Are Mutual Funds Doomed to Underperform?

Evidence from Managerial Turnover and Fund Flows

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We empirically investigate the impact of fund flows and managerial turnover on the investment performance of active equity mutual funds. Fund flows have been suggested by Berk and Green (2004) as mechanism that prevents performance persistence. We propose managerial turnover as an alternative explanation. One the one hand, withdrawing money from loser funds and sacking bad fund managers are measures of external and internal control in delegated money management, respectively. On the other hand, if winner funds receive excessive inflows or their star manager leaves the fund future performance might deteriorate.

Using a sample of 3,948 U. S. equity mutual funds from 1992 to 2007 our results confirm this relationship for both control mechanisms for the cross-section and over time. The performance of top funds strongly suffers from excessive inflows and leaving of the skilled fund manager. Loser funds benefit from a replacement of their apparently unskilled manager but cannot gain from cash outflows to the same degree. Thus, we offer empirical evidence that the managerial turnover channel is at least as important in explaining the lack in performance persistence as funds flows. Furthermore, we show that both channels have a marginal impact on performance which is mutually independent.

JEL Classification: G28, G29, G32.

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1 Introduction

U. S. investors paid on average 0.67 percent of their assets for active management in equities over the last 26 years (French, 2008). In 2006 this was equivalent to 101.8 billion U. S. Dollar which amounts to 0.77 percent of the GDP. The share of mutual funds in that costs rose from 0.11 percent in 1980 to 0.32 percent in 2006 due to an increase in assets under management. However, the overwhelming empirical evidence concludes that active mutual fund managers on average do not add value in the long run (Jensen, 1968; Malkiel, 1995; Carhart, 1997). This is usually interpreted as an indication against the existence of managerial skill among active mutual fund managers. However, the organizational design of the fund and its regulatory environment also determine the investment performance.[1] For a fair assessment of managerial skill both, managerial turnover and the impact of the organizational structure as well as the regulatory environment of the fund need to be considered. Thus, it is important to ask whether the amount of money spend on active management is not warranted as the average skill level is insufficient to compensate investors for the costs or if other determinants utterly hinder fund managers from persistently outperforming the market. Thus, are mutual funds doomed to underperform?

The obligation to offer daily redemption and creation, one of the cornerstones of the open-ended structure of mutual funds, imposes direct and indirect costs on fund investors. According to Berk and Green (2004) inflows into previously outperforming funds reduce their potential to outperform in the next period as a result of decreasing returns to scale in active management. Combined with investors chasing past returns, this might explain the lack of performance persistence among good fund managers reported in the literature. On the other hand, the daily liquidity of mutual funds offers an easy mechanism for investors to exercise external governance at underperforming managers. Money withdrawals from underperforming funds provide managers of these funds with the ability to regain performance. Consequently, fund flows are an important mechanism to wipe out performance persistence among both outperformers and underperformers.

We argue that managerial turnover might be a complementary explanation for the lack of performance persistence. Implicitly, existing studies on fund performance assume that fund managers and mutual funds are one intrinsically linked entity.[2] This is clearly not the case as fund managers move between funds and enter or exit the mutual fund industry due to various reasons.[3] At the top end of funds, highly skilled fund managers are poached away by competing

[1] Indeed, recent studies suggest that fund performance can only be explained to a certain degree by the manager and depends to a larger degree on the fund itself through e. g. information resources, in-house research and trading efficiency of the fund company (Baks, 2003; Kacperczyk and Seru, 2007).

[2] One notable exception is Baks (2003).

[3] Indeed, it has already been suggested by Hendricks, Patel, and Zeckhauser (1993, p. 102) that "superior analysts get bid away once they build a track record." Similarly, Tonks (2005, p. 1940) argues that "over

fund companies and subsequently manage larger funds. Speaking in terms of Berk and Green (2004) these managers increase their fees. However, contrary to the argument of Berk and Green (2004) this does not happen at the same fund. If investment performance depends on managerial skill, the funds previously managed by these managers do no longer outperform the market but, as the managers take performance with them, the funds that hired these managers now appear among the winner funds. In general mutual funds have only few measures to attract and keep skilled managers by rewarding them directly for superior performance. Under these circumstances, can we still expect mutual funds to deliver persistently abnormal returns?

On the other hand, the managers of badly performing funds might be sacked by the fund management company. From the perspective of Berk and Green (2004) their fees are essentially reduced to zero. Effective internal governance mechanisms should result in a replacement of underperforming managers by new managers with presumably higher skills. The new manager might alter the investment strategy aiming to improve subsequent performance. Consequently, the withdrawal of funds by investors and the replacement of a badly performing fund manager are two alternative control mechanisms in delegated fund management that help to end a period of inferior investment returns. However, one crucial difference between the fund flow channel of Berk and Green (2004) and the managerial turnover channel is that our argument does not rely on the assumption of decreasing returns to scale in active management.

The objective of this study is to shed further light on the determinants of performance persistence and, specifically, to quantify the impact of managerial turnover and fund flows on performance both in the cross-section and over time. We apply a ranked portfolio test in order to compare the performance of different fund groups and a pooled regression in order to assess the change in performance over time. The focus of our analysis is on extreme outperformers and underperformers in the top and bottom deciles of funds which allows us to analyze differences between extremely good and bad managers.

Our results show on one side that excessive inflows into winner funds have a tremendously negative impact on their performance but that, on the other side, loser funds cannot benefit from outflows to the same degree. Specifically, the performance of top funds with high inflows deteriorates in the subsequent year by 1.44 to 1.80 percent compared to winner funds that did not suffer from extreme inflows. Over time, the performance of average funds decreases by -2.53 to -3.39 percent in the subsequent year compared to the previous year following a one standard deviation increase in fund flows. The reduction for decile 10 funds is even higher at -3.88 to -6.61 percent. Funds that invest in narrow or illiquid markets also suffer by more from excessive inflows than funds with broad investment perspectives. Decile 1 funds benefit from a one standard deviation decrease in net inflows, i. e. an increase in outflows, and

time these individuals [fund managers] move between jobs, so that over longer horizons, the persistence in fund-management-house performance weakens.“

earn between 1.33 to 3.27 percent higher risk-adjusted returns compared to the previous year. However, this is a slightly lower performance improvement than for average funds. Furthermore, the performance differential between loser funds with high or low outflows is not statistically significant. This lower impact of flows on bottom funds might be a result of investors' reluctance to exercise external governance by withdrawing money from underperforming funds.

Managerial turnover has an important impact on performance persistence for both, winner and loser funds. On the one hand, loosing an outperforming manager subsequently results in -1.32 to -2.04 percent lower performance compared to winner funds that were able to keep their star manager. Over time, if a manager of a winner fund leaves this fund suffers from a reduction in performance by -0.50 to -0.65 percent compared to the previous year. This result indicates that some managerial skill exist. It seems to be essential for the success of fund families to attract and keep skilled managers. On the other hand, the replacement of an underperforming manager increases fund performance by 0.96 to 1.68 percent in the following year compared to previously underperforming funds that kept the same manager. Over time, a change in management increases fund performance of the average fund by 0.48 percent in the year following the manager replacement. This figure increases to 1.03 percent if the fund belongs to a large family. If a loser fund manager is replaced the improvement in performance is even 0.47 to 0.51 percent larger than for the average fund (0.95 to 0.99 percent). This result shows the importance and impact of internal governance mechanisms.

Both, managerial turnover and fund flows are important aspects for investors, investment management companies as well as regulators as they contain valuable information about future fund performance. Investors should incorporate the impact of both determinants on future performance in their investment decisions. Fund management companies should be interested in the importance of the investment process by a team as compared to the skills of a single fund manager. If returns depend too much on a single manager this becomes a risk factor for the investment company as well as for its investors. However, if the change of a manager has an impact on performance, this indicates the existence of skill at least among some managers. Regulators should be concerned about the possibility of negative side effects of their regulatory restrictions and the appropriateness of open-end fund constructions for eventually illiquid asset classes. Furthermore, it is questionable if funds used for retirement savings necessarily require the daily redemption feature or if its benefits are outweighed by the possibly higher performance of funds with restricted redemptions. As the share of U. S. equities held by mutual funds increased from 4.6 percent in 1980 to 32.4 percent in 2006 these aspects tend to become even more important (French, 2008).

Our paper contributes to the current literature in several ways. The major contribution of our paper, is that we empirically test and compare the impact of fund flows and managerial turnover on performance and performance persistence. We show that managerial turnover is

economically at least as important as fund flows. This analysis add to recent works on the impact of funds flows such as Berk and Green (2004), Alexander, Cici, and Gibson (2007) and Berk and Tonks (2007). Furthermore, it extents the work of Khorana (2001) on managerial turnover in that it relates changes in performance directly to persistence. Additionally, we are able to compare the economic significance of both effects and to analyze their relation as well as marginal effects of both mechanisms separately. Finally, we provide new results on performance persistence of active U. S. equity mutual funds using and extended data period up to the end of 2007 and recent statistical methodologies such as the Bayesian approach.

The rest of the paper proceeds as follows: The next section provides an overview of the literature on performance persistence and the regulatory and organizational determinants of fund performance. In the following section 3.1 we describe our data set and in section 3.2 we explain our methodology in more detail. Our results are discussed in section 4. General results on performance persistence based on different ranking methodologies are provided in section 4.1. Results for the ranked portfolio test in combination with manager changes are given in section 4.3 and results for the ranked portfolio test in combination with fund flows are given in section 4.2. Section 4.4 discusses the economic implications of our empirical results and analyzes the interactions using a pooled regression approach. Section 5 finally concludes and presents an outlook to further research.

2 Literature Review

Performance Persistence Mutual fund performance persist in the short run but not in the long run if survivorship bias is taken into account (Hendricks, Patel, and Zeckhauser, 1993; Elton, Gruber, and Blake, 1996a). Recent underperformers continue to significantly underperform the benchmarks whereas outperformers produce unsignificantly higher returns than the benchmark indicating that persistence is clustered around loser funds (Brown and Goetzmann, 1995; Carhart, 1997). Part of this is driven by higher fees. Winner funds merely happen by luck to hold last year's winner stocks (Carhart, 1997). Performance persistence seems to be strongest among young funds, small cap growth funds and no-load funds (Blake and Timmermann, 1998; Huij and Verbeek, 2007). More recent studies focus on improved statistical methods. Using daily data and ranking based on risk-adjusted returns Bollen and Busse (2005) document an economically and statistically significant outperformance of the top funds over quarterly periods. This outperformance vanishes over longer periods and if the methodology used the evaluate fund performance does not account for the time-variability inherent in the fund decile portfolios. Also based on daily data Busse and Irvine (2006) present evidence for the predictability of future fund performance using the the Bayesian methodology of Pástor and Stambaugh (2002). Huij and Verbeek (2007) employ an empirical Bayes approach and

show that even based on monthly data statistically significant outperformance can be found among top funds.

Brown and Goetzmann (1995) indicate that persistence is correlated across managers suggesting that persistence might be due to similar strategies used by fund managers that outperform common benchmarks for a certain period. Neither the common risk-adjustment methodologies nor fund style classifications seem to sufficiently control for this effect. Interestingly, restricting the analysis to funds that belong to the same style deteriorates the performance of the winner fund portfolio and underlines the importance of being in the right style at the right time (Huij and Verbeek, 2007). Consequently, ranking based on risk-adjusted measures improves persistence as compared to ranking based on raw returns (Elton, Gruber, and Blake, 1996a; Bollen and Busse, 2005).

Several organizational and regulatory issues might help to explain the unsatisfactory performance results and the lack of performance persistence of mutual funds over periods longer than one quarter. This includes the regulation on the daily pricing and liquidity of fund shares, restrictions on the investment strategy, the internal governance mechanisms, and the regulation on the use of incentive contracts.[4] An overview is given in figure 1

[Please insert **figure 1** about here]

Daily Pricing and Liquidity Service Open-end funds are obliged to report daily net asset values (NAV) of their portfolios and to allow daily creations and redemptions to this NAV making fund shares very liquid. This allows mutual fund investors to react quickly on personal liquidity shocks and to adjust their investments according to individual beliefs about the health of the economy on a timely basis. Furthermore, it allows for an effective external governance. However, this feature imposes costs on the fund investors and prevents mutual funds from pursuing certain investment strategies.[5]

In the short run, creations and redemptions of fund shares lead to transaction costs such as commissions and market impact. In order to avoid transactions, fund managers increase their cash holdings resulting in a cash drag on the fund's performance (Yan, 2006). Furthermore, investment decisions might be affected by inflows or outflows leading to poorer performance. Perverse timing can be a result of fund flows at inopportune times (Ferson and Schadt, 1996). An increased fund size makes trading more expensive and difficult to hide. Other investors can easily front-run and exploit the information contained in the trading behavior of large funds. Furthermore, the choice of possible investment targets is constrained and restricted to liquid

[4] Most of the following restrictions and regulations are governed by the Securities Act of 1933, the Securities Exchange Act of 1934, the Investment Company Act of 1940, and the Investment Advisors Act.

[5] Note that the negative impact of inflows on performance can be interpreted as a lack of internal governance. Driven by the fee interest of the investment management company funds are allowed to grow in size over an above the threshold that allows them to generate superior returns.

stocks. Good investment opportunities vanish as funds literally meet the capacity constraints of their formerly successful investment strategies. Consequently, the daily liquidity requirements limit the potential to outperform if money chases outperforming funds. Indeed investors' fund flows strongly respond to past performance. However, poor performance is not followed by outflows to the same degree as abnormal performance is followed by inflows (Sirri and Tufano, 1998; Lynch and Musto, 2003).

Empirical results support the view that excessive fund flows deteriorate performance. Funds with more volatile daily flows tend to underperform their peers with less volatile flows (Rakowski, 2003). Liquidity induced trades following excessive inflows or outflows significantly underperform discretionary trades based on superior information (Edelen, 1999; Alexander, Cici, and Gibson, 2007). Analyzing hedge funds Naik, Ramadorai, and Stromqvist (2007) report that capacity constraints exist in certain hedge fund styles, especially if these strategies rely on the liquidity of the underlying markets, such as relative value, fixed income and emerging markets. Consequently, some hedge funds impose redemption restrictions, such as lock up and redemption notice periods. This allows them to invest in illiquid strategies and to gain 4 percent to 7 percent higher returns than hedge funds without redemption restrictions (Aragon, 2007). Performance persistence is stronger among closed-and funds and exists up to 36 months (Bers and Madura, 2000).

On the other hand, the daily liquidity of mutual fund shares enables an efficient external governance mechanism. Investors do not have to rely on the investment management company or the fund board taking action after a period of unsatisfactory performance results but rather can quickly shift their assets to another, more promising, fund. This governance mechanism is enforced by the services of rating agencies such as Morningstar or Lipper, media coverage and performance rankings as well as sophisticated investors such as funds of funds and wealth managers to the benefit of less sophisticated retail clients (Del Guercio and Tkac, 2008). Restricting the daily liquidity might impose agency costs and give underperforming managers a chance to survive longer in the industry (Anderson, Coleman, Gropper, and Sunquist, 1996). Indeed, it has been suggested that if investors do not exercise external governance by withdrawing money these funds remain poor performers (Berk and Tonks, 2007). This might be a result of investors' expectations about a strategy change among underperforming funds, their reliance on internal governance, or a disposition effect. In recent years at least some investors react more quickly on past performance than previous studies concluded (Goriaev, Nijman, and Werker, 2008).

Investment Strategy and Instruments To ensure the ability of mutual funds to provide daily liquidity to investors, regulatory restrictions apply to the available instruments and markets. Investments in derivatives such as options, futures, forwards and swaps are restricted to covered positions. Most funds voluntarily further constrain the use of derivatives to risk and liquidity

management purposes in their prospectuses. Moreover, the use of leverage and the investment in illiquid or restricted securities is limited as well. The use of short sales is complicated and cost-intensive due to the requirement to reconcile all short sales daily between the mandatory independent custodian bank and the third-party broker executing the short sale. Additionally, up to 1997 the unfavorable tax treatment of profits from short-term trading and short sales prevented most funds from using these strategies.[6]

These rules not only help to maintain a certain level of liquidity in the funds' portfolio but are also aimed at sheltering investors from excessive risk taking of fund managers and to avoid misreporting of daily net asset values. Furthermore, some investment management companies might impose additional restrictions in an attempt to avoid large deviations from the benchmark and to protect their own reputation. However, these restrictions clearly limit the potential for the fund manager to generate abnormal returns which can be interpreted as indirect costs of the open-end fund structure.

Hedge funds can serve as a comparable investment product that is exposed to less regulation and lower investment restrictions.[7] Indeed, studies on hedge fund performance conclude that these products on average offer alphas of around five to seven percent annually (Kosowski, Naik, and Teo, 2007; Agarwal, Boyson, and Naik, 2008). Hedged mutual funds instead are governed by the regulation of traditional mutual funds and are obliged to offer daily pricing and liquidity. However, the restrictions with respect to the use of derivatives are relaxed. Hedged mutual funds can outperform conventional mutual funds due to their higher investment flexibility (Agarwal, Boyson, and Naik, 2008). However, real hedge funds still outperform hedged mutual funds. Interestingly, managers of hedged mutual funds who at the same time manage a hedge fund outperform those who do not. Managerial skill, regulation and investment restrictions all do have an impact on investment performance. Just loosening the ties of regulation does not guarantee an improvement in performance. The various dimensions of fund design have to be considered simultaneously in order to derive correct inferences about their impact on performance.

Internal Governance Mechanisms and Managerial Turnover Internal governance mechanisms of mutual funds are rather weak in general which can be seen as a result of effective external control. Fund managers are employed by the investment management company which is legally independent of the mutual fund itself. Investors, therefore, do not have direct control

[6] The 1997 Taxpayer Relief Act repealed Internal Revenue Code Section 851 (b)(3) which governed the taxation of short-term trading profits.

[7] Under the Investment Advisor Act, the SEC proposed the following regulation for hedge funds since February 2006: registration with SEC, designation of a Chief Compliance Officer, implementation of certain policies and a code of ethics to ensure that action is taken in the best interest of clients. The investment strategy is not directly addressed in this regulation. However, this rule is currently not being enforced as a federal appeals court decision recently invalidated the rule.

over the decision to replace underperforming managers.[8] In the U. S., fund boards exists that should control the investment management company in the interest of the fund investors. In 2004, as a result of the fund scandals in 2003, the SEC proposed a rule to increase the fraction of independent directors at fund boards to at least three quarters and required an independent chairman as well.[9] However, this rule was rejected twice in federal appeals court (SEC Remains Divided On Fund-Board Rule, WSJ, March 16, 2007). Fund boards in general do not have a direct impact on the replacement of the fund manager but can only appoint another fund management company which rarely happens in practice. Even worse, as the SEC delegates governance to boards of directors, which still lack the necessary power and full independence, investment advisors are insulated from direct SEC supervisory oversight (Haslem, 2008). It remains questionable if these mechanisms are sufficient to urge the fund manager to generate abnormal returns and to replace him if he does not. Empirical results are still mixed. According to Ding and Wermers (2005) the size of the board and its independence have a positive impact on the likelihood of a replacement of the manager. In contrast, Kong and Tang (2008) argue that unitary boards of small size, i. e. one fund board oversees all funds of the family, are more beneficial to investors than large independent fund boards.

Indirectly, the fund management company itself has an incentive to control the fund manager's performance. Superior performance leads to high inflows and increases the fee income which is usually based on the assets under management (Sirri and Tufano, 1998; Lynch and Musto, 2003). Consequently, several studies document an inverse relationship between fund performance and manager turnover (Khorana, 1996; Chevalier and Ellison, 1999; Gallagher and Nadarajah, 2004).[10] Promotions, i. e. the manager subsequently manages a larger fund, are positively and demotions, i. e. the fund manager subsequently manages a smaller fund, are negatively linked to past performance (Hu, Hall, and Harvey, 2000; Baks, 2003).[11] After the replacement of an underperforming manager returns improve significantly and after an out-

[8] Note that keeping an existing manager with a good performance record can be seen as an equally important aspect of internal governance.

[9] This was the last step in a sequence of reinforcements of this rule: The 1940 Investment Company Act requested that a maximum of 60 percent of the directors were affiliated with the investment company. The 1970 Amendment broadened that definition by allowing a maximum of 60 percent of *interested* persons. This was replaced by the 2001 Amendment that requested a majority of independent investors and, finally, in the 2004 Amendment three quarters were requested.

[10] This inverse relationship between manager turnover and financial performance (Coughan and Schmidt, 1985; Gilson, 1989) or operating performance (Murphy and Zimmerman, 1993) has also been documented for industrial companies. Furthermore, financial performance improves after a manager replacement (Denis and Denis, 1995).

[11] However, rather than sacking an underperforming manager investment companies might have an incentive to close or merge the losing fund and to open a new one as small and young funds are shown to exhibit a higher flow sensitivity than large and old funds (Sawicki and Finn, 2002). It has been documented that funds which disappear due to merger or death tend to have poor performance just prior to disappearance (Brown and Goetzmann, 1995; Elton, Gruber, and Blake, 1996b; Carpenter and Lynch, 1999; Carhart, Carpenter, Lynch, and Musto, 2005).

performing manager left a fund returns deteriorate (Khorana, 2001; Gallagher and Nadarajah, 2004). However, most of these results are based on performance measures that do not account for the general trend for mean reversion in fund returns over time. These results underscore that importance of internal governance mechanisms that lead to a replacement of bad managers but at the same time try to keep good managers.

Another important aspect of internal governance is to shelter the fund from excessive inflows in the interest of existing shareholders once it reaches a size that bloats organization and decreases the number of good investment ideas due to capacity constraints in the market. One possibility is to soft-close a fund which means that existing shareholders can still withdraw their money (and sometimes invest new money) but the fund is closed to new investors from outside. For example, Fidelity decided to close the Magellan Fund to new investors in August 1997 as a consequence of high inflows and low relative returns in the three previous years. However, investors have no direct influence on this decision. The fact that fees are usually based on assets under management might prevent the investment management company from closing a fund once it exceeds a certain size threshold. As a result, large funds remain in the market even though they might no longer be able to provide superior returns.

Incentive Structure An alternative to monitoring and controlling mutual fund managers is to introduce measures that align the interests of managers with those of investors. This can be done by performance-based compensation contracts and an own stake of the manager in the fund. However, investors have no direct influence on the characteristics of these contracts and can only choose from existing mutual funds. Even though performance-based compensation contracts are heavily used in the hedge fund industry they can still be very rarely found at mutual funds.[12] One reason for this might be that only fulcrum fees, i. e. symmetric fee contracts, are allowed according to the 1970 Amendment to the Investment Advisors Act of 1940 for mutual funds. Consequently, most mutual fund managers do not have a direct incentive to perform. Only indirectly compensation is linked to performance through the positive impact of past performance on subsequent flows (Sirri and Tufano, 1998; Lynch and Musto, 2003). Surprisingly, incentive fee mutual funds do on average add no value by security selection based on net of fee alphas (Elton, Gruber, and Blake, 2003).

Fund managers also usually do not hold significant portions of the funds they manage (French, 2008). If they do, this limits excessive risk taking (Kouwenberg and Ziemba, 2007) and improves performance as compared to funds with managers who do not hold an own stake in the fund (Khorana, Servaes, and Wedge, 2007). Consequently, for individual funds as well as for the

[12] Only 108 out of 6,716 mutual funds used performance fees in 1999 (Elton, Gruber, and Blake, 2003). However, these funds constitute 10.5 percent of total fund assets and grew faster in subsequent years than non-incentive fee funds.

mutual fund industry as a whole incentive contracts are important instruments to attract and keep talented managers.

To summarize, the organizational environment of mutual funds including the obligation to offer highly liquid fund shares, the restrictions with respect to allowed instruments and markets, the agency conflicts and divergent interests between the fund management company, the fund manager and the investors as well as the weak measures used to align interest might explain the unsatisfactory investment results of active mutual funds. We now turn to our empirical analysis of two important aspects, the liquidity of fund shares and the effectiveness of internal governance.

3 Data and Methodology

3.1 Data

The data on mutual funds and the benchmarks is obtained from the CRSP Survivorship Bias Free Mutual Fund Database from the University of Chicago. Our sample starts in 1992 as this is the first date where reliable information on manager changes is available and it ends in 2007. In constructing our sample we follow Pástor and Stambaugh (2002) as closely as possible.[13] Thus, we restrict ourselves to domestic equity mutual funds and exclude passive funds. During recent years many fund families started to offer different share classes of their funds that usually only differ in their expenses and minimum investment requirements whereas all share classes of one fund have the same underlying portfolio (Zhao, 2005). All share classes are managed by the same fund manager and fund flows on the level of share classes might cancel out on the portfolio level. However, the CRSP database treats each individual share class as a single observation. Consequently, we combine all share classes of the same fund using a matching algorithm based on the portfolio number that matches share class characteristics with holdings information and the fund name.[14]

These selection criteria result in a sample of 4,376 funds with a total of 11,798 share classes that existed at any time during the sample period from 1992 to 2007. These funds belong to 714 different fund families. However, we drop all observations prior to the IPO date given by CRSP and funds without names in order to account for a potential incubation bias (Evans, 2007). Additionally, we drop funds that have less than 12 months of return observations during our sample period. The final sample then includes 3,948 funds that belong to 672 fund families and have an average fund size of 899 million U. S. Dollar (table 2). Fund size constantly increased during our sample period whereas average fees dropped from 1.68 percent to 1.56

[13] Details about the data selection are given in appendix A.1.

[14] In a previous version of this paper we used single share classes and data up to the end of 2004. The results were qualitatively the same.

percent eventually as a result of economies of scale at the direct expenses involved in asset management.[15]

[Please insert **table 2** about here]

Monthly fund flows are constructed from the change in total net assets adjusted for internal growth due to investment returns:

$$flow_{it} = TNA_{it} - TNA_{it-1}(1 + r_{it}) \tag{1}$$

where TNA_{it} refers to the total net assets and of fund i at the end of period t and r_{it} is the return of fund i between $t-1$ and t assuming that all distributions are reinvested and net of fund expenses. Following the argument of Berk and Tonks (2007) absolute flows are scaled by $TNA_{it-1}(1 + r_{it})$ instead of TNA_{it-1} in order to obtain relative flows:

$$rel\_flow_{it} = \frac{TNA_{it} - TNA_{it-1}(1 + r_{it})}{TNA_{it-1}(1 + r_{it})}. \tag{2}$$

If several funds are merged we do not count assets that merge into another fund as fund flow for this funds as these assets are received in kind rather than in cash. Thus the portfolio manager does not have the immediate problem of investing the inflows but can adjust the portfolio weights according to his views over the following months which should not have a strong performance impact. Fund flows significantly decrease after the burst of the bubble and have not reverted since then to the same level as before. Furthermore, fund flows obviously become more volatile over our sample period especially after the burst of the tech bubble (figure 2). This might be interpreted as a result of more sophisticated and performance-sensitive investors in mutual funds in recent years.

[Please insert **figure 2** about here]

To obtain information on manager changes we focus on the variable `mgr_date` in the CRSP database instead of using the specific names of the managers.[16] This variable gives the date of the last change in management as reported by the fund company. By using the `mgr_date` variable we avoid any problems associated with different spellings of manager names. Furthermore, as the number of team-managed funds increased during recent years, the manager date variable has the advantage that fund management companies only report significant changes in management that might have an impact on performance (Massa, Reuter, and Zitzewitz, 2007).

[15] Fees are calculated as the sum of the annual expense ratio and $\frac{1}{7}$ of the sum of the front end and back end loads.

[16] This variable has also been used by Lynch and Musto (2003) and Cooper, Gulen, and Rau (2005).

During our sample period, 6,446 manager changes occurred in our sample.[17] The number of funds and the number of manager changes peak at the end of the tech bubble in 2000. On average, 19 percent of the fund managers are being replaced each year which is consistent with the 14 percent to 18 percent reported by Ding and Wermers (2005) using a more detailed database on fund managers constructed from various sources. In combination with fund closures or mergers this number leads to an average duration of 47.26 months or almost four years for each manager-fund combination. The number of manager changes follows closely the course of the market index (figure 3). The decrease at the end of the sample period results from a reporting lag but does not impact our results as we only use lagged manager changes in our analysis.

[Please insert **figure 3** about here]

Both, the higher level of managerial turnover in recent years as well as the stronger performance sensitivity of fund flows indicated by their higher volatility suggest that manager changes and fund flows became even more important in explaining mutual fund persistence in recent years.

3.2 Methodology

In order to test our two hypothesis that managerial turnover weakens the relationship between past and future performance and that inflows (outflows) have a negative (positive) impact on future performance of winner (loser) funds, we apply two different methodologies. First, we use ranked portfolio tests to compare the performance of funds in the cross section. Specifically, we compare subgroups with high and low funds flows and subgroups with and without a change in management. Second, we perform a pooled regression of the change in performance over time on fund flows and managerial turnover in order to quantify the effects over time.

Ranked portfolio tests have been widely used in persistence studies, e. g. Carhart (1997), Carpenter and Lynch (1999) and Tonks (2005). This test involves the ranking of the funds into deciles based on their performance in the ranking period and the evaluation of their performance in the subsequent evaluation period. Based on the decile fund portfolios from the first sorting we perform a second sorting of the top decile 10 and the bottom decile 1 funds based on manager changes or fund flows during the ranking period.[18] The intuition behind this is that we are interested in the different effects of managerial turnover and fund flows on good and bad managers. Specifically, we want to separate the effect of sacking an unskilled manager as internal governance or withdrawing money from a bad manager as external governance from

[17] Note that the sample of Khorana (2001) who also analyzes the impact of managerial turnover on performance contains only 393 funds.

[18] This methodology is similar to the one used for seasoned and unseasoned funds by Berk and Tonks (2007). However, their second sorting is based on the performance of the funds in the penultimate year.

the effect of a skilled manager leaving the fund or investors allocating large amounts of money with good managers. Thus, the first sorting based on past performance acts as a means so separate good from bad managers.

We then analyze the performance of these subgroups of the top and bottom deciles as well as the performance of spread portfolios constructed based on these subgroups in the ranking period which follows the ranking period. This procedure allows us to deal with the inherent endogeneity problem in the relation between managerial turnover and performance and between fund flows and performance. Specifically, it replicates a real time trading strategy and measures the economic value of information on past manager changes and past fund flows.

Ranking In order to employ the methodology outlined above we face two decisions. First, which performance measure should be used to evaluate managerial skill and, second, over which time horizon should performance persistence be analyzed. As these questions cannot be answered unambiguously from a theoretical perspective we propose to apply several measures for ranking and evaluating funds. The first measure is raw returns (in excess of the rate on the risk-free asset) which already has been used in the seminal work of Carhart (1997) (*return-sorting*). Raw returns have the advantage that they do not have to be estimated and that no assumptions about relevant risk factors have to be made. Additionally, investors seem to pay attention to past raw returns when allocating their money to mutual funds (Gruber, 1996). However, ranking mutual funds based on raw returns might result in a noisy separation between skilled and unskilled fund managers. Not only true investment skill produces high returns compared to the peer group. For example, being a growth fund manager during periods where growth stocks outperform value stocks increases the likelihood to end up in the top decile without possessing superior skills.[19] Additionally, some manager might just take on high risks and end up in the top decile by luck rather than by skill. To account for these issues we apply a Bayesian version of the Carhart four-factor model following Huij and Verbeek (2007) to rank the funds into deciles (*alpha-sorting*).[20] In order to deal with the question relating to the time horizon we consider different but symmetric lengths for the ranking and evaluation periods. Specifically, we analyze short term persistence over three months ranking and evaluation periods, mid-term persistence over one year ranking and evaluation periods and long-term persistence over two

[19] This relies on the assumption that most managers do not systematically change between a growth-oriented investment style and a value-oriented investment style over different cycles. If they switched styles successfully in a systematic manner this clearly should be classified as real skill.

[20] Additionally, we employed the following measures for ranking: the Sharpe ratio, the Jensen one-factor alpha, the t-statistic of the Jensen one-factor alpha as suggested by Elton, Gruber, and Blake (1996a) and a Bayesian version of the Jensen one-factor alpha. Additionally, we analyze the performance of non-equidistant quantiles using raw (excess) returns and the following cut-off points for our ten quantile groups: $perc = [5, 10, 20, 30, 50, 70, 80, 90, 95]$. However, as our results were not changed significantly we present only results based on a raw raw return-sorting and a ranking using Carhart four-factor alphas.

and three year ranking and evaluation periods.[21]

The Carhart four-factor model incorporates a size factor (SMB), a value factor (HML) and a momentum factor (MOM) in addition the the market proxy (er_{mt}) to explain fund returns and to account for different fund styles (Carhart, 1997):

$$er_{it} = \alpha_i + \beta_{1i} er_{mt} + \beta_{2i} SMB_{it} + \beta_{3i} HML_{it} + \beta_{4i} MOM_{it} + \epsilon_{it} \tag{3}$$

Specifically, funds are ranked based on the α from equation (3) estimated over the whole ranking period. In order to efficiently estimate a four-factor alphas over such short horizons as one year we apply an empirical Bayes approach (Huij and Verbeek, 2007). This procedure involves the estimation of the Carhart model for each fund separately using OLS. We use the average of the parameters of all other funds during that period as the prior. The final α and β parameters of each individual fund are then a weighted average of its OLS parameters and the average of the parameters of all other funds during that period, where the weights depend on the estimation efficiency of the OLS parameters.[22] Thus, the Bayesian approach shrinks extreme parameters towards a grand mean taking into account the cross-sectional distribution of the parameters. The intuition behind that approach is that it is less likely for a fund to generate high alphas if all other funds generate relatively low alphas during the same period. This argument is similar to the methodology of Cohen, Coval, and Pástor (2005) who attribute a higher skill measure to fund managers who produce their outperformance with similar strategies as other skilled fund managers as compared to manager who applied completely different strategies. The later are seen to be lucky rather than skilled. Consequently, the alpha-sorting based on Bayesian four-factor alphas accounts for a risk-adjustment of the performance measure used for the ranking, corrects for different investment styles and reduces the influence of high risk strategies on the ranking. We believe that in contrast to the raw return-sorting the alpha-sorting provides a much more reliable separation of skilled and unskilled but lucky fund managers.

Evaluation To be consistent, the same performance measures we use for ranking funds into deciles are applied in the evaluation period. Specifically, following Carhart (1997) we construct a concatenated time series as the cross-sectional equally-weighted average of the raw returns of all fund that belong to one specific decile (or subgroup of funds).[23] This results in one time series of portfolio returns for each decile that one could have earned by following our trading strategy over the sample period (*portfolio approach*).[24] Note, however, that the composition of these portfolios changes significantly over time as after each ranking period new decile portfolios

[21] Note that for the three month ranking we only use the return-sorting approach.
[22] More technical details are given in Huij and Verbeek (2007).
[23] If a fund drops out of the decile due to merger or closing the portfolio weights are adjusted accordingly.
[24] Assuming that short sales in mutual funds are allowed for the spread portfolios.

are formed.[25] Additionally, the funds itself change the composition of their portfolios in buying and selling stocks. Additionally, we consider the raw returns of the whole panel of funds that belong to a specific decile and report moments of their return distribution such as the mean and different quantiles (*panel approach*). Usually, households are not able to follow a trading strategy implied by a ranked portfolio test as this involves holding a large number of funds. Thus, return moments of the panel of all funds that belong to a certain decile are more relevant for private investors than the results based on the concatenated time series.

Additionally to raw returns we apply risk-adjusted returns based on the Carhart four-factor model from equation (3) in the evaluation period. The advantage of this procedure is that it gives direct estimates of the economic significance of the effects compared to a benchmark. First, we use the time series of the decile portfolios to estimate the Carhart four-factor model over the whole sample period (*concatenated alphas*). However, the high turnover of this portfolio described above gives rise to a high degree of time-variability in the model parameters that an unconditional model does not account for (Elton, Gruber, and Blake, 1996a). This might severely bias the results (Bollen and Busse, 2005). In order to deal with the time-variability of the parameters in the Carhart four-factor model we apply a rolling window regression that can be interpreted as a non-parametric version of conditional performance evaluation models of Ferson and Schadt (1996). Specifically, we estimate the parameters from equation (3) in the Bayesian version from above using a window of 24 months. The alpha at time $t = 13$ of this window is the realized return at time $t = 13$ minus the expected return for that month. Then we move on one months until we reach the end of the fund's return time series.[26]

$$\alpha^B_{i,t=13} = r_{i,t=13} - E(r_{i,t=13}) \tag{4}$$

$$= r_{i,t=13} - \hat{\beta}_{i,1} r_{m,t=13} - \hat{\beta}_{i,2} SMB_{t=13} - \hat{\beta}_{i,3} HML_{t=13} - \hat{\beta}_{i,4} MOM_{t=13} \tag{5}$$

As the performance measurement in the evaluation period is ex-post by nature this procedure does not suffer from a look-ahead bias. As a result, we obtain one alpha estimate for each fund and each month. Similar to the presentation of raw returns we construct a time series of decile portfolio alphas (and the alphas of the subgroups) for each decile as the cross-sectional equally-weighted average of the alphas of all funds that belong to a specific decile (*portfolio approach*).

$$\alpha^B_{p,t} = \frac{1}{n} \sum_{i=1}^{n} \alpha^B_{i,t} \tag{6}$$

[25] Table 6 shows that a strategy of buying decile 10 or decile 1 funds involves an annual turnover of about 84.31 percent or 84.30 percent, respectively.

[26] Elton, Gruber, and Blake (1996a) use a similar approach but estimate the model parameters at once over the whole life of the fund instead of using a rolling window.

We present in our tables the time-series mean of these portfolio alphas over the sample period. Additionally, we analyze the moments of the whole panel of alphas for each decile (*panel approach*). Note that the difference between the mean of the alpha from the portfolio approach and the panel mean lie in the weighting of the time periods. In the portfolio approach we take first the cross-sectional mean and then the time-series mean. This gives an equal weight to each month of our sample irrespective of the number of funds that existed during that period. Instead, the mean from the panel approach gives equal weight to each fund and as a result less weight to earlier time periods when less funds existed. This accounts for the increasing importance of mutual funds for investors in recent years.

Pooled regression In addition to the ranked portfolio test outlined above we perform a pooled regression with the difference in annualized raw returns or performance between this year and the previous year as dependent variable. These performance changes over time are then regressed on a set of control variables as well as fund flows and a managerial turnover dummy. Following French (2008) we winsorize all variables at the 1 percent and 99 percent quantile to avoid any bias resulting from extreme outliers. First, this regression offers insights into the impact of fund flows and managerial turnover on fund performance over time compared to the cross-sectional results of the ranked portfolio test. Furthermore, it gives us the possibility to separate the effects of fund flows and managerial turnover and to measure their marginal impact.

4 Empirical Results

4.1 Performance Persistence

First we analyze whether the funds in our sample show performance persistence. We start by discussing the results for mid-term persistence based on a one year ranking and evaluation period and later on turn to other lengths of these periods. Focusing first on the characteristics of the fund deciles significant differences emerge from table 3. There is a slightly higher number of managerial turnover among winner and loser funds as compared to funds with mediocre performance. This is consistent with our expectation that especially bad managers are being sacked and extremely good managers have a higher likelihood of being poached away by other investment management companies. Furthermore, decile 10 funds have high absolute and relative inflows and are relatively large in size. Investors seem to inflate the size of top funds by chasing good performers. Bottom funds in general experience outflows indicating the functioning of external governance. Furthermore, funds are closed or merged at a higher rate of 5.00 to 5.30 percent in the bottom decile as compared to the top decile where this rate is only 1.00 to 1.20 percent annually depending on the sorting mechanism (not reported in the table). This is

consistent with the findings of previous studies (Brown and Goetzmann, 1995; Elton, Gruber, and Blake, 1996b). Higher fees tend to be associated with lower performance. However, it exists a rather U-shaped pattern in that winner funds also have slightly higher fees than funds in the medium deciles.

[Please insert **table 3** about here]

The performance of the decile portfolios increases almost monotonically from the bottom decile 1 to the top decile 10 (tables 4 and 5). Thus, bad funds remain bad and good funds remain good. Based on the return-sorting decile 10 funds offer raw returns in excess of the rate on the risk-free asset of 0.75 to 0.83 percent per month (9.00 to 9.96 percent annually). The average raw returns of decile 10 funds for the alpha-sorting are 0.67 to 0.77 percent per month (8.04 to 9.24 percent annually). However, risk-adjusted returns of decile 10 funds are insignificant at between −0.11 and 0.25 percent for the return-sorting and between 0.07 and 0.18 percent for the alpha-sorting. Only in the subperiod from 1996 to 1999 top funds based on the alpha-sorting continue to outperform their benchmark by a statistically significant alpha of 0.44 percent per month. This is the only period in our sample which offers statistically significantly positive alphas based on a long-only investment strategy in mutual funds. In contrast, Huij and Verbeek (2007), using a very similar approach as we do, document a significant abnormal risk-adjusted return of 0.26 percent per month for an earlier period from 1984 to 2003.[27] Decile 1 funds have excess raw returns of 0.17 to 0.28 percent per months (2.04 to 3.36 percent annually) for the return-sorting and 0.36 to 0.45 percent per month (4.32 to 5.40 percent annually) for the alpha-sorting. Risk adjusted returns are negative yet insignificant between 0.03 and 0.37 percent for the return-sorting and even statistically significantly negative at between −0.21 and −0.24 percent per month for the alpha-sorting.

[Please insert **table 4** and **table 5**about here]

The spread in raw returns for a long position in decile 10 funds and a short position in decile 1 funds is on average between 0.55 and 0.57 percent per month (6.60 to 6.84 percent annually) for the return-sorting. However, it is significantly positive only for the panel approach but not for the portfolio approach. These numbers are slightly lower than the results of Carhart (1997) who documents a return spread of 0.67 percent per month. Based on the alpha-sorting our results show slightly smaller return spreads of 0.30 to 0.32 percent monthly (3.60 to 3.84 percent annually). However, the average spread in risk-adjusted returns between winner and loser funds

[27] This difference might be driven by their longer sample period, the higher turnover of their decile portfolios as they use a monthly rebalancing instead of annually rebalancing or their sample selection. Specifically, they do not combine all share classes of one fund but treat each share class as separately instead. Thus, if winner funds have several share classes they get a higher weight in the equally weighted decile portfolios.

is even significantly positive for the OLS alphas of the concatenated time series at 0.31 percent per month and the panel approach at 0.39 percent per month, which is slightly higher than the 0.29 percent reported by Carhart (1997). Thus, we find significant performance persistence based on spread portfolios if we use the Bayesian four factor alphas for ranking. Investors can earn annually between 3.72 and 4.68 percent of risk-adjusted abnormal returns by buying decile 10 funds and shorting decile 1 funds. The median spread between decile 10 and decile 1, which are more important to small investors who can only buy one fund, is significantly positive in all four cases. The spread in raw returns is 0.45 or 0.30 percent for the return-sorting and alpha-sorting, respectively, whereas the spread in risk-adjusted returns is 0.62 or 0.39 percent per month for the return-sorting and alpha-sorting, respectively. Consequently, the funds in our sample show some signs of performance persistence especially based on an alpha-sorting.

An analysis of different subperiods shows that persistence is stronger for the beginning of our sample period. In the subperiod from 1992 to 1995 the spread in raw returns between winner and loser funds based on the portfolio approach is significantly positive at 0.35 percent per month for the alpha-sorting and significantly positive 0.51 percent for the return-sorting. The corresponding number for the OLS four factor alphas of the concatenated time series are 0.25 percent per month for the alpha-sorting and the return-sorting, yet insignificant for the return-sorting. Even stronger, in 1996 to 1999 the return spread between decile 10 and decile 1 is 1.06 percent per month for both the return and the alpha-sorting and the corresponding four-factor alphas are significantly positive 0.62 percent for the return-sorting and significantly positive 0.95 percent for the alpha-sorting. Thus, we find strong performance persistence before 1999 and no persistence afterwards. These two periods correspond exactly with the different regimes of the fund flow volatility. Before 1999 funds flows are rather less volatile and after 1999 volatility increases significantly (figure 2). This already indicates the importance of fund flows for performance persistence.

The general conclusion about weak signs of performance persistence is supported by an analysis of the survival rates of funds in the top and bottom decile presented in figure 4 and table 6. The fraction of funds that survive for a second year, a third year etc. in the top decile (left panel) and bottom decile (right panel) are shown separately for each year in which the funds entered the decile.[28] If fund performance was independently identically distributed (*iid*) over time we would expect that ten percent of the funds stay in the same decile in the following year. However, in all but two years this fraction is higher for decile 10 funds indicating a positive relationship between past and future performance. The average share of top funds that survive a second year and third year in decile 10 is 15.69 percent and 2.61 percent, respectively, both significantly higher than the expected numbers based on *iid* performance. However, after three years persistence fades away as survival rates are no longer significantly higher than expected.

[28] Rankings are based on Bayesian four-factor alphas but the result for a return-sorting is very similar.

A very similar picture emerges for decile 1 funds where again significantly more funds survive in year two (15.70 percent) and three (1.85 percent) than expected under *iid* performance before persistence again vanishes for horizons longer than three years. Recall that one manager-fund combination on average lasts for 4 years which might explain why persistence starts to fade away around this period.

[Please insert **figure 4** and **table 6** about here]

If we compare different lengths of the ranking and evaluation periods we see that persistence is a short-lived phenomenon consistent with the findings of the previous literature (Bollen and Busse, 2005). This conclusion is independent of the combinations of ranking and evaluation methodologies we use. For example, the four-factor alphas of the portfolio approach based on a return-sorting are significantly positive at 0.80 percent per month for three month ranking and evaluation periods, decrease to insignificant 0.56 percent for 12 months periods and finally become negative yet insignificant at -0.25 percent for 24 months.

In the following sections we concentrate on the results of 12 months ranking and evaluation periods as this is the length with strongest signs of performance persistence where results on both, the return-sorting and the alpha-sorting, are available. Furthermore, we conjecture that the alpha-sorting is superior in separating investment skill from luck as compared to the return-sorting. First, this is based on theoretical arguments as the Bayesian four-factor alphas adjust for risk and investment style and correct for a potentially extreme impact of luck on performance by shrinking the alphas towards a grand mean. Second, empirical observations support our conjecture. For the return-sorting a clearly U-shaped pattern emerges for the 90 percent quantile and an inverted U-shape for the 10 percent quantile of risk-adjusted returns in the evaluation period (panel (a) of table 5). Thus, both the loser and winner deciles of funds have a large cross-sectional dispersion in alphas within their decile whereas funds in deciles 3 to 8 lie much closer together. We interpret this as evidence for a large impact of luck on the performance in the top and bottom deciles. If we compare the same numbers for the ranking based on Bayesian four-factor alphas the U-shape is much less pronounced (panel (b) of table 5) indicating that the deciles are more homogenous and thus driven by differences in skill rather than luck.

4.2 Fund Flows

In this section we present the results of a ranking of the funds in a first step into deciles based on their raw returns or Bayesian four-factor alphas over the preceding 12 months. In a second step we further subdivide decile 1 and decile 10 funds into funds with higher relative fund flows than the median fund flows for the respective decile during the previous 12 months (high flows)

and those with lower than median fund flows (low flows). Rebalancing of the decile portfolios occurs every January.

Our results for bottom funds lend only weak empirical support to the hypothesis of Berk and Green (2004). They argue that fund flows are the mechanism that leads to a mean reversion in performance. Specifically, investors withdraw money from badly performing funds. This gives fund managers the possibility to gain from diseconomies of scale in active management and to reorganize their portfolio. As expected, average raw returns of bottom funds with lower inflows, i. e. higher outflows, are higher than raw returns of bottom funds with higher inflows, i. e. lower outflows (table 7). However, the spread in raw returns between these two groups is significantly positive only for the panel approach based on the alpha-sorting at 0.11 percent per month but insignificantly positive for the other three measures. Risk-adjusted returns from the four factor model are more in line with the hypothesis of Berk and Green (2004) (table 8). Bottom funds that benefit from outflows have average risk-adjusted returns that are statistically indistinguishable from zero in five out of six cases whereas the alphas of bottom funds that do not benefit from outflows are significantly negative between -0.25 and -0.42 percent per month in five out of six cases. However, the spread between these two groups is again significantly positive only for the panel approach at on average 0.12 to 0.13 percent per month and 0.07 to 0.08 percent for the medians. A possible reason for the only weak support of the Berk and Green (2004) hypothesis for bottom funds by our results might be that a large fraction of investors is reluctant to withdraw money from underperforming funds as suggested by Berk and Tonks (2007). This might just not be enough for the fund manager to reorganize the fund's portfolio and to regain better performance results. Berk and Tonks (2007) compare this with the repayment behavior of mortgage borrowers. An alternative explanation might be a disposition effect among mutual fund investors.

Top funds clearly suffer from the impact of large inflows in the medium and long run lending strong support to our hypothesis and consistent with the model of Berk and Green (2004) (table 7 and table 8). However the results strongly depend on the length of the ranking and evaluation period. In the short term ranking and evaluation over three months, which is available only based on a return-sorting, excessive fund flows into decile 10 funds have a positive impact on future performance (not reported in table). The spread between winner funds with low inflows and winner funds with high inflows is highly significant between -0.14 and -0.16 percent in raw returns and -0.11 and -0.17 percent in alphas.[29] This result might be due to a short run momentum effect which is not accounted for by our momentum factor that is based on past 12 months returns. Additionally, funds might drive up the share prices of their own portfolio firms if they invest a large fraction of the excessive inflows into stocks they already

[29] Note that the OLS alpha based on the concatenated time series is not statistically significant for the whole period but only for the 1996 to 1999 subperiod.

hold. This price effect might be temporary rather than persistent but boosts fund performance in the short run. For a 12 months ranking and evaluation period this picture reverses. Based on the return-sorting, the spread portfolio long in winner funds with low inflows and short in winner funds with high inflows yields positive average raw returns between 0.06 and 0.07 percent per month and alphas between 0.05 and 0.09 percent per month. However, none of these numbers is statistically significant. Based on the alpha-sorting the spread portfolio has higher average raw returns of 0.11 to 0.12 percent per month which translate into alphas of 0.12 to 0.15 percent, the latter being significant in three out of five cases. These results are similar to the negative contribution of liquidity induced trading on alpha of 0.12 percent per month estimated by Edelen (1999). Our results also show that the positive OLS alpha for decile 10 funds of 0.07 percent can be divided into a positive alpha for top funds with low flows of 0.13 percent and a negative alpha of top funds with high flows of -0.03 percent. Focusing on long term persistence for 24 months ranking and evaluation periods the negative impact of fund flows becomes even more evident (not reported in tables). The average returns of the spread portfolio are highly significantly positive between 0.13 and 0.16 percent per month independent of the sorting mechanism used. Four-factor alphas are also highly significant in five out of six cases between 0.10 and 0.17 percent per month. Thus, what helps the fund manager in the short term to push his own prices has a tremendously negative effect in the long run. Our results strongly suggest the importance of mechanisms that shelter funds from excessive flows or reduce the costs that result from these flows.

[Please insert **table 7** and **table 8** about here]

Summarizing the results for fund flows we conclude that external governance at loser funds does not seem to have a large impact on the performance reversal of these funds. As the literature on the performance-flow relationship has shown investors still are reluctant to sell underperforming funds at the same rate as they buy outperforming funds (Sirri and Tufano, 1998; Lynch and Musto, 2003). Thus, we can only document weak signs of a positive impact of outflows on fund performance for loser funds. Fund flows can only to a certain degree explain the observed persistence among decile 1 funds. Contrary to that, fund flows play a major role in explaining persistence among winner funds which is consistent with the higher performance sensitivity of flows into these funds. In the short run, superior performers benefit from inflows but in the medium to long run excessive inflows hurt positive performance persistence. This is especially true for fund managers who end up in the top decile as a result of superior investment skills (alpha-sorting) as compared to investment style or just luck (return-sorting). The highest risk-adjusted alphas of significant 0.40 percent per month or 4.80 percent per year can be earned by a long position in top funds with low inflows and a short position in bottom funds with low outflows which is almost a third higher than the risk-adjusted return of applying the

long decile 10 and short decile 1 strategy without considering information on past fund flows. Thus, fund flows convey important information about future fund performance. We now turn over attention to managerial turnover as internal governance mechanism.

4.3 Managerial Turnover

In this section we present the results of a ranking of the funds in a first step into deciles based on their raw returns or Bayesian four-factor alphas over the preceding 12 months. In a second step we further subdivide decile 1 and decile 10 funds into funds that experienced a manager change during the previous 12 months (with manager change) and those that did not (without manager change). Rebalancing of the decile portfolios occurs every January.

Our hypothesis that bottom funds that sack their fund manager can improve their performance in the following year compared to bottom funds that stick to their presumably unskilled manager are strongly supported by our results. This is even more obvious for the alpha-sorting. Specifically, based on the return-sorting the average return spread is significant at 0.09 percent based on the portfolio approach and even higher yet insignificant at 0.14 percent based on the panel approach (table 9). The difference in medians is highly significant at 0.20 percent per month. For the alpha-sorting that only captures the effect of skill on performance the return spread between bottom funds with and without managerial turnover is highly significant at 0.10 to 0.16 percent per month or 1.20 to 1.92 percent per year. Turning to risk-adjusted returns based on the four-factor model lends even more support to our hypothesis (table 10). Based on the return-sorting, decile 1 funds without a change in management continue to underperform by -0.09 to -0.38 percent per month on average, which is statistically significant in two out of three measures. Based on the alpha-sorting all three measures are significantly negative at between -0.24 and -0.26 percent per month. In contrast, decile 1 funds that replaced their manager have still negative alphas but these are statistically indistinguishable from zero. This pattern results in a significant alpha spread between bottom funds with and without manager change of 0.08 to 0.14 percent per month or 0.96 to 1.68 percent per year. Consequently, managerial turnover is an important control mechanism that has a statistically and economically significant impact on fund performance. Furthermore, we show that the persistent underperformance of decile 1 funds which has also been documented by Carhart (1997) can be attributed completely to funds that do not apply internal governance (based on alpha-sorting).

Turning to winner funds a change in management has an important negative impact on fund performance. Decile 10 funds that lose their skilled manager underperform winner funds that can keep their manager by 0.09 (portfolio approach) to 0.13 percent (panel approach) on average, the former being statistically significant. The difference in risk-adjusted returns is

highly significant at 0.11 to 0.17 percent per month or 1.32 to 2.04 percent per year on average.[30] However, managerial turnover does not seem to have a similar impact on the performance of decile 10 funds based on the return-sorting. This is not very surprising as a large fraction of the funds presumably end up in the top decile just because of luck rather than skill and the return-sorting mechanism is not able to differentiate between these two. Consequently, it is not important if the manager is replaced or not as luck itself does not seem to be very persistent. In summary, our results show the importance of keeping skilled fund managers for example by linking their pay more closely to performance. The OLS alpha of decile 10 funds of 0.07 percent per months stems completely from top funds without managerial turnover (0.10 percent) whereas top funds with a change in management even display a negative alpha (-0.02). However, the lack of performance persistence among decile 10 funds can not be explained by managerial turnover as even winner funds that keep their manager do not show persistent outperformance.

[Please insert **table 9** and **table 10** about here]

Consistent with our hypotheses the performance of decile 1 funds with a manager change is significantly higher than the performance of decile 1 funds without a manager change and the performance of decile 10 funds without a manager change is significantly higher than the performance of decile 10 funds with a manager change. Thus, manager changes have a negative impact on the performance of top decile funds but a positive impact on the performance of bottom decile funds as both the spread portfolios long in decile 10 without manager change and short in decile 10 with manager change and long in decile 1 with manager change and short in decile 1 without manager change have statistically and economically significantly positive risk-adjusted returns (based on alpha-sorting). Speaking in terms of persistence, bad performance is more persistent at loser funds that kept their bad manager and superior performance is more persistent at good funds that kept their skilled manager. Both confirms our expectations and highlights that managerial turnover is at least as important as fund flows in explaining mutual fund performance.

Our results indicate that the replacement of an underperforming manager improves subsequent returns and highlight the importance of effective internal governance. On the other side, losing a star manager deteriorates performance. This result shows that at least some investment management companies do not seem to be able to keep their talented managers. Baks (2003) highlights to find some persistence by tracking individual managers instead of funds. Consequently, investment management companies need to improve their internal governance to retain skilled managers or investors should pay closer attention to the career paths of individual managers along different funds.

[30] This relationship is strongest for the subperiod 2000 to 2003.

4.4 Interaction of Fund Flows and Managerial Turnover

Internal governance for badly performing funds by managerial turnover seems to be more important than external governance by money withdrawals from investors. The performance of loser funds that sack their manager is on average 0.96 to 1.68 percent per year higher than the performance of loser funds that stick to their manager (ranking and evaluation based on four-factor alphas). This performance spread is economically meaningful as it is equivalent to about one third of the spread between decile 10 and decile 1 funds. On the other hand, external governance by outflows does not play the same role. Indeed, the improvement in risk-adjusted returns of funds with high outflows compared to loser funds with low outflows is only between 0.72 and 1.44 percent on average and statistically significant only for the panel approach. The difference between the panel and the portfolio approach lies in the weighting of different time periods with the panel approach overweighting more recent time periods due to a higher number of funds this result suggests that the importance of external governance might have increased during recent years. This is consistent with a larger share of institutional investors using mutual funds and with the results of Goriaev, Nijman, and Werker (2008) who show that a more sophisticated investor clientele emerged that quickly responds to performance.

The economic significance of the negative impact of inflows on top fund performance is comparable to the impact of managerial turnover. The former ranges between 1.44 and 1.80 percent annually and the later between 1.32 and 2.04 percent annually. Consequently, the hypothesis of diseconomies of scale in active management by Berk and Green (2004) seems to be supported by our data. However, we can show that managerial turnover is an equally important mechanism that keeps funds from delivering persistent outperformance. For this channel we do not even have to assume decreasing returns to scale but only different skill levels and the mobility of fund managers between different funds or even outside the mutual fund industry.

The composition of the subgroups based on managerial turnover and fund flows show distinct differences indicating that both channels independently have an impact on fund performance. Table 11 shows the fraction of fund-months in the subgroups of decile 10 and decile 1 with high and low fund flows and with and without managerial turnover.[31] It becomes obvious that our results are not driven by one mechanism alone as the composition of the different subgroups is comparable to the composition of the whole sample. Specifically, decile 10 funds with managerial turnover are almost equally distributed into the groups with high and low fund flows. Almost exactly half (49.36 percent) of the funds that suffer from a leaving of their star manager at the same time suffer from high inflows. Similarly, 20.01 percent of funds with high inflows at the same time have a change in management which is very close to the corresponding

[31] Note that the fraction of funds-months with lower (higher) than median fund flows is not exactly 50 percent as outflows seem to be associated with a higher number of fund closures or mergers.

number for all decile 10 funds at 20.11 percent. The results for decile 1 funds are similar. Of the 49.85 percent of loser funds with outflows 11.86 percent have a change in management. Thus, the share of funds with managerial turnover within the outflow group is 23.79 percent which is very close to the corresponding number of 22.00 percent for all decile 1 funds. Similarly, out of the group with a change in management 53.38 percent have outflows at the same time whereas 49.85 of all decile 1 funds have outflows. Thus, the negative effects of funds flows and managerial turnover documented in the previous section seem to be independent and cannot be driven by one another.

To further analyze the marginal effects we perform a pooled regression of the change in annualized fund raw returns and annualized Bayesian four-factor alphas between the previous year and this year on fund flows, managerial turnover and a set of control variables documented in the literature to have an impact on performance.[32] These controls are the fund size, fund fees, fund age and the turnover ratio.[33] As there is a strong tendency for fund performance to revert to the mean we add two dummy variables to our regression that indicate whether the fund is in decile 1 or decile 10. These dummies capture the mean reversion and assure that the other coefficients are not biased. The variables of interest are current and past fund flows. Additionally, we use an interaction term between fund flows and the decile 1 and decile 10 dummies in order to analyze the differences of funds flows on performance for top and bottom funds. Similarly, we use a manager change dummy indicating whether the fund manager has been replaced during the previous year and again an interaction term between managerial turnover and the decile 10 and decile 1 dummy. Our second model additionally analyzes the impact of being a small-cap fund or a sector fund on performance and the marginal impact of fund flows on these two investment style categories. We expect that capacity constraints are more prevalent in narrow and illiquid markets and as a result fund flows have a stronger impact on performance in these investment categories. The third model additionally captures the interaction effect between a change in management and the fund being a member of a large fund family. Gervais, Lynch, and Musto (2005) argue that the replacement of a manager of a large fund family discloses more information than the replacement of a manager of a small fund family. We assign a fund to the large family group if the number of funds offered by its fund family at the end of last year is higher than the 70 percent quantile.

We measure the change in performance from the previous year to this year. A significant

[32] Following French (2008) we winsorize all variables at the 1 percent and 99 percent quantile to avoid any bias resulting from extreme outliers.

[33] Chen, Hong, Huang, and Kubik (2004) and Cremers and Petajisto (2007) show a negative effect of fund size on performance, Carhart (1997) documents a negative effect of fees, Huij and Verbeek (2007) and Karoui and Meier (2008) report an outperformance of young funds. Results on turnover are ambiguous. Elton, Gruber, Sanjiv, and Hvlaka (1993) and Carhart (1997) find a negative relation, Wermers (2000) documents that turnover is not associated with fund performance and Dahlquist, Engström, and Söderlind (2000) and Chen, Jegadeesh, and Wermers (2000) find a positive relationship.

coefficient on one of the control variables would indicate a trend in performance over time rather than differences in the level of performance. Thus, most of the coefficients turn out to be insignificant as expected. The signs indicate that small and young funds with low costs can improve their performance over time as compared to old and large funds with high expense ratios. Turnover has a significantly positive impact on the change in fund performance in our sample. Funds with exceptionally high turnover in the previous year can improve their performance compared to low turnover funds. A possible explanation is that the fund flow measures in our regression capture the negative effect of liquidity driven trading and, thus, the turnover ratio only captures the effect of discretionary trades based on superior information and therefore is highly significantly positive (Edelen, 1999; Alexander, Cici, and Gibson, 2007). Funds that invest in narrow markets such as small-cap and sector funds have similar raw returns but higher alphas compared to large and mid-cap funds. The decile 1 and decile 10 dummies are both highly significant and indicate that loser funds improve their raw returns between 3.38 and 3.41 percent and their risk-adjusted returns between 3.18 and 3.25 percent in the following year. The raw returns of decile 10 funds deteriorate by 2.08 to 2.20 percent and their alphas by 3.09 to 3.26 percent in the year after they belonged to decile 10. Current fund flows have a significantly positive impact on raw returns and performance consistent with our findings of a positive short term impact in section 4.2.[34]

Fund performance declines significantly following past inflows. A one standard deviation increase in cumulated fund flows during the previous year decreases fund returns by -1.70 to -2.46 percent the following year. The impact on four-factor alphas is even higher at -2.53 to -3.39 percent. If the fund belongs to the winner fund group during the previous year it suffers even more from excessive inflows. Returns decrease between -5.53 and -6.68 percent and alphas between -3.88 to -6.61 percent following a one standard deviation increase in fund flows. This result is statistically and economically significant. Also consistent with our expectation is that the negative effect of inflows on performance is stronger if the fund operates in narrow markets. Specifically, a one standard deviation increase in previous year inflows decreases the raw return of small-cap and sector funds significantly by additional -2.55 percent and alphas by -2.70 percent compared to average large and mid-cap funds.

[Please insert **table 12** about here]

Similarly to the ranked portfolio test the hypothesis of Berk and Green (2004) that loser funds can benefit from outflows due to decreasing returns to scale in active management receives only limited empirical support by our pooled regression results. Only model 1 supports this hypothesis without any qualification in that a one standard deviation increase in outflows (or

[34] Note, however, that reverse causality cannot be excluded as possible explanation, i. e. investors might also allocate heavily to current winner funds.

decrease in net inflows) results in a subsequent improvement in raw returns of decile 1 funds by 3.63 percent which is higher than the 2.46 percent increase for the average fund. This effect is completely captured by the interaction between fund flows and narrow markets in models 2 and 3. Thus, large and mid-cap funds cannot benefit to the same degree as small-cap and sector funds. In contrast, the improvement in alphas for decile 1 funds is even significantly smaller than the improvement of the average fund at 1.33 to 1.34 percent when we control for the combined effect of narrow markets and fund flows. Still, all fund groups can gain from outflows as suggested by Berk and Green (2004). This result might be explained by the decreasing sensitivity of fund flows to performance in decreasing performance ranks (Sirri and Tufano, 1998; Lynch and Musto, 2003). Consequently, fund flows have a marginal impact on fund performance independent of managerial turnover.

A change in management in general improves subsequent performance. Decile 1 funds benefit more than average funds and decile 10 funds suffer if the manager leaves. Specifically, a change in management improves fund returns of the average fund in the subsequent year by significant 0.65 to 0.67 percent and alphas by significant 0.48 percent based on models 1 and 2. This effect is completely picked up by the interaction between a change in management and the dummy for a large fund family in model 3. The aggregate effect of managerial turnover among funds of large fund families is significantly (at 10 percent) positive at 1.25 percent for raw returns and 1.03 percent for alphas. Thus, we can confirm the hypothesis of Gervais, Lynch, and Musto (2005) for our sample that a replacement of a manager of a large fund family contains more information. If a top manager of a decile 10 fund leaves a fund raw returns subsequently decrease by significant -1.37 to -1.50 percent and the reduction in alpha is between -0.50 and -0.65 percent, yet insignificant. Bottom funds that replaced their manager can improve their raw returns by 1.10 to 1.17 percent and their alphas by 0.95 to 0.99 percent in the following year. However, these numbers are not statistically significantly higher than the performance improvement among average funds as documented above. These results confirm the conclusions from the ranked portfolio tests in section 4.3 and show that decile 10 funds suffer from a change in management whereas the average fund (and decile 1 funds) benefit. However, the results for the managerial turnover channel at bottom funds seem to be slightly weaker than the results based on the ranked portfolio tests in section 4.3. The ranked portfolio test measures the difference in the level of performance between bottom funds with and without a change in management whereas the pooled regression explains the change in performance over time. In general, our results confirm that managerial turnover affects performance independently from fund flows.

In summary, the pooled regression results confirm our results from the ranked portfolio test. Fund inflows deteriorate performance on average and especially do so for winner funds and funds investing in narrow markets. Loser funds can gain from outflows even though the magnitude

of the performance improvement is lower than for the average fund. Managerial turnover on average improves fund performance in the subsequent year which is especially true for large fund families. If a top manager leaves a decile 10 fund this turns into a negative impact on fund performance. However, a replacement of a bottom fund manager does not improve the performance of this fund to a larger degree than for an average fund. Our analysis confirms that both channels, fund flows and managerial turnover, have a significant marginal impact on fund performance.

5 Conclusion and Outlook

In this study we analyze the impact of funds flows and managerial turnover on mutual fund performance. Berk and Green (2004) have argued that fund flows in combination with decreasing returns to scale erode superior performance of winner funds and wipe out performance persistence. Similarly, the same mechanism in the context of outflows gives loser funds the possibility to regain performance. We argue that managerial turnover might result in a similar effect and, thus, might be a complementary mechanism to fund flows. Outperforming managers leave winner funds in order to increase their salary at another fund or even outside the mutual fund industry. The previously outperforming funds they left cannot generate the positive performance afterwards and as a result no performance persistence can be found at winner funds that lost their manager. Similarly among losing funds, the replacement of an underperforming manager serves as an internal governance mechanism. The new manager is likely to generate mediocre returns and again no persistence among loser funds can be observed if their manager has been replaced.

Our empirical results based on a set of 3,948 U. S. equity mutual funds supports this hypothesis. Keeping a star manager, leads to 1.32 to 2.04 percent higher risk-adjusted returns in the following year as compared to winner funds that lost their manager. Over time, losing a winner fund manager reduces performance by -0.50 to -0.65 percent in the year after the manager left. On the other side, replacing an underperforming manager increases subsequent risk-adjusted returns by 0.96 to 1.68 percent as compared to loser funds that stick to their manager. Over time this internal governance mechanism results in an increase in performance of 0.48 percent. Consistent with Berk and Green (2004) excessive inflows into top funds harm subsequent performance by 1.44 to 1.80 percent annually compared to funds with lower than median inflows. Somewhat surprisingly, bottom funds cannot gain from outflows to the same degree as winner funds suffer from inflows. Still, the performance of loser funds increases by 1.33 to 3.27 percent in the year following a one standard deviation increase in outflows. The somehow stronger results of the managerial turnover channel indicate that this channel might be even more important in explaining the observed lack of performance persistence than the

channel via fund flows. This is especially evident for exercising governance at bottom funds. Furthermore, we show that both channels, funds flows and managerial turnover, independently have a marginal impact on funds performance and do not depend on one another.

To answer our initial question our results show that at least some funds are able to outperform the market. However, these funds become victims or their own success. Large amounts of money flow into these funds and the likelihood increases that the fund manager quits his job as he is being offered more promising alternatives based on his successful track record. We conclude that it is not solely a lack of managerial skill that prevents persistent outperformance but that the organizational environment of mutual funds also plays a certain role in this relationship. Thus, mutual funds in their current design are to a certain extent doomed to fail.

Both results highlight the importance of the regulatory environment and the fund design for performance. Even though internal governance mechanisms are not developed to a large degree the indirect performance incentive of the investment management company seems to be strong enough to effectively punish bad fund managers. However, on the other side investment management companies are not able to keep good fund managers. One way to tie a fund manager stronger to a fund is to link his compensation directly to performance. Some studies already questioned the usefulness of the restriction that only fulcrum fees are allowed in the U. S. which prevents the more frequent use of these contracts (Das and Sundaram, 2002). A look at the hedge fund industry that usually combines asymmetric performance fees with own investments of the fund manager might prove beneficial for mutual funds as well.

Furthermore, our result questions the absolute benefit of the open-end fund structure for investors. Even though it gives investors a high degree of flexibility at the same time it imposes costs in the form of lower performance. These costs are hard to measure but our results present a first clue that they might be economically significant. Two conclusions emerge from this. First, funds need to invest more of their resources into measures that allow an efficient handling of fund flows including efficient tools for trading large liquidity driven orders. Second, it might be sensible to develop fund shares with restricted liquidity for the benefit of long-term profits. As mutual funds are more and more competing with life-insurance policies and similar long-term products for retirement saving investors might not require the daily liquidity feature. Lockup periods and redemption notice periods can be used as well as a closing of the fund once it reaches its capacity constraints.

Moreover, our study does not directly address the risk associated with the liquidity service of open-end funds. Especially as investment strategies become more focused and new asset classes are packaged into open-end fund structures these risks can be severe if the liquidity of fund shares is not chosen appropriately to the liquidity of the underlying assets. For example, some German open-end real-estate funds had to be closed at the end of 2005 as a response to heavy outflows. The liquidity of the fund shares was much higher than the liquidity of the underlying

real-estate assets. The same can happen when the liquidity of initially liquid markets dries up as a result of a market crash which happened to asset-backed-security funds at the end of 2007. One possible solution to shelter the fund from extreme flows but at the same time to preserve daily liquidity is an exchange listing of fund shares. However, as long as usual creation and redemption mechanisms still exist the net surplus or deficit of demand during one trading day will be traded directly with the mutual fund company. Consequently, net daily fund flow is not reduced compared to the case without exchange trading. Thus, exchange trading in combination with restrictions on the usual creation and redemption feature might be necessary to efficiently shelter the fund from excessive flows. However, in this case it cannot be guaranteed that the fund shares trade close to their NAV at all times. Fund investors with an immediate demand for liquidity services bear the costs of this liquidity by themselves if they sell (buy) fund shares at the exchange below (above) their current NAV. Under the current regulatory environment without a significant volume of exchange trading of mutual fund share, these costs are socialized among all fund investors (Zitzewitz, 2006).

Another way of looking at our result might be as an explanation for the trend to separate alpha and beta sources.[35] Mutual funds are supposed to deliver both, a diversified exposure to market risk and at the same time to add a little bit of alpha. Eventually the regulation and the fund design prevents them to deliver both successfully at the same time. One logical consequence was to look for alpha at hedge funds that are more flexible and to generate diversified market exposure through low-cost products such as index funds and exchange traded funds.

[35] According to McKinsey's Institutional Investor U. S. Institute Asset Management Benchmarking Survey the growth in assets under management in *higher alpha strategies* and in *cheap beta* strategies was significantly higher in 2004/2005 than that in *traditional actice/core* strategies.

A Appendix

A.1 Data Selection

In constructing our sample we follow Pástor and Stambaugh (2002) as closely as possible. Thus, we select only domestic equity funds and exclude all funds not investing primarily in equities such as money market or bond funds. In addition, we exclude international funds, global funds, balanced funds, flexible funds, and funds of funds. As CRSP does not provide an indicator whether a fund is an active or passive funds we further drop all funds containing one or more terms in their name that commonly refer to passive funds such as "index", popular index names and names of investment companies that solely offer passive products or exchange traded funds (we allow for different spellings and abbreviations of these terms). We require our funds to have at least 12 months of return data available to be included in our sample. Additionally, we drop all observations prior to the IPO date given by CRSP and funds without names in order to account for a potential incubation bias (Evans, 2007). This selection results in 3,948 funds that existed at any time during our sample period from 1992 to 2007. These funds belong to 672 different fund families.

Besides returns the two variable with the highest relevance for our analysis are funds flows which are constructed from the change in total net assets not attributable to internal growth through investment returns and the manager change date which gives the date of the last change in management. It is obvious that different share classes of one fund have the same manager and that fund flows that occur to two different classes of the same fund might cancel out on portfolio level. Thus, we combine all share classes that belong to the same fund and have the same underlying portfolio to one observation. We use a matching algorithm that combines information from the fund's name and the portfolio number variable (`crsp_portno`) given by CRSP. A matching solely based on the portfolio number variable is not possible as this variable is available only from December 1998 onwards. Furthermore, some cases exist where the portfolio number variable is missing for some share classes of the same fund which would result in an incomplete matching.[36] Fund characteristics such as the investment objective or the first offer date are taken from the oldest share class whereas quantitative information is either summed up, such as total net assets, or we take the weighted average over all share classes, such as returns and fees. If two share classes of the same funds have different manager change dates we keep the most recent date.

We classify the funds in our sample into three groups: (1) Large and mid-cap funds (LMC),

[36] For example, `crsp_fundno` 30107 has no observations on `crsp_portno` but forms together with `crsp_fundno` 30109 the *Touchstone Strategic Trust: Large Cap Growth Fund* with the underlying portfolio `crsp_portno` 1001571. Later on, this fund consists of the share classes with `crsp_fundno` 30107, 30108 and 30109 then 30107, 30108, 30109, 30110 and 30130 before the share class `crsp_fundno` 30107 is finally merged into `crsp_fundno` 30108.

(2) small-cap funds (SC) and (3) sector funds (SEC). However, as we use the 2008 cut of the CRSP mutual fund database Lipper is the primary data source. As a consequence, ICDI classification codes, which have been used by Pástor and Stambaugh (2002), are no longer available and have been replaced by Lipper codes. Thus we modify the selection criteria of Pástor and Stambaugh (2002) as follows. For our classification we use Lipper codes, Wiesenberger codes and Strategic Insight codes (priority is given in that order if different codes assign funds to different investment categories). Details are given in the following table:

Table 1: Classification of investment objectives

This table presents the classification codes we have used to construct our sample. We use Lipper codes, Wiesenberger codes and Strategic Insight codes (priority is given in that order if different codes assign funds to different investment categories) in order to classify our funds into the following three groups: (1) Large and mid-cap funds (LMC), (2) small-cap funds (SC) and (3) sector funds (SEC).

	Large and mid-cap (LMC)	Small-cap (SC)	Sector (SEC)
Lipper	CA, EI, EIEI, G, GI, I, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE	SCCE	FS, H, NR, S, SESE, TK, TL, UT
Wiesenberger	AGG, G, G-I, G-I-S, G-S, G-S-I, GCI, GRI, GRO, I-G, I-G-S, I-S, I-S-G, IEQ, ING, LTG, MCG, S-G, S-G-I, S-I-G, S-I, I*	SCG	ENR, FIN, HLT, TCH, UTL
Strategic Insight	AGG, GMC, GRI, GRO, ING	SCG	ENV, FIN, HLT, NTR, SEC, TEC, UTI

* Note that the Wiesenberger code I for income funds is not restricted to income equity funds but also contains income money market funds, income bond funds etc. Consequently we use a combination of Wiesenberger code I and policy code CS or I-S or Wiesenberger code I and an allocation to stocks of at least 50 percent as condition for funds to be included in our sample.

A fund is assigned to one of the three groups for the total sample period if it belonged to this group for at least 50 percent of the observations in our sample period. For example, if a fund has 72 months of data and belongs to the small-cap group for 12 months but eventually changes to the large and mid-cap group for the remaining 60 months it is assigned to the large and mid-cap group for the total of 72 months.

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Figure 1: Organizational Structure and Regulatory Environment

This figure gives an overview of the different organizational and regulatory determinants on mutual fund performance and persistence. Most of these restrictions and regulations are governed by the Securities Act of 1933, the Securities Exchange Act of 1934, the Investment Company Act of 1940, and the Investment Advisors Act.

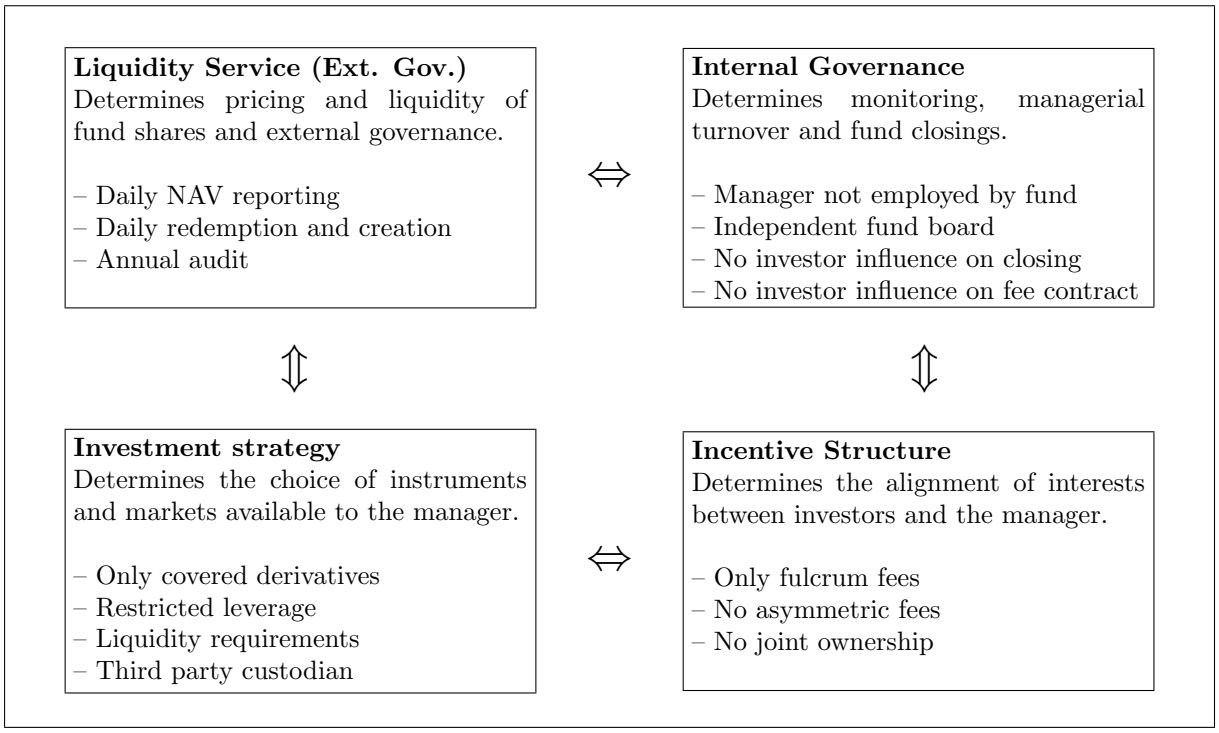

Figure 2: Fund flows

This figures presents the absolute fund flows in each months of the sample period as well as the rebased market index (dotted line).

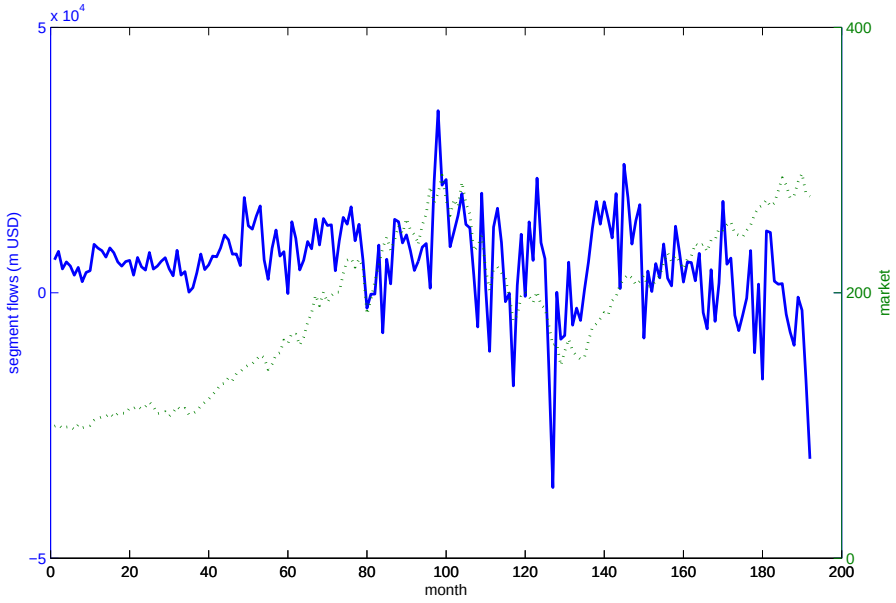

Figure 3: Number of manager changes

This figures presents the number of manager changes in each months of the sample period as well as the rebased market index (dotted line).

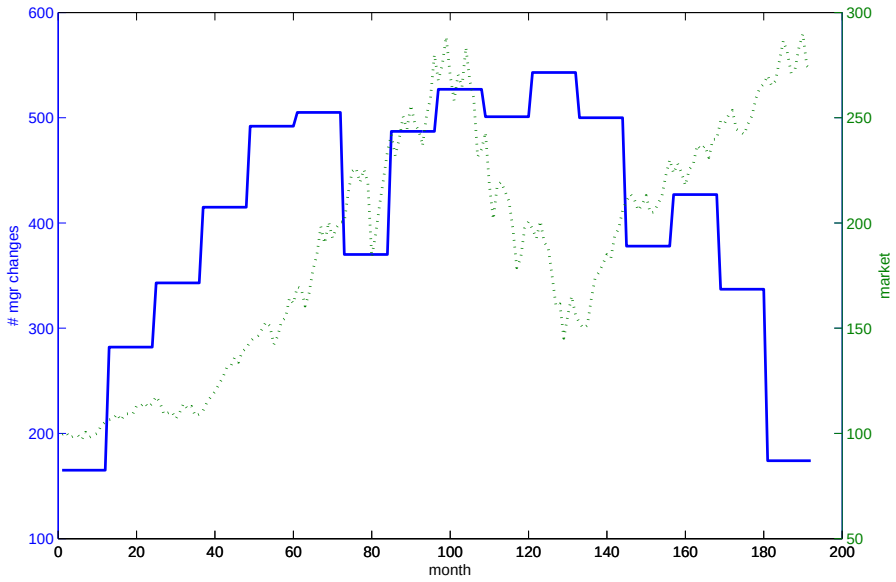

Figure 4: Survival function in top and bottom decile

This figures presents in the left panel the share of funds that survive more than one year in decile 10 and in the right panel the share of funds that survive more than one year in decile 1. The colors give the year of entering the respective decile and the bars give the percentage of funds still in the respective decile two, three, four and five years after entering the decile, respectively. Funds are ranked into deciles based on their previous year Bayesian four-factor alphas.

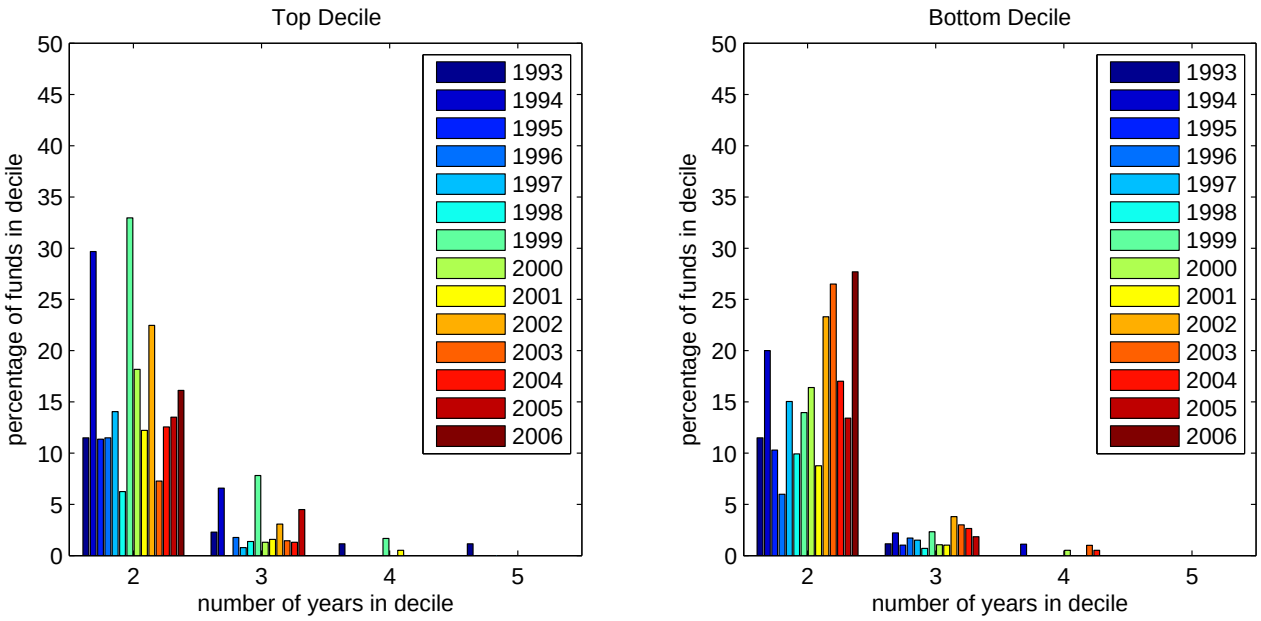

Table 2: Descriptive Statistics of fund sample

This table presents descriptive statistics for all 3,948 funds in the sample from 1992 to 2007. We restrict our sample to funds that have at least 12 months of available return data and information on the variable `mgr_date` in the CRSP database. The first row gives the number of months in the respective period. The second row gives monthly (arithmetic) mean excess raw returns in percent. The third row gives average fees. The fourth row gives the mean fund size in million U. S. Dollar. The fifth row gives monthly mean absolute fund flows in million U. S. Dollar. The sixths row gives the number of funds in existence. The seventh row gives the number of manager changes that occurred during this period.

	1992–1995	1996–1999	2000–2003	2004–2007	Whole Period
# months	48	48	48	48	192
returns	0.72	1.36	-0.29	0.62	0.51
fees	1.68	1.64	1.67	1.56	1.63
size	461.40	853.06	849.32	1178.74	899.28
flows	5.00	4.57	2.39	0.66	2.70
# funds	1,623	2,545	3,219	3,064	3,948
# man ch	1,205	1,854	2,071	1,316	6,446

Table 3: Descriptive statistics of decile portfolios (12 months)

This table presents descriptive statistics for the decile portfolios 1 (loser) to 10 (winner) and a spread portfolio long in decile 10 funds and short in decile 1 funds. The first column reports the number of manager changes per fund; columns two and three report the mean and median of fund size (in m USD), respectively; columns four and five report the mean and median of absolute fund flows (in m USD), respectively; columns six and seven report the mean and median of relative fund flows, respectively; and column eight reports the average fees (in percent). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. For differences in means we apply a two-sample t-test and for differences in medians we apply a Mann-Whitney-U-Test.

(a) Sorting based on returns

	mc/funds	size		absolute flows		relative flows		fees
		mean	median	mean	median	mean	median	mean
1 (loser)	0.21	461.84	77.27	−5.19	−0.55	0.02	−0.01	2.00
2	0.23	838.24	129.60	−8.56	−0.64	0.00	−0.01	1.71
3	0.21	898.82	144.50	−4.72	−0.39	0.04	−0.01	1.63
4	0.20	1,128.40	160.65	−3.48	−0.29	0.03	−0.00	1.57
5	0.20	1,137.85	172.70	0.61	−0.08	0.01	−0.00	1.54
6	0.20	1,283.33	182.70	2.56	−0.01	0.08	−0.00	1.52
7	0.19	1,139.48	195.20	4.01	0.05	0.01	0.00	1.55
8	0.18	1,196.28	196.04	7.84	0.20	0.02	0.00	1.56
9	0.19	1,282.99	193.95	13.17	0.59	0.55	0.01	1.57
10 (winner)	0.22	1,029.92	217.65	17.22	1.20	0.04	0.01	1.69
10 − 1	–	568.08***	140.37***	22.41***	1.75***	0.02*	0.02***	−0.31***

(b) Sorting based on Bayesian four-factor alphas

	mc/funds	size		absolute flows		relative flows		fees
		mean	median	mean	median	mean	median	mean
1 (loser)	0.22	673.54	100.10	−4.10	−0.52	0.01	−0.01	1.88
2	0.21	839.51	144.45	−3.80	−0.35	0.04	−0.01	1.70
3	0.21	1,044.91	155.07	−4.26	−0.26	0.01	−0.00	1.62
4	0.21	1,027.58	162.85	−1.08	−0.13	0.01	−0.00	1.63
5	0.21	962.69	170.50	1.32	−0.05	0.05	−0.00	1.60
6	0.18	1,176.30	170.40	1.85	−0.03	0.01	−0.00	1.54
7	0.19	1,179.21	181.60	4.62	−0.00	0.07	−0.00	1.55
8	0.18	1,333.25	193.47	6.35	0.06	0.02	0.00	1.55
9	0.21	1,115.10	184.00	8.48	0.12	0.03	0.00	1.59
10 (winner)	0.21	1,059.17	180.00	14.45	0.50	0.55	0.01	1.67
10 − 1	–	385.64***	79.90***	18.55***	1.02***	0.54	0.02***	−0.21***

Table 4: Returns of decile portfolios (12 months)

This table presents the raw returns (in excess of the rate on the risk-free asset) for the decile portfolios 1 (loser) to 10 (winner) and a spread portfolio long in decile 10 funds and short in decile 1 funds. The first two columns report the mean and the standard deviation, respectively, of a concatenated time series of decile portfolio returns following the methodology of Carhart (1997) (*portfolio* approach); columns three to six report the mean, median, 10 percent quantile and 90 percent quantile, respectively, of the panel of the monthly returns of all funds that belong to the respective decile portfolio (*panel* approach). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. For differences in means we apply a two-sample t-test and for differences in medians we apply a Mann-Whitney U-test.

(a) Sorting based on returns

	portfolio		panel			
	mean	std	mean	median	perc_{10}	perc_{90}
1 (loser)	0.28	5.22	0.17	0.45	−7.21	7.25
2	0.42	4.32	0.30	0.56	−5.80	6.17
3	0.47	4.03	0.38	0.62	−5.40	5.87
4	0.46	3.95	0.36	0.66	−5.32	5.77
5	0.50	3.84	0.40	0.69	−5.07	5.67
6	0.56	3.78	0.46	0.76	−4.93	5.69
7	0.65	3.89	0.57	0.79	−4.91	5.81
8	0.71	4.07	0.62	0.89	−5.02	6.11
9	1.02	5.56	1.00	0.90	−5.27	6.38
10 (winner)	0.83	5.58	0.75	0.89	−6.28	7.34
10 − 1	0.55	5.19	0.57^{***}	0.45^{***}	–	–

(b) Sorting based on Bayesian four-factor alphas

	portfolio		panel			
	mean	std	mean	median	perc_{10}	perc_{90}
1 (loser)	0.45	4.20	0.36	0.64	−6.08	6.54
2	0.52	4.11	0.42	0.66	−5.63	6.19
3	0.49	3.96	0.40	0.67	−5.33	5.92
4	0.53	3.89	0.44	0.68	−5.14	5.93
5	0.57	3.95	0.48	0.73	−5.10	5.86
6	0.53	3.82	0.45	0.70	−5.04	5.77
7	0.52	3.87	0.42	0.70	−5.16	5.87
8	0.59	4.02	0.49	0.74	−5.31	6.09
9	0.94	5.56	0.90	0.79	−5.61	6.50
10 (winner)	0.77	5.31	0.67	0.85	−6.14	7.07
10 − 1	0.32	3.19	0.30^{***}	0.21^{***}	–	–

Table 5: Four-factor alphas of decile portfolios (12 months

This table presents the performance based on a Carhart (1997) four-factor model for the decile portfolios 1 (loser) to 10 (winner) and a spread portfolio long in decile 10 funds and short in decile 1 funds. The first column reports the OLS estimate of a concatenated time series of decile portfolio returns following the methodology of Carhart (1997) (*concatenated* approach); column two reports the time series mean of the decile portfolio's Bayesian alphas computed as the cross-sectional mean of the individual alphas of all funds belonging to the respective decile in each time period (*portfolio* approach); columns three to six report the mean, median, 10 percent quantile and 90 percent quantile, respectively, of the panel of the monthly Bayesian alphas of all funds belonging to the respective decile portfolio (*panel* approach). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. For the concatenated time series (first column) we compute inferences using a conventional t-test on the regression coefficients of an OLS regression with White's heteroscedasticity-consistent standard errors. For the time series portfolio Bayesian alphas (second column) we apply a t-test on the time series of the portfolio alphas. For the means of the panel of Bayesian alphas (third column) we apply a conventional t-test to the individual fund alphas of each decile portfolio and a two-sample t-test to the spread portfolios. For the medians of the panel (fourth column) we apply a Wilcoxon signed rank test to the individual fund alphas of each decile portfolio and a Mann-Whitney U-test to the spread portfolios.

(a) Sorting based on returns

	concatenated	portfolio	panel			
	α^{OLS}	α^{B} mean	α^{B} mean	α^{B} median	α^{B} perc$_{10}$	α^{B} perc$_{90}$
1 (loser)	-0.08	-0.34	-0.37	-0.35^{***}	-5.43	4.75
2	-0.08	-0.21	-0.25	-0.29^{***}	-3.63	3.21
3	-0.08	-0.15	-0.16	-0.24^{***}	-3.14	2.87
4	-0.14^{*}	-0.17^{**}	-0.18^{**}	-0.23^{***}	-2.87	2.62
5	-0.10^{**}	-0.10^{*}	-0.12^{*}	-0.17^{***}	-2.67	2.46
6	-0.09^{**}	-0.04	-0.05	-0.11^{***}	-2.54	2.45
7	-0.08^{**}	0.05	0.06	-0.05^{**}	-2.60	2.65
8	-0.05	0.11	0.12	0.01^{***}	-2.65	2.84
9	0.16	0.17	0.18	0.10^{***}	-2.98	3.27
10 (winner)	-0.11	0.23	0.25	0.15^{***}	-4.38	4.56
$10-1$	-0.02	0.56	0.62^{***}	0.51^{***}	1.05	-0.19

(b) Sorting based on Bayesian four-factor alphas

	concatenated	portfolio	panel			
	α^{OLS}	α^{B} mean	α^{B} mean	α^{B} median	α^{B} perc$_{10}$	α^{B} perc$_{90}$
1 (loser)	-0.24^{**}	-0.21^{**}	-0.21^{**}	-0.19^{***}	-3.95	3.49
2	-0.16^{*}	-0.11	-0.11	-0.15^{***}	-3.28	3.13
3	-0.14^{**}	-0.13^{**}	-0.14^{**}	-0.15^{***}	-3.10	2.84
4	-0.11^{*}	-0.08	-0.08	-0.13^{***}	-2.97	2.83
5	-0.09^{*}	-0.05	-0.05	-0.11^{***}	-2.92	2.79
6	-0.10^{**}	-0.08^{*}	-0.08^{*}	-0.13^{***}	-2.89	2.75
7	-0.11^{*}	-0.08	-0.08	-0.14^{***}	-2.98	2.87
8	-0.05	0.00	-0.00	-0.10^{***}	-3.10	3.11
9	0.24	0.08	0.08	-0.07^{**}	-3.20	3.33
10 (winner)	0.07	0.18	0.18	0.01^{***}	-3.68	4.10
$10-1$	0.31^{*}	0.39	0.39^{***}	0.20^{***}	0.27	0.61

Table 6: Share of surviving funds

This table presents in panel (a) the share of funds that survive more than one year in decile 10 and in panel (b) the share of funds that survive more than one year in decile 1 (in percent). The rows give the year of entering the respective decile and the columns give the percentage of funds still in the decile two, three, four and five years after entering the decile, respectively. Additionally, we present the column means and the expected column means based on the assumption that fund performance is identically independently distributed (*iid*) over time. The last row give the p-value of a t-test on difference between the mean and the expected mean. Ranking is based on Bayesian four-factor alphas during the previous year.

Share of surviving funds

	(a) surviving funds in decile 10 in year				(b) surviving funds in decile 1 in year			
	2nd	3rd	4th	5th	2nd	3rd	4th	5th
1993	11.49	2.30	1.15	1.15	11.49	1.15	0.00	0.00
1994	29.67	6.59	0.00	0.00	20.00	2.22	1.11	0.00
1995	11.36	0.00	0.00	0.00	10.31	1.03	0.00	0.00
1996	11.50	1.77	0.00	0.00	5.98	1.71	0.00	0.00
1997	14.06	0.78	0.00	0.00	15.04	1.50	0.00	0.00
1998	6.25	1.39	0.00	0.00	9.93	0.71	0.00	0.00
1999	32.96	7.82	1.68	0.00	13.95	2.33	0.00	0.00
2000	18.18	1.30	0.00	0.00	16.40	1.06	0.53	0.00
2001	12.23	1.60	0.53	0.00	8.76	1.03	0.00	0.00
2002	22.47	3.08	0.00	0.00	23.31	3.81	0.00	0.00
2003	7.28	1.46	0.00	0.00	26.50	3.00	1.00	0.00
2004	12.55	1.30	0.00	–	17.02	2.66	0.53	–
2005	13.51	4.50	–	–	13.43	1.85	–	–
2006	16.13	–	–	–	27.70	–	–	–
mean	15.69	2.61	0.28	0.10	15.70	1.85	0.26	0.00
E(mean)	10.00	1.00	0.10	0.01	10.00	1.00	0.10	0.01
p-value	0.02	0.03	0.29	0.39	0.01	0.01	0.20	0.00

Table 7: Returns of subgroups based on fund flows (12 months)

This table presents the raw returns (in excess of the rate on the risk-free asset) for the following pairs of portfolios and the resulting spread portfolio: decile portfolio 10 (winner) and 1 (loser), decile 1 funds with lower than median fund flows (1 lo fl) and with higher than median fund flows (1 hi fl), decile 10 funds with lower than median fund flows (10 lo fl) and with higher than median fund flows (10 hi fl). The first two columns report the mean and the standard deviation, respectively, of a concatenated time series of decile portfolio returns following the methodology of Carhart (1997) (*portfolio* approach); columns three to six report the mean, median, 10 percent quantile and 90 percent quantile, respectively, of the panel of the monthly returns of all funds that belong to the respective decile portfolio (*panel* approach). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. For differences in means we apply a two-sample t-test and for differences in medians we apply a Mann-Whitney U-test.

(a) Sorting based on returns

	portfolio		panel			
	mean	std	mean	median	perc_{10}	perc_{90}
10 (winner)	0.83	5.58	0.75	0.89	−6.28	7.34
1 (loser)	0.28	5.22	0.17	0.45	−7.21	7.25
10 − 1	0.55	5.19	0.57^{***}	0.45^{***}	–	–
1 lo fl	0.33	5.00	0.24	0.42	−6.94	7.21
1 hi fl	0.25	5.46	0.14	0.49	−7.30	7.29
1 lo fl − 1 hi fl	0.09	1.05	0.10	-0.07^{***}	–	–
10 lo fl	0.85	5.48	0.75	0.90	−6.16	7.16
10 hi fl	0.78	5.70	0.69	0.88	−6.39	7.41
10 lo fl − 10 hi fl	0.07	0.71	0.06	0.02^{***}	–	–

(b) Sorting based on Bayesian four-factor alphas

	portfolio		panel			
	mean	std	mean	median	perc_{10}	perc_{90}
10 (winner)	0.77	5.31	0.67	0.85	−6.14	7.07
1 (loser)	0.45	4.20	0.36	0.64	−6.08	6.54
10 − 1	0.32	3.19	0.30^{***}	0.21^{***}	–	–
1 lo fl	0.50	4.03	0.43	0.66	−5.86	6.53
1 hi fl	0.41	4.37	0.32	0.63	−6.24	6.51
1 lo fl − 1 hi fl	0.08	0.87	0.11^{*}	0.03^{***}	–	–
10 lo fl	0.81	5.01	0.70	0.86	−5.96	6.92
10 hi fl	0.69	5.56	0.59	0.83	−6.25	7.07
10 lo fl − 10 hi fl	0.12^{*}	0.93	0.11	0.03^{***}	–	–

Table 8: Four-factor Bayesian alphas of subgroups based on fund flows (12 months)

This table presents the performance based on a Carhart (1997) four-factor model for the following pairs of portfolios and the resulting spread portfolio: decile portfolio 10 (winner) and 1 (loser), decile 1 funds with lower than median fund flows (1 lo fl) and with higher than median fund flows (1 hi fl), decile 10 funds with lower than median fund flows (10 lo fl) and with higher than median fund flows (10 hi fl). The first column reports the OLS estimate of a concatenated time series of decile portfolio returns following the methodology of Carhart (1997) (*concatenated* approach); column two reports the time series mean of the decile portfolio's Bayesian alphas computed as the cross-sectional mean of the individual alphas of all funds belonging to the respective decile in each time period (*portfolio* approach); columns three to six report the mean, median, 10 percent quantile and 90 percent quantile, respectively, of the panel of the monthly Bayesian alphas of all funds belonging to the respective decile portfolio (*panel* approach). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. For the concatenated time series (first column) we compute inferences using a conventional t-test on the regression coefficients of an OLS regression with White's heteroscedasticity-consistent standard errors. For the time series portfolio Bayesian alphas (second column) we apply a t-test on the time series of the portfolio alphas. For the means of the panel of Bayesian alphas (third column) we apply a conventional t-test to the individual fund alphas of each decile portfolio and a two-sample t-test to the spread portfolios. For the medians of the panel (fourth column) we apply a Wilcoxon signed rank test to the individual fund alphas of each decile portfolio and a Mann-Whitney U-test to the spread portfolios.

(a) Sorting based on returns

	concatenated	portfolio	panel			
	α^{OLS}	α^{B} mean	α^{B} mean	α^{B} median	α^{B} perc_{10}	α^{B} perc_{90}
10 (winner)	−0.11	0.23	0.25	0.15***	−4.38	4.56
1 (loser)	−0.08	−0.34	−0.37	−0.35***	−5.43	4.75
10 − 1	−0.02	0.56	0.62***	0.51***	1.05	−0.19
1 lo fl	−0.09	−0.27	−0.30	−0.32***	−5.15	4.68
1 hi fl	−0.07	−0.39*	−0.42*	−0.39***	−5.63	4.84
1 lo fl − 1 hi fl	−0.03	0.12	0.13**	0.07***	0.48	−0.16
10 lo fl	−0.10	0.25	0.27	0.16	−4.29	4.49
10 hi fl	−0.15	0.16	0.18	0.13	−4.52	4.57
10 lo fl − 10 hi fl	0.05	0.09	0.09	0.03***	0.22	−0.08

(b) Sorting based on Bayesian four-factor alphas

	concatenated	portfolio	panel			
	α^{OLS}	α^{B} mean	α^{B} mean	α^{B} median	α^{B} perc_{10}	α^{B} perc_{90}
10 (winner)	0.07	0.18	0.18	0.01***	−3.68	4.10
1 (loser)	−0.24**	−0.21**	−0.21**	−0.19***	−3.95	3.49
10 − 1	0.31*	0.39	0.39***	0.20***	0.27	0.61
1 lo fl	−0.21**	−0.15	−0.14	−0.15***	−3.92	3.71
1 hi fl	−0.27**	−0.25**	−0.26**	−0.23***	−3.93	3.25
1 lo fl − 1 hi fl	0.06	0.09	0.12***	0.08***	0.01	0.46
10 lo fl	0.13	0.22	0.21	0.02	−3.52	3.98
10 hi fl	−0.03	0.10	0.10	−0.02	−3.85	4.10
10 lo fl − 10 hi fl	0.15***	0.12	0.12**	0.04***	0.33	−0.11

Table 9: Returns of subgroups based on managerial turnover (12 months)

This table presents the raw returns (in excess of the rate on the risk-free asset) for the following pairs of portfolios and the resulting spread portfolio: decile portfolio 10 (winner) and 1 (loser), decile 1 funds with manager change (1 w mc) and without manager change (1 w/o mc), decile 10 funds without manager change (10 w/o mc) and with manager change (10 w mc). The first two columns report the mean and the standard deviation, respectively, of a concatenated time series of decile portfolio returns following the methodology of Carhart (1997) (*portfolio* approach); columns three to six report the mean, median, 10 percent quantile and 90 percent quantile, respectively, of the panel of the monthly returns of all funds that belong to the respective decile portfolio (*panel* approach). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. For differences in means we apply a two-sample t-test and for differences in medians we apply a Mann-Whitney U-test.

(a) Sorting based on returns

	portfolio		panel			
	mean	std	mean	median	perc_{10}	perc_{90}
10 (winner)	0.83	5.58	0.75	0.89	−6.28	7.34
1 (loser)	0.28	5.22	0.17	0.45	−7.21	7.25
10 − 1	0.55	5.19	0.57***	0.45***	–	–
1 w mc	0.36	5.33	0.28	0.61	−7.38	7.90
1 w/o mc	0.27	5.19	0.15	0.40	−7.16	7.08
1 w − 1 w/o	0.09*	0.63	0.14	0.20***	–	–
10 w/o mc	0.83	5.55	0.75	0.89	−6.19	7.27
10 w mc	0.88	5.75	0.73	0.91	−6.73	7.60
10 w/o − 10 w	−0.05	0.72	0.02	−0.02***	–	–

(b) Sorting based on Bayesian four-factor alphas

	portfolio		panel			
	mean	std	mean	median	perc_{10}	perc_{90}
10 (winner)	0.77	5.31	0.67	0.85	−6.14	7.07
1 (loser)	0.45	4.20	0.36	0.64	−6.08	6.54
10 − 1	0.32	3.19	0.30***	0.21***	–	–
1 w mc	0.52	4.32	0.49	0.77	−6.19	6.98
1 w/o mc	0.42	4.17	0.33	0.61	−6.06	6.43
1 w − 1 w/o	0.10***	0.53	0.15**	0.16***	–	–
10 w/o mc	0.79	5.25	0.69	0.86	−5.99	7.00
10 w mc	0.70	5.55	0.56	0.82	−6.76	7.38
10 w/o − 10 w	0.09*	0.65	0.13	0.04***	–	–

Table 10: Four-factor Bayesian alphas of subgroups based on managerial turnover (12 months)

This table presents the performance based on a Carhart (1997) four-factor model for the following pairs of portfolios and the resulting spread portfolio: decile portfolio 10 (winner) and 1 (loser), decile 1 funds with manager change (1 w mc) and without manager change (1 w/o mc), decile 10 funds without manager change (10 w/o mc) and with manager change (10 w mc). The first column reports the OLS estimate of a concatenated time series of decile portfolio returns following the methodology of Carhart (1997) (*concatenated* approach); column two reports the time series mean of the decile portfolio's Bayesian alphas computed as the cross-sectional mean of the individual alphas of all funds belonging to the respective decile in each time period (*portfolio* approach); columns three to six report the mean, median, 10 percent quantile and 90 percent quantile, respectively, of the panel of the monthly Bayesian alphas of all funds belonging to the respective decile portfolio (*panel* approach). ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. For the concatenated time series (first column) we compute inferences using a conventional t-test on the regression coefficients of an OLS regression with White's heteroscedasticity-consistent standard errors. For the time series portfolio Bayesian alphas (second column) we apply a t-test on the time series of the portfolio alphas. For the means of the panel of Bayesian alphas (third column) we apply a conventional t-test to the individual fund alphas of each decile portfolio and a two-sample t-test to the spread portfolios. For the medians of the panel (fourth column) we apply a Wilcoxon signed rank test to the individual fund alphas of each decile portfolio and a Mann-Whitney U-test to the spread portfolios.

(a) Sorting based on returns

	concatenated	portfolio	panel			
	α^{OLS}	α^{B} mean	α^{B} mean	α^{B} median	α^{B} perc_{10}	α^{B} perc_{90}
10 (winner)	−0.11	0.23	0.25	0.15***	−4.38	4.56
1 (loser)	−0.08	−0.34	−0.37	−0.35***	−5.43	4.75
10 − 1	−0.02	0.56	0.62***	0.51***	1.05	−0.19
1 w mc	−0.03	−0.26	−0.34	−0.34***	−5.29	4.95
1 w/o mc	−0.09	−0.35*	−0.38*	−0.36***	−5.46	4.70
1 w − 1 w/o	0.06	0.09*	0.05	0.02***	0.17	0.25
10 w/o mc	−0.11	0.22	0.25	0.15	−4.31	4.53
10 w mc	−0.09	0.24	0.23	0.16	−4.65	4.68
10 w/o − 10 w	−0.02	−0.01	0.03	−0.01***	0.34	−0.15

(b) Sorting based on Bayesian four-factor alphas

	concatenated	portfolio	panel			
	α^{OLS}	α^{B} mean	α^{B} mean	α^{B} median	α^{B} perc_{10}	α^{B} perc_{90}
10 (winner)	0.07	0.18	0.18	0.01***	−3.68	4.10
1 (loser)	−0.24**	−0.21**	−0.21**	−0.19***	−3.95	3.49
10 − 1	0.31*	0.39	0.39***	0.20***	0.27	0.61
1 w mc	−0.19	−0.12	−0.10	−0.17***	−3.77	3.69
1 w/o mc	−0.26**	−0.24**	−0.24**	−0.20***	−4.01	3.45
1 w − 1 w/o	0.08*	0.11***	0.14***	0.03***	0.25	0.24
10 w/o mc	0.10	0.20	0.21	0.03	−3.59	4.09
10 w mc	−0.02	0.09	0.04	−0.08	−4.10	4.19
10 w/o − 10 w	0.12**	0.11**	0.17**	0.12***	0.51	−0.09

Table 11: Overlap of fund flow and manager change subgroups

This table presents in panel (a) the share of decile 10 funds and in panel (b) the share of decile 1 funds in the low fund flow (lo fl) and high fund flow (hi fl) subgroup and in the manager change (w mc) and no manager change (w/o mc) subgroup, respectively, based on the total number of fund months on our sample. Ranking into deciles is based on Bayesian four-factor alphas during the previous year.

Share of funds in subgroups

	(a) decile 10 funds				(b) decile 1 funds		
	10 w mc	10 w/o mc	sum		1 w mc	1 w/o mc	sum
10 lo fl	10.07	39.79	49.86	1 lo fl	11.86	37.99	49.85
10 hi fl	10.03	40.10	50.14	1 hi fl	10.14	40.01	50.15
sum	20.11	79.89	100.00	sum	22.00	78.00	100.00

Table 12: Pooled regressions for change in fund performance

This table presents the results of a pooled panel regression for the change in annualized raw returns between the previous year and this year in panel (a) and for change in annualized Bayesian four-factor alphas between the previous year and this year in panel (b). The explanatory variables of model 1 are fund size (m USD), fees (percent), fund age and turnover at the end of the previous year, a dummy indicating whether the manager changed during the last year, relative fund flows for the current year and the previous year, a dummy indicating whether the fund belonged to decile 10 during the previous year, an interaction term between fund flows and the decile 10 dummy, an interaction term between a change in management and the decile 10 dummy, a dummy indicating whether the fund belonged to decile 1 during the previous year, an interaction term between fund flows and the decile 1 dummy and an interaction term between a change in management and the decile 1 dummy. Model 2 additionally contains a dummy indicating whether the fund is a small-cap or sector fund and an interaction term between fund flows and the investment style dummy. Model 3 additionally contains an interaction term between the manager change dummy and a dummy indicating whether the fund belongs to a large fund family. The last two rows present the number of observations and the adjusted R^2. Ranking into deciles is based on Bayesian four-factor alphas during the previous year.

Regression results

	(a) Annualized raw returns (in percent)						(b) Annualized Bayesian four factor alphas (in percent)					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	coeff.	p-val	coeff.	p-val	coeff.	p-val	coeff.	p-val	coeff.	p-val	coeff.	p-val
abs	0.62*	0.07	0.36	0.30	0.37	0.28	0.80**	0.01	0.53	0.10	0.55*	0.09
TNA	−0.10*	0.09	−0.09	0.11	−0.10*	0.09	−0.08	0.14	−0.07	0.18	−0.08	0.14
fees	−0.12	0.49	−0.05	0.80	−0.05	0.79	−0.16	0.35	−0.14	0.39	−0.15	0.38
age (·100)	−1.92*	0.05	−1.77*	0.07	−1.76*	0.08	−1.93**	0.03	−1.59*	0.08	−1.58*	0.08
turnover	0.39***	0.00	0.46***	0.00	0.45***	0.00	0.38***	0.00	0.41***	0.00	0.41***	0.00
mgr_ch	0.65**	0.04	0.67**	0.03	0.32	0.39	0.48*	0.10	0.48*	0.10	0.14	0.68
flows_t	0.88***	0.00	0.82***	0.00	0.82***	0.00	0.59***	0.00	0.52***	0.00	0.52***	0.00
flows_{t-1}	−1.72***	0.00	−1.19***	0.00	−1.19***	0.00	−2.37***	0.00	−1.77***	0.00	−1.77***	0.00
d10	−2.08***	0.00	−2.20***	0.00	−2.20***	0.00	−3.09***	0.00	−3.26***	0.00	−3.26***	0.00
flows_{t-1}· d10	−3.02***	0.00	−2.68***	0.00	−2.68***	0.00	−1.23***	0.00	−0.94***	0.00	−0.94***	0.00
mgr_ch· d10	−2.15**	0.03	−2.04**	0.03	−2.03**	0.04	−1.13	0.19	−0.98	0.25	−0.96	0.26
d1	3.41***	0.00	3.37***	0.00	3.38***	0.00	3.25***	0.00	3.18***	0.00	3.18***	0.00
flows_{t-1}· d1	−0.82*	0.06	−0.24	0.59	−0.23	0.60	0.08	0.84	0.83**	0.05	0.84**	0.04
mgr_ch· d1	0.52	0.60	0.43	0.67	0.45	0.65	0.51	0.58	0.47	0.61	0.48	0.59
style	–	–	0.24	0.38	0.22	0.42	–	–	0.62**	0.01	0.60**	0.02
flows_{t-1}· style	–	–	−1.78***	0.00	−1.78***	0.00	–	–	−1.89***	0.00	−1.89***	0.00
mgr_ch· lfam	–	–	–	–	0.93*	0.08	–	–	–	–	0.89*	0.06
Nobs	25,780	–	25,780	–	25,780	–	21,318	–	21,318	–	21,318	–
R^2	0.04	–	0.04	–	0.04	–	0.05	–	0.05	–	0.05	–