021 | 211.7 | 0.020 | 120.3 | 0.127 |
| $a_5$: Middle*egdp | 11.44 | 0.527 | 9.76 | 0.551 | 8.97 | 0.527 |
| $a_6$: Bottom*egdp | 1.304 | 0.973 | -18.3 | 0.699 | 110.4 | 0.070 |
| $a_4$-$a_6$ | 253.3 | 0.013 | 230.0 | 0.009 | 9.91 | 0.456 |
| $a_7$: Top*elnage | 217.9 | 0.411 | 169.3 | 0.513 | -126.2 | 0.553 |
| $a_8$: Middle*elnage | 256.8 | 0.000 | 237.8 | 0.000 | 177.8 | 0.002 |
| $a_9$: Bottom*elnage | -654.5 | 0.000 | -642.8 | 0.000 | -546.9 | 0.000 |
| $a_7$-$a_9$ | 872.4 | 0.001 | 812.1 | 0.001 | 420.7 | 0.025 |
| $a_{10}$: Top*elfee | -118.7 | 0.469 | -116.5 | 0.481 | -109.5 | 0.423 |
| $a_{11}$: Middle*elfee | -44.6 | 0.213 | -36.7 | 0.259 | -20.3 | 0.554 |
| $a_{12}$: Bottom*elfee | 130.8 | 0.025 | 132.7 | 0.018 | 91.39 | 0.061 |
| $a_{10}$-$a_{12}$ | -249.5 | 0.917 | -249.2 | 0.915 | -200.9 | 0.930 |
| $a_{13}$: Top*lrfsize | 254.3 | 0.222 | 274.3 | 0.130 | 163.6 | 0.306 |
| $a_{14}$: Middle*lrfsize | 147.0 | 0.000 | 135.4 | 0.000 | 122.4 | 0.000 |
| $a_{15}$: Bottom*lrfsize | -177.8 | 0.000 | -164.9 | 0.001 | -141.7 | 0.005 |
| $a_{13}$-$a_{15}$ | 432.1 | 0.016 | 439.2 | 0.007 | 305.2 | 0.018 |

**Table 6: Effect of Economic-Activity on the Tournament Behavior**

This table examines the economic activity effect on the tournament behavior. For each regression, the dependent variable, $\Delta\sigma_{i,t}$ , is defined as $\sigma(\varepsilon^2_{i,t}) - \sigma(\varepsilon^1_{i,t})$ , where $\sigma(\varepsilon^s_{i,t})$ is defined as the standard deviation of the monthly residuals $\varepsilon^s_{i,t}$ . The fund monthly residual, $\varepsilon^s_{i,t}$ , is estimated as: $\varepsilon^s_{i,t} = \{r_{i,t} - (\hat{\alpha}_{i,t} + \hat{\beta}_{i,t} r_{m,t})\}_{t\in\Gamma(s)}$ , where $\Gamma(s) = \{1,...,6\}$ for s=1; $\Gamma(s) = \{7,...,12\}$ for s=2; $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ are estimated by using monthly fund returns for the 24 months immediately preceding year t. Each year, funds are ranked between 0 and 1 based on their performance during the first six months of the year. Excess return is obtained as the fund's return less the value-weighted market portfolio return. Each month we estimate factor loadings of a one-factor/four-factor model using data from the previous 24 months. And the one-factor/four-factor alpha is obtained as the fund excess return less the sum of the products of each of the factor realizations and the corresponding factor loadings. *egdp* measures the deviations in percentage of the US real GDP growth rate from its sample mean.

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| lidiostd | -68.22 | 0.000 | -67.34 | 0.000 | -68.08 | 0.000 |
| $Size_{i,t-1}$ | -0.012 | 0.485 | -0.016 | 0.358 | -0.016 | 0.387 |
| $Age_{i,t}$ | -0.005 | 0.000 | -0.005 | 0.000 | -0.005 | 0.000 |
| $Expense_{i,t-1}$ | 0.259 | 0.000 | 0.259 | 0.000 | 0.252 | 0.000 |
| $Lnfsize_{i,t-1}$ | -0.014 | 0.043 | -0.013 | 0.054 | -0.015 | 0.034 |
| $Turnover_{i,t-1}$ | 0.047 | 0.000 | 0.048 | 0.000 | 0.048 | 0.000 |
| Rank | 0.218 | 0.000 | 0.176 | 0.000 | -0.131 | 0.000 |
| Rank*egdp | -0.032 | 0.256 | -0.210 | 0.000 | 0.045 | 0.093 |

**Table 7: Effects of Fund Attributes on the Tournament Behavior**

This table examines the fund attributes' effect on the tournament behavior. The separate effects of fund age, total fees, and family size on the flow-performance relationship are reported in Panel A, B, and C respectively. Panel D presents the cross-sectional joint effects. For each regression, the dependent variable, $\Delta\sigma_{i,t}$, is defined as $\sigma(\varepsilon^2_{i,t}) - \sigma(\varepsilon^1_{i,t})$. Each year, funds are ranked between 0 and 1 based on their performance during the first six months of the year. Each year, $e\ln age$ measures the deviations of the log(age) from its sample mean; *elfee* measures the deviations of prior total fees from its sample mean; *lrfsize* measures the prior relative family size.

**Panel A: Fund Age**

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| Lidiostd | -68.42 | 0.000 | -68.49 | 0.000 | -67.99 | 0.000 |
| $Size_{i,t-1}$ | -0.013 | 0.438 | -0.014 | 0.421 | -0.020 | 0.255 |
| $Expense_{i,t-1}$ | 0.260 | 0.000 | 0.260 | 0.000 | 0.256 | 0.000 |
| $Lnfsize_{i,t-1}$ | -0.014 | 0.043 | -0.014 | 0.047 | -0.015 | 0.032 |
| $Turnover_{i,t-1}$ | 0.046 | 0.000 | 0.047 | 0.000 | 0.048 | 0.000 |
| Rank | 0.263 | 0.000 | 0.240 | 0.000 | -0.103 | 0.003 |
| Rank*elnage | -0.165 | 0.000 | -0.170 | 0.000 | -0.132 | 0.000 |

**Panel B: Total Fees**

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| Lidiostd | -68.02 | 0.000 | -68.03 | 0.000 | -67.63 | 0.000 |
| $Size_{i,t-1}$ | -0.022 | 0.222 | -0.024 | 0.191 | -0.025 | 0.199 |
| $Age_{i,t}$ | -0.006 | 0.000 | -0.006 | 0.000 | -0.006 | 0.000 |
| $Lnfsize_{i,t-1}$ | -0.027 | 0.000 | -0.027 | 0.000 | -0.026 | 0.000 |
| $Turnover_{i,t-1}$ | 0.055 | 0.000 | 0.056 | 0.000 | 0.055 | 0.000 |
| Rank | 0.208 | 0.000 | 0.183 | 0.000 | -0.158 | 0.000 |
| Rank*etotalfee | 0.155 | 0.000 | 0.147 | 0.000 | 0.174 | 0.000 |

**Panel C: Family Size**

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| Lidiostd | -68.47 | 0.000 | -68.49 | 0.000 | -68.06 | 0.000 |
| $Size_{i,t-1}$ | -0.014 | 0.443 | -0.0140 | 0.423 | -0.023 | 0.215 |
| $Age_{i,t}$ | -0.005 | 0.000 | -0.005 | 0.000 | -0.005 | 0.000 |
| $Expense_{i,t-1}$ | 0.270 | 0.000 | 0.270 | 0.000 | 0.267 | 0.000 |
| $Turnover_{i,t-1}$ | 0.046 | 0.000 | 0.047 | 0.000 | 0.047 | 0.000 |
| Rank | 0.234 | 0.000 | 0.212 | 0.000 | -0.132 | 0.000 |
| Rank*lrfsize | -0.013 | 0.104 | -0.013 | 0.070 | -0.004 | 0.575 |

**Panel D: The Cross-Sectional Effects**

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| Lidiostd | -67.94 | 0.000 | -68.00 | 0.000 | -67.49 | 0.000 |
| $Size_{i,t-1}$ | -0.036 | 0.054 | -0.035 | 0.068 | -0.048 | 0.018 |
| $Turnover_{i,t-1}$ | 0.053 | 0.000 | 0.054 | 0.000 | 0.054 | 0.000 |
| Rank | 0.281 | 0.000 | 0.258 | 0.000 | -0.103 | 0.004 |
| Rank*elnage | -0.201 | 0.000 | -0.206 | 0.000 | -0.168 | 0.000 |
| Rank*etotalfee | 0.157 | 0.000 | 0.148 | 0.000 | 0.182 | 0.000 |
| Rank*lrfsize | -0.018 | 0.023 | -0.019 | 0.012 | -0.008 | 0.261 |

**Table 8: The Joint Effects on the Tournament Behavior**

This table examines the joint effects on the tournament behavior. For each regression, the dependent variable, $\Delta\sigma_{i,t}$, is defined as $\sigma(\varepsilon^2_{i,t}) - \sigma(\varepsilon^1_{i,t})$. Each year, funds are ranked between 0 and 1 based on their performance during the first six months of the year. *egdp* measures the deviations in percentage of the US real GDP growth rate from its sample mean. Each year, $e\ln age$ measures the deviations of the log(age) from its sample mean; *elfee* measures the deviations of prior total fees from its sample mean; *lrfsize* measures the prior relative family size.

| | I | | II | | III | |
|---|---|---|---|---|---|---|
| Rank based on: | Excess return | | 1-factor alpha | | 4-factor alpha | |
| | Coef. | P-value | Coef. | P-value | Coef. | P-value |
| Year dummies | YES | | YES | | YES | |
| Lidiostd | -67.70 | 0.000 | -66.79 | 0.000 | -67.54 | 0.000 |
| $Size_{i,t-1}$ | -0.037 | 0.049 | -0.039 | 0.040 | -0.048 | 0.018 |
| $Turnover_{i,t-1}$ | 0.053 | 0.000 | 0.055 | 0.000 | 0.054 | 0.000 |
| Rank | 0.277 | 0.000 | 0.230 | 0.000 | -0.096 | 0.009 |
| Rank*egdp | -0.027 | 0.332 | -0.207 | 0.000 | 0.049 | 0.068 |
| Rank*elnage | -0.199 | 0.000 | -0.186 | 0.000 | -0.171 | 0.000 |
| Rank*etotalfee | 0.158 | 0.000 | 0.153 | 0.000 | 0.182 | 0.000 |
| Rank*lrfsize | -0.018 | 0.024 | -0.018 | 0.016 | -0.008 | 0.265 |