JOOP HUIJ

New Insights into Mutual Funds

Performance and Family Strategies

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New Insights into Mutual Funds: Performance and Family Strategies

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van fondsgroepen

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Joop Huij
Rotterdam, maart 2007

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Chapter 1

Introduction

1.1 Mutual funds in a bird's-eye view

With more than 17.8 trillion dollars of assets under management by the end of 2005, the mutual fund industry is perhaps the largest financial industry worldwide.[1] Not surprisingly, numerous studies have been conducted to investigate how mutual funds serve investors' needs. In this dissertation we bundle four empirical studies that provide new insights into the mutual fund industry and mutual fund performance. To pin-point the main contributions of these studies, we first briefly sketch the institutional context of mutual funds, and provide an overview of some important developments in the academic literature.

Mutual funds are registered investment companies that pool capital from investors and collectively invest this capital in stocks, bonds, money market instruments, and other securities. Investors can participate in a mutual fund by purchasing a share that is issued by the fund, or that is traded in the open market. While the enormous growth of the mutual fund industry is only recent, mutual funds have been around for a long time and date back to the second half of the 18^{th} century. As a matter of fact, the first mutual fund *Eendragt Maakt Magt* originated in 1774 in Amsterdam, the Netherlands (*Eendragt Maakt Magt* was the maxim of the Dutch Republic at that time meaning "Unity Creates Strength", see Rouwenhorst (2004)). Although the mutual fund industry has undergone many changes over time, the main motivations for investors to invest through mutual funds remain unchanged. While by the end of 2005 the Investment Company Institute (i.e., the national association of the U.S. investment company industry) stresses the diversification benefits that are provided to investors through investing in mutual funds, the "prospectuses" of the first mutual funds in the 18^{th} century mention these

[1] This number is obtained from the Investment Company Institute (ICI, 2006).

very same benefits.

The rationale behind diversification is to minimize insurable risk to investors: negative returns of some investments in a portfolio can be compensated by the positive returns of others. Theoretically, the highest degree of diversification an investor can reach is obtained by holding a portfolio that includes a share of all tradable assets (i.e., the market portfolio).[2] However, there are several practical problems an individual investor is faced with when trying to hold such an optimally diversified portfolio. First of all, it requires a large investment budget to purchase a sufficiently large number of securities and reach a reasonable degree of diversification. Moreover, investment budgets are typically not divisible in a round lot of securities and individual investors may find it difficult to be fully invested at all times. Another problem is that managing such a portfolio involves significant transaction costs. Because transaction costs typically consist of a fixed and a variable part, the costs are larger for portfolios that hold more different securities. Diversification can therefore be costly to an investor with a limited investment budget and may not outweigh the transaction costs it brings along.

Basically, all problems mentioned here are related to the limited size of the investment budget of individual investors. Because mutual funds pool large amounts of capital, they can offer individual investors diversification at relatively low costs through economies of scale. The paragraph below is from the prospectus of one of the first mutual funds *Voordelig en Voorsigtig* ("Profitable and Prudent") that was organized in 1776 in Utrecht, the Netherlands, and is evidence that the diversification benefits to investors through investing in mutual funds are not a product of this age.

"... It is indisputable that prudent investing requires the manager to spread as much as possible monies over good and solid securities. Because nothing is completely certain but subject to fluctuations, it is dangerous for people to allocate their capital to a single or a small number of securities. Not everyone has the opportunity to invest his money in a variety of securities. ... For the sum of 525 guilders one can participate in this negotiatie. ..., which will be profitable with sufficient certainty. No one has reason to expect that all securities in this negotiatie will cease to pay off at the same time, and the entire capital be lost. If one had reason to fear such a general bankruptcy, one never ought to invest any money." (Rouwenhorst, 2004)

[2]Elton et al. (2003) conduct an international experiment, and demonstrate that 60–90 percent of the risk on an individual stock can be eliminated by holding a random portfolio of stocks within a selection of national markets and among national markets.

Another interesting commonality that is observed when we collate current mutual fund prospectuses with those from the old days is that mutual funds offer investors a service that is often referred to as "professional investment management". Here, professional investment management relates to the ability of fund managers to increase returns to investors by selecting the most profitable securities, and by buying or selling securities at the right time. For example, consider the following quotation from the prospectus of the *Fidelity Magellan Fund* (one of the largest mutual funds at the time writing) which states that the fund will use "fundamental analysis of each issuers financial condition and industry position and market and economic conditions to select investments". Now consider the following quotation from the prospectus of *Concordia Res Parvae Crescunt* (one of the first mutual funds introduced in 1779 in Amsterdam, the Netherlands, see Rouwenhorst (2004)): "the negotiatie would invest in solid securities and those that based on the decline in their price would merit speculation and could be purchased below their intrinsic value, ... of which one has every reason to expect an important benefit". Not unexpectedly, fund managers charge a fee to investors for these services; another feature of mutual funds that has not changed over time.[3]

Even though the benefits of diversification and professional investment management have been acknowledged by investors for a long time, it was only in the early 1960s when the first comprehensive studies were performed to assess how mutual funds actually serve investors' needs by offering them these services. The rise of this stream of literature was stimulated by several breakthroughs in asset pricing theory, the increasing availability of data, and advancements in technology. Below, we briefly describe these developments.

Asset pricing theory tells us that investors require a premium to compensate them for the time they have to wait for the pay-offs of their investments (i.e., the risk-free rate), and a premium for the risk or uncertainty that is involved with these pay-offs (i.e., the risk premium). While it might seem obvious that investors require higher returns on investments that are more risky, academics found it was a non-trivial task to precisely formulate the concept of "risk". In fact, Sharpe (1964) and Lintner (1965) were rewarded with the Nobel prize in Economics for their Capital Asset Pricing Model (CAPM) that

[3]For the reader's information: Rouwenhorst (2004) calculates that *Concordia Res Parvae Crescunt* charged investors a yearly expense ratio of 0.20 percent of assets under management. By comparison, the *Fidelity Magellan Fund* reports a total expense ratio of 0.59 percent in its prospectus, and the average expense ratio charged by U.S. equity funds at the time writing is about 1.5 percent.

provides us a testable framework to describe the risk-return relation.[4] This framework turned out to be successful in explaining the returns of securities both from a theoretical and an empirical point of view.

Basically, the CAPM states that financial markets reward investors only for taking necessary risk, not for unnecessary risk. As we mentioned earlier, investors can substantially reduce investment risk by holding a diversified portfolio. However, some part of the risk is inescapable and cannot be diversified away. This part is often referred to as market risk or systematic risk. The central prediction of the CAPM is that the more a security is exposed to overall market movements, the higher the expected return will be that investors require on the security. A security's exposure to market movements is often referred to as its "market beta", and the CAPM tells us that the relation between a security's market beta and its expected return is linear. The mechanism that causes the risk-return relation to be linear is arbitrage. For example, if a security is expected to yield a return that is lower than its market beta times the expected return on the market portfolio, investors would be better off by investing their money in a combination of the market portfolio and the risk-free rate.[5] (E.g., by doing so, investors are expected to earn a higher return per unit of market risk than what they would earn by investing in the security.) This would make the security an unattractive investment and cause investors to sell the security, thereby lowering its price and increasing its expected return. On the other hand, if a security has an expected return that is too high given its market beta, investors would exploit this "free lunch" and buy the security, thereby increasing its price and lowering its expected return. Consequently, in equilibrium the relation between all securities' market betas and their expected returns are linear.

Within the last few decades, a large body of literature has been dedicated to investigate to what extent the CAPM is able to describe security returns. Whereas several authors report that securities' market betas suffice to describe security returns (see e.g., Fama and MacBeth (1973)), others argue that the CAPM omits important risk factors and report significant anomalies. For example, stocks with a small market capitalization (i.e., small caps), and stocks with a high book-to-market value are found to have returns that are too high given their exposure to market risk (see e.g., Banz (1981) and Fama and French (1992)). Also, de Bondt and Thaler (1985) and Jegadeesh and Titman (1993) report

[4] Other models have been proposed by Merton (1973) and Ross (1976).

[5] Because the risk-free rate and the return on the market portfolio are uncorrelated by definition, investors can achieve any desired level of market beta by investing in a combination of the two assets. This mechanism is often referred to as "leverage".

reversal and momentum effects in stock returns that cannot be explained by the CAPM. As a response to these findings, several models have been proposed in the performance evaluation literature that augment a traditional CAPM specification as in Jensen (1968) with additional risk factors or benchmarks, such as size, value, and momentum (see e.g., Hendricks et al. (1993), Elton et al. (1996), and Carhart (1997)).[6]

While it is beyond the scope of this thesis to provide a detailed literature overview on the development of asset pricing theory, it is of crucial importance to understand the risk-return relation for securities when evaluating the performance of mutual funds: high fund returns are not necessarily evidence of managerial skill. They may well be premiums for the funds' exposures to common risk factors. The developments in the field of asset pricing made it possible to disentangle which part of a fund's return can be attributed to exposures to common risk factors (or could be obtained by following a passive strategy), and which part to the fund manager.

Another important development that stimulated the research on mutual fund performance was the increasing availability of data on mutual funds. In the aftermath of Black Thursday in 1929 when the New York Stock Exchange crashed, the U.S. congress wrote several Acts into federal law to better regulate financial markets and protect investors. Among these Acts was the Investment Company Act of 1940. This Act is regulated by the Securities and Exchange Commission (SEC) and requires investment companies (including mutual funds) to publicly disclose financial information. Commercial information services started to collect these data and set up comprehensive databases that became available to researchers.[7]

Finally, the advancements in technology over the past decades have also been of crucial importance to the research on mutual funds. The rise of computers and media to store large computer-readable files, and new insights in non-parametric methods enabled researchers to perform complex empirical analyses.

[6] It is unclear whether momentum can be attributed to a common risk factor. While Jegadeesh and Titman (1993) argue that momentum is caused by behavioral biases of investors, Harvey and Siddique (2000) demonstrate that momentum is related to systematic skewness. However, irrespective whether momentum represents risk, Carhart (1997) shows that it is important to include a momentum factor when evaluating mutual fund performance.

[7] The largest providers of data on mutual funds are currently the Center for Research in Security Prices (CRSP) and Morningstar.

1.2 Current status of the literature and contributions of this thesis

The central research questions in the literature are typically related to the extent to which mutual funds serve investors' needs by offering them the benefits of diversification and processional investment management.

Most authors acknowledge that mutual funds do a good job in offering investors diversification benefits, see e.g., Jensen (1968). A common approach to investigate the degree of diversification for mutual funds is to split up fund risk into a systematic part (i.e., risk that cannot be diversified away) and a non-systematic part (i.e., risk that can be diversified away). The higher the portion of systematic risk, the higher the degree diversification that is offered to investors, and vice versa. Basically all studies report that the largest part of mutual fund risk is systematic. To give the reader a more material impression about the proportion between systematic and non-systematic risk for mutual funds, we conduct an experiment and compute which part of mutual fund risk is because of systematic risk in a large sample of U.S. equity mutual funds over the period 1963–2003.[8] The results of this exercise indicate that on average 82 percent of the funds' variance is explained by exposures to common risk factors. The bottom quartile of variance explained by common risk factors is 80 percent, and the top quartile is 92 percent. Less than 6 percent of the funds have a higher exposure to non-systematic than systematic risk. Based on these figures one could indeed argue that most mutual funds offer investors a high degree of diversification.

However, when we consider the literature on the value added by professional investment management of mutual funds, empirical evidence does not appear to unambiguously indicate that fund managers are able to systematically increase returns through selecting the most profitable securities, and by buying or selling securities at the right time. In fact, there is evidence that indicates that most fund managers that pursue selection or timing strategies are not able to earn back the fees they charge to investors. The typical approach to investigate this issue is to test for persistence in fund performance. That is, it is investigated whether some funds systematically earn higher risk-adjusted returns than others, including index funds (i.e., passively managed funds whose main objective is to provide investors a high degree of diversification at relatively low costs). While studies

[8] The sample of mutual funds is described in the paper "One the Use of Multi-Factor Models to Evaluate Mutual Fund Performance" of this thesis. Funds with less than 36 consecutive monthly return observations over the entire sample period are excluded from the analyses. As a measure for systematic risk we employ the four factors from Carhart (1997).

by, among others, Hendricks et al. (1993), Goetzman and Ibbotson (1994), Elton et al. (1996), and Gruber (1996) report persistence in the returns of the top performing U.S. equity mutual funds, Carhart (1997) demonstrates that most of this is explained by differences in exposures to common risk-factors, including size, book-to-market, and one-year momentum. Moreover, the author reports that funds' expenses are better predictors of future performance than past performance (i.e., the higher a fund's expenses, the lower its expected return). These findings suggest that there is only little evidence to believe that fund managers are able to systematically increase returns through active stock selection and timing strategies, and that investors are better off by purchasing shares of passively managed index funds.

In the first paper of this thesis, we contribute to this steam of literature by investigating performance persistence for a large sample of diversified U.S. equity mutual funds over short horizons. Our motivation to investigate persistence over short horizons stems from the theoretical work of Berk and Green (2004) who argue that the lack of evidence of persistence in mutual fund performance over longer horizons does not imply that fund managers' selection and timing skills are nonexistent. Moreover, Bollen and Busse (2005) investigate persistence in mutual fund performance using high-frequency daily data and report that there is persistence in risk-adjusted performance over short horizons. We investigate three issues regarding this phenomenon. First, do we also observe this predictability in a large sample of funds over a more extensive (and recent) time period? Second, is the persistence effect economically significant? And third, does persistence vary across the cross-section of mutual funds? To investigate these issues, we employ a large sample of monthly fund returns in combination with a Bayesian estimation method to cope with short ranking periods.

Our results clearly support the idea that past performance of mutual funds has predictive power for future performance. When funds are ranked on their performance over the past 36 or 12 months, the top deciles subsequently outperform the bottom deciles across all subsamples and using alternative ex post performance measures. More interestingly, using our Bayesian estimation method we are able to capture short-run persistence in abnormal performance as documented by Bollen and Busse (2005) using monthly data for a much larger and more recent sample of US equity funds. When traditional frequentist approaches are used to estimate fund performance, the findings are only a weak indication of such a relation. Further, given the large cross-section of available funds and the limited demands imposed by our Bayesian procedure, we are able to investigate the persistence effect across different subsamples of funds. Accordingly, we investigate whether the superior performance of the top decile is canceled out by load fees. When we focus on the subsample of no-load funds, the persistence pattern is even stronger than for the entire sample. Apparently, the top deciles' superior performance is not reduced by load fees that are involved with a strategy of chasing winners. In addition, we form subgroups of different types of funds, and investigate whether the persistence effect is related to investment style. Indeed we find that persistence varies across styles, and manifests itself most strongly among relatively young, small cap/growth funds.

In the second paper, we investigate persistence in performance for mutual funds that invest in bonds. Despite the enormous size of the market for actively managed bond funds, surprisingly little is known about whether active portfolio management contributes to bond investment returns. Since research on bond funds is scarce and not well developed, this paper fills several gaps in the literature. First, to our knowledge, our study is the first to analyze the full universe of more than 3,500 bond funds in the CRSP survivorship-bias free mutual fund database over the period 1990–2003. This large sample helps us to overcome the small-sample problems that plague earlier studies on bond fund performance. Second, earlier bond fund studies use only a subset of all common approaches that were originally developed in research on equity funds to test for persistence. We show that these and other methods produce a consistent story regarding performance persistence of bond funds. In doing so, we provide new insights into long-running debates on the benefits of actively managed funds vis-à-vis passive portfolios. Previous studies suggest that bond index funds are a superior alternative compared to actively managed funds, once we take expenses into account. In contrast to earlier studies, we offer strong evidence of a "hot hands" phenomenon in the bond fund market that translates into strategies that yield both economically and statistically significant excess returns.

In the third paper, we contribute to the extant literature by testing the cross-sectional explanatory power of multi-factor models to explain mutual fund returns and the consequences for evaluating mutual fund performance.[9] The multi-factor models whose empirical performance is under investigation in this study are the Fama and French (1993, 1995, 1996) three-factor model, and the Carhart (1997) four-factor model. Our main motivation is that we are concerned that performance estimates resulting from these models suffer from systematic biases. The proxies that are used with factor model approaches are based on

[9]This paper also contributes to the stream of literature on the implications of benchmark misspecification for performance evaluation, e.g., Roll (1978), Lehman and Modest (1987), Grinblatt and Titman (1994), and Coles et al. (2006).

hypothetical stock portfolios. Because these proxies do not incorporate transaction costs and trading restrictions, the predicted factor premiums are likely to be over- or underestimated. Accordingly, resulting performance estimates for funds with significant exposure to these factors may be biased. While miscalculation of the factor premiums is a general concern (i.e., even if fund returns were fully described by a single-factor model, overestimation of the premium on this factor will cause performance estimates to be biased), the resulting biases are more important for multi-factor approaches.

Our results indicate that the factor premiums are indeed miscalculated, and that this miscalculation induces serious biases in performance estimates for mutual funds. More specifically, we find that funds with a value oriented style earn a premium that is smaller than projected by the commonly employed value factor, while the return differential between past winners and losers is larger than projected by the momentum proxy. As a result, the use of three- or four-factor alphas leads to systematically too pessimistic performance estimates for value funds compared to growth funds, and, similarly, performance estimates for past winner funds tend to be overestimated. We propose an alternative that does not suffer from these biases where the factors are constructed using mutual fund returns net of expenses rather than hypothetical stock returns. Resulting alphas from this model do not exhibit systematic patterns and appear to provide unbiased estimates of a fund manager's performance.

Finally, we add to the literature on how mutual fund families anticipate investor behavior to maximize cash flows into their funds. Most authors report that investors chase past winners, and that raw fund returns are important determinants of investors' cash flows to funds (see e.g., Gruber (1996), Sirri and Tufano (1998), Chevalier and Ellison (1999), and Del Guercio and Tkac (2002)). It seems that mutual fund companies are well aware of this, and anticipate investor behavior to maximize assets under management by pursuing certain strategies. For example, Brown et al. (1996) and Brown et al. (2001) report that fund managers strategically alter the risk of their portfolios to increase the change to be among the "winners". Other strategies that have been documented include marketing and distribution activities (see e.g., Sirri and Tufano (1998), Jain and Wu (2000), and Barber et al. (2005)), and organization into family complexes (see e.g., Sirri and Tufano (1998), Goetzmann and Ibbotson (1993), and Nanda et al. (2004)). Nanda et al. (2004) argue that the latter strategy is built upon the observation that cash flows are not only affected by the funds' own performance, but also by the performance of other funds in the family. The authors show that stellar performance of a fund generates substantial spillovers in the sense that cash inflows to other funds in the family are above and beyond what one would expect given the funds' own performance.

In the fourth paper, we investigate the impact of fund marketing on investor flows to other funds in the family. For example, do high-marketing funds generate spillovers, and enhance cash inflows to low-marketing funds in the family? We find that small and young low-marketing funds that are operated by a family with high marketing expenses have substantially larger inflows after positive returns than otherwise similar funds that are operated by a family with low marketing expenses. These results indicate that high-marketing families provide favorable conditions to incubate new funds. Given the findings of Khorana and Servaes (2005) that families that start more funds have higher market share, one might expect high-marketing families to have a considerable competitive advantage over low-marketing families. One interpretation of these results is that the observed spillovers are a by-product of individual fund marketing whereby the entire family is made more visible to investors, and search costs for small and young funds are lowered. A critical assumption underlying this interpretation is that funds' allocated marketing and distribution expenses are directly proportional to the funds' exposure in the media and broker-dealer channels. An alternative explanation of this observation is that funds with low marketing expenses are directly subsidized by family members with high marketing expenses. A family could pay for advertising and distribution activities of a certain fund through expenses allocated to other funds. We develop and perform a set of tests to evaluate the alternative hypotheses. The body of evidence in this paper supports the subsidization hypothesis and suggests that at least a part of the spillovers can be attributed to favoritism towards particular funds. These results suggest that conflicts of interest between investors and fund families have been exacerbated by competition in the mutual fund industry.

To summarize, in the first two papers we investigate performance persistence for both equity and bond mutual funds. In the third paper, we test the cross-sectional explanatory power of multi-factor models to evaluate the performance of equity mutual funds. Finally, in the fourth paper we investigate spillovers of marketing and distribution activities in fund families.

Chapter 2

Cross-Sectional Learning and Short-Run Persistence in Mutual Fund Performance*

2.1 Introduction

Despite the large growth of the mutual fund industry during the last decades, empirical evidence does not appear to unambiguously indicate that some funds managers systematically outperform passive benchmarks. While studies by, among others, Hendricks et al. (1993), Goetzman and Ibbotson (1994), Elton et al. (1996), and Gruber (1996) report persistence in superior performance, Carhart (1997) demonstrates that most of this is explained by differences in exposures to common risk-factors, including size, book-to-market, and one-year momentum. These results do not support the existence of "skilled" managers who are able to outperform passive benchmarks after expenses. Nevertheless, using high frequency daily data Bollen and Busse (2005) find short-term persistence in superior performance beyond momentum. Their results indicate that performance persistence is observable using short measurement horizons. In the present paper, we investigate three issues regarding this phenomenon. First, do we also observe this predictability in a large sample of funds over a more extensive (and recent) time period? Second, is the persistence effect economically significant? And third, does persistence vary across the cross-section of mutual funds? To investigate these issues, we employ a large sample of monthly fund returns in combination with a Bayesian estimation method to measure performance.

The typical approach to investigate persistence in fund performance is to sort funds

*This chapter is forthcoming as Huij and Verbeek (2007) in the *Journal of Banking & Finance*.

into rank portfolios based on a measure of past performance (e.g., three- or four-factor alphas), and evaluate the rank portfolios' subsequent performance. However, particularly when short horizons of monthly returns are used, pre-ranking alphas are hampered by potentially high levels of inaccuracy. With only a small number of observations available, it is notoriously difficult to separate managerial skill from simple luck. Funds that are less well-diversified and have higher levels of non-systematic risk experience a larger probability of ending up with an extreme ranking because the managers of these funds typically place larger bets. Consequently, the top and bottom deciles in performance rankings will to a large extent be attributable to simple luck rather than managerial skill. When subsequent performance of the ranked funds is analyzed, results may be biased towards finding no relation between past and future performance of these funds.

While it seems that the use of longer return histories leads to more accurate inferences when estimating a fund's performance, there are a number of disadvantages. First, fund performance may vary over time, for example relating to a change of fund manager or the age of the fund. Second, the investment style of the fund may change, resulting in time varying exposures to common risk or benchmark factors, see e.g., Ferson and Schadt (1996). Third, longer histories are only available for funds that have been active over an extended period. Focusing upon, e.g., three- or five-year return histories substantially reduces the number of available funds and may lead to several survival-related biases as documented by Brown et al. (1992). Finally, a stream of literature suggests that even though managerial skill is heterogeneous across fund managers, the relation between past performance and subsequent fund flows as documented by Sirri and Tufano (1998) causes performance persistence to fade out quickly (see Berk and Green (2004) and Zhao (2004)).

On the other hand, the use of higher frequency data (e.g., daily returns) is hampered by its limited availability, leading to a substantial reduction in the cross-section of funds or the relevant time span that can be investigated. Consequently, it is useful to consider more accurate ways to estimate performance measures on the basis of short monthly return histories. Recently, several papers have advocated the use of Bayesian alphas to measure fund performance. Using this approach prior information related to funds' expenses, investors' beliefs about managerial skills, benchmark pricing abilities, or the returns on other mutual funds and benchmark factors are incorporated in the resulting estimates (see Baks et al. (2001) and Pastor and Stambaugh (2002b,a)). However, although these approaches allow for more efficient inference, Jones and Shanken (2005) and Busse and Irvine (2006) demonstrate that the predictive accuracy of Bayesian alphas is greatly affected by the investor's prior belief about managerial skill.

In this paper, we consider Bayesian alphas exploiting the entire cross-section of mutual fund returns. This approach does not require investors to explicitly formulate their beliefs about managerial skill, or to make assumptions about cross-sectional characteristics that drive performance. Rather, inference is based upon monthly returns only. As stressed by Jones and Shanken (2005) such an approach can be motivated by cross-sectional learning of investors. In this case, investors' prior beliefs are not independent across funds and an investor's expectation about the performance of a fund is partly a belief about the abilities of mutual fund managers as a group. On the other hand, the use of Bayesian estimators can be motivated purely on the basis of statistical arguments. When the cross-section of alpha estimates is considered, the top and bottom decile are more than average subject to positive and negative estimation errors, respectively, and shrinking them towards the cross-sectional average may result in more accurate inferences.

The main advantage of our approach is that it is based on monthly return data only, which are much more readily available than daily frequency data. Based on the entire CRSP universe of more than 6,400 US equity funds over the past 20 year we find strong evidence that superior performance persists in the near future. When we rank funds on Bayesian alphas over the past 12 months, we find that the top decile of funds earns a statistically significant, superior return of 0.26 percent in the month after ranking. While these results confirm the findings of Bollen and Busse (2005) based on a sample of 230 mutual funds, it has not yet been investigated whether this effect is economically significant. It could be questioned whether superior performance persists beyond the transaction costs that are involved with a strategy of chasing winning funds, or that the effect is canceled out by the load fees that are charged by the majority of funds. Because we are able to study persistence across a large sample of funds, restricting our attention to a specific type leaves us with enough funds in the cross-section. When we only include strictly no-load funds in our sample, we find clear evidence that superior performance persists beyond load fees. Likewise, we are able to focus attention to subsamples of funds characterized by investment style or other characteristics such as age. Our findings indicate that superior performance varies across different types of funds, and is mainly concentrated in relatively young, small cap/growth funds.

The remainder of the paper is organized as follows. In the next section we briefly discuss the literature on Bayesian performance evaluation and learning priors, and introduce our approach. In Section 2.3, we describe our data. Section 2.4 presents the results of an analysis in which we analyze the efficiency of Bayesian alphas. In Section 2.5, we analyze performance persistence of US equity funds at different horizons, using monthly data from the CRSP Database over the period 1984–2003. We perform several robustness tests in Section 2.6. Finally, Section 2.7 concludes and discusses the main findings.

2.2 Mutual fund performance measurement and Bayesian estimation

Mutual fund performance is often measured by a fund's alpha, defined as the intercept term in a regression of the fund's excess returns on the excess returns of one or more benchmark factors. Denoting excess returns of benchmark factor j in period t by x_{jt}, consider the following linear model

$$r_{it} = \alpha_i + \beta_{1i}x_{1t} + \beta_{2i}x_{2t} + \ldots + \beta_{ki}x_{kt} + \varepsilon_{it}, \tag{2.1}$$

where r_{it} denotes the excess return of fund i in period t, β_{ji} denotes the sensitivity of fund i to factor j ($j = 1, ..., k$), and ε_{it} denotes the residual return. The intercept term α_i measures the expected return of fund i in excess of a factor-mimicking benchmark portfolio. As a result, alpha can be thought of the portion of return that can be attributed to the fund manager. We can write the above model in matrix notation as

$$r_i = X_i\theta_i + \varepsilon_i, \tag{2.2}$$

where r_i denotes a vector of the excess returns of fund i, X_i denotes the matrix of excess returns of the benchmarks factors, including an intercept, θ_i denotes a $k + 1$ vector of unknown parameters, containing alpha and the k factor sensitivities of fund i, and ε_i denotes the vector of the residual returns. The length of the evaluation period is denoted by T_i, which may be different across funds.

Traditionally, the above model is estimated by ordinary least squares (OLS). However, particularly with only a small number of observations available, the measurement error (or sampling error) of alpha estimates may be substantial. For example, consider the case where all true alphas are very close to zero. When a relatively high alpha estimate is reported for a given fund, this is likely to be an overestimate of the fund's true alpha. On the other hand, relatively low alpha estimates are likely to be underestimates of their true values. In the extreme case where there is no ability and all alphas are equal to zero, a large positive or negative alpha estimate is solely due to luck rather than managerial skill.

While OLS provides (under appropriate conditions) unbiased or asymptotically unbiased estimators for the underlying true alphas, it does not perform very well in reproducing the cross-section of true fund alphas. To obtain alpha estimates that more closely resemble the true underlying distribution of managerial skills, it is advisable to shrink, in some way, the raw alpha estimates towards zero, or some other value for the (long-run) cross-sectional average. Shrinking individual estimates towards a common mean has been advocated in the 1970s for the estimation of security market betas of individual stocks, see Blume (1971) and Vasicek (1973). Currently, commercial information services like Bloomberg and Merrill Lynch provide simple routines to compute adjusted betas based upon these ideas. More recently, several papers have advocated the use of more advanced shrinkage procedures within a formal Bayesian framework to estimate mutual fund alphas, see, e.g., Baks et al. (2001), Pastor and Stambaugh (2002b,a), Jones and Shanken (2005), and Busse and Irvine (2006). A full Bayesian approach requires the specification of a prior distribution for the parameters of interest, which may be based upon different assumptions about investors' prior beliefs about managerial skill and fund characteristics that drive performance. For example, an investor might incorporate, among other things, the stylized fact that funds with relative high expenses generally underperform those with lower expenses, see e.g., Elton et al. (1993). Intuitively, estimates of alpha are shrunk towards the negative of the funds' expenses conditional on how strongly one beliefs in managerial skill in general.

However, such a set-up assumes that there is a negative and monotonic relationship between funds' alphas and expenses. While empirical analyses indicate that the worst performing funds indeed have substantially higher expenses than the average fund, it does not appear to be the case that the best performing funds have below average expenses (see e.g., Gruber (1996) and Carhart (1997)). In fact, when the worst performing funds are excluded, the relation between funds' expenses and performance seems rather more U-shaped than monotonically decreasing. More generally, the use of Bayesian alphas typically requires the formulation of prior, often subjective, beliefs, which may be inappropriate. While using informative priors may introduce a substantial subjective element in performance evaluation, using less informative priors makes it more difficult to identify the worst and best performing funds. For example, Jones and Shanken (2005) and Busse and Irvine (2006) demonstrate that the accuracy of Bayesian alphas is greatly affected by the prior beliefs that are attributed to the investor.

Another issue with the formulation of subjective priors is the following: Studies by among others Malkiel (1995) and Brown and Goetzmann (1995) suggest that the degree to which managerial skill persists depends upon the time period observed. Consequently, a diffuse belief in managerial skill might dominate a sceptical belief over a certain time period, while it might yield inferior results over a different time period. These market dynamics make it necessary to allow beliefs in managerial skill to be time-varying.

In this study we incorporate the large cross-section of mutual fund alphas in measuring the skill of an individual fund manager. By allowing the prior to learn across other mutual funds, the resulting belief in managerial skill is no longer fully subjective, but entirely data-based. Furthermore, by incorporating cross-sectional information in this way, prior beliefs about alpha are 'adaptive' in the sense that they can vary over time and adjust to market dynamics and structural shifts.

To describe our Bayesian procedure, we start by specifying the cross-sectional distribution of funds' alphas and betas as normal

$$\theta_i \sim N\left(\mu, \Sigma\right), \tag{2.3}$$

where $\theta_i = (\alpha_i, \beta_{1i}, ..., \beta_{ki})'$, μ denotes a $(k+1)$-dimensional vector of cross-sectional means of alphas and factor sensitivities, and Σ denotes a $(k+1)$ by $(k+1)$ covariance matrix. Assuming that the error terms in Eq. (2.2) are $IIN(0, \sigma_i^2)$, the posterior distribution of θ_i is normal with expectation

$$E(\theta_i) = \left(\frac{1}{\sigma_i^2}X_i'X_i + \Sigma^{-1}\right)^{-1}\left(\frac{1}{\sigma_i^2}X_i'X_i\hat{\theta}_i + \Sigma^{-1}\mu\right), \tag{2.4}$$

where $\hat{\theta}_i$ denotes the OLS estimate, and σ_i^2 denotes the variance of ε_i (see for example Maddala et al. (1997)). The corresponding covariance matrix $V(\theta_i)$ is given by

$$V(\theta_i) = \left(\frac{1}{\sigma_i^2}X_i'X_i + \Sigma^{-1}\right)^{-1}. \tag{2.5}$$

Eq. (2.4) shows that the posterior "estimates" of alpha and betas are a matrix-weighted average of the OLS estimates $\hat{\theta}_i$ and the prior μ. We can interpret this equation as a shrinkage formula, which shrinks the raw OLS estimates towards a common mean, where the degree of shrinkage depends on the precision of the OLS estimates and the cross-sectional dispersion reflected in Σ. For example, raw alpha estimates for funds with higher levels of non-systematic risk are shrunk more towards the overall mean than passively managed funds, such as index-trackers, with lower levels of non-systematic risk. Similarly, the degree of shrinkage is higher for funds with short return histories. Note that shrinkage is applied to alphas as well as to the factor sensitivities, which may also be inaccurately estimated on the basis of short time series.

Bayesian alphas (and factor sensitivities) are determined using Eq. (2.4) and require a choice for the hyperparameters μ and Σ. Instead of fixing these parameters at some a priori values, we use the entire cross-section of funds to estimate μ, the cross-sectional mean, and Σ, the cross-sectional covariance matrix. A range of alternative approaches is available to implement this, including maximum likelihood estimation, (iterative) empirical Bayesian approaches, and Gibbs sampling (see Blattberg and George (1991), Casella and George (1992), Maddala et al. (1997), and Stern (2000)). Basically, the (iterative) empirical Bayesian approach initializes the (hyper)parameter with OLS estimates, and then re-estimates the (hyper)parameters until a pre-specified degree of convergence is reached. Using Gibbs sampling, conditional draws are simulated from the posterior distribution to generate a sample of this distribution rather than deriving it analytically. From Markov chain theory it follows that the simulated sample will eventually converge to the true density function of the posterior distribution. Parameter values are then estimated from this simulated sample.

2.3 Data

Consistent with most of the literature, we focus on non-specialized US equity funds. Monthly return data are extracted from the December 2003 CRSP database, which goes back to 1962. Given the results of Elton et al. (2001), who report that the differences in returns reported by CRSP and Morningstar are marginal when data are used after the mid-1980s, we examine the period 1984–2003. To select funds in our data set we follow a procedure similar to the one used by Pastor and Stambaugh (2002b). We use the information that CRSP provides about classifications by Wiesenberger, Micropal/Investment Company Data, Inc., Strategic Insight, and the funds themselves. We exclude funds with unknown objectives, no expense, or load data in the annual summary at the end of each previous year. Additionally, we exclude flexible funds, bond funds, mortgage-backed funds, multi-manager funds, money market funds, balanced funds, funds that invest in precious metals, international funds, and specialized funds. From the remaining funds, we select funds that are classified as small cap/growth, growth, or growth & income. These are the same types of funds that are included in the analyses of Carhart (1997) and Bollen and Busse (2005). In addition, we construct two subsamples of funds by whether or not they charge load fees. Exact details on our selection procedure are provided in the Appendix. Table 2.1 lists the number of available funds over the period 1984–2003. In total, our sample covers 6,429 equity funds that have more than 12 consecutive returns over the whole sample period. Since CRSP includes all funds that existed during this period, our data are free of survivorship bias as documented by Brown et al. (1992). Our subsamples cover 3,101 no-load, 2,134 small cap/growth, 3,349 growth, and 1,837 growth & income funds, respectively.

Throughout this study, fund performance is measured using the four-factor model employed by Carhart (1997):

$$r_{it} = \alpha_i + \beta_{1i} RMRF_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} UMD_t + \varepsilon_{it}, \tag{2.6}$$

where r_{it} is the return of fund i in month t in excess of the one-month Treasury bill rate, $RMRF_t$ is the excess return on the value-weighted aggregate market proxy, SMB_t and HML_t are returns of value-weighted, zero-investment factor-mimicking portfolios for size and book-to-market (Fama and French, 1992, 1993), and UMD_t captures one-year momentum (Jegadeesh and Titman, 1993) in month t, respectively. The intercept α_i is a measure for the performance of fund i, while β_{ji} is the sensitivity of fund i for benchmark factor j. Monthly returns on the benchmark factors are obtained from Kenneth French's webpage, while one-month Treasury bill rates are obtained from Ibbotson and Associates.

2.4 Efficiency of Bayesian alphas

Below we report the results of a simulation study to evaluate the efficiency of Bayesian alphas and compare them to those of standard OLS estimates. Additionally, we compare the implications for fund rankings based on the two alternatives. We use actual data of mutual fund and factor returns to determine the parameter values for the return generating processes. This ensures that data are generated in a realistic way, while the experimental setting allows us to compare estimates with the underlying true values that are used to generate the returns.

First, we estimate the long-run performance for each fund in our sample over the period 1984–2003. To do so, we estimate alpha and the benchmark sensitivities in Eq. (2.6) using standard OLS and the entire return history of each fund. Sample averages of the resulting parameter estimates and benchmark returns are reported in Table 2.2. Consistent with the current literature we find that the average fund underperforms the employed benchmarks with an average alpha of -0.22 percent per month. We use Eq. (2.6) to generate simulated samples of mutual fund returns. The simulated factor returns, fund alphas, and benchmark sensitivities are all drawings from an IID normal distribution with mean and standard deviation corresponding to the empirical estimates reported in Table 2.2. We also experiment with a GARCH(1,1) specification for the benchmark return variances. These results are qualitatively similar to those reported here, and are available upon request. The idiosyncratic returns (ε_{it}) are generated from a serially uncorrelated normal distribution with mean zero and variance σ_i^2. Following Brown et al. (1992), Hendricks et al. (1997), and ter Horst et al. (2001) we allow non-systematic risk to depend upon the fund's market beta β_{1i} as

$$\sigma_i^2 = \omega(1 - \beta_{1i})^2, \tag{2.7}$$

where ω captures the relation between non-systematic risk and market beta. We hereby impose that index funds, with a market beta close to one, typically have low values of non-systematic risk, while actively managed portfolios whose market betas deviate from one are generally less well diversified. In the simulations, we set the value for ω to 0.0050, which closely corresponds to the values reported by Brown et al. (1992) and ter Horst et al. (2001).

Simulated fund returns are generated for measurement horizons of 12, 24, 36 and 60 months. The number of funds in the cross-section is set to 1,000. We then estimate the factor models using standard OLS and our Bayesian estimator. Bayesian alphas are estimated using an empirical Bayes approach. Per simulation we evaluate the accuracy of OLS and Bayesian alphas, as well as their ranking ability. The number of replications for each measurement horizon is set to 1,000. The main question that we address is to what extent Bayesian alphas provide better estimates of (relative) fund performance than standard OLS estimates. An additional point of interest is whether this difference in accuracy remains substantial when more observations are available. Furthermore, to test whether our results are robust to non-normal errors, we run additional simulations where we generate the error terms from Student's t-distribution with 5 degrees of freedom, keeping all parameters at their previous values.

As a measure of accuracy we consider the cross-sectional average of the root mean squared error (RMSE) of both estimators. RMSE is the root of the average squared distance between the estimates and the true value of alpha, and can be interpreted as a standard error. $RMSE$ is computed as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\alpha_i - \hat{\alpha}_i)^2}, \tag{2.8}$$

where N is the number of funds in the cross-section, α_i is fund i's true alpha, and $\hat{\alpha}_i$ its estimate. To investigate the benefit of sorting on Bayesian alphas in the context of persistence analysis, we assign funds to decile portfolios based on their estimated rankings, and compute the average true alpha for the top and bottom deciles. The results of this exercise are reported in Table 2.3. Clearly, the average RMSEs of standard OLS are substantially higher than those of Bayesian alphas. For example, using a measurement horizon of 12 months, the RMSE of OLS is 0.67 percent, while this is 0.38 percent for Bayesian estimation. Hence, for this measurement horizon, Bayesian alphas are about 40 percent more accurate than standard OLS estimates. We find that the advantage of Bayesian estimation remains substantial when up to 60 observations are available. For measurement horizons of 24, 36, and 60 months, Bayesian alphas are about 30 percent, 25 percent, and 20 percent more accurate than standard OLS estimates.

Furthermore, the average true alpha of the top decile is higher for rankings on Bayesian alphas than for rankings on standard OLS alphas. From Table 2.3 it follows that the average true alpha of the top decile based on Bayesian alphas exceeds that of the top decile based on OLS alphas by 0.13 percent for measurement horizons of 12 months. For measurement horizons of 24, 36, and 60 months, these excess returns are 0.08 percent, 0.05 percent, and 0.03 percent, respectively. In a similar fashion, the results for the bottom decile indicate that Bayesian alphas are better in identifying poor performing funds. All differences are highly significant. In fact, the empirical p-values are zero for all simulations. The results of the simulations with t-distributed error terms are consistent with the results of the simulations with normal error terms in the sense that Bayesian alphas have lower RMSEs and produce better fund rankings. In fact, the difference between both estimators becomes larger. While the presence of "fat tails" increases the RMSE of standard OLS by about 30 percent, irrespective of the length of the estimation window, the corresponding increase for Bayesian alphas is only half. In an unreported experiment, we generate the error terms from Student's t-distribution with 3 degrees of freedom, keeping all parameters at their previous values. Compared to the results of the simulation with 5 degrees of freedom, we observe an increase in the difference between both estimators. These results indicate that the advantage of using Bayesian alphas over standard OLS becomes larger when the data are more leptokurtic, e.g., exhibit "fatter tails".

2.5 Empirical results

2.5.1 Methodology

In this section, we employ Bayesian alphas to study short-run persistence in the performance of US equity mutual funds over the period 1984–2003. The typical setup is to rank funds based on a measure of past performance, and analyze the relation between rank and subsequent performance. Hendricks et al. (1993) study relative performance persistence for 165 no-load growth funds over the period 1974–1988 using quarterly returns. In each quarter the authors assign funds to octile portfolios based on funds' raw returns over the past one to eight quarters. Post-ranking alphas are estimated for the stacked time series of equally weighted portfolio returns using several benchmark sets. Their results indicate that fund performance tends to persist in the near future. Using a monthly sample of 188 funds over the period 1977–1993, Elton et al. (1996) rank funds on one- and three-year alphas with respect to several benchmark indices, and demonstrate that when fund rankings are based on risk-adjusted returns, performance persists over holding periods up to three years. However, Carhart (1997) demonstrates that almost all of this persistence is explained by expenses and the one-year momentum effect documented by Jegadeesh and Titman (1993). He replicates the methodology of Hendricks et al. (1993) using a survivorship-bias free data set containing monthly returns of 1,892 funds over the period 1962 to 1993. When post-ranking alphas are estimated using a four-factor model that includes momentum, the spread in alphas between the portfolios disappears. Additionally, portfolios are formed based on four-factor alphas over the previous three-years. While there appears to be some consistency in risk-adjusted rankings, these results are only significant for the lowest ranked funds. More recently, using daily return data on 230 funds over the period 1985–1995, Bollen and Busse (2005) find significant short-term persistence in fund performance beyond momentum when short measurement horizons are used. Every quarter, funds are sorted into decile portfolios based on three-month ranking periods, and the portfolios' performance is evaluated over the subsequent quarter. Using this framework, they find that the top decile earns a statistically significant positive alpha over the subsequent period. When they employ longer measurement horizons, the superior performance disappears. These results suggest that superior performance is a short-lived phenomenon that is only observable using short measurement horizons.

We investigate short-run performance persistence using the entire CRSP universe of mutual funds. For the main tests of our empirical analysis, we form dynamic portfolios of mutual funds based on past performance, and evaluate the portfolios' post-ranking performance. Each month, funds are sorted into rank portfolios on their estimated alphas over the past period with respect to proxies for market, size, value, and momentum. Funds are required to have a complete return history available over the employed ranking period. Pre-ranking alphas are estimated using an empirical Bayes approach. We follow Hendricks et al. (1993) in assigning the funds to deciles based on their rank and calculate the equally weighted returns over the subsequent month for all rank portfolios. Portfolio weights are readjusted if a fund disappears after ranking. Finally, we estimate post-ranking alphas for the stacked time series of portfolio returns using OLS regression with Newey-West standard errors.

2.5.2 Short-run persistence in superior performance

We investigate performance persistence using measurement horizons of 36 and 12 months. We not only build portfolios of funds based on Bayesian alphas, but also on raw returns and standard OLS alphas as in Hendricks et al. (1993) and Carhart (1997). More specifically, portfolios of mutual funds are formed from January 1984 to December 2003, yielding a time series of monthly portfolio returns over a period of 20 years. The analysis is conducted on our entire sample of funds. We start by sorting funds into decile portfolios based on 36-month ranking periods. In the average month, 980 funds are available ranging from 261 funds in 1984 to 2,982 funds in 2003. To measure post-ranking performance, we additionally estimate the portfolios' raw returns and Sharpe ratios. As we discuss in more detail in Section 2.6, using different performance measures over the pre- and post-ranking period is one way to prevent spurious persistence patterns arising due to a misspecification of the performance evaluation model. The results in Table 2.4 indicate a relation between past and future performance over measurement horizons of 36 months. Higher ranked funds seem to earn higher post-ranking returns. However, most of this predictability is explained by differences in the funds' exposures to common risk factors. When we employ the Sharpe ratio to measure post-ranking performance, the findings are only a weak indication of such relation. Further, when we consider the deciles' post-ranking alphas, it appears that all predictability is concentrated in the bottom deciles. Only the worst performing funds earn post-ranking alphas that are significantly different from zero. The top decile of funds earns a post-ranking alpha that is economically and statistically indistinguishable from zero.

Apparently, fund managers are unable to outperform the passive benchmarks over longer periods of time. When we consider the portfolios' sensitivities to the benchmark factors, it appears that higher ranked funds are more exposed towards growth stocks (negative loading on HML), while lower-ranked funds are more exposed to value stocks (positive loading on HML). Further, funds with more extreme rankings are more exposed to SMB. Also, the pattern in R^2-values points out that funds in the more extreme deciles take more non-systematic risk. All in all, our results indicate relative performance persistence at a three-year measurement horizon. However, this effect is mainly concentrated in persistently underperforming funds. The top decile of funds appear to earn back their expenses, while the bottom deciles strongly underperform the market. These results are very similar to those of Carhart (1997), and hold irrespective of which method of estimation is used to rank the funds.

Next, we rerun the analysis with a measurement horizon of 12 months. In the average month, 1,461 funds are available with at least 12 months of return history ranging from 306 funds in 1984 to 4,348 funds in 2003. The results of this analysis, reported in Table 2.5, indicate that short-run performance predicts future performance better than performance estimated over longer measurement horizons. The expected alpha of the top (bottom) decile for rankings based on 12-month measurement horizons is substantially higher (lower) than that of rankings based on 36-month horizons. Furthermore, the relation between past and future performance is close to monotonic. These results hold irrespective of which method of estimating alpha is used. Moreover, Bayesian alphas appear to capture persistent superior performance of the top decile of funds. We find a statistically significant, superior return of 0.26 percent per month for the top decile when funds are ranked on Bayesian alphas. In contrast, sorts on raw returns and standard OLS alphas yield post-ranking alphas that are not or only marginally significant. It should be stressed that in this analysis the different pre-ranking performance measures are only relevant to the extent that they result in a different composition of the top (and bottom) deciles. For example, the funds in the OLS and Bayesian top deciles have an overlap of slightly less than 75 percent. Further, we observe similar patterns for the deciles' sensitivities to the benchmark factors: higher ranked funds are more growth oriented, and funds with extreme rankings are more exposed to the size factor.

2.5.3 Lifespan of persistence and fund age

Bollen and Busse (2005) find that the persistent outperformance of the top decile in their sample lasts over a period of slightly more than a month, while the bottom decile's underperformance declines at a constant rate over time. To investigate this issue in our sample, we rank funds on one-month lagged alpha estimates over the past 12 months, e.g., fund rankings in February 1984 are based on alphas estimated over the period January 1983 to December 1983. Consistent with Bollen and Busse, our results in Table 2.6 indicate that the superior performance of the top decile is only short-lived. While the top decile is still earning a positive alpha of 0.10 percent per month, this value is not significantly different from zero. We also find that the bottom decile's underperformance persists strongly. In fact, in tests not reported, we find that lagged alpha estimates over periods of 5, 11, and even 35 months are predictive for the bottom decile's future underperformance. This finding is consistent with persistent negative abnormal returns driven by funds' extremely high expenses as documented by Carhart (1997).

A potential explanation for the difference between the analyses with measurement horizons of 36 and 12 months is that the results are based on different samples of funds. In particular, the use of a measurement horizon of 36 months excludes relatively young funds from the analysis. This greatly influences the relevant cross-section of funds. By requiring funds to have 36 observations available over the past three years, on average more than one third of the existing funds are eliminated from our sample. When a full return history over the past year is required, less than 5 percent of the funds is left out our analysis. Furthermore, we find that almost 40 percent of the dead funds listed in our sample have been active for less than three years. Ignoring this group of funds might have substantial implications for inferences about the mutual fund industry as a whole, inducing some sort of survivorship bias. To investigate this issue, we conduct the analysis with the measurement horizon of 12 months on the same sample of funds that is used in the 36-month analysis. Likewise, we analyze performance persistence on a sample of only relative young funds (return history of 12 to at most 35 months). In the average month, 977 funds are classified as "old", and 480 funds as "young". The results of this analysis are presented in Table 2.7. When the analysis is conducted on older funds, the top decile of funds earns a statistically significant post-ranking alpha of 0.21 percent per month. When only relatively young funds are included in the analysis, the top decile's post-ranking alpha equals 0.35 percent per month, suggesting that the persistence effect is substantially stronger among for relatively young funds. It also seems that the bottom decile's underperformance is lower for younger funds. Most likely this can be attributed to the fact that a large part of the dead funds is left out of the analysis when a longer return history is required.

2.5.4 Economic significance and persistence across different types of funds

So far, we have demonstrated that the use of Bayesian estimation enables us to capture persistence in superior performance using monthly data. Our results, based on the entire CRSP universe of US equity funds over an extensive time period, complement the evidence provided by Bollen and Busse (2005) on the existence of short-run performance persistence. However, several additional questions are raised by these findings. For example, it is unclear whether the reported persistence is economically significant; a strategy of investing in past winners could involve significant transaction costs. Furthermore, it is not clear what the underlying economic reasons for these findings are. Empirical results on the relation between performance persistence and fund characteristics, such as investment style, may provide an insight into this phenomenon. To answer these questions, we repeat the analysis using particular subsets of funds, e.g., no-load funds. While doing so reduces the available cross-section of funds considerably, thereby exacerbating noise in portfolio returns, the benefit of our Bayesian approach in this context is evident. Because we only require monthly return data, which are much more readily available than daily frequency data, restricting attention to a specific type leaves us with a sufficiently large number of funds in the cross-section.

We first investigate whether superior performance persists beyond the transaction costs that are involved with a strategy of chasing winning funds. Only the 3,101 funds that do not charge load fees are included in the analysis. As before, funds are sorted into decile portfolios based on 12-month alpha estimates, and the rank portfolios post-ranking performance is evaluated. The results are presented in Panel A of Table 2.8, and provide clear evidence that the superior performance of the top decile (0.31 percent per month) persists beyond load fees. Apparently, the top funds' superior performance is not canceled out by load fees that are involved with a strategy of chasing winners. In fact, it even seems that managerial skill plays a more important part in the performance for no-load funds than for otherwise similar funds. To investigate this issue more closely, we also perform the analysis on funds that do charge load fees. Our sample covers 4,025 load funds. The results of this analysis are in Panel B of Table 2.8. With a post-ranking alpha of 0.20 percent per month for load funds versus 0.31 percent per month for no-load funds, our findings add to the evidence that load funds tend to underperform no-load funds (see Morey (2003)).

Second, we analyze persistence across different investment styles. Funds are sorted into deciles on 12-month raw returns, standard OLS alphas, and Bayesian alphas. Table 2.9

lists the top deciles' performance for the different types of funds. The post-ranking alpha of the top decile of small cap/growth funds has a statistically significant value of 0.24 percent per month (using Bayesian estimation). For growth funds and growth & income funds, the top decile's post-ranking alphas have (insignificant) values of 0.20 and 0.08 percent per month, respectively. When funds are ranked on raw returns or OLS alphas, we find only marginal evidence of persistence in superior performance for small cap/growth funds; the type of fund among which this effect manifests itself most strongly.

Interestingly, none of the three style-specific top deciles outperforms the top decile based on the pooled sample of funds. This indicates that the style composition of the top decile in Table 2.5 varies over time and that part of its superior performance can be attributed to style timing, i.e., being in the right investment style at the right time. Since we observe more homogeneity in funds' factor exposures within samples of funds with the same classification, one could expect the prior for alpha to be more precise when this value is based on funds with the same classification than when based on the entire cross-section of funds. Therefore, we perform an analysis where funds' raw alphas are shrunk to the cross-sectional average of similar funds. Using this setup, not only is the value of the prior dependent on the funds' classifications, but also the degrees of shrinkage varies across different types of funds. The results of this analysis are presented in Table 2.10. Compared to the results in Table 2.5 the post-ranking alpha of the top decile increases to 0.28 percent per month, with a t-value of 2.41. Apparently, the benefits from using conditional priors are only marginal.

Up to this point, the empirical results indicate that the Bayesian approach works well in capturing persistence in superior performance of the top decile of mutual funds. Even though the differences are sometimes small, Bayesian alphas are uniformly outperforming raw returns and standard OLS alphas; both in terms of economic and statistical significance. To compare the predictive power of standard OLS and Bayesian alphas formally, we perform a Diebold-Mariano test (Diebold and Mariano, 1995). This test basically involves a comparison of the average forecast error of both estimators, and is the standard approach in the econometric literature to compare forecasts. At the begin of each year during our sample period 1984–2003, we compute the root mean squared error (RMSE) of alpha forecasts over the preceding 12 months using both estimators, relative to the realized values over the subsequent year. Hereby, realized alphas are estimated using standard OLS. While OLS estimates obviously do not correspond to true alphas, they provide an unbiased measure of a fund's ex-post performance. We then consider the two sequences of forecasts errors, and test whether the average difference in RMSE between both estimators is equal to zero. The variance is computed using the Newey-West estimator. The analysis is performed on all subgroups of funds we defined earlier. Table 2.11 lists the results. It appears that the RMSE of Bayesian estimates is substantially (and significantly) lower than that of OLS alphas. When we consider the complete sample of funds, the average RMSE is 1.12 percent per month using OLS alphas, and 0.91 percent per month using Bayesian alphas. These outcomes are consistent and in the same order of magnitude across all subgroups of funds.

2.6 Robustness

2.6.1 Model specification

In this subsection, we report the results of several robustness tests. We first investigate whether our findings of short-run persistence are robust to a potential misspecification of the factor model we employ to evaluate fund performance. Misspecification of the employed factor model can lead to spurious persistence results, since any misspecification is also likely to persist. In particular, we investigate the sensitivity of the found persistence patterns to industry effects. For this purpose, we employ the approach advocated by Pastor and Stambaugh (2002b), and Jones and Shanken (2005) to evaluate post-ranking performance. Using this approach, we employ principal components analysis (PCA) to extract factors that represent returns in specific industries that are not captured by the funds' sensitivities to the common risk factors. More specifically, excess returns on the Fama and French 30 industry portfolios are regressed on a constant and the four Carhart (1997) factors. PCA is conducted on the time series of the residuals of each regression plus the intercept in that regression. Finally, the first three normalized components are taken as weights for the industry portfolios. The monthly return data on the 30 industry portfolios are obtained from Kenneth French's webpage. We augment our base four-factor model with the first three factor-mimicking principal components:

$$r_{it} = \alpha_i + \beta_{1i} RMRF_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} UMD_t + \\ \beta_{5i} IP1_t + \beta_{6i} IP2_t + \beta_{7i} IP3_t + \varepsilon_{it}, \tag{2.9}$$

where $IP1$, $IP2$, and $IP3$ are the three industry factors.

Additionally, we investigate the sensitivity of our results to time-varying exposures to common risk factors. For this purpose we employ the conditional performance measure of

Ferson and Schadt (1996) to evaluate the fund deciles' post-ranking performance. Using this approach, we extend our factor model with interaction terms of the benchmark returns with a set of pre-determined information variables:

$$\begin{aligned} r_{it} = \alpha_i + \beta_{1i}RMRF_t + B'_{1i}[z_{t-1}RMRF_t] + \beta_{2i}SMB_t + B'_{2i}[z_{t-1}SMB_t] + \\ \beta_{3i}HML_t + B'_{3i}[z_{t-1}HML_t] + \beta_{4i}UMD_t + B'_{4i}[z_{t-1}UMD_t] + \varepsilon_{it}, \end{aligned} \tag{2.10}$$

where z_{t-1} denotes a vector holding the lagged values of the information variables, and vector B'_{ji} captures the response of fund i's exposure to benchmark j to this information. Following Ferson and Schadt (1996), we employ the following information variables: (1) the lagged level of the one-month Treasury bill yield, (2) the lagged dividend yield of the S&P500, (3) a lagged measure of the slope of the term structure, and (4) a lagged default spread in the corporate bond market. The dividend yield is defined as the dividend per share as a percentage of the share price over the past 12 months for the index. The term spread is defined as a constant-maturity 10-year Treasury bond yield minus the 3-month Treasury bill yield. And the default spread is defined as Moody's BAA-rated corporate bond yield minus the AAA-rated corporate bond yield. One-month Treasury bill rates are obtained from Ibbotson and Associates, data on the dividend yield on the S&P500 are obtained from Thompson Financial, and the bond yield are obtained from the webpage of the Federal Reserve Bank. The resulting factor model includes 20 scaled factors, and an intercept. We evaluate the deciles post-ranking performance for fund rankings on 12-month raw returns, standard (four-factor) OLS alphas, and (four-factor) Bayesian alphas.

The results of the analyses are in Table 2.12. The differences between the alternative factor models used for evaluation are typically small. Irrespective of the model that is employed, the top decile based on Bayesian alphas over the past 12 months delivers a statistically significant positive alpha of about 0.3 percent per month. These results indicate that our finding of abnormal returns for the top decile is robust to alternative factor models and cannot be explained by the conditional performance measure of Ferson and Schadt (1996). Further, it suggests that the reported performance persistence is unlikely to be caused by misspecification of the factor model.

2.6.2 Persistence tests

An alternative methodology that is used to investigate mutual fund performance persistence are cross-sectional regressions, see e.g., Bollen and Busse (2005). In this section we explore the robustness of our findings with respect to this alternative approach. With the cross-sectional regressions, funds' post-ranking alphas are regressed on performance estimates over the pre-ranking period:

$$\hat{\alpha}_{i,post} = a_t + b_t Perf_{i,pre} + \epsilon_{i,t}, \tag{2.11}$$

where $\hat{\alpha}_{i,post}$ is the post-ranking alpha estimate of fund i, and $Perf_{i,pre}$ is fund i's pre-ranking performance. The funds' post-ranking alphas are estimated using standard OLS over 12-month periods, and the funds' pre-ranking performance is estimated using raw returns, standard OLS alphas, and Bayesian alphas over 36-month and 12-month periods. The cross-sectional regression is estimated for all available funds at the beginning of every year, and the average of the coefficient estimates is taken over the entire sample period from 1984 to 2003. The standard deviations of the cross-sectional regression estimates are used to generate the sampling errors for these estimates (see Fama and MacBeth (1973)). A significant loading on the slope coefficient would be consistent with persistence in relative fund performance.

We perform these regressions for all subsamples of funds. The results of these analyses are reported in Table 2.13. Clearly, performance over the past year is much more informative about future relative performance than performance over the past three years: the slope coefficients are generally higher and more significant for regressions for one-year horizons than three-year horizons. However, note that these tests check the persistence in relative performance and do not necessarily indicate that the winners provide abnormal positive returns. A positive loading on the slope coefficient could therefore be the result of persistent underperformance of a group of funds.

2.7 Conclusion

When evaluating mutual fund performance, it is notoriously difficult to separate managerial skill from simple luck, particularly at short measurement horizons. In this paper, we employ a simple and straightforward empirical Bayes approach, based upon monthly returns, that is able to measure fund performance substantially more efficiently than standard OLS. Using Bayesian alphas, we investigate the persistence in mutual fund performance using the entire sample of US equity funds reported by CRSP over the period 1984–2003.

The results in this paper clearly support the idea that past performance of mutual funds has predictive power for future performance. When funds are ranked on Bayesian four-factor alphas, estimated over horizons of 36 or 12 months, the top deciles subsequently outperform the bottom deciles across all subsamples and using alternative ex post performance measures. More interestingly, we are able to capture short-run persistence in abnormal performance as documented by Bollen and Busse (2005) using monthly data for a much larger and more recent sample of US equity funds. When funds are sorted into decile portfolios based on Bayesian alphas over the previous 12 months, we find a monotonically decreasing spread in post-ranking alphas between the top and bottom deciles, the top decile earning a significant positive abnormal return of 0.26 percent in the first month after ranking. When raw returns or standard OLS alphas rather than Bayesian alphas are used, the findings are only a weak indication of such a relation. The predictive accuracy of OLS alphas is also significantly lower than that of Bayesian alphas.

Given the large cross-section of available funds and the limited demands imposed by our Bayesian procedure, we are able to investigate the persistence effect across different subsamples of funds. Accordingly, we investigate whether the superior performance of the top decile is canceled out by load fees. When we focus on the subsample of no-load funds, the persistence pattern is even stronger than for the entire sample, with a post-ranking alpha of the top decile of 0.31 percent per month. Apparently, the top deciles superior performance is not reduced by load fees that are involved with a strategy of chasing winners. In addition, we form subgroups of different types of funds, and investigate whether the persistence effect is related to investment style. Indeed we find that persistence varies across styles, and manifests itself most strongly among relatively young, small cap/growth funds.

Appendix - Bayesian approaches

This appendix describes the methods that are applied in this study to estimate mutual fund alphas. Consider the following performance model

$$r_i = X_i\theta_i + \varepsilon_i, \tag{2.12}$$

where r_i denotes a T_i by 1 vector of the excess returns of fund i, X_i denotes a T_i by $k+1$ matrix of excess returns of the benchmarks factors, including an intercept, and θ_i denotes a $k+1$ vector of unknown parameters, containing alpha and the k factor sensitivities of fund i. Now assume that

$$\theta_i \sim N\left(\mu, \Sigma\right). \tag{2.13}$$

Under the assumption of i.i.d. normal error terms, the posterior distribution of θ_i is normal with expectation

$$\theta_i^* = E(\theta_i) = \left(\frac{1}{\sigma_i^2}X_i'X_i + \Sigma^{-1}\right)^{-1}\left(\frac{1}{\sigma_i^2}X_i'X_i\hat{\theta}_i + \Sigma^{-1}\mu\right), \tag{2.14}$$

and covariance $V(\theta_i)$ given by

$$V(\theta_i) = \left(\frac{1}{\sigma_i^2}X_i'X_i + \Sigma^{-1}\right)^{-1}. \tag{2.15}$$

In the empirical Bayesian approach (see Casella and George (1992) and Maddala et al. (1997)) the hyperparameters μ, σ_i^2, and Σ, are computed as follows:

$$\mu^* = \frac{1}{N}\sum_{i=1}^{N}\hat{\theta}_i, \tag{2.16}$$

$$\sigma_i^{2*} = \frac{1}{T_i - k}(r_i - X_i\hat{\theta}_i)'(r_i - X_i\hat{\theta}_i), \tag{2.17}$$

and

$$\Sigma^* = \frac{1}{N-1}\sum_{i=1}^{N}\left(\hat{\theta}_i - \frac{1}{N}\sum_{i=1}^{N}\hat{\theta}_i\right)\left(\hat{\theta}_i - \frac{1}{N}\sum_{i=1}^{N}\hat{\theta}_i\right)'. \tag{2.18}$$

Alternatively, an iterative procedure could be employed, where the preceding equations are solved iteratively with the OLS estimate $\hat{\theta}_i$ as initial value. To improve convergence with the iterative procedure, Maddala et al. (1997) advocate to estimate Σ^* as

$$\Sigma^* = \frac{1}{N-1}\left[D + \sum_{i=1}^{N}(\theta_i^* - \mu^*)(\theta_i^* - \mu^*)'\right], \tag{2.19}$$

where D denotes a diagonal matrix with small positive entries (e.g., 0.0001). This procedure is repeated until a prespecified degree of convergence is reached for the parameter estimates.

With Gibbs sampling (see Casella and George (1992) and Stern (2000)), drawings are simulated from the posterior distribution to generate a sample of this distribution rather than deriving it analytically. Parameter values such as the posterior means are then estimated from this simulated sample. For this purpose, the density function of the posterior distribution of the parameters is partitioned such that the resulting conditional densities are easy to simulate from. The conditional distribution of θ_i is simulated from the normal distribution with mean $E(\theta_i)$ given by Eq. (2.14) and covariance matrix $V(\theta_i)$ given by Eq. (2.15). The conditional distribution of μ is simulated from the normal distribution with mean $E(\mu)$ given by

$$E(\mu) = \frac{1}{N}\sum_{i=1}^{N}\theta_i, \tag{2.20}$$

and variance $V(\mu)$ given by

$$V(\mu) = \frac{1}{N}\sum_{i=1}^{N}[\theta_i - E(\mu)][\theta_i - E(\mu)]'. \tag{2.21}$$

The conditional distribution of σ_i is simulated from the χ^2-distribution:

$$\frac{(r_i - X_i\theta_i)'(r_i - X_i\theta_i)}{\sigma_i^2} \sim \chi^2(T_i + 4), \tag{2.22}$$

The conditional distribution of Σ is simulated from the inverted Wishart distribution with parameter matrix S given by

$$S = \sum_{i=1}^{N}(\theta_i - \mu)(\theta_i - \mu)' \tag{2.23}$$

and $k + 1$ degrees of freedom. Draws from these distributions are simulated iteratively, conditional on draws of the previous iteration using $\hat{\theta}_i$ as prior for θ_i. The first set of draws are then dropped for burn-in of the Markov Chain.

While the iterative procedure and Gibbs sampling are generally less sensitive to initialization, we conducted some simulation experiments, the results of which suggest that this advantage is only very marginal for the applications in this study. On the other hand, these approaches require us to make some arbitrary assumptions on the number of iterations, simulations, or the length of the burn-in period. Accordingly, the results presented in this study are based on the empirical Bayesian approach.

2.8 Appendix - Fund selection

To select funds from the 2003 CRSP database we follow a procedure similar to the one used by Pastor and Stambaugh (2002b). We use the information that CRSP provides about classifications by Wiesenberger (OBJ), Micropal/Investment Company Data, Inc. (ICDI OBJ), Strategic Insight (SI OBJ), and the funds themselves (POLICY). We exclude funds with unknown objectives, no expense, turnover, or load data in the annual summary at the end of each previous year. Additionally, we exclude flexible funds, bond funds, mortgage-backed funds, multi-manager funds, money market funds, balanced funds, funds that invest in precious metals, and international funds. Funds with the following classifications are excluded:

OBJ: BAL, BQ, BY, CBD, CGN, CHY, CIM, CSB, CSI, CSM, FLX, GB, GGN, GM, GOV, GPM, GS, GSM, IBD, ICA, IE, IFL, INT, IOH, IPA, MBD, MF, MGN, MHI, MHY, MIS, MMA, MMF, MMI, MNJ, MNY, MOH, MQ, MSS, MT, MTG, MTX, MVA, OI, OTH, SCU, SUT, TFG, TFM, TMM

ICDI OBJ: BL, BQ, BY, GB, GE, GM, GS, IE, MF, MG, MQ, MS, MT, MY, PM

SI OBJ: BAL, BGA, BGC, BGE, BGN, BGS, CGN, CHQ, CHY, CIM, CMQ, CPF, CPR, CSI, CSM, CVR, ECH, ECN, EGG, EGS, EGT, EGX, EID, EIG, EIS, EIT, EJP, ELT ,EPC, EPX, ERP, ESC, FLG, FLX, GBG, GBS, GGN, GIM, GLD, GMA, GMB, GSM, IAZ, ICA, ICO, ICT, IFL, IGA, IHI, IKS, IKY, IMA, IMD, IMI, IMN, IMT, IMX, INC, IND, INJ, INM, INY, IOH, IOR, IPA, ISC, ISD, ITN, ITX, IVA, IVT, IWA, IWV, JPN, LCA, LFL, LKY, LMA, LMD, LMI, LNC, LNY, LTN, LVA, MAL, MAR, MAZ, MCA, MCO, MCT, MDE, MFL, MGA, MGN, MHI, MHY, MIA, MID, MIL, MIM, MIN, MIS, MKS, MKY, MLA, MMA, MMD, MME, MMI, MMN, MMO, MMS, MMT, MNC, MND, MNE, MNH, MNJ, MNM, MNY, MOH, MOK, MOR, MPA, MPR, MRI, MSC, MSD, MSM, MTN, MTX, MUT, MVA, MVT, MWA, MWI, MWV, OPI, PAC, SBA, SBE, SBP, SBT, SBY, SCU, SIA, SIE, SIP, SIT, SIY, SPE, SPR, SPY, SUA, SUT, TAL, TAZ, TBG, TCA, TCT, TFG, TFI, TFL, TGA, TMA, TMD, TMI, TMN, TNC, TNJ, TNY, TOH, TPA, TTN, TTX, TVA

POLICY: B & P, Bal, Bonds, C & I, Flex, GS, Hedge, Leases, MF, MM, TFM

We assign the remaining funds to the following investment styles, using the classifications provided by CRSP:

Small cap/growth: OBJ: MCG, SCG, AGG; ICDI OBJ: AG, AGG; SI OBJ: SCG, AGG

Growth: OBJ: G, G-S, S-G, GRO, LTG; IDCI OBJ: LG; SI OBJ: GRO

Growth & income: OBJ: GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G, GRI; ICDI OBJ: GI; SI OBJ: GRI

Funds are classified as no-load fund when they charge no front-end load fees, nor deferred sales charges and redemption fees (TOT LOAD = 0). Finally, we exclude funds with less than 12 consecutive returns over the whole sample period.

2.9 Tables

Table 2.1: Number of US equity funds over time.

	Equity	No-load	Small cap/growth	Growth	Growth & income
1984	362	171	91	182	89
1985	398	199	94	207	97
1986	456	233	90	272	94
1987	533	263	97	326	110
1988	601	302	102	372	127
1989	673	336	104	419	150
1990	681	336	96	457	128
1991	691	353	142	331	218
1992	730	374	153	358	219
1993	962	433	287	455	298
1994	1,226	574	323	567	337
1995	1,684	786	471	742	473
1996	1,903	896	571	807	529
1997	2,203	1,030	668	942	597
1998	2,858	1,375	883	1,245	738
1999	3,233	1,457	1,019	1,417	809
2000	3,634	1,593	1,133	1,616	895
2001	3,947	1,702	1,244	1,759	947
2002	4,621	1,925	1,497	2,041	1,084
2003	4,973	2,130	1,607	2,235	1,132

The table lists the number of available US equity mutual funds over the period 1984–2003. The data are extracted from the CRSP database. To be included in our sample, funds must be classified as a non-specialized US equity fund, and expense and load data of the funds should be available in the annual summary report at the end of the preceding year. In total, the samples cover 6,429 US equity funds, 3,101 no-load funds, 2,134 small cap/growth, 3,349 growth, and 1,837 growth & income funds that have more than 12 consecutive returns over the whole sample period.

Table 2.2: Parameter values of the data generating process.

Alpha	RMRF	SMB	HML	UMD
A. Return				
-	0.64% (4.57%)	0.01% (3.46%)	0.35% (3.31%)	0.86% (4.54%)
B. Sensitivity				
-0.22% (0.49%)	0.99 (0.25)	0.20 (0.38)	0.05 (0.39)	0.03 (0.18)

Fund performance is measured using the four-factor Carhart (1997) model. Alphas and benchmark sensitivities are estimated using standard OLS and the entire return history of each fund. The sample is from 1984 to 2003 and covers 6,429 US equity funds. The table lists the benchmark factors' average returns (Panel A), and the cross-sectional means of funds' alphas and benchmark sensitivities (Panel B). The standard deviations are in parentheses.

Table 2.3: Monte Carlo results.

	1. Using normal error terms				*2. Using t-dist(5df) error terms*			
	OLS	*Bayes*	Difference	p-value	*OLS*	*Bayes*	Difference	p-value
A. RMSE								
12M	0.67%	0.38%	−0.28%	0.00	0.86%	0.45%	−0.42%	0.00
24M	0.41%	0.28%	−0.14%	0.00	0.53%	0.32%	−0.21%	0.00
36M	0.32%	0.24%	−0.09%	0.00	0.42%	0.27%	−0.14%	0.00
60M	0.24%	0.20%	−0.05%	0.00	0.32%	0.23%	−0.09%	0.00
B. Alpha D1 (top decile)								
12M	0.26%	0.39%	0.13%	0.00	0.18%	0.34%	0.16%	0.00
24M	0.42%	0.50%	0.08%	0.00	0.34%	0.46%	0.12%	0.00
36M	0.48%	0.54%	0.05%	0.00	0.42%	0.51%	0.09%	0.00
60M	0.54%	0.57%	0.03%	0.00	0.49%	0.54%	0.05%	0.00
C. Alpha D10 (bottom decile)								
12M	-0.70%	-0.83%	−0.13%	0.00	-0.61%	-0.77%	−0.16%	0.00
24M	-0.86%	-0.94%	−0.08%	0.00	-0.78%	-0.90%	−0.12%	0.00
36M	-0.93%	-0.98%	−0.05%	0.00	-0.86%	-0.95%	−0.09%	0.00
60M	-0.98%	-1.01%	−0.03%	0.00	-0.93%	-0.99%	−0.05%	0.00

Simulated fund returns are generated using the Carhart (1997) model for measurement horizons of 12, 24, 36, and 60 months. The number of funds in the cross-section is set to 1,000. We then estimate the factor models using standard OLS and an empirical Bayes approach. The number of replications for each measurement horizon is set to 1,000. The table lists the average RMSE of alpha using standard OLS and Bayesian estimation (Panel A), and the average true alpha for the top (D1) and bottom (D10) deciles of funds resulting from rankings based on both estimators (Panel B and C).

Table 2.4: Rankings on three-year measurement horizons.

	Return	Sharpe	Alpha	Alpha-t	RMRF	SMB	HML	UMD	R^2
A. Rankings on raw returns									
D1	0.58%	0.10	-0.13%	-1.18	0.98	0.43	-0.26	0.20	0.93
D2	0.66%	0.13	-0.02%	-0.23	0.98	0.27	-0.14	0.11	0.96
D3	0.55%	0.12	-0.11%	-2.03	0.97	0.19	-0.05	0.05	0.98
D4	0.55%	0.12	-0.09%	-2.36	0.97	0.11	-0.00	0.02	0.98
D5	0.54%	0.12	-0.08%	-1.64	0.96	0.07	0.01	0.00	0.98
D6	0.53%	0.12	-0.09%	-1.74	0.97	0.08	0.06	-0.02	0.98
D7	0.53%	0.12	-0.10%	-1.54	0.97	0.08	0.08	-0.03	0.97
D8	0.50%	0.11	-0.11%	-1.33	0.97	0.06	0.11	-0.06	0.94
D9	0.50%	0.11	-0.11%	-1.16	0.99	0.13	0.14	-0.08	0.92
D10	0.35%	0.08	-0.21%	-2.01	0.96	0.20	0.11	-0.11	0.90
B. Rankings on OLS alphas									
D1	0.60%	0.11	-0.01%	-0.10	0.98	0.39	-0.16	0.04	0.95
D2	0.60%	0.13	-0.02%	-0.39	0.97	0.20	-0.05	0.02	0.97
D3	0.59%	0.13	-0.03%	-0.56	0.97	0.08	0.03	-0.01	0.97
D4	0.54%	0.12	-0.10%	-2.32	0.98	0.10	0.06	-0.01	0.98
D5	0.54%	0.12	-0.07%	-1.54	0.95	0.08	0.02	-0.00	0.98
D6	0.52%	0.12	-0.12%	-2.42	0.98	0.06	0.04	-0.00	0.98
D7	0.51%	0.11	-0.13%	-2.64	0.97	0.09	0.05	-0.00	0.98
D8	0.53%	0.12	-0.13%	-2.18	0.98	0.12	0.04	0.01	0.97
D9	0.51%	0.11	-0.16%	-2.28	0.99	0.18	0.04	0.03	0.97
D10	0.35%	0.07	-0.28%	-3.18	0.96	0.32	-0.01	0.02	0.94

Each month funds are sorted into equally weighted decile portfolios based on 36-month ranking periods. Pre-ranking performance is measured using raw returns (Panel A), standard OLS alphas (Panel B), and Bayesian alphas (Panel C). The sample is from 1984 to 2003 and covers 6,429 US equity funds. The table lists the deciles' post-ranking excess returns, Sharpe ratios, parameter estimates of the Carhart (1997) model, and R^2-values. The deciles' post-ranking alphas are estimated using standard OLS over the stacked time series of portfolio returns.

Table 2.4 continued

	Return	Sharpe	Alpha	Alpha-t	RMRF	SMB	HML	UMD	R^2
C. Rankings on Bayesian alphas									
D1	0.62%	0.12	0.01%	0.11	0.99	0.30	-0.16	0.04	0.94
D2	0.58%	0.12	-0.03%	-0.44	0.98	0.17	-0.07	0.02	0.97
D3	0.56%	0.12	-0.08%	-1.35	0.98	0.15	-0.01	0.01	0.97
D4	0.51%	0.11	-0.10%	-1.88	0.95	0.15	0.02	-0.01	0.98
D5	0.58%	0.13	-0.03%	-0.64	0.95	0.11	0.02	-0.01	0.98
D6	0.52%	0.11	-0.13%	-2.26	0.99	0.11	0.04	0.01	0.98
D7	0.54%	0.12	-0.08%	-1.54	0.96	0.12	0.02	0.00	0.97
D8	0.52%	0.12	-0.12%	-1.73	0.97	0.11	0.06	-0.01	0.96
D9	0.50%	0.11	-0.17%	-2.13	0.98	0.17	0.05	0.02	0.96
D10	0.36%	0.08	-0.33%	-3.27	0.98	0.23	0.07	0.04	0.92

Table 2.5: Rankings on one-year measurement horizons.

	E(r)	Sharpe	Alpha	Alpha-t	RMRF	SMB	HML	UMD	R^2
A. Rankings on raw returns									
D1	0.97%	0.16	0.04%	0.36	0.96	0.57	-0.13	0.40	0.91
D2	0.77%	0.16	-0.04%	-0.51	0.97	0.36	-0.04	0.23	0.96
D3	0.68%	0.15	-0.06%	-1.13	0.97	0.21	-0.01	0.14	0.98
D4	0.59%	0.13	-0.12%	-3.22	0.97	0.13	0.03	0.08	0.98
D5	0.52%	0.12	-0.12%	-2.65	0.97	0.08	0.02	0.01	0.98
D6	0.48%	0.11	-0.12%	-2.22	0.97	0.04	0.04	-0.03	0.98
D7	0.47%	0.10	-0.09%	-1.53	0.96	0.04	0.03	-0.07	0.97
D8	0.38%	0.08	-0.13%	-1.60	0.96	0.07	0.04	-0.13	0.95
D9	0.30%	0.06	-0.17%	-1.63	0.97	0.08	0.06	-0.20	0.92
D10	0.12%	0.02	-0.21%	-1.54	0.94	0.15	0.03	-0.33	0.88
B. Rankings on OLS alphas									
D1	0.89%	0.16	0.24%	1.95	0.95	0.45	-0.15	0.11	0.90
D2	0.70%	0.14	0.03%	0.57	0.98	0.25	-0.04	0.06	0.97
D3	0.59%	0.13	-0.03%	-0.79	0.95	0.12	-0.00	0.02	0.98
D4	0.55%	0.13	-0.08%	-1.87	0.95	0.09	0.02	0.01	0.98
D5	0.54%	0.12	-0.08%	-1.72	0.95	0.05	0.03	-0.01	0.98
D6	0.51%	0.12	-0.11%	-2.29	0.96	0.07	0.03	-0.01	0.98
D7	0.46%	0.10	-0.16%	-2.86	0.96	0.09	0.04	-0.02	0.98
D8	0.43%	0.09	-0.19%	-3.32	0.97	0.13	0.04	-0.02	0.97
D9	0.42%	0.09	-0.21%	-2.79	0.99	0.18	0.04	-0.01	0.96
D10	0.18%	0.04	-0.44%	-4.22	0.98	0.30	0.07	-0.04	0.92

Each month funds are sorted into equally weighted decile portfolios based on 12-month ranking periods. Pre-ranking performance is measured using raw returns (Panel A), standard OLS alphas (Panel B), and Bayesian alphas (Panel C). The sample is from 1984 to 2003 and covers 6,429 US equity funds. The table lists the deciles' post-ranking excess returns, Sharpe ratios, parameter estimates of the Carhart (1997) model, and R^2-values. The deciles' post-ranking alphas are estimated using standard OLS over the stacked time series of portfolio returns.

Table 2.5 continued

	Return	Sharpe	Alpha	Alpha-t	RMRF	SMB	HML	UMD	R^2
C. Rankings on Bayesian alphas									
D1	0.95%	0.18	0.26%	2.26	0.93	0.44	-0.15	0.16	0.89
D2	0.74%	0.15	0.08%	0.99	0.97	0.25	-0.09	0.09	0.96
D3	0.61%	0.13	-0.04%	-0.74	0.96	0.17	-0.04	0.05	0.98
D4	0.59%	0.13	-0.04%	-0.76	0.97	0.12	0.00	0.00	0.98
D5	0.50%	0.11	-0.11%	-2.09	0.95	0.09	0.01	-0.00	0.97
D6	0.49%	0.11	-0.12%	-2.00	0.97	0.09	0.05	-0.03	0.97
D7	0.44%	0.10	-0.16%	-2.39	0.97	0.10	0.04	-0.04	0.97
D8	0.40%	0.09	-0.21%	-2.92	0.97	0.12	0.05	-0.04	0.96
D9	0.36%	0.08	-0.28%	-3.21	0.99	0.15	0.08	-0.03	0.95
D10	0.19%	0.04	-0.43%	-3.70	0.98	0.20	0.13	-0.06	0.91

Table 2.6: The lifespan of performance persistence.

	Return	Sharpe	Alpha	Alpha-t	RMRF	SMB	HML	UMD	R^2
D1	0.78%	0.14	0.10%	0.92	0.94	0.43	-0.20	0.16	0.90
D2	0.71%	0.15	0.04%	0.55	0.97	0.26	-0.09	0.10	0.97
D3	0.58%	0.12	-0.06%	-1.29	0.98	0.17	-0.06	0.05	0.98
D4	0.58%	0.13	-0.04%	-0.85	0.95	0.12	-0.01	0.01	0.98
D5	0.53%	0.12	-0.10%	-1.85	0.96	0.11	0.04	-0.01	0.98
D6	0.51%	0.11	-0.11%	-1.80	0.98	0.09	0.05	-0.03	0.97
D7	0.47%	0.11	-0.15%	-2.14	0.97	0.11	0.06	-0.02	0.96
D8	0.46%	0.10	-0.14%	-2.18	0.96	0.12	0.06	-0.04	0.96
D9	0.40%	0.09	-0.22%	-2.60	0.98	0.14	0.08	-0.05	0.95
D10	0.27%	0.06	-0.34%	-3.08	0.96	0.18	0.14	-0.05	0.90

Each month funds are sorted into equally weighted decile portfolios on 1-month lagged alpha estimates over the preceding 12 months. Pre-ranking performance is measured using Bayesian alphas. The sample is from 1984 to 2003 and covers 6,429 US equity funds. The table lists the deciles' post-ranking excess returns, Sharpe ratios, parameter estimates of the Carhart (1997) model, and R^2-values. The deciles' post-ranking alphas are estimated using standard OLS over the stacked time series of portfolio returns.

Table 2.7: Performance persistence of older versus younger funds.

	Return	Sharpe	Alpha	Alpha-t	RMRF	SMB	HML	UMD	R^2
A. Old Funds									
D1	0.89%	0.17	0.21%	2.04	0.94	0.39	-0.14	0.15	0.92
D2	0.73%	0.15	0.05%	0.67	0.97	0.23	-0.06	0.09	0.96
D3	0.61%	0.13	-0.04%	-0.99	0.96	0.16	-0.03	0.06	0.98
D4	0.63%	0.14	-0.01%	-0.11	0.97	0.13	-0.01	0.02	0.98
D5	0.56%	0.12	-0.06%	-1.17	0.96	0.08	0.01	-0.00	0.97
D6	0.47%	0.10	-0.15%	-2.52	0.97	0.08	0.05	-0.03	0.97
D7	0.44%	0.10	-0.16%	-2.40	0.98	0.09	0.03	-0.04	0.97
D8	0.40%	0.09	-0.20%	-2.83	0.98	0.11	0.05	-0.05	0.96
D9	0.33%	0.07	-0.31%	-3.35	1.00	0.14	0.06	-0.03	0.95
D10	0.22%	0.05	-0.38%	-3.36	0.99	0.20	0.09	-0.07	0.91
B. Young Funds									
D1	1.03%	0.17	0.35%	2.02	0.91	0.53	-0.17	0.16	0.74
D2	0.81%	0.16	0.14%	1.38	0.98	0.29	-0.10	0.08	0.93
D3	0.62%	0.13	0.02%	0.31	0.93	0.20	-0.06	0.02	0.96
D4	0.49%	0.11	-0.12%	-1.91	0.95	0.12	0.02	-0.01	0.96
D5	0.47%	0.11	-0.14%	-2.12	0.94	0.12	0.02	-0.00	0.95
D6	0.46%	0.11	-0.12%	-1.43	0.92	0.09	0.05	-0.03	0.95
D7	0.41%	0.09	-0.15%	-2.10	0.93	0.09	0.04	-0.05	0.94
D8	0.39%	0.09	-0.19%	-2.18	0.94	0.15	0.04	-0.05	0.94
D9	0.33%	0.07	-0.30%	-3.43	0.96	0.17	0.10	-0.03	0.93
D10	0.16%	0.04	-0.53%	-3.96	0.97	0.22	0.24	-0.02	0.85

Each month funds are sorted into equally weighted decile portfolios based on 12-month ranking periods. Pre-ranking performance is measured using Bayesian alphas. The analysis is conducted on funds that have at least 36 observations available (Panel A), and on funds with 12 to at most 35 observations available (Panel B). The sample is from 1984 to 2003 and covers 6,429 US equity funds. In the average month, 977 funds are classified as "old", and 480 funds as "young". The table lists the deciles' post-ranking excess returns, Sharpe ratios, parameter estimates of the Carhart (1997) model, and R^2-values. The deciles' post-ranking alphas are estimated using standard OLS over the stacked time series of portfolio returns.

Table 2.8: Performance persistence for no-load and load funds.

	Return	Sharpe	Alpha	Alpha-t	RMRF	SMB	HML	UMD	R^2
A. No-load Funds									
D1	0.98%	0.18	0.31%	2.48	0.92	0.45	-0.18	0.17	0.88
D2	0.75%	0.16	0.10%	1.47	0.95	0.24	-0.09	0.08	0.96
D3	0.59%	0.13	-0.05%	-1.08	0.96	0.16	-0.01	0.03	0.97
D4	0.59%	0.13	-0.04%	-0.77	0.96	0.13	0.01	0.01	0.97
D5	0.53%	0.12	-0.08%	-1.37	0.95	0.09	0.04	-0.01	0.97
D6	0.52%	0.12	-0.10%	-1.56	0.96	0.09	0.08	-0.03	0.96
D7	0.46%	0.10	-0.16%	-2.40	0.96	0.10	0.08	-0.03	0.96
D8	0.41%	0.09	-0.17%	-2.27	0.94	0.12	0.07	-0.05	0.95
D9	0.37%	0.08	-0.26%	-2.96	0.98	0.15	0.10	-0.03	0.94
D10	0.24%	0.05	-0.41%	-3.30	0.97	0.21	0.20	-0.06	0.88
B. Load Funds									
D1	0.89%	0.17	0.20%	1.79	0.94	0.43	-0.14	0.16	0.89
D2	0.76%	0.15	0.09%	1.05	0.97	0.25	-0.09	0.09	0.95
D3	0.59%	0.13	-0.05%	-0.73	0.95	0.18	-0.06	0.06	0.97
D4	0.55%	0.12	-0.07%	-1.64	0.97	0.12	-0.02	0.01	0.97
D5	0.53%	0.12	-0.08%	-1.47	0.97	0.08	-0.00	-0.01	0.97
D6	0.45%	0.10	-0.17%	-2.67	0.98	0.08	0.02	-0.02	0.97
D7	0.44%	0.10	-0.16%	-2.36	0.97	0.10	0.02	-0.04	0.97
D8	0.39%	0.08	-0.23%	-3.01	1.00	0.12	0.04	-0.03	0.96
D9	0.34%	0.07	-0.31%	-3.17	1.00	0.15	0.06	-0.02	0.94
D10	0.15%	0.03	-0.44%	-3.82	0.98	0.21	0.07	-0.07	0.91

Each month funds are sorted into equally weighted decile portfolios based on 12-month ranking periods. Pre-ranking performance is measured using Bayesian alphas. The analysis is performed on strictly no-load funds (Panel A), and on fund that do charge sales loads (Panel B). The samples are from 1984 to 2003 and cover 3,101 no-load funds, and 4,025 load funds. The table lists the deciles' post-ranking excess returns, Sharpe ratios, parameter estimates of the Carhart (1997) model, and R^2-values. The deciles' post-ranking alphas are estimated using standard OLS over the stacked time series of portfolio returns.

Table 2.9: Performance persistence across different investment styles.

	Return	Sharpe	Alpha	Alpha-t	RMRF	SMB	HML	UMD	R^2
A. Rankings on raw returns									
D1 Small cap/growth	1.06%	0.17	0.09%	0.73	0.98	0.67	-0.20	0.47	0.92
D1 Growth	0.92%	0.16	0.02%	0.20	0.99	0.42	-0.10	0.35	0.87
D1 Growth & income	0.74%	0.18	-0.03%	-0.44	0.90	0.09	0.09	0.18	0.95
B. Rankings on OLS alphas									
D1 Small cap/growth	0.93%	0.15	0.22%	1.85	1.01	0.65	-0.20	0.14	0.93
D1 Growth	0.81%	0.15	0.19%	1.42	0.95	0.31	-0.15	0.08	0.83
D1 Growth & income	0.65%	0.16	0.03%	0.46	0.92	-0.00	0.18	-0.03	0.93
C. Rankings on Bayesian alphas									
D1 Small cap/growth	0.99%	0.16	0.24%	2.01	1.00	0.65	-0.18	0.19	0.92
D1 Growth	0.87%	0.16	0.20%	1.57	0.95	0.29	-0.15	0.13	0.83
D1 Growth & income	0.71%	0.18	0.08%	1.20	0.91	-0.02	0.17	-0.02	0.93

Each month funds are sorted into equally weighted decile portfolios based on 12-month ranking periods. Pre-ranking performance is measured using raw returns (Panel A), standard OLS alphas (Panel B), and Bayesian alphas (Panel C). The analysis is conducted on different types of funds. The samples are from 1984 to 2003 and cover 2,134 small cap/growth, 3,349 growth, and 1,837 growth & income funds. The table lists the top deciles' post-ranking excess returns, Sharpe ratios, parameter estimates of the Carhart (1997) model, and R^2-values. The deciles' post-ranking alphas are estimated using standard OLS over the stacked time series of portfolio returns.

Table 2.10: Rankings on one-year measurement horizons using conditional priors.

	Return	Sharpe	Alpha	Alpha-t	RMRF	SMB	HML	UMD	R^2
D1	0.98%	0.18	0.28%	2.41	0.95	0.47	-0.17	0.17	0.89
D2	0.71%	0.15	0.05%	0.67	0.96	0.26	-0.09	0.09	0.96
D3	0.58%	0.13	-0.07%	-1.39	0.96	0.16	-0.03	0.04	0.98
D4	0.55%	0.12	-0.06%	-1.45	0.96	0.10	0.00	0.00	0.98
D5	0.51%	0.12	-0.12%	-2.40	0.95	0.07	0.04	-0.00	0.97
D6	0.52%	0.12	-0.08%	-1.43	0.95	0.06	0.04	-0.02	0.97
D7	0.43%	0.10	-0.18%	-2.89	0.97	0.09	0.06	-0.04	0.97
D8	0.41%	0.09	-0.20%	-2.92	0.98	0.12	0.05	-0.04	0.97
D9	0.36%	0.08	-0.26%	-2.93	0.98	0.15	0.06	-0.03	0.95
D10	0.19%	0.04	-0.43%	-3.75	0.98	0.25	0.11	-0.06	0.91

Each month funds are sorted into equally weighted decile portfolios based on 12-month ranking periods. Pre-ranking performance is measured using Bayesian alphas. Funds' raw alphas are shrunk towards the cross-sectional average of funds with the same investment style. The sample is from 1984 to 2003 and covers 6,429 US equity funds. The table lists the deciles' post-ranking excess returns, Sharpe ratios, parameter estimates of the Carhart (1997) model, and R^2-values. The deciles post-ranking alphas are estimated using standard OLS over the stacked time series of portfolio returns.

Table 2.11: Comparing forecasts of both estimators.

	$RMSE_{OLS}$	$RMSE_{Bayes}$	Difference	Difference-t
All equity	1.12%	0.91%	-0.21%	-9.98
No-load	1.10%	0.89%	-0.21%	-9.85
Small cap/growth	1.24%	1.02%	-0.21%	-11.46
Growth	1.14%	0.92%	-0.22%	-8.91
Growth & income	0.74%	0.61%	-0.13%	-8.15

Each year, the root mean squared error (RMSE) is computed for alpha forecasts based on the preceding 12 months, and realized values over the subsequent year. Forecasts are obtained using standard OLS and Bayesian estimation. Realized alphas are estimated using standard OLS. The analysis is conducted on different types of funds. The samples are from 1984 to 2003 and cover 6,429 US equity funds, 3,101 no-load funds, 2,134 small cap/growth, 3,349 growth, and 1,837 growth & income funds. The table lists both estimators' average RMSEs, and the Diebold-Mariano test on equality of the two.

Table 2.12: Robustness-tests: Industry effects and time-varying benchmark sensitivities.

			1. Carhart		*2. Carhart + industries*		*3. Ferson & Schadt*	
	Return	Sharpe	Alpha	Alpha-t	Alpha	Alpha-t	Alpha	Alpha-t
A. Ranking on raw returns								
D1	0.97%	0.16	0.04%	0.36	0.10%	0.84	-0.00%	-0.02
D2	0.77%	0.16	-0.04%	-0.51	-0.02%	-0.21	-0.09%	-1.34
D3	0.68%	0.15	-0.06%	-1.13	-0.03%	-0.55	-0.07%	-1.40
D4	0.59%	0.13	-0.12%	-3.22	-0.08%	-2.08	-0.11%	-2.83
D5	0.52%	0.12	-0.12%	-2.65	-0.08%	-1.80	-0.09%	-2.48
D6	0.48%	0.11	-0.12%	-2.22	-0.07%	-1.64	-0.07%	-1.81
D7	0.47%	0.10	-0.09%	-1.53	-0.05%	-0.88	-0.06%	-1.16
D8	0.38%	0.08	-0.13%	-1.60	-0.09%	-1.07	-0.08%	-1.25
D9	0.30%	0.06	-0.17%	-1.63	-0.12%	-1.19	-0.09%	-1.05
D10	0.12%	0.02	-0.21%	-1.54	-0.15%	-1.08	-0.11%	-0.92
B. Ranking on OLS alphas								
D1	0.89%	0.16	0.24%	1.95	0.32%	2.54	0.26%	2.02
D2	0.70%	0.14	0.03%	0.57	0.07%	1.12	0.05%	0.97
D3	0.59%	0.13	-0.03%	-0.79	0.00%	0.10	-0.02%	-0.39
D4	0.55%	0.13	-0.08%	-1.87	-0.05%	-1.11	-0.07%	-1.80
D5	0.54%	0.12	-0.08%	-1.72	-0.03%	-0.74	-0.05%	-1.32
D6	0.51%	0.12	-0.11%	-2.29	-0.06%	-1.39	-0.10%	-2.54
D7	0.46%	0.10	-0.16%	-2.86	-0.12%	-2.29	-0.16%	-3.54
D8	0.43%	0.09	-0.19%	-3.32	-0.16%	-2.80	-0.18%	-4.06
D9	0.42%	0.09	-0.21%	-2.79	-0.18%	-2.44	-0.18%	-2.70
D10	0.18%	0.04	-0.44%	-4.22	-0.39%	-3.89	-0.37%	-3.89

Each month funds are sorted into decile portfolios based on 12-month ranking periods. Pre-ranking performance is measured using raw returns (Panel A), standard OLS alphas (Panel B), and Bayesian alphas (Panel C). The sample is from 1984 to 2003 and covers 6,429 US equity funds. The table lists the deciles' post-ranking excess returns, Sharpe ratios, and alphas. The deciles' post-ranking alphas are estimated using the Carhart (1997) model, the Carhart model augmented with three industry factors, and the Ferson and Schadt (1996) model with standard OLS over the stacked time series of portfolio returns.

Table 2.12 continued

	Return	Sharpe	*1. Carhart* Alpha	Alpha-t	*2. Carhart + industries* Alpha	Alpha-t	*3. Ferson & Schadt* Alpha	Alpha-t
C. Ranking on Bayesian alphas								
D1	0.95%	0.18	0.26%	2.26	0.33%	2.70	0.28%	2.31
D2	0.74%	0.15	0.08%	0.99	0.11%	1.45	0.09%	1.24
D3	0.61%	0.13	-0.04%	-0.74	-0.01%	-0.23	-0.03%	-0.55
D4	0.59%	0.13	-0.04%	-0.76	-0.00%	-0.05	-0.01%	-0.19
D5	0.50%	0.11	-0.11%	-2.09	-0.06%	-1.14	-0.09%	-2.05
D6	0.49%	0.11	-0.12%	-2.00	-0.08%	-1.35	-0.11%	-2.23
D7	0.44%	0.10	-0.16%	-2.39	-0.11%	-1.58	-0.15%	-2.67
D8	0.40%	0.09	-0.21%	-2.92	-0.16%	-2.42	-0.19%	-3.15
D9	0.36%	0.08	-0.28%	-3.21	-0.24%	-2.87	-0.24%	-3.36
D10	0.19%	0.04	-0.43%	-3.70	-0.39%	-3.51	-0.35%	-3.36

Table 2.13: Robustness-tests: Fama and MacBeth (1973) regressions.

	1. Three-year horizon			*2. One-year horizon*		
	a	b	R^2	a	b	R^2
A. Regressions on raw returns						
All equity	-0.14 (-2.14)	0.07 (1.93)	0.01	-0.11 (-1.73)	0.13 (3.28)	0.04
No-load	-0.15 (-2.55)	0.10 (2.44)	0.02	-0.11 (-1.90)	0.14 (3.65)	0.05
Small cap/growth	-0.20 (-2.18)	0.16 (1.93)	0.05	-0.14 (-1.66)	0.16 (4.59)	0.06
Growth	-0.10 (-1.52)	0.03 (0.71)	0.02	-0.09 (-1.56)	0.12 (2.39)	0.04
Growth & income	-0.08 (-1.30)	0.01 (0.12)	0.03	-0.16 (-2.37)	0.15 (2.27)	0.06
B. Regressions on OLS alphas						
All equity	-0.08 (-1.45)	0.15 (4.54)	0.01	-0.07 (-1.39)	0.18 (6.46)	0.04
No-load	-0.08 (-1.45)	0.19 (5.99)	0.02	-0.07 (-1.34)	0.19 (6.02)	0.06
Small cap/growth	-0.11 (-1.21)	0.29 (4.64)	0.05	-0.10 (-1.20)	0.19 (10.84)	0.05
Growth	-0.07 (-1.34)	0.07 (1.76)	0.01	-0.06 (-1.24)	0.16 (4.14)	0.04
Growth & income	-0.06 (-1.84)	0.09 (1.43)	0.02	-0.07 (-2.56)	0.15 (3.85)	0.07
C. Regressions on Bayesian alphas						
All equity	-0.08 (-1.49)	0.26 (3.60)	0.01	-0.07 (-1.42)	0.33 (5.34)	0.04
No-load	-0.07 (-1.35)	0.30 (3.31)	0.02	-0.06 (-1.36)	0.37 (4.97)	0.05
Small cap/growth	-0.12 (-1.30)	0.36 (2.89)	0.04	-0.10 (-1.26)	0.34 (8.77)	0.04
Growth	-0.07 (-1.36)	0.17 (2.34)	0.01	-0.06 (-1.29)	0.31 (3.47)	0.04
Growth & income	-0.06 (-2.12)	0.16 (1.81)	0.02	-0.07 (-2.33)	0.27 (4.36)	0.04

At the begin of each year, realized alphas over the subsequent 12 months are regressed on a measure of performance over the preceding 36 and 12 months. Fund performance is measured using raw returns (Panel A), standard OLS alphas (Panel B), and Bayesian alphas (Panel C). The analysis is conducted on different types of funds. The samples are from 1984 to 2003 and cover 6,429 US equity funds, 3,101 no-load funds, 2,134 small cap/growth, 3,349 growth, and 1,837 growth & income funds. The table lists the regressions' intercept, slope coefficients, and R^2-values. Realized alphas are estimated using standard OLS. The t-statistics are in parentheses.

Chapter 3

"Hot Hands" in Bond Funds*

3.1 Introduction

Despite the enormous size of the market for actively managed bond funds, surprisingly little is known about whether active portfolio management contributes to bond investment returns. *A priori*, we might expect that the value added by active bond management would be only marginal. The returns of a fixed-income portfolio are almost fully driven by nondiversifiable processes that we know are very hard to predict. (See, e.g., Litterman and Scheinkman (1991), Knez et al. (1994), and Gultekin and Rogalski (1995). These studies suggest that only a few factors account for bond returns.)

There are also very few studies that provide empirical evidence to support the existence of skilled bond fund managers. For example, Blake et al. (1993) suggest that return spreads between actively managed bond portfolios can be explained either by differences in the maturity range or by differences in the risk premiums of the securities that are held. The absence of any predictability of risk-adjusted bond performance supports the oft-cited claim that none of the cross-sectional differences in bond fund returns are attributable to fund management skills.

If there is one variable that researchers can use to predict future bond fund performance, it is the fund's expenses. Bond funds with relatively high expenses generally underperform funds with lower expenses (see, e.g., Blake et al. (1993) and Detzler (1999)). Skeptism on managerial skill in the bond market combined with these empirical findings makes a strong case against active bond fund management. The investment implications seem clear: buy shares of bond index funds.

We demonstrate that this argument is not necessarily true. In this study, we show

*This chapter is based on the article by Huij and Derwall (2006).

that we can predict future bond fund performance by using historical excess returns. By applying dynamic fund sorts in the tradition of Hendricks et al. (1993) on a large and survivorship-bias free bond fund sample, we show strong evidence of relative out-of-sample predictability. We find that after we control for multiple benchmark return sensitivities, deciles of bond funds with high historical alphas outperform deciles of funds with lowest alphas out-of-sample by more than 3.5 percent per year.

To investigate whether investors can exploit the observed persistence pattern to earn abnormal returns, we simulate an investment strategy by applying modern portfolio theory on past returns. Even after taking the sales load into account, we find that our simulated portfolio of funds strongly outperforms a strategy that invests in passive indexes by more than 1.79 percent per year. Our evidence that bond funds can deliver positive abnormal returns tells an important story: active bonds funds can have incremental economic value.

Since research on bond funds is scarce and not well developed, this paper fills several gaps in the literature. First, to our knowledge, our study is the first to analyze the full universe of more than 3,500 bond funds in the CRSP survivorship-bias free mutual fund database over the period 1990–2003. This large sample helps us to overcome the small-sample problems that plague earlier studies on bond fund performance. Second, earlier bond fund studies use only a subset of all common approaches that were originally developed in research on equity funds to test for persistence. We show that these and other methods produce a consistent story in this study on performance persistence. Examples of persistence tests are the cross-sectional regression of current fund alphas on prior-period alphas, where the focus is on the significance of the regression's slope coefficient (see Blake et al. (1993)), and the allocation of funds to one of four cells in a (two-by-two) current-past performance contingency matrix, where persistence is proven when the frequency by which past winners (losers) repeat their performance exceeds a threshold probability (see, e.g., Kahn and Rudd (1995)). We complement prior studies by introducing variants of the methods used by Hendricks et al. (1993), Elton et al. (1996), and Carhart (1997), which enable us to investigate the economic significance of strategies based on short-run persistence in bond fund performance. In doing so, we provide new insights into long-running debates on the benefits of actively managed funds vis-à-vis passive portfolios. Although Hendricks et al. (1993) find that equity fund managers with "hot hands" in the past continue to outperform managers with "icy hands" in the near future, their top-performing fund portfolio does not outperform standard benchmark indexes. Equivalently, previous studies in the bond area suggest that bond index funds are a superior alternative compared to actively managed funds, once we take expenses into account. In contrast to earlier studies, we offer strong evidence of a "hot hands" phenomenon in the bond fund market that translates into strategies that yield both economically and statistically significant excess returns.

We also perform a bootstrap analysis to cover the possibility that our results are driven by distributional features of the data that could make tests of performance persistence prone to a Type I error. We find that this is not the case. We simulate persistence tests based on artificially generated data, in which we preserve non-normality features and intentionally impose zero alpha. By doing so, we can determine the distributions of the tests statistics when persistence is predetermined to be a chance result. Even the most extreme values for the simulated test statistics are not in the order of the ones we obtain from the actual bond fund data.

The paper is organized as follows. Section 3.2 discusses our methods in the empirical analysis. Section 3.3 describes the bond fund sample. Section 3.4 presents the empirical results. Sections 3.5 and 3.6 compare the robustness of our results to a wide range of model specifications and bootstrapped test statistics. Section 3.7 concludes.

3.2 Methodology

3.2.1 Performance measurement

Consistent with most studies that hunt for new performance evaluation models for bonds, we measure bond fund performance relative to the return predicted by a multi-index model:

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_{j=1}^{K} \beta_{j,i}(I_{j,t} - R_{f,t}) + \epsilon_{i,t}, \tag{3.1}$$

where $R_{i,t}$ is the total return of fund i, $R_{f,t}$ is the risk-free rate at time t , α_i is the average risk-adjusted performance of fund i, $I_{j,t}$ is the return on index j at time t, $\beta_{j,i}$ is the sensitivity of the excess return of fund i to index j, K is the number of indexes we use, and $\epsilon_{i,t}$ is the residual return of fund i at time t.

We can interpret models that include a mixture of indexes along several lines. One interpretation is that these models are similar to multi-factor models for stocks. Theoretically, these models can be justified by various alternatives to the CAPM of Sharpe (1964) and Lintner (1965), such as the ICAPM of Merton (1973) and the APT of Ross (1976). In this setup, the factors are proxies for the underlying term and default risks in the economy that are of hedging concern to investors. The models' betas measure the funds' systematic risk, and their residual returns reflect risk-adjusted performance.[1] An alternative interpretation is that the indexes are control variables in a performance attribution model, as in Kahn (1991) and Carhart (1997), where the passive indexes multiplied by their estimated weights (betas) most closely reproduce a fund's return variation. In that case, we are using a set of bond indexes to describe bond portfolio returns but make no claim about their role in the return-generating process. Either way, one can think of the model's intercept (alpha) as the portion of return that is not explained by factors that do not involve active management. In both scenarios, we can assume that alpha conveys information about the skill of a bond fund manager.

Our base model is from Blake et al. (1993), who indicate that only a few factors are necessary to describe the return on a bond portfolio:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(BIG_t - R_{f,t}) + \beta_{2,i}(HY_t - R_{f,t}) + \beta_{3,i}(GNMA_t - R_{f,t}) + \epsilon_{i,t}, \quad (3.2)$$

where BIG is a proxy for returns of the overall bond market, HY is a proxy for the returns from holding low-grade debt.

$GNMA$ is a proxy for returns of mortgage-backed securities. Contrary to normal bonds, mortgage-backed securities have an uncertain maturity, because consumers have the right to sell or refinance their homes at any time. If interest rates decrease, consumers tend to sell or refinance more often, thereby shortening the life of the securities. As a result, returns on mortgage securities typically exhibit option-like characteristics.

With this model, we capture term risk by the funds' betas to the overall bond market. We interpret these betas as a first-order approximation of the yield curve, (duration). Funds with a higher (lower) duration than the index will have a bond market beta above (below) one.

3.2.2 Persistence tests

At the heart of persistence in mutual fund performance lies the relation between past and future fund returns. However, in practice there is no consensus on which method is best for testing persistence. To ensure that our results are not a manifestation of exogenously specified parameters, we use four different approaches to investigating performance persistence. These alternatives have been used in many equity fund performance studies up to

[1] Consistent with this interpretation, Gebhardt et al. (2005) suggest that proxies for term and default risk are successful in explaining the cross-section of corporate bond returns. However, their focus is only on investment-grade bonds.

this point (see, e.g., Hendricks et al. (1993), Malkiel (1995), Carhart (1997)), but have not been used rigorously in the bond fund literature. In all our analyses, we essentially consider an evaluation period and an (out-of-sample) post-evaluation period. We estimate funds' risk-adjusted performance over both periods and investigate the relation between past and future performance. In other words, we ask if past performance predicts future performance for bond funds. More importantly, we investigate whether any of this predictability is attributable to managerial skill.

We start with two basic methods, regression and correlation, to describe the relation between past and future performance. First, with the regression method, we estimate all funds' alphas over both the evaluation and the post-evaluation period for nonoverlapping time periods of 12 months. At the beginning of each year, we run a cross-sectional regression of past performance on future performance:

$$\hat{\alpha}_{i,t} = a_t + b_t \hat{\alpha}_{i,t-1} + \epsilon_{i,t}, \tag{3.3}$$

where $\hat{\alpha}_{i,t}$ is fund i's alpha over year t, $\hat{\alpha}_{i,t-1}$ is fund i's alpha over the previous year, and $\epsilon_{i,t}$ the residual.

We follow Fama and MacBeth (1973), estimating the intercept and the slope in Eq. (3.3) by using standard OLS tests, and take the time-series average of the coefficient estimates over the whole sample period. We use the standard deviations of the cross-sectional regression estimates to generate the sampling errors for these estimates. A significant loading on the slope coefficient would be consistent with a relation between past and future performance, that is, with persistence in bond fund performance.

In addition, we use the Sharpe ratio as a measure of post-evaluation performance, and run the following cross-sectional regression:

$$Sharpe_{i,t} = a_t + b_t \hat{\alpha}_{i,t-1} + \epsilon_{i,t}, \tag{3.4}$$

where $Sharpe_{i,t}$ is the Sharpe ratio of fund i over year t. This alternative regression prevents that spurious persistence patterns arise due to a misspecification of the factor model.

Second, we measure the correlation between the past and future performance of bond funds with the Spearman rank correlation coefficient. The most attractive feature of this statistic is that we can use it to give an R-estimate when the distribution of the data makes the standard Pearson's correlation coefficient undesirable.

At the beginning of each year, we estimate performance for all available funds over both the preceding and the subsequent year. We then rank funds on the selected performance measure, and compute the Spearman rank correlation coefficient between the rankings in the previous period and those in the subsequent period:

$$\rho_{t,t-1} = 1 - \frac{6 \sum d_{t,t-1}^2}{N(N^2-1)}, \tag{3.5}$$

where $\sum d_{t,t-1}^2$ is the sum of the squared differences between the funds' ranks over the evaluation and the post-evaluation period, and N is the number of ranks.

As with the cross-sectional regressions, we estimate rank correlations year by year and compute the time-series average of correlation coefficients. We use the time-series standard deviation to gauge the significance of the correlation between past and future performance.

Third, we use contingency tables to investigate performance persistence. We assign funds to one of the four cells in a two-by-two contingency table, based on a measure of performance relative to the median. Every year, we assign all funds to one of the following cells: past loser (alpha below median over preceding year)/future loser; past loser/future winner (alpha above median over subsequent year); past winner/future loser; and past winner/future winner. Under the null hypothesis of no relation between historical and future performance, the probabilities in each cell of the matrix are equal, i.e., 25 percent.

The alternative hypothesis is that at least one cell has a frequency different from 25 percent. To gauge the statistical significance of these frequencies, we perform a chi-square test with one degree of freedom. Again, we measure fund performance over the subsequent year with the Sharpe ratio.

The methods we have discussed thus far are well suited for discovering persistence in relative performance among bond funds, but do little for the funds' returns relative to a set of passive indexes. Our fourth method tackles this shortcoming. We form mutually exclusive portfolios of funds ranked on past performance and evaluate their returns over post-formation periods. Every month, we separate our universe of funds into deciles, using the funds' alphas over the last 36 months as the discriminating criterion. For example, the top decile contains the 10 percent best-performing bond funds over the past three years, the second decile the next 10 percent, etc.

Before we allocate the funds to rank portfolios, we follow Elton et al. (1996) by excluding funds from our analysis that have a R^2-value that is lower than 0.4 over the pre-ranking period in the factor regression. After sorting the funds into rank portfolios, we calculate the equally weighted returns over the subsequent month for all deciles. After one month, we re-estimate the prior three-year alphas for all funds and re-form the decile portfolios accordingly. We also readjust the portfolios' weights if a fund disappears after ranking.

After having repeated this procedure up to the end of the sample period, we estimate alphas over the post-ranking period January 1993 to December 2003. (The first 36 observations of our dataset January 1990 to December 1992 are used to initialize the procedure.)

Although our performance attribution models should be able to detect managers with investment skills among all bond funds, we apply our tests on both the full bond fund sample and subsamples composed of funds for specific classes of debt.

There are reasons why examining persistence of fund performance within specific segments of the bond market is informative. First, due to risk and liquidity restrictions, investment practitioners might not be able to exploit persistence across the entire fund spectrum. Second, subsample analysis adds to our understanding of the robustness of our results.

3.3 Data

To our knowledge, ours is the first study on bond fund performance that fully exploits the information content of the CRSP mutual fund database. In our study we use the largest sample of bond funds investigated to date. It does not suffer from survivorship-bias of the kind described in Brown et al. (1992) and Brown and Goetzmann (1995).[2] The 2003 CRSP universe includes data on all mutual funds in the United States for any given date since 1962, including funds that are defunct. The database covers monthly total returns of more than 21,400 open-ended mutual funds over the period 1962–2003. Of these funds, about 7,000 are defunct. The database also includes important supplementary data, such as fund classifications by Wiesenberger, Micropal/Investment Company Data Inc. and Strategic Insight, and each fund's expense history.

We select all bond funds that CRSP classifies as government, corporate, high-yield, or mortgage-backed at the final quarter of each year. Our sample comprises bond funds with the following classifications: Wiesenberger (OBJ): CBD, CHY, GOV, MTG; Micropal/Investment Company Data, Inc. (ICDI OBJ): BQ, BY, GM, GS; Strategic Insight (SI OBJ): CGN, CHQ, CHY, CIM, CMQ, CSM, GGN, GIM, GMA, GMB, GSM. Following Blake et al. (1993), we omit money market and municipal bond funds. In total, 3,549 funds satisfy these criteria over the 1990–2003 period.[3]

[2]Elton et al. (2001) point out that CRSP does suffer from a form of survivorship bias called omission bias because only some small funds under $15 million in total net assets have monthly data in the CRSP database. Unreported persistence tests on a sample free of such small funds does not affect the conclusions of this paper. The results are available upon request.

[3]We remove one outlier: CRSP reports a return of 391 percent over March 1995 for the IDS Strategy

In separate tests, we split our sample in two subgroups of funds, based on whether or not these funds charge load fees. Our no-load subsample comprises 1,837 funds over the 1990–2003 period. Table 3.1 lists the number of funds and some of the funds' characteristics over our sample period, such as the average total net assets, expense ratio, maximum sales loads, and turnover ratio. We note that for 1991, the 2003 CRSP mutual fund database does not report turnover ratios.

We use the following bond indexes to measure bond fund performance: the 30-day Treasury-bill rate from Ibbotson and Associates as our proxy for the risk-free rate; the Citigroup U.S. broad investment grade index (US BIG) as our proxy for the overall bond market; the Merrill Lynch High Yield index as our proxy for low-grade debt; and the Citigroup Government National Mortgage Association (GNMA, "Ginnie Mae") index as our proxy for mortgage-backed securities. The total investment returns on the CGBI U.S. Broad Investment-Grade Bond Index, the Merrill Lynch High Yield index, and the Citigroup GNMA index are from Thompson Financial. The Citigroup bond indexes provide us with stable and easily replicated benchmarks by including all investment opportunities that are available to market participants under regular conditions. U.S. BIG is a value-weighted index that includes fixed-rate Treasury, government-sponsored, mortgage, asset-backed, and investment-grade issues that have a remaining maturity of at least one year. The issues are eligible for inclusion when they pass a size criterion that is designed to ensure the bonds are reasonably accessible.

3.4 Empirical results

3.4.1 Performance persistence

Our first series of results involve the nonoverlapping cross-sectional regressions of future alpha on past alpha, which we estimate at the beginning of each year over 12-month horizons. We regress bond fund alphas over 1991 on alphas over 1990, alphas over 1992 on those over 1991, and so forth. On average, 1,128 funds are available. The number of available funds ranges from 420 over 1990–1991 to 1,745 over 2002–2003.

Panel A in Table 3.2 reports the Fama and MacBeth (1973) averages of the cross-sectional coefficient estimates and corresponding t-values derived from the time series standard errors. Panel A1 shows the estimated relation between future alpha and past alpha according to Eq. (3.3) for the full sample, the investment-grade fund sample, the

Short Term Income Fund (CRSP-Identifier: 19890).

high-yield fund sample, and the mortgage-backed fund sample, respectively. The full-sample slope coefficient in Panel A1 is 0.17, and the corresponding t-statistic points out that the observed positive association between past and future fund performance is significant at the conventional cut-off level (e.g., 2.18 at a 5 percent level of significance with 12 degrees of freedom). Panel B1, which reports the regression estimates when we measure fund performance with the Sharpe ratio (see Eq. (3.4)), corroborates our previous results.

Our analyses of samples broken up into subsets generally support our full-sample evidence. The relation between the past and future excess returns of investment-grade bond funds is similar to full-sample results and highly significant, regardless of whether we use alpha or the Sharpe ratio as the regressant in the Fama and MacBeth (1973) models (see Panels A1 and B1). In the high-yield fund sample, the regressions produce marginally significant evidence of persistence. The slopes suggest that high-yield funds that display relatively high excess returns repeat their relative performance in the next year. The significance of the slope estimates varies across the different specifications. For the mortgage-backed fund sample, we again find strong evidence of persistence.

Our second set of results concerns the Spearman test on the rank ordering. Panel B in Table 3.2 shows the relation we measure between future alpha and past alpha (Panel B1), and between future Sharpe ratio and past alpha (Panel B2). Consistent with the Fama and MacBeth (1973) regression results, the Spearman rank correlation coefficients indicate a significant persistence pattern in bond fund performance. The results are robust across subsamples. All t-values are large and far above their critical values, thus rejecting the null hypothesis of randomness in fund orderings.

In Panel C of Table 3.2, we present the contingency table, reporting initial fund rankings paired with subsequent rankings. In Panel C1, we base the subsequent rankings on fund alphas. In Panel C2, we report the subsequent rankings based on the Sharpe ratio. As explained earlier, the null hypothesis of no persistence in bond fund performance implies that all quadrants contain probabilities equal to 25 percent. Our results provide clear evidence to the contrary, regardless of the choice of performance measure. A sizeable portion of funds that are classified as "losers" in the first period continue to be "losers" in the second, and a considerable number of "winner" funds also repeat their superior performance in the subsequent period. Regardless of whether we measure performance by alphas or by the Sharpe ratio, both the probability that a winning fund continues to be a winner and the probability that a loser remains a loser is about 60 percent. Again, we find that the results prevail for high-quality, high-yield, and mortgage-backed bond funds. For all subgroups we obtain chi-square statistics that are beyond critical values, thus rejecting the null hypothesis strongly.

Our final out-of-sample results on relative fund performance concern our periodical sorting of funds into decile portfolios, based on their return relative to our passive benchmarks. On average, over the evaluation period more than 97 percent of all available funds at each point in time have a R^2-value that is higher than 0.4 in the factor regressions. We conclude that the models do a good job of explaining bond fund returns.

Table 3.3 presents the post-ranking performance of fund deciles that we estimate with the three-factor benchmark model. The results in Panel A involve sorts applied on the entire fund sample; those in B focus exclusively on high-quality funds; and the results in Panels C and D concentrate on high-yield funds and mortgage-backed funds, respectively. For each decile, we report the post-ranking annualized average return, the annualized Sharpe ratio, annual alpha, and benchmark factor sensitivities.

We note several striking observations that are common to all samples in our study. First, on average we find below-zero alphas. The vast majority of deciles earn negative and statistically significant risk-adjusted returns. The underperformance is most pronounced for high-yield funds.

Second, the out-of-sample excess return of the fund decile, as measured by either alpha or the Sharpe ratio, increases almost monotonically with the decile rank. A portfolio composed of funds ranked highest according to their recent alphas considerably outperforms worst-performing funds in the subsequent period. Over the entire post-ranking evaluation period, the difference in alpha between the top decile and the bottom decile amounts to about 3.5 percent per annum (see Panel A). Moreover, the predictability of (relative) fund returns is prevalent within high-quality, high-yield, and mortgage-backed fund markets (see Panels B, C, and D). The top decile of high-quality bond funds outperformed its lowest-ranked counterpart by 1.8 percent. For high-yield and mortgage-backed funds, these figures are 4.6 and 1.5 percent per year, respectively. In all cases, the difference in Sharpe ratio is also substantial.

Third, across all panels we observe that the difference in return between the funds is largely due to the strong and statistically significant underperformance of the lowest deciles. The returns of the top-performing deciles do not differ significantly from those predicted by the benchmark model. The sensitivities to the three benchmark factors tend to vary from one decile rank to another. However, there are no clear commonalities in factor loadings across the subsamples. For example, although the results in Panel A suggest that the top and bottom deciles tend to load less strongly on BIG and stronger on the high-yield index compared to the other deciles, Panels B and C show that these patterns disappear when we split funds according to investment policy. The top and bottom deciles of high-quality funds have a higher than average exposure to BIG. Top-performing high-yield funds have a lower than average exposure to high-yield index returns.

3.4.2 Persistence and expenses

In this section, we examine the extent to which persistence in bond fund performance can be explained by persistent differences in funds' expenses. To do so, we run two alternative tests.

First, we simply examine the pre-expense returns of the rank portfolios from Table 3.3 over the post-ranking period, where pre-expense returns are obtained every month by taking the sum of a fund's monthly return and one-twelfth of the yearly expense ratio reported by the fund in the respective year. Table 3.4 gives an impression of the explanatory power of expense ratios by showing post-rank risk-adjusted returns both before and after expenses are added back. It appears that most of the 3.5 percent post-expense return difference is not subsumed by difference in expenses between the top and bottom deciles. The spread in pre-expense return between the top and bottom fund deciles continues to be large (2.9 percent) and statistically significant.

Second, we run regressions of funds' contemporaneous risk-adjusted returns before expenses on prior-year pre-expense returns in the Fama and MacBeth (1973) setup. The slope coefficient and respective t-statistic are 0.14 and 2.57. When we use pre-expense Sharpe ratios in our regressions as dependent variable, we obtain a slope of 0.25 and a t-statistic of 3.76.

In conclusion, the persistence uncovered by earlier tests is not unique to post-expense samples.

3.4.3 Economic significance

So far, we have demonstrated that relative bond fund performance persists in the near future. We now investigate whether an investor can exploit this knowledge to earn an abnormal return. For this purpose, we follow Elton et al. (1996) and simulate an investment strategy for which we use modern portfolio theory (MPT). This strategy consists of three steps. First, at each point in time, we evaluate funds' performance over the past 36 months using the three-factor model, as specified earlier. As in the previous section, we exclude funds with an R^2 below 40 percent from our sample. Second, we construct a portfolio from the top decile of funds. The weight assigned to a particular fund is given by

$$w_i = \frac{(\alpha_i/\sigma_{\epsilon_i})}{\sum_{i=1}^{N}(\alpha_i/\sigma_{\epsilon_i})}, \tag{3.6}$$

where σ_{ϵ_i} is the standard deviation of fund i's error term in Eq. (3.1). Besides excluding funds with a low R^2, to ensure that the resulting portfolio has long positions only we also exclude funds with a negative pre-ranking alpha estimate from the top decile. Third, we compute the portfolio's weighted return over the subsequent month. We readjust portfolio weights if a fund disappears after ranking.

We form portfolios of funds as from January 1993 to December 2003, yielding a time series of monthly portfolio returns over a period of 11 years. On average, each portfolio consists of 95 funds, ranging from 38 funds in 1993 to 142 funds in 2003. The maximum weight that we assign to a particular fund over the entire sample period is 26.5 percent, the average weight is about 1 percent, and the minimum is zero by construction. Hence, the resulting portfolio of funds is well diversified.

In Table 3.5 we present performance evaluation results for the MPT-weighted fund portfolio after we allow for changes in two important parameters.

First, we believe it is important to bear in mind that returns reported for load bond funds do not fully represent the net income to fund holders, because holders of these funds are charged with sales loads when entering or exiting the fund[4]. Table 3.1 shows that these loads can easily amount to 2 percent per round-trip transaction. To strengthen the practical implications of our study, we additionally report the outcomes from a separate analysis (Panel B in Table 3.5). To ensure that we obtain economically significant results, we omit all 1,712 load funds from the sample, because loads are not incorporated in reported fund returns.

Second, we also believe it is important to explore performance subject to changes in portfolio rebalancing frequency. From the perspective of mutual fund investors, exploiting short-term performance persistence through frequent fund ranking may come at the expense of high rebalancing costs.

However, all results in Table 3.5 display strong parallels. Panel A shows that the top-performing MPT-weighted bond fund portfolio delivers a post-ranking return above that predicted by the factor models. The alphas are economically large and their corresponding

[4]The separation between load and no-load funds is also important to avoid persistency mechanically induced by different share classes of the same fund.

t-statistics are far beyond critical levels. Panel B shows that the benefits of chasing winner funds are independent of sales loads. For example, the monthly rebalanced no-load portfolio yields a post-ranking abnormal return of almost 1.8 percent and a t-value of 8.55. Panel C shows that investors using MPT can earn abnormal returns in the high-quality bond fund market. The top decile of high-quality funds earns a statistically significant alpha in the range of 0.8 to 1.3 percent.

Moreover, the excess returns on the portfolios in Panels A, B, and C of all tables withstand a decrease in rebalancing frequency. Changing the rebalancing frequency from monthly to quarterly has little influence on the post-ranking alphas. Remarkably, even annually rebalanced fund portfolios can enjoy "hot hands" in bond funds. The annually rebalanced decile outperforms the benchmark indexes by more than 0.5 percent per year in the full-sample case, by 1.3 percent in the restricted (no-load) sample, and by approximately 0.8 percent in the high-quality fund sample.

Panels D and E, which report our results for the high-yield and mortgage-backed fund sample, suggest that MPT marginally improves the performance of the top high-yield decile. The excess return on the monthly rebalanced portfolio is not significantly different from zero. The performance deteriorates with rebalancing frequency.

There are several possible reasons for interpreting the high-yield and mortgage-backed results with caution. The first is that the samples are small and each decile contains a small number of funds, which potentially induces estimation error. The second and most important reason to interpret the results carefully is that the market for high-yield and mortgage-backed debt does not offer index funds. Therefore, relative performance is the most important criterion for fund selection in these segments of the market, not abnormal performance.

Overall, the results strongly suggest that an investment strategy based on MPT enables investors to beat passive benchmarks.

3.5 Alternative model specifications

In this section, we examine whether the persistence we found in previous sections of the paper can be explained by more complex models that account for managers' timing ability, funds' time-varying risk exposures, sensitivities to changes in fundamental economic variables, and changes in the term structure that are not fully picked up by duration. Here, we ask whether these extra performance attribution variables eliminate the persistence in the performance of the portfolios we formed based on past performance. Although models that incorporate these components consume considerable degrees of freedom, we can still use them for *ex post* performance evaluation of the deciles introduced in the previous section.

Our principal benchmark model does not explicitly incorporate a component that separates timing from security selection skills. Therefore, we measure the timing ability of fund managers with models analogous to those developed by Treynor and Mazuy (1966) and Hendricksson and Merton (1981). Our variant takes the form:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(BIG_t - R_{f,t}) + \beta_{2,i}(HY_t - R_{f,t}) + \beta_{3,i}(GNMA_t - R_{f,t}) + \\ \gamma_i(BIG_t - R_{f,t})^2 + \epsilon_{i,t}, \end{aligned} \tag{3.7}$$

where the first three factors are the ones from the Blake et al. (1993) three-factor model, and γ_i measures the timing ability of the manager of fund i. As explained by Chen et al. (2005), timing ability implies a convex relation between bond fund returns and the return on an aggregate market index. We follow Bollen and Busse (2005) and compute abnormal returns as:

$$R_{i,\gamma} - R_{f,t} = \frac{1}{N}\sum_{t=1}^{N}\left[\alpha_i + \gamma_i(BIG_t - R_{f,t})^2\right]. \tag{3.8}$$

We also follow studies that account for funds' time-varying exposure to common risk factors. We use a variant of the Ferson and Schadt (1996) model to arrive at a conditional version of the Blake et al. (1993) model. Time variation in factor sensitivity is captured by variables describing the interaction between benchmark factor returns and a set of lagged instrumental variables:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(BIG_t - R_{f,t}) + B'_{1i}[z_{t-1}(BIG_t - R_{f,t})] + \beta_{2,i}(HY_t - R_{f,t}) + \\ B'_{2i}[z_{t-1}(HY_t - R_{f,t})] + \beta_{3,i}(GNMA_t - R_{f,t}) + B'_{3i}[z_{t-1}(GNMA_t - R_{f,t})] + \epsilon_{i,t}, \end{aligned} \tag{3.9}$$

where z_{t-1} is a vector that consists of lagged values of pre-determined information variables, and B'_{ji} captures the response fund i's exposure to benchmark factor j to this information. We use the variables that Ferson et al. (2006) identify as relevant in predicting variation in exposures to common risk factors for fixed income funds: the lagged level of the one-month Treasury bill rate, the lagged default spread in the corporate bond market, and a measure of industrial production and capacity utilization. We define the default spread as Moody's BAA-rated corporate bond yield minus the AAA-rated corporate bond yield. We obtain our data on industrial production and capacity utilization from the Federal Reserve Board website. The resulting model includes 12 scaled factors and an intercept.

Further, we use the APT setup advanced by Elton et al. (1995) to extend the Blake et al. (1993) three-factor model with premiums for sensitivities to changes in innovation and in economic development:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(BIG_t - R_{f,t}) + \beta_{2,i}(HY_t - R_{f,t}) + \beta_{3,i}(GNMA_t - R_{f,t}) + \\ \beta_{4,i}(INF_{t-1} + \lambda_{INF}) + \beta_{5,i}(GDP_{t-1} + \lambda_{GDP}) + \epsilon_{i,t}, \end{aligned} \tag{3.10}$$

where INF_{t-1} is the one month lagged unexpected change in inflation, GDP_{t-1} is the one month lagged change in economic growth, and λ_{INF} and λ_{GDP} are the risk premia for sensitivities to changes in inflation and economic growth, respectively. As in Elton et al. (1995), we obtain the risk premiums by simultaneously estimating the following regression for a set of passive benchmark indexes using nonlinear least squares:

$$\begin{aligned} R_{i,t} - R_{f,t} = \delta_i + \beta_{1,i}(BIG_t - R_{f,t}) + \beta_{2,i}(HY_t - R_{f,t}) + \beta_{3,i}(GNMA_t - R_{f,t}) + \\ \beta_{4,i}INF_{t-1} + \beta_{5,i}GDP_{t-1} + \epsilon_{i,t}, \end{aligned} \tag{3.11}$$

subject to the restriction:

$$\delta_i = \beta_{4,i}\lambda_{INF} + \beta_{5,i}\lambda_{GDP}. \tag{3.12}$$

As a measure of economic growth, we use the growth rates from the Federal Reserve Board's production and capacity utilization index. We base our inflation variable on the monthly data from the Survey Research Center of the University of Michigan. The advantage of survey data stems from the data's ability to quantify unexpected changes in inflation, which we measure as the monthly change in the expected inflation rate.

To calibrate the parameters in the APT model for determining the risk premiums, we use the following bond indexes as the dependent variables: subsets of the U.S. BIG for maturities of one to three years, three to seven years, and seven to ten years; and 10+ years, Treasury subsets of the U.S. BIG for maturities of one to three years, three to seven years, seven to ten years, 10+ years, and 20+ years; AAA/AA-rated corporate subsets of the US BIG for maturities of one to three years, three to seven years, and seven to ten years; and A-rated corporate subsets of the U.S. BIG for maturities of one to three years, three to seven years, and seven to ten years. When we jointly estimate the regressions for the 15 passive benchmarks over the period 1990-2003, we obtain $\hat{\lambda}_{INF} = -0.71$ and $\hat{\lambda}_{GDP} = -0.25$.

Finally, we introduce a new method for assessing bond fund performance. To capture the effect of changes in the term structure of Treasury yields that are not fully picked up by duration, we rely on a Principal Components Analysis (PCA) similar to the analyses of Pastor and Stambaugh (2002b,a) and Jones and Shanken (2005). We use PCA to extract factors that represent yield changes in certain ranges of the maturity spectrum that are not captured the funds' sensitivities to aggregate bond return variation. The advantage of PCA is that removes redundant dimensions in multivariate data, caused by a high degree of correlation among the indexes, by re-expressing the returns so that the first few components capture the majority of information about expected bond returns. We develop time series of residual excess returns for Treasury subsets of the U.S. BIG for maturities of one to three years, three to seven years, seven to ten years, 10+ years, and 20+ years by regressing the returns on the indexes on a constant and the three benchmark variables described in Eq. (3.2). Then, we conduct a PCA on the time series of the residuals of each regression plus the intercept from that regression. We take the first three normalized components as portfolios weights for the Treasury portfolios. Because Litterman and Scheinkman (1991) report that most of the variance in the yield curve is described by three factors, we add the first three factor-mimicking principal components to the baseline three-factor model (PCA6FM):

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(BIG_t - R_{f,t}) + \beta_{2,i}(HY_t - R_{f,t}) + \beta_{3,i}(GNMA_t - R_{f,t}) + \\ \beta_{4,i}PC1_t + \beta_{5,i}PC2_t + \beta_{6,i}PC3_t + \epsilon_{i,t}. \end{aligned} \tag{3.13}$$

Inspection of the eigenvectors, which we do not report here due to space constraints, shows that the principal components jointly explain 99 percent of the variation in index returns that is left unexplained by the three-index model. In all cases, we estimate the models' parameters by using standard ordinary least squares (OLS) tests.

We measure the deciles' post-ranking performance using these models for sorts on three-factor alphas. We analyze all subsamples of funds and present the results in Table 3.6. The table reports fund alphas for the ten deciles we extract from the four bond fund (sub)universes. None of the benchmark models is able to eliminate the monotonic decline in performance that we observe as we move from the first to the tenth decile. The magnitude of the risk-adjusted difference between the top and bottom deciles remains on the order of the return difference reported earlier (which is also reported in the first row of each panel), regardless of which segment of the fund market we test.

3.6 Bootstrap analysis

Although the evidence of a hot-hands phenomenon in the bond mutual fund industry is compelling, the distributional assumptions that typically underlie tests of performance persistence might be too stringent. Recent studies show that fund returns do not follow the normality assumption inherent in most popular research designs. Violation of the normality assumption could induce a Type I error, in the sense that empirical tests reject evidence of no persistence when persistence patterns are actually absent. This problem motivates us to explore the size of our persistence tests. We perform a bootstrap simulation that enables persistence tests in an environment of artificially generated data. In this environment, predictable patterns in fund performance are predetermined to be a chance outcome, and non-normality features are preserved in the data. Our bootstrap approach is comparable to the residual and factor resampling procedure outlined in Kosowski et al. (2006) and Kosowski et al. (2007).

First, we estimate all funds' alphas, factor loadings, and residual returns using the Blake et al. (1993) three-factor model:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(BIG_t - R_{f,t}) + \beta_{2,i}(HY_t - R_{f,t}) + \beta_{3,i}(GNMA_t - R_{f,t}) + \epsilon_{i,t}. \quad (3.14)$$

We store the coefficient estimates $\{\hat{\beta}_{1,i}, \hat{\beta}_{2,i}, \hat{\beta}_{3,i}, i = 1, 2, \ldots, N\}$, and the time-series of estimated residuals $\{\hat{\epsilon}_{i,t}, i = 1, 2, \ldots, N, t = 1, 2, \ldots, T\}$.

Next, for each bootstrap iteration b, we draw samples by using replacements from the funds' stored residuals $\{\hat{\epsilon}^b_{i,t_e}, t_e = s^b_1, s^b_2, \ldots, s^b_T\}$, and the factors' excess returns $\{(BIG^b_{t_F} - R^b_{t_F}), (HY^b_{t_F} - R^b_{t_F}), (GNMA^b_{t_F} - R^b_{t_F}), t = u^b_1, u^b_2, \ldots, u^b_T\}$, where $s^b_1, s^b_2, \ldots, s^b_T$ and $u^b_1, u^b_2,$ $\ldots, u^b_T$ are the time reorderings imposed by the bootstrap. We then construct time-series of simulated fund returns for all funds using zero alphas:

$$R^b_{i,t} - R^b_{f,t_F} = \hat{\beta}_{1,i}(BIG^b_{t_F} - R^b_{f,t_F}) + \hat{\beta}_{2,i}(HY^b_{t_F} - R^b_{f,t_F}) + \hat{\beta}_{3,i}(GNMA^b_{t_F} - R^b_{f,t_F}) + \hat{\epsilon}^b_{i,t_e} \quad (3.15)$$

The resulting simulated sample of fund returns has the same length, number of funds in the cross-section, and number of return observations as our empirical sample.

We then perform the four persistence tests described in Section 3.2 on the simulated sample, and store the following variables: the slope of the cross-sectional Fama and MacBeth (1973) regression for regressions of 12-month alphas on their lagged values, b^b; the Spearman rank correlation coefficient for correlations between 12-month alphas and their lagged values, ρ^b; the frequency of the past winner/future winner cell of a contingency table based on funds' 12-month consecutive alphas, WW^b; and the difference in post-ranking alphas of the top and bottom decile for sorts on 36-month alphas, α^b_{TMB}. We run a total of 1,000 bootstrap iterations.

Because we impose a zero alpha condition, we can develop a cross-section of alphas arising entirely from sampling variation. If we find that only few bootstrap iterations yield a cross-section of alpha estimates similar to those observed in our actual fund sample, such a finding would reinforce the idea that our results indicate managerial skill and are not attributable to any distributional features of the data.

Figure 3.1 presents the simulated distributions for each persistence test. We note that the bootstraps apply to the entire fund sample. The simulated test results that are based on data that by construction do not harbor skill support our intuition: the average Fama and MacBeth (1973) cross-sectional coefficient and the Spearman rank correlation are hardly different from zero; the frequency with which winner funds repeat superior relative performance matches the expected frequency of 25 percent; and the post-ranking performance differential between the top-ranked and bottom-ranked decile portfolios is zero on average, and only 1 percent in the most extreme scenario. The extreme tail values resulting from the bootstrap exercise show we can reject the idea that our evidence of persistence in bond fund performance is a statistical artifact. Under the imposed condition that managerial skill is nonexistent, the most extreme simulation outcomes (i.e., values in the tails of the distributions in Figure 3.1) are not in the order of the empirical values we obtain from the four persistence tests that are central to this study. Thus, the bootstrap outcomes that we report permit a strong judgment about the size of our tests, indicating that there is little reason to expect that our evidence is prone to data-driven inferences.

3.7 Conclusion

Despite the massive size of the bond retail industry, empirical evidence on the performance persistence of actively managed bond mutual funds is surprisingly scarce. In this study we provide a rigorous investigation into bond fund performance by using the entire fund population in the United States over the period 1990–2003. The central question that underlies our research asks if active bond fund performance in the past persists in the future.

We find strong evidence of performance persistence in bond funds. We use a wide range of common methods, all of which consistently show that past fund performance predicts future performance. Funds that report strong (weak) performance in the past repeat their performance in the subsequent period. The influence of managerial skill on excess fund returns is prevalent with both high-quality and high-yield bonds. We demonstrate that simple bond fund selection strategies based on modern portfolio theory earn average returns above those predicted by a wide range of benchmark models, which indicates that investors in bond funds can enjoy hot-hands effects. A battery of robustness checks confirms that our results are neither model-specific nor data-driven.

We conclude this study with one important note. Although our evidence of performance persistence is strong, we believe that bond index funds remain valuable investment vehicles. Since previous research has pointed out that on average, bond fund managerial skill cannot outweigh fees and expenses, index funds are feasible, low-cost alternatives for unsophisticated investors who lack the ability to exploit performance persistence. However, sophisticated investors with sizable financial capacity, such as institutional investors, can take advantage of predictable patterns in bond fund returns.

3.8 Tables and Figures

Table 3.1: Bond funds characteristics over time.

	A. All funds					*B. Government/Investment grade*				
	#Funds	TNA	Expenses	Sales loads	Turnover	#Funds	TNA	Expenses	Sales loads	Turnover
1990	480	317.67	0.99%	2.41%	1.11	223	339.44	0.93%	2.14%	1.21
1991	487	412.63	0.80%	2.29%	NA	236	417.26	0.74%	2.06%	NA
1992	787	344.84	0.97%	2.39%	1.25	325	258.05	0.92%	2.07%	1.31
1993	1,058	316.74	0.97%	2.14%	1.43	474	219.00	0.91%	1.88%	1.43
1994	1,326	209.88	1.03%	1.94%	1.58	621	152.79	0.97%	1.71%	1.62
1995	1,550	219.98	1.04%	1.94%	1.54	703	166.82	0.98%	1.73%	1.62
1996	1,605	225.03	1.06%	1.89%	1.53	731	171.76	0.99%	1.68%	1.64
1997	1,745	239.33	1.05%	1.76%	1.55	860	187.61	0.99%	1.56%	1.61
1998	1,792	269.25	1.06%	1.81%	2.13	865	227.96	1.00%	1.61%	2.34
1999	1,840	259.97	1.08%	1.89%	1.42	859	224.57	1.00%	1.67%	1.49
2000	1,849	242.48	1.07%	1.84%	1.41	877	227.64	0.99%	1.61%	1.51
2001	1,905	278.75	1.08%	1.81%	1.70	893	268.34	1.02%	1.60%	1.86
2002	1,905	349.98	1.07%	1.77%	1.67	906	338.33	1.00%	1.61%	1.78
2003	2,199	316.06	1.08%	1.79%	1.77	1,027	274.37	1.02%	1.64%	1.89

The table lists number of available funds, the average total net assets (TNA), expense ratios, maximum sales loads, and turnover of our sample of bond funds. The sample covers 3,549 U.S. bond funds over the period 1990–2003. Expense ratio is management, administrative, and 12b-1 expenses divided by the average TNA. Sales load is the sum of maximum front-end, back-end, and deferred sales charges. Turnover is the minimum of aggregate purchases of securities or aggregate sales of securities, divided by the average TNA. We obtain our data from the CRSP database. To be included in our sample, funds must be classified as government, corporate, high yield, or mortgage-backed at the final quarter of each year.

Table 3.1 continued

	C. High yield					*D. Mortgage-backed*				
	#Funds	TNA	Expenses	Sales loads	Turnover	#Funds	TNA	Expenses	Sales loads	Turnover
1990	87	216.89	1.26%	3.34%	0.70	44	344.50	0.95%	2.74%	1.17
1991	79	319.93	1.15%	3.25%	NA	46	535.63	0.69%	2.49%	NA
1992	93	421.14	1.32%	4.12%	0.99	138	718.22	0.98%	2.73%	1.29
1993	99	493.94	1.35%	3.62%	1.06	191	616.47	0.99%	2.42%	1.64
1994	120	371.79	1.41%	3.14%	0.85	217	379.27	1.09%	2.28%	1.77
1995	144	389.34	1.42%	3.09%	0.91	248	374.55	1.13%	2.27%	1.54
1996	170	435.19	1.37%	2.90%	0.96	228	343.00	1.17%	2.29%	1.41
1997	217	441.92	1.31%	2.62%	1.15	215	344.31	1.15%	2.19%	1.49
1998	260	394.35	1.31%	2.58%	1.33	209	367.88	1.13%	2.16%	1.68
1999	310	344.66	1.35%	2.64%	1.05	199	357.05	1.16%	2.16%	1.47
2000	345	230.52	1.31%	2.51%	0.95	182	375.44	1.17%	2.22%	1.58
2001	364	236.38	1.31%	2.43%	1.05	177	444.42	1.09%	2.12%	1.87
2002	351	251.62	1.34%	2.33%	1.01	168	651.07	1.05%	1.94%	2.13
2003	406	343.38	1.35%	2.33%	1.08	189	681.99	1.03%	1.90%	2.29

Table 3.2: Persistence tests.

A. Cross-sectional regressions

	1. $Alpha_{i,t}, Alpha_{i,t-1}$			2. $Sharpe_{i,t}, Alpha_{i,t-1}$		
	a	b	R^2	a	b	R^2
All funds	-0.06 (-3.68)	0.17 (3.23)	0.05	0.28 (2.16)	0.24 (4.03)	0.06
Gov/Corp	-0.05 (-4.52)	0.25 (3.36)	0.08	0.27 (2.06)	0.39 (4.72)	0.05
High yield	-0.01 (-0.09)	0.12 (1.71)	0.06	0.44 (2.36)	0.12 (2.41)	0.10
Mortgage-backed	-0.07 (-2.41)	0.35 (2.65)	0.24	0.28 (2.02)	0.39 (2.77)	0.16

B. Rank correlations

	1. $Alpha_{i,t}, Alpha_{i,t-1}$	2. $Sharpe_{i,t}, Alpha_{i,t-1}$
	rho	rho
All funds	0.20 (4.99)	0.21 (3.98)
Gov/Corp	0.26 (7.88)	0.24 (5.94)
High yield	0.13 (2.51)	0.21 (3.91)
Mortgage-backed	0.37 (7.14)	0.23 (3.23)

C. Contingency tables

	1. $Alpha_{i,t}, Alpha_{i,t-1}$					2. $Sharpe_{i,t}, Alpha_{i,t-1}$				
	LL	LW	WL	WW	χ^2	LL	LW	WL	WW	χ^2
All funds	0.30	0.20	0.20	0.30	524.68	0.29	0.21	0.21	0.29	347.95
Gov/Corp	0.31	0.19	0.19	0.31	577.05	0.29	0.21	0.21	0.29	311.50
High yield	0.27	0.23	0.23	0.27	18.49	0.29	0.21	0.21	0.29	48.17
Mortgage-backed	0.33	0.17	0.17	0.33	162.35	0.31	0.18	0.18	0.32	121.59

Each year, we investigate the relation between fund performance over the subsequent year and alpha estimates over the preceding year. We measure fund performance over the subsequent year using alpha (Panel A1, B1, and C1), and the Sharpe ratio (A2, B2, and C2). In Panel A we report on Fama and MacBeth (1973) cross-sectional regressions. Panel B shows rank correlations. Panel C presents a two-by-two contingency table, based on a measure of performance relative to the median fund: loser (past year) /loser (subsequent year); loser/winner; winner/loser; and winner/winner. We estimate alphas by using a three-factor model specification that includes a broad investment-grade bond index, a high yield index, and a mortgage index. The sample is from 1990 to 2003. The t-statistics are in parentheses. Performance persistence in tested based on a sample that includes, respectively, all funds, government/ corporate bond funds, high yield funds, and mortgage-backed funds.

Table 3.3: Three-factor rank portfolios.

	Return	Sharpe	Alpha	Alpha-t	BIG	HY	$GNMA$	R^2
A. All funds								
D1 (TOP)	3.44%	0.96	0.35%	0.77	0.57	0.25	0.07	0.85
D2	2.24%	0.79	-0.29%	-1.21	0.59	0.09	0.11	0.93
D3	2.13%	0.73	-0.42%	-2.72	0.68	0.06	0.06	0.97
D4	1.88%	0.63	-0.71%	-4.87	0.73	0.07	0.02	0.98
D5	1.90%	0.62	-0.75%	-5.45	0.74	0.06	0.04	0.98
D6	1.95%	0.60	-0.81%	-6.77	0.79	0.05	0.03	0.99
D7	1.71%	0.51	-1.15%	-8.40	0.84	0.09	-0.05	0.98
D8	1.69%	0.49	-1.26%	-8.94	0.90	0.12	-0.13	0.98
D9	1.49%	0.41	-1.74%	-8.24	0.82	0.18	-0.05	0.97
D10 (BOTTOM)	0.94%	0.17	-3.12%	-4.84	0.74	0.57	-0.31	0.87
B. Government/Investment grade								
D1 (TOP)	2.99%	0.82	0.18%	0.49	0.97	0.04	-0.13	0.90
D2	1.88%	0.62	-0.57%	-2.91	0.78	0.01	-0.00	0.96
D3	1.92%	0.62	-0.51%	-3.73	0.83	0.00	-0.05	0.98
D4	2.03%	0.66	-0.39%	-3.41	0.86	0.01	-0.09	0.99
D5	1.86%	0.56	-0.78%	-5.40	0.88	0.01	-0.03	0.98
D6	1.88%	0.55	-0.81%	-7.38	0.95	0.01	-0.10	0.99
D7	1.80%	0.51	-0.92%	-6.75	1.00	0.01	-0.15	0.99
D8	1.94%	0.53	-0.88%	-5.85	1.06	0.01	-0.18	0.98
D9	1.68%	0.44	-1.25%	-7.73	1.09	0.02	-0.19	0.98
D10 (BOTTOM)	1.61%	0.35	-1.72%	-4.72	1.42	0.06	-0.48	0.94

Each month, we sort all available bond funds into equally weighted decile portfolios based on their alpha estimated over the preceding 36 months. We estimate alphas by using a three-factor model specification that includes a broad investment-grade bond index (BIG), a high yield index (HY), and a mortgage index ($GNMA$). The sample is from 1990 to 2003. The table lists the deciles' excess returns, Sharpe ratios, alphas, and factor loadings over the post-ranking period. Returns, Sharpe ratios, and alphas are annualized. Performance persistence in tested based on a sample that includes, respectively, all bond funds (Panel A), government/ corporate bond funds (Panel B), high yield bond funds (Panel C), and mortgage-backed bond funds (Panel D).

Table 3.3 continued

	Return	Sharpe	Alpha	Alpha-t	BIG	HY	$GNMA$	R^2
C. High yield								
D1 (TOP)	3.88%	0.62	0.12%	0.15	-0.22	0.77	0.31	0.88
D2	3.68%	0.55	-0.35%	-0.44	-0.06	0.84	0.13	0.89
D3	2.81%	0.41	-1.49%	-1.89	-0.16	0.86	0.30	0.91
D4	2.23%	0.32	-2.03%	-2.75	-0.16	0.88	0.25	0.92
D5	2.45%	0.35	-1.64%	-2.24	-0.03	0.87	0.06	0.91
D6	2.27%	0.31	-2.22%	-2.55	-0.17	0.92	0.28	0.90
D7	2.41%	0.33	-1.87%	-2.16	-0.14	0.92	0.17	0.90
D8	1.94%	0.26	-2.34%	-2.60	-0.22	0.95	0.20	0.90
D9	1.27%	0.16	-2.94%	-3.04	-0.20	0.96	0.14	0.86
D10 (BOTTOM)	-0.15%	-0.02	-4.56%	-3.98	-0.17	0.98	0.16	0.81
D. Mortgage-backed								
D1 (TOP)	2.09%	0.88	-0.12%	-0.65	0.18	-0.00	0.60	0.95
D2	1.79%	0.71	-0.52%	-2.80	0.22	-0.01	0.61	0.95
D3	1.65%	0.60	-0.91%	-5.89	0.24	-0.01	0.67	0.97
D4	1.85%	0.66	-0.73%	-4.90	0.25	-0.02	0.68	0.97
D5	1.83%	0.66	-0.73%	-4.43	0.28	-0.01	0.64	0.97
D6	1.62%	0.60	-0.86%	-5.57	0.26	-0.02	0.63	0.97
D7	1.31%	0.45	-1.29%	-6.71	0.32	-0.02	0.61	0.96
D8	1.19%	0.40	-1.45%	-8.12	0.36	-0.02	0.58	0.96
D9	1.15%	0.38	-1.45%	-6.23	0.45	-0.02	0.47	0.94
D10 (BOTTOM)	1.01%	0.33	-1.58%	-6.70	0.51	-0.02	0.40	0.94

Table 3.4: Three-factor rank portfolios before expenses.

		A. Pre-expense			B. Post-expense		
	Expenses	Sharpe	Alpha	Alpha-t	Sharpe	Alpha	Alpha-t
All funds							
D1 (TOP)	0.82%	1.19	1.17%	2.60	0.96	0.35%	0.70
D2	0.76%	1.05	0.47%	1.99	0.79	-0.29%	-1.21
D3	0.79%	1.00	0.37%	2.38	0.73	-0.42%	-2.72
D4	0.84%	0.91	0.14%	0.95	0.63	-0.71%	-4.87
D5	0.89%	0.91	0.15%	1.05	0.62	-0.75%	-5.45
D6	0.96%	0.90	0.14%	1.18	0.60	-0.81%	-6.77
D7	1.06%	0.84	-0.08%	-0.61	0.51	-1.15%	-8.40
D8	1.22%	0.85	-0.04%	-0.30	0.49	-1.26%	-8.94
D9	1.35%	0.79	-0.39%	-1.84	0.41	-1.74%	-8.24
D10 (BOTTOM)	1.40%	0.42	-1.73%	-2.69	0.17	-3.12%	-4.84

Each month, we sort all available bond funds into equally weighted decile portfolios based on their alpha estimated over the preceding 36 months. We estimate alphas by using a three-factor model specification that includes a broad investment-grade bond index, a high yield index, and a mortgage index. The sample is from 1990 to 2003. We then examine the pre-expense returns of the rank portfolios, where pre-expense returns are obtained every month by taking the sum of a fund's monthly return and one-twelfth of the yearly expense ratio reported by the fund in the respective year. The table lists the deciles' average expense ratios, Sharpe ratios and alphas over the post-ranking period. All values are annualized.

Table 3.5: Three-factor MPT portfolios.

	Return	Sharpe	Alpha	Alpha-t	BIG	HY	$GNMA$	R^2
A. All funds								
monthly	3.22%	1.43	1.27%	5.04	0.44	0.07	0.11	0.88
quarterly	3.08%	1.38	1.13%	4.68	0.43	0.06	0.13	0.89
yearly	2.53%	1.14	0.53%	2.20	0.38	0.07	0.19	0.89
B. No-load funds								
monthly	3.45%	1.73	1.79%	8.55	0.44	0.04	0.04	0.89
quarterly	3.36%	1.70	1.72%	8.37	0.44	0.03	0.04	0.89
yearly	2.92%	1.55	1.33%	6.32	0.38	0.03	0.10	0.88
C. Government/Investment grade								
monthly	3.03%	1.35	1.30%	6.12	0.57	0.01	-0.03	0.91
quarterly	2.97%	1.32	1.22%	5.67	0.55	0.01	0.00	0.90
yearly	2.66%	1.19	0.86%	3.74	0.50	0.02	0.06	0.90
D. High yield								
monthly	4.02%	0.70	0.55%	0.74	-0.12	0.70	0.22	0.87
quarterly	3.78%	0.66	0.27%	0.35	-0.14	0.70	0.25	0.87
yearly	2.95%	0.48	-0.69%	-0.81	-0.13	0.74	0.22	0.85
E. Mortgage-backed								
monthly	2.17%	0.94	0.02%	0.09	0.07	-0.00	0.70	0.90
quarterly	2.10%	0.90	-0.08%	-0.32	0.07	-0.00	0.71	0.90
yearly	2.24%	0.93	-0.02%	-0.08	0.12	-0.00	0.69	0.92

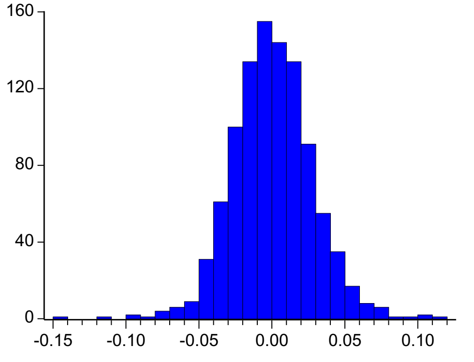
Each month, we sort all available bond funds into equally weighted decile portfolios on their alpha estimated over the preceding 36 months. We estimate alphas by using a three-factor model specification that includes a broad investment-grade bond index (BIG), a high yield index (HY), and a mortgage index ($GNMA$). We then construct a portfolio from the top decile of funds, where the weights assigned to the funds in that portfolio are based on modern portfolio theory described in Elton et al. (1996). We rebalance the portfolio at monthly, quarterly, and yearly basis. We conduct our analysis on a sample that includes, respectively, all bond funds (Panel A), no-load bond funds (Panel B), government/ corporate bond funds (Panel C), high yield bond funds (Panel D), and mortgage-backed bond funds (Panel E). The table lists the portfolios' alphas and factor loadings over the post-ranking period. Alphas are annualized.

Table 3.6: Alternative model specifications.

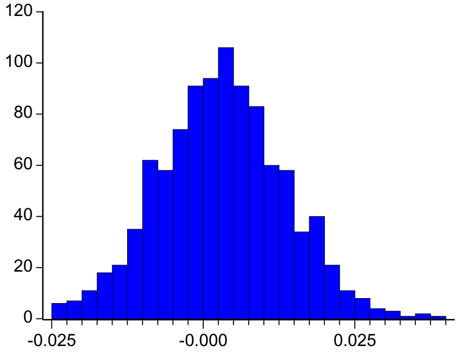
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
A. All funds										
TM4FM	0.35%	-0.29%	-0.42%	-0.71%	-0.78%	-0.83%	-1.17%	-1.27%	-1.76%	-3.19%
FS/FKH12FM	0.31%	-0.41%	-0.54%	-0.78%	-0.86%	-0.90%	-1.12%	-1.22%	-1.83%	-2.74%
EGB5FM	0.12%	-0.36%	-0.15%	-0.60%	-0.64%	-0.67%	-1.04%	-0.93%	-1.43%	-3.87%
PCA6FM	0.50%	-0.26%	-0.45%	-0.72%	-0.76%	-0.81%	-1.13%	-1.22%	-1.69%	-2.83%
B. Government/Investment grade										
TM4FM	0.22%	-0.58%	-0.49%	-0.36%	-0.80%	-0.82%	-0.94%	-0.87%	-1.24%	-1.77%
FS/FKH12FM	0.27%	-0.61%	-0.59%	-0.50%	-0.82%	-0.92%	-1.08%	-0.97%	-1.36%	-1.74%
EGB5FM	-0.06%	-0.50%	-0.53%	-0.33%	-0.68%	-0.66%	-0.72%	-0.74%	-0.86%	-2.16%
PCA6FM	0.36%	-0.57%	-0.56%	-0.46%	-0.81%	-0.82%	-0.92%	-0.90%	-1.30%	-1.70%
C. High yield										
TM4FM	-0.00%	-0.46%	-1.65%	-2.17%	-1.79%	-2.36%	-2.05%	-2.46%	-3.11%	-4.55%
FS/FKH12FM	0.34%	-0.22%	-1.08%	-1.64%	-1.53%	-2.01%	-1.81%	-2.37%	-2.68%	-3.88%
EGB5FM	0.15%	0.36%	-1.72%	-1.24%	-1.50%	-2.41%	-1.81%	-2.56%	-3.10%	-3.59%
PCA6FM	0.21%	-0.25%	-1.35%	-1.85%	-1.34%	-2.08%	-1.70%	-2.09%	-2.53%	-4.38%
D. Mortgage-backed										
TM4FM	-0.12%	-0.55%	-0.97%	-0.79%	-0.78%	-0.87%	-1.37%	-1.44%	-1.53%	-1.61%
FS/FKH12FM	-0.09%	-0.51%	-0.96%	-0.75%	-0.73%	-0.95%	-1.29%	-1.49%	-1.54%	-1.78%
EGB5FM	-0.49%	-0.17%	-0.66%	-0.53%	-0.29%	-0.16%	-0.50%	-1.55%	-0.80%	-1.36%
PCA6FM	-0.18%	-0.52%	-0.87%	-0.70%	-0.75%	-0.89%	-1.29%	-1.47%	-1.42%	-1.62%

Each month, we sort all available bond funds into equally weighted decile portfolios based on their alpha estimated over the preceding 36 months. We estimate alphas by using a three-factor model specification that includes a broad investment-grade bond index, a high yield index, and a mortgage index. The sample is from 1990 to 2003. The table lists the portfolios' post-ranking alphas, which we estimate by using the following model specifications: Treynor and Mazuy (1966) 4-factor model (TM4FM), Ferson and Schadt (1996) 12-factor model (FS/FKH12FM), Elton et al. (1995) 5-factor model (EGB5FM), and a 6-factor model based on PCA (PCA6FM).

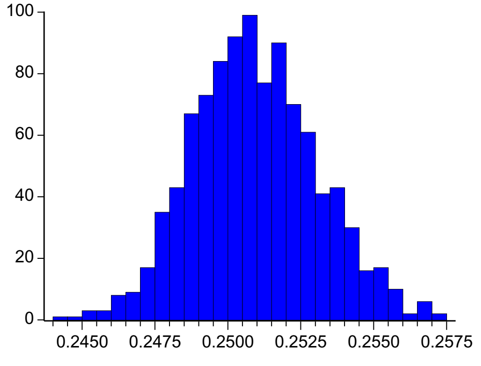
Figure 3.1: Bootstrap results.



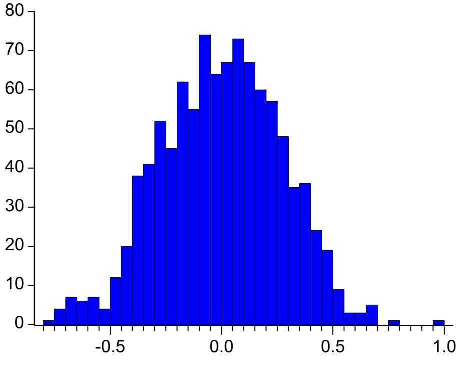
(a) Fama-McBeth slope b



(b) Rank correlation



(c) Winner/Winner frequency



(d) Alpha TMB

We generate a simulated sample of fund returns by using the bootstrap procedure we discuss in Section 3.5. We then perform the four persistence tests described in Section 3.2 on the simulated sample, and store the following variables: (i) the slope of the cross-sectional Fama and MacBeth (1973) regression for regressions of 12-month alphas on their lagged values; (ii) the Spearman rank correlation coefficient for correlations between 12-month alphas and their lagged values; (iii) the frequency of the past winner/future winner cell of a contingency table based on funds' 12-month consecutive alphas; and (iv) the difference in post-ranking alphas of the top and bottom decile for sorts on 36-month alphas. We run 1,000 bootstrap iterations. The figure panels present the simulated distribution of these test statistics.

Chapter 4

On the Use of Multi-Factor Models to Evaluate Mutual Fund Performance*

4.1 Introduction

In the academic literature it is common practice to evaluate the performance of mutual funds on the basis of multi-factor models (see e.g., Hendricks et al. (1997), Elton et al. (1996), Carhart (1997), Bollen and Busse (2005)). Such models extend the Sharpe (1964) and Lintner (1965) single-factor Capital Asset Pricing Model (CAPM) with proxies for specific investment styles (e.g., small cap, value, or momentum). Inclusion of these additional factors is important to identify managerial skill, irrespective whether or not the factors represent risks in the economy. For example, if factor exposures are not taken into account, fund managers can generate nonzero alphas by simply following an anomalous style (see e.g., Elton et al. (1993) and Carhart (1997)).

In this paper we evaluate the cross-sectional explanatory power of multi-factor models to explain mutual fund returns and the consequences for evaluating mutual fund performance. First, this allows us to identify to what extent professional money managers are able to capture the value, size, and momentum premiums implied by the hypothetical hedge portfolios that underly these factors. Second, we analyze to what extent the use of these factor proxies systematically biases performance estimates of mutual funds. Our main concern is that the factor proxies in the standard multi-factor approaches are based on hypothetical stock portfolios, which do not incorporate transaction costs and trading

*This chapter is based on the article by Huij and Verbeek (2006a).

restrictions. Accordingly, the predicted factor premiums are likely to be over- or under-estimated and the resulting performance estimates for funds with significant exposure to these factors may be biased.

For example, consider two zero-alpha fund managers (i.e., managers with no skill) of which the first one manages a fund with unit exposure to the market factor, and the second one a fund with unit exposure to the value factor. Suppose that the market premium is overestimated by 0.3 percent. It is easy to show that alpha estimates for the first fund asymptotically converge to minus 0.3 percent. Now suppose that there is a positive value premium, but that this premium is overestimated by 3 percent. This will cause alpha estimates for the second fund to converge to minus 3 percent. Based on the alpha estimates for both funds, one might falsely infer that the manager of the first fund is more skilled. In fact, one might even falsely infer that some funds systematically outperform the passive factors. To illustrate this point, consider a third zero-alpha fund manager. However, suppose that this manager follows a growth strategy, and has an exposure of minus one to the value factor. Now, because the employed value proxy projects a larger return differential between growth and value funds than there actually is, the fund's alpha estimate converges to plus 3 percent. Thus, miscalculation of the factor premiums might not only lead to false inferences about relative fund performance, but also about market efficiency as a whole.

While miscalculation of the factor premiums is a general concern (i.e., even if fund returns were fully described by a single-factor model, overestimation of the premium on this factor will cause performance estimates to be biased), we argue that there are good reasons to believe that the resulting biases are more important for multi-factor approaches. Because the transaction costs involved with tracking the market index are as low as 30 basis points per year, it is unlikely that the resulting biases in CAPM performance estimates are economically significant. However, the costs that are involved with mimicking the hypothetical hedge portfolios used with multi-factor approaches are many times larger. Several studies indicate that there is a large dispersion in transaction costs for different investment styles (Keim and Madhaven, 1997), and that the size, value, and momentum anomalies are concentrated in small cap stocks (see e.g., Loughran (1997), Hong et al. (2000), and Post and Vliet (2005)), or stocks with higher transaction costs (see e.g., Stoll and Whaley (1983), Ali et al. (2003), Lesmond et al. (2004), and Houge and Loughran (2006)). Another reason to believe that the factor premiums earned by fund managers are different from the ones projected by the factors' proxies is that fund managers face certain trading restrictions such as short sales constraints and position limits when implementing style strategies. For example, most mutual fund managers are required to hold a reasonably diversified portfolio, and are restricted not to sell short. While a strategy of tracking the market involves long positions only, a size or value strategy may involve significant short positions. Thus, it is unlikely that the anomalous returns are in the same order of magnitude as those projected by the hypothetical hedge portfolios used in multi-factor approaches.

The main questions we address in this study are the following: to what extent are fund managers able to exploit the anomalies reported in the literature? Do the proxies that are used with multi-factor approaches systematically over- or underestimate the premiums fund managers actually earn by following the anomalous styles? And if so, how does this affect the performance estimates of mutual funds based on multi-factor models. Answering these questions allows us to determine the economic significance of the small-cap, value and momentum anomalies, by considering the investment performance of open-end mutual funds that try to exploit them. Moreover, we can determine the impact of a particular form of benchmark misspecification upon mutual fund performance estimates.[1] To answer these questions we employ the mutual funds database of the Center for Research in Security Prices (CRSP) and analyze monthly mutual fund returns over the period 1963–2003.

The main findings of this paper can be summarized as follows. First, we document a clear value premium and a momentum effect in the cross-section of fund returns, but do not find evidence of a small firm-effect. However, while funds with a value-oriented style earn returns higher than predicted by the single-factor CAPM, their premium is significantly smaller than projected by the Fama and French (1993) value proxy HML that is employed with most multi-factor approaches. A fund with unit exposure to the value factor actually earns an abnormal return of 2 percent per annum, while the value proxy HML predicts a premium of more than 5 percent per annum. Similarly, funds that hold stocks that did well over the past year, earn returns that are higher than predicted by the CAPM, but the return differential between past winners and losers is much larger than predicted by the commonly employed momentum proxy WML. While the momentum proxy WML predicts a return differential of 11 percent per year between past winners and losers, we observe a differential of more than 19 percent on an annual basis.

Our second set of results concerns the implications of these findings for the evalua-

[1]Other studies that investigate the implications of benchmark misspecification for performance evaluation are Roll (1978), Lehman and Modest (1987), Grinblatt and Titman (1994), and Coles et al. (2006).

tion of mutual fund performance. Because of the miscalculation of the premiums of the hypothetical hedge portfolios, standard three- and four-factor alphas for value funds are systematically biased downwards, while those for growth funds are biased upwards. Further, the performance of past loser funds is underestimated, while that of winner funds is overestimated. We also demonstrate that these results cannot be explained by time-varying market betas. Finally, our results indicate that factor proxies based on mutual fund returns rather than stock returns provide better benchmarks to evaluate professional money managers.

The remainder of this paper is organized as follows: Section 4.2 describes the data and methodology, Section 4.3 tests the cross-sectional explanatory power of the factor models, Section 4.4 examines the robustness of our results to time-varying betas, Section 4.5 presents the results using factor proxies based on fund returns, and finally Section 4.6 concludes.

4.2 Data Sources and Construction of Style Portfolios

Data on returns of mutual funds are extracted from the 2003 CRSP Mutual Fund Survivorship-bias Free Database. This database covers monthly total returns of more than 21,400 open-end mutual funds over the period 1962–2003. Of these funds, about 7,000 are dead. We follow a procedure similar to Pastor and Stambaugh (2002a,b) and use the additional information CRSP provides on fund classifications, expenses, and load data to construct a sample of US equity funds. We exclude funds with no classification, expense, or load data in the annual summary at the end of each previous year. Additionally, we examine fund classifications at the end of each previous year, and exclude flexible funds, bond funds, mortgage-backed funds, multi-manager funds, money market funds, balanced funds, funds that invest in precious metals, and international funds. From the remaining funds, we select funds that are classified as small/cap growth, growth, growth & income, income, or sector fund. The selection of these types of funds is consistent with the literature, see e.g., Carhart (1997) and Bollen and Busse (2005). Finally, we drop funds with less than 12 consecutive returns over the entire sample period. For a comprehensive documentation on the data extraction procedure, we refer to Huij and Verbeek (2007). In total, our sample covers 7,852 funds over the period 1963–2003. Since CRSP basically includes all funds that existed during this period, our data are free of the survivorship-bias as documented by Brown et al. (1992) and Brown and Goetzmann (1995). As we require funds to have an annual summary available at the end of each previous year to be included in our sample, the first return observation is over January 1963. All returns are reported net of operating expenses.

We build quantile portfolios of funds based on the funds' styles. As explained by Fama and MacBeth (1973), using such an approach we reduce the "errors-in-variables" problem in the estimated factor exposures. More specifically, the style portfolios are constructed in the following way. Each month, all available funds are sorted into 10, 20, or 30 mutually exclusive portfolios based on one of the following characteristics of their stock holdings: (i) market beta, (ii) exposure to the size factor, (iii) exposure to the value factor, and (iv) past return. Funds' market betas are obtained by running the CAPM regressions for all available funds using ordinary least squares (OLS) with a rolling window over the preceding 36 months:

$$r_{i,t} = \alpha_i + \beta_i RMRF_t + \epsilon_{i,t}, \tag{4.1}$$

where $r_{i,t}$ is the excess return of fund i in month t, $RMRF_t$ is the excess return on the market portfolio in month t, α_i is Jensen's alpha (Jensen, 1968), β_i is the market beta of fund i, and $\epsilon_{i,t}$ is the residual return of fund i in month t. Funds' exposures to the size and value factor are obtained by estimating the Fama and French (1993, 1995, 1996) (3FM) using OLS with a rolling window over the preceding 36 months:

$$r_{i,t} = a_i + \beta_{1i} RMRF_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \epsilon_{i,t}, \tag{4.2}$$

where SMB_t and HML_t are the returns on factor mimicking portfolios for market equity (Small Minus Big) and book-to-market-equity (High Minus Low) in month t. The benchmark returns on $RMRF$, SMB, and HML are obtained from Kenneth French's data library. As a proxy for the risk-free rate, the one-month Treasury bill rate from Ibbotson and Associates is used. Momentum portfolios are based on the funds' average return over the past 12 months consistent with most of the literature.

With sorts on market beta, market equity, and book-to-market-equity, the top quantile contains the funds with the highest estimated exposure to the relevant factor (e.g., β_{1i}, β_{2i}, and β_{3i}). For example, if funds are sorted into deciles based on their SMB loadings, the top decile contains the 10 percent of funds with the highest small cap exposure, and the bottom decile contains the 10 percent of funds with the highest large cap exposure. If the sorts are based the funds' HML loadings, the top decile contains the 10 percent of funds with the highest value exposure, and the bottom decile the 10 percent of funds with the highest growth exposure. For momentum portfolios, the top quantile contains the funds with the highest average return over the past year.

After sorting the funds into quantile portfolios, the equally weighted returns over the subsequent (out-of-sample) month are calculated for all portfolios. The portfolio weights are readjusted if a fund disappears from our sample after ranking. The first three years of our dataset (January 1963 to December 1965) are used to initialize the style portfolios. Thus, the style portfolio returns cover the period January 1966 to December 2003.

4.3 Empirical Results

4.3.1 To what extent are fund managers able to exploit the anomalies reported in the literature?

The first question we address in this study is whether the returns of the style portfolios are fully described by a linear function of their market betas. Our first series of results involve scatter plots of the style portfolios' expected returns on their market betas. For all style portfolios, we compute average excess returns over the entire sample period, and plot these values on the portfolios' post-ranking market betas that are estimated using the CAPM in Eq. (4.1). These beta estimates are also based on the entire sample period. The resulting scatter plots are presented in Figure 4.1. Since our results are robust to the number of portfolios, we concentrate on the 20-portfolio results. The solid line in the graphs draws the Security Market Line (SML) predicted by the CAPM, and the dashed line draws the empirical relation between average excess return and market beta by fitting a regression line to the displayed data points. For all sorts, we clearly observe the celebrated anomalies in the literature: from the scatter plot for quantile portfolios of funds based on market beta, it appears that the risk-return relation is flatter than the Sharpe-Lintner CAPM predicts, i.e., funds that hold stocks with high (low) betas earn returns that are too low (high) given their betas. We also observe evidence of the small firm-effect as documented by Banz (1981), Reinganum (1981), and Brav et al. (2005). The empirical SML is steeper than the CAPM prediction. Funds that have high exposure to large cap stocks (data points to the left in the plot) earn excess returns that are too low given their market betas, while funds with high exposure to small cap stocks (data points to the right in the plot) earn excess returns that are too high. Portfolios resulting from sorts on book-to-market-equity also display a large variation in excess returns that is not explained by differences in market beta. Funds following a value oriented style (data points to the left in the plot) have a substantially lower market beta than funds with a growth style (data points to the right in the plot), but earn higher excess returns. Finally, most prominently we observe the momentum effect. Funds that hold stocks that did well over the past year earn abnormal positive returns in the near future, while funds that hold stocks that did poorly earn abnormal negative returns.

Next, we perform time-series regressions in the spirit of Black et al. (1972), and run CAPM regressions as in Eq. (4.1) for all style portfolios over the entire post-ranking period using OLS. The parameter estimates and R-squared values for sorts into 10 style portfolios are reported in Table 4.1. Additionally, Figure 4.2 presents the style portfolios' alphas resulting from running the CAPM regressions for sorts into 20 portfolios. Again both for sorts on beta, market equity, book-to-market-equity, and price momentum our results are consistent with the style anomalies in the literature. The portfolios' alphas increase with the quantile ranks when funds are sorted on their market betas. For sorts on market equity, we observe evidence of the small-firm effect. In a similar fashion, alphas decrease with the quantile ranks when funds are sorted on book-to-market-equity and price momentum. On a yearly basis, the spread in alpha between the top and bottom deciles is about 1.3 to 2.4 percent for sorts on market beta, market equity, and book-to-market-equity. For sorts on momentum, this spread even mounts to more than 11 percent.

Finally, we employ the pooled time-series-cross-sectional methodology of Gibbons et al. (1989) to test whether the style portfolios' alphas are jointly equal to zero, and whether the portfolios' returns are fully described by a linear function of their market betas. Formally, the condition that we test for is given by:

$$E(r_i) = \beta_i E(r_m), \tag{4.3}$$

where $E(r_i)$ is the expected return on portfolio i in excess of the risk-free rate, $E(r_m)$ is the expected return on the market portfolio in excess of the risk-free rate, and $\beta_i = cov(r_i, r_m)/var(r_m)$. We compute the Gibbons-Ross-Shanken statistic (Gibbons et al. (1989)) as:

$$GRS \equiv \left(\frac{T-N-1}{N}\right) \hat{\alpha}' \left[\left(1 + \frac{\overline{r_m}}{\hat{\sigma}_m}\right)^2 \hat{\Sigma}\right]^{-1} \hat{\alpha}, \tag{4.4}$$

where $\hat{\alpha}$ is a N by 1 vector of estimated alphas, $\hat{\Sigma}$ is an N by N matrix that holds the unbiased estimate of the residual variance-covariance matrix, $\overline{r_m}$ is the sample mean of the excess return on the market portfolio, and $\hat{\sigma}_m^2$ is an unbiased estimate of the variance of the excess return on the market portfolio. Assuming that the errors are independently and normally distributed, uncorrelated with the returns on the market portfolio, the GRS statistic follows an F-distribution with N degrees of freedom in the numerator and $T-N-1$ degrees in the denominator under the null of zero alphas. Apart from the GRS statistic, we also compute the following test statistic to test if all alphas are jointly equal to zero:

$$T\left[\left(1+\frac{\overline{r_m}}{\hat{\sigma}_m}\right)^2\right]^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}, \tag{4.5}$$

This test statistic does not require normality of the error terms. Assuming homoscedasticity this test statistic obeys an asymptotic χ^2-distribution with N degrees of freedom under the null of zero alphas. The results are listed in Table 4.2. Although it seems that the empirical SML for sorts on market beta is flatter than the Sharpe-Lintner CAPM predicts, this deviation is statistically insignificant at any conventional significance level. There is also no strong evidence supporting the small-firm effect; only for the 20-portfolio data set the GRS test statistic indicates a significant deviation from the CAPM prediction. On the other hand, the CAPM appears unable to explain the returns on the style portfolios based on book-to-market and momentum. Whether we use 10, 20, or 30 portfolios, the resulting p-values tell a consistent story. Funds that hold value stocks have higher alphas than funds holding growth stocks, and funds that hold winners have higher alphas than funds holding losers. Neither phenomenon is explained by differences in market betas.

4.3.2 Do the factor proxies systematically miscalculate the premiums fund managers actually earn?

In this section, we estimate the factor premiums fund managers actually earn, and compare these values to the returns predicted by the hypothetical stock portfolios $RMRF$, SMB, HML and WML. Here, WML (Winner Minus Loser) is the proxy for the momentum effect documented by Jegadeesh and Titman (1993) that is used with the four-factor Carhart (1997) model (4FM)[2]

$$r_{i,t} = a_i + \beta_{1i}RMRF_t + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}WML_t + \epsilon_{i,t}. \tag{4.6}$$

We perform cross-sectional Fama and MacBeth (1973) regressions, and estimate Eq. (4.1), Eq. (4.2) and Eq. (4.6) for the style portfolios using a rolling window, and solve for the

[2]The authors would like to thank Mark Carhart for generously providing the data on the momentum factor used in Carhart (1997).

expected returns for funds with unit exposure to $RMRF$, SMB, HML, and WML, as a function of the estimated betas from the time-series regressions. For example, for the 4FM:

$$\begin{bmatrix} r_{\beta 1,t} \\ r_{\beta 2,t} \\ r_{\beta 3,t} \\ r_{\beta 4,t} \end{bmatrix} \equiv \left(\begin{bmatrix} \hat{\beta}'_{1,t-1} \\ \hat{\beta}'_{2,t-1} \\ \hat{\beta}'_{3,t-1} \\ \hat{\beta}'_{4,t-1} \end{bmatrix} \begin{bmatrix} \hat{\beta}_{1,t-1} \hat{\beta}_{2,t-1} \hat{\beta}_{3,t-1} \hat{\beta}_{4,t-1} \end{bmatrix} \right)^{-1} \begin{bmatrix} \hat{\beta}'_{1,t-1} \\ \hat{\beta}'_{2,t-1} \\ \hat{\beta}'_{3,t-1} \\ \hat{\beta}'_{4,t-1} \end{bmatrix} r_t \tag{4.7}$$

where r_t is a N by 1 vector of excess returns on the style portfolios at time t, $\hat{\beta}_{1,t-1}$, $\hat{\beta}_{2,t-1}$, $\hat{\beta}_{3,t-1}$, and $\hat{\beta}_{4,t-1}$ are N by 1 vectors of the style portfolios' exposures to $RMRF$, SMB, HML, and WML, estimated using a 36-month rolling window that ends at $t-1$, and $r_{\beta 1,t}$, $r_{\beta 2,t}$, $r_{\beta 3,t}$, and $r_{\beta 4,t}$ are the implied excess returns for funds with unit exposure to $RMRF$, SMB, HML, and WML, respectively. The analysis is performed on 30 quantile portfolios based on the factor exposure for which we want to obtain the premium. This ensures that the style portfolios exhibit a large cross-sectional spread in exposure to the factor for which we estimate the premium. For example, to obtain an estimate of the size premium we perform the cross-sectional regressions on 30 quantile portfolios of funds based on the funds' exposures to market equity, and to obtain an estimate of the value premium we perform the regressions on 30 quantiles based on exposures to book-to-market-equity. The style portfolios returns cover the period January 1966 to December 2003. The first 36 months of this period (January 1966 to December 1968) are used to initialize the procedure, so we obtain returns on the unit-beta style portfolios over the period January 1969 to December 2003.

First, we determine the excess returns for funds with unit exposure to $RMRF$ as a function of the estimated betas from the CAPM regression Eq. (4.1) for 30 quantile portfolios sorted on market beta. We find a time-series average of 0.37 percent per month for $r_{\beta 1,t}$ (t-value of 1.59). The average excess return of the hypothetical stock portfolio $RMRF$ over the same period is 0.42 percent per month (t-value of 1.83). The average difference between both portfolios is about 60 basis points on a yearly basis, and statistically insignificant (t-value of 1.16). We can thus conclude that fund managers earn a premium for exposure to the market that is statistically and economically not much different from the return projected by the hypothetical stock portfolio $RMRF$.

Second, we determine the excess returns for funds with unit exposure to SMB and HML as a function of the estimated betas from 3FM regression as in Eq. (4.2) for 30 quantile portfolios based on market equity and book-to-market-equity, respectively. We find a time-series average of 0.11 percent per month for $r_{\beta 2,t}$ (t-value of 0.62), which is only slightly lower than the size premium based on SMB of 0.13 percent per month (t-value of 0.78). However, the average return of 0.16 percent per month (t-value of 0.97) for $r_{\beta 3,t}$ is substantially lower than the return of 0.43 percent per month (t-value of 2.83) that is projected by HML. While the hypothetical hedge portfolio HML indicates that the value premium is more than 5 percent on a yearly basis, $r_{\beta 3,t}$ indicates that fund managers with unit exposure to HML earn a return of only 2 percent per year. The t-value of the difference between $r_{\beta 3,t}$ and HML is 2.86. These results indicate that fund managers that follow a value oriented style earn returns that are too high given their market betas, but that the abnormal returns are smaller than projected by the hypothetical hedge portfolio HML.

Finally, we solve for the expected returns for a fund with unit exposure to WML as a function of the estimated betas in Eq. (4.6) for 30 quantile portfolios based on price momentum. We find an average value of 1.64 percent per month for $r_{\beta 4,t}$ (t-value of 4.13), while WML indicates that the momentum effect is only 0.94 percent per month (t-value of 3.72). The t-value of the difference between $r_{\beta 4,t}$ and WML is -1.98. These results indicate that the actual return differential between past winners and losers is larger than projected by the hypothetical hedge portfolio WML. The observation that price momentum for mutual funds is stronger than predicted by the proxy that is used with multi-factor approaches has also been documented by Wermers (2003) who studies mutual fund portfolio holdings. The author argues that this phenomenon might be caused by flow-related buying/selling of fund managers and the resulting price impact of the trades.

Another way to correct for transaction costs and trading restrictions when estimating the factor premiums is to look at the net returns of index funds that closely track the hypothetical stock portfolios. Baks et al. (2001) propose to take the low-cost index funds from the Vanguard mutual fund family as investable alternatives for $RMRF$, SMB, and HML.[3] We extract return data from CRSP for the index funds offered by Vanguard in the overall market, small cap value, small cap neutral, small cap growth, large cap value, large cap neutral, and large cap growth categories. First, we perform a simple linear regression of the excess returns of the Vanguard Total Stock Market Index fund on $RMRF$. The resulting return series covers the fund's inception date May 1992 to December 2003. The estimated intercept in this regression of 0.0007 percent is consistent with our earlier finding

[3] As pointed out by Baks et al. (2001), there are no low-cost index alternatives available for WML, since momentum strategies have high turnover by nature.

that fund managers earn a premium for exposure to the market that basically is the same as the return projected by $RMRF$. Next, we build portfolios of the index funds to obtain investable alternatives for SMB and HML. We take the return differential between the average returns of the funds in the small cap and the large cap categories for SMB, and the return differential between the average returns of the value and growth categories for HML. The resulting return series cover the period December 1992 to December 2003. We perform simple linear regressions of the portfolios' returns on SMB and HML. For the regression on SMB, the estimated intercept is -0.06 percent, and for HML the intercept is -0.25 percent. These results are very similar to those obtained from the cross-sectional regressions, and indicate the actual size premium is very similar to the return projected by SMB, while the hypothetical hedge portfolio HML overestimates the value premium by about 3 percent per year.

4.3.3 Multi-factor approaches to evaluate mutual fund performance

So far, we clearly observed a value premium and a momentum effect in the cross-section of fund returns. However, the premiums that fund managers actually earn for exposure to these factors are different from the returns projected by the usual proxies that are used with multi-factor approaches. The second objective of this study is to investigate how this miscalculation of the factor premiums affects the cross-sectional explanatory power of the 3FM and the 4FM we introduced earlier. To investigate this issue, we consider the style portfolios' alphas resulting from the 3FM in Eq. (4.2) and the 4FM in Eq. (4.6). Table 4.3 lists the three- and four-factor alpha estimates for all style portfolios. For sorts on market beta, book-to-market-equity, and momentum, the alphas still point to distinctive patterns from one decile rank to another. More interestingly, for beta and book-to-market-equity sorts, we now observe a perverse pattern: funds with low beta stocks appear to have lower alphas than those with high beta stocks, and growth funds appear to have higher alphas than value funds. For sorts on momentum, three-factor alphas exhibit the same pattern as CAPM-alphas, and are in the same order of magnitude. In economic terms, the spreads between the top and bottom deciles are substantial. On a yearly basis, the spread in alpha between the top and bottom decile for sorts on book-to-market-equity is about 3.6 percent, while this spread even mounts up to more than 12 percent for sorts on momentum. When we consider the 4FM results, we basically perceive the same patterns for sorts on market beta and book-to-market-equity. For sorts on momentum, past losers still underperform past winners, but the spread between the top and bottom deciles is smaller than for the 3FM results. However, this spread is still more than 3.5 percent per year. While past winners have positive alphas, these deviations are only marginally significant. For losers, however, the returns predicted by the 4FM are substantially higher than those generated by the fund managers.

To test whether the alphas are jointly equal to zero we perform multi-variate extensions to the test statistics we introduced previously:

$$GRS \equiv \left(\frac{T-N-K}{N}\right)\left(1+\hat{\mu}'\hat{\Omega}^{-1}\hat{\mu}\right)^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha} \sim F(N, N-T-K) \tag{4.8}$$

and

$$T\Big(1+\hat{\mu}'\hat{\Omega}^{-1}\hat{\mu}\Big)^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha} \sim \chi^2_N, \tag{4.9}$$

where $\hat{\mu}$ is a K by 1 vector of sample means of the style portfolios' excess returns, $\hat{\Omega}$ is an K by K matrix that holds the unbiased estimate of the factor portfolios covariance matrix, and K is the number of benchmark factors that are employed in the factor model. The resulting test statistics and the accompanying p-values are presented in Table 4.4. We first consider the results for the 3FM. For sorts on market beta and market equity the null of zero alphas is not rejected in all cases, except for sorts in 20 portfolios based on market equity. For sorts into 30 portfolios, the results are mixed. However, for sorts on book-to-market-equity and momentum the null is clearly rejected. When we consider the 4FM results, the results are not much different: the null of zero alphas is rejected for sorts on book-to-market-equity for all analyses, and for sorts into 10 and 20 quantiles for sorts on momentum.

Apparently, both the 3FM and the 4FM are unable to explain the cross-section of fund returns for sorts on book-to-market-equity and momentum. The observation that the 3FM is unable to explain the returns of style portfolios sorted on momentum is not unexpected, since the 3FM makes no attempt to control for this effect. However, both the 3FM and the 4FM explicitly attempt to correct for the value premium. The observed perverse patterns in the style portfolios' alphas for sorts on book-to-market-equity is consistent with our finding that the premium that fund managers actually earn for following a value oriented style is smaller than the return projected by the hypothetical hedge portfolio HML. Also, the return differential between past winners and losers that is unexplained by the 4FM is consistent with our previous finding that the hypothetical hedge portfolio WML underestimates the momentum effect for mutual funds.

Overall, our results permit a strong judgment about the empirical performance of the multi-factor approaches, indicating that the 3FM and the 4FM do not adequately control for the reported anomalies. An important implication of these findings is that the usual three- and four factor-alphas are systematically biased. In particular, performance estimates for value funds and past losers are biased downwards, while those for growth funds and past winners are biased upwards.

4.4 Time-varying market betas and conditioning variables

In this section, we demonstrate that our findings cannot be explained by time-varying market betas. As in Ferson and Schadt (1996) and Ferson and Harvey (1999), we estimate the style portfolios' alphas using a conditional CAPM, thereby allowing market betas to vary over time conditional on a set of predetermined variables:

$$r_{it} = \alpha_i + \beta_{1i} RMRF_t + B'_{1i}[z_{t-1} RMRF_t] + \varepsilon_{it}, \tag{4.10}$$

where z_{t-1} denotes a vector holding the lagged values of the information variables, and vector B'_{ji} captures the response of fund i's exposure to benchmark j to this information. We employ the following information variables: (1) the lagged level of the one-month Treasury bill yield, (2) the lagged dividend yield of the S&P500, (3) a lagged measure of the slope of the term structure, and (4) a lagged default spread in the corporate bond market. The dividend yield is defined as the dividend per share as a percentage of the share price over the past 12 months for the index. The term spread is defined as a constant-maturity 10-year Treasury bond yield minus the one-month Treasury bill yield, while the default spread is defined as Moody's BAA-rated corporate bond yield minus the AAA-rated corporate bond yield. Dividend yield data on the S&P500 are obtained from Thompson Financial, and the bond yield data are from the webpage of the Federal Reserve Bank. The resulting factor model includes 5 scaled factors, and an intercept. In addition, we employ a conditional version of the 3FM and the 4FM that augment the conditional CAPM with factors for size, value, and momentum:

$$r_{it} = \alpha_i + \beta_{1i} RMRF_t + B'_{1i}[z_{t-1} RMRF_t] + \beta_{2i} SMB_t + \beta_{3i} HML_t + \varepsilon_{it} \tag{4.11}$$

and

$$\begin{aligned} r_{it} = \alpha_i + \beta_{1i} RMRF_t + B'_{1i}[z_{t-1} RMRF_t] + \beta_{2i} SMB_t + \beta_{3i} HML_t + \\ \beta_{4i} WML_t + \varepsilon_{it}. \end{aligned} \tag{4.12}$$

These factor models include 7 and 8 scaled factors, respectively, and an intercept. We estimate the style portfolios' alphas using the three conditional models over the entire post-ranking period using OLS and test whether the alphas are jointly equal to zero. The results for sorts into decile portfolios are presented in Table 4.5.

The alpha estimates for the conditional models are very similar to those for the unconditional models. The null hypothesis of zero alphas is rejected for sorts on market equity, book-to-market-equity, and momentum. For the conditional CAPM, we observe the same pattern as for unconditional CAPM regressions: funds that follow a value (growth) oriented style earn returns that are too high (low) given their betas, and funds that hold stocks that did well (poorly) over the past year earn abnormal positive (negative) returns in the near future. The inclusion of the Fama and French (1993, 1995, 1996) and Carhart (1997) factors leads to the same perverse patterns we observed for the unconditional multi-factor models. Performance estimates for value funds and past losers are biased downwards, while those for growth funds and past winners are biased upwards. In economic terms, the spreads between alphas of the top and bottom deciles are of the same order of magnitude as those reported earlier for the unconditional models. Overall, our results indicate that observed anomalies cannot be explained by conditional models that allow for time-varying market betas.

4.5 Results using factor proxies based on fund returns

Finally, we construct factor proxies based on mutual fund returns. The first factor, that acts as some sort of broad market proxy, is set to the average return for all available funds at each period in time. The factor proxies for size, value, and momentum, are constructed as follows. Each month, we estimate the 3FM in Eq. (4.2) for all available funds using OLS with a rolling window over the preceding 36 months. Our size proxy is defined as the average return of all funds with $\beta_{2,i}$ above the size breakpoint minus the average return of all funds with $\beta_{2,i}$ equal or below the breakpoint, our value proxy as the average return of all funds with $\beta_{3,i}$ above the value breakpoint minus the average return of all funds with $\beta_{3,i}$ equal or below the breakpoint, and our momentum proxy as the average return of all funds with 12-month returns above the momentum breakpoint minus the average return of all funds below the breakpoint. The size breakpoint is set to the median loading on SML, the book-to-market-equity breakpoint to the median loading on HML, and the momentum breakpoint to the median fund return over the past 12 months. To ensure that the results are robust to our choice of the breakpoints, we additionally construct factors where the breakpoints are set to the 33rd and 67th percentile loading on SML and HML, and the 33rd and 67th percentile fund return over the past 12 months. While the resulting proxies for size, value, and momentum are non-investable, we argue that if the observed biases in the multi-factor performance estimates are indeed due to miscalculation of the factor premiums, these proxies might yield better results, because they are based on net fund returns, and therefore incorporate transaction costs and trading restrictions.

We now compute the style portfolios' alphas resulting from 3FM and 4FM specifications using factor proxies based on fund returns, and test if the resulting alphas are jointly equal to zero using the multivariate test statistics Eq. (4.8) and Eq. (4.9). The resulting alphas and test statistics for the decile style portfolios are displayed in Table 4.6. When we consider the results for sorts on book-to-market-equity, the perverse pattern in the deciles' alphas has disappeared. In fact, we do not observe a pattern at all. The alphas are also small from an economic point of view. Furthermore, the tests indicate that the null of zero alphas cannot be rejected for any reasonable level of significance. These results hold irrespective of how we define the factors' breakpoints. Finally, we consider the results for sorts on momentum. The observation that the 3FM is unable to explain the returns of style portfolios sorted on momentum is not unexpected, since the 3FM makes no attempt to control for this effect. However, the 4FM model appears to be able to cope with the momentum effect, as the corresponding alphas are not significantly different from zero. Again, the results hold irrespective of how we define the factors' breakpoints. Our findings indicate that factor proxies based on mutual fund returns rather than stock returns provide better benchmarks to evaluate professional money managers.

4.6 Conclusion

A large number of studies employ multi-factor models to evaluate mutual fund performance. This paper provides evidence that market betas by themselves do not suffice to describe the cross-section of fund returns. We use the pooled time-series-cross-sectional test methodology of Gibbons et al. (1989) to test whether CAPM alphas of style portfolios of funds based on (i) market beta, (ii) market equity, (iii) book-to-market-equity, and (iv) price momentum are jointly equal to zero. We reject the null of zero alphas for sorts on book-to-market-equity and momentum. Funds with a value (growth) oriented style, and funds that hold stocks that did well (poorly) over the past year, earn returns that are higher (lower) than predicted by the CAPM. The funds' alphas are up to more than 6 percent per year. Our findings indicate that the value-premium and the momentum effect reported in the literature are economically significant, and persist beyond transaction costs and trading restrictions.

However, the premiums that fund managers actually earn for exposure to these factors are different from the returns projected by the typical proxies that are used with the multi-factor approaches. The value premium in the cross-section of fund returns is smaller than predicted by the hypothetical hedge portfolio HML. Further, the return differential between past winners and losers is much larger than predicted by the hypothetical hedge portfolio WML.

This miscalculation of the factor premiums affects the cross-sectional explanatory power of multi-factor models to evaluate mutual fund performance. We find that the usual three- and four-factor alphas do not adequately control for the anomalies. In particular, multi-factor performance estimates for value funds and past losers are biased downwards, while those for growth funds and past winners are biased upwards. These results are robust to time-varying betas.

One alternative that does not suffer from these biases is based on the use of a four-factor model where the factors are constructed using mutual fund returns rather than stock returns. Resulting alphas from this model do not exhibit systematic patterns and appear to provide unbiased estimates of a fund manager's performance.

4.7 Tables and Figures

Table 4.1: Single-factor CAPM regressions.

	Return	Sharpe	Alpha	Alpha-t	RMRF	R^2
	Sorts on market beta					
D1	6.00%	0.24	-1.13%	-0.66	1.40	0.82
D2	5.62%	0.28	-0.47%	-0.41	1.20	0.88
D3	4.92%	0.27	-0.75%	-0.87	1.11	0.92
D4	4.85%	0.29	-0.45%	-0.81	1.04	0.96
D5	4.65%	0.29	-0.40%	-0.66	0.99	0.95
D6	4.24%	0.28	-0.52%	-1.30	0.93	0.97
D7	4.78%	0.33	0.22%	0.42	0.89	0.95
D8	4.47%	0.32	0.18%	0.33	0.84	0.94
D9	4.11%	0.32	0.23%	0.37	0.76	0.91
D10	2.92%	0.30	0.18%	0.24	0.54	0.78
	Sorts on market equity					
D1	6.10%	0.28	0.01%	0.00	1.20	0.79
D2	6.00%	0.31	0.40%	0.31	1.10	0.84
D3	5.73%	0.32	0.39%	0.42	1.05	0.90
D4	5.08%	0.31	0.05%	0.07	0.99	0.93
D5	4.75%	0.31	-0.09%	-0.17	0.95	0.96
D6	4.38%	0.29	-0.27%	-0.51	0.91	0.95
D7	4.05%	0.28	-0.53%	-1.25	0.90	0.97
D8	3.88%	0.27	-0.55%	-1.36	0.87	0.97
D9	3.39%	0.24	-1.07%	-2.57	0.87	0.97
D10	3.17%	0.21	-1.35%	-1.76	0.89	0.90

Data on returns of mutual funds are extracted from the 2003 CRSP Mutual Fund Survivorship-bias Free Database. In total, our sample cover 7,852 US equity funds over the period 1963–2003. Funds are sorted into 10 quantile portfolios based on the following characteristics of their stock holdings: (i) market beta, (ii) market equity, (iii) book-to-market-equity, and (iv) price momentum. For the resulting style portfolios, we run single-factor CAPM regressions. The table lists the portfolios' post-ranking returns, Sharpe ratios, CAPM parameter estimates, and R-squared values. All values are annualized.

Table 4.1 continued

	Return	Sharpe	Alpha	Alpha-t	RMRF	R^2
	Sorts on book-to-market equity					
D1	5.55%	0.39	1.57%	1.46	0.78	0.78
D2	5.57%	0.40	1.44%	1.75	0.81	0.87
D3	4.89%	0.35	0.62%	0.87	0.84	0.90
D4	4.25%	0.29	-0.25%	-0.46	0.88	0.94
D5	4.19%	0.28	-0.58%	-1.23	0.94	0.96
D6	4.13%	0.26	-0.82%	-1.61	0.97	0.96
D7	4.12%	0.25	-1.08%	-1.84	1.02	0.95
D8	3.93%	0.22	-1.50%	-2.05	1.07	0.93
D9	4.24%	0.22	-1.52%	-1.61	1.13	0.91
D10	5.78%	0.25	-0.85%	-0.55	1.30	0.83
	Sorts on momentum					
D1	11.19%	0.58	5.66%	3.26	1.03	0.68
D2	8.91%	0.52	3.51%	3.17	1.00	0.84
D3	7.07%	0.45	1.86%	2.52	0.97	0.91
D4	5.64%	0.37	0.45%	0.82	0.96	0.95
D5	4.58%	0.30	-0.59%	-1.18	0.96	0.96
D6	4.36%	0.29	-0.77%	-1.54	0.95	0.96
D7	3.52%	0.23	-1.59%	-3.07	0.95	0.95
D8	2.47%	0.16	-2.74%	-3.97	0.97	0.92
D9	1.47%	0.09	-3.76%	-4.41	0.97	0.89
D10	-0.93%	-0.05	-6.09%	-4.41	0.96	0.75

Table 4.2: Univariate test results for zero alphas.

	χ^2	p-value	GRS	p-value
$N = 10$				
beta	6.79	0.74	0.67	0.76
ME	11.14	0.35	1.09	0.37
BE/ME	21.14	**0.02**	2.07	**0.03**
momentum	27.22	**0.00**	2.67	**0.00**
$N = 20$				
beta	22.27	0.33	1.07	0.38
ME	37.62	**0.01**	1.80	**0.02**
BE/ME	42.37	**0.00**	2.03	**0.01**
momentum	39.09	**0.01**	1.87	**0.01**
$N = 30$				
beta	23.94	0.77	0.75	0.83
ME	40.33	0.10	1.26	0.17
BE/ME	51.27	**0.01**	1.60	**0.03**
momentum	42.96	**0.06**	1.34	0.11

Data on returns of mutual funds are extracted from the 2003 CRSP Mutual Fund Survivorship-bias Free Database. In total, our sample cover 7,852 US equity funds over the period 1963–2003. Funds are sorted into 10, 20, and 30 quantile portfolios based on the following characteristics of their stock holdings: (i) market beta, (ii) market equity, (iii) book-to-market-equity, and (iv) price momentum. For the resulting style portfolios, we run single-factor CAPM regressions, and test whether the estimated alphas are jointly equal to zero. The table lists the results of pooled time-series-cross-sectional tests in the spirit of Gibbons et al. (1989). p-values below the significance level of 10 percent are highlighted.

Table 4.3: Multiple-factor regressions.

	A. Fama and French 3FM						*B. Carhart 4FM*						
	Alpha	Alpha-t	RMRF	SMB	HML	R^2	Alpha	Alpha-t	RMRF	SMB	HML	WML	R^2
	Sorts on market beta												
D1	0.36%	0.37	1.15	0.63	-0.42	0.94	-0.72%	-0.73	1.16	0.65	-0.40	0.08	0.95
D2	0.31%	0.41	1.04	0.41	-0.24	0.95	-0.86%	-1.18	1.05	0.43	-0.23	0.08	0.96
D3	-0.28%	-0.41	1.02	0.25	-0.15	0.95	-1.18%	-1.76	1.03	0.27	-0.14	0.06	0.96
D4	-0.26%	-0.50	1.00	0.12	-0.07	0.97	-0.74%	-1.45	1.00	0.13	-0.06	0.03	0.97
D5	-0.55%	-0.91	0.98	0.07	0.00	0.95	-0.86%	-1.38	0.98	0.08	0.01	0.02	0.95
D6	-0.88%	-2.19	0.94	0.02	0.05	0.97	-0.87%	-2.12	0.94	0.02	0.05	0.00	0.97
D7	-0.70%	-1.39	0.93	0.02	0.14	0.96	-0.78%	-1.52	0.93	0.02	0.14	0.01	0.96
D8	-0.92%	-1.83	0.89	0.01	0.17	0.95	-1.05%	-2.04	0.89	0.01	0.17	0.01	0.95
D9	-1.18%	-2.18	0.81	0.04	0.21	0.94	-1.32%	-2.39	0.81	0.04	0.21	0.01	0.94
D10	-1.57%	-2.42	0.60	0.06	0.26	0.84	-2.11%	-3.21	0.60	0.07	0.26	0.04	0.84
	Sorts on market equity												
D1	-0.86%	-0.91	1.02	0.72	-0.08	0.93	-1.89%	-2.01	1.03	0.74	-0.07	0.07	0.94
D2	-0.29%	-0.34	0.98	0.51	-0.05	0.93	-1.48%	-1.77	0.99	0.54	-0.03	0.09	0.94
D3	-0.04%	-0.06	0.96	0.36	-0.04	0.95	-1.07%	-1.64	0.97	0.38	-0.02	0.07	0.95
D4	-0.11%	-0.19	0.93	0.23	-0.04	0.96	-0.96%	-1.73	0.94	0.25	-0.03	0.06	0.96
D5	-0.28%	-0.56	0.92	0.11	0.00	0.96	-0.77%	-1.56	0.93	0.12	0.00	0.04	0.97
D6	-0.55%	-1.01	0.92	0.02	0.04	0.95	-0.79%	-1.43	0.92	0.03	0.04	0.02	0.95
D7	-0.83%	-1.96	0.92	-0.02	0.05	0.97	-0.92%	-2.11	0.92	-0.02	0.05	0.01	0.97
D8	-0.76%	-1.94	0.89	-0.06	0.05	0.97	-0.78%	-1.95	0.90	-0.06	0.05	0.00	0.97
D9	-1.07%	-2.75	0.90	-0.09	0.03	0.97	-1.08%	-2.71	0.90	-0.09	0.03	0.00	0.97
D10	-0.94%	-1.30	0.92	-0.17	-0.01	0.92	-0.77%	-1.03	0.92	-0.17	-0.02	-0.01	0.92

Data on returns of mutual funds are extracted from the 2003 CRSP Mutual Fund Survivorship-bias Free Database. In total, our sample cover 7,852 US equity funds over the period 1963–2003. Funds are sorted into 10 quantile portfolios based on the following characteristics of their stock holdings: (i) market beta, (ii) market equity, (iii) book-to-market-equity, and (iv) price momentum. For the resulting style portfolios, we run 3FM and 4FM regressions. The table lists the portfolios' post-ranking returns, Sharpe ratios, 3FM and 4FM parameter estimates, and R-squared values. All values are annualized.

Table 4.3 continued

	A. Fama and French 3FM						*B. Carhart 4FM*						
	Alpha	Alpha-t	RMRF	SMB	HML	R^2	Alpha	Alpha-t	RMRF	SMB	HML	WML	R^2
	Sorts on book-to-market equity												
D1	-1.70%	-2.09	0.86	0.22	0.44	0.88	-1.72%	-2.06	0.86	0.22	0.44	0.00	0.88
D2	-0.79%	-1.16	0.87	0.12	0.31	0.91	-0.91%	-1.31	0.87	0.12	0.31	0.01	0.91
D3	-0.95%	-1.49	0.89	0.07	0.22	0.93	-0.92%	-1.41	0.89	0.07	0.22	0.00	0.93
D4	-1.37%	-2.71	0.90	0.10	0.14	0.96	-1.63%	-3.16	0.91	0.11	0.15	0.02	0.96
D5	-1.12%	-2.52	0.93	0.10	0.05	0.97	-1.46%	-3.25	0.93	0.11	0.06	0.02	0.97
D6	-0.78%	-1.58	0.95	0.08	-0.03	0.96	-1.27%	-2.55	0.95	0.09	-0.02	0.04	0.97
D7	-0.75%	-1.52	0.96	0.15	-0.10	0.97	-1.57%	-3.30	0.97	0.16	-0.08	0.06	0.97
D8	-0.37%	-0.70	0.96	0.18	-0.23	0.97	-1.20%	-2.37	0.97	0.20	-0.22	0.06	0.97
D9	0.22%	0.36	0.99	0.23	-0.34	0.96	-0.71%	-1.20	1.00	0.25	-0.33	0.07	0.97
D10	1.95%	1.95	1.06	0.39	-0.55	0.93	0.87%	0.87	1.07	0.41	-0.54	0.08	0.94
	Sorts on momentum												
D1	5.58%	3.94	0.86	0.57	-0.17	0.80	0.89%	0.82	0.90	0.65	-0.10	0.34	0.89
D2	3.13%	3.49	0.90	0.38	-0.06	0.90	0.37%	0.51	0.93	0.43	-0.02	0.20	0.94
D3	1.63%	2.53	0.91	0.22	-0.03	0.94	-0.13%	-0.24	0.93	0.25	-0.01	0.13	0.96
D4	0.10%	0.21	0.93	0.15	0.00	0.96	-1.08%	-2.42	0.94	0.17	0.02	0.09	0.97
D5	-1.04%	-2.19	0.95	0.11	0.03	0.96	-1.66%	-3.53	0.95	0.12	0.04	0.04	0.97
D6	-1.07%	-2.15	0.94	0.07	0.02	0.96	-1.07%	-2.11	0.94	0.07	0.02	0.00	0.96
D7	-1.95%	-3.75	0.94	0.06	0.03	0.96	-1.58%	-2.99	0.94	0.06	0.03	-0.03	0.96
D8	-3.22%	-4.67	0.96	0.09	0.04	0.93	-2.18%	-3.23	0.95	0.07	0.03	-0.08	0.93
D9	-4.24%	-4.93	0.96	0.10	0.04	0.89	-2.66%	-3.24	0.95	0.07	0.02	-0.12	0.91
D10	-6.51%	-4.64	0.94	0.13	0.02	0.75	-2.84%	-2.31	0.90	0.06	-0.03	-0.27	0.82

Table 4.4: Multivariate test results for zero alphas.

	A. Fama and French 3FM				*B. Carhart 4FM*			
	χ^2	p-value	*GRS*	p-value	χ^2	p-value	*GRS*	p-value
$N = 10$								
beta	10.87	0.37	1.06	0.39	13.87	0.18	1.34	0.20
ME	13.10	0.22	1.27	0.24	11.26	0.34	1.09	0.37
BE/ME	20.07	**0.03**	1.95	**0.04**	27.09	**0.00**	2.63	**0.01**
momentum	32.19	**0.00**	3.13	**0.00**	19.32	**0.04**	1.87	**0.05**
$N = 20$								
beta	25.28	0.19	1.20	0.25	31.09	**0.05**	1.47	**0.09**
ME	39.06	**0.01**	1.85	**0.01**	34.87	**0.02**	1.65	**0.04**
BE/ME	43.11	**0.00**	2.05	**0.01**	57.85	**0.00**	2.74	**0.00**
momentum	44.29	**0.00**	2.10	**0.00**	30.37	**0.06**	1.44	0.10
$N = 30$								
beta	27.66	0.59	0.86	0.68	35.10	0.24	1.08	0.35
ME	41.23	**0.08**	1.27	0.16	37.57	0.16	1.16	0.26
BE/ME	46.23	**0.03**	1.43	**0.07**	51.07	**0.01**	1.58	**0.03**
momentum	47.72	**0.02**	1.48	**0.05**	33.84	0.29	1.04	0.41

Data on returns of mutual funds are extracted from the 2003 CRSP Mutual Fund Survivorship-bias Free Database. In total, our sample cover 7,852 US equity funds over the period 1963–2003. Funds are sorted into 10, 20, and 30 quantile portfolios based on the following characteristics of their stock holdings: (i) market beta, (ii) market equity, (iii) book-to-market-equity, and (iv) price momentum. For the resulting style portfolios, we run 3FM and 4FM regressions, and test whether the estimated alphas are jointly equal to zero. The table lists the results of pooled time-series-cross-sectional tests in the spirit of Gibbons et al. (1989). p-values below the significance level of 10 percent are highlighted.

Table 4.5: Time-varying market betas and conditioning variables.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	χ^2	p-value	*GRS*	p-value
	Conditional CAPM													
beta	-1.95	-0.91	-1.15	-0.60	-0.63	-0.59	-0.35	-0.22	-0.19	0.15	6.60	0.76	0.64	0.78
ME	-1.02	-0.29	-0.03	0.21	-0.53	-0.72	-0.92	-0.86	-1.21	-1.13	19.21	**0.04**	1.85	**0.05**
BE/ME	0.87	0.92	-0.06	-0.75	-0.97	-0.93	-1.06	-1.77	-1.56	-1.30	26.27	**0.00**	2.53	**0.01**
momentum	6.15	3.01	1.92	0.15	-0.82	-1.36	-2.06	-3.66	-4.80	-7.03	33.65	**0.00**	3.24	**0.00**
	Conditional Fama and French 3FM													
beta	0.06	0.33	-0.28	-0.27	-0.66	-0.89	-1.16	-1.23	-1.51	-1.44	12.32	0.26	1.18	0.30
ME	-1.21	-0.36	-0.03	0.20	-0.51	-0.87	-1.16	-1.09	-1.26	-0.74	24.33	**0.01**	2.33	**0.01**
BE/ME	-2.05	-0.88	-1.39	-1.68	-1.38	-0.82	-0.54	-0.48	0.33	1.81	29.46	**0.00**	2.82	**0.00**
momentum	6.61	3.18	1.92	0.06	-0.97	-1.49	-2.26	-3.85	-5.00	-7.04	34.95	**0.00**	3.35	**0.00**
	Conditional Carhart 4FM													
beta	-1.15	-0.99	-1.15	-0.75	-0.89	-0.76	-1.14	-1.22	-1.57	-2.05	14.39	0.16	1.38	0.19
ME	-2.22	-1.40	-0.97	-0.65	-1.06	-1.02	-1.07	-1.10	-1.32	-0.83	18.26	**0.05**	1.75	**0.07**
BE/ME	-1.87	-0.62	-1.24	-1.81	-1.63	-1.10	-1.37	-1.40	-0.97	0.35	36.18	**0.00**	3.46	**0.00**
momentum	1.10	0.12	0.09	-1.21	-1.42	-1.43	-1.73	-2.52	-3.00	-2.85	21.33	**0.02**	2.04	**0.03**

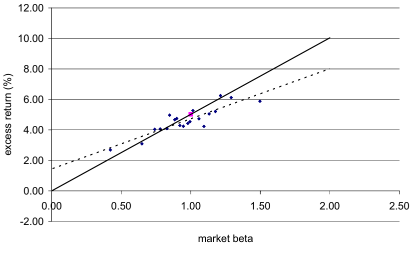
Data on returns of mutual funds are extracted from the 2003 CRSP Mutual Fund Survivorship-bias Free Database. In total, our sample cover 7,852 US equity funds over the period 1963–2003. Funds are sorted into 10 quantile portfolios based on the following characteristics of their stock holdings: (i) market beta, (ii) market equity, (iii) book-to-market-equity, and (iv) price momentum. For the resulting style portfolios, we run conditional CAPM, 3FM, and 4FM regressions, and test whether the estimated alphas are jointly equal to zero. The table lists the results of pooled time-series-cross-sectional tests in the spirit of Gibbons et al. (1989). All values are annualized. p-values below the significance level of 10 percent are highlighted.

Table 4.6: Results using factors proxies based on fund returns.

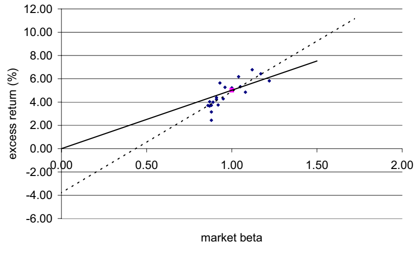
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	χ^2	p-value	GRS	p-value
	3FM results with top minus bottom 50 percent factors													
beta	-0.13	0.32	-0.16	0.17	0.01	-0.08	0.32	0.12	-0.09	-0.41	4.42	0.93	0.43	0.93
ME	-0.75	-0.08	0.33	0.32	0.31	0.12	-0.01	0.04	-0.23	-0.00	6.76	0.75	0.66	0.76
BE/ME	0.09	0.54	0.16	-0.39	-0.39	-0.31	-0.38	-0.38	-0.09	1.15	10.99	0.36	1.07	0.39
momentum	5.94	3.59	2.15	0.63	-0.43	-0.55	-1.45	-2.68	-3.88	-6.05	37.01	**0.00**	3.60	**0.00**
	4FM results with top minus bottom 50 percent factors													
beta	0.04	0.14	-0.42	0.24	-0.07	0.14	0.60	0.25	-0.10	-0.76	8.51	0.58	0.83	0.60
ME	-0.41	-0.21	0.23	0.14	0.39	0.16	0.11	0.08	-0.32	-0.12	6.99	0.73	0.68	0.75
BE/ME	0.03	0.43	0.33	-0.35	-0.43	-0.34	-0.61	-0.43	-0.00	1.38	13.92	0.18	1.35	0.20
momentum	0.23	0.22	0.03	-0.47	-0.73	0.09	-0.12	-0.23	-0.47	-0.02	12.17	0.27	1.18	0.30
	3FM results with top minus bottom 33 percent factors													
beta	-0.04	0.38	-0.15	0.17	-0.04	-0.11	0.29	0.09	-0.12	-0.40	4.82	0.90	0.47	0.91
ME	-0.69	-0.04	0.35	0.34	0.32	0.05	-0.05	0.01	-0.25	-0.00	4.83	0.90	0.47	0.91
BE/ME	0.05	0.50	0.10	-0.38	-0.39	-0.35	-0.40	-0.36	-0.05	1.27	12.21	0.27	1.19	0.30
momentum	6.02	3.62	2.15	0.62	-0.45	-0.59	-1.46	-2.68	-3.88	-6.03	36.99	**0.00**	3.59	**0.00**
	4FM results with top minus bottom 33 percent factors													
beta	0.03	0.13	-0.43	0.25	-0.12	0.15	0.62	0.27	-0.10	-0.75	8.80	0.55	0.85	0.58
ME	-0.40	-0.17	0.25	0.14	0.37	0.11	0.13	0.08	-0.31	-0.15	4.33	0.93	0.42	0.94
BE/ME	0.00	0.41	0.30	-0.30	-0.39	-0.37	-0.66	-0.42	-0.01	1.43	14.25	0.16	1.38	0.19
momentum	-0.06	0.06	-0.06	-0.49	-0.67	0.04	-0.09	-0.11	-0.29	0.28	9.73	0.46	0.94	0.49

Data on returns of mutual funds are extracted from the 2003 CRSP Mutual Fund Survivorship-bias Free Database. In total, our sample cover 7,852 US equity funds over the period 1963–2003. Funds are sorted into 10 quantile portfolios based on the following characteristics of their stock holdings: (i) market beta, (ii) market equity, (iii) book-to-market-equity, and (iv) price momentum. For the resulting style portfolios, we run 3FM and 4FM regressions using factor proxies based on fund returns, and test whether the estimated alphas are jointly equal to zero. The table lists the results of pooled time-series-cross-sectional tests in the spirit of Gibbons et al. (1989). All values are annualized. p-values below the significance level of 10 percent are highlighted.

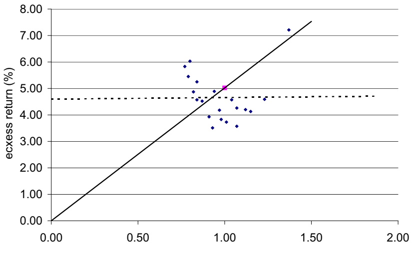
Figure 4.1: Mutual funds' average excess returns vs market betas.



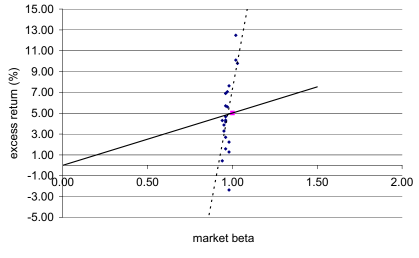
(a) market beta



(b) market equity



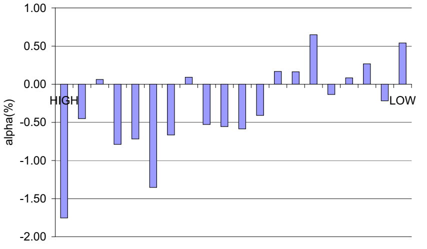
(c) book-to-market-equity



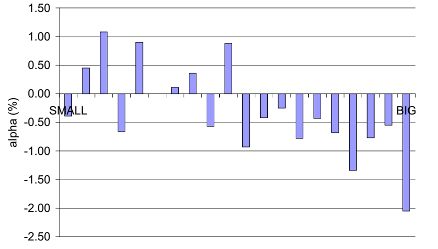
(d) momentum

Data on returns of mutual funds are extracted from the 2003 CRSP Mutual Fund Survivorship-bias Free Database. In total, our sample cover 7,852 US equity funds over the period 1963–2003. Funds are sorted into 20 quantile portfolios based on the following characteristics of their stock holdings: (i) market beta, (ii) market equity, (iii) book-to-market-equity, and (iv) price momentum. For the resulting style portfolios, we compute average excess returns, and plot these values on the portfolios' market betas that are estimated using single-factor CAPM regressions. The solid line in the graphs draws the SML predicted by the CAPM, and the dashed line draws the empirical relation between expected excess return and market beta. All values are annualized.

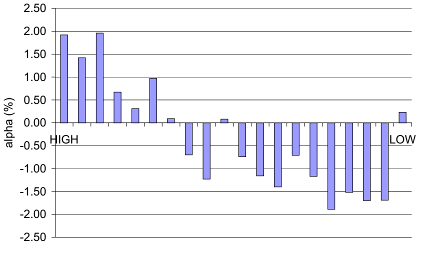
Figure 4.2: Single-factor CAPM alphas.



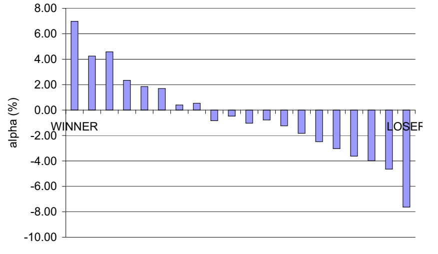
(a) market beta



(b) market equity



(c) book-to-market-equity



(d) momentum

Data on returns of mutual funds are extracted from the 2003 CRSP Mutual Fund Survivorship-bias Free Database. In total, our sample cover 7,852 US equity funds over the period 1963–2003. Funds are sorted into 20 quantile portfolios based on the following characteristics of their stock holdings: (i) market beta, (ii) market equity, (iii) book-to-market-equity, and (iv) price momentum. For the resulting style portfolios, we run single-factor CAPM regressions. The graphs list the style portfolios' alphas. All values are annualized.

Chapter 5

Spillover Effects of Marketing in Mutual Fund Families*

5.1 Introduction

When we consider the mutual fund industry over the past decade, one of the most notable developments is the enormous growth of funds that are operated by fund families. While almost 20 percent of all US equity funds were offered as stand-alone in 1992, this figure rapidly declined to less than 4 percent by the end of 2002. Plausible reasons for this phenomenon are the competitive advantages that family membership brings along, such as economies of scale. In addition, recent studies document substantial spillover effects between funds in a family. For example, several authors report spillovers in fund performance.

Past performance is one of the most important determinants of investors' cash flows to funds (see e.g., Gruber (1996), Sirri and Tufano (1998), Chevalier and Ellison (1999), and Del Guercio and Tkac (2002)). Funds with strong track records are rewarded with large cash flows into the funds, while losers are not disciplined with equally large outflows. However, Ivkovic (2001) and Nanda et al. (2004) report that cash flows are not only affected by a fund's own performance, but also by the performance of other funds in the family. Stellar performance of a fund generates substantial spillovers in the sense that cash inflows to other funds in the family are above and beyond what one would expect given the funds' own performance. On the other hand, poor performance of a fund does not seem to result in abnormal cash outflows from its family members. Consistent with these findings, Khorana and Servaes (2005) find that the presence of a star fund in a family has a positive effect on

*This chapter is based on the article by Huij and Verbeek (2006b).

the family's market share. Other spillover effects have been documented by Zhao (2004), who finds evidence that fund families that signal superior performance by closing a star fund to new investments enjoy higher cash inflows into the rest of the family.

There are several possible explanations for this behavior: investors might believe that the performance of an individual fund conveys information about the quality of the family to which the fund belongs, e.g., quality of research, or monitoring activities of fund managers. Another reason is that funds with extreme performance typically receive more media attention, thereby making the family to which the fund belongs more visible to investors (Sirri and Tufano, 1998).

Goetzmann and Ibbotson (1993) and Nanda et al. (2004) argue that fund families are well aware of these spillover effects, and anticipate investor behavior to maximize cash flows into their funds. Families that manage many funds with large cross-sectional dispersion in performance are more likely to generate a star, and attract larger cash flows in the funds. Moreover, Nanda et al. (2004) assert that this mechanism especially induces lower ability families to pursue this type of strategy.

In this study we investigate the presence of spillover effects of marketing in fund families. It is abundantly clear that fund management companies consider marketing to be an important method to attract new investors. In the sample we use in this study, US equity funds spent more than 9 billion dollars on marketing and distribution activities in 2003; an amount that is more than 0.4 percent of their total net assets under management over the year. For comparison, all operating expenses summed together (including management fees) amount to less than one percent of total net assets under management.[1] Several authors confirm that marketing is an effective method for funds to garner new money. Jain and Wu (2000) find that funds that are advertised in *Barron's* or *Money* magazine attract significantly larger cash flows in comparison to other funds, even though these funds do not exhibit superior performance. Sirri and Tufano (1998) document that funds with higher fees (and presumably higher marketing expenses) receive larger cash inflows as a response to their performance than funds with lower fees. Consistent with these findings, Barber et al. (2005) report a positive relation between funds' marketing expenses and subsequent inflows, especially when these expenses are less salient to investors. More recently, a few studies have examined the impact of marketing on cash flows at the aggregate family-level. Gallaher et al. (2006) report that fund families with the highest levels of advertising

[1] As a measure of funds' marketing and distribution expenses we take the funds' reported 12b1 fees plus one-seventh of the funds' front-end load fees.

receive greater cash inflows, but the authors do not find that advertising affects the flow-performance relation at the family-level. Further, Khorana and Servaes (2005) examine the relation between marketing expenses and family market share, and find that there is a positive relation for small families.

However, none of these studies has investigated the impact of fund marketing on investor flows to other funds in the family. For example, do high-marketing funds generate spillovers, and enhance cash inflows to low-marketing funds in the family? To investigate the presence of such intrafamily marketing spillovers, we employ a regression-based methodology investigating cash flows of US equity funds that are operated within a fund family. In particular, we test whether the flow-performance relationship is affected by marketing and distribution expenses at the individual fund and fund family level. Analyzing data over the period 1992–2003, we address the following questions. First, do high-marketing funds have a stronger flow-performance relation than low-marketing funds, and how is this affected by fund age and size? Second, do cash flows respond differently to past performance when a fund is operated in a family that has high-marketing expenses?

The main conclusions of our study can be summarized as follows. First, we find that funds with high marketing expenses draw substantially larger inflows as a response to their performance. More specifically, cash inflows following positive returns are almost twice as large for high-marketing funds compared to low-marketing funds. On the other hand, on the other hand, cash outflows following negative returns are only marginally larger for high-marketing funds compared to low-marketing funds. These results provide further evidence that mutual fund marketing is very effective in making good performance more visible to investors. Second, we find that small and young funds with low marketing expenses that are operated by a family with high marketing expenses have substantially larger inflows after positive returns than otherwise similar funds that are operated by a family with low marketing expenses. Furthermore, these funds appear to have smaller outflows following negative returns. These results indicate that high-marketing families provide favorable conditions to incubate new funds. Given the findings of Khorana and Servaes (2005) that families that start more funds have higher market share, one might expect high-marketing families to have a considerable competitive advantage over low-marketing families.

One way to interpret the spillovers is that they are a by-product of individual fund marketing whereby the entire family is made more visible to investors. An alternative explanation of this observation is that funds with low marketing expenses are directly subsidized by family members with high marketing expenses. A family could pay for marketing of a particular fund through expenses allocated to other funds. We develop and perform a set of tests to evaluate the alternative hypotheses. The results of all tests support the subsidization hypothesis and suggest that at least part of the spillovers can be attributed to families favoring some funds by transferring marketing exposure across member funds. These results suggest that conflicts of interest between investors and fund families have been exacerbated by competition in the mutual fund industry.

5.2 Data

5.2.1 Sources and fund selection

Our primary data are from the 2003 Mutual Fund Survivorship-bias Free Database compiled by the Center for Research in Security Prices (CRSP). This database covers returns, supplemental data, and fund classifications on all US open-end mutual funds, including defunct funds. Since CRSP basically includes all funds that existed during this period, our data are free of survivorship-bias as documented by Brown et al. (1992) and Brown and Goetzmann (1995). We extract data on returns, total net assets, family membership, and marketing and distribution expenses for all diversified US equity funds over the period January 1992 to December 2003. The return data come in monthly frequency. Data on the funds' total net assets, family membership, and marketing and distribution expenses come in yearly frequency. We follow a procedure similar to Pastor and Stambaugh (2002b,a) and Huij and Verbeek (2007) and use the additional information CRSP provides on fund classifications, expenses, and load data to construct a sample of diversified US equity funds. We exclude funds with no classification, expense, or load data in the annual summary at the end of each previous year. Additionally, we examine fund classifications at the end of each previous year, and exclude flexible funds, bond funds, mortgage-backed funds, multi-manager funds, money market funds, balanced funds, funds that invest in precious metals, and international funds. From the remaining funds, we select funds that are classified as small/cap growth, growth, growth & income, or income fund. Finally, we drop funds with less than two calendar years of consecutive returns over the entire sample period.

5.2.2 Measurement of performance, investor flows, and marketing and distribution expenses

For the main tests in our analyses, we investigate the impact of mutual fund marketing on the relation between investor flows and past performance. The definitions of most variables (i.e., investor flows and performance), and the regression methodology we use to investigate the flow-performance relation are standard in this stream of literature. The main innovation of our study is that we investigate the interaction of fund marketing with cash flows to other funds in the family. In particular, we investigate whether high-marketing funds generate spillovers, and enhance cash inflows to low-marketing funds in the family. Below we describe how we measure fund performance, investor flows, and marketing and distribution expenses.

Consistent with most of the literature, we take each fund's cumulative total return over year t as a measure for fund performance:

$$CTR_{i,t} = [(1 + r_{i,t,1}) \cdot (1 + r_{i,t,2}) \cdot \ldots \cdot (1 + r_{i,t,12})] - 1, \tag{5.1}$$

where $r_{i,t,j}$ is fund i's total return (change in net asset value plus distribution) over month j in year t .

To compute the dollar flow of fund i in year t, we follow the approach advocated by among others Sirri and Tufano (1998) , Zheng (1999), and Del Guercio and Tkac (2002):

$$DF_{i,t} = [TNA_{i,t} - TNA_{i,t-1} \cdot (1 + CTR_{i,t})], \tag{5.2}$$

where $TNA_{i,t}$ denotes the total net assets under management of fund i at the end of year t. We then normalize the dollar flows by the funds' total net assets under management to obtain a measure for the funds' percentage flows, i.e., $F_{i,t} = DF_{i,t}/TNA_{i,t-1}$. We remove observations of fund flows below -90 percent and above 1,000 percent. As pointed out by Bollen (2006), these observations are likely to be the results of misplacement of the decimal point. The resulting sample holds 2,200 funds in the average year, ranging from 714 funds in 1993 to 4,199 funds in 2002. In total, the sample covers 22,004 fund-years.

Marketing and distribution expenses are measured by the funds' front-end load fees and 12b1 fees. Front-end load fees are upfront sales commissions paid by investors when entering a fund, and are used to cover marketing related costs such as compensation for broker-dealer sales professionals, advertising, and other sales-promotion activities. While 12b1 fees are used for virtually the same purposes, these fees are paid periodically by the funds out of their assets, rather than directly by the investors. Barber et al. (2005) argue that 12b1 fees could therefore be expected to be less salient than front-end load fees, and more effective to attract new investors. Further, given the results of Nanda et al. (2006) that 12b1 funds cater a more myopic investor clientele, investors in these type of funds are likely to respond more strongly to marketing and distribution activities. Another difference between front-end load fees and 12b1 fees is that 12b1 fees are explicitly earmarked for marketing and distribution activities. For example, amounts spent under 12b1 plans and the reasons for these expenses must be be approved by the funds' directors. Shareholders must also approve increases in a fund's 12b1 fee. As a measure of fund i's total marketing expenses in year t ($TX_{i,t}$) we take the fund's reported 12b1 fee ($12B1_{i,t}$) plus one-seventh of the fund's front-end load fee ($LOAD_{i,t}$). Consistent with most of the literature, we hereby assume that the average holding period of a load-fund is seven years, see. e.g., Sirri and Tufano (1998), Barber et al. (2005), and Khorana and Servaes (2005).

Next, we compute performance, investor flows, and marketing and distribution expenses at the aggregate family level. We measure the performance of family f in year t as the value-weighted average cumulative total return of all funds in the family:

$$CTR_{f,t} = \frac{\sum_i CTR_{i,t} \cdot TNA_{i,t}}{\sum_i TNA_{i,t}}, \tag{5.3}$$

where the summation is over all funds in family f. Percentage flows to family f in year t are computed as the dollar flows of all funds in the family as a percentage of the family's lagged total net asset under management:

$$F_{f,t} = \frac{\sum_i DF_{i,t}}{\sum_i TNA_{i,t-1}}. \tag{5.4}$$

Finally, we compute the average front-end load fee charged by family f for each dollar under management over year t as

$$LOAD_{f,t} = \frac{\sum_i LOAD_{i,t} \cdot TNA_{i,t}}{\sum_i TNA_{i,t}}. \tag{5.5}$$

Similarly, we compute the average 12b1-fee charged by family f for each dollar under management over year t ($12B1_{f,t}$). As a measure of the total marketing expenses of family f over year t ($TX_{f,t}$), we take $12B1_{f,t}$ plus one-seventh of $LOAD_{f,t}$.

The relation between investor flows and performance, and the impact of mutual fund marketing on this relation, is modeled using the regression framework described in next section.

5.2.3 Growth of fund families and marketing and distribution expenses

The two most notable developments in the mutual fund industry over the past decade are the growth of fund families, and the enormous increase in the the dollar amount spend on marketing and distribution activities. In Figures 5.1, 5.2, and 5.3 we portray both developments. Figure 5.1 presents the number of diversified US equity funds in our sample over the period 1993 to 2003. From the 714 funds that were available in 1993, 141 funds were offered as stand-alone fund. While the number of stand-alone funds remains more or less constant over time, the total number of funds increases to 4,199 in 2002. Thus, while about 20 percent of the funds in 1993 were offered as stand-alone fund, this figure rapidly declined to less than 4 percent by the end of 2002. In Figure 5.2 we present a graph with the number of equity fund families (i.e., families that consist of at least two diversified US equity funds) and the average number of funds per family in our sample over the period 1993 to 2003. Where the number of equity fund families increased from 139 in 1993 to 283 in 2002, the average number of fund per family increased from 5.14 in 1993 to 14.84 in 2002.

Figure 5.3 presents an estimate of the dollar amount spent on mutual fund marketing and distribution over the period 1993 to 2003. In addition, the graph presents marketing and distribution expenses as a percentage of total net assets under management. Several interesting patterns show up. First, we observe an enormous increase in the dollar amount spent on marketing and distribution; while slightly more than $1.6 billion was spent on marketing and distribution activities in 1993, this amount increased to more than $9.2 billion in 2002. Second, it appears that the portion of marketing and distribution activities that is financed by 12b1 fees has grown substantially over time. In 1993, less than 25 percent of the marketing and distribution activities were financed by 12b1 fees. However, in 2002 this number was almost 50 percent. Finally, the dollar amount spent on marketing and distribution activities has five folded, whereas marketing and distribution expenses as percentage of total net assets have decreased over time. While 0.51 percent on total-net-assets under management was spent on marketing in 1993, this number decreased to 0.42 percent in 2002.

5.3 The impact of fund marketing on the flow-performance relation

In our first analysis, we investigate whether high-marketing funds experience differential in- and outflows in response to their performance versus low-marketing funds. We concentrate on family-operated funds (i.e., funds that have at least one family member), and drop all stand-alone funds. The resulting sample comprises 2,054 funds in the average year, ranging from 573 funds in 1993 to 4,043 funds in 2002. In total, the sample covers 20,542 fund-years.

While there is no consensus in the literature on how to specify the fund flow-performance relation, most researchers employ a non-linear model specification.[2] Sirri and Tufano (1998) perform piecewise linear regressions of investor flows on the funds' fractional ranks based on one-year raw returns; Barber et al. (2005) include squared returns in their regression of investor flows on funds' returns; and Bollen (2006) employs an interaction variable to capture potential asymmetries in the relation between investor flows and fund returns. We run regressions in spirit similar to Bollen (2006) and estimate the following model using ordinary-least-squares (OLS):

$$\begin{aligned} F_{i,t+1} = (b_0 + b_1 \cdot HIGHTX_{i,t} + b_2 \cdot I_{i,t} + b_3 \cdot HIGHTX_{i,t} \cdot I_{i,t}) \cdot CTR_{i,t} + \\ a_{0,t} + a_{1,t} \cdot HIGHTX_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{5.6}$$

where $HIGHTX_{i,t}$ is a dummy variable that indicates whether fund i is a high-marketing fund over year t. The dummy equals one if the fund's marketing and distribution expenses are greater than the median, and zero otherwise. Further, $I_{i,t}$ is an indicator variable that equals one if fund i's return over year t is negative, and zero otherwise. The regression model includes year dummies to capture year-specific effects. As explained by Bollen (2006), the coefficients in this regression model can be interpreted as follows:

b_0:	Percentage flow to *low-marketing* funds for every one percent increase in prior year return when returns are *positive*
$b_0 + b_1$:	Percentage flow to *high-marketing* funds for every one percent increase in prior year return when returns are *positive*
$b_0 + b_2$:	Percentage flow to *low-marketing* funds for every one percent increase in prior year return when returns are *negative*
$b_0+b_1+b_2+b_3$:	Percentage flow to *high-marketing* funds for every one percent increase in prior year return when returns are *negative*

To ensure that the results are not driven by small or young funds it is recommended to control for fund size and age in model Eq. (5.6). Sirri and Tufano (1998) and Barber et al. (2005) include the natural logarithms of the funds' lagged total net assets and age

[2] While most authors report a convex relation between fund flows and past performance (see e.g., Sirri and Tufano (1998) and Chevalier and Ellison (1999)), some recent evidence indicates that the relation has become more linear during the nineties compared to the previous two decades (Sigurdsson, 2004).

as control variables; Barber et al. (2005) and Bollen (2006) perform their analyses on subgroups of funds based on their size and age. Following these studies, we employ a model specification that extends our base model Eq. (5.6) with the natural logarithms of the funds' total net assets under management ($ln(TNA_{i,t})$) and age ($ln(AGE_{i,t})$):

$$\begin{aligned} F_{i,t+1} = {} & (b_0 + b_1 \cdot HIGHTX_{i,t} + b_2 \cdot I_{i,t} + b_3 \cdot HIGHTX_{i,t} \cdot I_{i,t}) \cdot CTR_{i,t} + \\ & b_4 \cdot ln(TNA_t) + b_5 \cdot ln(AGE_t) + a_{0,t} + a_{1,t} \cdot HIGHTX_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{5.7}$$

In addition, we run regressions Eq. (5.6) and Eq. (5.7) on the following subgroups of the funds: (i) funds with at least \$15 million of total-net-assets under management, (ii) funds with at least \$100 million of total net assets under management, (iii) funds that are at least 3 years old, and (iv) funds that are at least 5 years old. The results are presented in Table 5.1.

We first consider the results for the entire sample of funds. The coefficient estimate for $CTR_{i,t}$ is positive and highly significant, which indicates a strong relation between positive returns and future cash flows for low-marketing funds. The results in column B indicate that inflows to low-marketing funds increase with 1.05 percent for every one percent increase in prior year return when the return is positive.

Further, the coefficient estimate for $HIGHTX_{i,t} \cdot CTR_{i,t}$ indicates that the differential inflows to high-marketing funds as a response to positive returns are significantly different from zero. The estimate in column B of 0.94 indicates that for every one percent increase in prior year return, inflows to high-marketing funds increase with 1.99 percent (1.05 percent plus 0.94 percent) when returns are positive. Thus, it appears that cash inflows following positive returns are almost twice as large for high-marketing funds compared to low-marketing funds.

In addition, we investigate investors' response to negative returns. The coefficient estimates for $CTR_{i,t} \cdot I_{i,t}$ and $HIGHTX_{i,t} \cdot I_{i,t} \cdot CTR_{i,t}$ point to an asymmetric flow-performance relation for both low- and high-marketing funds. The estimates in column B indicate that outflows following negative returns increase by 0.96 percent (1.05 percent minus 0.09 percent) for every one percent decrease in prior year return for low-marketing funds, and by 1.18 percent (1.05 percent plus 0.94 percent minus 0.09 percent minus 0.72 percent) for high-marketing funds. Finally, the negative coefficient estimates for $ln(TNA_{i,t})$ and $ln(AGE_{i,t})$ indicate that small and young funds experience larger inflows than large and mature funds.

In Figure 5.4, we give a graphical representation of the estimated flow-performance relation for high- and low-marketing funds. The solid line draws the estimated relation between fund flow and lagged returns for high-marketing funds, and the dashed line draws this relation for low-marketing funds. The flows to high-marketing funds after positive returns are almost twice as large. While high-marketing funds also seem to experience somewhat larger outflows after negative returns, the outflows are substantially smaller than the inflows due to marketing.

When we consider the results for the subgroups of funds based on their total net assets or age in Table 5.1, we consistently observe that high-marketing funds have a much stronger flow-performance relation than low-marketing funds after positive returns. On the other hand, high-marketing funds also have somewhat larger outflows after negative returns. However, the outflows are substantially smaller than the inflows due to marketing.

In the analyses above, the models Eq. (5.6) and Eq. (5.7) are estimated using a pooled regression framework as in Bollen (2006). We also experiment with a cross-sectional regression framework, where we estimate regression Eq. (5.7) year-by-year for all funds, and average the regression coefficients using the Fama and MacBeth (1973) approach.[3] The results are in Table 5.2, and are qualitatively very similar to those using the pooled regression framework. Given the relatively small number of years in our sample, and given that the number of available funds at the end of the sample period is several times larger than at the beginning, we believe that the pooled framework is preferred to the cross-sectional framework in this specific situation. Throughout the remainder of this study, we therefore employ pooled regressions.

In summary, our results indicate a direct positive relation between lagged fund performance and investor flows. This flow-performance relation is asymmetric in the sense that inflows after positive performance are larger than outflows after negative performance. More importantly, high-marketing funds attract substantially larger inflows as a response to their performance than do low-marketing funds. Our results provide strong evidence that mutual fund marketing is very effective in making positive returns more visible to investors. An additional interesting finding is that it appears that almost all asymmetry in the flow-performance relation reported in the literature is found for funds that have above median marketing and distribution expenses. When the relation between fund performance and investor flows is investigated for low-marketing funds, the relation is almost linear.

[3]With the cross-sectional Fama and MacBeth (1973) regressions, we replace the year dummies with a constant.

5.4 Spillover effects of marketing in mutual fund families

Because all funds in our sample are family-operated, marketing expenses at the family level may also have an impact on the flow-performance relation of a given fund. To investigate this issue, we examine whether there is an interaction between the flow-performance relation of funds with low marketing expenses and membership of a family with high marketing expenses. To this end, we estimate the following regression for low-marketing funds in our sample (i.e., funds with total marketing expenses below the median):

$$F_{i,t+1} = (b_0 + b_1 \cdot HIGHTX\_F_{i,t} + b_2 \cdot I_{i,t} + b_3 \cdot HIGHTX\_F_{i,t} \cdot I_{i,t}) \cdot CTR_{i,t} + \\ a_{0,t} + a_{1,t} \cdot HIGHTX\_F_{i,t} + \epsilon_{i,t}, \tag{5.8}$$

where $HIGHTX\_F_{i,t}$ is a dummy variable indicating whether fund i is member of a high-marketing family over year t. The dummy equals one if the fund is member of a family with marketing and distribution expenses that are greater than the median, and zero otherwise. In addition, we employ a model specification that extends regression model Eq. (5.8) with the natural logarithms of the funds' total net assets under management and age. We also perform subgroup analyses as in the previous section, and estimate the regressions for the following subsamples of funds: (i) low-marketing funds with at least \$15 million of total net assets under management, (ii) low-marketing funds with at least \$100 million of total net assets under management, (iii) low-marketing funds that are at least 3 years old, and (iv) low-marketing funds that are at least 5 years old. The regression results are in Table 5.3.

The coefficient estimates for $HIGHTX\_F_{i,t} \cdot CTR_{i,t}$ and $HIGHTX\_F_{i,t} \cdot I_{i,t} \cdot CTR_{i,t}$ capture the differential flows to low-marketing funds that are member of a high-marketing family versus low-marketing funds that are member of a low-marketing family. The results for the entire sample of low-marketing funds in columns A and B indicate significant positive differential inflows after positive returns, and significant negative differential outflows after negative returns. Low-marketing funds that are member of a high-marketing family have substantially larger inflows after positive returns than otherwise similar funds that are operated by a low-marketing family. The results in column B indicate that inflows to low-marketing funds that are operated by a high-marketing family increase with 1.17 percent (0.97 percent plus 0.20 percent) for every one percent increase in prior year return when the return is positive, while inflows to low-marketing funds that are operated by a low-marketing family increase with only 0.97 percent. The difference is statistically significant.

Further, low-marketing funds that are operated by a high-marketing family appear to experience lower outflows after negative performance: while low-marketing funds that are not member of a high-marketing family lose 0.87 percent (0.96 percent minus 0.09 percent) of their assets under management for every one percent decrease in prior year return, funds that are member of a high-marketing family lose only 0.73 percent (0.96 percent plus 0.18 percent minus 0.09 percent minus 0.32 percent) of their assets under management.

However, for the subgroups that exclude small and young funds, we do not observe such spillovers. In fact, we observe some sort of cannibalization effects: large and mature funds with low marketing expenses that are member of a high-marketing family appear to have lower inflows after positive returns than otherwise similar funds that are member of a low-marketing family. We do not observe differential outflows after negative returns for these groups of funds. Apparently, membership of a high-marketing family is only beneficial to low-marketing funds that are relatively small and young. This effect could be due to these types of funds having larger search costs (see e.g., Sirri and Tufano (1998)). Nonetheless, our results indicate that high-marketing families provide favorable conditions to incubate new funds. Given the findings of Khorana and Servaes (2005) that families that start more funds have higher market share, one might expect high-marketing families to have a considerable competitive advantage over low-marketing families.

5.5 Interpreting the spillovers: hypothesis development

One of the most notable observations in the previous section is that high-marketing funds appear to generate spillovers and enhance cash inflows to smaller and younger funds in the family that have low marketing expenses themselves. In the remainder of the paper we take a closer look at this phenomenon.

One interpretation is that the observed spillovers are a by-product of individual fund marketing and distribution whereby the entire family is made more visible to investors, and search costs for small and young funds are lowered. However, a critical assumption underlying this interpretation is that funds' allocated marketing and distribution expenses are directly proportional to the funds' exposure in the media and broker-dealer channels. An alternative explanation for the observed spillovers is that funds with low marketing expenses are directly subsidized by family members with high marketing expenses. A family could pay for advertising and distribution activities of a particular fund through expenses allocated to other funds. There is some anecdotical evidence that lends support to this interpretation. For example, a large number of the funds that are advertised do not charge front-end load fees or 12b1 fees themselves. Further, Gallaher et al. (2006) refer to conversations they had with mutual fund family executives, in which the executives indicated that the intent of mutual fund marketing is often not a particular fund, but the fund family itself. Investors who call in on an advertisement of a certain fund may be counseled to invest in other funds of the family. Besides this anecdotical evidence, several academic studies also indicate that families play favorites with their funds. For example, Guedj and Papastaikoudi (2005) and Gaspar et al. (2006) report that families strategically transfer performance across member funds to favor those more likely to increase overall family profits. Cici et al. (2006) even find that institutional managers who engage in side-by-side management of mutual funds and hedge funds, improve the performance of hedge funds at the expense of mutual fund investors. These findings give rise to the notion that the observed spillovers might be related to cross-fund subsidizations.

We develop and perform a set of tests to evaluate the two alternative hypotheses, i.e., spillovers as a by-product of individual fund marketing and distribution versus spillovers resulting from favoritism. A direct approach to test the subsidization hypothesis would be to investigate whether there are any discrepancies between funds' allocated marketing and distribution expenses and their actual expenditures on marketing and distribution activities. However, while data on funds' allocated marketing and distribution expenses are readily available because of legal requirements, data on funds' actual marketing and distribution expenditures are only very limitedly available.[4] Because of these data limitations, we employ an indirect approach to investigate whether the observed spillovers are related to intrafamily subsidizations. With this approach, we sort funds into two mutually exclusive groups, where the funds in the first group are member of a family that has strong incentives to engage in subsidization, and the funds in the second group are not. We then test whether there are differences in the observed spillovers between both groups.

The more families finance their marketing and distribution activities by front-end load fees, the stronger their incentives are to pay for advertising and distribution activities of a particular fund through expenses allocated to other funds. Families that finance their

[4]While Competitive Media Research (CMR) distributes data on mutual funds' actual advertising expenditures, we are not aware of any information service that provides an extensive database on the entire spectrum of mutual fund marketing and distribution activities, including sales-promotion activities and compensation for broker-dealer sales professionals.

marketing and distribution activities by 12b1 fees are restricted to engage in significant subsidization because 12b1 fees are explicitly earmarked to cover marketing related costs of the funds that charge the fees. Amounts spent under 12b1 plans and the reasons for these expenses must be approved by a vote of the funds' directors. Shareholders must also approve increases in a fund's 12b1 fee. Because the regulations for charging, spending, and reporting front-end load fees are less strict, fund management companies have fewer restrictions in appropriating them. For example, while funds that are closed to new investors are not allowed to charge 12b1 fees, funds that neither advertise, nor use brokers are allowed to consistently charge load fees.[5]

On the other hand, if the spillovers are a by-product of individual fund marketing and distribution, we expect them to be more prevalent in families that finance their marketing and distribution activities by 12b1 fees: several authors document that marketing is more effective when financed by 12b1 fees because these fees are less salient to investors than front-end load fees (see e.g., Barber et al. (2005)). Further, as mentioned earlier, 12b1 families cater a more myopic investor clientele (i.e., investors with shorter investment horizons that are more sensitive to past performance, see Nanda et al. (2006)) which is expected to respond more strongly to marketing and distribution activities. Consequently, if the subsidization hypothesis is true, the spillovers are more prevalent in families with high front-end load fees than in families with high 12b1 fees. Otherwise, if the spillovers are a by-product of individual fund marketing and distribution, the spillovers are more prevalent in families with high 12b1 fees than in families with high front-end load fees. Hence, we formulate the first testable implication of the subsidization hypothesis:

Hypothesis 1: Spillovers are more prevalent in families with high front-end load fees than in families with high 12b1 fees.

Further, since families have fewer restrictions to divert a fund's front-end load fees to subsidize other funds' marketing and distribution activities than 12b1 fees, we expect any subsidies to be largely financed by front-end load fees. Therefore, if the subsidization hypothesis is true, front-end load fees are not fully spent on marketing and distribution activities of the load funds themselves. Thus, our second hypothesis is:

[5]Closed funds are allowed to spread marketing and distribution expenses over several years, and may charge 12b-1 fees to fulfill obligations for past distribution efforts.

Hypothesis 2: Funds with high front-end load fees have a weaker flow-performance relation than funds with high 12b1 fees.

Finally, if the subsidization hypothesis is true, there should be a motive for families to subsidize the marketing and distribution of a particular fund through expenses allocated to other funds. Given the observation that a family's overall profits are a direct function of their assets under management, and investors' tendency to disproportionably put their money into particular funds (i.e., young funds, funds with stellar performance, or funds that follow the current "hot" style (Chevalier and Ellison, 1997; Cooper et al., 2005)), families that strategically increase the marketing exposure of some funds at the expense of others are expected to have a stronger flow-performance relation than families that do not pursue such a subsidization strategy. Therefore, our third hypothesis reads:

Hypothesis 3: Families with high front-end load fees have a stronger flow-performance relation than families with high 12b1 fees.

We test these hypotheses using the empirical framework described in the following section.

5.6 Interpreting the spillovers: empirical framework and results

5.6.1 Differential flows to low-marketing funds that are member of a high-load and a high-12b1 family

Our first hypothesis states that if the observed spillovers are because of intrafamily subsidizations, they are more prevalent in families with high front-end load fees than in families with high 12b1 fees. To test this hypothesis, we split our sample of low-marketing funds that are member of a high-marketing family into two mutually exclusive groups: low-marketing funds that are member of a high-load family, and low-marketing funds that are member of a high-12b1 family. High-load families are defined as high-marketing families with front-end load fees greater than the median, and high-12b1 families are defined as high-marketing families with front-end load fees less than or equal to the median. We then test whether there are differences in spillovers between both groups.

First, we investigate spillovers in high-load families, and estimate the following regression model for low-marketing funds that are member of either a high-load or a low-marketing family:

$$F_{i,t+1} = (b_0 + b_1 \cdot HIGHLOAD\_F_{i,t} + b_2 \cdot I_{i,t} + b_3 \cdot HIGHLOAD\_F_{i,t} \cdot I_{i,t}) \cdot CTR_{i,t} + a_{0,t} + a_{1,t} \cdot HIGHLOAD\_F_{i,t} + \epsilon_{i,t}, \tag{5.9}$$

where $HIGHLOAD\_F_{i,t}$ is a dummy variable that equals one if fund i is member of a high-load family over year t, and zero otherwise. The coefficient estimates for $HIGHLOAD\_F_{i,t} \cdot CTR_{i,t}$ and $HIGHLOAD\_F_{i,t} \cdot I_{i,t} \cdot CTR_{i,t}$ capture the differential flows to low-marketing funds that are member of a high-load family compared to low-marketing funds that are member of a low-marketing family. We also employ a model specification that extends regression models Eq. (5.9) with the natural logarithms of the funds' lagged total net assets under management and age. The results are in columns A and B of Table 5.4. The significant positive coefficient estimates for $HIGHLOAD\_F_{i,t} \cdot CTR_{i,t}$ indicate the presence of substantial spillovers in high-load families. The results in column B indicate that inflows to low-marketing funds that are member of a high-load family increase with 1.43 percent (0.97 percent plus 0.46 percent) for every one percent increase in prior year return when the return is positive, whereas inflows to low-marketing funds that are member of a low-marketing family increase with only 0.97 percent. Further, the significant negative coefficient estimates for $HIGHLOAD\_F_{i,t} \cdot I_{i,t} \cdot CTR_{i,t}$ indicate that low-marketing funds in high-load families experience lower outflows after negative performance than low-marketing funds that are member of a low-marketing family.

Next, we investigate spillovers in high-12b1 families, and estimate the following regression model for low-marketing funds that are member of either a high-12b1 or a low-marketing family:

$$F_{i,t+1} = (b_0 + b_1 \cdot HIGH12B1\_F_{i,t} + b_2 \cdot I_{i,t} + b_3 \cdot HIGH12B1\_F_{i,t} \cdot I_{i,t}) \cdot CTR_{i,t} + a_{0,t} + a_{1,t} \cdot HIGH12B1\_F_{i,t} + \epsilon_{i,t}, \tag{5.10}$$

where $HIGH12B1\_F_{i,t}$ is a dummy variable that equals one if fund i is member of a high-12b1 family over year t, and zero otherwise. We additionally employ a model specification that augments model Eq. (5.10) with the natural logarithms of the funds' lagged total net assets under management and age. The results of these regressions are in columns C and D. Surprisingly, we observe no spillovers whatsoever in high-12b1 families. In fact, the significant negative coefficient estimates for $HIGH12B1\_F_{i,t} \cdot CTR_{i,t}$ and the significant positive coefficients estimates for $HIGH12B1\_F_{i,t} \cdot I_{i,t} \cdot CTR_{i,t}$ indicate cannibalization of low-marketing funds in high-12b1 families.

Finally, to test whether the observed differences in spillovers between high-load and high-12b1 families are statistically significant, we estimate regression Eq. (5.9) for low-marketing funds that are member of either a high-load or a high-12b1 family. The results are presented in column E. The significant positive coefficient estimate for $HIGHLOAD\_F_{i,t} \cdot CTR_{i,t}$ and the negative estimate for $HIGHLOAD\_F_{i,t} \cdot I_{i,t} \cdot CTR_{i,t}$ indicate that the spillovers are more prevalent in high-load families, and lend support for the subsidization hypothesis. We also run a model specification that extends regression Eq. (5.9) with the natural logarithms of the funds' lagged total net assets under management and age. The results of this regression in column F confirm our previous findings.

We also perform subgroup analyses, and estimate the regressions for (i) low-marketing funds with at least \$15 million of total net assets under management; (ii) low-marketing funds with at least \$100 million of total net assets under management; (iii) low-marketing funds that are at least 3 years old; and (iv) low-marketing funds that are at least 5 years old. The regression results are in Table 5.5 and 5.6. The spillovers in high-load families are observed for all subgroups except for low-marketing funds that are at least 5 years old. Further, the cannibalization of low-marketing funds that are member of a high-12b1 family can be observed across all subgroups of funds.

Overall, the results in this subsection are consistently in favor of Hypothesis 1, and lend support to the notion that the observed spillovers are related to intrafamily subsidizations and favoritism.

5.6.2 Differential flows to high-load and high-12b1 funds

We now turn to the examination of our second hypothesis. Under the subsidization hypothesis, we expect that funds with high front-end load fees have a weaker flow-performance relation than funds with high 12b1 fees. To test this hypothesis, we split our sample of high-marketing funds into two mutually exclusive groups: high-load funds (i.e., high-marketing funds that have front-end load fees greater than the median), and high-12b1 funds (i.e., high-marketing funds that have front-end load fees less than or equal to the median). We then investigate whether there are differences in the flow-performance relation between both groups.

To this end, we estimate the following regression for high-load funds and low-marketing funds:

$$F_{i,t+1} = (b_0 + b_1 \cdot HIGHLOAD_{i,t} + b_2 \cdot I_{i,t} + b_3 \cdot HIGHLOAD_{i,t} \cdot I_{i,t}) \cdot CTR_{i,t} + a_{0,t} + a_{1,t} \cdot HIGHLOAD_{i,t} + \epsilon_{i,t}, \tag{5.11}$$

and the following regression for high-12b1 funds and low-marketing funds:

$$F_{i,t+1} = (b_0 + b_1 \cdot HIGH12B1_{i,t} + b_2 \cdot I_{i,t} + b_3 \cdot HIGH12B1_{i,t} \cdot I_{i,t}) \cdot CTR_{i,t} + a_{0,t} + a_{1,t} \cdot HIGH12B1_{i,t} + \epsilon_{i,t}, \tag{5.12}$$

where $HIGHLOAD_{i,t}$ is a dummy variable that indicates if fund i is a high-load fund over year t, and $HIGH12B1_{i,t}$ is a dummy variable that indicates if fund i is a high-12b1 fund over year t. We also run regressions that augment regression models Eq. (5.11) and Eq. (5.12) with the natural logarithms of the funds' lagged total net assets under management and age. The results of these regressions are in columns A to D in Table 5.7.

The significantly positive coefficient estimates for $HIGHLOAD_{i,t} \cdot CTR_{i,t}$ and $HIGH12B1_{i,t} \cdot CTR_{i,t}$ indicate that both high-load and high-12b1 funds have differential inflows after positive returns versus low-marketing funds. However, the differential inflows to high-12b1 funds are larger. For example, when we consider the results in column B and D, we observe that inflows to high-load funds increase with 1.76 percent (1.05 percent plus 0.71 percent) for every one percent increase in return when returns are positive, while the inflows to high-12b1 funds increase with 2.21 percent (1.05 percent plus 1.17 percent). Further, the significant negative coefficient estimates for $HIGHLOAD_{i,t} \cdot I_{i,t} \cdot CTR_{i,t}$ and $HIGH12B1_{i,t} \cdot I_{i,t} \cdot CTR_{i,t}$ indicate that both high-load and high-12b1 funds have differential outflows after negative returns.

To test whether the observed differences in the flow-performance relation between high-load and high-12b1 funds are statistically significant, we estimate regression Eq. (5.11) for high-load and high-12b1 funds. In these regressions, the coefficient estimates for $HIGHLOAD_{i,t} \cdot CTR_{i,t}$ and $HIGHLOAD_{i,t} \cdot I_{i,t} \cdot CTR_{i,t}$ capture the differential flows to high-load funds versus high-12b1 funds. The results are in columns E and F, and clearly indicate that the flow-performance relation for high-12b1 funds is stronger than for high-load funds. This finding lends further support to the subsidization hypothesis.

5.6.3 Differential flows to high-marketing families

Finally, we move on to our third hypothesis which states that families with high front-end load fees have a stronger flow-performance relation than families with high 12b1 fees. We use a similar approach as in the previous subsections to test this hypothesis, and split our sample of high-marketing families into two mutually exclusive groups of high-load families and high-12b1 families, and test whether there are any differences in the flow-performance relation between both groups.

However, before we perform this test, we first investigate whether high-marketing families have a differential flow-performance relation versus low-marketing families. To this end, we estimate the following regression model:

$$F_{f,t+1} = (b_0 + b_1 \cdot TOP50TX_{f,t} + b_2 \cdot I_{f,t} + b_3 \cdot TOP50TX_{f,t} \cdot I_{f,t}) \cdot CTR_{f,t} + a_{0,t} + a_{1,t} \cdot TOP50TX_{f,t} + \epsilon_{f,t}, \tag{5.13}$$

where $TOP50TX_{f,t}$ is a dummy variable that equals one if the family's marketing and distribution expenses are greater than the median over year t, and zero otherwise. Further, $I_{f,t}$ is an indicator variable that equals one if family f's return over year t is negative, and zero otherwise. Additionally, we employ a regression specification that extends Eq. (5.13) with family f's total net assets under management ($ln(TNA_{f,t})$) and average fund age ($ln(AGE_{f,t})$. The results of these regressions in columns A and B of Table 5.8 indicate that high-marketing families do not appear to have a stronger flow-performance relation than low-marketing families. In fact, the negative coefficient estimates for $TOP50TX_{f,t} \cdot CTR_{f,t}$ indicate that low-marketing families have larger inflows following positive returns, and the positive coefficient estimates for $TOP50TX_{f,t} \cdot I_{f,t} \cdot CTR_{f,t}$ indicate that low-marketing families have lower outflows after negative returns. Given the results of Gallaher et al. (2006) that marketing only works for top-advertising families, we re-estimate the regressions where we replace $TOP50TX_{f,t}$ with a dummy variable that equals one if the family's marketing and distribution expenses are greater than the 3rd quartile over year t, and zero otherwise ($TOP25TX_{f,t}$). The results of these regressions are in columns C and D. Now we find clear evidence that families with the highest marketing and distribution expenses have a stronger flow performance relation. For example, when we consider the results in column D, it appears that inflows to low-marketing families (bottom 75 percent) increase with 0.68 percent for every one percent increase in prior year return when the return is positive, while inflows to high-marketing families (top 25 percent) increase with 1.56 percent (0.68 percent plus 0.88 percent).

This bring us to Hypothesis 3. First, we split our sample of high-marketing families (top 25 percent) into two mutually exclusive groups: high-load families (i.e., high-marketing families that have front-end load fees greater than the 3rd quartile), and high-12b1 families (i.e., high-marketing families that have front-end load fees less than or equal to the

3rd quartile.). We then estimate the following regression for high-load families and low-marketing families:

$$F_{f,t+1} = (b_0 + b_1 \cdot TOP25LOAD_{f,t} + b_2 \cdot I_{f,t} + b_3 \cdot TOP25LOAD_{f,t} \cdot I_{i,t}) \cdot CTR_{f,t} + a_{0,t} + a_{1,t} \cdot TOP25LOAD_{f,t} + \epsilon_{f,t}, \tag{5.14}$$

and the following regression for high-12b1 families and low-marketing families:

$$F_{f,t+1} = (b_0 + b_1 \cdot TOP2512B1_{f,t} + b_2 \cdot I_{f,t} + b_3 \cdot TOP2512b1_{f,t} \cdot I_{i,t}) \cdot CTR_{f,t} + a_{0,t} + a_{1,t} \cdot TOP2512B1_{f,t} + \epsilon_{f,t}, \tag{5.15}$$

where $TOP25LOAD_{f,t}$ is a dummy variable that equals one if family f is a high-load family over year t, and zero otherwise, and $TOP2512B1_{f,t}$ is a dummy variable that equals one if family f is a high-12b1 family over year t, and zero otherwise. In addition, we employ augmented specifications that include the families' total net assets under management and average fund age. The results are in columns E to H. It appears that only the high-load families have a stronger flow performance relation. To test the statistical significance of the difference in the flow-performance relation between high-load and high-12b1 families, we estimate regression Eq. (5.14) and the augmented specification for high-load families and high-12b1 families. The results in column I and J indicate that high-load families have larger inflows following positive returns than high-12b1 families, and provide further evidence supporting the subsidization hypothesis.

5.7 Conclusion

In this paper, we investigate the impact of mutual fund marketing and distribution activities on other funds in the family. We find that high-marketing funds generate spillovers, and enhance cash inflows to low-marketing funds in the same family. Small and young low-marketing funds that are operated by a family with high marketing expenses have substantially larger inflows after positive returns than otherwise similar funds that are operated by a family with low marketing expenses.

One interpretation of these results is that the observed spillovers are a by-product of individual fund marketing whereby the entire family is made more visible to investors, and search costs for small and young funds are lowered. A critical assumption underlying this interpretation is that funds' allocated marketing and distribution expenses are directly proportional to the funds' exposure in the media and broker-dealer channels. An alternative explanation of this observation is that funds with low marketing expenses are directly subsidized by family members with high marketing expenses. A family could pay for advertising and distribution activities of a certain fund through expenses allocated to other funds. We develop and perform a set of tests to evaluate the alternative hypotheses. The body of evidence in this paper supports the subsidization hypothesis, and suggests that at least a part of the spillovers can be attributed to favoritism towards particular funds.

While it is conceivable that fund families engage in cross-subsidization, these results are remarkable. As argued by Khorana and Servaes (2005), given the low entry barriers of the mutual fund industry and the large number of participants, one might expect that conflicts of interest between investors and investment companies are mitigated by competition. However, our finding that families that play favorites with their funds and pay for the marketing of a particular fund through expenses allocated to other funds suggests that conflicts of interest between investors and fund families have actually been exacerbated by competition in the mutual fund industry.

5.8 Tables and Figures

Table 5.1: Differential flows to high-marketing funds.

	High- vs low-marketing funds									
	Entire sample		TNA 15M+		TNA 100M+		AGE 3Y+		AGE 5Y+	
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)
CTR	1.03	1.05	0.86	0.82	0.69	0.64	1.09	1.12	0.98	1.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGHTX * CTR$	0.86	0.94	0.84	0.86	0.57	0.59	0.62	0.66	0.43	0.42
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$I * CTR$	-0.20	-0.09	-0.11	-0.01	0.08	0.15	-0.39	-0.40	-0.37	-0.38
	(0.00)	(0.00)	(0.00)	(0.73)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGHTX * I * CTR$	-0.47	-0.72	-0.53	-0.61	-0.35	-0.35	-0.18	-0.36	-0.10	-0.13
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
$ln(TNA)$	–	-7.78	–	-3.61	–	-0.93	–	-6.42	–	-4.44
	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.00)
$ln(AGE)$	–	-13.70	–	-13.75	–	-10.53	–	-9.18	–	-6.65
	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.00)
N	20,542	20,542	15,962	15,962	9,456	9,456	17,068	17,068	11,070	11,070
Adj.Rsq	0.08	0.15	0.09	0.14	0.10	0.13	0.08	0.13	0.08	0.11

Table 5.1 continued

The sample covers diversified US equity funds over the period January 1992 to December 2003. The table reports the OLS coefficient estimates of separate regressions using fund i's percentage flow over year $t+1$ ($F_{i,t+1}$) as dependent variable. The independent variables include fund i's return over year t ($CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is a high-marketing fund times fund i's return over year t ($HIGHTX_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy that equals one if fund i's return is negative times fund i's return over year t ($I_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is a high-marketing fund times a dummy that equals one if fund i's return is negative times fund i's return over year t ($HIGHTX_{i,t} * I_{i,t} * CTR_{i,t}$); and the natural logarithms of fund i's TNA and age ($ln(TNA_{i,t})$ and $ln(AGE_{i,t})$). Columns A and B report the results for the entire sample. Columns C and D report the results for funds with TNA of at least \$15 million. Columns E and F report the results for funds with TNA of at least \$100 million. Columns G and H report the results for funds that are at least 3 years old. Columns I and J report the results for funds that are at least 5 years old. p-values are given in parentheses below the coefficient estimates.

Table 5.2: Year-by-year estimates of differential flows to high-marketing funds.

	High- vs low-marketing funds										
	1993 (A)	1994 (B)	1995 (C)	1996 (D)	1997 (E)	1998 (F)	1999 (G)	2000 (H)	2001 (I)	2002 (J)	Average (K)
CTR	1.75	3.21	9.78	3.49	4.12	2.06	2.25	0.52	2.57	1.59	3.13
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGHTX * CTR$	2.77	0.29	1.17	1.56	1.07	2.40	2.35	0.41	1.31	0.34	1.37
	(0.00)	(0.62)	(0.62)	(0.01)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)	(0.44)	(0.00)
$I * CTR$	2.80	0.59	-5.86	-7.79	-9.01	-1.94	-2.32	0.95	-2.54	-0.83	-2.59
	(0.43)	(0.94)	(0.00)	(0.00)	(0.04)	(0.33)	(0.00)	(0.06)	(0.00)	(0.01)	(0.02)
$HIGHTX * I * CTR$	-5.59	-3.81	0.22	N/A	-3.20	-7.91	-2.20	3.54	-1.20	-0.08	-2.25
	(0.38)	(0.67)	(0.95)	N/A	(0.74)	(0.08)	(0.07)	(0.02)	(0.04)	(0.89)	(0.02)
$ln(TNA)$	-6.19	-4.28	-13.62	-11.74	-9.65	-7.90	-10.09	-10.16	-5.41	-5.85	-8.49
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$ln(AGE)$	-15.33	-8.74	-11.37	-16.68	-13.70	-17.62	-21.41	-9.72	-10.33	-4.73	-12.96
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	573	742	1,038	13,23	1,628	2,131	2,561	3,073	3,430	4,043	20,542
Adj.Rsq	0.15	0.19	0.22	0.22	0.19	0.17	0.24	0.16	0.17	0.10	0.18

The sample covers diversified US equity funds over the period January 1992 to December 2003. The table reports the OLS coefficient estimates of separate regressions using fund i's percentage flow over year $t+1$ ($F_{i,t+1}$) as dependent variable. The independent variables include fund i's return over year t ($CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is a high-marketing fund times fund i's return over year t ($HIGHTX_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy that equals one if fund i's return is negative times fund i's return over year t ($I_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is a high-marketing fund times a dummy that equals one if fund i's return is negative times fund i's return over year t ($HIGHTX_{i,t} * I_{i,t} * CTR_{i,t}$); and the natural logarithms of fund i's TNA and age ($ln(TNA_{i,t})$ and $ln(AGE_{i,t})$). The regression are run year-by-year. Columns A to J report the results for the years 1993 to 2002. Column K reports the average regression coefficients over the years. The standard errors of the average regression coefficients are calculated using the Fama and MacBeth (1973) approach. p-values are given in parentheses below the coefficient estimates.

Table 5.3: Differential flows to low-marketing funds that are member of a high-marketing family.

	Low-marketing funds that are member of a high- vs a low-marketing family									
	Entire sample		TNA 15M+		TNA 100M+		AGE 3Y+		AGE 5Y+	
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)
CTR	0.96	0.97	0.87	0.83	0.74	0.70	1.12	1.16	1.13	1.19
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGHTX\_F * CTR$	0.18	0.20	-0.05	-0.04	-0.15	-0.14	-0.08	-0.10	-0.34	-0.38
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$I * CTR$	-0.09	0.02	-0.10	-0.05	0.03	0.09	-0.40	-0.40	-0.33	-0.36
	(0.04)	(0.66)	(0.00)	(0.14)	(0.30)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGHTX\_F * I * CTR$	-0.32	-0.33	-0.02	0.06	0.10	0.12	0.01	-0.03	-0.09	-0.06
	(0.00)	(0.00)	(0.83)	(0.43)	(0.22)	(0.13)	(0.94)	(0.74)	(0.33)	(0.52)
$ln(TNA)$	–	-7.37	–	-3.12	–	-0.85	–	-6.31	–	-4.22
	–	(0.00)	–	(0.00)	–	(0.05)	–	(0.00)	–	(0.00)
$ln(AGE)$	–	-12.34	–	-12.64	–	-9.14	–	-8.17	–	-4.76
	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.01)
N	10,762	10,762	8,602	8,602	5,306	5,306	9,085	9,085	6,021	6,021
Adj.Rsq	0.05	0.11	0.06	0.09	0.07	0.09	0.05	0.09	0.06	0.08

The sample covers diversified US equity funds over the period January 1992 to December 2003. The table reports the OLS coefficient estimates of separate regressions using fund i's percentage flow over year $t+1$ ($F_{i,t+1}$) as dependent variable. The independent variables include fund i's return over year t ($CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is member of a high-marketing family times fund i's return over year t ($HIGHTX\_F_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy that equals one if fund i's return is negative times fund i's return over year t ($I_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is member of a high-marketing family times a dummy that equals one if fund i's return is negative times fund i's return over year t ($HIGHTX\_F_{i,t} * I_{i,t} * CTR_{i,t}$); and the natural logarithms of fund i's TNA and age ($ln(TNA_{i,t})$ and $ln(AGE_{i,t})$). The regressions are performed on low-marketing funds. Columns A and B report the results for the entire sample. Columns C and D report the results for funds with TNA of at least \$15 million. Columns E and F report the results for funds with TNA of at least \$100 million. Columns G and H report the results for funds that are at least 3 years old. Columns I and J report the results for funds that are at least 5 years old. p-values are given in parentheses below the coefficient estimates.

Table 5.4: Differential flows to low-marketing funds that are member of a high-load and a high-12b1 family.

	Low-marketing funds that are member of a high-load vs a low-marketing family		Low-marketing funds that are member of a high-12b1 vs a low-marketing family		Low-marketing funds that are member of a high-load vs a high-12b1 family	
	(A)	(B)	(C)	(D)	(E)	(F)
CTR	0.96	0.97	0.96	0.96	0.83	0.86
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGHLOAD\_F * CTR$	0.44	0.46	–	–	0.56	0.58
	(0.00)	(0.00)	–	–	(0.00)	(0.00)
$HIGH12B1\_F * CTR$	–	–	-0.13	-0.13	–	–
	–	–	(0.00)	(0.00)	–	–
$I * CTR$	-0.09	0.02	-0.09	0.02	0.51	0.60
	(0.03)	(0.66)	(0.05)	(0.67)	(0.11)	(0.04)
$HIGHLOAD\_F * I * CTR$	-0.75	-0.76	–	–	-1.35	-1.39
	(0.00)	(0.00)	–	–	(0.00)	(0.00)
$12B1\_F * I * CTR$	–	–	0.59	0.65	-	-
	–	–	(0.11)	(0.06)	–	–
$ln(TNA)$	–	-7.20	–	-6.55	–	-8.89
	–	(0.00)	–	(0.00)	–	(0.00)
$ln(AGE)$	–	-12.62	–	-14.51	–	-7.81
	–	(0.00)	–	(0.00)	–	(0.03)
N	10,029	10,029	6,925	6,925	4,570	4,570
Adj.Rsq	0.05	0.11	0.05	0.10	0.06	0.12

The sample covers diversified US equity funds over the period January 1992 to December 2003. The table reports the OLS coefficient estimates of separate regressions using fund i's percentage flow over year $t+1$ ($F_{i,t+1}$) as dependent variable. The independent variables include fund i's return over year t ($CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is member of a high-load family times fund i's return over year t ($HIGHLOAD\_F_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is member of a high-12b1 family times fund i's return over year t ($HIGH12B1\_F_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy that equals one if fund i's return is negative times fund i's return over year t ($I_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is member of a high-load family times a dummy that equals one if fund i's return is negative times fund i's return over year t ($HIGHLOAD\_F_{i,t} * I_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is member of a high-12b1 family times a dummy that equals one if fund i's return is negative times fund i's return over year t ($HIGH12b1\_F_{i,t} * I_{i,t} * CTR_{i,t}$); and the natural logarithms of fund i's TNA and age ($ln(TNA_{i,t})$ and $ln(AGE_{i,t})$). The regressions in columns A and B are performed on low-marketing funds that are member of either a high-load or a low-marketing family. The regressions in columns C and D are performed on low-marketing funds that are member of either a high-12b1 or a low-marketing family. The regressions in columns E and F are performed on low-marketing funds that are member of a high-marketing family. p-values are given in parentheses below the coefficient estimates.

Table 5.5: Differential flows to low-marketing funds that are member of a high-load family (subgroups)

	Low-marketing funds that are member of a high-load vs a low-marketing family							
	TNA $15M+$		TNA $100M+$		AGE $3Y+$		AGE $5Y+$	
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
CTR	0.87	0.83	0.74	0.70	1.12	1.16	1.13	1.19
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGHLOAD\_F * CTR$	0.26	0.27	0.25	0.26	0.30	0.27	-0.02	-0.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.38)	(0.01)
$I * CTR$	-0.10	-0.04	0.03	0.09	-0.40	-0.40	-0.33	-0.36
	(0.00)	(0.16)	(0.28)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGHLOAD\_F * I * CTR$	-0.52	-0.43	-0.57	-0.55	-0.63	-0.66	-0.56	-0.53
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$ln(TNA)$	–	-2.98	–	-0.69	–	-6.17	–	-4.29
	–	(0.00)	–	(0.12)	–	(0.00)	–	(0.00)
$ln(AGE)$	–	-13.04	–	-9.28	–	-8.37	–	-5.29
	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.00)
N	8,035	8,035	4,961	4,961	6,964	6,964	5,610	5,610
Adj.Rsq	0.06	0.10	0.08	0.10	0.06	0.10	0.06	0.09

The sample covers diversified US equity funds over the period January 1992 to December 2003. The table reports the OLS coefficient estimates of separate regressions using fund i's percentage flow over year $t+1$ ($F_{i,t+1}$) as dependent variable. The independent variables include fund i's return over year t ($CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is member of a high-load family times fund i's return over year t ($HIGHLOAD\_F_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy that equals one if fund i's return is negative times fund i's return over year t ($I_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is member of a high-load family times a dummy that equals one if fund i's return is negative times fund i's return over year t ($HIGHLOAD\_F_{i,t} * I_{i,t} * CTR_{i,t}$); and the natural logarithms of fund i's TNA and age ($ln(TNA_{i,t})$ and $ln(AGE_{i,t})$). The regressions are performed on low-marketing funds that are member of either a high-load or a low-marketing family. Columns A and B report the results for funds with TNA of at least \$15 million. Columns C and D report the results for funds with TNA of at least \$100 million. Columns E and F report the results for funds that are at least 3 years old. Columns G and H report the results for funds that are at least 5 years old. p-values are given in parentheses below the coefficient estimates.

Table 5.6: Differential flows to low-marketing funds that are member of a high-12b1 family (subgroups).

	Low-marketing funds that are member of a high-12b1 vs a low-marketing family							
	TNA $15M+$		TNA $100M+$		AGE $3Y+$		AGE $5Y+$	
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
CTR	0.87	0.83	0.74	0.69	1.12	1.15	1.13	1.16
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGH12B1\_F * CTR$	-0.47	-0.47	-0.55	-0.55	-0.57	-0.58	-0.67	-0.70
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$I * CTR$	-0.10	-0.04	0.03	0.10	-0.40	-0.40	-0.33	-0.35
	(0.00)	(0.21)	(0.38)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGH12B1\_F * I * CTR$	0.93	0.98	1.39	1.44	1.29	1.32	0.55	0.61
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.02)
$ln(TNA)$	–	-3.12	–	-1.66	-	-5.25	–	-2.21
	–	(0.00)	–	(0.04)	–	(0.00)	–	(0.00)
$ln(AGE)$	–	-13.31	–	-9.92	–	-10.57	–	-7.56
	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.00)
N	5,714	5,714	3,617	3,617	4,819	4,819	3,965	3,965
Adj.Rsq	0.05	0.09	0.07	0.09	0.05	0.09	0.07	0.08

The sample covers diversified US equity funds over the period January 1992 to December 2003. The table reports the OLS coefficient estimates of separate regressions using fund i's percentage flow over year $t+1$ ($F_{i,t+1}$) as dependent variable. The independent variables include fund i's return over year t ($CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is member of a high-12b1 family times fund i's return over year t ($HIGH12B1\_F_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy that equals one if fund i's return is negative times fund i's return over year t ($I_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is member of a high-12b1 family times a dummy that equals one if fund i's return is negative times fund i's return over year t ($HIGH12B1\_F_{i,t} * I_{i,t} * CTR_{i,t}$); and the natural logarithms of fund i's TNA and age ($ln(TNA_{i,t})$ and $ln(AGE_{i,t})$). The regressions are performed on low-marketing funds that are member of either a high-12b1 or a low-marketing family. Columns A and B report the results for funds with TNA of at least \$15 million. Columns C and D report the results for funds with TNA of at least \$100 million. Columns E and F report the results for funds that are at least 3 years old. Columns G and H report the results for funds that are at least 5 years old. p-values are given in parentheses below the coefficient estimates.

Table 5.7: Flows to high-load vs high-12b1 funds.

	High-load vs low-marketing funds		High-12b1 vs low-marketing funds		High-load vs high-12b1-funds	
	(A)	(B)	(C)	(D)	(E)	(F)
CTR	1.03	1.05	1.03	1.05	2.08	2.22
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGHLOAD * CTR$	0.69	0.71	–	–	-0.36	-0.45
	(0.00)	(0.00)	–	–	(0.00)	(0.00)
$HIGH12B1 * CTR$	–	–	1.05	1.17	–	–
	–	–	(0.00)	(0.00)	–	–
$I * CTR$	-0.20	-0.10	-0.20	-0.08	-0.51	-0.78
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$HIGHLOAD * I * CTR$	-0.66	-0.79	–	–	-0.35	-0.11
	(0.00)	(0.00)	–	–	(0.00)	(0.28)
$HIGH12B1 * I * CTR$	–	–	-0.31	-0.69	–	–
	–	–	(0.00)	(0.00)	–	–
$ln(TNA)$	–	-7.33	–	-7.89	–	-8.44
	–	(0.00)	–	(0.00)	–	(0.00)
$ln(AGE)$	–	-11.64	–	-14.69	–	-13.60
	–	(0.00)	–	(0.00)	–	(0.00)
N	15,859	15,859	15,445	15,445	9,780	9,780
Adj.Rsq	0.05	0.12	0.08	0.15	0.12	0.20

The sample covers diversified US equity funds over the period January 1992 to December 2003. The table reports the OLS coefficient estimates of separate regressions using fund i's percentage flow over year $t + 1$ ($F_{i,t+1}$) as dependent variable. The independent variables include fund i's return over year t ($CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is a high-load fund times fund i's return over year t ($HIGHLOAD_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is a high-12b1 fund times fund i's return over year t ($HIGH12B1_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy that equals one if fund i's return is negative times fund i's return over year t ($I_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is a high-load fund times a dummy that equals one if fund i's return is negative times fund i's return over year t ($HIGHLOAD_{i,t} * I_{i,t} * CTR_{i,t}$); an interaction term that is the product of a dummy variable that equals one if fund i is a high-12b1 fund times a dummy that equals one if fund i's return is negative times fund i's return over year t ($HIGH12B1_{i,t} * I_{i,t} * CTR_{i,t}$); and the natural logarithms of fund i's TNA and age ($ln(TNA_{i,t})$ and $ln(AGE_{i,t})$). The regressions in column A are performed on high-load and low-marketing funds. The regressions in column B are performed on high-12b1 and low-marketing funds. The regressions in column C are performed on high-marketing funds. p-values are given in parentheses below the coefficient estimates.

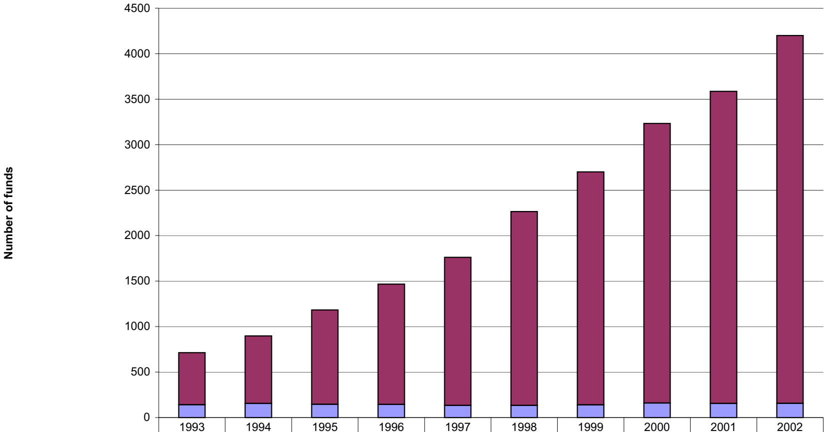
Table 5.8: Differential flows to high-marketing families.

	High- vs low-marketing families (TOP50)		High- vs low-marketing families (TOP25)		High-load vs low-marketing families (TOP25)		High-12b1 vs low-marketing families (TOP25)		High-load vs high-12b1 families (TOP25)	
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)
CTR	0.86	0.84	0.69	0.68	0.69	0.68	0.69	0.68	0.67	0.58
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$TOP50TX * CTR$	-0.06	-0.07	–	–	–	–	–	–	–	–
	(0.00)	(0.00)	–	–	–	–	–	–	-	–
$TOP25TX * CTR$	–	–	0.92	0.88	–	–	–	–	–	–
	–	–	(0.00)	(0.00)	–	–	–	–	–	–
$TOP25LOAD * CTR$	–	–	–	–	1.23	1.20	–	–	1.25	1.29
	–	–	–	–	(0.00)	(0.00)	–	–	(0.00)	(0.00)
$TOP2512B1 * CTR$	–	–	–	–	–	–	-0.02	-0.10	–	–
	–	–	–	–	–	–	(0.91)	(0.53)	–	–
$I * CTR$	-0.29	-0.24	0.05	0.11	0.05	0.12	0.05	0.12	-0.02	0.30
	(0.00)	(0.00)	(0.30)	(0.03)	(0.32)	(0.03)	(0.31)	(0.03)	(0.99)	(0.80)
$TOP50TX * I * CTR$	0.66	0.71	–	–	–	–	–	–	–	–
	(0.00)	(0.00)	–	–	–	–	–	–	–	–
$TOP25TX * I * CTR$	–	–	-0.60	-0.52	–	–	–	–	–	–
	–	–	(0.08)	(0.12)	–	–	–	–	–	–
$TOP25LOAD * I * CTR$	–	–	–	–	-0.92	-0.89	–	–	-0.85	-1.05
	–	–	–	–	(0.04)	(0.04)	–	–	(0.57)	(0.46)
$TOP2512B1 * I * CTR$	–	–	–	–	–	–	-0.07	0.20	–	–
	–	–	–	–	–	–	(0.96)	(0.90)	–	–
$ln(TNA)$	–	-2.09	–	-2.18	–	-2.33	–	-2.29	–	-1.37
	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.03)
$ln(AGE)$	–	-8.36	–	-8.34	–	-8.56	–	-7.79	–	-10.44
	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.00)	–	(0.28)
N	2209	2209	2209	2209	2065	2065	1801	1801	552	552
Adj.Rsq	0.08	0.11	0.09	0.12	0.09	0.13	0.07	0.10	0.21	0.25

Table 5.8 continued

The sample covers families of diversified US equity funds over the period January 1992 to December 2003. The table reports the OLS coefficient estimates of separate regressions using family f's percentage flow over year $t+1$ ($F_{f,t+1}$) as dependent variable. The independent variables include family f's lagged return ($CTR_{f,t}$); an interaction term that is the product of a dummy variable that equals one if family f is a high-marketing family (top 50 percent) times family f's return over year t ($TOP50TX_{f,t} * CTR_{f,t}$); an interaction term that is the product of a dummy variable that equals one if family f is a high-marketing family (top 25 percent) times family f's return over year t ($TOP25TX_{f,t} * CTR_{f,t}$); an interaction term that is the product of a dummy variable that equals one if family f is a high-load family (top 25 percent) times family f's return over year t ($TOP25LOAD_{f,t} * CTR_{f,t}$); an interaction term that is the product of a dummy variable that equals one if family f is a high-12b1 family (top 25 percent) times family f's return over year t ($TOP2512B1_{f,t} * CTR_{f,t}$); an interaction term that is the product of a dummy that equals one if family f's return is negative times family f's return over year t ($I_{f,t} * CTR_{f,t}$); an interaction term that is the product of a dummy variable that equals one if family f is a high-marketing family (top 50 percent) times a dummy that equals one if family f's return is negative times family f's return over year t ($TOP50TX_{f,t} * I_{f,t} * CTR_{f,t}$); an interaction term that is the product of a dummy variable that equals one if family f is a high-marketing family (top 25 percent) times a dummy that equals one if family f's return is negative times family f's return over year t ($TOP25TX_{f,t} * I_{f,t} * CTR_{f,t}$); an interaction term that is the product of a dummy variable that equals one if family f is a high-load family (top 25 percent) times a dummy that equals one if family f's return is negative times family f's return over year t ($TOP25LOAD_{f,t} * I_{f,t} * CTR_{f,t}$); an interaction term that is the product of a dummy variable that equals one if family f is a high-12b1 family (top 25 percent) times a dummy that equals one if family f's return is negative times family f's return over year t ($TOP2512B1_{f,t} * I_{f,t} * CTR_{f,t}$); and the natural logarithms of family f's TNA and average fund age ($ln(TNA_{f,t})$ and $ln(AGE_{f,t})$). Columns A to D report the results for the entire sample. The regressions in columns E and F are performed on high-load (top 25 percent) and low-marketing families (bottom 75 percent). The regressions in columns G and H are performed on high-12b1 (top 25 percent) and low-marketing families (bottom 75 percent). The regressions in columns I and J are performed on high-marketing families (top 25 percent). p-values are given in parentheses below the coefficient estimates.

Figure 5.1: Number of diversified US equity funds.

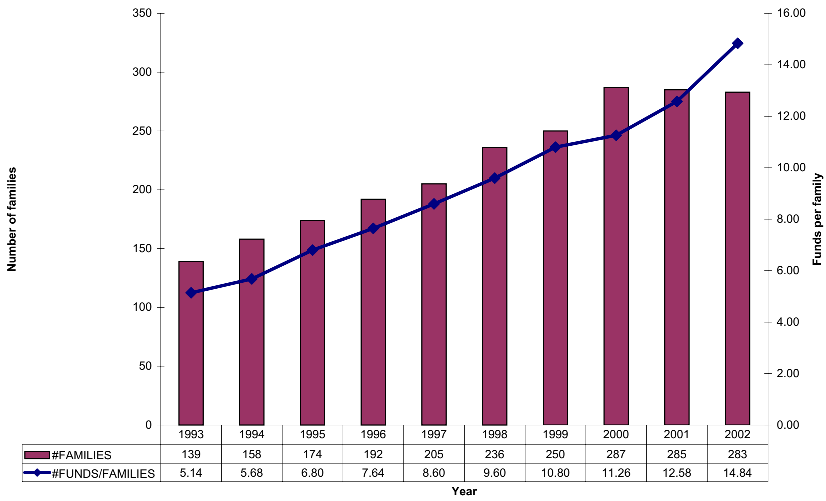


	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
#MEMBER OF FAMILY	573	742	1038	1323	1628	2131	2561	3073	3430	4043
#STAND ALONE	141	155	145	144	134	134	139	159	155	156

Year

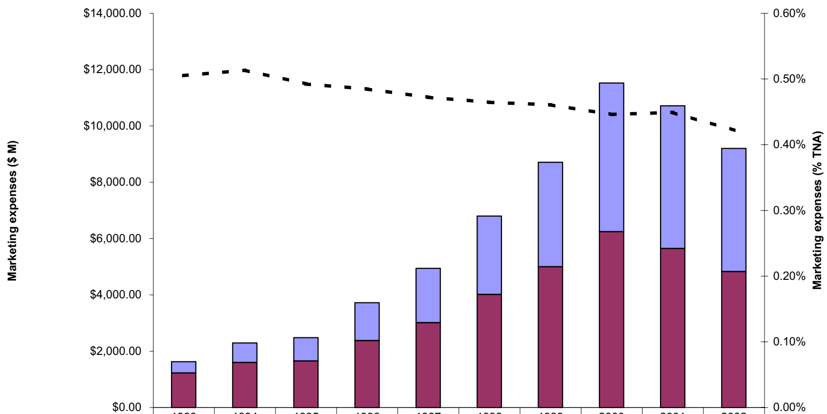
The figure presents a graph with the number of diversified US equity funds in our sample over the period 1993 to 2003.

Figure 5.2: Number of fund families and average number of funds per family.



The figure presents a graph with the number of fund families and the number of average funds per family in our sample over the period 1993 to 2003.

Figure 5.3: Expenditures on mutual fund marketing.

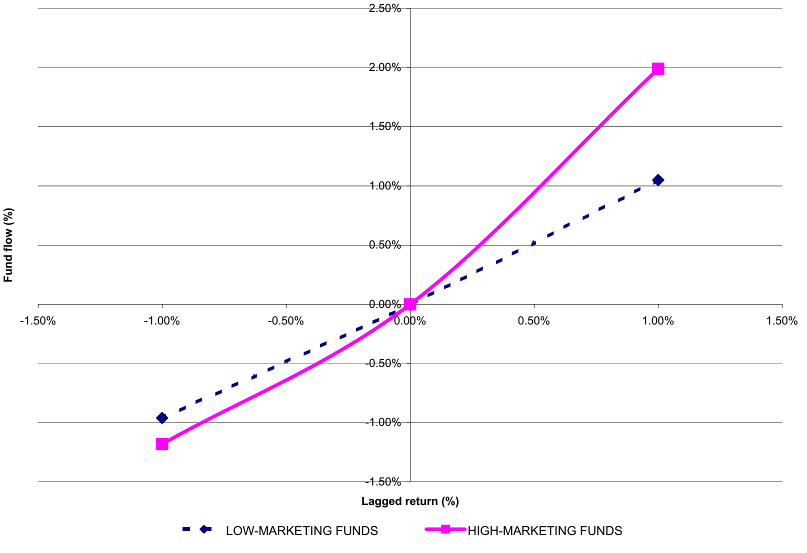


	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
12B-1 FEES	$400.54	$695.97	$830.70	$1,346.24	$1,932.51	$2,780.48	$3,713.63	$5,280.74	$5,066.59	$4,373.54
1/7 LOAD FEES	$1,227.05	$1,595.57	$1,652.10	$2,375.07	$3,011.14	$4,016.34	$4,996.30	$6,242.23	$5,649.58	$4,828.94
TOTAL FEES	0.51%	0.51%	0.49%	0.48%	0.47%	0.46%	0.46%	0.45%	0.45%	0.42%

Year

The figure presents an estimate of the dollar amount spent on mutual fund marketing over the period 1993 to 2003. In addition, the graph presents marketing and distribution expenses as a percentage of total net assets under management.

Figure 5.4: Flow-performance relation for high- and low-marketing funds.



The figure gives a graphical representation of the estimated flow-performance relation for high- and low-marketing funds. The solid line draws the estimated relation between fund flow and lagged returns for high-marketing funds, and the dashed line draws this relation for low-marketing funds.

Chapter 6

Summary and concluding comments

In this dissertation we bundle four empirical studies that provide new insights into the mutual fund industry and mutual fund performance.

In the first paper, we investigate the performance of equity mutual funds. Using monthly return data of more than 6,400 US equity mutual funds we investigate short-run performance persistence over the period 1984–2003. We sort funds into rank portfolios based on past performance, and evaluate the portfolios' out-of-sample performance. To cope with short ranking periods, we employ an empirical Bayes approach to measure past performance more efficiently. Our main finding is that when funds are sorted into decile portfolios based on 12-month ranking periods, the top decile of funds earns a statistically significant, abnormal return of 0.26 percent per month. This effect persists beyond load fees, and is mainly concentrated in relatively young, small cap/growth funds.

In the second paper, we investigate persistence in the performance of bond mutual funds. Our sample covers 3,549 bond mutual funds from 1990 to 2003. We show that bond funds that display strong (weak) performance over a past period continue to do so in future periods. The out-of-sample difference in risk-adjusted return between the top and bottom decile of funds ranked on their alphas over the past 36 months exceeds 3.5 percent per year. We demonstrate that a strategy based on past fund returns earns an economically and statistically significant abnormal return, suggesting that bond fund investors can exploit the observed persistence. Our results are robust to a wide range of model specifications and bootstrapped test statistics.

In the third paper, we test the cross-sectional explanatory power of multi-factor models to explain mutual fund returns and the consequences for evaluating mutual fund performance. This paper shows that multi-factor performance estimates for mutual funds suffer from systematic biases as a result of miscalculation of the factor premiums. Because the employed factor proxies are based on hypothetical stock portfolios, and do not incorporate transaction costs and trading restrictions, the predicted factor premiums are either over- or underestimated. We find that funds with a value oriented style earn a premium that is smaller than projected by the Fama and French (1993) value proxy, while the return differential between past winners and losers is larger than projected by the Carhart (1997) momentum proxy. As a result, the use of three- or four-factor alphas leads to systematically too pessimistic performance estimates for value funds compared to growth funds, and, similarly, performance estimates for past winner funds tend to be overestimated. We suggest that factor proxies based on mutual fund returns rather than stock returns provide better benchmarks to evaluate professional money managers.

Finally, the fourth paper investigates the presence of spillover effects of marketing in mutual fund families. We find that funds with high marketing expenses generate spillovers, and enhance cash inflows to family members with low marketing expenses. In particular, low-marketing funds that are operated by a family with high marketing expenses have substantially larger inflows after positive returns than otherwise similar funds that are operated by a family with low marketing expenses. Furthermore, these funds appear to have smaller outflows following negative returns. One way to interpret the spillovers is that they are a by-product of individual fund marketing whereby the entire family is made more visible to investors. An alternative explanation of this observation is that funds with low marketing expenses are directly subsidized by family members with high marketing expenses. We develop and perform a set of tests to evaluate these two alternative hypotheses. The results of all tests support the subsidization hypothesis, and suggest that at least part of the spillovers can be attributed to favoritism. These results suggest that conflicts of interest between investors and fund families have been exacerbated by competition in the mutual fund industry.

A number of important lessons can be learned from these studies.

(1) Some mutual fund managers are able to systematically outperform a strategy that invests in passive indexes. This “hot hands” phenomenon is not unique to equity mutual funds, and can be observed for bond mutual funds as well. Even though our evidence of performance persistence is strong, we argue that index funds remain valuable investment vehicles for unsophisticated investors who lack the ability to exploit performance persistence. However, sophisticated investors with sizable financial capacity, such as institutional

investors, can take advantage of predictable patterns in mutual fund returns.

(2) The usual three- and four-factor alphas do not adequately control for the value and momentum anomalies when evaluating the performance of equity mutual funds. One alternative that does not suffer from these biases is based on the use of a four-factor model where the factors are constructed using mutual fund returns rather than stock returns. Another (yet unexplored) approach would involve non-parametric measures to evaluate fund performance. We believe this approach is a promising path ahead for academic research on mutual funds.

(3) Cash inflows following positive returns are almost twice as large for high-marketing funds compared to low-marketing funds. On the other hand, cash outflows following negative returns are only marginally larger for high-marketing funds compared to low-marketing funds. These results indicate that mutual fund marketing is very effective in making good performance more visible to investors.

(4) It seems that mutual fund families play favorites with their funds by strategically transferring marketing exposure across member funds. Investors should be aware that load fees are not explicitly earmarked for marketing and can be appropriated to other uses.

Nederlandse samenvatting (Summary in Dutch)

Inleiding

Met een vermogen van meer dan 17.8 biljoen (10^{12}) dollar onder beheer vormen beleggingsfondsen wellicht het grootste onderdeel van de financiële industrie wereldwijd.[1] Het is dan ook niet verrassend dat reeds vele studies zijn verricht om te onderzoeken in hoeverre beleggingsfondsen voorzien in de behoeften van investeerders. Dit proefschrift is een bundeling van een viertal empirische studies welke nieuwe inzichten bieden in de beleggingsindustrie en de prestaties van beleggingsfondsen. Om de exacte contributies van deze studies aan te duiden, zullen we eerst de institutionele context van de beleggingsindustrie in vogelvlucht beschrijven en een overzicht geven van de belangrijkste ontwikkelingen in de academische literatuur.

Beleggingsfondsen zijn geregistreerde investeringsmaatschappijen die kapitaal van investeerders bundelen en dit collectief investeren in aandelen, obligaties, geldmarkt instrumenten en andere effecten. Investeerders kunnen participeren in een beleggingsfonds door een aandeel te kopen dat uitgegeven wordt door het fonds zelf, of dat verhandeld wordt op de publieke markt. Beleggingsfondsen bestaan al geruime tijd. Om precies te zijn, vindt het eerste beleggingsfonds *Eendracht Maakt Magt* haar oorsprong in Amsterdam. ("Eendracht maakt macht" was de lijfspreuk van de Republiek der Zeven Verenigde Nederlanden in de 18^e eeuw.) Hoewel de beleggingsindustrie in de loop der tijden vele veranderingen heeft ondergaan, zijn de redenen voor investeerders om vandaag de dag in beleggingsfondsen te beleggen niet anders dan in de 18^e eeuw. Als belangrijkste argument om in een beleggingsfonds te beleggen, wordt dikwijls de mogelijkheid tot "diversificatie" aangevoerd. Opmerkelijk genoeg werd dit argument reeds in de prospectussen van de eerste beleggingsfondsen genoemd.

[1] Deze schatting is verkregen van het Investment Company Institute (ICI, 2006).

Het idee achter diversificatie is dat verliezen op bepaalde investeringen gecompenseerd kunnen worden door winsten die op andere investeringen worden behaald. Theoretisch gezien kan een investeerder de hoogste graad van diversificatie behalen door een portefeuille aan te houden met daarin alle verhandelbare effecten (deze portefeuille wordt doorgaans de marktportefeuille genoemd). Echter, een investeerder die een dergelijke portefeuille probeert aan te houden, wordt geconfronteerd met een aantal praktische problemen. Allereerst is een groot vermogen nodig om voldoende effecten te kopen en een redelijke graad van diversificatie te behalen. Daarnaast zijn investeringsbudgetten dikwijls niet op te delen in een geheel aantal effecten, waardoor het niet mogelijk is om het budget volledig te investeren. Een ander probleem wordt gevormd door de transactiekosten die gemoeid zijn met het beheren van een dergelijke portefeuille. Transactiekosten zijn over het algemeen opgebouwd uit een vast en een variabel gedeelte en daardoor hoger voor een portefeuille die meer verschillende effecten bevat. Als gevolg hiervan kan diversificatie erg kostbaar zijn voor een investeerder met een beperkt budget en niet opwegen tegen de kosten die ermee gemoeid zijn. De hier genoemde problemen hebben voornamelijk betrekking op het beperkte investeringsbudget van individuele investeerders. Omdat beleggingsfondsen kapitaal bundelen, kunnen zij investeerders door middel van schaalvoordelen een hoge graad van diversificatie bieden tegen relatief lage kosten.

Een andere interessante overeenkomst, die we waarnemen als we prospectussen van beleggingsfondsen van vandaag de dag vergelijken met die uit vroegere tijden, is dat beleggingsfondsen "professioneel vermogensbeheer" aanbieden. Onder professioneel vermogensbeheer wordt hier de bekwaamheid van vermogensbeheerders verstaan waarmee zij de meest winstgevende effecten selecteren, en het gunstigste tijdstip kiezen om effecten te kopen of verkopen. Niet geheel onverwacht vragen fondsbeheerders een vergoeding voor deze diensten; een andere karakteristiek van beleggingsfondsen die niet is veranderd in de loop der tijd.

Hoewel de voordelen van diversificatie en professioneel vermogensbeheer al geruime tijd door investeerders worden erkend, zijn pas in het begin van de 60er jaren van de vorige eeuw de eerste uitvoerige studies verricht om te onderzoeken in hoeverre beleggingsfondsen werkelijk voorzien in de behoeften van investeerders door deze diensten aan te bieden. De opkomst van deze literatuurstroming is voorafgegaan door een doorbraak in het onderzoek naar de prijsvorming van effecten, de toenemende mate waarin data beschikbaar zijn geworden en technologische vernieuwingen. Hieronder geven we een korte beschrijving van deze ontwikkelingen.

Economische theorie over de prijsvorming van effecten stelt dat investeerders een vergoeding vragen voor de tijd die zij moeten wachten tot het moment dat hun investeringen geld opleveren (i.e., de risicovrije rente), en een vergoeding voor de risico's of de onzekerheden die hiermee gemoeid zijn (i.e., de risico premie). Hoewel het logisch lijkt dat investeerders een hoger rendement eisen op investeringen die meer risico met zich mee brengen, hebben academici ondervonden dat het absoluut geen triviale taak is om het concept "risico" precies te formuleren. Sterker nog, Sharpe (1964) en Lintner (1965) zijn beloond met de Nobel prijs voor Economie voor het door hen ontwikkelde Capital Asset Pricing Model (CAPM) dat de relatie tussen risico en rendement beschrijft. Dit model bleek zowel vanuit een theoretisch als een empirisch perspectief succesvol te zijn in het verklaren van rendementen op effecten.

Het CAPM stelt dat financiële markten investeerders alleen belonen voor het dragen van noodzakelijk risico. Zoals we eerder hebben uitgelegd, kunnen investeerders een aanzienlijk deel van het risico dat zij dragen, elimineren door een gediversificeerde portefeuille aan te houden. Echter, aan een bepaald deel van het risico kan men niet ontkomen door middel van diversificatie. Dit gedeelte wordt marktrisico of systematisch risico genoemd. Het CAPM voorspelt dat naarmate effecten gevoeliger zijn voor marktbewegingen, investeerders een hoger rendement eisen op deze effecten.

De laatste decennia is een groot aantal studies uitgevoerd om te onderzoeken in hoeverre het CAPM in staat is om de rendementen op effecten te beschrijven (op aandelen in het bijzonder). Hoewel sommige onderzoekers melden dat het CAPM hiertoe goed in staat is, rapporteren andere onderzoekers dat het CAPM belangrijke factoren over het hoofd ziet. Zo lijken aandelen met een kleine marktkapitalisatie en een lage waardering (i.e., waarde-aandelen) rendementen op te leveren die systematisch hoger zijn dan door het CAPM voorspeld wordt (zie bijvoorbeeld Banz (1981) en Fama en French (1992)). Als gevolg hiervan worden bij het evalueren van de prestaties van beleggingsfondsen dikwijls multi-factormodellen gebruikt, die het CAPM uitbreiden met additionele factoren om te corrigeren voor deze anomalieën.

Hoewel het buiten het bestek van dit manuscript valt om een complete beschrijving te geven van de ontwikkelingen in het onderzoek naar de prijsvorming van effecten, is het van cruciaal belang om de relatie tussen risico en verwacht rendement te begrijpen om de prestaties van beleggingsfondsen te evalueren: hoge rendementen hoeven geen bewijs te zijn voor bekwaamheid van een vermogensbeheerder. Deze kunnen namelijk net zo goed een premie zijn voor het nemen van hoge risico's. De ontwikkelingen in het onderzoek naar de prijsvorming van effecten hebben het mogelijk gemaakt om vast te stellen welk deel van het rendement dat een beleggingsfonds behaalt, kan worden toegekend aan bekwaamheid van de vermogensbeheerder en welk deel aan het nemen van risico's of aan andere factoren.

Een andere belangrijke ontwikkeling die het onderzoek naar de prestaties van beleggingsfondsen heeft gestimuleerd, is de toenemende mate waarin data beschikbaar zijn geworden. In de nasleep van Zwarte Donderdag in 1929 toen de aandelenbeurs van New York ten onder ging, besloot de volksvertegenwoordiging van de Verenigde Staten om een aantal wetsvoorstellen in het leven te roepen om financiële markten beter te reguleren en investeerders te beschermen. Onder deze wetten was de Investment Company Act van 1940. Deze verordening wordt uitgevoerd door de Securities and Exchange Commission (SEC) en verplicht bedrijven (beleggingsfondsen inbegrepen) om financiële informatie te openbaren. Commerciële dataleveranciers zijn begonnen deze gegevens te verzamelen en hebben uitgebreide databanken opgezet die toegankelijk zijn voor wetenschappers.[2]

Tenslotte zijn technologische vernieuwingen gedurende de laatste decennia van cruciaal belang geweest voor de ontwikkeling van het onderzoek naar beleggingsfondsen. De opkomst van computers, digitale opslagmedia en nieuwe inzichten in rekenmethoden hebben het onderzoekers mogelijk gemaakt om complexe analyses uit te voeren.

Onderzoek naar de prestaties van beleggingsfondsen

De centrale onderzoeksvragen in de academische literatuur over de prestaties van beleggingsfondsen hebben voornamelijk betrekking op de mate waarin beleggingsfondsen voorzien in de behoeften van investeerders door ze diversificatie en professioneel vermogensbeheer aan te bieden.

De meeste academische studies laten zien dat beleggingsfondsen goed werk verrichten wat het aanbieden van diversificatie betreft. Een veelgebruikte manier om de graad van diversificatie van een beleggingsfonds te beoordelen, is door het totale risico van het fonds op te delen in een systematisch gedeelte (i.e., risico dat *niet* weggediversificeerd kan worden) en een niet-systematisch gedeelte (i.e., risico dat *wel* weggediversificeerd kan worden). Hoe groter het gedeelte van systematisch risico, hoe hoger de graad van diversificatie die investeerders wordt aangeboden en vice versa. Vrijwel alle studies rapporteren dat het grootste gedeelte van het risico van beleggingsfondsen systematisch is. Om de lezer een

[2]De grootste dataleveranciers zijn momenteel het Center for Research in Security Prices (CRSP) en Morningstar.

wat concreter beeld te geven van de verhouding tussen systematisch en niet-systematisch risico bij beleggingsfondsen, berekenen we welk gedeelte van het risico van beleggingsfondsen systematisch van aard is.[3] De resultaten van deze analyse laten zien dat gemiddeld 82 procent van de variantie in de rendementen van beleggingsfondsen verklaard wordt door systematisch risico. Het eerste kwartiel van het gedeelte van de variantie in de rendementen van beleggingsfondsen dat verklaard wordt door systematisch risico is 80 procent, en het derde kwartiel is 92 procent. Minder dan 6 procent van de beleggingsfondsen draagt meer niet-systematisch dan systematisch risico. Op basis van deze uitkomsten zou men inderdaad kunnen stellen dat beleggingsfondsen investeerders een hoge graad van diversificatie bieden.

Echter, wanneer we de literatuur over de toegevoegde waarde van professioneel vermogensbeheer beschouwen, is het niet zo dat empirisch bewijs eenduidig aantoont dat vermogensbeheerders bekwaam zijn in het selecteren van de meest winstgevende effecten en het kiezen van het gunstigste tijdstip om effecten te kopen of verkopen. Sterker nog, er is bewijs dat aantoont dat de meeste vermogensbeheerders niet in staat zijn hun kosten terug te verdienen door actieve beleggingsstrategieën te volgen. Een veelgebruikte manier om de bekwaamheid van vermogensbeheerders te onderzoeken, is door te toetsen in hoeverre rendementen van beleggingsfondsen persistent zijn. Met andere woorden, door te toetsen of sommige beleggingsfondsen systematisch beter presteren dan andere fondsen (inclusief passief beheerde indexfondsen waarvan de belangrijkste doelstelling is om investeerders een zo hoog mogelijke graad van diversificatie te bieden tegen zo laag mogelijke kosten). Hoewel sommige onderzoekers persistentie vinden in de rendementen van beleggingsfondsen, laten andere onderzoekers zien dat deze resultaten verklaard worden doordat bepaalde factoren over het hoofd worden gezien (zie bijvoorbeeld Carhart (1997)). Wanneer rekening gehouden wordt met deze factoren, is vrijwel geen persistentie meer waarneembaar. De enige persistentie die overblijft, is gelegen in de voortdurende slechte prestaties van beleggingsfondsen met hoge kosten. Deze bevindingen suggereren dat er weinig bewijs is om aan te nemen dat vermogensbeheerders bekwaam zijn in het selecteren van de meest winstgevende effecten, en het kiezen van het gunstigste tijdstip om effecten te kopen of verkopen. Investeerders lijken het beste af te zijn door te beleggen in passief beheerde

[3]De steekproef die we gebruiken beslaat 5.275 aandelenfondsen in de Verenigde Staten over de periode 1963–2003 en wordt beschreven in de studie "On the Use of Multi-Factor Models to Evaluate Mutual Fund Performance". Fondsen met minder dan 36 opeenvolgende observaties van maandelijkse rendementen over de gehele tijdsperiode zijn uitgesloten van de analyse. Als maatstaf voor systematisch risico gebruiken we de vier factoren van Carhart (1997).

indexfondsen.

Korte-termijnpersistentie in de rendementen van aandelenfondsen

In de eerste studie van deze bundel onderzoeken we in hoeverre rendementen van aandelenfondsen in de Verenigde Staten op korte termijn persistent zijn. De aanleiding om persistentie op korte termijn te onderzoeken, is het theoretische werk van Berk en Green (2004), waarin beargumenteerd wordt dat het gebrek aan bewijs voor persistentie op lange termijn niet noodzakelijk impliceert dat vermogensbeheerders niet bekwaam zijn. Bovendien vinden Bollen en Busse (2005) korte-termijnpersistentie in de rendementen van aandelenfondsen wanneer zij gebruik maken van dagelijkse data. (In het overgrote merendeel van de studies in deze literatuurstroming wordt gebruik gemaakt van maandelijkse data.) Wij onderzoeken een drietal vragen met betrekking tot korte-termijnpersistentie. Allereerst, is deze vorm van voorspelbaarheid ook waarneembaar in een grote steekproef van beleggingsfondsen over een langere (en meer recente) tijdsperiode? Ten tweede, is dit effect economisch significant? Ten derde, is er variatie waarneembaar in korte-termijnpersistentie tussen verschillende groepen beleggingsfondsen? Om deze punten te onderzoeken, maken we gebruik van een grote databank met maandelijkse rendementen van aandelenfondsen en een Bayesiaanse schattingsmethodiek om op basis van slechts een beperkt aantal observaties de prestaties van beleggingsfondsen te evalueren.

Onze resultaten ondersteunen de opvatting dat prestaties van aandelenfondsen uit het verleden een voorspellende waarde hebben voor hun toekomstige prestaties. Wanneer we aandelenfondsen rangschikken op basis van hun prestaties over de afgelopen 36 tot 12 maanden, dan zien we dat de 10 procent best presterende fondsen de maand daarna een aanzienlijk hoger rendement behalen dan de 10 procent slechtst presterende fondsen. Hierbij houden we rekening met factoren als marktkapitalisatie, waardering en momentum. Bovendien stelt de Bayesiaanse schattingsmethodiek ons in staat de door Bollen en Busse (2005) gedocumenteerde korte-termijnpersistentie in de prestaties van de best presterende fondsen vast te leggen door gebruik te maken van maandelijkse data over een veel grotere steekproef van aandelenfondsen. Wanneer we gebruik maken van traditionele schattingsmethodieken zijn we niet in staat deze relatie vast te leggen. Daarnaast zijn we door het grote aantal fondsen in onze data en de beperkte eisen, die opgelegd worden door de Bayesiaanse methode, in staat om persistentie te onderzoeken onder verschillende groepen van beleggingsfondsen. Allereerst onderzoeken we in hoeverre korte-termijnpersistentie gerelateerd is aan de transactiekosten die investeerders moeten betalen wanneer ze een beleggingsfonds kopen of verkopen. Wanneer we alleen aandelenfondsen in beschouwing nemen, die geen transactiekosten in rekening brengen, dan is de persistentie zelfs duidelijker waarneembaar dan wanneer we de gehele steekproef in beschouwing nemen. Blijkbaar wordt de korte-termijnpersistentie niet teniet gedaan door transactiekosten die gemoeid zijn met het investeren in de best presterende fondsen. Daarnaast vinden we dat persistentie voornamelijk waarneembaar is bij beleggingsfondsen die beleggen in aandelen met een kleine marktkapitalisatie en een hoge waardering (i.e., groei-aandelen).

De prestaties van obligatiefondsen

In de tweede studie van deze bundel onderzoeken we persistentie in de rendementen van obligatiefondsen. Ondanks de omvang van de markt voor actief beheerde obligatiefondsen is er verrassend weinig bekend over de prestaties van deze fondsen. Omdat het onderzoek naar obligatiefondsen nog niet ver ontwikkeld is, vult deze studie verschillende hiaten in de literatuur op. Allereerst is dit naar ons weten de eerste studie die het volledige universum van meer dan 3.500 obligatiefondsen uit de CRSP databank over de periode 1990-2003 bestudeert. De omvang van de steekproef stelt ons in staat het hoofd te bieden aan verscheidene econometrische problemen. Ten tweede, eerdere studies naar de prestaties van obligatiefondsen maken gebruik van slechts een klein deel van de beschikbare methoden om persistentie te toetsen. We laten zien dat al deze methoden een consistent beeld geven van de prestaties van obligatiefondsen. Hierdoor biedt ons onderzoek nieuwe inzichten in langlopende discussies over de toegevoegde waarde van professioneel vermogensbeheer bij obligatiefondsen. In tegenstelling tot eerdere studies vinden we sterk bewijs dat het mogelijk is om op basis van rendementen uit het verleden een groep obligatiefondsen aan te wijzen, die systematisch een passieve beleggingsstrategie verslaat.

Een kritische blik op het gebruik van multi-factormodellen

De derde studie levert een bijdrage aan de bestaande literatuur door te onderzoeken in hoeverre multi-factormodellen in staat zijn de rendementen van beleggingsfondsen te verklaren. Er wordt een tweetal veelgebruikte multi-factormodellen onderzocht, te weten het drie-factormodel van Fama en French (1993, 1995, 1996) en het vier-factormodel van Carhart (1997). De voornaamste reden om deze studie te verrichten, is ons vermoeden dat prestatiemetingen door deze modellen verkeerde schattingen opleveren. Multi-factormodellen maken namelijk gebruik van rendementen op hypothetische aandelenportefeuilles als referentiepunt en houden geen rekening met transactiekosten en handelsrestricties. Als gevolg hiervan zouden prestatiemetingen van bepaalde fondsen een onjuist beeld kunnen weergeven van hun werkelijke prestaties.

Onze resultaten tonen aan dat prestatiemetingen door multi-factormodellen inderdaad verkeerde schattingen opleveren. We vinden dat de prestaties van fondsen met een waardestijl (i.e., fondsen die beleggen in aandelen met een lage waardering) systematisch onderschat worden ten opzichte van de prestaties van fondsen met een groeistijl (i.e., fondsen die beleggen in aandelen met een hoge waardering). Daarnaast vinden we dat de prestaties van fondsen met hoge rendementen in het verleden systematisch overschat worden ten opzichte van de prestaties van fondsen met lage rendementen in het verleden. We stellen een alternatieve methode voor, waarbij gebruik gemaakt wordt van de rendementen van andere beleggingsfondsen als referentiepunt. We laten zien dat deze methode een beter beeld geeft van de prestaties van beleggingsfondsen.

Marketing van fondsgroepen

Het laatste onderzoek draagt bij aan de literatuur over reacties van investeerders op de prestaties van beleggingsfondsen. De meeste onderzoekers rapporteren dat investeerders hun geld voornamelijk beleggen in fondsen met de hoogste rendementen in het verleden. Het lijkt erop dat vermogensbeheerders zich hier goed van bewust zijn en op dit gedrag anticiperen door bepaalde strategieën te volgen. Zo documenteren Brown et al. (1996) dat beleggingsfondsen hun risicoprofiel manipuleren om de kans te vergroten om tot de best presterende fondsen te behoren. Andere strategieën die in de literatuur genoemd worden, zijn marketing activiteiten en het organiseren in fondsgroepen. Deze laatste strategie is gebaseerd op de waarneming dat geldstromen naar beleggingsfondsen niet alleen afhankelijk zijn van de prestaties van de fondsen zelf, maar ook van de prestaties van andere fondsen binnen de fondsgroep. Als een bepaald fonds het namelijk goed doet, profiteren andere fondsen binnen de fondsgroep er ook van.

In de vierde studie onderzoeken wij in hoeverre marketing activiteiten van bepaalde fondsen een positieve invloed hebben op geldstromen naar andere fondsen binnen de fondsgroep. Is het bijvoorbeeld zo dat fondsen, die veel aan marketing uitgeven, geldstromen genereren naar fondsen binnen de fondsgroep die dat niet doen? We vinden dat kleine en jongere beleggingsfondsen, die zelf weinig aan marketing uitgeven, maar onderdeel zijn van een fondsgroep die als geheel wel veel aan marketing uitgeeft, aanzienlijk grotere geldstromen ontvangen dan vergelijkbare fondsen die geen onderdeel zijn van een dergelijke fondsgroep. Deze resultaten zouden als een neveneffect van marketing geïnterpreteerd kunnen worden, waardoor de fondsgroep als geheel zichtbaarder wordt gemaakt. Echter, deze verklaring veronderstelt dat de marketingkosten die fondsen bij investeerders in rekening brengen, één-op-één gerelateerd zijn aan de aandacht die de fondsen krijgen in de media en de verkoopkanalen. Een alternatieve verklaring voor deze resultaten is dat beleggingsfondsen met lage marketinguitgaven gesubsidieerd worden. Met andere woorden, een fondsgroep zou kunnen betalen voor de marketing activiteiten van een bepaald fonds, terwijl ze de kosten hiervan bij andere fondsen in rekening brengt. We ontwikkelen en toetsen een aantal hypothesen om deze verschillende verklaringen te evalueren. Onze resultaten wijzen uit dat fondsgroepen bepaalde beleggingsfondsen inderdaad systematisch bevoordelen ten koste van andere fondsen.

Conclusies en aanbevelingen

In zijn geheel beschouwd, kent dit proefschrift een viertal belangrijke conclusies.

(1) Op basis van rendementen uit het verleden is het mogelijk een groep beleggingsfondsen aan te wijzen, die systematisch een passieve beleggingsstrategie verslaat. Dit geldt zowel voor aandelenfondsen, als voor obligatiefondsen. Hoewel de prestaties van beleggingsfondsen duidelijk persistent zijn, willen we er op wijzen dat alleen professionele en vermogende partijen gebruik kunnen maken van deze voorspelbaarheid. Voor de meeste investeerders blijven passief beheerde indexfondsen een waardevolle belegging.

(2) Zowel het drie-factormodel van Fama en French als het vier-factormodel van Carhart overschatten (onderschatten) de prestaties van aandelenfondsen met een groeistijl (waardestijl). Om de prestaties van beleggingsfondsen te evalueren, kan men beter de rendementen van andere beleggingsfondsen als referentiepunt gebruiken. Een andere (nog niet onderzochte) methode is het gebruik van niet-parametrische prestatiemaatstaven. Een dergelijke benaderingswijze biedt een interessant uitgangspunt voor vervolgonderzoek naar de

prestaties van beleggingsfondsen.

(3) Aandelenfondsen die veel aan marketing uitgeven, ontvangen aanzienlijk grotere geldstromen na goede prestaties dan fondsen die weinig aan marketing uitgeven. Deze resultaten tonen aan dat marketing een effectieve manier is om goede prestaties van beleggingsfondsen zichtbaar te maken voor investeerders.

(4) Het lijkt erop dat fondsgroepen systematisch de marketingkosten van bepaalde beleggingsfondsen bij andere fondsen binnen de fondsgroep in rekening brengen. Investeerders zouden zich ervan bewust moeten zijn dat marketingkosten voor andere doeleinden aangewend kunnen worden dan waarvoor ze eigenlijk bestemd zijn.

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Joop Huij was born in Amsterdam on August 11, 1979. He attended the Marnix Gymnasium in Rotterdam, at which he obtained a Gymnasium diploma (Dutch classical pre-university education) in 1997. From 1997 to 2002 Joop studied at Erasmus University Rotterdam. In 2002 he received his Master's degree in Informatics & Economics with appellation *cum laude*. In November 2002 he joined the Department of Financial Management of RSM Erasmus University as a PhD Candidate. His PhD trajectory was supported by the Erasmus Research Institute of Management (ERIM). He presented his research at several international conferences and seminars, including the 2003 OxMetrics Conference in London, the 2005 Eastern Finance Association meeting in Norfolk, the 2005 Financial Management Association meeting in Chicago, and the 2006 European Finance Association meeting in Zurich. The article version of the Chapter "Cross-sectional Learning and Short-run Persistence in Mutual Fund Performance" of his dissertation is accepted for publication in the *Journal of Banking & Finance*. During his PhD trajectory Joop visited London Business School and Vanderbilt University's Owen Graduate School of Management. Joop's teaching experience include Bachelor and Master courses in the (International) Business Administration programme as well as supervision of Bachelor and Master theses at RSM Erasmus University. Currently, Joop holds a position as Assistant Professor of Finance at RSM Erasmus university. His research interests include mutual funds, alternative investments, and empirical asset pricing.

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