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Overconfidence among Professional Investors: Evidence from Mutual Fund Managers

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Abstract

We examine overconfidence among equity mutual fund managers. While overconfidence has been extensively documented among retail investors, evidence from professional investors is scarce. Consistent with theories of overconfidence, we find that fund managers trade more after good past performance. The higher trading activity after good performance is driven by individual portfolio performance, while the market performance has no significant impact. We rule out some alternative explanations for our results like increased trading as a response to tournament incentives, as a response to inflows, or as a rational reaction due to managerial learning about abilities.

JEL-Classification Codes: D83, G10, G12

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1 Introduction

In this paper, we examine whether professional investors behave rationally or whether they show signs of irrationality. Specifically, we examine whether fund managers become overconfident after good past performance.

There is ample evidence that retail investors are prone to behavioral biases. While there is little doubt that behavioral biases can be harmful from the individual investor's point of view, there is less agreement on the probably more important question of whether this has serious implications for asset prices. It is often implicitly assumed that mainly retail investors behave irrationally and that their behavior does not lead to systematic distortions in asset markets because the group of retail investors is small, it does not behave systematically, and any distortions would be arbitraged away fast. While these arguments have also been challenged,[1] it would obviously be more critical if professional investors (usually believed to behave more rationally) were also found not to be so rational after all. Analyzing the behavior of professional investors is particularly important because institutional investors as a group increasingly dominate and are likely to be marginal price setters in stock markets. According to Lewellen (2009), nearly 70% of all stocks in the US were held by institutional investors at the end of 2007. If we can provide additional evidence that professional investors are irrational, too, it would support behavioral approaches to asset pricing.[2]

In our examination of professional investors' rationality we focus on overconfidence for the following two reasons: first, overconfidence is one of the most widely documented and stable aspects of irrational behavior in the general population (see, e.g., Svenson, 1981). It has been widely documented to influence the behavior of retail investors (see Odean, 1999; Grinblatt and Keloharju, 2009). Second, and more importantly, it can lead to inefficient asset prices and several pricing anomalies.[3]

[1] See, e.g., Benos (1998), Shumway et al. (2010), Shleifer and Vishny (1997), Kumar (2009), and Barber et al. (2009).

[2] See, e.g., Barberis et al. (2001), Daniel et al. (2001), Grinblatt and Han (2005).

[3] Theoretical models show that overconfidence of market participants can lead to over- and underreaction on securities markets and eventually to positive (negative) price autocorrelation in the short (long) run as well as excess volatility and return predictability (see Daniel et al., 1998), to increased volatility (see Gervais and Odean, 2001), and speculative bubbles in asset markets (see Scheinkman and Xiong, 2003).

Overconfidence can be explained by biased self-attribution (see Bem, 1965), which leads individuals to attribute positive outcome to their own skills, while they attribute bad outcomes to chance (see Miller and Ross, 1975; Hastorf et al., 1970). Biased self-attribution leads investors to falsely attribute a good past performance of their investments to their own skill rather than to luck, while they tend to attribute a bad performance to chance. Consequently, they become more overconfident after a good past performance, but not less overconfident after a bad past performance (see Gervais and Odean, 2001).

Overconfident individuals tend to overestimate their abilities (see Frank, 1935) and the precision of their knowledge (see Fischhoff et al., 1977). In a financial context, this can lead investors to an overestimation of their own trading skills and of the precision of their private information regarding security values. In this case, investors weight their private information too heavily and believe it is more precise than it actually is. Jaffe and Winkler (1976) find that trading probability positively depends on information precision of investors. Consequently, overconfident investors subsequently trade too much based on their false beliefs about their trading skills and information precision (see Odean, 1999).[4] Overall, if professional investors are subject to an overconfidence bias, we should see a high trading activity after a good previous performance.

To analyze this hypothesis, we examine the trading activity of US equity mutual fund managers as reflected in their fund's turnover ratio. We find that fund managers with good past performance subsequently trade more. Specifically, for fund managers with a performance in the top quintile in the previous year, the fund's turnover ratio positively depends on past performance. Overall, the relationship between past performance and subsequent trading activity is non-linear. The best past performers as well as the worst past performers show high subsequent turnover rates. The latter result is consistent with the idea that bad performers change their strategy (see Ippolito, 1992; Khorana, 1996; Coval and Stafford, 2007). The first result supports our main hypothesis that good performance leads to overconfidence which eventually leads to a higher turnover ratio. Fund managers seem to ascribe a good past portfolio performance to their own skills.

While this result is a strong indication of fund managers' overconfidence, the observed pattern is also consistent with at least four alternative explanations: First, it is possible that fund managers trade more, because they change their fund's risk due to tournament incentives as, for example, in Brown et al. (1996). We find that risk changes lead to higher

[4]This effect might also explain the surprisingly high trading activity on financial markets in general (see DeBondt and Thaler, 1995).

trading activity, but they do not drive our main result. Second, high levels of trading activity might be a response to new money inflows following top performance. According to Pollet and Wilson (2008), funds usually respond to new flows by scaling up their existing investments. The definition of the turnover ratio we use makes sure that our results are not driven by trading activity due to investments of new money flows and by scaling up of holdings.[5] However, if they face limits to the scalability of their portfolios due to a large portfolio size, they might have to change their overall strategy (e.g. from illiquid to more liquid stocks) and subsequently trade more. Our results also hold for funds that should not face any limits to scalability. Thus, strategy changes in response to high inflows after good performance are also not a likely explanation for our findings. Third, it is possible that increased trading is a rational decision of fund managers that learn about their abilities. This would be the case if fund managers do not suffer from biased self-attribution. Then, they would rationally update their believes about the precision of their private information (and eventually their skills to produce and use such information) in a Bayesian learning context. In that case, past performance would be a signal the manager can use to learn about the precision of her information. If past performance is superior and the manager thus learns that the information she produces is more precise, it would be rational for her to trade more based on this information. This should eventually result in a better performance of the fund. We can also reject this alternative explanation. In contrast to this explanation, we find that fund managers with a top past performance and high levels of trading activity do significantly worse than past top performers with a lower turnover ratio. This shows that the higher trading activity is not due to the implementation of profitable trading ideas but just causes higher trading costs. This finding is also consistent with similar evidence provided in Odean (1999) for retail investors. Finally, and similar to the third explanation, fund managers might face less restriction on their trading activity after a good performance. However, if managers were rational they would only increase turnover ratio in response to those alleviated restrictions if this allows them to implement an optimal strategy that they could not implement before. However, then we should see a better subsequent performance. Our results of worse performance after increased turnover show that this is not the case. Thus, even if some funds just raise turnover due to less restrictions this still would be driven by overconfidence.

[5] For a detailed discussion of the influence of flows on the turnover ratio, see Section 2.1.

In additional analysis, we also examine the impact of market performance versus individual performance on the subsequent turnover ratio. Gervais and Odean (2001) suggest that overconfidence could also increase if investors experience high returns just because the market performed well.[6] We find no strong evidence for a positive impact of market returns on fund managers' overconfidence. Fund managers do not seem to falsely ascribe a good past performance of the market to their own abilities.

Finally, we also examine the impact of a fund's management structure on trading activity. Baer et al. (2010) show significant differences in investment styles between fund manager teams and single managers. However, our results provide no evidence for differences in overconfidence between team- and single-managed funds.

Our paper contributes to two main strands of the literature. First, our findings contribute to the large empirical literature on behavioral biases among investors. While there are many papers documenting various biases retail investors are prone to,[7] there is less and generally inconclusive evidence on biased behavior of professional investors. Varying degrees of disposition bias are documented among mutual fund managers (see Jin and Scherbina, 2010). Kaustia et al. (2008) show experimentally that financial market professionals are prone to the anchoring effect, but not as strongly as a sample of university students. Comparing the behavior of students and professional traders from the CBOT in an experimental setting, Haigh and List (2010) find that professional traders show a greater extent of myopic loss aversion than students, while Alevy et al. (2007) in another experiment find that professionals are less loss averse. Coval and Shumway (2005) also provide evidence that CBOT traders are loss averse. Only a few studies examine overconfidence among professional investors.[8] Ekholm and Pasternack (2008) find that overconfidence decreases with investor size. O'Connell and Teo (2009) use data on the trading behavior of institutional currency traders and find that they increase risk-taking following gains. They can show that this can also be explained by overconfidence. Glaser et al. (2010) report

[6] Evidence for this effect is documented in Glaser and Weber (2009).

[7] For an overview, see Barberis and Thaler (2003). Closely related to the approach chosen in our paper is Nicolosi et al. (2009). They also examine the impact of past success on trading activity and find a positive impact among retail investors. However, they interpret their findings as evidence for investor's learning about their abilities.

[8] In concurrent independent work, Choi and Lou (2010) also examine overconfidence among fund managers. Their results are broadly consistent with ours. They also find evidence for fund managers becoming more overconfident due to self-attribution bias. Our paper differs from their work in several aspects: first, they do not examine the role of market returns versus individual portfolio returns for fund manager's overconfidence. Second, unlike their work, we also examine differences between single- and team-managed funds. Finally, we focus on the fund's turnover ratio as a proxy for overconfidence, while they focus on portfolio holdings data and use a fund's active share (i.e., the fraction to which the fund's holdings deviate from the benchmark) as their main proxy for overconfidence.

results from experimental studies that suggest that German investment professionals are more overconfident than students. Consistent with these results, the experimental results in Griffin and Tversky (1992) suggest that experts may be more overconfident than inexperienced participants when predictability is low, as is the case in securities markets. In the context of corporations, Malmendier and Tate (2005) provide evidence for behavioral biases and particularly overconfidence among top managers.[9]

Second, our paper also relates to the literature on the determinants and consequences of mutual fund manager behavior. Pollet and Wilson (2008) and Coval and Stafford (2007) examine how fund managers react if they face inflows or outflows. The first paper shows that fund managers usually respond to asset growth by simply scaling up their existing investments. Coval and Stafford (2007) analyze flow driven transactions of funds. They focus on the consequences on asset prices if mutual funds quickly have to sell their holdings after poor performance.[10] Poor performing funds are also in the focus of Khorana (1996). He documents higher portfolio turnover rates in a sample of badly performing funds and conjectures that this is due to managers trying to get rid of their poorly performing stocks. A similar argument is suggested in Ippolito (1992). Brown et al. (1996) show how the tournament like nature of competition in the mutual fund industry can affect a manager's risk taking decisions.[11] We complement this stream of the literature by showing that past performance is an important determinant of fund manager trading behavior, too.

The remainder of this paper is organized as follows. In Section 2, we introduce our methodology and data. Section 3 contains the empirical analysis and our results and Section 4 concludes.

2 Methodology

2.1 Turnover Ratio as a Proxy for Overconfidence

Trading activity is the most widely used proxy for investor overconfidence (see Barber and Odean, 2000). Odean (1998) and Benos (1998) show theoretically that overconfidence leads to an increase in trading activity. The mechanism driving this effect is that overconfident

[9] Similar evidence is provided in Malmendier and Tate (2008, 2009), Ben-David et al. (2007), and Billett and Qian (2008).

[10] Other papers that examine the impact of flow-induced trading of mutual funds on capital markets include Koch et al. (2010) and Antón and Polk (2010).

[11] Tournament behavior of fund managers is also examined in, e.g., Chevalier and Ellison (1997), Elton et al. (2003), and Kempf et al. (2009).

investors overestimate the precision of their private information and eventually put too much weight on this information. Additionally, if managers overestimate the precision of their private information, they might also invest more in producing such information. This, in turn, leads to even more information whose precision is overestimated. Overall, this leads managers to trade too heavily based on their existing or newly produced private information.[12]

While trading activity seems to be a good proxy for overconfidence among retail investors, the same does not have to be true for mutual fund managers. The reason for this is that mutual fund managers often have to trade because of inflows or outflows. Obviously, only voluntary trading can be a reasonable proxy for overconfidence. Using total trading activity is particularly problematic in our context because there is ample evidence that past performance has a strong impact on fund flows (see, e.g., Sirri and Tufano, 1998) and we conjecture a positive impact of past performance on overconfidence, too. Consequently, the conjectured increase in trading activity after good performance might be driven by higher inflows and the need to invest this new money. Such trading activities could not be ascribed to overconfidence.

Fortunately, the definition of the turnover ratio as reported in the CRSP database we use corrects for the direct impact of flow-induced trading. It is defined as:

$$TR = \frac{\min(\textit{aggregated sales or aggregated purchases of securities})}{\textit{average 12-month Total Net Assets of the fund}} \tag{1}$$

If a fund faces high net inflows (outflows), this is not going to heavily affect the fund's turnover ratio, because purchases would exceed (fall below) sales. Consider the following simplified example: a fund's portfolio has an initial value of \$100 million. The fund's manager sells securities with a value of \$40 million over a period of 12 months and reinvests the money to purchase new securities. Additionally, assume that she receives a net inflow of \$30 million at the middle of the year, that is also used to purchase new securities. Then, the aggregated purchases equal \$70 million, the portfolio has a new value of \$130 million, and the 12-month average portfolio value is \$115 million.[13] In this case the turnover

[12] Another possibility is that mutual fund managers follow a buy-and-hold strategy that represents a particular investment style (that is not captured by the performance measures we will use) and that this style has performed very well in the past year. Thus, they become convinced that this style is great and shift to a buy-and-hold strategy that puts even more weight on that style. This shift would also lead to an increase in the turnover ratio.

[13] For simplicity, we assume that the rate of return earned on the portfolio is zero.

ratio equals $TR = \frac{\min(\$70 \text{ million}, \$40 \text{ million})}{\$115 \text{ million}} = 34.8\%$. Consequently, the net inflows of \$30 million do not change the turnover ratio's numerator. The numerator only captures the level of transactions at which there were purchases and sales of equal amount (\$40 million), indicating a completed turnover rather than just a buy or sell due to flows:[14] the definition of the turnover ratio is corrected for the direct impact of investments and divestments due to positive or negative net flows. However, there is still an indirect effect of flows that could impact the turnover ratio: flows do not change the nominator, but might change the average TNA of the fund in the denominator. Thus, high inflows can lead to an increase in average TNA and eventually to a lower turnover ratio.[15] Besides this indirect effect, the turnover ratio clearly reflects management decisions to change portfolio structures rather than just flow-induced trading. Therefore, a fund's turnover can be used as a reasonable proxy to capture the voluntary trading activity and eventually overconfidence of a fund manager.

2.2 Data

Our primary data source is the CRSP Survivor Bias Free Mutual Fund Database.[16] It covers virtually all U.S. open-end mutual funds and provides information on fund returns, fund management structures, total net assets, investment objectives, fund managers' identity, and other fund characteristics.

We use the Lipper objective codes to define the market segment in which a fund operates. We focus on actively managed, domestic equity funds and exclude bond, money market, index, and balanced funds, because they are not directly comparable to pure equity funds. Some of the fund segments defined by Lipper are very small. Thus, we aggregate the smaller Lipper segments into broader categories. Specifically, we assign the individual Lipper codes to the following six broad categories: Aggressive Growth, Growth and Income, Income, Growth, Sector Funds, and Utility Funds.[17] As the Lipper objective codes are available from 1999 on and there are some inconsistencies in the turnover ratio due to missing information on the fund's fiscal year-end before 1999, our sample starts in this year and it ends in 2008.

[14] For a more detailed discussion on the derivation of the turnover ratio and alternative ways to capture the trading activity of a mutual fund, see Brown and Vickers (1963).

[15] In our later analysis, we will thus explicitly control for the impact of inflows.

[16] Source: CRSP, Center for Research in Security Prices. Graduate School of Business, The University of Chicago. Used with permission. All rights reserved.

[17] A table specifying the assignment of the particular Lipper codes to the segments is presented in the Appendix.

Many funds offer multiple share classes which are listed as separate entries in the CRSP database. They usually only differ with respect to their fee structure or minimum purchase requirements. However, the different share classes of a fund are always backed by exactly the same portfolio of assets and have the same portfolio manager. Thus, to avoid multiple counting, we aggregate all share classes of the same fund.[18]

We also classify each fund as being either team- or single-managed. This allows us to later examine the impact of the management structure of a fund on the relationship between past performance and overconfidence (Section 3.3). CRSP typically either reports the name of one manager, the names of several managers, or it indicates that a fund is team-managed without giving the names of the managers. In the first case, the fund is defined as being single-managed, in the latter two cases it is defined as being team-managed.

The main variable we analyze is a fund's turnover ratio. To make sure our results are not driven by the impact of some extreme turnover observations, we restrict our dataset by excluding outliers. We exclude the 1% of funds with the highest turnover ratio.[19] In doing so, we exclude all funds with a turnover ratio greater than 724%. Furthermore we exclude all fund year observations for which not all information used in our regressions is available or for which less than 12 months of return data is available.

Our final sample consists of 17,486 fund year observations. Summary statistics of our resulting sample are presented in Table I.

– Please insert TABLE I approximately here –

The number of funds in our sample increases from 1,528 in 1999 to 1,669 in 2008. The mean turnover ratio of all funds in our sample is 90.55%. Its mean value per year varies between 82.89% in 2005 and 105.09% in 2001. The average fund size is more than 900 million USD. The average fund is smallest in 2002 at about 600 million USD and grows to more than 1.1 billion USD in 2007. The mean fund age is relatively constant at about 12 years.

[18]Through 2002 we identify the share classes of a fund by matching fund names and characteristics such as fund management structures, turnover, and fund holdings in asset classes. From 2003 on, the CRSP database reports a unique portfolio number for each fund, which is used to aggregate share classes from 2003 through 2008.

[19]Alternatively, we also winsorize these extreme observations by setting their turnover ratio equal to the 99%-fractile of the turnover ratio of all funds, i.e., to 724%. Results (not reported) are not affected by this.

3 Results

We start our empirical investigation by analyzing the relationship between a fund's current turnover ratio and its past individual performance (Section 3.1). This will allow us to get an idea of the impact of a fund manager's past success on that manager's overconfidence. In Section 3.2 we examine whether there is an additional impact of the market return on an individual fund manager's overconfidence. In Section 3.3 we investigate whether the management structure of a fund (being either single- or team-managed) has any impact on the performance-overconfidence relationship. Finally, in Section 3.4 we analyze whether our results could also be driven by some alternative explanation, like strategy changes or rational learning about managerial abilities after a good performance, rather than by overconfidence.

3.1 Overconfidence and Past Performance

We examine whether fund managers get overconfident after good past performance by relating a fund i's turnover ratio in year t, $TR_{i,t}$, to its performance in year $t-1$, $Perf_{i,t-1}$, using the following base model.

$$TR_{i,t} \quad = \quad f(Perf_{i,t-1}, Controls) \tag{2}$$

where $Controls$ is a vector of further control variables described below.
Our conjecture is that an outstanding past performance of a fund will lead managers that are subject to a self-attribution bias to believe they are better than they actually are, i.e., to become overconfident. This eventually leads to a high turnover ratio of the fund.

Instead of relating the past level of performance to the level of the turnover ratio, one could also examine the relationship between changes in performance and subsequent changes in the turnover ratio. However, this alternative model would not allow us to test our conjecture of a positive and non-linear impact of a good past performance on overconfidence for many of the relevant cases as illustrated by the following examples: if a manager's performance increases from a bad performance to average performance, we would not expect this to have a strong effect on overconfidence, while an improvement from a performance slightly above average to an excellent performance should have a much stronger effect on overconfidence. Similarly, if a manager is able to repeat an excellent past performance, it is likely that her overconfidence and eventually her turnover ratio would continue to rise. Both cases could not be captured by looking at differences in performance rather than levels of performance.[20]

Thus, we relate turnover ratio in one year to performance in the previous year. It is possible that fund managers also react to past performance on a more short-term or long-term basis, respectively. However, the calendar year seems a natural choice because yearly performance measures are very salient and important figures for fund managers (see Brown et al., 1996): their compensation typically is tied to yearly performance and a lot of highly visible fund rankings are published at the end of the year. Thus, it is very likely that their self-assessment will also be based on such yearly figures to a large degree.

To capture a fund's past performance, $Perf_{i,t-1}$, we calculate the rank of its yearly performance as compared to the other funds.[21] Ranks are equally distributed between zero and one and the best (worst) fund gets assigned the rank number one (zero). We use ranks rather than absolute performance because fund managers are mainly concerned about their relative position compared to the other equity fund managers rather than about absolute differences.[22]

We base rankings upon three different performance measures: (1) raw returns, (2) Jensen (1968) one-factor alphas, and (3) Carhart (1997) four-factor alphas.[23]

When modeling the impact of past performance on the turnover ratio, we have to take into account potential non-linearities. A non-linear relationship might arise for the following two reasons: first, we mainly expect the very best fund managers to become overconfident, while neither a fund manager with poor past performance nor a fund manager with average past performance will be very likely to become overconfident. Thus,

[20]There is one potential reason for using differences of the turnover ratio rather than the level of the turnover ratio. Using differences is one way to preclude the possibility that our results are driven by a persistent hidden fund-level variable that positively impacts the performance and the turnover ratio of some funds at the same time. If we just look at levels and if such an influence is stable over time, we might find a mechanical positive relationship between past performance and the turnover ratio, too. This case seems to be highly unlikely, as the literature provides ample evidence for a negative relationship between performance and trading activity (see, e.g., Carhart, 1997). Nevertheless, we will also use a fund fixed effects approach in our following analysis, which would also preclude such a potential static relationship by controlling for the average turnover ratio of each fund.

[21]Results (not reported) are similar, if we calculate past performance based on a fund's ranking within its market segment.

[22]In robustness examinations we also use absolute performance measures instead of ranks. Results are very similar. In Section 3.2 we also include the absolute market return as additional independent variable. This will allow us to test our assumption that managers' behavior is mainly driven by their own individual performance rather than by broad market movements.

[23]The latter two performance measures are determined based on a yearly estimation of the respective one- and four-factor model. Alternatively, we also estimate Fama and French (1993) three-factor alphas. Results (not reported) are very similar to those for the Carhart (1997) four-factor alpha.

we expect a positive relationship between past performance and turnover due to increased overconfidence mainly among the funds with a very good past performance. Second, a manager with poor past performance is likely to change her strategy because the old strategy proved to not work very well (see Khorana, 1996; Ippolito, 1992). Consequently, the manager has to do some trading in order to adjust the fund's portfolio to a new strategy. This would also eventually lead to an increase in the turnover ratio. Thus, we expect a negative relationship between past performance and the turnover ratio for poorly performing funds. We expect no strong relationship between past performance and turnover ratio for funds with mediocre past performance. Thus, overall we expect a U-shaped relationship between past performance and turnover ratio.

We use two alternative modeling approaches to capture this potential non-linearity: (1) we apply a piecewise linear regression approach; (2) we estimate a quadratic relationship between past performance and turnover by adding past performance as linear term and as quadratic term.

Applying a piecewise linear regression approach allows us to estimate slope coefficients for the impact of past performance on the turnover ratio for different sections of past performance separately. We estimate separate slope coefficients for the bottom performance quintile, the three middle quintiles, and the top quintile:

$$\begin{aligned} TR_{i,t} &= \alpha + \beta_1^L LOW_{i,t-1} + \beta_1^M MID_{i,t-1} + \beta_1^T TOP_{i,t-1} \\ &\quad + \beta_2 Flow_{i,t} + \beta_3 lnTNA_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where

$$\begin{aligned} LOW_{i,t-1} &= \min(Perf_{i,t-1}, 0.2) \\ MID_{i,t-1} &= \min(Perf_{i,t-1} - LOW_{i,t-1}, 0.6) \\ TOP_{i,t-1} &= Perf_{i,t-1} - LOW_{i,t-1} - MID_{i,t-1}. \end{aligned}$$

We expect a negative slope coefficient for the bottom quintile of past performance ($\beta_1^L < 0$) and a positive slope coefficient for the top quintile of past performance ($\beta_1^T > 0$). We have no specific hypothesis regarding the sign of the coefficient for the middle quintiles

(β_1^M). However, we expect the slope coefficient to be smaller in terms of absolute value as compared to the other two slope coefficients.

We also include several control variables that might impact a fund's turnover ratio. First, we include contemporaneous inflows, $Flow_{i,t}$. To take into account the time structure of the flows as exactly as possible, we start by calculating monthly flow figures based on the following method suggested by Sirri and Tufano (1998):

$$Flow_{i,m} = \frac{TNA_{i,m} - TNA_{i,m-1}(1 + r_{i,m})}{TNA_{i,m-1}},$$

where $TNA_{i,m}$ is fund i's total net asset value at the end of month m, and $r_{i,m}$ is the fund's return earned over this month. Then, monthly flows are aggregated into yearly flows: $Flow_{i,t} = \prod_{m=1}^{12}(1 + Flow_{i,m}) - 1$.[24]

Although the definition of the turnover ratio is already adjusted for the direct impact of inflows (see Section 2.1), there might still be an indirect impact that we can capture by including flows as control variable: Pollet and Wilson (2008) find that fund managers usually use new money inflows to scale up their existing investments.[25] This leads to an increase of the fund's TNA and, ceteris paribus, to a decrease of the turnover ratio (see Section 2.1). Thus, we expect a negative coefficient for the impact of $Flow_{i,t}$.

Further, we add the natural logarithm of the fund's size at the end of the previous year, $lnTNA_{i,t-1}$, as larger funds can be expected to turn over a relatively smaller proportion of their overall portfolio (see Brown and Vickers, 1963; Jin and Kogan, 2008). Fund size is measured as the logarithm of the fund's total net assets under management in million USD. We use the logarithm of fund size, as we expect the marginal impact of one additional unit on turnover to be smaller, if the level of fund size is already high, than if it is small.

If we apply the quadratic specification, our model reads:

$$\begin{aligned} TR_{i,t} &= \alpha + \beta_{1a}Perf_{i,t-1} + \beta_{1b}(Perf_{i,t-1})^2 \\ &\quad + \beta_2 Flow_{i,t} + \beta_3 lnTNA_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{4}$$

[24] In unreported tests, when calculating $Flow_{i,t}$ we assume that all flows occur at the beginning, the middle, or the end of the year, respectively, or alternatively add four quarterly flow variables instead of $Flow_{i,t}$. Results remain very similar.

[25] Funds facing limits to the scalability of their existing portfolios might change their whole portfolio structure instead, which would eventually lead to more trading. As money inflows are usually positively correlated with past top performance (see Sirri and Tufano, 1998), such limits to scalability might also be a possible explanation for high turnover ratios following top performance. We explicitly examine this possibility in more detail in Section 3.4.1.

For this model we expect a negative estimate for the impact of the linear term ($\beta_{1a} < 0$) and a positive estimate for the impact of the quadratic term ($\beta_{1b} > 0$).

We estimate Models (3) and (4) using three different regression methods. First, we apply a pooled regression approach (OLS) with time and segment fixed effects. Including time and segment fixed effects controls for the average turnover ratio of all funds in a specific year and segment, respectively. To correctly account for the dependence of observations in our panel data set, we cluster standard errors by fund in this and the following two approaches.[26]

Second, we estimate a random effects (RE) model by feasible generalized least squares. This is an alternative approach to correct standard errors for serial correlation due to unobserved fund heterogeneity. If the unobserved fund heterogeneity is uncorrelated with each explanatory variable in all time periods, then estimating an ordinary-least-squares (OLS) model would generate consistent but inefficient estimates of the parameters. In contrast, using random effects results in consistent and efficient estimates.

Third, we add fund fixed effects (FE) using a standard within estimator to control for omitted or unobservable fund characteristics that differ between funds but are constant over time. Although we already control for fund characteristics that might impact a fund's turnover ratio, there could be other fund specific but unobservable characteristics, like a fund's investment philosophy. By subtracting the fund-specific mean from the observed values of each variable, the fixed effects approach allows us to take the impact of such characteristics into account by controlling for the average level of trading activity of a given fund. From the coefficients of this approach we can infer how a manager changes her turnover ratio as compared to her average turnover ratio.[27] Results are presented in Table II.

– Please insert TABLE II approximately here –

Estimation results for Model (3) are presented in Panel A. Our main focus is on the coefficient for the impact of past past performance on the turnover ratio in the top performance quintile (β_1^T). Here, we find a significant positive relationship between a fund's past

[26]See Petersen (2009) for a further discussion on this issue. In our setup, there is no economic reason to include the lagged value of the dependent variable as explanatory variable. As panel estimations with lagged dependent variables are not trivial, we thus choose to use clustered standard errors to remove potential serial correlation rather than to include a fund's lagged turnover ratio.

[27]As a fourth, alternative, approach, we also ran Fama and MacBeth (1973) regressions, by first estimating Models (3) and (4) separately for each year. The coefficients and significance levels are then determined based on the time series of the yearly estimates. Results (not reported) are very similar.

performance and its subsequent turnover ratio. This result holds irrespective of whether we capture past performance by raw returns (Columns 1 to 3), one-factor alphas (Columns 4 to 6), or four-factor alphas (Columns 7 to 9). Coefficients are typically significant at the 1%-level. Only in the fund fixed effects specification the coefficient is only significant at the 5%-level if we base ranks on raw returns or Jensen's alphas, respectively. Nevertheless, even in this case the effect we find is still economically significant: holding the other variables constant, there is a difference in the turnover ratio between a top performing fund (rank 1) and a fund at the bottom of the top quintile (rank 0.8) of about 6 percentage points, if performance ranks are based on raw returns. The economic magnitudes are even substantially larger if we use the other estimation approaches and if we base performance ranks on the other performance measures, respectively. Our results are consistent with our conjecture that fund managers become overconfident after a good past performance, as reflected in the subsequent high turnover ratio of their fund.[28]

In contrast, we find significantly negative coefficients for the impact of past performance on the turnover ratio for the bottom quintile of past performance. This result confirms our expectation of a non-linear relationship. Consistent with the findings in Khorana (1996), our results suggest that funds that experience a relatively bad performance in the previous year will change their (unsuccessful) previous strategy.

The coefficient for the three middle quintiles of past performance is also negative in all specifications. However, only some of the coefficients are statistically significant and their magnitude is always considerably smaller in absolute terms than those estimated for the top and bottom quintile. The hypothesis that the absolute value of the coefficient for the middle quintiles is not smaller than those for the extreme quintiles can be rejected at the 1%-level for most coefficient combinations (and at the 5%-level for all others). Overall, these estimates show a clear U-shaped relationship between a fund's past performance and its turnover ratio.

The results for the quadratic specification of Model (4) are presented in Panel B of Table II. They confirm our findings from above. We find negative coefficients for the linear impact of last year's performance, $Perf_{i,t-1}$, on the turnover ratio and positive coefficients for the impact of squared past performance, $(Perf_{i,t-1})^2$. Both coefficients are significantly different from zero at the 1%-level. Thus, the relationship between a fund's

[28]Some alternative explanations for our results based on strategy changes or rational Bayesian learning are analyzed in Section 3.4.

past performance and its subsequent turnover ratio exhibits a shape similar to the one found in the piecewise linear specification.

A comparison of the predicted turnover ratio of these two approaches from the fund fixed effects specification is presented in Figure 1.

– Please insert FIGURE 1 approximately here –

It clearly shows the U-shaped relationship between a fund's past performance and its turnover ratio. The estimated relationships using the piecewise linear regression approach and the quadratic approach are very similar.

Regarding the control variables, we find a negative impact of contemporaneous flows, $Flow_{i,t}$, on the fund's turnover ratio. This is consistent with the aforementioned findings of Pollet and Wilson (2008): funds usually scale up their investments and therefore indirectly impact the turnover ratio by changing the average TNA of the fund in the denominator. Furthermore, fund size has the expected negative impact on the fund's turnover ratio. This result confirms earlier evidence presented in Jin and Kogan (2008).

3.2 Impact of Market Returns

In our above analysis we use ranks to capture a fund's past performance. In doing so, we assume that fund managers are mainly concerned about their relative position as compared to the other equity fund managers. However, some authors argue that not only individual relative performance but also overall market performance can be an important factor driving overconfidence.[29] Deaves et al. (2010) argue that good past market returns push the entire market towards greater overconfidence. Similarly, Statman et al. (2006) find strong evidence for a higher overall trading volume in the stock market after good market returns. They attribute this effect to investors' becoming overconfident. However, this effect is stronger among stocks that are mainly held by retail investors. Consistent with this, Nicolosi et al. (2009) and Glaser and Weber (2009) find that retail investors increase trading activity not only after a good individual portfolio performance but also after high market returns.

It is possible that fund managers are subject to a similar effect: an increase in market return goes along with an increase in the average fund's portfolio return. Fund managers

[29] It is also possible, that a manager who manages more than one fund becomes overconfident with respect to all funds she manages after good past performance of one of these funds. Additional analyses (not reported) reveal that no such spillover effects can be observed among fund managers.

might then falsely attribute high fund returns to their own abilities even if they are just a consequence of high market returns. In that case, we would expect them to raise their fund's trading volume after good past market returns, too.

To examine whether fund managers are influenced by market returns, we now examine whether the rate of return of the market they invest in has an additional effect on a fund's turnover ratio. Thus, we add the lagged return of the market segment the fund belongs to as an additional explanatory variable in Model (3):[30]

$$\begin{aligned} TR_{i,t} = {} & \alpha + \beta_1^L LOW_{i,t-1} + \beta_1^M MID_{i,t-1} + \beta_1^T TOP_{i,t-1} + \beta_2 Market_{i,t-1} \\ & + \beta_3 Flow_{i,t} + \beta_4 lnTNA_{i,t-1} + \epsilon_{i,t}. \end{aligned} \tag{5}$$

As there are no appropriate benchmarks readily available for all the different market segments funds belong to, we define $Market_{i,t-1}$ as the value-weighted and equal-weighted, respectively, average of the returns of all funds belonging to the same segment as fund i in year $t-1$. The other variables are defined as above. Estimation results for Model (5) are presented in Table III.

– Please insert TABLE III approximately here –

There is no significant influence of the value weighted past returns of a fund's market segment on the fund's subsequent turnover ratio (Columns 1 to 3). We find similar evidence, if we investigate the impact of equal weighted past returns of the fund's market segment (Columns 4 to 6). Again, coefficients are positive but typically insignificant.[31]

Our result differs from evidence from retail investors presented in Nicolosi et al. (2009) and Glaser and Weber (2009). They find a positive and highly significant relation between past market returns and trading volume. We find no support for such an effect among fund managers. Fund managers do not seem to attribute market gains to their own abilities. Consequently, they do not raise their subsequent trading volume.

Our main result of a positive impact of the past relative performance of a good performing fund on its turnover ratio remains unaffected. This shows that - although managers are

[30] Since piecewise linear regressions allow us to more easily analyze the influence of past performance on subsequent trading activity separately for different performance quintiles, we concentrate on this approach in the following analysis. For the sake of brevity, we only report results based on four-factor alphas as this approach delivers the highest R^2 in Table II.

[31] The only exception is found for the impact of equal-weighted market returns in the OLS approach (Column 4).

able to distinguish between high portfolio returns that are due to market returns and high portfolio returns that are due their individual decisions - they still attribute the individual component of their performance to skill rather than luck.

3.3 Management Structure

In recent years the number of funds managed by teams has grown rapidly (see Baer et al., 2010). In this section, we examine whether there are differences between team-managed and single-managed funds with respect to their reaction to past performance. There are two effects that might play an important role here and that predict opposite outcomes: (1) possibly, teams act more rationally than individuals because they are able to correct each other's errors. The results from several experimental studies suggest that teams are indeed more rational than individuals.[32] If fund management teams act more rationally than individual managers, they should be less at risk of becoming overconfident after a good past performance. Additionally, they should be more willing to change an unsuccessful strategy after bad past performance. (2) At the same time, teams are also often subject to groupthink (see Janis, 1972). Groupthink manifests itself in teams that become more and more self-assuring over time and are no longer open to outside criticism. If fund management teams are subject to groupthink, this might lead to reinforced self-attribution and eventually even stronger overconfidence than among single managers. Furthermore, groupthink would lead teams to be less willing to change their strategy in response to bad past performance.

To examine possible differences in the reaction to past success (or failure) between single managers and teams, we interact the performance quintiles with a team dummy. Additionally, we also include a team dummy without any interaction to capture possible differences in the level of the turnover ratio between team- and single-managed funds. Our regression model then reads:

[32] See Kocher and Sutter (2005) and Cooper and Kagel (2005).

$$
\begin{aligned}
TR_{i,t} \quad = \quad & \alpha + \beta_1^L LOW_{i,t-1} + \beta_1^M MID_{i,t-1} + \beta_1^T TOP_{i,t-1} \\
& + \beta_2 TeamDummy_{i,t} \\
& + \beta_3^L TeamDummy_{i,t} \cdot LOW_{i,t-1} + \beta_3^M TeamDummy_{i,t} \cdot MID_{i,t-1} \\
& + \beta_3^T TeamDummy_{i,t} \cdot TOP_{i,t-1} \\
& + \beta_4 Flow_{i,t} + \beta_5 lnTNA_{i,t-1} + \epsilon_{i,t}
\end{aligned} \qquad (6)
$$

In this equation, $TeamDummy_{i,t}$ is a binary variable that takes on the value one, if fund i is managed by a team in year $t-1$ and t, and zero otherwise.[33] Results are presented in Table IV.

– Please insert TABLE IV approximately here –

The impact of the team dummy itself is negative but insignificant in all specifications. Furthermore, the impact of past performance on the turnover ratio interacted with the team dummy is negative for the bottom as well as the top quintile of past performance in all cases, except of one positive estimate for the bottom quintile in the OLS approach. Negative interactions coefficients for the bottom quintile are consistent with the view that teams are more willing to change their strategy after a bad past performance. At the same time negative interaction coefficients for the top quintile would indicate that they are less likely to increase their trading activity after good past performance, i.e., to be less likely to become overconfident. However, all of the interaction terms are insignificant at conventional levels. Overall, we find no strong differences with respect to the impact of past performance on the turnover ratio between team- and single-managed funds.

3.4 Alternative Explanations

So far, we have shown that a fund's turnover ratio is significantly higher following good past performance. This increase is consistent with overconfidence models that predict higher trading volume due to the self-attribution bias following an investor's past success. In the following, we will explore whether our results are also consistent with alternative explanations other than overconfidence. Specifically, we investigate whether our results might be

[33]In this examination, we drop observations for which the management structure changes from team to single management, or vice versa, between year $t-1$ and year t.

driven by strategy changes due to tournament incentives or inflows (3.4.1), whether they might be due to a rational response of fund managers learning about their true abilities (3.4.2) or due to a rational response of a fund manager facing less constraints on trading activity after a good performance (3.4.3).

3.4.1 Strategy Change

It is possible that a higher turnover ratio after a good past performance is the consequence of a manager's change of the fund's strategy. Such a strategy change of successful managers might be due to risk-changes as a response to tournament incentives (see Brown et al., 1996) or a reaction to new money inflows which might require a new strategy, e.g. because the fund is now too large to continue with the old strategy.

In the first case, according to the tournament theory of Brown et al. (1996), managers who have performed well in the past try to maintain their top position and consequently reduce their risk in order to "lock-in" their current performance rank.[34] However, there are also theoretical and empirical papers that show that fund managers might actually increase risk in response to good past performance under some circumstances (see Taylor, 2003; Basak and Makarov, 2010; Kempf et al., 2009). Irrespective of the direction of their risk change, funds with past top performance would show a higher turnover ratio if they have to buy and sell stocks in order to adjust risk.

To capture the impact of risk changes on turnover, we add the absolute change in volatility as explaining variable to our regression. We use the absolute value of the change to make sure positive and negative changes do not cancel out. Our model then reads:

$$\begin{aligned} TR_{i,t} = {} & \alpha + \beta_1^L LOW_{i,t-1} + \beta_1^M MID_{i,t-1} + \beta_1^T TOP_{i,t-1} \\ & + \beta_2 |\Delta\sigma_{i,t}| + \beta_3 Flow_{i,t} + \beta_4 lnTNA_{i,t-1} + \epsilon_{i,t}. \end{aligned} \tag{7}$$

In this equation, $|\Delta\sigma_{i,t}|$ is the absolute value of the change in fund i's return volatility between year $t-1$ and year t. The results are reported in Table V.

- Please insert TABLE V approximately here -

[34] Typically, tournament incentives lead to risk-changes within a calendar year in order to maximize the chances of achieving a top position by the end of the year. However, longer-horizon incentives might also play a role and induce fund managers to change risk between years based on past performance.

We find a significantly positive impact of $|\Delta\sigma_{i,t}|$ on the turnover ratio, i.e., changes in the fund's volatility increase its turnover ratio. More importantly, the coefficient for the impact of the top quintile of past performance is still positive and statistically significant. Therefore, our results show that a change in the fund's volatility does indeed lead to higher levels of the turnover ratio. Nevertheless, there is still an additional strong impact of past top performance on the turnover ratio even after controlling for this effect. Hence, the high turnover ratio following top performance documented above can not be explained by risk changes due to tournament incentives.

The second reason why managers might change their strategy could be due to high inflows into a fund after good performance. According to Pollet and Wilson (2008), funds usually respond to new flows by just scaling up their existing investments. Note, that this would not directly influence the fund's turnover ratio per se, because in this case managers just purchase new shares of firms they already hold, but do not sell any securities at the same time. Consequently, purchases exceed sales and the nominator of the turnover ratio does not change (see Section 2.1). Pollet and Wilson (2008) use holdings data to show that fund managers only reduce the extent to which they are scaling up existing positions if they face limits to the scalability of their portfolios. Such limits could be a high price impact due to a large portfolio size or high liquidity costs when increasing their ownership share in small-cap stocks. These managers might have to change their portfolio structure instead of just scaling up their existing investments. According to Pollet and Wilson (2008), these managers then start to diversify by increasing the number of distinct equity holdings in their portfolio. Such a diversifying strategy would still have no direct impact on the turnover ratio if it is just implemented by investing new money differently from old money. However, if fund managers in such a situation not just change their strategy by investing in other stocks than those they already own, but also adjust the structure of their existing portfolio, then this would eventually result in a higher turnover ratio.

Our strategy to rule out this alternative explanation is to focus on cases where funds should face no limits to scalability. In these cases, funds are not forced to change their strategy. If our previous results were really driven by funds that have to change their strategy due to inflows, we should find no strong impact of past top performance on the turnover ratio among those funds without limits to scalability.

We create three subsamples of funds that would either face no problems when they scale up their investments or that have no need to scale up. According to Pollet and Wilson

(2008), large-cap funds and funds that are small are less constrained and can still easily scale up their investments. Therefore, the first subsample of funds that we expect not to change their strategy consists of small funds and the second subsample consists of funds that invest in large-cap equities.[35] Our third subsample consists of funds that do not face net inflows at all in a given year and thus have no need to scale up their investments.[36] We estimate Model (3) for these subsamples. Results are reported in Table VI.

- Please insert TABLE VI approximately here -

In all three subsamples, the impact of the top quintile on the subsequent turnover ratio is still positive and significant in all specifications. The funds in the first two subsamples are able to easily scale up their investments and do not need to change their portfolio structure due to new inflows. Nonetheless, they show high turnover ratios following a good past performance. While this supports an overconfidence story, this finding does also not contradict the findings of Pollet and Wilson (2008): the negative impact of flows shows that they might well use the new money to scale up existing holdings. However, at the same time they start to turn over their existing positions much more frequently after a good performance. The funds in the third subsample do not even face net inflows, but also show a high turnover ratio after a top performance. In all three subsamples, the slope coefficient for the impact of past top performance is even slightly higher than in the overall sample (see Table II, Panel A).

Overall, these findings strongly suggest that the increase in turnover ratio after a top performance is not just caused by a strategy change due to tournament incentives or due to limits in scalability. Rather, it is a voluntary decision of the fund's manager to trade heavily, which is consistent with an overconfidence story.

3.4.2 Rational Learning about Abilities

An increased trading activity after a good performance is not necessarily a sign of overconfidence. It is also possible that a higher turnover ratio after a good past performance is a rational response. That would be the case if the fund manager is rationally learning

[35] Small funds are defined as funds with a below median beginning of year TNA and large-cap funds are defined as funds with a below median exposure to the SMB factor in the Fama and French (1993) three factor model.

[36] As new inflows due to past top performance are most likely to occur in the first quarter of a year, in unreported tests we also look at a subset of observations for which no positive flows occur in the first quarter. Results remain very similar.

about her own abilities in a Bayesian sense. In this case, managers initially do not know (much) about their abilities (see Gervais and Odean, 2001). However, they can update their believes about their abilities based on their past performance realizations. One important aspect of ability is the precision of a manager's private information that she can use for trading. A manager will learn from good (bad) past performance outcomes that her private information is more (less) precise than initially thought. Consequently, it is then rational for her to put a larger or smaller weight on her private information when estimating expected returns or when looking for trading indications. This can lead to changes in her optimal portfolio weights and eventually to trading activity. If the process described above is really rational, such trading would result in better portfolio allocation and the realization of profitable trading opportunities which would eventually lead to better (or at least not worse) performance. Thus, we should observe an increase in performance if a rational manager with good past performance chooses a high turnover ratio.

In contrast, if managers are overconfident and subject to biased self-attribution rather than being rational, they would only update their believes about the precision of their private information after good performance, but not after bad performance. Over time, this leads to an overestimation of the precision of private information and to increased trading activity based on this information which is less precise than the manager thinks. High levels of trading volume that are due to overconfidence should reduce portfolio performance, because they just generate additional trading costs (see Odean, 1999).

Thus, to distinguish whether our results are due to overconfidence or a sign of managerial rationality, we now analyze how the performance of funds that belong to the top performers in the previous year differs between those with subsequently high turnover ratios and those with subsequently low turnover ratios. To answer this question, we apply a simple portfolio approach (see, e.g., Carhart, 1997): at the beginning of each year, we take the 10% (20%) best performing funds according to their performance in the previous year. We focus on the top performers, both because overconfidence should be especially relevant for the best performing funds and because a top performance should provide the strongest signal about managerial abilities. Based on this pre-selection, we form two equal-weighted portfolios: the first portfolio consists of high turnover ratio funds, the second of low turnover ratio funds. We distinguish between high turnover ratio funds and low turnover ratio funds based on the median turnover ratio within the market segment of each fund among the 10% (20%) best performing funds according to their Carhart (1997) four-factor alpha. This yields a time series of monthly returns for each portfolio from 1999 to 2008.

If fund managers have a high turnover ratio because of rational Bayesian learning about their abilities, we would expect the first portfolio to outperform the second portfolio, and vice versa if the overconfidence explanation holds. To directly test which explanation is consistent with the data, we calculate the excess return over the risk free rate, the Jensen (1968) one-factor alpha, the Fama and French (1993) three-factor alpha, and the Carhart (1997) four-factor alpha of a hypothetical difference portfolio that invests in the low turnover ratio funds and shorts the high turnover ratio funds as described above. Results are presented in Table VII.

– Please insert TABLE VII approximately here –

The difference portfolio based on an initial selection among the top 10% of all funds delivers a positive performance between 1.6% and 1.9% p.a. which is usually significant at the 5%-level. If we base the selection on the top 20% of all funds, the difference between the portfolios gets weaker and is only significant if we measure performance by four-factor alphas. This is consistent with the view that overconfidence is the more pronounced the better the fund performed before. Therefore, the difference in performance is stronger among the best funds. In both cases, the hypothesis of a negative return of the difference portfolio can clearly be rejected, i.e., we find no support for fund managers increasing their turnover ratio due to rational Bayesian learning about their own abilities. Rather, increased turnover hurts performance, which supports our overconfidence explanation.

3.4.3 Less Internal Constraints after Good Performance

Another potential explanation for our results might be that fund managers internal constraints vary over time. It could be the case that fund managers first face relative restrictive upper limits on trading volume. After a good performance, the fund management company might allow the manager to trade more. If the fund manager already was trading at the upper limit in the prior year and is now allowed to increase her turnover ratio, this might also lead to the observed pattern. However, this case would still be consistent with an overconfidence story: As it is very unlikely that the fund manager would now face lower limits for trading activity that force her to trade more, the decision to increase the turnover ratio would still be a voluntary one. If it was not driven by overconfidence, we should see that the increased turnover ratio leads to better (or at least not worse) performance (see Section 3.4.2). Our previous findings (Table VII) show that this is not the case.

4 Conclusion

Deviations from rational behavior can create distortions in asset markets. While many studies have analyzed and provided ample evidence of irrational behavior among retail investors, the literature on behavioral biases among professional investors is scarce. If professional investors are also subject to such biases, this is likely to have much more serious consequences for the efficient functioning of financial markets.

In this paper, we examine overconfidence among mutual fund managers. We analyze whether fund managers become overconfident after a good past performance, using their funds' turnover ratio as proxy for overconfidence. We document several new findings: 1. funds that performed well in the past have high subsequent turnover ratios. This is consistent with the view that good past performance increases overconfidence. 2. Funds that performed very poorly in the past also have high turnover ratios, i.e., overall the relationship between past performance and turnover ratio is U-shaped. 3. A fund's turnover ratio is driven by individual portfolio performance but not the performance of the market segment the fund belongs to. 4. The relationship between past performance and overconfidence is very similar for single managers and management teams.

In additional tests we can show that some plausible alternative explanations based on strategy changes after good performance due to tournament incentives or inflows as well as increased turnover as rational response due to Bayesian learning about managerial abilities are not likely candidates that might explain our findings. Still, it would be interesting to speculate what other alternative explanations could drive the correlation between good past performance and increased turnover ratio we find. Additionally, it would also be interesting to examine in more detail what components of past performance (stock picking performance, timing performance, etc.) lead managers to become overconfident and how this impacts future behavior and performance. These two questions are left for future research.

Overall, our results contribute to the ongoing debate about behavioral biases among professionals. They suggest that fund managers are prone to overconfidence, too. This also offers one potential explanation for the lack of performance persistence among good performing fund managers (see Carhart, 1997): although some managers could possibly outperform the market consistently based on their true abilities, the fact that they become overconfident keeps them from doing so.

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Appendix:

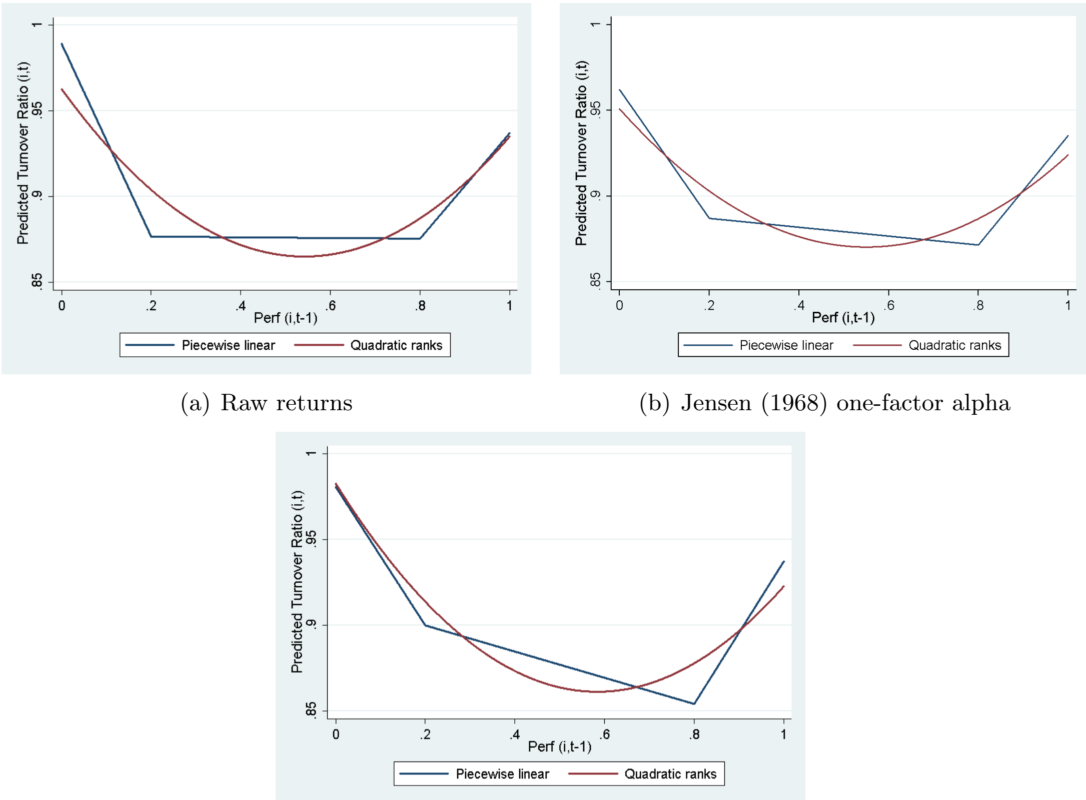
Definition of market segments

This table contains the Lipper segment classifications.

Segment	Lipper code	Lipper code name
Aggressive Growth	CA	Capital Appreciation Funds
	SG	Small-Cap Funds
	MR	Micro-Cap Funds
Growth & Income	GI	Growth and Income Funds
Income	EI	Equity Income Funds
Growth	G	Growth Funds
Sector Funds	S	Specialty/Miscellaneous Funds
	H	Health/Biotechnology Funds
	FS	Financial Services Funds
	NR	Natural Resources Funds
	RE	Real Estate Funds
	TK	Science & Technology Funds
	TL	Telecommunication Funds
Utility Funds	UT	Utility Funds

Figure 1: Predicted Turnover Ratio

Figure 1 shows the estimated relationship between a fund's past performance rank and its current turnover ratio based on the results from the fund fixed effects specification in Table II. Performance ranks are based on raw returns (a), Jensen's one-factor alphas (b), and Carhart (1997) four-factor alphas (c), respectively.



(a) Raw returns

(b) Jensen (1968) one-factor alpha

(c) Carhart (1997) four-factor alpha

Table I: Descriptive Statistics

Table I presents summary statistics of the funds in our sample. It includes actively managed, domestic equity funds from the following six segments: Aggressive Growth, Growth and Income, Income, Growth, Sector Funds, and Utility Funds. Funds with a turnover ratio greater than 724% (99%-fractile) are excluded. Furthermore all fund year observations are excluded for which less than 12 months of return data is available.

Year	Number of funds	Mean TNA (Mio USD)	Mean age in years	Mean Turnover Ratio
1999	1,528	1,157.34	10.38	0.8717
2000	1,589	1,045.67	10.63	0.9702
2001	1,817	829.41	10.21	1.0509
2002	1,863	593.46	10.70	0.9812
2003	1,827	817.82	11.43	0.9105
2004	1,804	939.66	11.89	0.8439
2005	1,775	991.59	12.48	0.8289
2006	1,775	1,135.77	12.97	0.8332
2007	1,839	1,179.59	12.85	0.8425
2008	1,669	671.24	13.78	0.9210
Mean	1,749	932.07	11.75	0.9055

Table II: Past Performance and Turnover Ratio

Table II presents the estimation results of Model (3) and (4) from the main text. The dependent variable in all regressions is the fund's turnover ratio. The independent variables are contained in the first column. Panel A shows the results from a piecewise linear regression approach where $LOW_{i,t-1}$ represents the bottom quintile of past performance, $MID_{i,t-1}$ the three middle quintiles, and $TOP_{i,t-1}$ the top quintile. In Panel B past performance is added as linear term, $Perf_{i,t-1}$, and as quadratic term, $(Perf_{i,t-1})^2$. Control variables are contemporaneous inflows, $Flow_{i,t}$, and the natural logarithm of the fund's size at the end of the previous year, $lnTNA_{i,t-1}$. Past performance ranks are based on raw returns (Columns (1) to (3)), Jensen's one-factor alphas, (Columns (4) to (6)), and Carhart's four-factor alphas (Columns (7) to (9)), respectively. The models are estimated using a pooled regression approach (OLS), a random effects model (RE), and a fund fixed effects approach (FE), respectively. Time and segment fixed effects are included in all regressions. Robust t statistics in parentheses are based on standard errors clustered at the fund level. ***, ** and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Panel A: Piecewise linear

Ranks based on		Returns			Jensen's alpha			Four-factor alpha	
	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$LOW_{i,t-1}$	-1.220^{***}	-0.664^{***}	-0.564^{***}	-1.358^{***}	-0.467^{***}	-0.375^{***}	-1.748^{***}	-0.580^{***}	-0.405^{***}
	(-5.45)	(-4.62)	(-3.87)	(-6.60)	(-3.34)	(-2.66)	(-7.53)	(-4.14)	(-2.89)
$MID_{i,t-1}$	-0.093^{**}	-0.007	-0.002	-0.068^{*}	-0.026	-0.026	-0.151^{***}	-0.076^{***}	-0.076^{***}
	(-2.54)	(-0.26)	(-0.076)	(-1.80)	(-0.99)	(-0.98)	(-4.09)	(-3.16)	(-3.16)
$TOP_{i,t-1}$	0.529^{***}	0.338^{***}	0.308^{**}	0.635^{***}	0.356^{***}	0.319^{**}	0.906^{***}	0.511^{***}	0.417^{***}
	(2.71)	(2.80)	(2.54)	(3.25)	(2.85)	(2.54)	(4.42)	(3.96)	(3.24)
$Flow_{i,t}$	-0.029^{***}	-0.029^{***}	-0.031^{***}	-0.031^{***}	-0.029^{***}	-0.030^{***}	-0.029^{***}	-0.028^{***}	-0.030^{***}
	(-2.67)	(-3.90)	(-3.95)	(-2.80)	(-3.87)	(-3.88)	(-2.65)	(-3.82)	(-3.85)
$lnTNA_{i,t-1}$	-0.047^{***}	-0.064^{***}	-0.077^{***}	-0.047^{***}	-0.065^{***}	-0.077^{***}	-0.046^{***}	-0.065^{***}	-0.077^{***}
	(-7.67)	(-9.24)	(-6.96)	(-7.68)	(-9.29)	(-6.98)	(-7.53)	(-9.39)	(-7.08)
$Constant$	1.512^{***}	1.548^{***}	1.432^{***}	1.522^{***}	1.520^{***}	1.407^{***}	1.600^{***}	1.551^{***}	1.432^{***}
	(25.1)	(29.3)	(8.28)	(26.3)	(29.0)	(8.07)	(26.0)	(28.9)	(8.06)
Observations	14,638	14,638	14,638	14,638	14,638	14,638	14,638	14,638	14,638
$R^2(Within)$		3.32%	3.46%		3.24%	3.39%		3.39%	3.56%
$R^2(Between)$		6.88%	1.47%		6.71%	1.32%		7.41%	1.70%
$R^2/R^2(Overall)$	6.00%	5.77%	1.80%	6.00%	5.74%	1.75%	7.00%	6.17%	2.08%

Table II: continued

Panel B: Quadratic ranks

Ranks based on	Returns			Jensen's alpha			Four-factor alpha		
	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Perf_{i,t-1}$	-0.878^{***}	-0.435^{***}	-0.361^{***}	-0.964^{***}	-0.359^{***}	-0.293^{***}	-1.345^{***}	-0.535^{***}	-0.416^{***}
	(-7.09)	(-5.71)	(-4.66)	(-8.20)	(-4.97)	(-4.02)	(-9.97)	(-6.99)	(-5.44)
$(Perf_{i,t-1})^2$	0.733^{***}	0.396^{***}	0.334^{***}	0.836^{***}	0.327^{***}	0.266^{***}	1.138^{***}	0.467^{***}	0.356^{***}
	(6.13)	(5.41)	(4.48)	(7.24)	(4.57)	(3.68)	(8.81)	(6.37)	(4.86)
$Flow_{i,t}$	-0.029^{***}	-0.029^{***}	-0.031^{***}	-0.031^{***}	-0.029^{***}	-0.030^{***}	-0.029^{***}	-0.028^{***}	-0.029^{***}
	(-2.68)	(-3.88)	(-3.93)	(-2.84)	(-3.86)	(-3.86)	(-2.63)	(-3.76)	(-3.79)
$lnTNA_{i,t-1}$	-0.047^{***}	-0.064^{***}	-0.077^{***}	-0.047^{***}	-0.064^{***}	-0.076^{***}	-0.046^{***}	-0.064^{***}	-0.077^{***}
	(-7.72)	(-9.27)	(-6.96)	(-7.70)	(-9.29)	(-6.97)	(-7.52)	(-9.33)	(-7.02)
$Constant$	1.469^{***}	1.518^{***}	1.402^{***}	1.471^{***}	1.504^{***}	1.393^{***}	1.550^{***}	1.543^{***}	1.432^{***}
	(27.0)	(29.7)	(8.14)	(27.8)	(29.8)	(8.05)	(27.8)	(30.1)	(8.09)
Observations	14,638	14,638	14,638	14,638	14,638	14,638	14,638	14,638	14,638
$R^2(Within)$		3.28%	3.43%		3.22%	3.36%		3.42%	3.58%
$R^2(Between)$		6.92%	1.38%		6.76%	1.29%		7.47%	1.74%
$R^2/R^2(Overall)$	6.00%	5.76%	1.71%	6.00%	5.75%	1.71%	7.00%	6.24%	2.14%

Table III: Impact of Market Returns

Table III presents the estimation results of Model (5) from the main text. The dependent variable in all regressions is the fund's turnover ratio. The independent variables are contained in the first column. $LOW_{i,t-1}$ represents the bottom quintile of past performance, $MID_{i,t-1}$ the three middle quintiles, and $TOP_{i,t-1}$ the top quintile. $Market_{i,t-1}$ $(Value)$ and $Market_{t-1}$ $(Equal)$ are defined as the value-weighted and equal-weighted, respectively, average of the returns of all funds belonging to the same segment as fund i in year $t-1$. Control variables are contemporaneous inflows, $Flow_{i,t}$, and the natural logarithm of the fund's size at the end of the previous year, $lnTNA_{i,t-1}$. Past performance ranks are based on Carhart's four-factor alphas. The models are estimated using a pooled regression approach (OLS), a random effects model (RE), and a fund fixed effects approach (FE), respectively. Time and segment fixed effects are included in all regressions. Robust t statistics in parentheses are based on standard errors clustered at the fund level. ***, ** and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Ranks based on	Four-factor alpha					
	OLS	RE	FE	OLS	RE	FE
	(1)	(2)	(3)	(4)	(5)	(6)
$LOW_{i,t-1}$	-1.748^{***}	-0.580^{***}	-0.405^{***}	-1.756^{***}	-0.584^{***}	-0.408^{***}
	(-7.53)	(-4.14)	(-2.89)	(-7.56)	(-4.16)	(-2.91)
$MID_{i,t-1}$	-0.151^{***}	-0.076^{***}	-0.076^{***}	-0.148^{***}	-0.074^{***}	-0.075^{***}
	(-4.09)	(-3.15)	(-3.15)	(-3.99)	(-3.08)	(-3.08)
$TOP_{i,t-1}$	0.906^{***}	0.510^{***}	0.415^{***}	0.882^{***}	0.497^{***}	0.403^{***}
	(4.39)	(3.95)	(3.22)	(4.26)	(3.83)	(3.11)
$Market_{t-1}$ $(Value)$	0.000	0.003	0.013			
	(0.00)	(0.06)	(0.21)			
$Market_{t-1}$ $(Equal)$				0.236^{**}	0.125	0.122
				(2.07)	(1.36)	(1.32)
$Flow_{i,t}$	-0.029^{***}	-0.028^{***}	-0.030^{***}	-0.029^{***}	-0.028^{***}	-0.030^{***}
	(-2.65)	(-3.82)	(-3.85)	(-2.67)	(-3.83)	(-3.87)
$lnTNA_{i,t-1}$	-0.046^{***}	-0.065^{***}	-0.077^{***}	-0.046^{***}	-0.065^{***}	-0.078^{***}
	(-7.53)	(-9.39)	(-7.08)	(-7.55)	(-9.43)	(-7.11)
$Constant$	1.600^{***}	1.551^{***}	1.431^{***}	1.566^{***}	1.543^{***}	1.425^{***}
	(25.4)	(28.8)	(8.07)	(24.7)	(28.5)	(8.03)
Observations	14,638	14,638	14,638	14,638	14,638	14,638
$R^2(Within)$		3.39%	3.56%		3.4%	3.57%
$R^2(Between)$		7.41%	1.69%		7.42%	1.68%
$R^2/R^2(Overall)$	7%	6.17%	2.07%	7%	6.17%	2.07%

Table IV: Impact of the Management Structure

Table IV presents the estimation results of Model (6) from the main text. The dependent variable in all regressions is the fund's turnover ratio. The independent variables are contained in the first column. $LOW_{i,t-1}$ represents the bottom quintile of past performance, $MID_{i,t-1}$ the three middle quintiles, and $TOP_{i,t-1}$ the top quintile. $TeamDummy_{i,t}$ is a binary variable that takes on the value one, if fund i is managed by a team in year $t-1$ and t, and zero otherwise. Control variables are contemporaneous inflows, $Flow_{i,t}$, and the natural logarithm of the fund's size at the end of the previous year, $lnTNA_{i,t-1}$. Past performance ranks are based on Carhart's four-factor alphas. The models are estimated using a pooled regression approach (OLS), a random effects model (RE), and a fund fixed effects approach (FE), respectively. Time and segment fixed effects are included in all regressions. Robust t statistics in parentheses are based on standard errors clustered at the fund level. ***, ** and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Ranks based on	Four-factor alpha		
	OLS	RE	FE
	(1)	(2)	(3)
$TeamDummy_t$	-0.069	-0.050	-0.036
	(-0.77)	(-0.86)	(-0.61)
$LOW_{i,t-1}$	-1.882^{***}	-0.599^{**}	-0.356
	(-4.56)	(-2.50)	(-1.53)
$MID_{i,t-1}$	-0.207^{***}	-0.114^{***}	-0.119^{***}
	(-2.98)	(-2.60)	(-2.73)
$TOP_{i,t-1}$	1.192^{***}	0.540^{***}	0.415^{**}
	(3.74)	(2.78)	(2.16)
$TeamDummy_t \cdot LOW_{i,t-1}$	0.183	-0.019	-0.123
	(0.37)	(-0.060)	(-0.40)
$TeamDummy_t \cdot MID_{i,t-1}$	0.108	0.066	0.072
	(1.29)	(1.21)	(1.32)
$TeamDummy_t \cdot TOP_{i,t-1}$	-0.585	-0.128	-0.039
	(-1.38)	(-0.49)	(-0.15)
$Flow_{i,t}$	-0.019^{*}	-0.026^{***}	-0.029^{***}
	(-1.68)	(-3.37)	(-3.58)
$lnTNA_{i,t-1}$	-0.042^{***}	-0.061^{***}	-0.075^{***}
	(-6.78)	(-8.89)	(-6.72)
$Constant$	1.573^{***}	1.563^{***}	1.342^{***}
	(18.0)	(22.7)	(8.09)
Observations	12,732	12,732	12,732
$R^2(Within)$		3.44%	3.65%
$R^2(Between)$		7.11%	1.17%
$R^2/R^2(Overall)$	7.00%	6.15%	1.34%

Table V: Influence of Risk Change on Turnover Ratio

Table V presents the estimation results of Model (7) from the main text. The dependent variable in all regressions is the fund's turnover ratio. The independent variables are contained in the first column. $LOW_{i,t-1}$ represents the bottom quintile of past performance, $MID_{i,t-1}$ the three middle quintiles, and $TOP_{i,t-1}$ the top quintile. $|\Delta\sigma_{i,t}|$ is defined as the absolute value of a volatility change from year $t-1$ to year t. Control variables are contemporaneous inflows, $Flow_{i,t}$, and the natural logarithm of the fund's size at the end of the previous year, $lnTNA_{i,t-1}$. Past performance ranks are based on Carhart's four-factor alphas. The models are estimated using a pooled regression approach (OLS), a random effects model (RE), and a fund fixed effects approach (FE), respectively. Time and segment fixed effects are included in all regressions. Robust t statistics in parentheses are based on standard errors clustered at the fund level. ***, ** and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Ranks based on	Four-factor alpha		
	OLS	RE	FE
	(1)	(2)	(3)
$LOW_{i,t-1}$	-1.627^{***}	-0.553^{***}	-0.385^{***}
	(-6.97)	(-3.91)	(-2.73)
$MID_{i,t-1}$	-0.159^{***}	-0.081^{***}	-0.081^{***}
	(-4.35)	(-3.35)	(-3.34)
$TOP_{i,t-1}$	0.620^{***}	0.401^{***}	0.324^{**}
	(3.08)	(3.17)	(2.56)
$\|\Delta\sigma_{i,t}\|$	5.589^{***}	2.728^{***}	2.446^{***}
	(6.85)	(4.57)	(4.16)
$Flow_{i,t}$	-0.029^{***}	-0.031^{***}	-0.033^{***}
	(-2.70)	(-4.12)	(-4.22)
$lnTNA_{i,t-1}$	-0.046^{***}	-0.067^{***}	-0.082^{***}
	(-7.63)	(-9.89)	(-7.60)
$Constant$	1.466^{***}	1.443^{***}	1.343^{***}
	(23.3)	(23.9)	(7.67)
Observations	14,638	14,638	14,638
$R^2(Within)$		3.75%	3.93%
$R^2(Between)$		7.96%	2.06%
$R^2/R^2(Overall)$	8.00%	6.73%	2.40%

Table VI: Unconstrained Subsamples

Table VI presents the estimation results of Model (3) from the main text for three subsamples of funds. The first subsample consists of small funds that have a TNA below the median TNA at the beginning of year t (Columns (1) to (3)). The second subsample consists of funds that invest in large-cap equities, according to their exposure to the size factor of the Fama and French (1993) three-factor model (Columns (4) to (6)). The third subsample consists of funds that do not face net inflows (Columns (7) to (9)). The dependent variable in all regressions is the fund's turnover ratio. The independent variables are contained in the first column. $LOW_{i,t-1}$ represents the bottom quintile of past performance, $MID_{i,t-1}$ the three middle quintiles, and $TOP_{i,t-1}$ the top quintile. Control variables are contemporaneous inflows, $Flow_{i,t}$, and the natural logarithm of the fund's size at the end of the previous year, $lnTNA_{i,t-1}$. Past performance ranks are based Carhart's four-factor alphas. The models are estimated using a pooled regression approach (OLS), a random effects model (RE), and a fund fixed effects approach (FE), respectively. Time and segment fixed effects are included in all regressions. Robust t statistics in parentheses are based on standard errors clustered at the fund level. ***, ** and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Ranks based on:	Four-factor alpha								
Subsamples:		Small funds			Large-cap funds			Funds with net outflow	
	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$LOW_{i,t-1}$	-1.928^{***}	-0.619^{***}	-0.313	-0.920^{***}	-0.482^{**}	-0.317	-1.518^{***}	-0.554^{***}	-0.316^{*}
	(-5.62)	(-2.82)	(-1.41)	(-2.79)	(-1.98)	(-1.26)	(-5.77)	(-3.20)	(-1.79)
$MID_{i,t-1}$	-0.098^{*}	-0.079^{*}	-0.092^{**}	-0.195^{***}	-0.104^{***}	-0.099^{***}	-0.150^{***}	-0.066^{*}	-0.055
	(-1.66)	(-1.94)	(-2.21)	(-4.15)	(-3.14)	(-2.96)	(-3.12)	(-1.92)	(-1.58)
$TOP_{i,t-1}$	1.008^{***}	0.707^{***}	0.593^{***}	0.984^{***}	0.573^{***}	0.437^{**}	0.999^{***}	0.680^{***}	0.565^{***}
	(3.12)	(3.31)	(2.76)	(3.58)	(3.13)	(2.32)	(3.24)	(3.55)	(2.98)
$Flow_{i,t}$	-0.013	-0.021^{**}	-0.025^{***}	-0.009	-0.021^{**}	-0.028^{***}	-0.310^{***}	-0.194^{***}	-0.136^{**}
	(-1.09)	(-2.45)	(-2.70)	(-0.68)	(-2.37)	(-2.90)	(-4.10)	(-3.84)	(-2.53)
$lnTNA_{i,t-1}$	-0.037^{***}	-0.057^{***}	-0.074^{***}	-0.034^{***}	-0.058^{***}	-0.079^{***}	-0.045^{***}	-0.052^{***}	-0.059^{***}
	(-2.68)	(-4.07)	(-3.40)	(-5.47)	(-8.21)	(-6.13)	(-6.22)	(-6.90)	(-3.79)
Constant	1.656^{***}	1.558^{***}	1.183^{***}	1.653^{***}	1.693^{***}	1.133^{***}	1.509^{***}	1.442^{***}	1.210^{***}
	(18.8)	(19.3)	(4.06)	(14.2)	(15.7)	(2.99)	(21.0)	(23.4)	(6.49)
Observations	6,630	6,630	6,630	7,360	7,360	7,360	8,516	8,516	8,516
$R^2(Within)$		2.55%	3.16%		2.22%	2.58%		2.39%	2.70%
$R^2(Between)$		5.10%	1.57%		7.72%	0.93%		7.84%	0.01%
$R^2/R^2(Overall)$	6.00%	5.29%	1.07%	7.00%	6.01%	1.02%	8.00%	6.63%	0.09%

Table VII: Performance Comparison among Past Top Funds with High and Low Turnover Ratios

Table VII presents the results of a simple portfolio approach (see, e.g., Hendricks et al., 1993; Carhart, 1997): on January 1 of each year, we take the 10% (20%) best performing funds according to their performance based on Carhart's four-factor alpha in the previous year. Based on this pre-selection, we form two equal-weighted portfolios: the first portfolio consists of high turnover ratio funds (High TR), the second of low turnover ratio funds (Low TR). We distinguish between high turnover ratio funds and low turnover ratio funds based on the median turnover ratio within the market segment of each fund among the 10% (20%) best performing funds. This yields a time series of monthly returns on each portfolio from 1999 to 2008. Low TR - High TR is a hypothetical difference portfolio that invests in the low turnover ratio funds and shorts the high turnover ratio funds. The performance of these portfolios is measured by the excess return over the risk free rate, the Jensen (1968) one-factor alpha, the Fama and French (1993) three-factor alpha, and the Carhart (1997) four-factor alpha, respectively. t statistics are in parentheses. ***, ** and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Ranks based on			Four-factor alpha		
Performance measured by	Returns	Jensen's alpha	Three-factor alpha	Four-factor alpha	Best
Low TR - High TR	0.019^{**}	0.018^{**}	0.016^{*}	0.016^{**}	10%
	(2.24)	(2.15)	(1.93)	(2.00)	
Low TR	0.026	0.061^{***}	0.048^{***}	0.041^{**}	10%
	(0.40)	(2.64)	(2.73)	(2.43)	
High TR	0.007	0.043^{*}	0.033^{**}	0.025^{*}	10%
	(0.10)	(1.89)	(2.16)	(1.78)	
Low TR - High TR	0.013	0.011	0.007	0.010^{*}	20%
	(1.37)	(1.24)	(1.04)	(1.76)	
Low TR	0.010	0.042^{***}	0.027^{***}	0.026^{**}	20%
	(0.18)	(3.17)	(2.68)	(2.55)	
High TR	-0.003	0.031^{*}	0.020^{**}	0.016^{*}	20%
	(-0.05)	(1.92)	(2.10)	(1.73)	

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