



2003

How Investors Interpret Past Fund Returns

Anthony W. Lynch

David K. Musto
University of Pennsylvania

Follow this and additional works at: https://repository.upenn.edu/fnce_papers

 Part of the [Finance Commons](#), and the [Finance and Financial Management Commons](#)

Recommended Citation

Lynch, A. W., & Musto, D. K. (2003). How Investors Interpret Past Fund Returns. *The Journal of Finance*, 58 (5), 2033-2058. <http://dx.doi.org/10.1111/1540-6261.00596>

This paper is posted at ScholarlyCommons. https://repository.upenn.edu/fnce_papers/276
For more information, please contact repository@pobox.upenn.edu.

How Investors Interpret Past Fund Returns

Abstract

The literature documents a convex relation between past returns and fund flows of mutual funds. We show this to be consistent with fund incentives, because funds discard exactly those strategies which underperform. Past returns tell less about the future performance of funds which discard, so flows are less sensitive to them when they are poor. Our model predicts that strategy changes only occur after bad performance, and that bad performers who change strategy have dollar flow and future performance that are less sensitive to current performance than those that do not. Empirical tests support both predictions.

Disciplines

Finance | Finance and Financial Management

How Investors Interpret Past Fund Returns

Anthony W. Lynch and David K. Musto^{*}

^{*} Lynch is from New York University and NBER and Musto is from University of Pennsylvania. We are grateful for comments from Franklin Allen, Stephen Brown, Jennifer Carpenter, Doug Diamond, Ned Elton, Will Goetzmann, Gary Gorton, Bruce Grundy, Rudi Schadt, René Stulz, S. Viswanathan and participants in the Corporate Finance and Friday lunchtime seminars at Wharton, and also for research support from Dan Mingelgrin. Two anonymous referees get special thanks.

How Investors Interpret Past Fund Returns

ABSTRACT

The literature documents a convex relation between past returns and fund flows of mutual funds. We show this to be consistent with fund incentives, because funds discard exactly those strategies which underperform. Past returns tell less about the future performance of funds which discard, so flows are less sensitive to them when they are poor. Our model predicts that strategy changes only occur after bad performance, and that bad performers who change strategy have dollar flow and future performance that are less sensitive to current performance than those that do not. Empirical tests support both predictions.

How Investors Interpret Past Fund Returns

Investors who condition open-end mutual fund allocations on past performance appear to be relatively indifferent among bad returns. Several recent papers (e.g., Sirri and Tufano (1998), Ippolito (1992)) show net new investment to be much less sensitive to past returns in the region of bad returns, as if all returns below some threshold send roughly the same signal to investors about future prospects. Brown, Harlow and Starks (1996) and Chevalier and Ellison (1997) interpret this pattern as the fund's implicit compensation scheme and ask whether this induces the asset substitution associated with convex compensation; our goal here is to determine why the pattern occurs in the first place and provide empirical support for our explanation.

A mutual fund's shareholders delegate its productive decisions to an investment advisor. The shareholders and other investors can not usually observe these decisions directly, but they can infer them from the fund's operating performance, and invest accordingly. The finance literature usually models this inference/investment process as: 1) estimating a fund's past risk-adjusted expected return, and 2) investing on the assumption that the past risk-adjusted expected return will persist into the future (e.g. Ippolito (1992)). This paradigm has some intuitive appeal and empirical support, but it does not take into account the investment advisor's option to disconnect past and future performance. We propose an explanation for the empirical results on fund flows by way of a model that incorporates this option.

The use of performance measures as estimates of future performance assumes (among other things) that the relevant personnel and management techniques carry forward from the past. Our point, building on the argument of Heinkel and Stoughton (1994), is that funds respond to bad - but not good - performance by replacing the personnel or techniques that

produced it. What we can observe of investment advisors' operating decisions, such as manager replacements (Khorana (1996)) and mergers (Elton, Gruber and Blake (1996)) bears out this intuition. This abandonment option transforms the relationship between new investment and past returns, because if a bad return and a very bad return both mean that the next return will reflect a new strategy, the magnitude of their difference has little predictive power, and therefore little effect on investment decisions. With the exception of the very worst funds, this dynamic also fits the actual shape of performance persistence - flatter in the region of bad past returns.

Our model has several implications. First, strategy changes only occur after bad fund performance. Second, bad performers who change strategy have dollar flow and future performance that are less sensitive to current performance than those who do not. We test these implications using daily mutual fund returns from Micropal and manager-change dates from the CRSP mutual fund data set. We use three proxies for strategy change. The first two are based on a fund's average absolute change in risk loading, where one proxy is the loading change itself, while the other takes those funds in the top quartile of loading changes for each fund type in each year to be those that changed strategy. Risk loadings are obtained from the four-factor model of Carhart (1997) and Busse (1999). Manager change is used as the third proxy.

To test the first implication, we define bad performance to be either negative or bottom-quartile performance and we use two measures of performance, four-factor alpha and group-adjusted four-factor alpha. For all combinations of performance measure and bad-performance definition but one, we find a significantly greater incidence of both manager changes and top-quartile loading changes among bad performers than good performers, as well as a significantly higher average loading change. The only exception defines bad performance to be

negative absolute alpha. These results are consistent with the first implication of the model.

We then test the second implication by running piece-wise linear regressions of future performance or dollar flow on current performance, with a single breakpoint at zero. Thus, the sensitivity of the dependent variable to performance is allowed to differ between bad performers and good performers. Each of these sensitivities is also allowed to differ based on the value of the strategy-change proxy. The model predicts that the sensitivity of dollar flow to current performance for bad performers is lower for those bad performers who change strategy. Consistent with the model, we always obtain this result, irrespective of which of the three strategy change proxies is used or whether performance is measured using absolute or relative four-factor alpha. Moreover, the difference is significant in five of the six cases. The model also predicts that the sensitivity of future performance to current performance for bad performers is lower for those bad performers who change strategy. But when future performance is used as the dependent variable in the regression, we are only able to confirm this prediction when we use manager change as the strategy change proxy. Considered together, these empirical results provide strong support for the model.

The rest of this paper is in six sections. In Section I we discuss the literature on performance persistence and fund flows, and outline our reasoning. Section II describes and solves a simple model which captures this reasoning, and in Section III we discuss the main implications of the model and their correspondence to the existing empirical literature. Section IV extends the model to allow for multiple funds. Our empirical testing of the model is described in Section V while Section VI summarizes and concludes.

I. Background

The information content of fund returns is one of the oldest and most popular topics in finance. A large portion of the academic literature has considered how to measure it, and much of the popular press has tried to report it. It is not surprising in this context that the relation between new investment and past returns is positive. What is surprising is that the relation is qualitatively different for lower and higher past returns. Ippolito (1992), Sirri and Tufano (1998) and Chevalier and Ellison (1997) all find a small positive slope in the lower region and a considerably larger slope in the higher region. Goetzmann and Peles (1996) find a significant relation between flows and past returns only for the top quartile of past returns.

The asymmetric flow-response pattern is consistent with investors expecting a relation between past and future performance with a convex shape. That is, investors put slightly less cash into bad funds than mediocre ones because bad funds' prospects are slightly worse than those of mediocre funds, whereas they put considerably more cash into good funds than mediocre ones because good funds' prospects are considerably better than those of mediocre funds. This fits the published results on performance persistence, with the notable exception of the very worst funds. Hendricks, Patel and Zeckhauser (HPZ) (1993) estimated the past return/future performance relationship with a sample of fund returns covering 1974 to 1988 by sorting funds at each quarter-end into octile portfolios by their total returns over the past year,¹ then measuring the portfolios' performance over the following quarter. Brown and Goetzmann (BG) (1995) ran the same test on a sample covering 1976 to 1988, except they rebalanced every year-end and held for a year. Carhart (1997) ran this test over the period 1963 to 1993, using decile portfolios and calculating monthly returns. Figure 1 reports the returns net of the risk-free

rate reported for these portfolios, and Figure 2 reports the returns net of market-risk exposure (i.e. Jensen's alphas). The HPZ quarterly numbers are multiplied by four and the Carhart numbers are multiplied by 12 to approximate the scale of the annual BG numbers. Setting aside the worst group, these point estimates reproduce the fund-flow pattern, where the slope of flows on performance is flatter on the left than on the right. This result is not sensitive to the choice of risk-adjustment; Gruber (1996) forms and evaluates portfolios of funds using intercepts from regressions on four factors² and finds the same pattern, as reproduced in Figure 3. However, notice that some risk adjustment is important since the pattern is less discernable in Figure 1 using excess returns than in the other two figures using risk-adjusted performance.

The correspondence between the fund-flow and persistence patterns begs two questions. The first is how to explain the continued investment in the worst performers, a puzzle already noted by BG, Gruber (1996) and others. We do not attempt to resolve these investors' behavior with rational decision-making, which, evidence suggests, may be futile in any case. For example, Goetzmann and Peles (1996) document biases in investor information sets which could encourage bottom-fund investors to stay put, and Sawaya (1992), Brandstrader (1992) and Rukeyser (1996) argue that many bottom-fund investors may be dead. Gruber (1996) posits the existence of a "disadvantaged clientele," which includes investors who are either locked into bad funds by institutional restrictions (e.g. pension plan menus) or accrued capital gains, or who follow the advice of advertisements or brokers, and Christoffersen and Musto (2002) provide evidence that bottom-fund investors are relatively less sensitive to performance and price. The population of bottom-fund investors appears, in any case, to be small; Goetzmann and Peles (1996) estimate the fraction of mutual fund investors in bottom-octile funds at two to three

percent (as opposed to around 28 percent in octile 8).

The other question raised by the empirical results is the source of the asymmetry. Our response is that the investment advisor, like most other enterprises, holds an option to replace its production method. Heinkel and Stoughton (1994) (HS) argue that “a manager is retained if his performance is ‘good enough’ relative to an alternative for the client.” In the equilibrium of their two-period model with a risk-neutral investor and a risk-neutral manager with unknown skill, the manager must outperform a threshold return in the first period to keep his job for the second. This analysis delivers several predictions about the design and purpose of management contracts, but not about fund flows, since the risk-neutral investor simply invests all his money with whatever manager he hires. We modify and extend the HS analysis to study the fund flows, and find that it predicts the observed convex relationship.

HS model the situation where an investor delegates the choice between asset-selection algorithms to a portfolio manager. The fund-flow results refer to open-end mutual funds, which insert an additional layer of delegation: investors delegate the choice of a portfolio manager to an investment advisor (e.g. Fidelity Management Corporation), and the portfolio manager (e.g. Peter Lynch) chooses the asset-selection algorithm. By the same logic as in HS, retail investors can expect that the investment advisor will retain exactly those managers whose performance is “good enough” compared to other potential managers.³ As a consequence, a fund’s realized returns convey two facts to investors: the expected future performance of the same manager, and whether or not the manager will actually persist. If a fund’s past return is below the retention threshold, investors know the next return will reflect a new manager so it hardly matters just how bad the past return was. If the return signals that last period’s manager will be next period’s

manager, then it does matter. Expected future returns, and therefore the net new investments of risk-averse consumers, are consequently more sensitive to past returns above the threshold.

Our reasoning applies to more than just the investment advisor's choice between retaining and replacing his manager. The manager himself can retain or replace his asset-selection algorithm, and this decision also hinges on the past return. A manager deploys an algorithm (momentum, book-to-market, etc.) with some prior belief about its value, but has some residual uncertainty that its realized returns can help resolve. As in HS, there will be a threshold past return that determines whether or not the manager's past algorithm persists in the future, and investors can invest on the knowledge that the manager must have abandoned his old algorithm without actually observing him do it.

The argument is based on the idea that underperforming managers and algorithms are abandoned. For managers, this is obvious: a portfolio manager is either retained or replaced. But in the portfolio-selection context there is the possibility of short-selling. A manager may, depending on transactions costs, be able to transform a money-losing strategy into a money-making strategy by selling it short in the next period. If mutual funds could short-sell, they might be expected to reverse, rather than abandon, underperforming strategies. But for practical purposes this is not an issue, because mutual funds can not (see the Investment Company Act of 1940, section 18) engage in meaningful short-selling.

We do not directly observe many of the internal decisions of mutual funds, such as whether or when the stock-picking algorithm changes, but empirical evidence does indicate that investment advisors replace managers with low recent returns. Khorana (1996) finds a significantly negative relationship between managerial turnover and past performance. The

point estimates for replacement in the year after bottom-half performance are two times the top-half estimates (10.5 percent vs. 5.3 percent).⁴ A bad return reflects poorly on a fund but it also increases the probability that the old manager will not persist into the future, whereas a good return reflects well on the fund and increases the probability that the manager will persist.

The next section embeds this intuition in a model of money management. Investors hire an investment advisor, who in turn chooses a strategy that can be retained or abandoned after a period of experience. The strategy can be thought of as either the fund's manager or the manager's stock-picking algorithm; it is an element of the fund's productive activity that persists only if persistence is desirable. We endogenize the decision whether to let it persist, and show how it delivers the convex fund-flow pattern.

II. The Model

A. *Description of the model*

There are two periods. The first begins at time-0 and ends at time-1, and the second begins at time-1 and ends at time-2. An investment advisor (IA) operates a mutual fund in both periods, and consumes his wealth at time-2. Investor 0 invests at time-0 and consumes at time-1, and Investor 1 invests at time-1 and consumes at time-2. The investors can allocate any positive amount to the fund, and can borrow and lend at the risk-free rate r_F , set at zero. The IA charges investors a fraction δ of end-of-period assets under management for managing their money, and can invest in the riskless asset and any positive position he wants in the fund's return. That is, he has the same investment opportunity set as the investors except that he doesn't pay management fees. The IA and both investors get utility $-e^{-\alpha W}$ ($\alpha > 0$) from consuming wealth W .

We model the return on a fund as a sum of individually unobservable and independently distributed random variables. The IA is endowed permanently with an ability level A which is a draw from $N(\mu_0, \sigma_a^2)$. Even the IA can not observe A . The value of A reflects his ability in that it indexes the distribution his strategies come from. A strategy the IA develops pays returns which are independent draws from $N(S, \sigma_p^2)$, where S is an unobservable draw from $N(A, \sigma_s^2)$. We give the IA one decision to make after the first period, which is whether to keep his old strategy, which means S stays the same, or abandon the old strategy in favor of a new one, which means drawing a new S from $N(A, \sigma_s^2)$. Equivalently, we can write the fund's first-period return r_1 as a constant μ_0 plus three individually unobservable random variables:

$$r_1 = \mu_0 + \varepsilon_a + \varepsilon_{s,1} + \varepsilon_{p,1} \quad (1)$$

where ε_a , $\varepsilon_{s,1}$ and $\varepsilon_{p,1}$ are independently distributed $N(0, \sigma_a^2)$, $N(0, \sigma_s^2)$ and $N(0, \sigma_p^2)$. After the first period, the manager can keep his strategy for the second period (*i.e.* S stays the same), in which case

$$r_2 = \mu_0 + \varepsilon_a + \varepsilon_{s,1} + \varepsilon_{p,2} \quad (2)$$

where $\varepsilon_{p,2}$ is a new draw from $N(0, \sigma_p^2)$, independent of $\varepsilon_{p,1}$, or he can change strategies, (*i.e.* draw a new S from $N(A, \sigma_s^2)$), in which case

$$r_2 = \mu_0 + \varepsilon_a + \varepsilon_{s,2} + \varepsilon_{p,2} \quad (3)$$

where $\varepsilon_{s,2}$ is a new draw from $N(0, \sigma_s^2)$, independent of $\varepsilon_{s,1}$. So the stochastic part of r_t contains one element ε_a which always persists to the next period, another element $\varepsilon_{p,1}$ which never persists, and a third element $\varepsilon_{s,1}$ which persists if and only if the IA wants it to persist.

B. Some comments on modeling choices

The two-investor setup greatly simplifies the computations without materially affecting the results. A model with one investor for both periods would behave about the same, since the IA's incentives to keep or abandon would stay the same, but the mathematics of the investor's initial allocation would be complicated enormously by the (nonlinear) relationship between the first-period return and the second-period investment opportunity set.

We also simplify the IA's choice between strategies at time-1 by letting him choose his allocation between the fund's return and the riskless asset. If his exposure to the fund were constrained to equal the management fee (as it is elsewhere in the literature), his choice would interact with his wealth level, which in turn interacts with the first-period return. This would complicate our discussion of the relationship between current and past returns without affecting the basic result that bad strategies are replaced.

Instead, this assumption causes the manager to make the same strategy choices as he would if he were investing just his own money in the fund. Because the manager can buy or sell the fund on personal account, a fee of δ at the end of the period is equivalent to a fee of δ at the start. Thus, once the investor has decided how much to invest with the fund, the dollar value today of the manager's fee is known (for any δ) and his current wealth is determined. Since the manager has exponential utility, he wants the strategy that maximizes $(\mu - r_f)/\sigma$. Consequently, the management fee is not crucial to the model; all our arguments go through with any δ , including $\delta=0$.

We constrain the IA to a mutually exclusive choice between the old strategy and a new one. In particular, we do not, for the reasons discussed above, allow a negative weight on the

first-period strategy in the second period. We also rule out convex combinations of the old strategy and a new strategy, but this restriction is not important to the results. If the manager could use a convex combination he would still put zero weight in the second period on strategies which did badly enough in the first, causing fund flow to be less sensitive to performance below that point.

We have a fund-specific ability term (ϵ_a) in addition to a strategy-specific term (ϵ_s) to capture the idea that a component of fund performance cannot be altered simply by changing strategy. This may reflect a fund's inability to completely turn over its management team, to completely turn over its set of strategies or to completely change its algorithm for hiring managers. Stickiness on any one of these dimensions leads to a fund-specific ability term. The presence of a fund-specific ability term whose value is unknown means that the time-1 fund return can convey some information about the time-2 fund return, even when the fund decides to change strategy. Consequently, its inclusion makes the sensitivity of fund flow to the time-1 fund return more positive. However, the asymmetry of fund flow to time-1 fund return occurs irrespective of the presence of the fund-specific ability term. Instead, the kink in the relation between fund flow and time-1 fund return is caused by the strategy-specific term and the fund's capacity to change strategy. Thus, with respect to fund flow as a function of time-1 fund return, the precision of the fund-specific ability term determines the average slope, while the precision of the strategy-specific term determines the severity of the kink. These results are derived and discussed in Section III below.

C. Derivation of fund flows

The flow of funds studied by Ippolito (1992) and others corresponds in this model to the difference between Investor 1's initial allocation to the fund at the beginning of the second period and Investor 0's terminal position at the end of the first, and the flow-response relationship corresponds to the dependence of this difference on r_I . To explore this dependence we need to characterize three decisions: 1) Investor 0's initial allocation at time-0, 2) the IA's choice between keeping and abandoning the first-period strategy, and 3) Investor 1's allocation at time-1, which takes into account the IA's incentives to keep or abandon.

D. Investor 0's allocation

Before fees, the fund's first-period return r_I is distributed $N(\mu_0, \sigma_a^2 + \sigma_s^2 + \sigma_p^2)$. However, the investor pays a management fee δ , making his net return $(1-\delta)(1+r_I)-1$, so from his perspective the fund's return is distributed $N((1-\delta)\mu_0 - \delta, (1-\delta)^2(\sigma_a^2 + \sigma_s^2 + \sigma_p^2))$. A well-known implication of the utility function $-e^{-aW}$ is that it drives an investor allocating between a riskless asset paying r_F and a risky asset with returns distributed $N(\mu, \sigma^2)$ to allocate $(\mu - r_F)/(\alpha\sigma^2)$ to the risky asset. Thus, it is straightforward that Investor 0's allocation I_0 is

$$I_0 = \frac{(1-\delta)\mu_0 - \delta}{\alpha(1-\delta)^2(\sigma_a^2 + \sigma_s^2 + \sigma_p^2)} \quad (4)$$

and the terminal value of this allocation at time-1 is $(1-\delta)(1+r_I)I_0$.

E. IA's decision to keep or abandon

As discussed above, the IA prefers the strategy which maximizes $(\mu - r_F)/\sigma$, known as the Sharpe ratio, so his decision reduces to calculating the Sharpe ratios from switching and from

holding, and choosing the strategy associated with the larger Sharpe ratio. The IA's choice is therefore between the return r_S from replacing the old strategy, which follows

$$r_S \sim N \left(\mu_0 + \left(\frac{\sigma_a^2}{\sigma_a^2 + \sigma_s^2 + \sigma_p^2} \right) (r_1 - \mu_0), \left(\frac{\sigma_s^2 + \sigma_p^2}{\sigma_a^2 + \sigma_s^2 + \sigma_p^2} \right) (\sigma_a^2 + \sigma_s^2 + \sigma_p^2) \right) \quad (5)$$

and the return r_K from keeping the old strategy, which follows

$$r_K \sim N \left(\mu_0 + \left(\frac{\sigma_a^2 + \sigma_s^2}{\sigma_a^2 + \sigma_s^2 + \sigma_p^2} \right) (r_1 - \mu_0), \left(\frac{\sigma_p^2}{\sigma_a^2 + \sigma_s^2 + \sigma_p^2} \right) (\sigma_a^2 + \sigma_s^2) + \sigma_p^2 \right) \quad (6)$$

These conditional distributions differ in two important ways. First, variance is higher for r_S than for r_K , reflecting the uncertainty added by replacing a strategy we know something about with one we know nothing about. In either distribution, variance does not depend on r_I . Secondly, the expected return is linear and increasing in r_I in both distributions, but the slope is steeper for r_K . So there is a number R^* such that r_K has a higher Sharpe ratio than r_S if and only if $r_I > R^*$. The IA and Investor 1 both know that the IA keeps his first-period strategy for the second period if and only if $r_I > R^*$. Appendix A contains an expression for R^* .

F. Investor 1's allocation

Investor 1 simply backs out the μ and σ^2 of the net second-period return from r_I and, like Investor 0, allocates $(\mu - r_F)/(\alpha\sigma^2)$ to the fund. We label this allocation $I_I(r_I)$ and Appendix A presents an expression for $I_I(r_I)$. As expected, investment always increases with the past return, but at a faster rate if the past return exceeds the R^* threshold. The next section puts these results together to address the issue of fund flows.

III. Discussion

A. Fund flows as a function of time-1 fund return

The object of interest in this section is the net fund flows at time-1 as a function of r_1 , $F(r_1)$, which satisfies:

$$F(r_1) = I_1(r_1) - I_0 (1-\delta) (1+r_1). \quad (7)$$

In words, $F(r_1)$ equals Investor 1's initial investment minus the terminal value of Investor 0's investment, net of fees. We are interested in comparing the slope of the function when $r_1 > R^*$ to the slope when $r_1 < R^*$ and are able to obtain the following result:⁵

Proposition 1: For any time-1 fund returns $a < R^*$ and $b > R^*$, the difference in the slopes of the function $F(\cdot)$ at the two returns b and a is positive if $\sigma_s^2 > 0$, and 0 otherwise. Moreover, the magnitude of the kink $[F'(b) - F'(a)]$ is increasing in σ_s^2 .

So long as the strategy-specific component has a positive variance ($\sigma_s^2 > 0$), fund flow as a function of time-1 return has a kink at R^* . Thus, it is the existence of an uncertain strategy-specific portion of the return together with the manager's capacity to change strategies that makes fund flows convex in past returns. When time-1 fund return is low, the manager is inclined to switch strategies, which decreases the predictive power of past fund return for future fund return. In contrast, a high time-1 fund return prompts the manager to retain the same strategy which gives the past fund return predictive power for future fund returns. Moreover, when the uncertainty about the strategy-specific component is higher, time-1 return conditional on no switching (i.e., being above R^*) has greater predictive ability for future fund return, which is why the kink is larger.

We are also interested in the effect of uncertainty about fund-specific ability on the flow-past return relation which can be summarized by the following proposition:

Proposition 2: Setting the uncertainty associated with fund-specific ability to zero ($\sigma_a^2 = 0$) does not eliminate the kink in the flow-past return relation. Instead, the slope of the function $F'(\cdot)$ is increasing in σ_a^2 , both above and below the kink.

Thus, the presence of an uncertain fund-specific return component is not driving the kink in the flow-past return relation. Rather, uncertainty about fund-specific ability increases the slope of fund flow, both above and below the kink. The intuition for this result is that greater uncertainty about fund-specific ability makes past fund return more informative about future fund return, irrespective of whether the manager switches strategy or not.

This result offers an explanation for Chevalier and Ellison's (1997) finding that the fund flows of relatively older funds are less responsive to recent returns. We have just shown that the response of new investment to recent returns is lower everywhere when uncertainty about fund-specific ability, as indexed by σ_a^2 , is relatively low. This uncertainty declines over time for a given fund as more returns are realized, which implies that this uncertainty is lower for older than younger funds. Thus, the result implies that fund flow should be less responsive to recent fund returns for older than newer funds, just as Chevalier and Ellison report.

Finally, increased uncertainty about the period-specific component of fund return can be expected to reduce the slope of flow as a function of past return. Indeed, some algebra (not reproduced) confirms that $F'(r_1)$ decreases as σ_p^2 increases for any r_1 . The intuition is as follows: the information in r_1 about r_2 is smaller when the period-specific portion of the return is larger, so Investor 1 is less responsive to the time-1 return.

B. A numerical example

A sample vector of parameters illustrates how the model can generate an asymmetric flow-past return relation like we see in the data. Suppose the IA and investors get utility $-e^{-(0.0001)W}$ from consuming W , the management fee δ is one percent, the unconditional mean μ_0 of managed portfolios is eight percent, and $(\sigma_a^2, \sigma_s^2, \sigma_p^2) = (0.005, 0.02, 0.025)$. This economy follows the fund-flow relationship of Figure 4, which shows much higher sensitivity to past returns above $R^* = 5.49$ percent than below. When investors account for the IA's motive and opportunity to keep or abandon his old strategy, the result is a flow-response relationship like the one we actually observe. The vertical jog at R^* is not visible in the flow data averaged across funds, but this would be a natural consequence of R^* varying across funds.

The role of the strategy-specific component is apparent in Figure 5, which shows the effect on the fund-flow relationship from moving σ_s^2 up from 0.02 to 0.03 and then 0.04. Convexity increases as the slope on the below- R^* side flattens and the slope on the above- R^* side steepens.

IV. Extending the Model to Allow for Multiple Funds

The model developed above can be generalized to an economy with arbitrarily many funds. Suppose Investor 0 and Investor 1 have access to N actively-managed funds, the risk-free rate and a market-index futures contract. Let the return on fund i in period t be given by:

$$R_t^i = \beta_t^i R_t^M + r_t^i \quad (8)$$

where r_t^i is defined as in (1) for $t=1$ and as in (2) or (3) for $t=2$, β_t^i is a known constant, and R_t^M is the market-index return. Thus, r_t^i is the fund-specific component of fund i 's return in period t .

All return components are multivariate normal with $\rho[R^M_t, r^i_t]=0$ for all i and $\rho[r^i_t, r^j_t]=0$ for all $i \neq j$. Investors can allocate any positive amount to any fund, borrow or lend at the risk-free rate, and buy or sell the index futures. Each IA can go short or long in the risk-free rate, his fund's return and the futures. All IAs and both investors get utility $-e^{-\alpha W}$ ($\alpha > 0$) from consuming wealth W .

Fund i 's IA charges the investor a fraction δ^i of the end-of-period assets under management less the dollar return from the market-wide component over the period. This is a variety of the benchmark-adjusted fees that have become popular (see, e.g., Admati and Pfleiderer (1997)): a fraction δ^i of the start-of-period assets under management plus the same fraction δ^i of any dollar performance in excess of a benchmark, where the benchmark is the market-wide return component. Letting I^i_t be the investor's allocation to fund i at the end of period t , we see that fund i 's fee for period t is $I^i_{t-1} \delta^i (1 + r^i_t)$.

The futures contract allows the investors to target their market exposures separately from their fund allocations, so their effective opportunity set is the risk-free rate plus $N+1$ independent returns: N fund-specific returns, and that of the market. Similarly, the IA of fund i , because his fee income is linear in his fund-specific return, can choose any linear combination of the risk-free rate and two independent returns, r^i_t and R^M_t . Since the IA's fee is net of the market-wide dollar return component, it follows that the values taken by the β^i_t do not affect the IA's strategy-adoption decision nor the investor's allocations to the N funds.

Thus, without loss of generality, we set β^i_t equal to zero for all i and all t . Note, with this simplification, it is easy to see that a fund's IA continues to make the same strategy adoption decision as in Section II. Turning to the investor's allocation decision, recall that an

exponential-utility investor with access to a riskless asset paying r_F and $N+1$ uncorrelated assets each distributed $N[\mu^i, (\sigma^i)^2]$ allocates $(\mu^i - r_F)/(\alpha(\sigma^i)^2)$ to each risky asset i , where α is the investor's risk aversion. Consequently, Investor 0 and Investor 1 make the same dollar allocation to each fund i as they made to the single fund in Section II. Thus, Section II's analysis of the relation between the single fund's first-period performance and its fund flow at the end of the first period holds for each fund in the extended model.

Note that a badly-performing fund in the first period cannot invest in the second period in a fund that performed well. The badly-performing fund's only choices are to keep the first period strategy or switch. This assumption is consistent with restrictions on managers in the U.S. mutual fund industry. On the other hand, the investors are allowed to invest any positive amount in each of the N funds. Consistent with intuition, Investor 1 (who invests in period 2) allocates more to a fund that performed well in the first period than to a fund that performed poorly. However, Investor 1 chooses to invest positive amounts in badly performing funds because there are diversification benefits from holding these funds.⁶ In particular, because badly performing managers switch strategies, the positive relation between fund flow and performance is flatter for bad performance than good performance (see Section II and III for details). Thus, the model developed in Section II is robust to the existence of multiple funds.

One final point is worth making. In the current model, the fund managers are precluded from indexing. However, a straight-forward extension could make this an option available to the manager. In such a model, a manager would index in the second period if his return in the first is sufficiently bad to make the index more attractive than a draw from the manager's distribution of

strategies. Importantly, the model would still imply an asymmetric flow response to performance.

V. Empirical Evidence

This section presents empirical tests of the theory. As noted, the existing empirical literature is generally consistent with the predictions, in that net new investment is convex in past performance, as is future performance, the very worst funds excepted. But the predictions are more specific than this, and with the help of some proxies they become rejectable hypotheses.

The theory predicts that funds replace poor-performing strategies, and that this reduces the sensitivities of fund flow and expected future performance to differences between poor performances. That is, the sensitivities are lower among poor performers specifically because the strategies of these funds are replaced. So to the extent that replacement is observable and frictions keep a group of poor performers from replacing, the theory predicts greater sensitivities in this group than in the group of poor performers who replace. Strategy replacement is not directly observable so to test this prediction we calculate proxies, and then compare the sensitivities among those poor performers that replace (according to the proxy) to the sensitivities among those that do not.

We have three proxies for strategy replacement. One is manager replacement. Both Khorana (1996) and Chevalier and Ellison (1999) argue that managerial turnover following poor performance reflects firing or demotion, and therefore an intention of the investment advisor to change the distribution of fund returns. Managers also sometimes leave after good performance,

but this is more likely to reflect promotion or other career improvement (or retirement), and not an intention to change the distribution of fund returns. So managerial turnover should reduce the sensitivities of fund flow and future performance to past performance among poor performers. Managerial turnover could reduce sensitivities among good performers, depending on how instrumental the departing managers were to the strategies.

The other two proxies are based on loading change. By one of these proxies, a fund replaces strategy if the change in its regression coefficients on the four factors of Carhart (1997) is relatively large. By the other proxy, the likelihood of a strategy change is increasing in the magnitude of the loading change. The rationale for these proxies is that a fund's expected loading change is larger if it changes strategy than if it does not.⁷ The finding of Chan, Chen and Lakonishok (2002) that funds change style (e.g. large-cap, high book-to-market) after poor performance is consistent with this view. The benefit of these proxies, relative to manager replacement, is that they can detect strategy replacements of all types, not just those involving managerial turnover. The cost is that regression-coefficient changes are noisy estimates of factor-loading changes, whereas managerial turnover is observed with little or no error. Moreover, these proxies should again reduce sensitivity to past performance primarily among poor performers, as large loading change after good performance is more likely due to something other than strategy replacement.

The test design assumes some incidence of poor performers not replacing which is reasonable for three reasons. First, the model does not dictate the evaluation schedule, i.e., the first and last dates of the first period. We use the standard one-calendar-year schedule but funds could take more or less time, and could start on other days, so some funds who perform badly on

our schedule will not immediately replace even if funds always replace immediately on their own schedules. Second, the performance cutoff that triggers replacement depends on parameters that would vary across funds, so when our cross-sectional regressions impose the same cutoff on all funds, some performances are bound to be in the wrong bin. That is, some performances we take to be poor are actually good relative to the cutoffs implied by their fund-specific parameters. Finally, strategy replacement may be costly. So, for all these reasons, there should be some incidence of measured poor performance not followed in short order by strategy replacement, providing the contrast necessary for our tests.

A. Data

The database combines daily returns from Micropal, annual fund data from CRSP and factor returns. The Micropal data run from 1985 through 1995, with 2435 funds as of the terminal date 12/31/1995. Disappearing funds are included until their disappearance dates, except for some of the funds that disappeared before 1991. Micropal divides the funds into six categories: Aggressive Growth (AG), Growth and Income (GI), Income (IN), International (IE), Long-Term Capital Gains (LG), and Sector (SF). Since the four factor model of Carhart (1997) is not designed to measure the performance of foreign equities or bonds, we use only the fund categories that hold U.S. equities exclusively. This criterion rules out the IE and IN funds. The SF funds are also omitted because their latitude to change strategies is relatively low. This leaves us with three categories of funds: AG, GI and LG funds. These are the same three categories used by Sirri and Tufano (1998) to study the relation between fund flow and past performance.

We use the standard four factors, all of which are daily returns on zero-investment portfolios (see Busse (1999) for details): 1) VW CRSP index minus the risk-free rate (RMRF); 2) small-cap minus big cap (SMB); 3) high book-to-market minus low book-to-market (HML); and, 4) recent (six-month) winners minus losers (MOM). To calculate excess returns we use the daily risk-free return, also from Busse (1999).⁸ From the CRSP mutual-fund database we take the variable MGR_DATE, which comes from the annual snapshot of fund information assembled by ICDI, and later Micropal, and is available annually for the four year period from 1992 through 1995.⁹ We also take $TNA_{i,y}$ and $r_{i,y}$, the total net assets at the end of year y and the total return for year y , respectively, for fund i .

For year y of fund i we calculate several statistics. If there are at least 20 daily returns then we regress excess returns, i.e., the daily returns minus the daily risk-free rate, on the four factors and save the intercept and coefficients as $\alpha_{i,y}$, $b_{RMRF,i,y}$, $b_{SMB,i,y}$, $b_{HML,i,y}$ and $b_{MOM,i,y}$. $R\alpha_{i,y}$ is $\alpha_{i,y}$ minus the average $\alpha_{i,y}$ of the funds of i 's type (AG, GI or LG) in year y . If we have $TNA_{i,y}$, $TNA_{i,y-1}$ and $r_{i,y}$ then dollar flow is $DFL_{i,y} = TNA_{i,y} - (1+r_{i,y})TNA_{i,y-1}$.

We use two loading change proxies. The first is the average absolute change in fund i 's factor loadings from year $y-1$ to year $y+1$, i.e. $LDEL_{i,y} = (1/4)\sum |b_{f,i,y+1} - b_{f,i,y-1}|$ for $f=RMRF, SMB, HML$ and MOM . The second loading-change proxy $QLCH_{i,y}$ is "1" if $LDEL_{i,y}$ is in the top quartile of the $LDEL_{i,y}$ for funds of the same type as fund i in year y , and is "0" otherwise.¹⁰ The manager-change proxy for fund i 's strategy change, $QMCH_{i,y}$ is "1" if the most recent manager change date recorded on CRSP for year $y+1$ occurred either sometime during year y (if no month is given) or between July of year y and June of year $y+1$; and $QMCH_{i,y}$ is "0" if the most recent manager change date lies outside these ranges. A $QMCH_{i,y}$ value of "1" is changed to "0" if: a)

year y is the commencement year for the fund as recorded on CRSP; b) the most recent manager change date recorded on CRSP for year $y+1$ occurred sometime during year y ; and, c) the first fund return on CRSP is not for a month prior to the most recent manager change date.

B. Empirical results

Each table contains the empirical results for one strategy-change proxy. The *LDEL* results are in Table I, the *QLCH* results are in Table II, and the *QMCH* results are in Table III. The first empirical question is whether the proxies show more evidence of strategy replacement after poor, as opposed to good, performance. We use two definitions of poor performance, negative and bottom-quartile performance, applied to two performance measures, the four-factor alpha α and the group-adjusted four-factor alpha $R\alpha$. For each proxy, the results are in Panel A of the relevant table.

Overall, the results for the two proxies based on loading change are consistent with the literature and the theory. Chan, Chen and Lakonishok (2002) find increased style migration following poor performance. Using *LDEL* to measure loading change, we find higher average absolute loading changes for all definitions of poor performance except negative α , and we always find a greater incidence of large loading changes for poor performers. However, when using *LDEL* to measure loading change, funds with the most extreme measured performance are likely to be those with the largest measurement error in performance and *LDEL*. Consistent with this effect, Panel A of Table I documents a u-shaped pattern in average *LDEL* across the performance quartiles. Moreover, since only one third of funds are positive- α , this effect can

also explain why average *LDEL* is significantly lower (3.7 percent one-tail) for negative- α than positive- α funds.

In an attempt to correct for this effect, we also use an estimate of average loading change, *LCOR*, that deflates absolute regression-loading changes by estimates of their standard errors.¹¹ While use of *LCOR* reduces sorting based on measurement error, it also reduces one's ability to sort on the basis of true changes in loadings. Despite this disadvantage of using *LCOR*, we still find that loading change is significantly higher for the bottom performance quartile, irrespective of performance measure, and for the negative $R\alpha$ funds.

Turning to the manager change results, Panel A of Table III documents a significantly higher incidence of managerial turnover after worse performance, for both definitions of poor performance and both performance measures. Again this result is consistent with earlier literature (see Khorana, 1996). To summarize, these Panel A results all bear out the prediction that the investment advisors of poor performers exercise the option to replace strategy.

Does strategy replacement have the predicted effect on fund flows? Theory predicts that it lowers the sensitivity to differences between poor past performances. This is testable in a regression model that allows different slopes for good and poor performances, interacted with the proxies for replacement. That is, we fit the regression model

$$DFL_{i,y+1} = b_0 + b_1 proxy_{i,y} + b_2 (perf_{i,y})^+ + b_3 (proxy_{i,y})(perf_{i,y})^+ + b_4 (perf_{i,y})^- + b_5 (proxy_{i,y})(perf_{i,y})^- + \epsilon_{i,y+1}$$

where $(x)^+$ is x for $x > 0$ and 0 otherwise, $(x)^-$ is x for $x < 0$ and 0 otherwise, *perf* is either α or $R\alpha$, and *proxy* is either *LDEL*, *QLCH* or *QMCH*.¹² The prediction is that $(proxy_{i,y})(perf_{i,y})^-$ enters negatively. Panel B of Table I reports the results using *LDEL* as the strategy-change proxy.

Consistent with the theory, we find that the sensitivity of flow to poor performance is

significantly lower when *LDEL* is higher, for both definitions of poor performance.¹³ Panel B of Tables II and III reports the results for the dummy proxies which also bear out the theory. In three of the four cases, the sensitivity of flow to differences between poor performances is significantly reduced when the proxies indicate replacement. Thus, strategy replacement, as captured by manager and loading change, reduces the significance to new investment of how poor a poor performance was.

The predictions for the relation between future and past performance are analogous, so we can test them with the same regression framework. We have two alternative performance measures, so we fit the model

$$perf_{i,y+1} = b_0 + b_1 proxy_{i,y} + b_2(perf_{i,y})^+ + b_3(proxy_{i,y})(perf_{i,y})^+ + b_4(perf_{i,y})^- + b_5(proxy_{i,y})(perf_{i,y})^- + \varepsilon_{i,y+1}$$

first with $perf = \alpha$ on both sides of the equation, and then with $perf = R\alpha$ on both sides, and test the prediction that $(proxy_{i,y})(perf_{i,y})^-$ enters negatively. Results are in Panel B of Tables I (*LDEL*), II (*QLCH*) and III (*QMCH*) and provide additional support for the theory. As predicted, the interactions come in significantly negative for $(perf)^-$ after manager change, with either performance measure. However, the regressions do not pick up a significant effect using either loading change proxy. Significance is not as consistent as in the fund-flow tests, which is not surprising given that fund flows are observed directly and expected performance is observed only with substantial noise.

By embedding the optionality of persistence into the money-management problem, we predict not only much of the previously documented patterns in fund flows and performance persistence, but also additional dynamics along the new dimension of strategy replacement.

Replacement should weaken the link between poor performance and subsequent performance and investment, and these new results are evidence that it does.

VI. Conclusion

Previous research shows that open-end funds with better performance tend to perform better in the future, and tend to attract more new investment. It is natural, as Gruber (1996) argues, that the first pattern causes most or all of the second, but why is the new investment relationship convex? What could investors be thinking, and for what reason? We make two points. First, the relationship between past and future performance of all but the worst funds also appears to be convex. But more importantly, we show that convexity follows directly from the strategic environment of investment advisors. We propose that some money management strategies are better than others, and that the information about a strategy is the returns it pays. Given the widespread restrictions on short-selling, it follows that investment advisors replace strategies with bad past performance, so that future performance and net new investment are relatively insensitive to past returns below some threshold.

In our model, returns that are sufficiently bad will always induce replacement. This is sufficient, but not necessary for the results about convexity. For example, agency problems within the fund family could impose a probability that managers or algorithms are not replaced when they should be. As long as investors view persistence as very likely after returns that are good enough and very unlikely after returns that aren't, the rational fund-flow response is convex. This is also consistent with the evidence in Chevalier and Ellison (1999) that bad performers that change managers suffer less outflow than those that retain; outsiders know when

the investment advisor *should* replace the manager, but they don't count on it until it actually happens.

This paper relates to a growing literature on the connection between fund flows and future performance. Gruber (1996) and Zheng (1999) confirm what the fund-flow and persistence literatures suggest, that investors bias their allocations toward tomorrow's winners. We make the additional point that fund flows capture useful information that a linear extrapolation of past returns would miss.

Appendix A: Mathematical Expressions and Proofs

Expression for R^* :

Some algebra shows that

$$R^* = \mu_0 \left[\frac{\sigma_p^2 \sqrt{(\sigma_s^2 + \sigma_p^2)(2\sigma_a^2 + \sigma_s^2 + \sigma_p^2)} - (\sigma_s^2 + \sigma_p^2) \sqrt{\sigma_p^2(2\sigma_a^2 + 2\sigma_s^2 + \sigma_p^2)}}{\sigma_a^2 \sqrt{\sigma_p^2(2\sigma_a^2 + 2\sigma_s^2 + \sigma_p^2)} - (\sigma_a^2 + \sigma_s^2) \sqrt{(\sigma_s^2 + \sigma_p^2)(2\sigma_a^2 + \sigma_s^2 + \sigma_p^2)}} \right] \quad (9)$$

Expression for $I_1(r_1)$:

The allocation $I_1(r_1)$ is given by

$$I_1(r_1) = \frac{\sigma_a^2 r_1 + (\sigma_s^2 + \sigma_p^2) \mu_0 - (\sigma_a^2 + \sigma_s^2 + \sigma_p^2) \left(\frac{\delta}{1-\delta} \right)}{\alpha(1-\delta)(\sigma_s^2 + \sigma_p^2)(2\sigma_a^2 + \sigma_s^2 + \sigma_p^2)} \quad (10)$$

for $r_1 < R^*$; that given for $r_1 > R^*$ is

$$I_1(r_1) = \frac{(\sigma_a^2 + \sigma_s^2) r_1 + \sigma_p^2 \mu_0 - (\sigma_a^2 + \sigma_s^2 + \sigma_p^2) \left(\frac{\delta}{1-\delta} \right)}{\alpha(1-\delta) \sigma_p^2 (2\sigma_a^2 + 2\sigma_s^2 + \sigma_p^2)}. \quad (11)$$

Proof of Proposition 1:

From the equations above, the slope of the function $F(\cdot)$ is given by

$$F'(r_1) = \left(\frac{1}{\alpha(1-\delta)} \right) \frac{\sigma_a^2}{(\sigma_s^2 + \sigma_p^2)(2\sigma_a^2 + \sigma_s^2 + \sigma_p^2)} - \left(\frac{(1-\delta)\mu_0 - \delta}{\alpha(1-\delta)} \right) \frac{1}{\sigma_a^2 + \sigma_s^2 + \sigma_p^2} \quad (12)$$

for $r_1 < R^*$, and

$$F'(r_1) = \left(\frac{1}{\alpha(1-\delta)} \right) \frac{\sigma_a^2 + \sigma_s^2}{\sigma_p^2(2\sigma_a^2 + 2\sigma_s^2 + \sigma_p^2)} - \left(\frac{(1-\delta)\mu_0 - \delta}{\alpha(1-\delta)} \right) \frac{1}{\sigma_a^2 + \sigma_s^2 + \sigma_p^2} \quad (13)$$

for $r_1 > R^*$. For any time-1 fund returns $a < R^*$ and $b > R^*$, the difference in the slopes of the function at the two returns b and a is given by:

$$F'(b) - F'(a) = \frac{\sigma_s^2}{\alpha(1-\delta)} \left(\frac{(\sigma_a^2 + \sigma_s^2)(2\sigma_a^2 + \sigma_s^2 + 2\sigma_p^2) + \sigma_p^2 \sigma_p^2}{(\sigma_s^2 + \sigma_p^2)(2\sigma_a^2 + \sigma_s^2 + \sigma_p^2)\sigma_p^2(2\sigma_a^2 + 2\sigma_s^2 + \sigma_p^2)} \right) \quad (14)$$

Notice that the difference is zero if and only if σ_s^2 equals zero. Otherwise, the difference is positive.

To prove the second part of the proposition, note that the derivative of the slope differential with respect to the variance σ_s^2 is positive:

$$\frac{d [F'(b) - F'(a)]}{d\sigma_s^2} = \frac{1}{\alpha(1-\delta)} \left(\frac{1}{(2\sigma_a^2 + 2\sigma_s^2 + \sigma_p^2)^2} + \frac{2\sigma_a^2(\sigma_a^2 + \sigma_s^2 + \sigma_p^2)}{(\sigma_s^2 + \sigma_p^2)^2(2\sigma_a^2 + \sigma_s^2 + \sigma_p^2)^2} \right) \quad (15)$$

for any $a < R^*$ and any $b > R^*$.

Proof of Proposition 2:

The first part of the proposition can be seen by noting that (14) is still positive when $\sigma_a^2 = 0$, so long as the uncertainty about the strategy-specific component remains non-zero ($\sigma_s^2 > 0$).

The second part can be seen by differentiating (12) and (13) with respect to σ_a^2 :

$$\frac{dF'(r_1)}{d\sigma_a^2} = \frac{1}{\alpha(1-\delta)(2\sigma_a^2 + \sigma_s^2 + \sigma_p^2)^2} + \frac{(1-\delta)\mu_0 - \delta}{\alpha(1-\delta)(\sigma_a^2 + \sigma_s^2 + \sigma_p^2)^2} \quad (16)$$

for $r_1 < R^*$, and

$$\frac{dF'(r_1)}{d\sigma_a^2} = \frac{1}{\alpha(1-\delta)(2\sigma_a^2 + 2\sigma_s^2 + \sigma_p^2)^2} + \frac{(1-\delta)\mu_0 - \delta}{\alpha(1-\delta)(\sigma_a^2 + \sigma_s^2 + \sigma_p^2)^2} \quad (17)$$

for $r_1 > R^*$. Since we are assuming that $(1-\delta)\mu_0 - \delta > 0$, equations 16 and 17 are both positive.

Appendix B: Test of an Alternate Hypothesis

A straightforward way to check whether our results reflect managers moving toward factor portfolios after bad performance is to examine average loading change as a function of performance. Table B.I contains the results, with Panel A examining loading change as a function of performance and Panel B attempting to control for category-wide shifts in loading by measuring loading as the deviation from the category average. For each panel, averaging is performed over a number of different sets of factors: all four factors; all but the RMRF factor; and, each factor individually. Under the alternative hypothesis, fund managers exploit the fact that Jensen's alpha can be inflated by increasing the fund's loadings on factors with a positive risk price other than the market. This explains why we examine loading change averaged over all but the market factor. Loading changes are also reported for each factor separately to identify which factors (if any) the fund managers load up on after bad performance.

The alternative hypothesis relies on expected returns being positive for the three factors other than the market. Empirical work using sample periods going back in time much further than ours have found that all three have positive average returns. During our sample period, the SMB, HML and MOM zero-investment portfolios earned average (annualized) returns of five, -2.5 and 425 basis points respectively. Thus, it appears that only the momentum effect works over our sample period. However, managers learning of the Fama and French (1992, 1993) results would expect both SMB and HML to have positive mean returns.

The results in Table B.I provide very little support for the alternative hypothesis described in this subsection. The first row of Panel A averages loading changes over all four factors and shows that the average loading change is significantly negative over the sample

period. The second row reports that the average loading change becomes insignificantly negative when the loading on the market is excluded. Moreover, irrespective of whether the change in market Beta is included, average loading change does not vary from the lowest performance quartile to the other three.

We now turn to the results for the individual loading changes which are contained in the last four rows of each panel. The last column of Panel A shows that only the SMB loading has increased over the sample period, though not significantly, while both the market Beta and the momentum loading have actually decreased significantly over the period. Comparing the loading change for the bottom performance quartile to the average for the other three, both panels indicate that funds increase their MOM loading and decrease their HML loading after poor performance, relative to average and good performers. However, with respect to the MOM result, it appears to be driven by good performers decreasing their MOM loadings, rather than by bad performers increasing theirs. Finally, neither market Beta nor SMB loading is systematically affected by fund performance.

Taken as a whole, the evidence in Table B.I provides little support for the alternative hypothesis that managers are learning about size, book-to-market and momentum effects over the period and inflating their loadings, particularly after bad performance, to earn high CAPM abnormal returns.

References

- Admati, Anat R., and Paul Pfleiderer, 1997, Does it all add up? Benchmarks and the compensation of active portfolio managers, *Journal of Business* 70, 323-350.
- Brandstrader, J.R., 1992, Better (in the) red than dead. *Barron's*, October 26, M14-M15.
- Brown, Stephen J., and William N. Goetzmann, 1995, Performance persistence, *Journal of Finance* 50, 679-698.
- Brown, Keith C., W.V. Harlow, and Laura T. Starks, 1996, Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry, *Journal of Finance* 51, 85-110.
- Busse, Jeffrey, 1999, Volatility timing in mutual funds: Evidence from daily returns, *Review of Financial Studies* 12, 1009-1041.
- Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.
- Carhart, Mark M., J. N. Carpenter, A.W. Lynch, and David K. Musto, 2002, Mutual fund survivorship, forthcoming, *The Review of Financial Studies*.
- Carpenter, Jennifer N., and Anthony W. Lynch, 1999, Survivorship bias and attrition effects in measures of performance persistence, *Journal of Financial Economics* 54, 337-374.
- Chan, Louis K. C., Hsiu-Lang Chen, and Josef Lakonishok, 2002, On mutual fund investment styles, forthcoming, *The Review of Financial Studies*.
- Chevalier, Judith, and Glen Ellison, 1997, Risk-taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167-1200.
- Chevalier, Judith, and Glen Ellison, 1999, Career concerns of mutual fund managers, *Quarterly Journal of Economics* 114, 389-432.
- Christoffersen, Susan K., and David K. Musto, 2002, Demand curves and the pricing of money management, forthcoming, *The Review of Financial Studies*.
- Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 1996, Survivorship bias and mutual fund performance, *The Review of Financial Studies* 9, 1097-1120.
- Fama, Eugene F. and Ken R. French, 1992. The cross-section of expected stock returns. *Journal of Finance* 47, 427-465.

Fama, Eugene F. and Ken R. French, 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.

Goetzmann, William N., and Nadav Peles, 1996, Cognitive dissonance and mutual fund investors, *Journal of Financial Research* 20, 145-158.

Gruber, Martin J., 1996, Another puzzle: the growth in actively managed mutual funds, *Journal of Finance* 51, 783-810.

Heinkel, Robert, and Neal M. Stoughton, 1994, The dynamics of portfolio management contracts, *The Review of Financial Studies* 7, 351-388.

Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser, 1993, Hot hands in mutual funds: short-run persistence of relative performance, 1974-1988, *Journal of Finance* 48, 93-130.

Ippolito, Richard A., 1992, Consumer reaction to measures of poor quality: evidence from the mutual fund industry, *Journal of Law and Economics* 35, 45-70.

Khorana, Ajay, 1996, Top management turnover: An empirical investigation of mutual fund managers, *Journal of Financial Economics* 40, 403-426.

Musto, David K., 1999, Investment decisions depend on portfolio disclosures, *Journal of Finance* 54, 935-952.

Rukeyser, William S., 1996, Bird brain outperforms Steadman, *CNN* (2:41 PM ET, 9/28/96).

Sawaya, Zina, 1992, Losers, weepers. *Forbes*, August 17, 131.

Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589-1622.

Zheng, Lu, 1999, Is money smart? A study of mutual fund investors' fund selection ability, *Journal of Finance* 54, 901-933.

Footnotes

- 1.They also sorted on one-, two- and eight-quarter returns. The four-quarter results are most appropriate here since that is the period studied in the fund-flow literature.
- 2.Market index minus Tbill, small stocks minus large stocks, high “growth” minus high “value,” and long-maturity bonds minus Tbill. These are his results for three-year formation and holding periods; he also reports one-year results, which are somewhat noisier.
- 3.Though the investment advisor could have trouble retaining managers with extremely good performance, like Peter Lynch.
- 4.Also, funds which disappear due to merger or death tend to have bad performance just prior to disappearance (Elton, Gruber and Blake (1996)). Brown and Goetzmann (1995), Carpenter and Lynch (1999) and Carhart, Carpenter, Lynch and Musto (2002)).
- 5.Both propositions are proved in Appendix A.
- 6.The diversification benefit from holding multiple funds follows from the assumption that the fund-specific return components are uncorrelated across funds. However, the same qualitative results are obtained if those components are correlated, so long as the correlation is less than perfect.
- 7.A fund does not have to think about a strategy change explicitly in terms of changing factor loadings for loading change to be a useful proxy for strategy change. Rather, it is enough that a strategy change (however implemented) results in larger loading changes on average than not changing strategy at all. Moreover, loading change does not need to be perfectly correlated with strategy change to be a useful proxy. This is important since certain types of strategies, by definition, do cause loading changes. For example, a strategy in which the manager tries to identify periods when the expected returns on the factors are high. For our purposes, it is enough

that larger absolute loading changes by a fund increases the likelihood that the fund has changed strategy.

8. We are grateful to Jeff Busse for providing this data.

9. The snapshot is taken some time early in the year following the year it describes. The date of the most recent manager change could have been in this following year, in which case it could have been reported in that snapshot. We see examples of this in the data. We also see a few occasions when *MGR_DATE* goes down, i.e. its value in a later snapshot is actually earlier. This presumably reflects a change in ICDI's (later Micropal's) opinion as to when the current manager took control.

10. We measure loading change from $y-1$, rather than from y , because the estimation errors in year- y loadings are related to the estimation errors in year- y performance, as they are estimated in the same regression. Inserting a year between the estimates also avoids confusion with window-dressing effects, because while year $y-1$'s loser funds are more likely to distort their portfolios at the end of $y-1$ (Musto (1999)), this distortion is unlikely to persist through y all the way to $y+1$.

11. *LCOR* is defined to be *LDEL* but with each component loading change deflated by an estimate of its standard error, which is based on standard errors from the four-factor OLS regressions.

12. While Sirri and Tufano (1998) estimate piecewise flow-performance regressions that allow the slopes to vary by performance quintile, we have much less data and thus only allow for one kink at zero performance.

13. Note that the measurement error associated with *LDEL* as an estimate of true loading change is unlikely to be related to next year's *DFL* and so it's likely to downward bias the magnitudes of

the interaction coefficients. This downward bias makes it harder to obtain results that support our model.

Table I
Loading-Change Results

For y from 1985 to 1995 for each fund i in the Micropal universe, daily fund returns are regressed on the simultaneous returns of the Carhart (1997) four factors for each year from $y-1$ to $y+1$ with at least 20 daily fund returns. The fitted coefficients are an intercept $\alpha_{i,t}$ and estimated factor loadings $b_{RMRF,i,t}$, $b_{SMB,i,t}$, $b_{HML,i,t}$ and $b_{MOM,i,t}$ for $t = y-1, y$, and $y+1$. The initial sample of 6243 fund observations i,y are those with loadings data for years $y-1, y$ and $y+1$. $R\alpha_{i,t}$ is $\alpha_{i,t}$ minus the average $\alpha_{i,t}$ of the funds of i 's type (Aggressive Growth, Growth and Income, and Long-Term Capital Gains) in the Micropal universe with a usable loading observation in year t . $LDEL_{i,y}$ is the average absolute change of fund i 's factor loadings from $y-1$ to $y+1$ while $LCOR_{i,y}$ is $LDEL_{i,y}$ scaled by an estimate of its standard error. The fund flow variable used is $DFL_{i,t} \equiv (TNA_{i,t} - TNA_{i,t-1}(1+r_{i,y}))$ where $TNA_{i,t}$ is the total net assets of fund i at the end of year t , and $r_{i,t}$ is the total return of fund i in year t . Any fund observation i,y without a value for $DFL_{i,y+1}$ is omitted: 283 observations are omitted for this reason, leaving 5960 observations.

Panel A reports average $LDEL_{i,y}$ and $LCOR_{i,y}$ among the funds with the indicated performance. The Quartiles p-value column reports p-values for a t-test of a higher average for the bottom than top three performance quartiles while the Sign Groups p-value column reports p-values for a t-test of a higher average for the <0 than the >0 performance groups. Panel B reports results for regressions of year- $(y+1)$ flow or year- $(y+1)$ performance on year- y performance, allowing for a kink in the regression line at zero year- y performance. $LDEL_{i,y}$ is included as an independent variable and is allowed to interact both with negative and positive year- y performance. T-statistics based on White standard errors are below, in italics.

Panel A: Average $LDEL_{i,y}$ for subsamples formed on year- y performance (in %)

<i>perf</i>	All	Quartiles					Sign Groups			
		Bottom	3rd	2nd	Top	Top 3	p-val	<0	>0	p-val
$R\alpha$	0.177	0.204	0.169	0.154	0.183	0.169	<i><0.001</i>	0.183	0.171	<i>0.003</i>
α		0.205	0.163	0.150	0.191	0.169	<i><0.001</i>	0.175	0.183	<i>0.963</i>
Average $LCOR_{i,y}$ for subsamples formed on year-y performance (in %)										
<i>perf</i>	All	Quartiles					Sign Groups			
		Bottom	3rd	2nd	Top	Top 3	p-val	<0	>0	p-val
$R\alpha$	1.841	1.931	1.825	1.809	1.812	1.814	<i>0.001</i>	1.874	1.804	<i>0.005</i>
α		1.894	1.847	1.758	1.866	1.824	<i>0.016</i>	1.834	1.854	<i>0.742</i>

Panel B: Regressions of year- $(y+1)$ flow or year- $(y+1)$ performance on year- y performance

$$Y_{i,y+1} = b_0 + b_1 LDEL_{i,y} + b_2 (perf_{i,y})^+ + b_3 (LDEL_{i,y})(perf_{i,y})^+ + b_4 (perf_{i,y})^- + b_5 (LDEL_{i,y})(perf_{i,y})^- + \varepsilon_{i,y+1}$$

where $(\cdot)^+ \equiv \max(0, \cdot)$ and $(\cdot)^- \equiv \min(0, \cdot)$.

<i>Y</i>	<i>perf</i>	b_0	b_1	b_2	b_3	b_4	b_5
<i>DFL</i>	$R\alpha$	34.49	-21.70	2779	-1551	1328	-1799
		<i>5.03</i>	<i>-0.93</i>	<i>5.38</i>	<i>-0.93</i>	<i>6.80</i>	<i>-3.20</i>
	α	54.66	-35.92	1185	279	1488	-1905
		<i>7.24</i>	<i>-1.56</i>	<i>2.37</i>	<i>0.19</i>	<i>6.86</i>	<i>-3.31</i>
<i>perf</i>	$R\alpha$	-0.00	-0.005	0.107	-0.246	0.270	0.192
		<i>-0.29</i>	<i>-1.12</i>	<i>1.76</i>	<i>-0.97</i>	<i>5.22</i>	<i>0.92</i>
	α	-0.01	-0.007	0.113	-0.216	0.323	0.107
		<i>-8.66</i>	<i>-1.63</i>	<i>1.41</i>	<i>-0.66</i>	<i>7.42</i>	<i>0.57</i>

Table II
Loading-Change Dummy Results

For y from 1985 to 1995 for each fund i in the Micropal universe, daily fund returns are regressed on the simultaneous returns of the Carhart (1997) four factors for each year from $y-1$ to $y+1$ with at least 20 daily fund returns. The fitted coefficients are an intercept $\alpha_{i,t}$ and estimated factor loadings $b_{RMRF,i,t}$, $b_{SMB,i,t}$, $b_{HML,i,t}$ and $b_{MOM,i,t}$ for $t = y-1, y$, and $y+1$. The initial sample of 6243 fund observations i,y are those with loadings data for years $y-1, y$ and $y+1$. $R\alpha_{i,t}$ is $\alpha_{i,t}$ minus the average $\alpha_{i,t}$ of the funds of i 's type (Aggressive Growth, Growth and Income, and Long-Term Capital Gains) in the Micropal universe with a usable loading observation in year t . $LDEL_{i,y}$ is the average absolute change of fund i 's factor loadings from $y-1$ to $y+1$. The fund flow variable used is $DFL_{i,y+1} = (TNA_{i,t} - TNA_{i,t-1}(1+r_{i,yt}))$ where $TNA_{i,t}$ is the total net assets of fund i at the end of year t , and $r_{i,t}$ is the total return of fund i in year t . Any fund observation i,y without a value for $DFL_{i,y+1}$ is omitted: 283 observations are omitted for this reason, leaving 5960 observations. $QLCH_{i,y}$ is "1" if $LDEL_{i,y}$ is in the top $LDEL$ -quartile in year y for the funds in i 's category included in the sample, and "0" otherwise.

Panel A reports the incidence of $QLCH_{i,y}=1$ among the funds with the indicated performance. The Quartiles p-value column reports p-values for a χ^2 tests of equal proportions across the bottom and top three performance quartiles while the Sign Groups p-value column reports p-values for a χ^2 tests of equal proportions across the <0 and >0 performance groups. Panel B reports results for regressions of year-($y+1$) flow or year-($y+1$) performance on year- y performance, allowing for a kink in the regression line at zero year- y performance. The $QLCH_{i,y}$ dummy is used in the regressions to estimate two separate regression lines, one for funds with $QLCH_{i,y} = 1$ and another for funds with $QLCH_{i,y} = 0$. T-statistics based on White standard errors are below, in italics.

Panel A: Proportion of funds with $QLCH_{i,y}=1$ for subsamples formed on year- y performance (in %)

<i>perf</i>	All	Quartiles					Sign Groups			
		Bottom	3rd	2nd	Top	Top 3	p-val	<0	>0	p-val
$R\alpha$	25.17	33.75	22.27	18.49	26.51	22.46	<i><0.001</i>	26.53	23.60	<i>0.009</i>
α		27.50	23.55	19.23	30.40	24.42	<i>0.019</i>	25.33	24.85	<i>0.687</i>

Panel B: Regressions of year-($y+1$) flow or year-($y+1$) performance on year- y performance

$$Y_{i,y+1} = b_0 + b_1 QLCH_{i,y} + b_2 (perf_{i,y})^+ + b_3 (QLCH_{i,y})(perf_{i,y})^+ + b_4 (perf_{i,y})^- + b_5 (QLCH_{i,y})(perf_{i,y})^- + \varepsilon_{i,y+1}$$

where $(.)^+ \equiv \max(0,.)$ and $(.)^- \equiv \min(0,.)$.

<i>Y</i>	<i>perf</i>	b_0	b_1	b_2	b_3	b_4	b_5
<i>DFL</i>	$R\alpha$	29.49	6.91	2741	-1023	1136	-470
		<i>5.20</i>	<i>0.63</i>	<i>6.03</i>	<i>1.40</i>	<i>6.94</i>	<i>-2.06</i>
	α	47.42	3.13	1434	-491	1252	-452
		<i>7.66</i>	<i>0.27</i>	<i>3.24</i>	<i>-0.75</i>	<i>7.00</i>	<i>-1.85</i>
<i>perf</i>	$R\alpha$	-0.00	-0.00	0.067	-0.077	0.299	0.051
		<i>-0.86</i>	<i>-1.07</i>	<i>1.55</i>	<i>-0.74</i>	<i>8.06</i>	<i>0.66</i>
	α	-0.01	-0.00	0.069	-0.064	0.358	-0.004
		<i>-12.84</i>	<i>-1.42</i>	<i>1.43</i>	<i>-0.55</i>	<i>11.14</i>	<i>-0.05</i>

Table III
Manager-Change Results

For y from 1991 to 1994 for each fund i in the Micropal universe, daily fund returns are regressed on the simultaneous returns of the Carhart (1997) four factors for each year from y to $y+1$ with at least 20 daily fund returns. The fitted coefficients are an intercept $\alpha_{i,t}$ and estimated factor loadings $b_{RMRF,i,t}$, $b_{SMB,i,t}$, $b_{HML,i,t}$ and $b_{MOM,i,t}$ for $t=y$ and $y+1$. The initial sample of 4663 fund observations i,y are those with loadings data for years y and $y+1$. $R\alpha_{i,t}$ is $\alpha_{i,t}$ minus the average $\alpha_{i,t}$ of the funds of i 's type (Aggressive Growth, Growth and Income, and Long-Term Capital Gains) in the Micropal universe with a usable loading observation in year t . $QMCH_{i,y}$ is "1" if the most recent manager change date recorded on CRSP for year $y+1$ occurred either sometime during year y (if no month is given) or between July of year y and June of year $y+1$; $QMCH_{i,y}$ is "0" if the most recent manager change date lies outside these ranges. A $QMCH_{i,y}$ value of "1" is changed to "0" if: a) year y is the commencement year for the fund as recorded on CRSP; b) the most recent manager change date recorded on CRSP for year $y+1$ occurred sometime during year y ; and, c) the first fund return on CRSP is not for a month prior to the most recent manager change date. The fund flow variable used is $DFL_{i,t} \equiv (TNA_{i,t} - TNA_{i,t-1}(1+r_{i,t}))$ where $TNA_{i,t}$ is the total net assets of fund i at the end of year t , and $r_{i,t}$ is the total return of fund i in year t . Any fund observation i,y without a value for $QMCH_{i,y}$ or $DFL_{i,y+1}$ is omitted: 312 observations were omitted for these reasons, leaving 4351 observations.

Panel A reports the incidence of $QMCH_{i,y}=1$ among the funds with the indicated performance. The Quartiles p-value column reports p-values for a χ^2 tests of equal proportions across the bottom and top three performance quartiles while the Sign Groups p-value column reports p-values for a χ^2 tests of equal proportions across the <0 and >0 performance groups. Panels B reports results for regressions of year-($y+1$) flow or year-($y+1$) performance on year- y performance, allowing for a kink in the regression line at zero year- y performance. The $QMCH_{i,y}$ dummy is used in the regressions to estimate two separate regression lines, one for funds with $QMCH_{i,y} = 1$ and another for funds with $QMCH_{i,y} = 0$. T-statistics based on White standard errors are below, in italics.

Panel A: Proportion of funds with $QMCH_{i,y}=1$ for subsamples formed on year- y performance (in %)

<i>perf</i>	All	Quartiles					Sign Groups			
		Bottom	3rd	2nd	Top	Top 3	p-val	<0	>0	p-val
$R\alpha$	9.08	13.45	10.25	6.91	5.94	7.68	<0.001	10.23	6.17	<0.001
α		11.87	11.63	7.01	5.96	8.18	<0.001	11.94	6.42	<0.001

Panel B: Regressions of year-($y+1$) flow or year-($y+1$) performance on year- y performance

$$Y_{i,y+1} = b_0 + b_1 QMCH_{i,y} + b_2 (perf_{i,y})^+ + b_3 (QMCH_{i,y})(perf_{i,y})^+ + b_4 (perf_{i,y})^- + b_5 (QMCH_{i,y})(perf_{i,y})^- + \varepsilon_{i,y+1}$$

where $(\cdot)^+ \equiv \max(0, \cdot)$ and $(\cdot)^- \equiv \min(0, \cdot)$.

<i>Y</i>	<i>perf</i>	b_0	b_1	b_2	b_3	b_4	b_5
<i>DFL</i>	$R\alpha$	60.56	-22.28	592	-83	969	-451
		10.30	-1.26	3.58	-0.18	4.69	-1.30
	α	74.93	-29.89	343	94	1140	-621
		10.85	-1.72	2.34	0.20	5.62	-1.98
<i>perf</i>	$R\alpha$	-0.00	-0.00	0.043	0.056	0.285	-0.222
		-0.16	-1.97	2.06	0.93	3.99	-2.35
	α	-0.01	-0.00	-0.003	0.108	0.259	-0.197
		-14.61	-2.23	-0.14	1.61	4.98	-2.60

Table B.I
Signed Loading-change Results

For y from 1986 to 1994 for all funds i with data from $y-1$ to $y+1$, daily fund returns are regressed on the simultaneous returns of the Carhart (1997) four factors for each year from $y-1$ to $y+1$. The fitted coefficients are an intercept $\alpha_{i,t}$ and estimated factor loadings $b_{RMRF,i,t}$, $b_{SMB,i,t}$, $b_{HML,i,t}$ and $b_{MOM,i,t}$ for $t = y-1$, y , and $y+1$. $DEL_{F,i,y}$ is the average change of fund i 's factor loadings from $y-1$ to $y+1$ for the set of factors F . Six sets of factors are considered: all four factors (all four); all factors but RMRF (not RMRF); and each factor individually. For $j = 2, 3$, and 4 , $Q_{j,i,y}$ is "1" if $\alpha_{i,y}$ is in the j th quartile in year y for i 's category, and "0" otherwise. Regressions are run for the entire sample and have 6243 observations:

$$DEL_{F,i,y} = \nu_{F,1} + \varphi_{F,2}Q_{2,i,y} + \varphi_{F,3}Q_{3,i,y} + \varphi_{F,4}Q_{4,i,y} + \varepsilon_{F,i,y}$$

For $j = 2, 3$, and 4 , the regression coefficient $\varphi_{F,j}$ measures the difference between the average factor change for performance (α) quartiles j and 1, while the intercept $\nu_{F,1}$ measures the average factor change for the bottom (first) performance quartile. Two hypotheses are tested: average factor change for quartile 1 equals the average factor change across the other three quartiles: $(\varphi_{F,4} + \varphi_{F,3} + \varphi_{F,2})/3 = 0$; and, average factor change across all four quartiles equals zero: $\nu_{F,1} + (\varphi_{F,4} + \varphi_{F,3} + \varphi_{F,2})/4 = 0$. T-statistics based on White standard errors are in bold.

F (set of factors)	$\nu_{F,1}$	$\varphi_{F,2}$	$\varphi_{F,3}$	$\varphi_{F,4}$	$(\varphi_{F,4} + \varphi_{F,3} + \varphi_{F,2})/3$	$\nu_{F,1} + (\varphi_{F,4} + \varphi_{F,3} + \varphi_{F,2})/4$
all four	-0.010	-0.007	0.001	0.005	-0.001	-0.010
	-1.61	-0.91	0.08	0.63	-0.10	-4.18
not RMRF	-0.004	-0.005	-0.000	0.007	0.001	-0.003
	-0.58	-0.62	-0.03	0.91	0.08	-1.26
RMRF	-0.027	-0.012	0.003	-0.003	-0.004	-0.030
	-3.96	-1.40	0.34	-0.37	-0.56	-10.33
SMB	0.011	-0.017	-0.004	0.005	-0.005	0.007
	1.04	-1.32	-0.38	0.40	-0.49	1.65
HML	-0.019	0.005	0.014	0.056	0.025	-0.000
	-2.12	0.44	1.25	4.34	2.46	-0.09
MOM	-0.003	-0.005	-0.010	-0.039	-0.018	-0.016
	-0.34	-0.44	-1.10	-3.79	-2.11	-4.78

Figure 1. Mean future returns net of risk-free rate. HPZ is the first row of Table III, Panel C of that paper, times four; BG is the first row of Table VII, Panel A of that paper; and, Carhart is from the first column of Table III of that paper, times twelve.

Figure 2. Mean future returns net of market risk. HPZ is the sixth row of Table III, Panel C of that paper, times four; BG is the fourth row of Table VII, Panel A of that paper; and, Carhart is from the third column of Table III of that paper, times twelve.

Figure 3. Relationship between past and future monthly four-index alphas. From Gruber (1996); last column of Table II of that paper, times twelve.

Figure 4. Fund flows as a function of past return. Flow/performance relation predicted by the model with $\alpha=0.0001$, $\delta=0.01$, $\mu_0=0.08$, $\sigma_a^2=0.005$, $\sigma_s^2=0.02$ and $\sigma_p^2=0.025$.

Figure 5. Effect of strategy-specific portion on fund-flow response. Flow/performance relation predicted by the model with $\alpha=0.0001$, $\delta=0.01$, $\mu_0=0.08$, $\sigma_a^2=0.005$, $\sigma_p^2=0.025$, and the three indicated values for σ_s^2 .









