DIANA P. BUDIONO

The Analysis of Mutual Fund Performance

Evidence from U.S. Equity Mutual Funds

The Analysis of Mutual Fund Performance: Evidence from U.S. Equity Mutual Funds

The Analysis of Mutual Fund Performance: Evidence from U.S. Equity Mutual Funds

Performance analyse van beleggingsfondsen:
Empirische onderzoek naar Amerikaanse aandelenfondsen

Proefschrift

ter verkrijging van de graad van doctor
aan de Erasmus Universiteit Rotterdam
op gezag van de rector magnificus
Prof.dr. H.G. Schmidt
en volgens besluit van het College voor Promoties.

De openbare verdediging zal plaatsvinden op
donderdag 4 februari 2010 om 09.30 uur

door
Diana P. Budiono
Geboren te Surabaya, Indonesia

ERASMUS UNIVERSITEIT ROTTERDAM

Promotiecommissie

Promotor(en):
Prof.dr. M.J.C.M. Verbeek
Dr.ir. M. Martens

Overige leden:
Prof.dr. W.F.C. Verschoor
Prof.dr. J. Spronk
Prof.dr. J.R. ter Horst

Erasmus Research Institute of Management - ERIM
Rotterdam School of Management (RSM)
Erasmus School of Economics (ESE)
Erasmus University Rotterdam
Internet: http://www.erim.eur.nl

ERIM Electronic Series Portal: http://hdl.handle.net/1765/1

ERIM PhD Series in Research in Management, 185
Reference number ERIM: EPS-2009-185-F&A
ISBN 978-90-5892-224-3

Design: B&T Ontwerp en advies www.b-en-t.nl
Print: Haveka www.haveka.nl

Preface

This doctorate program is one of the milestones in my life. It takes only four years, yet it is an unforgettable journey and worth it. I have faced many mountains and valleys that make doing a Ph.D. not an easy task. However, I am fortunate that there are some people around me that support and make my days enjoyable. Therefore, I want to take this opportunity to thank those who have contributed in the completion of my Ph.D.

The story began when I contacted Martin Martens at the end of my Master program in the University of Twente. We had been communicating via emails until we found a common interesting topic and finally got approval from ERIM (Erasmus Research Institute of Management). On September 1^{st} 2005 I started my first day in the totally new environment, living in Rotterdam and officially working at Erasmus University for the first time. I thank Martin Martens for supervising me especially during my first year of the Ph.D. Certainly there is a lot to be learned in that period. As time goes by, I have more understanding about the literatures and doing research. I enjoyed working together and having discussions with him for four years, and additionally thank him for being open to my ideas. At the end of my third year of the Ph.D. Marno Verbeek became my promotor. I would like to thank him for his availability and all discussions we had despite his busy schedule. It has been a pleasant opportunity to work together with him. Furthermore, I would like to thank the members of the inner doctoral committee, Jenke ter Horst, Jaap Spronk, and Willem Verschoor, for reading and evaluating this dissertation.

Moreover, I am grateful to my paranimfen, Nuno Camacho and Milan Lovric, who have shared an office with me for about four years. It is such a great experience that we always support and encourage each other, and at the same time have fun together. I also enjoy having an office on the ninth floor where most Ph.D. fellows work. I thank my past and current Ph.D.

fellows, among others, Amit, Andrey, Arjan, Bart, Carlos, Chen, Dan, Felix, Francesco, Haikun, Harris, Julia, Karim, Lenny, Marielle, Michiel, Nalan, Paul, Philippe, Rui, Simon, Viorel and Vitalie. I also thank Ank, Elizabeth, Mary, Veliana, and my friends in TIFF for their support and having good times together.

My deepest thanks go to my parents, grandmother, Peter, Paul and Anne. No words can perfectly describe my gratitude for their love, inspiration, encouragement, and ears to listen. I am really fortunate to have them in my life.

Above all, I am very grateful to my Father in heaven, who pours his love in my life. All glories and praises go to him for his love endures forever.

Finally, to my friends who are still pursuing a Ph.D., my final words are 'never give up'. Being persistent is rewarding.

Diana Patricia Budiono

Rotterdam, August 2009

Contents

List of Tables

List of Figures

Chapter 1

Introduction

This dissertation aims to analyze and discuss mutual fund performance extensively. To initialize the discussion we first give a general introduction about mutual funds and elaborate the history and the growth of these financial institutions in Section 1.1. Subsequently, in Section 1.2 we address the main discussions and issues in the literature that analyze mutual fund performance and how this dissertation contributes to the literature.

1.1 The Introduction, History and Growth of Mutual Funds

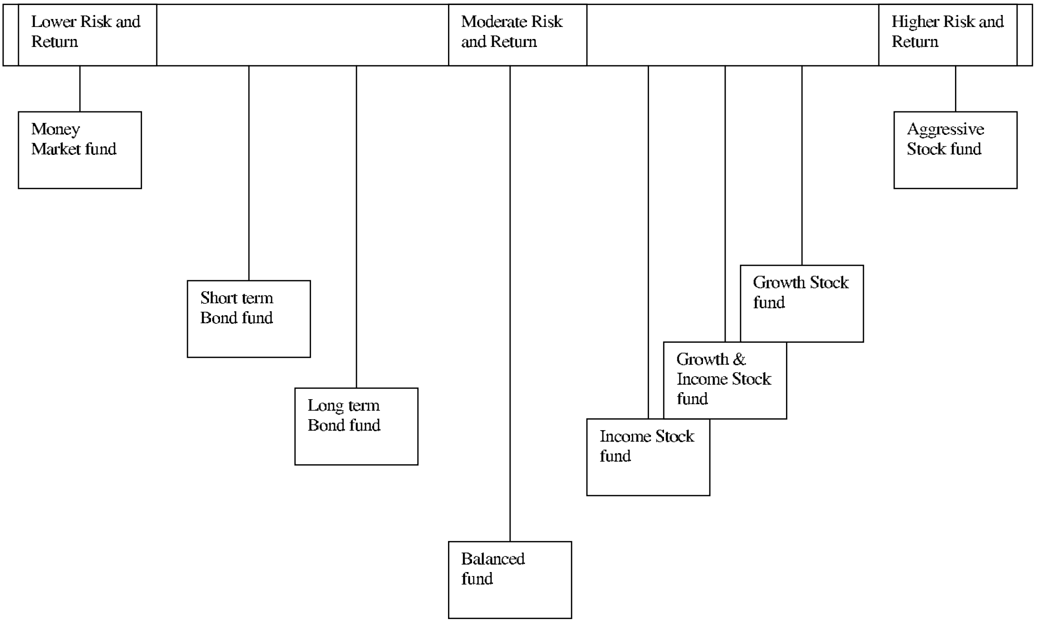
This section is divided into three subsections. Subsection 1.1.1 introduces a mutual fund as a financial institution with certain characteristics. Subsequently, Subsection 1.1.2 and 1.1.3 cover the history and the growth of the mutual fund industry over time, respectively.

1.1.1 What is a Mutual Fund ?

A mutual fund is a financial institution that pools and professionally manages money from many investors. Generally, it allocates the money to equity, bond and cash instruments. Other mutual funds can invest in, for example, real estate. Because it pools money from many investors, a mutual fund is able to invest in diversified asset classes and diversified securities within an asset class more optimally than a single investor. From risk theory, total risk can be divided into two components: systematic risk and idiosyncratic risk. Systematic risk is related to the market, while idiosyncratic risk is related to the conditions of individual securities. With a diversification technique, the risk of a portfolio is reduced because we can diversify away all idiosyncratic risks, such that only the systematic risks remain (see, for example, Tole (1982) and Wilson (1998)). Although there is still discussion about how many securities are needed to form a diversified portfolio (see, for example, Statman (1987) and Lhabitant and Learned (2002)), a mutual fund has more capital and hence has more capabilities to invest in more various securities than a single investor. Therefore, mutual funds have advantages from investing in diversified portfolios, and this makes mutual funds attractive for investment purposes. According to the financial report by the Investment Company Institute in 2000, mutual funds can be classified based on a level of risk and return (See Figure 1.1). A mutual fund that invests in equity, bonds or money market shares is called equity fund, bond fund or money market fund, respectively, whereas a balanced fund is a fund that allocates its money to both equity and bonds. An aggressive growth stock fund invests in high growth stocks. It focuses on capital appreciation and there is no income from dividends. A growth stock fund is similar to an aggressive growth stock fund, but the aggressive growth stock fund aims to have higher capital gain by, for example, trading options. A growth & income stock fund invests in stocks with high growth rate and dividend. As opposed to an aggressive growth stock fund, an income fund invests on dividend paying-stocks. In the U.S. most mutual funds are equity funds. From the whole amount of capital that is invested in mutual funds, equity funds hold about 50 percent of it, while bond funds and money market funds hold about 18 percent and 26 percent, respectively. In this dissertation, our analyses focus on equity funds.

Besides the classification that is elaborated above, mutual funds can also be classified as open-end or closed-end funds. Generally, the term ”mutual fund” is the common name for what is classified as an open-end fund. It is called open-end because everyday it sells and buys back fund shares from investors that wish to leave the fund. A closed-end fund, on the other hand, has a limited number of shares that are available publicly. Usually it also determines in advance the date when the value of the fund will be distributed among the shareholders. In 1929 there

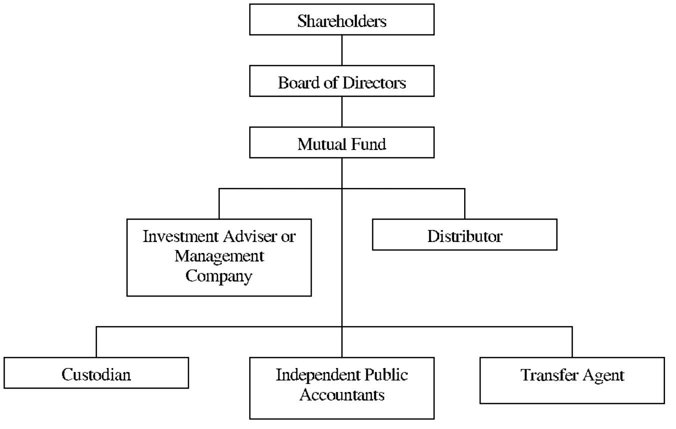
Figure 1.1: The Type of Funds Based on The Level of Risk and Return



were much more closed-end funds than open-end funds. The number of closed-end funds was about 700 while the number of open-end funds was about 20. However, after stock market crash (Great Depression) in 1929 the popularity of closed-end funds was plummeted while the popularity of open-end funds started to surge.

To protect the investors of mutual funds, in 1933 the U.S. government formed the Securities and Exchange Commission (SEC) to regulate mutual funds. Every mutual fund in the U.S. should register to the SEC before its operation. Besides the SEC, there are people within a board structure of mutual funds that protect the interest of investors and inspect the fund from a criminal negligence. Figure 1.2 demonstrates the typical structure of a mutual fund that can also be seen in the financial report by Investment Company Institute in 2000. A board of directors has the function to inspect the fund's activities such as approving a contract with an investment adviser, a contract about the fees that are paid by shareholders, etc. About 40 percent of this board are independent directors. Next, an investment adviser manages the capital of the fund

Figure 1.2: The Structure of Mutual Fund



based on its investment objective that is written in the prospectus. For example, if the investment objective is aggressive growth, the investment adviser allocates fund capital to high growth stocks. Furthermore, to connect the fund with public shareholders, a distributor has a task to sell fund shares either to the public or through other firms. A custodian holds and maintains the asset of a fund to protect shareholder interest. Moreover, an independent public accountant inspects and certifies the financial reports of the fund, while a transfer agent processes the orders to buy and redeem fund shares.

1.1.2 The History of Mutual Fund

The first mutual fund was founded in the Netherlands. It was called ”Eendragt Maakt Magt”, which means unity creates strength, and was formed in 1774 by a Dutch merchant and broker, Abraham van Ketwich, after the financial crisis from 1772 to 1773. His motivation was to provide diversification for small investors. During this financial crisis, many British banks were bankrupt because of the overextension of their positions in the British East India Company. This crisis also infected many banks in Amsterdam. By observing this financial crisis, Van Ketwich realized the potential benefits of diversification. To turn his idea into reality, he initiated to attract some investors and invested the pooled money to banks, plantation loans in

Central and South America, and bonds that were issued by Austrian, Danish, German, Spanish, Swedish, and Russian governments. Furthermore, this first trust already had a prospectus to document its policies about, among others, the investment strategy, portfolio formation, potential places for investments, fees and payout policy. It regulated the role of commissioners to monitor the investment policy of the trust, and assigned someone who was responsible for daily administration. During this time the first trust had also made regulations to protect investors. For example, Van Ketwich was required to provide a yearly financial report to commissioners and to interested parties. Furthermore, the life of this trust was limited to 25 years in which the value of the trust at the end of its life was liquidated and shared to all shareholders. Hence, we can see that the pioneer of mutual funds already had a good regulated mechanism and it is similar to the regulation for modern closed-end funds nowadays.

After Eendragt Maakt Magt pioneered mutual funds in the Netherlands, in 1868 a foreign and colonial government trust was founded in London and this marked the beginning of mutual funds in the Anglo-Saxon countries. The securities that were traded are not the same as those that are traded nowadays. Mainly, the funds at that time invested in contracts of survival and plantation loans. There were two famous kinds of survival contracts, namely life annuities and tontines. A life annuity was a contract where the lender received annual payment from the borrower and the borrower paid the principal at the end of the contract. This mechanism is similar to a modern bond nowadays. A tontine resembled a life annuity, except that a tontine had a group of lenders, instead of an individual lender. In this contract, a borrower paid an annual amount to the group of lenders. If some of the lenders passed away, the same amount of payment was divided among the surviving lenders. Additionally, the borrower was required to give a collateral to the lenders. In 1875 there were already about 18 new trusts in London and in 1890s several mutual funds were established in the U.S. However, these mutual funds still published a limited number of shares, which resembled the mechanism of closed-end funds. In July 1924, the first open-end fund was founded in the U.S. This fund was called Massachusetts Investors Trust and still exists today. Because this type of fund was permitted to continuously issue and redeem shares, an open-end fund became more favorable among the investors. Hence, after the stock market crash in 1929 the number of open-end funds was increasing but the number of closed-end funds was decreasing. During this period, the stock market experienced a difficult situation and hence some major legislative acts were implemented. By law, mutual funds were required to be registered in the SEC and followed the operating standards. Furthermore, mutual funds had to clarify their policies such as the structure in the institution, the fees, and the investment objective in the prospectus. A more detailed history about mutual funds can be found in Rouwenhorst (2004). From that point of time until now the number of mutual funds has grown because of several reasons. We will elaborate the growth of the mutual fund industry in Section 1.1.3.

1.1.3 The Growth of Mutual Funds

According to the 2008 Investment Company Fact Book 48^{th} edition, the total net assets of the U.S. mutual fund industry have grown from about US$ 17 billions in 1960 to about US$ 10,000 billions in 2006. These numbers show that mutual funds become popular and significant as investment tools, and hence mutual funds have become an interesting subject for research. The growth of mutual funds is not surprising as there are several advantages in investing in mutual funds. First, the capital in a mutual fund is managed professionally. For example, the fund manager decides what, where and when to allocate the capital. Second, as discussed above the investor enjoys the benefit of diversification. As many investors pool their money in a mutual fund, the mutual fund can invest the pooled money in more diversified markets and sectors. Furthermore, depending on its investment objective, a mutual fund also diversifies on the types of securities. Third, a mutual fund share is a liquid tool of an investment as investors can trade it every business day. Fourth, mutual funds are regulated by the SEC. According to these regulations, mutual funds have to follow some operating standards, obey anti-fraud rules and disclose a complete information to investors. In this way, mutual funds are quite transparent and investors are protected against fraud. Despite the advantages, mutual funds also have disadvantages. First, a mutual fund can not follow a flexible investment strategy as a hedge fund. For example, a mutual fund is constrained to do short-selling. Second, investors are charged a fixed cost that is independent of how well or badly the fund performs.

Although the mutual fund was originated in Europe, the modern mutual funds grow faster in the U.S. Hence, at this moment the U.S. has the largest mutual fund market in the world (see Figure 1.3). This may trigger more research about mutual funds in the U.S. rather than other regions. This dissertation also focuses on U.S. mutual funds. From Figure 1.3 it can be observed that the U.S. has almost half of the total worldwide mutual fund assets while Europe has about one third of the total worldwide mutual fund assets. Other countries in the American continent besides the U.S. such as Argentina, Brazil, Canada, Chile, Costa Rica, Mexico have the smallest portion of the total worldwide mutual fund assets. Furthermore, the equity funds hold more than half of mutual fund assets in the U.S., whereas the bond funds, the money market funds and the hybrid funds hold only 14 percent, 26 percent and 6 percent, respectively. Figure 1.4 demonstrates the detailed percentages of the different mutual fund types.

Figure 1.3: The Worldwide Mutual Fund Asset

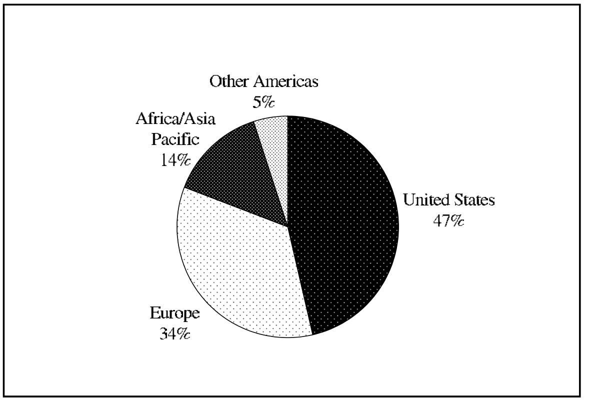
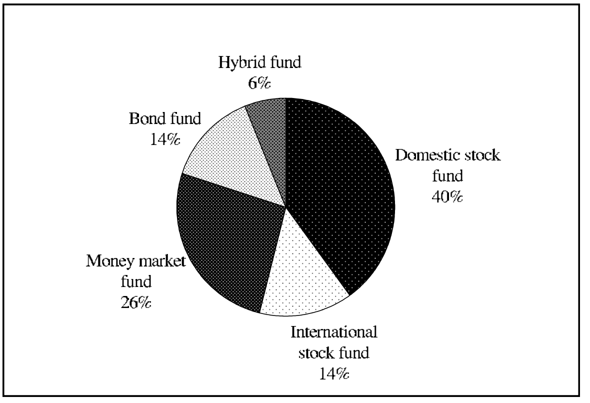


Figure 1.4: The Type of US Mutual Fund



1.2 Current Literature and The Contributions of This Dissertation

Section 1.1 has introduced a mutual fund, and described the history as well as the growth of mutual funds. This section will continue to explain the performance measures that are commonly used in the literature (Subsection 1.2.1), elaborate the issues and questions that are discussed in the current literature about the analysis of mutual fund performance (Subsection 1.2.2), and outline the contributions of this dissertation (Subsection 1.2.3).

1.2.1 Performance Measures

Compared to the condition of early funds, the development of modern mutual funds has been fascinating, especially the growth of equity mutual funds in the U.S. Therefore the performance of this financial institution has attracted many researchers to do some studies. There are many alternatives to evaluate the performance of mutual funds. The most common performance measure is the average return of a mutual fund over a particular period. This return is calculated either as total return or relative return (for example, the return in excess of risk-free rate[1], and

[1]To proxy a risk-free rate, many people use a one-month T-bill rate as it has the lowest risk (see, for example, Fama and French (1993), Carhart (1997), and Wermers (2000))

the relative returns to indices or benchmarks). Observing the relative returns of mutual funds is more appealing than observing their total returns because mutual funds are not risk-free assets and investing in an active mutual fund portfolio involves transaction costs. Hence, the investors of mutual funds would like to know how much mutual funds perform above or below what they would have earned if they had invested in a risk-free asset or a passive portfolio of indices with the same risk level. Furthermore, Elton et al. (2004) also shows that a failure to include certain indices in analyzing the funds performance will lead to a substantial overestimation of their performance. This underlines the importance of using relative performance to study mutual funds. In general, the relative performance of equity mutual funds is measured by alpha, α_i (or risk-adjusted returns). Several studies use the Capital Asset Pricing Model (CAPM) in equation (1.1) to estimate alpha (see, for example, Ippolito (1989) and Malkiel (1995)).

$$r_{i,t} = \alpha_i + \beta_i RMRF_t + \varepsilon_{i,t}. \tag{1.1}$$

where $r_{i,t}$ is the return of fund i in month t in excess of risk-free rate, $RMRF_t$ is the return on the market index in excess of risk-free rate, β_i is the systematic risk that fund i takes towards market risk ($RMRF_t$), and $\varepsilon_{i,t}$ is the residual return of fund i in month t. The concept of the CAPM was introduced by Sharpe (1964) and Lintner (1965) independently. According to this model, a fund can obtain higher return when it has higher market risk (β_i).

Besides alpha, it is also common to use a Sharpe ratio that was first introduced by Sharpe (1966) as a performance measure relative to risk. It is calculated from the ratio between the portfolio return and its standard deviation. While the Sharpe ratio is appropriate to evaluate the risk-return trade off of an entire portfolio, alpha is more suited to identify the marginal contribution of a mutual fund when added to an existing diversified portfolio. Furthermore, researchers also study whether mutual fund managers have timing skill. For an active portfolio management, it is important that a mutual fund manager anticipates the direction of the market and adjusts his portfolio accordingly, for example, by increasing the market exposure (β) of his portfolio when the market does well but decreasing the market exposure of his portfolio when the market does badly. The common method to evaluate the market timing skill of a mutual fund is using the Henriksson and Merton (1981) model in equation (1.2). From this equation, a mutual fund has market timing skill if $\beta_{2,i}$ is negative.

$$r_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} max(0, -RMRF_t) + \varepsilon_{i,t}, \tag{1.2}$$

Next, Black et al. (1972) and Fama and MacBeth (1973) demonstrate that the returns and the market betas in equation (1.1) have positive relation during the pre-1969 period. Fama and French (1992), however, show that the relation between the returns and the market betas disappear during more recent period, 1963 to 1990. Additionally, they also find the equity risks are multidimensional and that the cross-section equity returns are better explained by adding two other proxies of risk factors (the return on the factor mimicking portfolio for size, and the return on the factor mimicking portfolio for the book-to-market ratio), in addition to the market factor (see equation (1.3)). Based on this finding, several papers (see, for example, Cooper et al. (2005) and Jones and Shanken (2005)) use the three-factor model to study the performance of equity funds (alpha).

$$r_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \varepsilon_{i,t}. \tag{1.3}$$

where SMB_t is the return on the factor mimicking portfolio for size in excess of risk-free rate (Small Minus Big), HML_t is the return on the factor mimicking portfolio for the book-to-market ratio (High Minus Low) in excess of risk-free rate, and β_i is the systematic risk that fund i takes towards a risk factor ($RMRF_t$, SMB_t, or HML_t).

1.2.2 Current Literature

Measuring and analyzing mutual fund performance is not a simple task. A lot of studies have discussed several issues about this subject. One of the issues is related with the risks that a mutual fund has. In reality the risks or the exposures to systematic risk factors (β) of a mutual fund is time-varying (see, for example, Kon and Jen (1978)) and ignoring the time-variation of the risks causes a biased estimation of a fund risk-adjusted performance (alpha). Subsequently, this bias will lead to a wrong conclusion about the analysis of mutual fund performance. To capture the time-varying risks, several studies use public information such as dividend yield, term spread, and default spread (see, for example, Ferson and Schadt (1996) and Ferson and Harvey (1999)). By using this approach, Ferson and Schadt (1996) finds that the risk-adjusted performance of mutual funds looks higher after considering time-varying market risks. Furthermore, Ghysels (1998) also shows that capturing the time-varying risks is not straightforward, and mistakenly estimating the time-varying risks will even results in larger errors than assuming constant risks[2].

Furthermore, the accuracy of the performance estimation is also influenced by the choice of a benchmark or a proxy of risk factors. For evaluating the equity mutual funds, some studies use NYSE, AMEX and NASDAQ as a market benchmark (for example, Fama and French (1993), and Carhart (1997)), and some other studies use S&P 500 for a market benchmark (for example, Cremers et al. (2008), and Elton et al. (2004)). Cremers et al. (2008) and Huij and Verbeek (2009) show further that using inappropriate benchmarks or proxies for risk premiums can mislead the analysis of the performance. This accentuates the importance of using good proxies for risk factors. By using the commonly used and tradeable indices such as S&P 500 and Russel indices, Cremers et al. (2008) demonstrate that the model provides better performance evaluation and asset pricing tests. Moreover, Huij and Verbeek (2009) conclude that the factor proxies based on mutual fund returns provide better benchmarks than those based on stock returns to evaluate mutual fund managers.

Besides the issue of how to measure the performance accurately, there are a lot of discussions whether mutual funds perform persistently or they are just (un)lucky. Another related question is whether the persistence of mutual funds comes from the winner funds or loser funds. It is an important question for an active investor of mutual funds because if their performance

[2]To estimate time-varying market risk, Ghysels (1998) uses instrument variables such as the return on a one-month T-bill, dividend yield, the detrended stock price level, the slope of the term structure, a quality yield spread in the corporate bond market.

do not persist, it becomes more difficult to make a profitable active fund portfolio. Additionally, the investors of mutual funds can not do short-selling. Hence, for the mutual fund investors it is more important to know whether there are funds that win persistently rather than funds that lose persistently. Jensen (1969) documents that the performance of mutual funds (alpha) do not persist during 1955 to 1964. However, by using larger cross-section data in 1980s to 1990s, several papers (see, for example Goetzmann and Ibbotson (1994) and Elton et al. (1996)) find evidence that the performance of mutual funds persists. Goetzmann and Ibbotson (1994) also find that the past winners of the CAPM alpha repeat to be the future winners of the CAPM alpha. Moreover, Carhart (1997) shows that the persistence of fund performance comes from the common factors in stock returns that are not considered in the CAPM model, and that the unexplained persistence of fund performance is concentrated in the loser funds. Furthermore, studying about the persistence of mutual fund performance also investigates to a certain degree whether the mutual fund performance is predictable. Previous studies that report the persistence of mutual fund performance give an indication that the past performance (alpha) predicts the future performance (alpha) of mutual funds. Some other studies also observe that ranking funds on certain characteristics can differentiate the good-performing funds from the bad-performing funds. For example, Wermers (2000) shows that funds which have high turnover level outperform those that have low turnover level. Additionally, Elton et al. (2004) demonstrate that the low-expense funds have higher performance than the portfolio of index funds.

Furthermore, several studies have investigated whether mutual funds have skills (alpha and timing skills) that drive their performance[3]. This is a crucial issue because if mutual funds are just lucky, basically it is a random exercise or a gamble to choose which funds to invest in. However if mutual funds do have skills, it supposes to be possible to identify these funds ex-ante and make an ex-post profit from the selected funds. Grinblatt and Titman (1989) and Bollen and Busse (2004) conclude that stock selectivity skill exists. Additionally, Bollen and Busse (2004) shows that the stock selectivity skill is a short-lived phenomenon. This finding supports Berk and Green (2004) that whenever investors direct their capital to past fund winners, the size

[3]Alpha that we mention previously is also often called stock selectivity skill.

of these fund managers increases and consequently their skill fade away. Chen et al. (2004) further explain that the size of mutual fund erodes its alpha (stock selectivity skill) because this fund can not allocate their money optimally due to a liquidity problem. Moreover, Bollen and Busse (2001) demonstrate that the market timing skill of funds exists and is more accurately estimated by high frequency returns. In addition to the return-based analysis, some studies use non-return data such as fund holdings, and cash flow data to do the market timing analysis (see, for example, Chance and Hemler (2001), Jiang et al. (2007), and Friesen and Sapp (2007)).

1.2.3 The Contributions of This Dissertation

This dissertation is devoted to the study of equity mutual fund performance. Chapter 2 analyzes whether the persistence of mutual fund performance exists. Ferson and Schadt (1996) suggests that the persistence may be more easily identified by using a model that considers the time-varying exposures, but they leave this to future research. In this study we take the time-varying exposures into account to analyze performance persistence and propose a new conditional version of the Fama and French (1993) model in equation (1.3). An important aspect of our conditional model is the conditioning information that contains the sign and magnitude of the past year factor returns, as well as the dispersion in the exposures of individual mutual funds. The intuition is the following. The persistence in mutual fund returns usually is studied by ranking mutual funds on their past year returns, forming decile portfolios and rebalancing monthly. Then the resulting time-series of the risk-adjusted return difference between the top and bottom deciles is analyzed to determine whether winning funds stay winners, and losing funds stay losers. The Fama and French (1993) factor returns can turn positive or negative over time. When, for example, the market return is large and positive in a particular year, ranking funds on their past year returns in the end of this year will select high (low) beta funds in the top (bottom) decile. On the other hand, when the market return is large and negative, ranking funds on their past year returns will select low (high) beta funds in the top (bottom) decile. This argument also extends to the size factor, and value-growth factor. Hence, over time the return differential between the top and bottom deciles have time-varying exposures (betas) to the Fama and French (1993) factors based on the sign and magnitude of past factor returns. Additionally, the dispersion of individual mutual fund exposures is also important. Suppose all mutual funds have a market beta of one, the exposures of the return differential between the top and bottom deciles will not depend on the past market return at all. By using a bootstrap analysis where we know the true risk-adjusted performance (alphas) and exposures of funds, we find that our model provides the most accurate estimate of alpha and time-varying exposures to the Fama and French (1993) factors among other models in our study. Additionally, ignoring the time-variation in exposures will overestimate the persistence, whereas inadequately modeling the time-variation in the factor exposures will underestimate the persistence. Furthermore, our empirical analysis finds evidence that the persistence of mutual fund performance exists. We also observe that the persistence of the fund performance comes from good-performing funds as well as poor-performing funds.

Chapter 3 studies whether mutual funds characteristics predict the risk-adjusted returns (alphas) of mutual funds. Moreover, we investigate whether using fund characteristics in addition to past information of risk-adjusted returns to select funds can create an investment strategy that is superior to a strategy that uses only past risk-adjusted returns. The popular investment strategy in the literature is to select mutual funds based on their past performance. For example, Elton et al. (1996) rank mutual funds on their risk-adjusted performance and subsequently find that the top decile funds outperform the bottom decile funds. Similarly, Elton et al. (2004) rank mutual funds on their risk-adjusted performance and observe that the rank correlation between the deciles that are based on past and realized risk-adjusted performance is high. However, several studies (eg. Hendricks et al. (1993) and Carhart (1997)) document that the top funds portfolio of this strategy produces positive risk-adjusted returns but they are insignificant. This is rather disappointing news for the investors of mutual funds because they can only long mutual fund shares but not short-sell. Our study examines if investors can improve upon selecting mutual funds by also using fund characteristics. We observe that past performance, turnover ratio and ability (or the risk-adjusted fund performance from the time a fund exists until the moment we want to predict future performance) of mutual funds predict the risk-adjusted returns of mutual funds.

Additionally, after considering the fees of funds we find that combining information on these three fund characteristics produces a yearly excess net return of 8.0 percent, while an investment strategy that uses only past performance generates 7.1 percent. Adjusting for systematic risks, and then additionally using fund characteristics increases yearly alpha significantly from 0.8 percent to 1.7 percent. Importantly, the strategy that also uses fund characteristics requires less turnover.

Chapter 4 analyzes how the performance (or alpha) of average mutual funds changes over time and what explains its variation over time. This is an interesting issue because actively managed investments has been a long-time subject for debate. For example, several studies discuss whether the costs of active investment are adequately paid off by the performance of active management (see, for example, Jensen (1969), Odean (1999), and French (2008)). Additionally, some other studies analyze whether the market is too efficient for active management (see, for example, Coggin et al. (1993), Malkiel (2003), and Malkiel (2005)). One way to measure the contribution of an active management is by looking at the average alpha of mutual funds. Moreover, we also critically look at the methodology to compute average mutual fund alphas that can provide substantial different results, to the extent that the average alpha over the full sample period turns from negative to positive. We add to the debate on active versus passive management, and observe what factors are more appropriate to evaluate the performance of actively managed mutual funds. Additionally, we find that average fund turnover times costs divided by the skilled ratio is the most important variable to explain the dynamics of average alpha. The reason is that the average mutual fund is not skilled, and hence turnover hurts the average fund performance due to higher trading costs. Furthermore, we find that the difference between the skilled and unskilled fund ratios, the average expense ratio, and the ratio between the number of mutual funds and hedge funds also explain the dynamics of alpha, although the last variable is only available in a shorter period.

Chapter 5 investigates whether style timing skills exist and how to identify the style timers ex-ante. It is not easy to answer these questions because of estimation errors in the style exposures (see, for example, Jagannathan and Korajczyk (1986)). Furthermore, Kon (1983), Henriksson (1984), Jagannathan and Korajczyk (1986), and Bollen and Busse (2001) have documented that there is negative correlation between the alpha and the timing skills. This results in a poor ex-post performance when selecting mutual funds on style timing. In this study we contribute a method that alleviates the biases. This method selects funds by using the full return history (the ex-ante period from the inception of a fund until the point we stand), high frequency returns (daily returns), and including alpha and all three timing skills: market timing, size timing, and value-growth timing. To illustrate which method provides the most accurate estimation, we use a bootstrap analysis where we know the true alpha and level of style timing for each fund. Furthermore, by using our approach we demonstrate that style timing skills exist and those style timers can be successfully identified ex-ante. Additionally, we find that investing each month in the top decile of mutual funds that are selected by our approach produces an excess return of 8.01 percent per annum with a Sharpe ratio of 0.476.

Chapter 2

Persistence in Mutual Fund Performance and Time-Varying Risk Exposures

2.1 Introduction

Studies on the persistence in mutual fund returns usually rank mutual funds on their past year return, form decile portfolios and rebalance monthly. The resulting time-series of the return difference between the top and bottom deciles is then analyzed to determine whether winning funds stay winners, and losing funds stay losers. In order to do so we need to properly adjust for the risk exposures of this strategy. If the risk-adjusted alpha of the return differential between the top and bottom deciles is significant, it indicates that persistence exists. In this study we propose a new conditional Fama and French (1993) model which we believe is more accurate in measuring persistence than existing models in the literature. With our model we find that the risk-adjusted alpha is significant at 6.7 percent and hence persistence exists. The important aspect of our model is that the conditioning information contains the sign and magnitude of the past year factor returns, as well as the dispersion in the exposures of individual mutual funds. Below we explain why this is important.

Early studies like Hendricks et al. (1993) and Elton et al. (1996) analyze the return differential between the top and bottom decile funds and find that there is a high level of persistence in the performance of mutual funds. In fact with our data from 1962 to 2006 we confirm this result finding a risk-adjusted alpha of 10.6 percent per annum for the return differential between the top and bottom deciles. Carhart (1997), however, also includes equity momentum (WML) as a fourth factor and concludes that persistence does not exist. Indeed the risk-adjusted alpha drops to an insignificant 1.9 percent per annum for our data. Huij et al. (2007) provide an explanation for the high explanatory power of WML. Take, for example, a year in which the market return is highly positive. Ranking mutual funds at the end of this year on their past year returns will result in selecting high (low) beta funds in the top (bottom) decile. At the same time, however, equity momentum will also select high (low) beta stocks in the top (bottom) decile. Obviously this argument extends to negative market returns, when low beta funds/stocks are selected in the top decile, and to the size and value-growth factors. Hence the exposures to the Fama and French factors vary over time with the past factor returns, both for the mutual fund portfolio and WML. Huij et al. (2007) also point out that the Carhart model will lead to a serious underestimation of mutual fund persistence. The return differential of top and bottom ranked mutual funds will load positively on WML due to the similarity in time-varying risk exposures, but in doing so also incorporates the very high alpha of equity momentum. For this reason they recommend to use the Fama and French model, with exposures that are a function of the sign of the past year factor returns.

In this study we use bootstrap analysis to analyze in detail the aforementioned dependence of the risk exposures on the past factor returns. The key advantage of the bootstrap analysis is that we know the true risk-adjusted performance and the time-varying risk exposures. This way we illustrate why both the unconditional Fama and French model and the Carhart model are inadequate to measure persistence. In addition we show that the conditional model proposed by Huij et al. (2007) also underestimates persistence. The reason is that not only the sign of the past factor return is important, but also the magnitude. In addition it is important to consider the dispersion in the mutual fund exposures. If, for example, all mutual funds have a market beta of one, the exposures of the return differential between the top and bottom ranked mutual funds would not depend on the past market return at all. Our proposed model takes into account the dependence of the factor exposures on the sign and magnitude of the past factor returns, as well as the dispersion of the mutual fund exposures. In the bootstrap we show that this results in the most accurate estimate of alpha as well as the most accurate estimates of the time-varying exposures to the Fama and French factors.

In the empirical analysis we provide further evidence that our model is superior in describing the time-variation in the factor exposures. In particular we show that our model has the highest adjusted R-squared of all considered models. Our model explains 78 percent of the variation in the return differential of the top and bottom ranked mutual funds. This compares to just 9 percent for the Fama and French model, 48 percent for the Carhart model, and 64 percent for the Huij et al. (2007) model. The remainder of the paper is organized as follows. Section 2.2 describes the data and Section 2.3 specifies the models used in this paper. Next, Section 2.4 elaborates on the methodology and the results from the bootstrap analysis as well as discusses the time-varying exposures. After that we continue our analysis for empirical data in Section 2.5. Finally, Section 2.6 concludes.

2.2 Data

Monthly return data of equity mutual funds are extracted from the CRSP Mutual Fund Survivorship-bias-Free Database from January 1962 to December 2006. Hereby, we use the information provided by CRSP about the classification by Wiesenberger, Micropal/Investment Company Data, Inc., Strategic Insight, S&P, and the funds themselves. We select funds that are classified as small company growth, aggressive growth, growth, income, growth & income or maximum capital gains. This selection of fund types is similar to that of Carhart (1997) and Pastor and Stambaugh (2002). We drop funds with less than 12 consecutive return observations over the entire sample period from our sample. The resulting sample covers 12,348 funds. The data are free from survivorship bias as documented by Brown et al. (1992) and Brown and Goetzmann

(1995).

We obtain the FF factors (RMRF, SMB, and HML) 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. The proxy for the momentum is the one used by Carhart (1997).[1]

Following Hendricks et al. (1993), we assign funds to equally weighted decile portfolios based on their return during one-year ranking periods.[2] For each portfolio the excess return during a one-month investment period is computed. For example, the first ranking period in our sample comprises January 1962 to December 1962, and the first investment period is January 1963. The second ranking period moves one month ahead. The last ranking period comprises December 2004 to November 2005, and the last investment period is December 2005.

2.3 Factor models

In this section we introduce the various factor models that we will use to analyze the persistence in mutual fund performance. In the previous section we described how we construct each month equally weighted decile portfolios of mutual funds based on the performance in the previous twelve months. To analyze persistence we are then interested in the risk-adjusted performance of the top decile funds minus the bottom decile funds. The common approaches in the literature to compute risk-adjusted performance is first, to regress the return differential of the top and bottom deciles funds, $r_{D1-D10,t}$, on the Fama and French (1993) factors,

$$r_{D1-D10,t} = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t. \tag{2.1}$$

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

[2]Hendricks et al. (1993) assign a fund i to decile j such that the following equation is satisfied:

$$(j-1)(N_t/10) + \sum_{k=1}^{j-1} F_k < rank(i) \leq j(N_t/10) + \sum_{k=1}^{j} F_k,$$

where N_t is the number of available funds, $rank(i)$ is the rank of fund i, and $F_k = 1$ if $k \leq N_t$ mod 10 and $F_k = 0$ otherwise. Following Grundy and Martin (2001), the return during the one-year ranking period is the cumulative return. We also produce all results for compounded returns, and this leads to the same conclusions. The results are available upon request.

The second approach includes the equity momentum factor (WML) to equation (2.1), known as the Carhart model following its introduction in Carhart (1997),

$$r_{D1-D10,t} = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 WML_t + \varepsilon_t. \tag{2.2}$$

Huij et al. (2007) argue that the importance of WML in explaining the return differential is largely due to WML picking up the time-variation in the exposures to the Fama and French factors. These exposures will co-vary with the factor returns during the ranking period. If, for example, the market return is positive in the past twelve months, the top-ranked mutual funds are likely to have larger betas than the bottom-ranked funds. Similarly the equity momentum strategy is likely to be long in high beta stocks and short in low beta stocks. Hence at the same time both the return differential of the top and bottom decile of mutual funds and the corresponding differential for individual stocks have a positive market beta. Obviously the same arguments apply to negative market returns during the ranking period, where both will have a negative beta exposure, and these arguments also apply to the size and value-growth factors. Hence the loadings in equation (2.1) vary over time. Therefore Huij et al. (2007) propose the following model:

$$\begin{aligned} r_{D1-D10,t} = \alpha + (\beta_1 D^{RMRF}_{t,UP} + \beta_2 D^{RMRF}_{t,DOWN}) RMRF_t + (\beta_3 D^{SMB}_{t,UP} + \beta_4 D^{SMB}_{t,DOWN}) SMB_t \\ + (\beta_5 D^{HML}_{t,UP} + \beta_6 D^{HML}_{t,DOWN}) HML_t + \varepsilon_t \end{aligned} \tag{2.3}$$

where $D^F_{t,UP}$ $\left(D^F_{t,DOWN}\right)$ is a dummy variable that is equal to 1 if $\sum_{i=t-1}^{t-12} F_i/12$ is positive (negative) and zero otherwise. And F is the factor return (i.e., $RMRF$, SMB, or HML). Hence in this model the factor loadings depend on the sign of the factor return in the past year.

Whereas the model in equation (2.3) is much better in explaining the return differential between the mutual fund winners and losers than the Fama and French model in equation (2.1) and the Carhart model in equation (2.2), we propose here two extensions. First, the factor loadings will not only depend on the sign of the lagged factor return, but also on its magnitude. If, for example, the lagged 12-month market return is very large and positive, the winner (loser) decile of mutual funds will be dominated by the highest (lowest) market beta funds in the universe. In contrast, when the lagged 12-month market return is small and positive the mutual fund alphas and the size and value-growth contributions will determine which funds are in the top and the bottom deciles.

Second, the dispersion in individual mutual fund loadings will be important. The higher the dispersion in factor loadings, the higher the absolute beta of the return differential between the top and bottom deciles funds and the higher the difference between up and down betas. If, for example, all market betas are one, we do not expect the return differential to be explained by lagged market returns at all. On the other hand, if mutual fund market betas differ substantially from each other, the up and down market betas will be very large. We therefore propose the following model,

$$\begin{aligned} r_{D1-D10,t} = \alpha + \sum_F \left(\beta_1^F D_{t,UP}^F F_t + \beta_2^F D_{t,DOWN}^F F_t\right) + \sum_F \left(\beta_3^F D_{t,UP}^F MAG_t^F F_t + \beta_4^F D_{t,DOWN}^F MAG_t^F F_t\right) \\ + \sum_F \left(\beta_5^F D_{t,UP}^F DISP_t^F F_t + \beta_6^F D_{t,DOWN}^F \sigma_t^F F_t\right) \\ + \sum_F \left(\beta_7^F D_{t,UP}^F MAG_t^F DISP_t^F F_t + \beta_8^F D_{t,DOWN}^F MAG_t^F DISP_t^F F_t\right) + \varepsilon_t, \end{aligned} \tag{2.4}$$

where $D_{t,UP}^F$ $\left(D_{t,DOWN}^F\right)$ is a dummy variable that is equal to 1 if $\sum_{i=t-1}^{t-12} F_i/12$ is positive (negative) and zero otherwise. MAG_t^F is $\sum_{i=t-1}^{t-12} F_i/12$, and $DISP_t^F$ is the standard deviation of individual funds exposures, and F is the factor return (i.e., $RMRF$, SMB, and HML). Note that this model includes the model in equation (2.3) as a special case, with the restrictions that β_3^F, β_4^F, ..., β_8^F are equal to zero.

We will also include the model Grundy and Martin (2001) apply to equity momentum, which in a simple way takes into account the magnitude of each factor return using three categories, UP, FLAT and DOWN,

$$r_{D1-D10,t} = \alpha + \sum_F \left(\beta_1 G_{t,UP}^F F_t + \beta_2 G_{t,FLAT}^F F_t + \beta_3 G_{t,DOWN}^F F_t\right) + \varepsilon_t, \tag{2.5}$$

where $G^F_{t,UP}$, $G^F_{t,FLAT}$, and $G^F_{t,DOWN}$ are dummy variables that are equal to 1 if $\sum_{i=t-1}^{t-12} F_i/12$ are one standard deviation above its mean, within one standard deviation of the mean, and one standard deviation below the mean, respectively, and zero otherwise. For comparison we also look at the model in equation (2.4) without dispersion by restricting that β^F_5,..., β^F_8, are equal to zero. This way we can compare the robust specification of Grundy and Martin with our more continuous specification.

2.4 Bootstrap Analysis

Applying the various factor models in Section 2.3 to determine the persistence in mutual fund returns, i.e. the risk-adjusted performance of going long in the past winners and short in the past losers, will provide different estimates of alpha. Yet it is unclear what the most accurate estimate is. In this section we describe the outcomes of a comprehensive bootstrap analysis to compare the models. In the simulation we know what the true alpha is, as well as how the true betas vary over time. Hence, given the realistic settings of the bootstrap, we can determine which model is the best to measure the persistence in mutual fund performance. This is an important contribution of this study.

Section 2.4.1 explains the set up of the bootstrap analysis. Section 2.4.2 demonstrates the results for all models introduced in Section 2.3. To estimate persistence correctly, the model has to first estimate the time-varying exposures correctly. Therefore, in Section 2.4.3 we show how well each model estimates the time-varying exposures by comparing them to the true exposures.

2.4.1 Bootstrap methodology

In the simulation set up mutual fund returns are governed by a mutual fund specific alpha and mutual fund specific loadings on the Fama and French factors. The simulated mutual fund returns are bootstrapped to make them as representative as possible for the actual returns. To this end, we follow Kosowski et al. (2006) and Kosowski et al. (2007). First, we estimate all funds' alphas, factor exposures, and residual returns using the Fama and French model in equation (2.1). We store the coefficient estimates $\{\hat{\alpha}_i, \hat{\beta}_{1,i}, \hat{\beta}_{2,i}, \hat{\beta}_{3,i}, i = \text{fund } 1,2,\dots,N\}$, and the time-series of estimated residuals $\{\hat{\varepsilon}_{i,t}, i = \text{fund } 1,2,\dots,N, t = \text{month } 1,2,\dots,T\}$. Next, we draw a sample with replacement from the funds' stored residuals $\{\hat{\varepsilon}_{i,t_e}, t_e = s_1, s_2, \dots, s_T\}$, where $s_1, s_2, \dots, s_T$ is the reordering imposed by the bootstrap. We then construct time-series of simulated fund returns for all funds using the following equation[3]:

$$\tilde{r}_{i,t} = \hat{\alpha}_i + \hat{\beta}_{1,i} RMRF_t + \hat{\beta}_{2,i} SMB_t + \hat{\beta}_{3,i} HML_t + \hat{\varepsilon}_{i,t_e} \tag{2.6}$$

The resulting simulated sample of fund returns has the same length and number of funds in the cross-section as our empirical sample. Using this simulated sample we construct rank portfolios as discussed in Section 2.2.

2.4.2 Bootstrap results

The advantage of using bootstrap analysis is that we know the true risk-adjusted return as well as the true exposures. Hence, we will know which model produces the correct conclusion on the existence of persistence, additionally which model most accurately estimates the level of persistence. We generate the simulated returns that are built by the methodology explained in Section 2.4.1. The results are presented in Table 2.1.

First note that in the simulated world the true alpha of the return differential between the top and bottom deciles is 3.92 percent, as shown in the final column of Table 2.1, panel A (row "D1-D10"). Hence persistence exists, and its level is 3.92 percent per annum. We can now proceed with comparing the results of the factor models in Section 2.3. In particular, what is the level of the estimated alpha of each model, is it significant, and what is the explanatory power of each model measured by the adjusted R-squared.

[3]The momentum factor is not included in equation (2.6) because in the bootstrap analysis we would like to show how the momentum factor indirectly estimates the time variation in the exposures to the Fama and French factors, even when individual funds do not load on WML.

Table 2.1: Bootstrap Results Where True Persistence Exists

This table shows the results of a bootstrap analysis where true persistence exists. Mutual funds are sorted into equally weighted decile portfolios based on 12-month returns. The decile portfolios, with D1 containing the winners and D10 the losers, are rebalanced monthly. In Panel A to F, the decile post-ranking returns are evaluated using the Fama and French model, the Carhart model, the Conditional Fama and French model from equation (2.3), the Grundy and Martin model in equation (2.5), the Conditional Fama and French model from equation (2.4) that excludes dispersion and the complete Conditional Fama and French model from equation (2.4), respectively. The alphas, t-values, MSE, the exposures to the risk factors, the adjusted R^2, and the true alphas are shown. MAG is the past year factor return, and DISP is the standard deviation of individual funds exposures.

Panel A. Fama and French model

	Alpha	Alpha-t	MSE	RMRF	SMB	HML	Adj. R^2	True Alpha
D1	2.94	3.03	0.0203	0.71	0.43	-0.08	0.82	1.27
D2	0.69	1.03	0.0056	0.78	0.28	0.00	0.90	-0.18
D3	-0.14	-0.25	0.0012	0.79	0.20	0.05	0.92	-0.50
D4	-0.77	-1.73	0.0003	0.80	0.14	0.07	0.94	-0.71
D5	-1.23	-2.75	0.0012	0.80	0.11	0.07	0.95	-0.86
D6	-1.46	-2.12	0.0020	0.78	0.09	0.07	0.92	-0.97
D7	-1.72	-1.86	0.0037	0.76	0.09	0.06	0.86	-1.02
D8	-1.97	-1.80	0.0047	0.75	0.09	0.05	0.82	-1.18
D9	-2.25	-1.80	0.0031	0.76	0.10	0.02	0.78	-1.63
D10	-3.57	-2.64	0.0065	0.81	0.15	-0.02	0.75	-2.65
D1-D10	6.51	3.01	0.0482	-0.10	0.28	-0.06	0.06	3.92

Panel B. Carhart model

	Alpha	Alpha-t	MSE	RMRF	SMB	HML	WML	Adj. R^2	True Alpha
D1	0.23	0.26	0.0083	0.74	0.48	-0.05	0.20	0.87	1.27
D2	-0.92	-1.47	0.0041	0.80	0.31	0.02	0.12	0.92	-0.18
D3	-1.08	-2.07	0.0027	0.80	0.21	0.06	0.07	0.93	-0.50
D4	-1.19	-2.57	0.0019	0.80	0.15	0.07	0.03	0.94	-0.71
D5	-1.09	-2.29	0.0006	0.80	0.10	0.07	-0.01	0.95	-0.86
D6	-0.81	-1.05	0.0005	0.77	0.07	0.06	-0.05	0.92	-0.97
D7	-0.55	-0.55	0.0019	0.74	0.07	0.04	-0.09	0.87	-1.02
D8	-0.15	-0.13	0.0076	0.74	0.06	0.02	-0.13	0.85	-1.18
D9	0.31	0.24	0.0266	0.73	0.06	-0.02	-0.19	0.83	-1.63
D10	0.09	0.07	0.0530	0.77	0.08	-0.07	-0.27	0.84	-2.65
D1-D10	0.14	0.07	0.1008	-0.04	0.40	0.02	0.47	0.41	3.92

Panel C. Conditional Fama and French (sign)

	Alpha	Alpha-t	MSE	RMRF UP	RMRF DOWN	SMB UP	SMB DOWN	HML UP	HML DOWN	Adj. R^2	True Alpha
D1	0.91	1.70	0.0017	0.91	0.50	0.48	0.22	0.14	-0.41	0.93	1.27
D2	-0.63	-1.43	0.0017	0.90	0.65	0.31	0.14	0.15	-0.21	0.95	-0.18
D3	-0.94	-2.12	0.0017	0.88	0.70	0.20	0.12	0.14	-0.09	0.95	-0.50
D4	-1.14	-2.51	0.0016	0.85	0.74	0.13	0.12	0.11	-0.01	0.95	-0.71
D5	-1.19	-2.52	0.0010	0.80	0.79	0.09	0.12	0.08	0.06	0.95	-0.86
D6	-1.04	-1.69	0.0003	0.72	0.85	0.07	0.12	0.04	0.11	0.93	-0.97
D7	-0.89	-1.20	0.0004	0.63	0.90	0.07	0.16	0.01	0.15	0.89	-1.02
D8	-0.74	-0.91	0.0016	0.59	0.94	0.06	0.20	-0.05	0.21	0.88	-1.18
D9	-0.53	-0.59	0.0088	0.56	0.98	0.05	0.28	-0.13	0.24	0.88	-1.63
D10	-1.31	-1.47	0.0133	0.58	1.05	0.09	0.39	-0.25	0.32	0.88	-2.65
D1-D10	2.22	1.91	0.0218	0.33	-0.55	0.38	-0.17	0.38	-0.73	0.68	3.92

Table 2.1 continued

Panel D. Grundy and Martin model

	Alpha	Alpha-*t*	MSE	RMRF UP	RMRF FLAT	RMRF DOWN	SMB UP	SMB FLAT	SMB DOWN	HML UP	HML FLAT	HML DOWN	Adj R^2	True Alpha
D1	1.06	2.33	0.0011	0.92	0.83	0.51	0.56	0.33	0.11	0.43	-0.02	-0.53	0.94	1.27
D2	-0.48	-1.15	0.0010	0.92	0.85	0.66	0.36	0.23	0.06	0.35	0.03	-0.28	0.95	-0.18
D3	-0.79	-1.75	0.0009	0.90	0.83	0.73	0.23	0.16	0.09	0.28	0.06	-0.14	0.94	-0.50
D4	-1.00	-2.30	0.0009	0.85	0.80	0.80	0.14	0.12	0.13	0.20	0.07	-0.05	0.95	-0.71
D5	-1.17	-2.92	0.0009	0.74	0.78	0.85	0.08	0.09	0.17	0.10	0.07	0.03	0.95	-0.86
D6	-1.23	-2.68	0.0008	0.58	0.76	0.90	0.04	0.07	0.22	0.03	0.07	0.09	0.94	-0.97
D7	-1.27	-2.22	0.0007	0.46	0.73	0.92	0.02	0.08	0.30	-0.06	0.07	0.14	0.91	-1.02
D8	-1.27	-2.04	0.0003	0.36	0.73	0.95	0.00	0.09	0.38	-0.17	0.05	0.22	0.90	-1.18
D9	-1.13	-1.47	0.0021	0.33	0.71	0.98	-0.04	0.13	0.49	-0.30	0.00	0.28	0.90	-1.63
D10	-1.96	-2.66	0.0042	0.32	0.74	1.06	-0.04	0.22	0.61	-0.51	-0.05	0.38	0.91	-2.65
D1-D10	3.01	3.23	0.0075	0.60	0.09	-0.55	0.60	0.12	-0.50	0.94	0.04	-0.91	0.77	3.92

Panel E. Conditional Fama and French (sign and magnitude)

	Alpha	Alpha-*t*	MSE	RMRF UP	RMRF DOWN	RMRF MAG UP	RMRF MAG DOWN	SMB UP	SMB DOWN	SMB MAG UP	SMB MAG DOWN	HML UP	HML DOWN	HML MAG UP	HML MAG DOWN	Adj R^2	True Alpha
D1	1.29	3.39	0.0009	0.81	0.64	0.07	0.06	0.40	0.27	0.03	0.07	-0.10	-0.10	0.17	0.27	0.95	1.27
D2	-0.33	-0.86	0.0005	0.84	0.71	0.05	0.02	0.25	0.19	0.03	0.06	0.00	-0.04	0.11	0.14	0.96	-0.18
D3	-0.71	-1.65	0.0006	0.84	0.68	0.04	-0.02	0.18	0.15	0.01	0.03	0.05	-0.01	0.07	0.07	0.95	-0.50
D4	-0.95	-2.14	0.0007	0.82	0.67	0.02	-0.05	0.14	0.12	0.00	-0.01	0.07	0.02	0.03	0.03	0.95	-0.71
D5	-1.13	-2.64	0.0008	0.82	0.71	-0.02	-0.06	0.11	0.10	-0.02	-0.03	0.08	0.06	0.00	0.01	0.95	-0.86
D6	-1.21	-2.59	0.0006	0.83	0.78	-0.09	-0.05	0.10	0.08	-0.04	-0.06	0.08	0.11	-0.02	0.02	0.93	-0.97
D7	-1.25	-2.27	0.0006	0.81	0.84	-0.14	-0.03	0.11	0.10	-0.05	-0.08	0.09	0.12	-0.04	0.01	0.91	-1.02
D8	-1.34	-2.37	0.0005	0.87	0.88	-0.21	-0.03	0.11	0.13	-0.06	-0.10	0.09	0.14	-0.09	-0.01	0.91	-1.18
D9	-1.24	-1.96	0.0014	0.87	0.92	-0.24	-0.02	0.14	0.19	-0.09	-0.13	0.08	0.10	-0.13	-0.07	0.91	-1.63
D10	-2.16	-3.51	0.0025	0.92	0.98	-0.27	-0.01	0.21	0.30	-0.11	-0.13	0.10	0.11	-0.24	-0.13	0.93	-2.65
D1-D10	3.44	5.24	0.0034	-0.11	-0.34	0.34	0.07	0.19	-0.04	0.14	0.20	-0.19	-0.21	0.41	0.40	0.86	3.92

Table 2.1 continued

Panel F. Conditional Fama and French (sign, magnitude and dispersion)

	Alpha	Alpha-t	MSE	RMRF UP	RMRF DOWN	RMRF MAG UP	RMRF MAG DOWN	RMRF DISP UP	RMRF DISP DOWN	RMRF MAG DISP UP	RMRF MAG DISP DOWN	SMB UP	SMB DOWN	SMB MAG UP	SMB MAG DOWN
D1	1.35	4.97	0.0009	1.09	1.18	0.00	0.03	-0.91	-1.62	0.29	0.17	-0.42	-0.41	0.52	-0.26
D2	-0.24	-0.84	0.0004	1.06	1.18	0.00	-0.24	-0.70	-1.35	0.18	0.94	-0.32	-0.18	0.24	-0.46
D3	-0.60	-2.11	0.0004	1.07	1.44	0.01	-0.18	-0.78	-2.31	0.14	0.60	-0.13	-0.18	0.12	-0.38
D4	-0.85	-3.20	0.0005	1.17	1.72	-0.02	0.10	-1.20	-3.35	0.21	-0.47	-0.05	-0.14	0.13	-0.19
D5	-1.14	-4.61	0.0008	1.22	1.73	0.03	0.23	-1.42	-3.31	-0.02	-0.96	-0.01	-0.23	0.19	-0.13
D6	-1.41	-5.13	0.0016	1.32	1.48	0.11	0.18	-1.85	-2.25	-0.35	-0.73	-0.10	-0.43	0.35	0.18
D7	-1.57	-4.98	0.0024	1.45	1.19	0.15	0.08	-2.42	-1.11	-0.52	-0.38	-0.41	-0.46	0.55	0.24
D8	-1.62	-5.91	0.0017	1.28	1.09	0.27	0.07	-1.71	-0.69	-1.08	-0.32	-0.47	-0.38	0.32	0.44
D9	-1.53	-4.88	0.0005	1.31	1.04	0.20	0.07	-1.74	-0.42	-1.01	-0.31	-0.25	-0.28	-0.07	0.54
D10	-2.44	-6.47	0.0011	1.12	1.02	0.10	0.12	-0.89	-0.22	-0.86	-0.52	-0.24	-0.15	-0.04	0.66
D1-D10	3.79	8.50	0.0019	-0.03	0.16	-0.10	-0.09	-0.02	-1.40	1.15	0.68	-0.17	-0.26	0.56	-0.91

	SMB DISP UP	SMB DISP DOWN	SMB MAG DISP UP	SMB MAG DISP DOWN	HML UP	HML DOWN	HML MAG UP	HML MAG DOWN	HML DISP UP	HML DISP DOWN	HML MAG DISP UP	HML MAG DISP DOWN	Adj R^2	True Alpha
D1	2.47	2.05	-1.51	1.08	-0.10	0.20	0.12	0.00	0.06	-1.08	0.09	0.51	0.96	1.27
D2	1.78	1.09	-0.64	1.72	-0.25	-0.04	0.29	0.01	0.69	-0.01	-0.51	0.29	0.97	-0.18
D3	0.99	0.94	-0.33	1.38	-0.15	-0.01	0.24	0.06	0.45	0.03	-0.45	0.03	0.97	-0.50
D4	0.58	0.74	-0.40	0.68	-0.04	0.05	0.16	0.09	0.18	-0.03	-0.34	-0.14	0.98	-0.71
D5	0.36	1.03	-0.63	0.41	-0.02	0.08	0.12	0.15	0.13	-0.03	-0.30	-0.32	0.98	-0.86
D6	0.65	1.59	-1.17	-0.67	0.12	0.21	0.03	0.29	-0.23	-0.28	-0.11	-0.68	0.97	-0.97
D7	1.64	1.76	-1.85	-0.94	0.29	0.13	-0.08	0.25	-0.68	-0.03	0.12	-0.58	0.97	-1.02
D8	1.83	1.62	-1.16	-1.68	0.29	0.00	-0.09	0.02	-0.67	0.32	0.05	-0.12	0.97	-1.18
D9	1.29	1.47	-0.04	-2.08	0.34	-0.35	-0.14	-0.26	-0.86	1.24	0.07	0.47	0.97	-1.63
D10	1.45	1.34	-0.15	-2.56	0.30	-0.17	0.08	0.00	-0.92	0.80	-0.67	-0.33	0.96	-2.65
D1-D10	1.03	0.70	-1.36	3.64	-0.40	0.37	0.04	0.00	0.98	-1.88	0.76	0.85	0.90	3.92

We start with the Fama and French model in equation (2.1), where risk exposures are assumed to be constant. The results are shown in Panel A of Table 2.1. In the final row we see that this model estimates alpha at 6.51 percent per annum. Hence it overestimates alpha by 2.59 percent. It can also be seen in column 3 that the Fama and French model has a Mean Squared Error (MSE) of 0.0482. As already explained in Huij et al. (2007) this is caused by ignoring the time-variation in the factor loadings, combined with a positive correlation between factor returns in the ranking period and factor returns in the investment period.

We proceed with the Carhart model in equation (2.2). Again the exposures to the four factors are assumed to be constant in this model, but as illustrated in Huij et al. (2007) WML introduces time-varying exposures to the Fama and French factors. Unfortunately it also means that with loading positively on WML we also load positively on the (positive) risk-adjusted return of WML. This leads to a downward bias in the estimated persistence in mutual fund returns. In fact the results in Panel B of Table 2.1 show that alpha is indeed downward biased and estimated at an insignificant 0.14 percent. This is 3.78 percent lower than the true alpha of 3.92 percent. Due to this large bias the MSE is even larger than that for the Fama and French model at 0.1008.

Next in Panel C of Table 2.1 we present the results of the model proposed in Huij et al. (2007), see equation (2.3). Now the exposures to the Fama and French factors are allowed to attain two values, depending on the factor return during the ranking period. The alpha is now estimated at an insignificant 2.22 percent. Hence, it is 1.70 percent lower than the true alpha of 3.92 percent. The MSE is now 0.0218. Hence this is a substantial improvement over both the Fama and French model and the Carhart model, but the bias is still disappointingly large.

Panel D of Table 2.1 shows the outcomes for the model introduced by Grundy and Martin (2001) in equation (2.5), be it to analyze WML rather than mutual fund persistence. In this model the exposures to the Fama and French factors can have three values, and implicitly requires the past factor returns to have a large enough value before it affects the loadings. With this model alpha is estimated at 3.01 percent with an MSE of 0.0075. Hence it improves over the model of Huij et al. (2007). Still, the estimated alpha is 0.91 percent lower than the true alpha of 3.92 percent.

Now we proceed with our proposed model in equation (2.4). In this model we not only consider the sign of the lagged factor returns, but also let the exposures to the Fama and French factors depend in a continuous way to the magnitude of the lagged factor returns and the dispersion in individual mutual fund loadings. Panel F in Table 2.1 shows the results. The estimated alpha is 3.79 percent. It is just 0.13 percent different from the true alpha of 3.92 percent per year. The MSE has dropped to 0.0019. Hence in this simulated world with realistic settings this is by far the best model.

To show that dispersion matters, we also estimated our proposed model in equation (2.4) leaving out dispersion, i.e. setting β_5^F,..., β_8^F to zero. The results in Panel E of Table 2.1 show that indeed dispersion matters, with the estimated alpha of 3.44 percent. It is 0.48 percent lower than the true alpha. By including dispersion the difference was only 0.13 percent. Also the MSE rises from 0.0019 with dispersion to 0.0034 without dispersion. These results also illustrate that letting the factor loadings depend on the magnitude of the past factor returns in a continuous way (our model) improves over the discrete approach of Grundy and Martin (2001).

So far we have discussed how accurate each model estimates alpha. Now we discuss the goodness of fit in each model in explaining the cross-section of mutual fund returns. Here we can observe that taking into account the time-varying exposures we can explain the cross-section of returns much better. The Fama and French model in equation (2.1) assumes that risk exposures are constant. This results in disappointingly low explanatory power across decile portfolios. For example the adjusted R-squared of the return differential between the top and bottom deciles is equal to 6 percent (See Panel A of Table 2.1). Similarly, the Carhart model in equation (2.2) also assumes four constant exposures, but the fourth factor (WML) introduces time-varying exposures to the Fama and French factors (See Huij et al. (2007)). Hence we do see that the adjusted R-squared is much higher now at 41 percent. This illustrates that WML is capable of picking up a substantial part in the time-variation in the Fama and French factor loadings. Furthermore, the model proposed in Huij et al. (2007) attempts to account time-varying exposures by allowing two values of an exposure, depending on the factor return during the ranking period. We see an improvement in the adjusted R-squared of 68 percent, the highest so far. Hence a large portion of the time-variation to the Fama and French factors is picked up by the simple up and down dummies. Next, the model proposed by Grundy and Martin (2001) considers the magnitude of the factor returns in a discrete way to affect the time variation in the exposures. The adjusted R-squared increases to 77 percent. And with our model in equation (2.4) leaving out dispersion, we take into account the magnitude in a continuous way and the adjusted R-squared becomes 86 percent. Furthermore, by using our complete model in equation (2.4), the adjusted R-squared is now 90 percent illustrating that we are getting close to the true time-variation in the factor loadings. And among the models that we discuss here, our model is the best in explaining the cross-section of mutual fund returns.

Hence from all the results in Table 2.1 we can conclude that our proposed model in equation (2.4), allowing the factor exposures to vary with the sign and the magnitude of lagged factor returns and the dispersion of individual factor loadings, is the best model for the return differential between the winner and loser mutual funds. This model is the most accurate in measuring the level of alpha, and hence in the best position to reach the correct conclusion on the existence of persistence in mutual fund performance.

2.4.3 Time-Varying Exposures

In Section 2.4.2, we discuss and compare the six considered models regarding their ability to make the right conclusion on persistence and estimate the correct level of persistence. The estimated persistence of a model is the result of how the model estimates the time-varying exposures to the factor returns (RMRF, SMB, HML). If a model is able to estimate the exposures well, it is also able to estimate the persistence more accurately. In this section, we demonstrate how each model estimates the time-varying exposures to RMRF, SMB and HML. This will provide useful insights into why several of the models had large biases in the alphas.

Figure 2.1, Panel A, B and C show the estimated exposures to RMRF, SMB and HML, respectively, of the return differential between the top and bottom deciles for all but our most complete model in equation (2.4)[4]. For each model, we show the estimated exposures as a

[4]The estimated exposures to the factor returns for the full model in equation (2.4) can not be shown in Figure

function of the factor returns. The Fama and French model estimates constant exposures to RMRF, SMB and HML. Hence, the Fama and French estimated exposures (-0.10, 0.28, -0.06) are horizontal lines, while the true exposures scatter among positively sloped lines.

The Carhart model uses the three Fama and French factors and WML, with the latter indirectly estimating the time variation in the exposures to the Fama and French factors. We approximate how the Carhart model estimates the time-varying exposures by applying (restricted versions of) equation (2.4) to the WML returns and subsequently let the estimated equation replace WML in equation (2.2). The results of applying equation (2.4) to WML can be found in Table 2.2. The large explanatory power up to 48 percent of the full model in equation (2.4), combined with the expected signs of the parameters, underscores the claim that WML shows similar time-varying exposures to the Fama and French factors as the return differential for mutual funds. In Figure 2.1 we see the implied exposures of WML when using equation (2.4) without dispersion. We see that the implied exposures of WML have a too small slope compared to the true exposures.

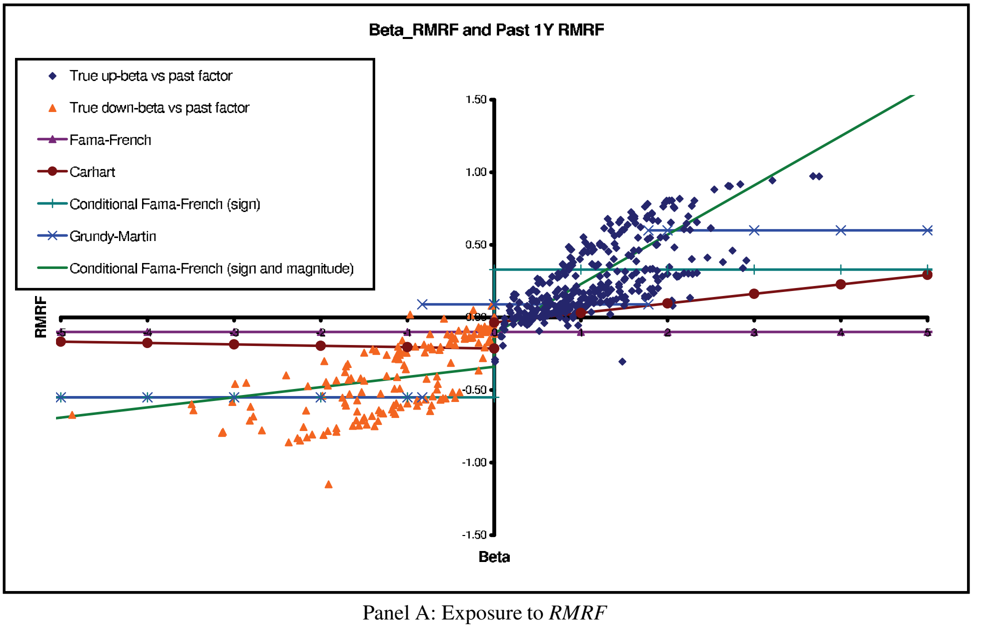
Next consider the time-varying loadings of the model in equation (2.3). In this model the loadings can only attain two values, depending on the sign of the factor return. The two resulting horizontal lines in each of the three panels of Figure 2.1 show that this ignores the impact of the magnitude of the factor returns, in turn explaining the substantial MSE of 0.0218 reported in Panel C of Table 2.1.

Similarly, the Grundy and Martin model fits the true exposures by three horizontal lines. This only partly moves towards the relation between the magnitudes of the factor returns and the exposures. This is an improvement over the model of Huij et al. (2007), but still ignoring larger exposures for larger factor returns.

2.1 because the figure needs another dimension to visualize the dispersion factor. Instead, in Figure 2.2 we show how its estimated exposures fit the true values by plotting the estimated and true exposures against each other.

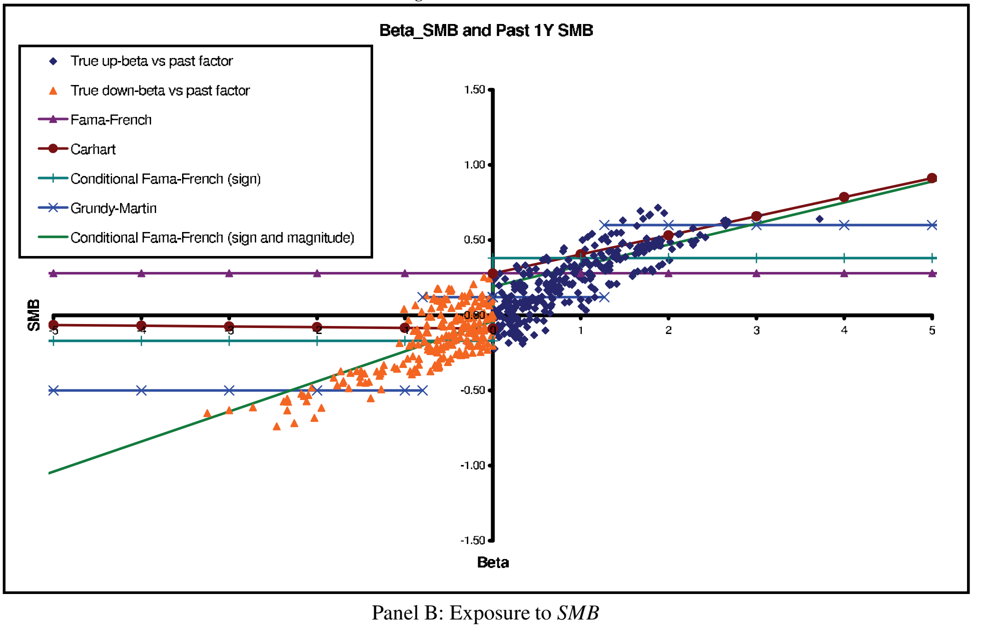
Figure 2.1: Past Year Factor Return and Exposure

This figure shows the true exposures and the fitted lines of estimated exposures of the return difference between the winner and loser deciles from the Fama and French model, the Carhart model, the Conditional Fama and French model from equation (2.3), the Grundy and Martin model in equation (2.5), and the Conditional Fama and French model from equation (2.4) that excludes dispersion. The x-axis and y-axis represent the past year factor returns and exposures, respectively. Diamond (triangle) dots represent the true exposures when past year factor returns are positive (negative). The fitted line symbol of each model is noted in the legend of the figure. Panel A, B and C show the exposures to *RMRF*, *SMB* and *HML*, respectively.



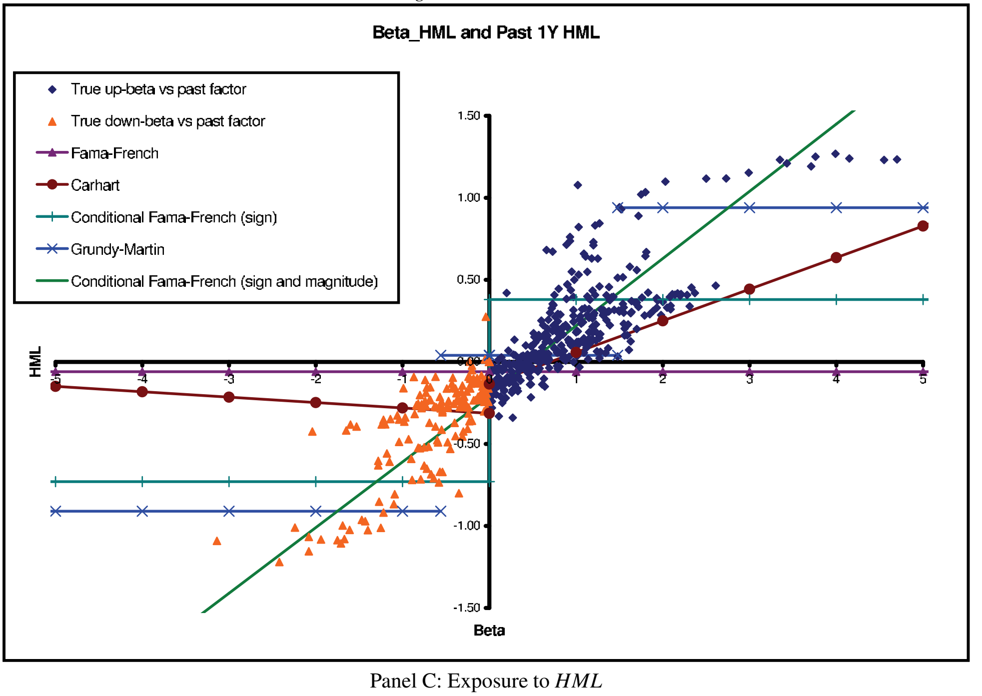
Panel A: Exposure to *RMRF*

Figure 2.1 continued



Panel B: Exposure to *SMB*

Figure 2.1 continued



Panel C: Exposure to *HML*

Table 2.2: Momentum and Time-Varying Risk Exposures

The momentum factor (WML) is analyzed by the Fama and French model both before and after considering time-varying exposures. We make use of equation (2.1) (constant exposures), the sign model in equation (2.3), and equation (2.4) either setting the dispersion parameters to zero or using the full model. The adjusted R^2, loadings and t-values are shown.

	Alpha	RMRF	SMB	HML
AdjR^2 0.04				
load	13.37	-0.13	-0.24	-0.18
t	5.26	-2.42	-3.57	-2.32

	Alpha	RMRF UP	RMRF DOWN	SMB UP	SMB DOWN	HML UP	HML DOWN
AdjR^2 0.37							
load	8.54	0.21	-0.44	0.05	-0.98	0.21	-0.70
t	4.11	3.94	-7.00	0.72	-11.00	2.66	-7.25

	Alpha	RMRF UP	RMRF DOWN	RMRF MAG UP	RMRF MAG DOWN	SMB UP	SMB DOWN	SMB MAG UP	SMB MAG DOWN	HML UP	HML DOWN	HML MAG UP	HML MAG DOWN
AdjR^2 0.42													
load	9.60	0.02	-0.37	0.14	-0.02	-0.25	-1.01	0.27	0.01	-0.32	-0.70	0.41	-0.06
t	4.79	0.19	-4.02	1.97	-0.40	-2.30	-8.04	3.67	0.11	-2.78	-4.35	5.78	-0.51

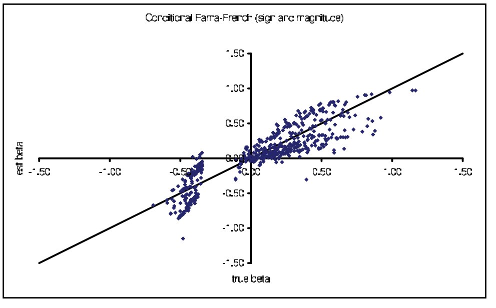
	Alpha	RMRF UP	RMRF DOWN	RMRF MAG UP	RMRF MAG DOWN	RMRF DISP UP	RMRF DISP DOWN	RMRF MAG DISP UP	RMRF MAG DISP DOWN	SMB UP	SMB DOWN	SMB MAG UP	SMB MAG DOWN	SMB DISP UP	SMB DISP DOWN	SMB MAG DISP UP	SMB MAG DISP DOWN	HML UP	HML DOWN	HML MAG UP	HML MAG DOWN	HML DISP UP	HML DISP DOWN	HML MAG DISP UP	HML MAG DISP DOWN
AdjR^2 0.48																									
load	9.31	1.17	-0.90	-0.46	-0.72	-3.38	2.06	1.72	2.60	-0.75	-1.11	1.15	1.28	1.61	0.40	-2.78	-3.83	-1.43	-0.31	-0.17	0.63	4.29	-0.85	1.02	-1.59
t	4.86	2.93	-2.06	-1.61	-2.30	-2.86	1.46	2.17	2.48	-0.75	-0.90	1.59	0.79	0.52	0.10	-1.24	-0.74	-2.91	-0.46	-0.45	1.06	3.14	-0.41	1.13	-0.98

Finally we show the results of the restricted version of our proposed model, i.e. the model in equation (2.4) without dispersion. This model's exposures are closer to the true values. From Figure 2.1, Panel A, we see that the slope of the line in the down state is lower than that of the up state. The low slope of the line in the down state can be explained from the 1973-1974 period containing large negative 12-month market returns of -3.49, -4.87, -3.47 during September 1973 to August 1974, October 1973 to September 1974 and November 1973 to October 1974, respectively. If we remove these outliers, the slope of the line in the down state increases from 0.07 to 0.17. Furthermore, during these periods the true market exposures are more positive than what the model estimates after removing the outliers. However, we observe that during these periods the true market exposures can not be more negative as the most negative (positive) market exposure funds are already in the top (bottom) decile. Additionally, we observe that the much more negative (positive) market exposure funds just exist in the later years. Hence, the correlation between the exposure and the magnitude of the factor return is non-constant, and this correlation is influenced by the dispersion of the fund exposures. This is exactly the reason why the full model in equation (2.4) also includes dispersion.

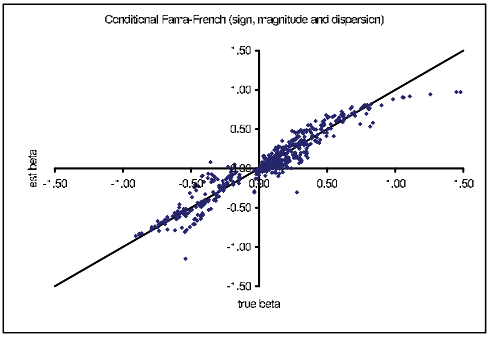
To show the importance of dispersion in Figure 2.2 we plot the true and estimated exposures for the model in equation (2.4) with and without dispersion. The improved fit is visible in that the dots are lying closer to the 45 degree line, see Figure 2.2b (the market), 2.2d (SMB) and 2.2f (HML). Additionally, we observe an improvement in the R^2 of the fitted lines after using dispersion. The R^2 of the exposures to RMRF, SMB, and HML without dispersion are equal to 0.77, 0.74, and 0.79, respectively. Whereas the R^2 of the exposures to RMRF, SMB, and HML with dispersion are equal to 0.91, 0.75, and 0.88, respectively. With Figures 2.1 and 2.2 we supported the importance of considering sign and magnitude of factor returns as well as dispersion in the factor loadings of individual funds.

Figure 2.2: True Exposures vs. Estimated Exposures

This figure shows the scatter plot where the x-axis and y-axis are estimated and true exposures of the return difference between the winner and loser deciles, respectively. Subfigure a and b show the estimated and true exposures to *RMRF* of the Conditional Fama and French model from equation (2.4) that excludes and includes dispersion, respectively. Similarly, subfigure c and d demonstrate the exposures to *SMB* and subfigure e and f depict the exposure to *HML*.

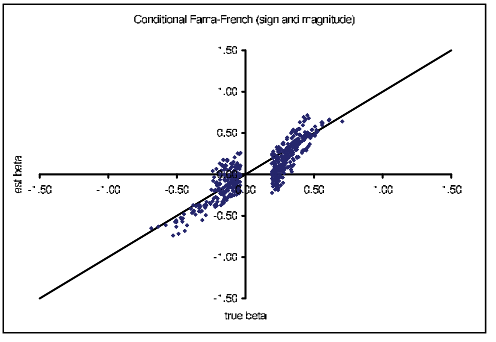


(a) *RMRF* and the Conditional Fama and French (sign and magnitude)

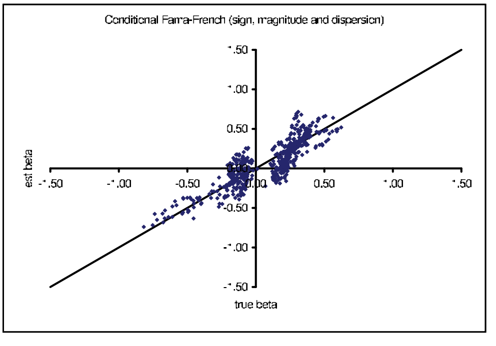


(b) *RMRF* and the Conditional Fama and French (sign, magnitude and dispersion)

Figure 2.2 continued

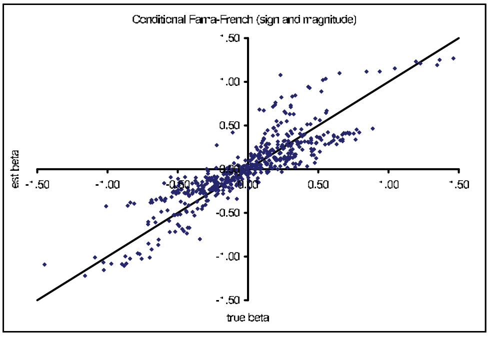


(c) *SMB* and the Conditional Fama and French (sign and magnitude)

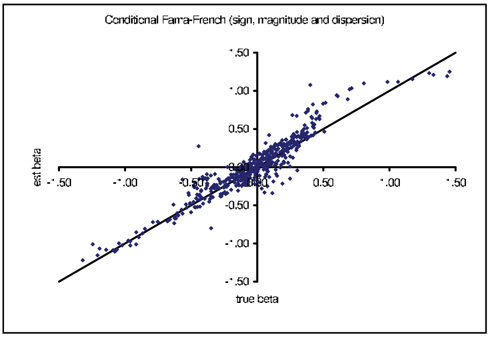


(d) *SMB* and the Conditional Fama and French (sign, magnitude and dispersion)

Figure 2.2 continued



(e) *HML* and the Conditional Fama and French (sign and magnitude)



(f) *HML* and the Conditional Fama and French (sign, magnitude and dispersion)

Next, we want to show in numbers how well each model estimates the true time-varying exposures. Table 2.3 demonstrates the mean, standard deviation and MSE of the time-varying exposures. First, in Panel A we consider all exposures together. If we add the three MSEs obtained for RMRF, SMB and HML, respectively, we get 0.486 for the Fama and French model. Adding WML improves this to 0.406. The conditional model of Huij et al. (2007) only considering the sign of the factor returns has an aggregate MSE of 0.281. Adding a third parameter the Grundy and Martin model lowers the MSE further to 0.231. It is, however, much more accurate to include the magnitude of the factor return, lowering the MSE to 0.108. Finally also adding dispersion gives a MSE of 0.066, which is a reduction of about 86 percent, compared to the MSE of the Fama and French model. Furthermore, we also show in Panel B and C that our proposed model in equation (2.4) always perform the best amongst other models in all states (e.g. when the past year factor return is positive, or when a positive past year factor return is followed by a negative factor return in the investment month). On the other hand several alternatives may only outperform other models during certain states. For example, when the past year market return is positive, the Carhart model provides better estimation than the Fama and French model. However, when the past year SMB is positive, the Fama and French model provides better estimates than the Carhart model. Additionally, we show in Table 2.3 that the true exposures vary across time (Panel A) as well as during certain states (Panel B and C). However, several models assume constant exposures during certain states and this causes a bias. For example, in Panel A the standard deviations of the true exposures across time are not equal to zero, but the standard deviations of the exposures that are estimated by the Fama and French model are zero. And in Panel B the standard deviations of the true exposures in the up and down states are not equal to zero, but the standard deviations of the exposures that are estimated by the conditional model of Huij et al. (2007) are zero. Hence as expected our proposed model in equation (2.4) not only most accurately estimates the alpha but also the betas.

Table 2.3: Time-Varying Exposures

This table demonstrates the true values as well as the estimated exposures of the return difference between the winner and loser deciles from the six models mentioned in the table head. Panel A shows the value across time, while panel B shows the exposure in UP and DOWN states. UP (DOWN) state is the condition when the past year factor return is positive (negative). Panel C demonstrates the results in UP UP, UP DOWN, DOWN UP, and DOWN DOWN states, where the first word refers to the condition of the past year factor return and the second word refers to the condition of factor return in the investment month. The mean, standard deviation and MSE of the exposures are shown.

Panel A. Three Factors

		True Exposure	Fama and French	Carhart	Cond. Fama and French (sign)	Grundy and Martin	Cond. Fama and French (sign and magnitude)	Cond. Fama and French (sign, magnitude and disperision)
RMRF	mean	0.056	-0.100	-0.030	0.067	0.044	0.075	0.061
	std	0.394	0.000	0.118	0.403	0.324	0.382	0.392
	MSE		0.181	0.101	0.073	0.065	0.039	0.017
SMB	mean	0.067	0.280	0.016	0.149	0.124	0.110	0.075
	std	0.288	0.000	0.177	0.272	0.292	0.267	0.272
	MSE		0.133	0.143	0.056	0.045	0.027	0.026
HML	mean	0.018	-0.060	-0.169	0.032	0.010	-0.001	-0.014
	std	0.404	0.000	0.204	0.516	0.488	0.420	0.396
	MSE		0.172	0.163	0.153	0.121	0.042	0.024
	MSE all betas		**0.486**	**0.406**	**0.281**	**0.231**	**0.108**	**0.066**

Table 2.3 continued

Panel B. Three Factors In Up and Down states

		True Exposure	Fama and French	Carhart	Cond. Fama and French (sign)	Grundy and Martin	Cond. Fama and French (sign and magnitude)	Cond. Fama and French (sign, magnitude and disperision)
RMRF UP	mean	0.253	-0.100	0.042	0.330	0.186	0.289	0.270
	std	0.251	0.000	0.046	0.000	0.200	0.230	0.241
	MSE		0.189	0.096	0.069	0.059	0.035	0.015
RMRF DOWN	mean	-0.410	-0.100	-0.201	-0.550	-0.288	-0.427	-0.431
	std	0.253	0.000	0.014	0.000	0.316	0.062	0.187
	MSE		0.163	0.112	0.083	0.080	0.049	0.022
SMB UP	mean	0.236	0.280	0.023	0.380	0.259	0.318	0.275
	std	0.206	0.000	0.204	0.000	0.218	0.095	0.112
	MSE		0.048	0.165	0.063	0.032	0.042	0.028
SMB DOWN	mean	-0.168	0.280	0.007	-0.170	-0.061	-0.176	-0.200
	std	0.210	0.000	0.132	0.000	0.283	0.126	0.170
	MSE		0.250	0.111	0.044	0.061	0.072	0.023
HML UP	mean	0.200	-0.060	-0.119	0.380	0.206	0.209	0.167
	std	0.309	0.000	0.221	0.000	0.349	0.307	0.291
	MSE		0.167	0.204	0.128	0.104	0.042	0.024
HML DOWN	mean	-0.378	-0.060	-0.275	-0.730	-0.417	-0.460	-0.408
	std	0.290	0.000	0.096	0.000	0.476	0.224	0.298
	MSE		0.185	0.073	0.208	0.159	0.044	0.022

Table 2.3 continued

Panel C. Three Factors In Up-Up, Up-Down, Down-Up and Down-Down states

		True Exposure	Fama and French	Carhart	Cond. Fama and French (sign)	Grundy and Martin	Cond. Fama and French (sign and magnitude)	Cond. Fama and French (sign, magnitude and disperision)
RMRF UP UP	mean	0.232	-0.100	0.038	0.330	0.174	0.266	0.249
	std	0.244	0.000	0.043	0.000	0.190	0.214	0.224
	MSE		0.173	0.087	0.069	0.055	0.032	0.012
RMRF UP DOWN	mean	0.288	-0.100	0.050	0.330	0.205	0.326	0.304
	std	0.259	0.000	0.049	0.000	0.214	0.250	0.263
	MSE		0.217	0.110	0.068	0.065	0.041	0.019
RMRF DOWN UP	mean	-0.390	-0.100	-0.201	-0.550	-0.287	-0.425	-0.419
	std	0.256	0.000	0.014	0.000	0.317	0.064	0.193
	MSE		0.154	0.107	0.091	0.079	0.051	0.022
RMRF DOWN DOWN	mean	-0.429	-0.100	-0.200	-0.550	-0.289	-0.430	-0.442
	std	0.250	0.000	0.013	0.000	0.317	0.060	0.179
	MSE		0.169	0.116	0.074	0.081	0.047	0.022
SMB UP UP	mean	0.232	0.280	0.034	0.380	0.266	0.319	0.280
	std	0.198	0.000	0.213	0.000	0.222	0.094	0.116
	MSE		0.045	0.156	0.061	0.034	0.038	0.026
SMB UP DOWN	mean	0.243	0.280	0.007	0.380	0.248	0.316	0.269
	std	0.218	0.000	0.188	0.000	0.213	0.098	0.106
	MSE		0.052	0.180	0.066	0.030	0.046	0.029
SMB DOWN UP	mean	-0.173	0.280	0.016	-0.170	-0.067	-0.175	-0.199
	std	0.210	0.000	0.139	0.000	0.286	0.128	0.175
	MSE		0.255	0.116	0.044	0.066	0.073	0.025
SMB DOWN DOWN	mean	-0.163	0.280	0.001	-0.170	-0.056	-0.177	-0.200
	std	0.210	0.000	0.127	0.000	0.281	0.125	0.167
	MSE		0.244	0.106	0.043	0.057	0.071	0.022
HML UP UP	mean	0.197	-0.060	-0.103	0.380	0.233	0.222	0.170
	std	0.312	0.000	0.225	0.000	0.370	0.307	0.291
	MSE		0.169	0.188	0.131	0.106	0.039	0.025
HML UP DOWN	mean	0.203	-0.060	-0.146	0.380	0.161	0.188	0.163
	std	0.306	0.000	0.211	0.000	0.308	0.307	0.290
	MSE		0.166	0.234	0.124	0.103	0.046	0.024
HML DOWN UP	mean	-0.356	-0.060	-0.274	-0.730	-0.367	-0.448	-0.397
	std	0.290	0.000	0.104	0.000	0.473	0.238	0.305
	MSE		0.168	0.066	0.218	0.148	0.047	0.028
HML DOWN DOWN	mean	-0.405	-0.060	-0.277	-0.730	-0.482	-0.476	-0.422
	std	0.290	0.000	0.085	0.000	0.476	0.205	0.288
	MSE		0.199	0.079	0.186	0.167	0.038	0.014

2.5 Empirical Results

In this section we discuss the persistence in mutual fund performance by using the empirical data and the knowledge that the bootstrap has identified the model in equation (2.4) as the most accurate to make conclusions regarding persistence in mutual fund returns. The empirical results are shown in Table 2.4.

Panel A shows the results when using the Fama and French model in equation (2.1). Consistent with persistence found by Hendricks et al. (1993) we see that the alpha of going long in the past winners and short in the past losers is estimated at 10.62 percent with a t-statistic of 4.2. The alphas also monotonously decrease from decile 1 to decile 10.

Next we confirm Carhart's (1997) results that adding momentum in stock returns (WML) as explanatory variable renders the alpha insignificant at 1.89 percent. Hence this result suggests that persistence in mutual fund returns is basically non-existent. Additionally, the Carhart model in our data also suggests that neither the top decile funds nor the bottom decile funds outperform or underperform persistently. We know, however, from Section 2.4 that the Carhart model underestimates the alpha. What is notable from Panel B is that the Carhart model explains 48 percent of the variation in the return differential of mutual funds, much larger than the 9 percent for the Fama and French model.

Given that we concluded in Section 2.4 that to model the time-variation in the factor exposures we should consider the sign and magnitude of the factor return as well as the dispersion in mutual fund exposures we now proceed to Panel F in Table 2.4. The results for the model in equation (2.4) show that the alpha is 6.72 percent per annum, which is highly significant with a t-statistic of 5.3. Hence although this is much lower than what the Fama and French model suggests, our results do not support Carhart's conclusion that there is no persistence. Also the adjusted R-squared of 78 percent shows that our model adequately describes the time-varying risk exposures of the return differential of mutual funds.

Table 2.4: Empirical Results

This table shows the results from empirical data. Mutual funds are sorted into equally weighted decile portfolios based on 12-month returns. The decile portfolios, with D1 containing the winners and D10 the losers, are rebalanced monthly. In Panel A to F, the decile post-ranking returns are evaluated using the Fama and French model, the Carhart model, the Conditional Fama and French model from equation (2.3), the Grundy and Martin model in equation (2.5), the Conditional Fama and French model from equation (2.4) that excludes dispersion and the complete Conditional Fama and French model from equation (2.4), respectively. The alphas, t-values, the exposures to the risk factors, and the adjusted R^2 are shown. MAG is the past year factor return, and DISP is the standard deviation of individual funds exposures.

Panel A. Fama and French model

	Alpha	Alpha-t	RMRF	SMB	HML	Adj. R^2
D1	5.52	4.08	0.76	0.55	-0.15	0.76
D2	2.45	2.76	0.79	0.36	-0.04	0.86
D3	0.76	1.14	0.82	0.23	0.02	0.91
D4	-0.32	-0.60	0.83	0.16	0.05	0.94
D5	-1.07	-2.33	0.83	0.11	0.05	0.95
D6	-1.40	-2.38	0.80	0.07	0.05	0.91
D7	-1.85	-2.41	0.78	0.06	0.05	0.85
D8	-2.13	-2.30	0.78	0.07	0.05	0.80
D9	-3.92	-3.45	0.77	0.08	0.03	0.73
D10	-5.10	-3.42	0.81	0.12	0.00	0.64
D1-D10	10.62	4.21	-0.04	0.43	-0.15	0.09

Panel B. Carhart model

	Alpha	Alpha-t	RMRF	SMB	HML	WML	Adj. R^2
D1	0.93	0.87	0.81	0.63	-0.09	0.34	0.86
D2	-0.10	-0.13	0.82	0.40	-0.01	0.19	0.90
D3	-0.82	-1.33	0.84	0.26	0.04	0.12	0.93
D4	-1.32	-2.57	0.84	0.18	0.07	0.07	0.94
D5	-1.34	-2.86	0.83	0.11	0.05	0.02	0.95
D6	-1.16	-1.92	0.80	0.06	0.05	-0.02	0.91
D7	-0.97	-1.27	0.77	0.05	0.03	-0.07	0.86
D8	-0.43	-0.48	0.76	0.04	0.03	-0.13	0.82
D9	-1.52	-1.42	0.75	0.04	0.00	-0.18	0.77
D10	-0.96	-0.74	0.77	0.04	-0.06	-0.31	0.74
D1-D10	1.89	0.97	0.04	0.59	-0.03	0.65	0.48

Panel C. Conditional Fama and French (sign)

	Alpha	Alpha-t	RMRF UP	RMRF DOWN	SMB UP	SMB DOWN	HML UP	HML DOWN	Adj. R^2
D1	2.65	2.79	1.02	0.50	0.66	0.19	0.10	-0.52	0.88
D2	0.68	1.04	0.96	0.62	0.43	0.14	0.11	-0.26	0.92
D3	-0.24	-0.42	0.93	0.70	0.26	0.13	0.10	-0.10	0.94
D4	-0.80	-1.60	0.90	0.76	0.17	0.11	0.09	0.01	0.94
D5	-1.01	-2.17	0.84	0.82	0.10	0.12	0.04	0.07	0.95
D6	-1.00	-1.74	0.75	0.85	0.06	0.10	0.01	0.11	0.92
D7	-1.02	-1.46	0.68	0.89	0.05	0.14	-0.03	0.17	0.88
D8	-0.66	-0.87	0.62	0.96	0.03	0.22	-0.08	0.25	0.87
D9	-1.90	-2.15	0.57	0.99	0.01	0.31	-0.15	0.29	0.84
D10	-2.43	-2.15	0.53	1.11	0.04	0.40	-0.25	0.38	0.80
D1-D10	5.08	3.17	0.49	-0.61	0.62	-0.21	0.35	-0.90	0.64

Table 2.4 continued

Panel D. Grundy and Martin model

	Alpha	Alpha-*t*	RMRF UP	RMRF FLAT	RMRF DOWN	SMB UP	SMB FLAT	SMB DOWN	HML UP	HML FLAT	HML DOWN	Adj R^2
D1	3.12	3.29	1.02	0.93	0.48	0.77	0.46	0.01	0.43	-0.09	-0.60	0.88
D2	1.11	1.62	0.95	0.88	0.64	0.47	0.32	0.02	0.36	-0.04	-0.30	0.92
D3	0.09	0.16	0.94	0.87	0.72	0.27	0.23	0.05	0.28	0.00	-0.12	0.93
D4	-0.54	-1.04	0.89	0.86	0.78	0.16	0.15	0.13	0.21	0.02	0.01	0.94
D5	-0.91	-1.98	0.82	0.83	0.83	0.07	0.12	0.15	0.08	0.02	0.08	0.95
D6	-1.09	-2.05	0.61	0.81	0.87	0.01	0.07	0.21	0.03	0.01	0.15	0.93
D7	-1.36	-2.14	0.45	0.78	0.91	-0.01	0.07	0.27	-0.06	0.01	0.22	0.90
D8	-1.15	-1.65	0.40	0.75	0.95	-0.05	0.09	0.41	-0.19	0.01	0.32	0.89
D9	-2.52	-3.10	0.33	0.72	1.00	-0.10	0.11	0.57	-0.30	-0.02	0.36	0.86
D10	-3.26	-3.14	0.21	0.73	1.12	-0.10	0.17	0.70	-0.52	-0.04	0.45	0.83
D1-D10	6.38	4.21	0.81	0.20	-0.64	0.86	0.29	-0.69	0.95	-0.05	-1.05	0.68

Panel E. Conditional Fama and French (sign and magnitude)

	Alpha	Alpha-*t*	RMRF UP	RMRF DOWN	RMRF MAG UP	RMRF MAG DOWN	SMB UP	SMB DOWN	SMB MAG UP	SMB MAG DOWN	HML UP	HML DOWN	HML MAG UP	HML MAG DOWN	Adj R^2
D1	2.99	3.35	0.91	0.63	0.08	0.05	0.61	0.31	0.04	0.15	-0.16	-0.38	0.20	0.09	0.90
D2	0.78	1.23	0.92	0.70	0.02	0.03	0.44	0.21	-0.01	0.09	-0.06	-0.24	0.13	0.01	0.93
D3	-0.15	-0.26	0.88	0.71	0.03	0.00	0.31	0.16	-0.02	0.05	0.00	-0.15	0.08	-0.04	0.94
D4	-0.78	-1.57	0.86	0.77	0.02	0.01	0.23	0.09	-0.02	-0.02	0.05	-0.09	0.03	-0.08	0.95
D5	-1.08	-2.36	0.82	0.81	0.01	0.00	0.18	0.11	-0.05	-0.01	0.05	-0.04	-0.01	-0.09	0.95
D6	-1.42	-2.60	0.90	0.84	-0.12	-0.01	0.13	0.04	-0.05	-0.07	0.06	-0.02	-0.02	-0.09	0.93
D7	-1.68	-2.58	0.92	0.86	-0.19	-0.01	0.12	0.07	-0.07	-0.08	0.06	0.04	-0.04	-0.08	0.90
D8	-1.37	-1.99	0.88	0.93	-0.20	0.00	0.10	0.13	-0.06	-0.11	0.08	0.07	-0.10	-0.12	0.89
D9	-2.79	-3.51	0.88	0.96	-0.24	0.00	0.11	0.17	-0.09	-0.17	0.07	0.10	-0.14	-0.12	0.87
D10	-3.66	-3.72	0.96	1.08	-0.33	0.02	0.15	0.25	-0.11	-0.19	0.15	0.16	-0.28	-0.13	0.85
D1-D10	6.65	4.92	-0.04	-0.45	0.41	0.04	0.46	0.06	0.15	0.34	-0.32	-0.54	0.48	0.22	0.75

Table 2.4 continued

Panel F. Conditional Fama and French (sign, magnitude and dispersion)

	Alpha	Alpha-t	RMRF UP	RMRF DOWN	RMRF MAG UP	RMRF MAG DOWN	RMRF DISP UP	RMRF DISP DOWN	RMRF MAG DISP UP	RMRF MAG DISP DOWN	SMB UP	SMB DOWN	SMB MAG UP	SMB MAG DOWN
D1	2.99	3.62	1.73	1.29	-0.26	0.00	-2.64	-2.01	1.09	0.21	-0.62	-1.29	1.15	-1.52
D2	1.03	1.89	1.38	1.57	-0.14	0.01	-1.47	-2.71	0.54	0.13	-0.56	-0.46	0.62	-0.95
D3	0.01	0.02	1.27	1.41	-0.09	-0.10	-1.24	-2.13	0.42	0.37	0.06	-0.01	0.19	-0.25
D4	-0.79	-1.92	1.52	1.40	-0.21	-0.09	-2.11	-1.96	0.78	0.34	0.12	-1.09	0.18	-0.83
D5	-1.15	-3.02	1.53	1.34	-0.20	0.08	-2.31	-1.67	0.71	-0.23	0.25	-0.76	0.07	-0.24
D6	-1.53	-3.77	1.36	1.54	0.06	0.24	-1.70	-2.27	-0.32	-0.79	0.10	-1.27	0.13	-0.43
D7	-1.79	-3.81	1.37	1.48	0.18	0.31	-1.75	-2.03	-0.80	-1.06	-0.30	-0.80	0.30	0.01
D8	-1.55	-3.35	1.55	1.00	0.09	-0.02	-2.44	-0.18	-0.56	0.08	-0.50	-0.82	0.13	0.30
D9	-2.94	-5.34	1.61	1.10	0.09	0.03	-2.67	-0.39	-0.64	-0.09	-0.71	-0.86	0.13	0.74
D10	-3.73	-4.42	1.37	1.27	0.07	0.22	-1.64	-0.66	-0.87	-0.73	-0.83	-0.93	0.07	0.15
D1-D10	6.72	5.28	0.37	0.02	-0.32	-0.21	-1.00	-1.35	1.96	0.94	0.21	-0.36	1.08	-1.67

	SMB DISP UP	SMB DISP DOWN	SMB MAG DISP UP	SMB MAG DISP DOWN	HML UP	HML DOWN	HML MAG UP	HML MAG DOWN	HML DISP UP	HML DISP DOWN	HML MAG DISP UP	HML MAG DISP DOWN	Adj R^2
D1	3.76	4.93	-3.39	5.37	-0.44	0.45	0.31	0.67	0.82	-2.54	-0.32	-1.62	0.91
D2	3.13	2.03	-1.94	3.41	-0.30	-0.16	0.30	0.14	0.62	-0.15	-0.46	-0.32	0.95
D3	0.79	0.48	-0.66	1.03	-0.17	-0.24	0.17	0.00	0.42	0.38	-0.28	-0.01	0.95
D4	0.35	3.62	-0.67	2.66	-0.25	-0.13	0.21	-0.06	0.83	0.22	-0.49	0.03	0.96
D5	-0.17	2.70	-0.36	0.80	-0.07	-0.12	0.00	0.04	0.36	0.34	-0.05	-0.24	0.97
D6	0.14	4.14	-0.55	1.23	0.08	-0.20	-0.06	0.09	-0.10	0.66	0.07	-0.35	0.96
D7	1.38	2.80	-1.11	-0.21	0.00	-0.19	-0.03	0.06	0.11	0.73	-0.04	-0.29	0.95
D8	1.94	2.99	-0.59	-1.25	0.28	-0.22	-0.19	-0.22	-0.58	0.76	0.24	0.21	0.95
D9	2.66	3.23	-0.63	-2.84	0.26	-0.30	-0.21	-0.13	-0.53	1.16	0.20	0.02	0.94
D10	3.14	3.71	-0.51	-1.09	0.25	-0.34	0.00	-0.16	-0.56	1.46	-0.60	0.07	0.89
D1-D10	0.62	1.22	-2.88	6.47	-0.70	0.79	0.30	0.82	1.38	-4.00	0.29	-1.69	0.78

The significant persistence that we find in the model in equation (2.4) comes from two sides. First, the top decile return funds have persistently outperformed with the alpha of 2.99 percent per annum and a t-statistic of 3.62. And second, the bottom decile return funds have persistently underperform with the alpha of -3.73 percent per annum and a t-statistic of -4.42. From an economic perspective, it is relieving for funds investors that the existence of persistence comes from both the winners as well as losers and that the strategy of selecting a fraction of past winners still returns profitable outcome during ex-post periods. Furthermore, we observe that the alphas of the ten deciles monotonically decline from the top decile to the bottom decile, with only the top 10 percent of funds has significant positive alpha and about half of the fund universe has significant negative alpha. Additionally, we observe that the time varying exposures of the return differential between the top and bottom deciles are pretty strong. For example, for a comparison a constant market exposure of the Fama and French model is equal to -0.04. And from the model in equation (2.4), the market exposure can be strongly different depending on the sign and magnitude of the factor return as well as the dispersion in mutual fund exposures. For example, the loading of the sign is 0.37 or 0.02, the loading of the sign and magnitude is -0.32 or -0.21, the loading of the sign and dispersion is -1 or -1.35 and the loading of the sign, magnitude and dispersion is 1.96 or 0.94 depending on the state of factor return. Moreover, by taking into account the time-varying exposures as in equation (2.4), the spread of exposures between deciles are more visible. For example, the decile market exposures of the Fama and French model ranges from 0.76 to 0.83, while the decile market exposures of the sign in up state market return ranges from 1.27 to 1.73.

Table 2.4 also shows the results for the Grundy and Martin model (Panel D) and the restricted versions of equation (2.4) that only consider the sign (equation (2.3)) or the sign and magnitude. Just like in the bootstrap analysis we find that when going from Panel C to Panel E the alpha is lower but closing in on the alpha of our preferred model. Also in all cases the alpha is statistically significant suggesting persistence exists. And the R-squared shows the gradual improvement in explaining the return differential of mutual funds when adding additional variables to the time-varying loadings.

To summarize, by considering the time-varying exposures, we conclude that persistence exists. And the persistence exists from both the winner funds as well as the loser funds. Additionally ignoring the time-variation in exposures will overestimate the persistence, while inadequately modelling the time-variation in the factor exposures results in the underestimation of the persistence.

2.6 Conclusion

The standard in the academic literature to evaluate persistence in mutual fund performance is to compute the risk-adjusted return differential between winner and loser funds. By ranking mutual funds on their past return, Carhart (1997) shows that the persistence found by Hendricks et al. (1993) can be mostly attributed to momentum in stock returns.

In this study we use bootstrap analysis to show that the Carhart model underestimates persistence, whereas the Fama and French model overestimates persistence. The main reason is that the return differential between winner and loser funds has systematic time-variation in the exposures to the Fama and French factors. In particular these exposures depend strongly on the sign and magnitude of the past year factor returns, as well as the dispersion in individual mutual fund exposures. This has two consequences. First, ignoring this time-variation leads to overestimation of the persistence in mutual fund returns, because factor returns show positive autocorrelation. Second, because WML has the same time-variation in the factor loadings, the return differential will load positively on WML. This, however, will also downward bias the estimated level of persistence due to also incorporating the large alpha of WML. The bootstrap reveals that the true persistence is somewhere in the middle of what is obtained with the Fama and French and Carhart models. It also shows that it is important to take into account all three reasons for time-variation in the factor exposures, which are the sign and magnitude of the past year factor returns, and the dispersion of funds exposures. Only considering the sign of the past year factor returns (Huij et al. (2007)) also underestimates the true level of persistence.

The empirical results confirm our proposed conditional Fama and French model. In particular our model has the largest explanatory power for the return differential between winner and loser funds, with an adjusted R-squared of 78 percent. From our proposed conditional Fama and French model we conclude that persistence exists and both winner funds as well as loser funds outperform and underperform persistently. From the economic point of view, this conclusion indicates that the fund investors can have profitable strategy by using the past information.

We want to end with noting that any strategy for any asset class that is based on sorting returns will lead to similar dynamics in factor exposures to factors relevant for the asset class under investigation. Hence it will be interesting for future research to also consider our model for analyzing the risk-adjusted performance of such strategies.

Chapter 3

Mutual Funds Selection Based on Fund Characteristics

3.1 Introduction

Existing studies document that past performance of mutual funds can be used to predict future performance. See, for example, Elton et al. (1996) who rank mutual funds on their risk-adjusted performance and subsequently find that the top decile funds outperform the bottom decile funds. Similarly, Elton et al. (2004) rank mutual funds on their risk-adjusted performance and observe that the rank correlation between the deciles that are based on past and realized risk-adjusted performance is high. Moreover, Hendricks et al. (1993) base their ranking on returns and performance persists for a one-year evaluation horizon. Accordingly, investors can implement the momentum strategy, i.e. buying the past winner funds. As documented by many studies (eg. Hendricks et al. (1993) and Carhart (1997)), this strategy produces positive risk-adjusted returns but is not statistically significant. This study examines whether investors can improve upon selecting mutual funds by also using fund characteristics. In short, we find that some fund characteristics significantly predict future performance and that investors can improve the performance of their portfolios by using those variables in their investment strategy.

Table 3.1 summarizes the findings of influential studies that discuss the relation between fund characteristics and fund performance. Besides explaining mutual fund performance by regression, several of these papers use one characteristic to rank funds. Bollen and Busse (2004) investigate whether mutual fund performance persists by ranking funds on their risk-adjusted returns and find that short persistence exists. Carhart (1997) discovers that investment expenses and turnover explain persistence in mutual fund risk-adjusted returns. Furthermore, Chen et al. (2004) document that the size of mutual fund erodes its performance and Elton et al. (1996) conclude that mutual fund past performance (eg. 3 year alpha, t-statistic of 3-year alpha) can predict its future risk-adjusted return. Moreover, Elton et al. (2004) report that the performance of low expense funds or high past returns funds is higher than that of the portfolio of index funds that are selected by investors. Grinblatt and Titman (1994) show that fund turnover explains the risk-adjusted returns of mutual funds and Kacperczyk et al. (2005) demonstrate that fund size and turnover determine the fund performance. Moreover, Kosowski et al. (2007) report that ranking funds on their t-statistics of alphas demonstrates more persistent performance than ranking funds on their alphas. And Wermers (2000) finds that funds which trade more frequently produce better performance than funds which trade less. In summary, past performance always appears to play a significant role in predicting future performance and in most cases turnover ratio also explains fund performance significantly. However, the conclusions about expense ratio, size and the t-statistic of the 3-year Fama and French (1993) alpha are mixed as some authors agree that they can explain or predict performance while others conclude the opposite. Finally, fund age has never appeared to significantly explain performance.

In this study, we test a new predictive variable ”ability” that measures risk-adjusted fund performance from the time the fund exists until the moment we want to predict future performance. In short, it is the t-statistic of the Fama and French (1993) alpha that is measured over the life of a fund. The intuition is the following. Given two funds that have the same age, we prefer to choose the fund that has the highest performance during its whole life. Additionally, given two funds that have a similar risk-adjusted performance, we prefer the fund that has already made this performance over a longer period. In a way, it combines age and risk-adjusted performance. Previous studies use the t-statistic of alpha over a particular window, usually three years but not over the full life of a fund. As far as we know only Barras et al. (2009) use the t-statistic for ability to identify the number of (un-)skilled funds in the universe but not to predict alphas.

Table 3.1: Existing Findings

This table shows the summary of what other outstanding papers find about the relation between the mutual fund performance and fund characteristics (alpha, expense, size, age, turnover, t-statistic of 3 year alpha). v marks which fund characteristics is studied by the corresponding paper in each row. * denotes that the variable significantly explains fund performance at the 5 percent significance level. If the author uses a single variable to rank mutual funds, * denotes that the difference of the performance between the top and bottom portfolios is significant at the 5 percent significance level.

Paper	alpha	expense	size	age	turnover	t-statistic of 3y alpha
Bollen and Busse (2004)	v*					
Carhart (1997)		v*	v		v*	
Carhart (1997)	v*					
Chen et al. (2004)		v	v*	v	v	
Elton et al. (1996)	v*					v*
Elton et al. (2004)	v*	v*				
Grinblatt and Titman (1994)		v			v*	
Kacperczyk et al. (2005)		v	v*	v	v*	
Kosowski et al. (2007)	v					v
Wermers (2000)					v*	

Having investigated all aforementioned fund characteristics, we find that past performance, turnover ratio and ability of mutual funds can significantly predict future performance. Past performance predicts future performance because enough of those winners are skilled managers. Additionally, skilled managers that trade more often (high turnover funds) use their skills and information more often resulting in better performance than low turnover funds. The significance of the turnover ratio corresponds to the findings of Grinblatt and Titman (1994), Kacperczyk et al. (2005) and Wermers (2000). Since the turnover ratio in subsequent years is highly correlated, we find it does not only explain but also predict mutual fund performance.

Next, we use all three variables together to select funds. Hence, instead of ranking funds on past performance, we rank them on their predicted performance based on three variables. Thus, we use several fund characteristics to select funds while other papers rank funds based on one characteristic. By selecting funds that have the highest 10 percent predicted performance (the predicted alpha strategy) and then forming and rebalancing the portfolios yearly, our investment strategy delivers a risk-adjusted return that is significantly higher than selecting funds that have the highest 10 percent past performance (the momentum strategy). The difference between the risk-adjusted returns of both strategies is 0.86 percent per year, with a t-statistic of 2.98. The risk-adjusted returns of the predicted alpha strategy and the momentum strategy are 1.70 percent and 0.84 percent per year, respectively. These risk-adjusted returns are already estimated from net returns and in excess of the one-month Treasury bill rate. The results are still robust if we select the top 5 percent, the top 20 percent, or the top 20 funds. Moreover, the predicted alpha strategy does not only have higher risk-adjusted return, but also higher total net return, Sharpe ratio and less turnover than the momentum strategy. Hence, the implementation of the predicted alpha strategy is cheaper than that of the momentum strategy.

3.2 Data and Methodology

We extract the data from the CRSP Survivorship-Bias-Free U.S. Mutual Fund database that covers the period from 1962 to 2006. We exclude balanced funds, bond funds, flexible funds, money market funds, mortgage-backed funds, multi-manager funds and international funds. Each fund that is included in the sample is classified as either small company growth, aggressive growth, growth, income, growth and income or maximum capital gains, according to the classification provided by Wiesenberger, Micropal/Investment Company Data, Inc (ICDI) and Standard & Poors. This funds selection is similar to that of Pastor and Stambaugh (2002). We only include funds that do not charge front and rear load fees because the net return data from the CRSP database is net of expenses and fees, except load fees. At the same time, the magnitude of load fees can be quite significant. For example, Livingston and O'Neal (1998) show that the annual front load fees can vary from 1 percent to 8.5 percent. Since this paper aims to fund strategies that have better net performance, we want the return data of individual mutual fund to be net of load fees as well.

Fund returns are available monthly, whereas fund characteristics are reported annually. Returns are calculated in excess of the one-month Treasury bill rate. The fund characteristics that are included in our analysis are (i) alpha which is estimated in equation (3.1) below from monthly returns during a 3-year window; (ii) ability which is calculated from the t-statistic of alpha in equation (3.1) and is estimated from the time when the fund exists until the time of observation; (iii) expense ratio which is the ratio between all expenses (e.g. 12b-1 fee, management fee, administrative fee) and total net assets; (iv) size which is proxied by the fund's total net assets that is reported in millions of U.S. dollars; (v) age which is the duration between the time the fund exists until the time of observation and reported in the number of months; (vi) turnover ratio which is the minimum of aggregated sales or aggregated purchases of securities, divided by total net assets; and (vii) volatility which is standard deviation of returns over a 12-month window.

$$r_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \varepsilon_{i,t}. \tag{3.1}$$

where $r_{i,t}$ is the excess return of fund i in month t, $RMRF_t$ is the excess return on the market portfolio, SMB_t is the excess return on the factor mimicking portfolio for size (Small Minus Big), HML_t is the excess return on the factor mimicking portfolio for the book-to-market ratio (High Minus Low)[1], and $\varepsilon_{i,t}$ is the residual return of fund i in month t.

We divide the sample into two groups each of which have about 4000 funds. The first group is used to analyze which fund characteristics predict performance whereas the second group is used to validate the selected fund characteristics from the previous analysis. Subsequently, we use all funds to implement the momentum strategy and the strategy that also uses fund characteristics besides past performance. To measure risk-adjusted performance for the strategies we use 3-year alphas from equation (3.1). We divide the funds according to several criteria in sequence. These criteria are return, alpha, size, expense ratio, turnover ratio, age and volatility of fund returns. For example, the entire sample is first split between high and low return funds. Then each of these is divided into high and low alpha funds. Hence, in total there are four groups of funds (high return-high alpha funds, high return-low alpha funds, low return-high alpha funds and low return-low alpha funds). We proceed with other characteristics in the same manner. At the end, there are 128 subsets of funds. Next, we put half of each subset in the first

[1]We thank Kenneth French for providing the RMRF, SMB and HML factor data.

group, and the other half in the second group.

3.3 Predictability of Mutual Fund Performance

To analyze the predictability of mutual fund performance, we regress the alphas of individual funds on their characteristics in the previous period,

$$\begin{aligned}\alpha_{t+1\ to\ t+3,i} = \hat{z}_0 + \hat{z}_1\alpha_{t-2\ to\ t,i} + \hat{z}_2 ability_{t,i} + \hat{z}_3 expense_{t,i} \\ + \hat{z}_4 size_{t,i} + \hat{z}_5 age_{t,i} + \hat{z}_6 turnover_{t,i} + \hat{z}_7 volatility_{t,i} + \hat{\varepsilon}_{t,i}\end{aligned} \tag{3.2}$$

where $\alpha_{t+1\ to\ t+3,i}$ is estimated from fund i's monthly returns during year $t+1$ until year $t+3$ using equation (3.1). The fund characteristics in each year are standardized by deducting the cross-sectional mean and dividing by the cross-sectional standard deviation. This avoids numerical problems and makes the loadings of the different characteristics comparable. Following Fama and Macbeth (1973), the cross-sectional regression is implemented every year, and we compute the mean and t-statistic from the yearly loadings.

As we mention in Section 3.2, we create two group of funds based on several criteria. The first group is used to analyze which fund characteristics predict performance whereas the second group is used to validate the selected fund characteristics. By using the first group of funds from 1962 to 2006, Panel A of Table 3.2 shows whether a fund characteristic predicts fund performance. We find that the past alpha and turnover ratio most significantly predict the future alpha, which confirms results in existing literature summarized in Table 3.1. However, if we divide the sample into two sub-periods, we observe that past alpha becomes insignificant in the second sub-period, whereas ability becomes highly significant (see Panel B of Table 3.2). In unreported results we also run the regression without alpha and find that ability is significant in both sub-periods. Similarly, when leaving out ability, the past alpha is significant in both sub-periods. Moreover, by using the F test, we reject the null hypothesis that the omitted variable has a zero coefficient. Hence, it is important to include both alpha and ability in the analysis despite their correlation being 0.68. From these results, the selected variables for the implementation of an investment strategy are, therefore, alpha, ability and turnover.

Table 3.2: Predictability Power of Fund Characteristics
We divide the sample into two groups of funds according to seven criteria in sequence. Every time funds are split into two based on a criterion. Hence, after we use all criteria to split funds, there are 128 subsets of funds that have different characteristics. Next, for each subset we put half in the first group and the other half in the second group. The first group is used to analyze which fund characteristics predict performance and the second is used to validate the findings from the first group. This table shows the results of the first group of funds. 3-year alphas of individual funds are regressed on their characteristics (alpha, ability, expense, log size, log age, turnover and volatility) in the previous period by using equation (3.2). The results of the full period use the data from 1962 to 2006, whereas those of the first and second sub-periods use the data from 1962 to 1984 and 1985 to 2006, respectively.

Panel A: Full period

	load	t
Adj R2	0.119	
Intercept	0.036	1.722
alpha	0.160	3.793
ability	0.059	1.765
expense	-0.062	-1.439
log size	-0.050	-1.506
log age	-0.028	-1.986
turnover	0.076	2.477
volatility	0.039	1.002

Panel B: Sub-periods

	First sample		Second sample	
	load	t	load	t
Adj R2	0.160		0.080	
Intercept	0.054	1.296	0.019	2.252
alpha	0.256	3.628	0.064	1.736
ability	0.028	0.436	0.089	5.954
expense	-0.100	-1.190	-0.023	-1.448
log size	-0.070	-1.084	-0.029	-1.867
log age	-0.025	-1.042	-0.031	-2.012
turnover	0.130	2.345	0.021	1.010
volatility	0.019	0.307	0.058	1.271

The significance of past alpha and ability shows that funds that had good (bad) performance will continue to do well (poorly). Using both alpha and ability is more accurate than just using alpha, because ability takes into account how long the fund has been performing well. Additionally, the fund turnover ratio has a positive relation with future alpha. According to Grinblatt and Titman (1994) turnover ratio explains performance because a skilled manager who uses his superior information to trade more often will improve performance. Additionally, Korkie and Turtle (2002) have documented that a manager creates value for his portfolio from both the frequency and the timing of trading assets. Furthermore, we observe that turnover ratio is highly auto-correlated, which indicates that a fund that trades actively will continue to do so. These findings show that a skilled fund manager who trades actively will deliver a good future alpha.

Next alpha, ability and turnover ratio are validated on the other half of the fund universe. The predicted alpha of each fund is estimated from the three variables and then funds are ranked on their predicted alphas. We find that the difference of alphas between the top and bottom decile of predicted alpha portfolios is equal to 2.52 percent per year and significant (t-statistic = 2.44). Moreover, the alpha differences are still significant in both sub-periods (1978 to 1992 and 1993 to 2006) with significance level of 5 percent. From 1978 to 1992, the alpha difference is equal to 3.31 percent per year with a t-statistic of 1.85 and from 1993 to 2006 it is equal to 1.60 percent per year with a t-statistic of 1.80. These results can be seen in Table 3.3. Hence, the part of the universe that is kept for out-of-sample testing confirms that the three variables (alpha, ability and turnover ratio) predict future alpha. For comparison, we also show the results for the first half of the fund universe that is used to analyze which fund characteristics predict alpha in Table 3.3. We observe that the t-statistics of the alphas from the first and second half of the fund universe are similar during the full sample (1978 to 2006). The t-statistics are 2.81 and 2.44. Additionally, we also test and find that the alphas between both groups of funds are not significantly different (t-statistic of 1.1). Furthermore, when we test the difference of the returns between both group of funds we again find that their returns are not significantly different (t-statistic of 0.8). The conclusion stays the same when we analyze the difference in alphas and returns between both groups in sub-periods from 1978 to 1992 and from 1993 to 2006.

3.4 Investment Strategies

In this section, we implement both the predicted alpha and the momentum strategies by using the entire mutual fund universe. To implement the predicted alpha strategy, we first estimate the loadings on the fund characteristics for the in-sample period using equation (3.2) with past alpha, ability and turnover as the three regressors. The in-sample period expands over the years. In order to have enough data to estimate the loadings, the first in-sample period from 1962 to 1977 is used to predict the mutual fund alphas of 1978 to 1980. Based on these predicted

Table 3.3: The Predictability of Alpha From Fund Characteristics

We divide the sample into two groups of funds according to seven criteria in sequence. Every time funds are split into two based on a criterion. Hence, after we use all criteria to split funds, there are 128 subsets of funds that have different characteristics. Next, for each subset we put half in the first group and the other half in the second group. The first group of funds is used to analyze which fund characteristics predict the future alpha, whereas the second group is used to validate the selected fund characteristics that significantly predict the future alpha. Next, mutual funds are ranked on their predicted alphas that are estimated from previous alpha, ability and turnover ratio. This table shows the results of the differential returns between the top and bottom deciles of predicted alpha portfolios. The full sample reports the results from 1978 to 2006. The annual Fama and French alpha, the t-statistics of the Fama and French alpha, the annual return and the annual Sharpe ratio of the differential returns between the top and bottom deciles are shown. "Difference" is the Fama and French alpha of the return differential between the first group and the second group, whereas "Difference-t" shows the t-statistics of "Difference".

	Full sample		1978-1992		1993-2006	
	First group	Second group	First group	Second group	First group	Second group
Alpha	4.140	2.519	5.452	3.311	2.042	1.597
Alpha-t	2.806	2.440	2.349	1.848	1.286	1.796
Return	2.615	1.426	4.649	2.200	0.436	0.596
Sharpe	0.254	0.214	0.484	0.291	0.039	0.107
Difference	1.621		2.141		0.445	
Difference-t	1.119		0.881		0.381	

alphas, we form ten decile portfolios and rebalance these portfolios yearly. For comparison, we also implement the momentum strategy that ranks funds only on their past alphas. Panel A of Table 3.4 shows the results of both strategies for the top 10 percent, bottom 10 percent and the differential returns between the top and bottom 10 percent portfolios. We will focus mainly on the results of the top portfolio since regulation does not allow the short selling of mutual funds. The results in Panel A of Table 3.4 show that the top portfolio of the predicted alpha strategy has higher alpha than that of the momentum strategy. The difference between both alphas is 0.86 percent per year and this difference is at the 1 percent significance level. To calculate the significance of the difference between the alphas of both strategies we first compute the yearly differences between the top decile returns of the momentum and the predicted alpha strategies, and subsequently use equation (3.1) to calculate the alpha and its t-statistic. The t-statistic is 2.98. This method is used by Wermers (2000) among others. Alternatively, following Bollen and Busse (2004) we first estimate non-overlapping 3-year alphas from 1978 to 2006, so that we have 10 alphas for each strategy. Then we compute the mean difference and do a mean-test. In this case the t-statistic is 2.67. These results demonstrate that a fund of funds manager can select funds better by using ability and turnover ratio, in addition to past alpha. Given that the average alpha of mutual funds is equal to -0.17 percent per year, these findings clearly show that both strategies can select funds well.

Table 3.4: The Momentum and Predicted Alpha Strategies

”T”, ”B” and ”T-B” denote the top decile portfolio, the bottom decile portfolio and the difference between the top and bottom decile portfolios. This table reports the annual Fama and French alpha, the t-statistics of the Fama and French alpha, the annual return, the annual Sharpe ratio and the annual turnover ratio of ”T”, ”B” and ”T-B”. ”Difference” is the Fama and French alpha of the return differential between the top portfolio returns of the momentum and the predicted alpha strategies whereas ”Difference-t” shows the t-statistics of ”Difference”. All values are ex-post performance of the strategies from 1978 to 2006.

	Momentum strategy			Predicted Alpha strategy		
	T	B	T-B	T	B	T-B
Alpha	0.839	-1.536	2.376	1.699	-1.561	3.260
Alpha-t	0.881	-1.994	1.910	1.837	-2.311	2.817
Return	7.094	6.223	0.871	7.946	5.986	1.961
Sharpe	0.433	0.469	0.109	0.482	0.489	0.230
Turnover	1.037	1.109	1.074	0.891	0.977	0.935
	T					
Difference	-0.860					
Difference-t	-2.983					

The total return and Sharpe ratio of the top decile from the predicted alpha strategy are also higher than those of the top decile from the momentum strategy. The average annual return is 7.95 percent with a Sharpe ratio of 0.482 for the predicted alpha strategy, compared to 7.09 percent and 0.433 for the momentum strategy. For comparison, the average mutual fund return is 4.27 percent with a Sharpe ratio of 0.319. Furthermore, the implementation of the predicted alpha strategy is cheaper than that of the momentum strategy because fewer trades are required to hold the top 10 percent every year. Investing in the top decile of the momentum strategy requires on average replacing almost 52 percent of the top decile names of the previous year whereas for the predicted alpha strategy almost 45 percent of the names need to be changed[2]. Figure 3.1 demonstrates the loadings of the three variables over time and Figure 3.2 shows the cumulative returns of the momentum strategy and the predicted alpha strategy. These are total returns that have not been adjusted for systematic risks or transaction costs.

Next, we investigate what kinds of funds both strategies select in the top portfolio. Table 3.5 shows that compared to the average of all funds shown in the final column, both strategies select funds that have higher return, higher alpha, higher ability, lower expense, bigger size,

[2]It is impossible to draw a conclusion about the net (risk-adjusted) returns of the strategies. We exclude load funds, but this leaves possible purchase fees, redemption fees, exchange fees, and account fees. Such fund data are not available although such costs are probably minimal for most funds. Boudoukh et al. (2002) say on trading no-load funds that there are ”limited transaction costs in many cases”.

Figure 3.1: The Fund Characteristics Loadings
Fund alphas are regressed on previous alphas, abilities and turnover ratios by using equation (3.2), except that we drop the four other variables. This figure shows the loadings of the three predictors when we implement the predicted alpha strategy in Table 3.4.

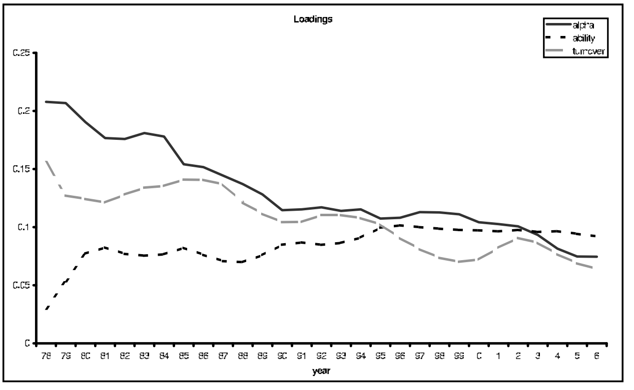
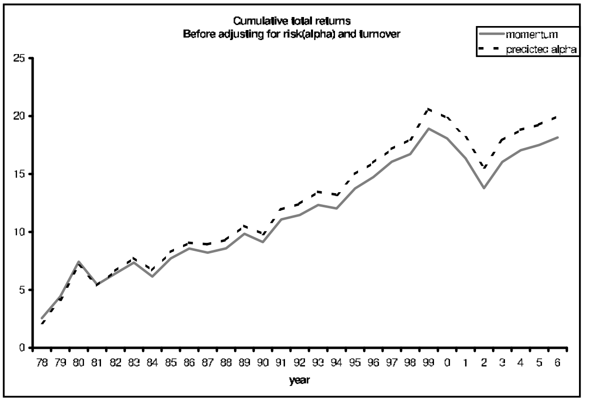


Figure 3.2: The Cumulative Returns
This figure shows the cumulative returns of the momentum strategy and the predicted alpha strategy from 1978 to 2006.



higher volatility, higher age and a larger exposure to small-cap stocks and growth stocks. The main difference is that the predicted alpha strategy selects higher turnover funds in the top, while the momentum strategy selects funds in the top and bottom 10 percent with a similar average turnover ratio. In addition, the predicted alpha strategy emphasizes less strongly 3-year alpha and has a larger difference in ability between top and bottom. We also note that both strategies choose lower expense funds in the top portfolio, compared to those in the bottom portfolio. This is not surprising since it is already documented in literature that expense ratio has a negative correlation (either significant or not) with performance. Additionally, the top portfolio from both strategies contains funds that have higher volatility than those in the bottom portfolio. Moreover, high ability funds are bigger. If all funds are ranked only on their ability, the average size of a fund in the top and bottom portfolio is 147.78 and 18.79 million dollars, respectively. Moreover, because both the momentum and the predicted alpha strategies have high ability funds in the top portfolios, these portfolios also contain funds with more assets under management than the average. Finally, similar to what existing literature has documented (see Kosowski et al. (2006) and Huij and Verbeek (2007)), the top performance funds have higher exposure to SMB, but lower exposure to HML.

Table 3.5: Fund Characteristics in The Top and Bottom Deciles Portfolios
This table demonstrates the ex-ante characteristics of funds that are selected in the top and bottom portfolios when we implement the momentum and the predicted alpha strategies from 1978 to 2006. ”T” and ”B” denote the top and bottom decile portfolios. ”Diff” shows the average difference between the characteristic values of the top and bottom decile portfolios while ”Diff-t” reports the t-statistics of the difference. Additionally, we also show the average characteristics of all funds.

	Momentum strategy				Predicted Alpha strategy				All funds
	T	B	Diff	Diff-t	T	B	Diff	Diff-t	
return	12.42	-1.31	13.73	8.83	11.50	-0.95	12.45	7.53	4.15
3-year alpha	8.60	-8.23	16.84	24.56	7.42	-7.19	14.59	20.17	-0.04
ability	1.33	-0.88	2.22	25.14	1.54	-1.38	2.92	28.42	0.08
expense	1.22	1.53	-0.31	-5.22	1.26	1.48	-0.23	-3.63	1.28
size	75.72	26.56	49.17	3.83	99.51	18.18	81.33	3.96	42.26
age	120.54	130.88	-10.34	-3.88	116.56	123.83	-7.27	-2.14	87.35
turnover	0.78	0.86	-0.07	-1.12	1.78	0.52	1.26	5.64	0.87
volatility	5.63	4.98	0.65	2.85	5.65	4.61	1.04	4.44	4.72
exposure to RMRF	0.90	0.91	-0.003	-0.12	0.86	0.86	0.002	0.05	0.89
exposure to SMB	0.34	0.32	0.03	0.74	0.33	0.25	0.08	2.84	0.202
exposure to HML	-0.19	0.02	-0.21	-4.94	-0.20	0.06	-0.26	-6.67	-0.05

3.5 Robustness Checks

In this section, we do a number of checks on the robustness of the predicted alpha strategy results. First, the predicted alpha strategy is implemented based on an expanding window to estimate the in-sample parameters. Here we observe whether the performance of the strategy changes significantly if rolling windows are used. Table 3.6 demonstrates the performance of the top 10 percent portfolio when the parameters are estimated with 1-year to 10-year rolling windows. We also show the difference with the alphas based on the expanding window, and the t-statistic of this difference. The performance of the predicted alpha strategy turns out to be similar regardless of a rolling or an expanding window.

Table 3.6: N-Year Moving Window

The table shows the results (the annual Fama and French alpha, the t-statistics of the Fama and French alpha, the annual return, the annual Sharpe ratio and the annual turnover ratio) of the predicted alpha strategy when it uses 1 year, 2 year, ..., 10 year moving window to estimate the loadings of the fund characteristics. "(N-Expanding)" denotes the difference of the alphas that use n-year moving window and expanding window while "(N-Expanding)-t" reports the t-statistics of the difference.

	1 year	2 year	3 year	4 year	5 year	6 year	7 year	8 year	9 year	10 year
Alpha	1.508	1.830	1.390	1.426	1.487	1.620	1.691	1.744	1.810	1.735
Alpha-t	2.111	2.264	1.947	2.064	1.919	1.932	2.038	2.127	2.165	2.042
Return	8.016	8.141	7.859	7.975	7.854	8.009	8.191	8.404	8.264	8.144
Sharpe	0.497	0.511	0.487	0.492	0.486	0.492	0.500	0.509	0.501	0.492
Turnover	0.966	0.863	0.852	0.826	0.782	0.764	0.759	0.776	0.767	0.772
(N-Expanding)	-0.192	0.130	-0.310	-0.274	-0.212	-0.079	-0.010	0.044	0.110	0.036
(N-Expanding)-t	-0.476	0.324	-0.732	-0.612	-0.540	-0.220	-0.027	0.123	0.331	0.127

Second, several studies use the 4-factor alphas (including momentum as a 4th factor in equation (3.1)) to rank mutual funds, see e.g. Carhart (1997) and Bollen and Busse (2004). Here we investigate whether the predicted alpha strategy still outperforms the momentum strategy if the 4-factor alphas, instead of the 3-factor alphas, are used to rank mutual funds and to determine the risk-adjusted performance of the strategies. Table 3.7 shows that the predicted alpha strategy still outperforms the momentum strategy at the 5 percent significance level. The difference of the out of sample alphas between both strategies is 0.67 percent per year (t-statistic = 2.47). We do note that the ex-post 4-factor alphas are lower than the ex-post 3-factor alphas in Panel A of Table 3.4. Also for Carhart alphas the predicted alpha strategy has a higher return, higher Sharpe ratio, and a lower turnover than the momentum strategy.

Table 3.7: The Carhart Alpha

Mutual funds are ranked and analyzed by the Carhart alpha. This table reports the Carhart alpha, the t-statistics of the Carhart alpha, the annual return, the annual Sharpe ratio and the annual turnover ratio of the momentum and the predicted alpha strategy. "T", "B" and "T-B" denote the top decile portfolio, the bottom decile portfolio and the difference between the top and bottom decile portfolios. "Difference" is the Fama and French alpha of the return differential between the top portfolio returns of the momentum and the predicted alpha strategies whereas "Difference-t" shows the t-statistics of "Difference".

	Momentum strategy			Predicted Alpha strategy		
	T	B	T-B	T	B	T-B
Alpha	0.338	-1.561	1.900	1.006	-1.980	2.986
Alpha-t	0.391	-2.163	1.645	1.219	-2.844	2.836
Return	6.960	6.720	0.240	7.644	6.002	1.642
Sharpe	0.448	0.482	0.022	0.502	0.453	0.270
Turnover	1.109	1.115	1.112	0.899	0.987	0.944
	T					
Difference	-0.667					
Difference-t	-2.466					

Third, so far we only show the results of the top and bottom 10 percent portfolios. The number of funds in each decile varies from 15 to 300. In Table 3.8 we show the top and bottom 20 percent and 5 percent of both strategies. In addition, we show the results when selecting 20 funds that have the highest and the lowest past alphas. We find that the top portfolio of the predicted alpha strategy always has higher alpha than that of the momentum strategy and the bottom portfolio of the predicted alpha strategy always has lower alpha than that of the momentum strategy. Additionally, the turnover needed for the predicted alpha strategy is always lower than that of the momentum strategy. It is remarkable that selecting the top 20 funds using predicted alpha gives a risk-adjusted performance of 3.03 percent per annum at the 5 percent significance level, a total return of 7.93 percent per annum and a Sharpe ratio of 0.394. Hence it is feasible to have a fully quantitative fund-of-fund manager.

Fourth, Table 3.9 demonstrates how each strategy performs in the two sub-periods from 1978 to 1992 and 1993 to 2006. In both sub-periods the predicted alpha strategy significantly outperforms the momentum strategy. The difference between the alphas of both strategies is equal to 0.86 percent and 0.90 percent per year with t-statistics of 1.93 and 2.79 for the two sub-periods, respectively. We do note that the alphas of both strategies are negative from 1993 to 2006. Barras et al. (2009) find that the proportion of skilled funds decreases over time. Replicating their methodology, we find that the proportion of skilled funds decreases from 6.8 percent in the 1978-1992 period to 3.5 percent in the 1993-2006 period. Hence it is not surprising that

Table 3.8: The Portfolios of the Top and Bottom 20 percent, 5 percent and 20 funds
The table demonstrates the results (the annual Fama and French alpha, the t-statistics of the Fama and French alpha, the annual return, the annual Sharpe ratio and the annual turnover ratio) of the top and bottom 20 percent and 5 percent funds as well as the top and bottom 20 funds.

	20 percent			5 percent			20 funds		
	T	B	T-B	T	B	T-B	T	B	T-B
Momentum strategy									
Alpha	0.511	-1.202	1.714	1.480	-2.102	3.582	2.032	-0.949	2.982
Alpha-t	0.737	-2.113	1.902	1.085	-1.988	2.023	1.200	-1.390	1.584
Return	6.922	6.264	0.658	7.102	5.851	1.252	6.754	6.667	0.088
Sharpe	0.458	0.487	0.112	0.405	0.421	0.116	0.341	0.501	0.007
Turnover	0.907	0.914	0.911	1.187	1.209	1.199	1.221	1.623	1.423
Predicted Alpha strategy									
Alpha	1.109	-1.256	2.365	2.408	-2.362	4.770	3.034	-1.124	4.157
Alpha-t	1.633	-2.434	3.103	1.844	-2.437	2.812	1.964	-1.598	2.302
Return	7.568	5.874	1.694	8.158	5.384	2.773	7.925	6.455	1.470
Sharpe	0.495	0.489	0.280	0.460	0.428	0.244	0.394	0.529	0.106
Turnover	0.741	0.791	0.766	1.053	1.159	1.109	1.127	1.591	1.359

the average alpha of the top 10 percent is negative for both strategies, also given that the average alpha over all mutual funds is -1.38 percent from 1993 to 2006. Given the low number of skilled funds in this period, we also looked at the performance of the top 20 funds according to the predicted alpha. We find it to be positive at 0.50 percent. In comparison the top 20 funds according to the momentum strategy gives an alpha of -0.14 percent.

Table 3.9: Sub-periods performances
"T", "B" and "T-B" denote the top decile portfolio, the bottom decile portfolio and the difference between the top and bottom decile portfolios. This panel reports the annual Fama and French alpha, the t-statistics of the Fama and French alpha, the annual return, the annual Sharpe ratio and the annual turnover ratio of "T", "B" and "T-B" from 1978 to 1992 and from 1993 to 2006. "Difference" is the Fama and French alpha of the return differential between the top portfolio returns of the momentum and the predicted alpha strategies whereas "Difference-t" shows the t-statistics of "Difference".

	1978-1992						1993-2006					
	Momentum strategy			Predicted Alpha strategy			Momentum strategy			Predicted Alpha strategy		
	T	B	T-B	T	B	T-B	T	B	T-B	T	B	T-B
Alpha	2.645	-0.792	3.437	3.505	-0.733	4.240	-1.553	-2.339	0.785	-0.658	-2.426	1.769
Alpha-t	1.774	-0.696	1.805	2.366	-0.716	2.293	-1.506	-2.425	0.513	-0.688	-3.080	1.370
Return	8.364	6.163	2.201	9.322	6.019	3.302	5.735	6.287	-0.552	6.472	5.950	0.522
Sharpe	0.521	0.437	0.287	0.573	0.459	0.415	0.343	0.509	-0.067	0.385	0.528	0.057
Turnover	1.003	1.073	1.040	0.911	0.996	0.955	1.074	1.147	1.111	0.871	0.956	0.914
	T						T					
Difference	-0.860						-0.896					
Difference-t	-1.933						-2.785					

Finally, we compare the performance of the predicted alpha strategy and the buy and hold benchmark strategy. We choose the S&P 500 index for the benchmark. The 3-factor alpha of the S&P 500 index is -2.62 percent per year for the 1978-2006 period, whereas the out-sample

3-factor alpha of the predicted alpha strategy is 1.70 percent per year. Additionally, the average annual return and Sharpe ratio of the S&P 500 index are 4.55 percent and 0.306, respectively, whereas the out-sample annual return and Sharpe ratio of the predicted alpha strategy are 7.95 percent and 0.482, respectively. Hence the predicted alpha strategy is more profitable than the aforementioned buy and hold strategy. Table 3.10 demonstrates these results.

Table 3.10: The Buy and Hold Strategy

This table shows the annual Fama and French alpha, the annual return and the annual Sharpe ratio of S&P 500 index from 1978 to 2006.

	S&P 500
Alpha	-2.615
Return	4.549
Sharpe	0.306
Turnover	0.000

3.6 Conclusion

A common investment strategy in literature uses only past performance information to select mutual funds. We show that a fund of funds manager can select funds better by not only using past performance but also the turnover ratio and ability. This improves the out-of-sample alpha, total return and Sharpe ratio. These findings demonstrate that some fund characteristics significantly predict performance. Moreover, the newly proposed strategy also requires less turnover and hence, it is economically more interesting than the strategy that uses only past performance. Furthermore, selecting the top 20 funds based on alpha, ability and the turnover ratio results in a significant risk-adjusted performance of 3.03 percent per annum, an excess return of 7.93 percent per annum, and a Sharpe ratio of 0.394 from 1978 to 2006. This compares favorably to the average mutual fund which has a risk-adjusted performance of -0.17 percent per annum, an excess return of 4.27 percent per annum, and a Sharpe ratio of 0.319. It also exceeds the S&P 500 index which over the same period has a negative alpha of -2.61 percent per annum, an excess return of 4.55 percent per annum, and a Sharpe ratio of 0.306.

Chapter 4

The Dynamics of Average Mutual Fund Alphas

4.1 Introduction

The merits of actively managed investments have long be subject to debate, in particular whether the costs of actively managed portfolios are sufficiently compensated by the performance, see for example Jensen (1969), Odean (1999), and French (2008). Or whether the market is simply too efficient for active management, see for example Coggin et al. (1993), Malkiel (2003), and Malkiel (2005). One way to measure the merits of active management is to look at the average alpha of mutual funds. Jensen (1968), Blake et al. (1993), Elton et al. (1996), Huij and Verbeek (2007), and Elton et al. (2007) all find that the average alpha of mutual funds is negative.

Whereas the aforementioned studies focus on the average alpha, few say anything about how average alphas change over time, and what drives average alphas. Barras et al. (2009) show that average mutual fund alphas decrease over time and they also provide an explanation for it. In particular they use the statistical significance of alphas to classify funds as skilled, unskilled or neither. They show that whereas the skilled ratio is decreasing over time, the unskilled ratio is increasing. The main contribution of our study is to identify a number of additional variables that explain the dynamics in average alphas over time. Furthermore, we show that the chosen methodology to compute average alphas can lead to substantial differences, to the extent that the average alpha over the full sample period turns from negative to positive. As such we add to the debate on active versus passive management, and provide insights into what factors are relevant for evaluating the relative performance of actively managed mutual funds.

Given the lack of earlier work on explaining the dynamics of average mutual fund alphas we need to apply logic to formulate a number of additional candidate explanatory variables. A first place to look is at the literature that uses fund characteristics to select ex-ante the best mutual funds. Elton et al. (2004), for example, show that the performance of low expense funds is higher than that of high expense funds. Hence a logical candidate to explain average alpha is the average expense ratio, where a higher average expense ratio will lead to a lower average alpha, all else equal. French (2008) reports that the expense ratios of mutual funds have increased over time, and we hypothesize that this reduces the average alpha. Next, Wermers (2000) finds that funds with a high turnover have higher performance than funds with a low turnover. The intuition is that applying your skill more often leads to a higher performance. This intuition is captured by the fundamental law of active management by Grinold (1989), which states that the risk-adjusted performance depends on both skill and how often this skill is applied. If this applies also at the aggregate level, we would expect that a combination of the average turnover ratio, costs and the Barras et al. (2009) skilled ratio can explain average alpha: turnover times the proportion of skilled funds divided by the average transaction costs, where we expect a positive sign. On the other hand, if the average mutual fund is not skilled, more turnover will simply generate more costs and hence average alpha will decline. Hence we also look at the average turnover ratio times costs divided by the proportion of skilled funds. We then expect a negative sign. The empirical results will show which hypothesis turns out to be valid.

Second, we come up with a number of other candidates to explain the dynamics of average mutual fund performance. For example, we look at the ratio between the number of mutual funds and the number of hedge funds. If hedge funds can attract the best mutual fund managers, a lower ratio (relatively more hedge funds) will lower alpha[1]. We also test the dividend yield. Mutual funds pay taxes on the dividends received. When the dividend yield increases, taxes increase and this reduces the net return of funds relative to the ”tax-free” Fama and French factors, and hence it reduces alpha. Finally we consider the proportion of equity that is managed unprofessionally, for example by households and non-profit organizations. If investment is a zero sum game (Fama and French (2008)), the average mutual fund can only gain from other investors, especially the unprofessional ones. Hence the more unprofessional investors there are, the larger the average mutual fund alpha can be.

Of the aforementioned variables we find that turnover times costs divided by the skilled ratio is the most important variable. It explains 25 to 30 percent of the dynamics in the average alphas. The alternative to use turnover times the skilled ratio divided by costs has no explanatory power. Hence it appears that the average mutual fund is not skilled and as a result turnover simply hurts performance due to higher trading costs. A good second explanatory variable is the difference between the skilled and unskilled ratios, which explains 16 to 25 percent. Finally the ratio of the number of mutual funds and hedge funds has a large explanatory power, be it that we only have this variable from 1992 to 2006. Of the other variables we find statistically significant explanatory power of the average expense ratio. However, the dividend yield and the proportion of unprofessionally managed money cannot significantly explain the dynamics in alphas.

We also critically look at different ways to estimate average mutual fund alphas. First there is no agreement in the literature on the methodology, with for example Becker et al. (1999), Daniel and Titman (1999), and Naik et al. (2007) first computing average mutual fund returns and then alphas using these average returns; and for example Jensen (1968), Ippolito (1989), Elton et al. (2003), Huij and Verbeek (2007), and Barras et al. (2009) averaging over individual fund alphas. We show in Section 4.3 that both lead to biases related to the fund universe changing over time. Second, Cremers et al. (2008) argue that the Fama and French factors used to

[1]Fortune Magazine reported on June 8, 1998: ”Everybody’s going to hedge funds. It seems that almost anyone with a brain is fleeing Wall Street to start a hedge fund. Why? Because the job offers power, autonomy, and the fastest way on earth for a competent money manager to get seriously rich.”

compute alphas give disproportionate weights to small-value stocks. We show in detail how our analysis is affected when switching from Fama and French alphas to alphas based on the alternative index factors proposed in Cremers et al. Our main conclusions regarding the explanatory variables for alphas are robust to the different ways to compute these alphas. But we do find that for the Fama and French alphas the lagged market return has a substantial explanatory power which we ascribe to the biases cited by Cremers et al.

The remainder of this study is organized as follows. First, Section 4.2 describes the mutual fund data and the explanatory variables. Section 4.3 discusses the methodology and the effects of a changing fund universe as well as the choice of factor returns on the average mutual fund alphas. The results are presented in Section 4.4. Finally, Section 4.5 concludes.

4.2 Data

The sample consists of the monthly return data of equity mutual funds from the CRSP Mutual Fund Survivorship-bias-free Database from 1979 to 2006[2]. We use the information about the classification of funds by Wiesenberger, Micropal/Investment Company Data, Inc. and S&P. The data are free from survivorship bias as documented by Brown et al. (1992) and Brown and Goetzmann (1995). To compute excess returns we use the one-month Treasury bill rate from Ibbotson and Associates as a proxy for the risk-free rate.

In addition we use the Kenneth French's data library for return data on the three Fama and French (1993) factors (the excess return on the equity market portfolio RMRF, the excess return on the factor mimicking equity portfolio for size SMB, and the excess return of the factor mimicking equity portfolio for the book-to-market ratio HML). We also use the index-based factors suggested by Cremers et al. (2008)[3]. They use the S&P500 index minus the risk-free rate, the difference between the Russell 2000 and S&P500, and the difference between the Russell 3000 Value minus Russell 3000 Growth as alternatives to the Fama and French factors. These index factors are available from 1979 to 2006. To compare the factor returns from Fama

[2]The starting date is related to the availability of the factors from Cremers et al. (2008) used later in the analysis.
[3]These data are available from http://www.som.yale.edu/Faculty/petajisto/data.html.

and French, and Cremers et al., we show means and standard deviations in Table 4.1. The market factors are similar. The average return for the size and value-growth factors of Fama and French, however are higher than those of Cremers et al. This is not surprising given that Cremers et al. mention that the Fama and French factors give disproportionate weight to small stocks and value stocks that have performed well.

Table 4.1: The Sample Statistics of The Factor Returns

This table shows the annualized mean (in %) and standard deviation of the Fama and French (1993) factors and Cremers et al. (2008) factors from 1979 to 2006.

Panel A. Fama and French (1993)

	RMRF	SMB	HML
mean	7.84	2.00	5.01
std	15.23	11.12	10.78

Panel B. Cremers et al. (2008)

	S&P 500	Russell 2000 minus S&P 500	Russell 3000 Value minus Russell 3000 Growth
mean	7.96	0.65	2.02
std	14.90	11.51	9.98

For the candidate variables to explain the dynamics of the average alpha of mutual funds the expense ratio and turnover ratio mutual funds are extracted from the CRSP Database. These data are available on an annual basis. Each year we compute the average expense ratio and turnover ratio over all funds in the universe in that year. Yearly transaction cost data of investing in U.S. stocks are obtained from French (2008). Next, the yearly number of existing hedge funds from 1994 to 2006 are extracted from TASS Lipper. Furthermore, to calculate the proportion of equity that is held by household and non-profit organizations, we extract the amount of equity in U.S. dollars that is held by all parties from Flow of Funds Data Index of the U.S. Federal Reserve Board of Governors. Next, following Ferson and Schadt (1996), to estimate the average dividend yield we withdraw both the with and without dividends value-weighted returns index from the CRSP database. It is calculated from the previous 12 months of dividend payments for the CRSP index, divided by the index level with dividend at the end of the previous month. Finally, we estimate the proportion of skilled and unskilled funds using the same method as

Barras et al. (2009). In particular the proportion of skilled (unskilled) funds is estimated from the proportion of funds having positive significant alphas (negative significant alphas) minus the expected proportion of lucky (unlucky) funds[4]. We compute the alphas and their significance either from the Fama and French factors following Barras et al. (2009), or using the factors from Cremers et al. (2008).

Figure 4.1 shows the aforementioned variables. For the difference between the skilled and unskilled ratio we confirm the Barras et al. results that through time this difference is declining over time, going from positive (more skilled funds) to negative (more unskilled funds). The average expense ratio increases over time, confirming results in French (2008). Finally, despite average transaction costs declining (French (2008)) and the number of skilled funds decreasing, turnover at some points in time is sufficiently rising to make [turnover x cost]/[skilled ratio] increasing. This is particularly the case in 2002-2003.

4.3 Methodology

4.3.1 Two methods to compute average alphas

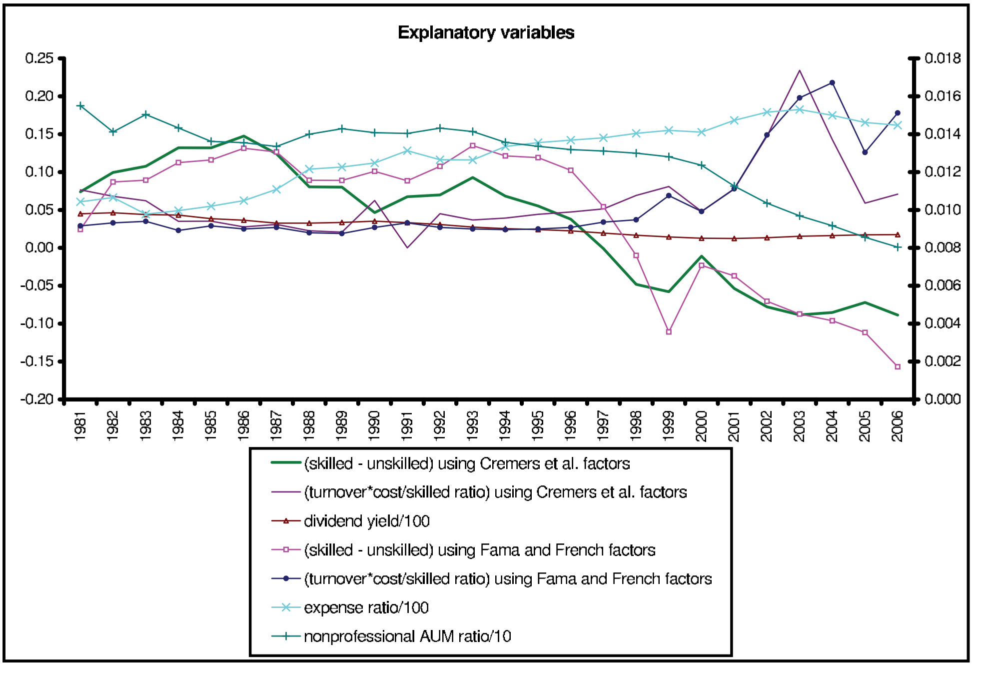
There are two methods that are commonly used in the literature to estimate the average mutual fund alphas. The first method is taking average returns of all funds that are available in the universe at a particular time. Subsequently the alpha is computed from these average returns, see for example Becker et al. (1999), Daniel and Titman (1999), and Naik et al. (2007). The second method is estimating the alphas of individual funds and subsequently take the average over all individual alphas, see for example Jensen (1968), Ippolito (1989), Elton et al. (2003), Huij and Verbeek (2007), and Barras et al. (2009).

In case the universe does not change over time, both methods will yield identical results. In reality, however, the universe changes over time. Every year funds disappear and new funds emerge. At first sight it seems that only the method based on individual alphas introduces a

[4]At the five percent significance level, for example, the expected proportion of lucky funds is the proportion of zero-alpha funds times 2.5 percent.

Figure 4.1: The Explanatory Variables Over Time

This figure displays the candidate variables to explain the dynamics alpha of mutual funds over time. Skilled ratio and unskilled ratio are the proportion of skilled funds and unskilled funds, respectively, that are estimated by the same methodology as Barras et al. (2009). Expense ratio is the average funds ratio between all expenses (e.g. 12b-1 fee, management fee, administrative fee) and total net assets. Turnover ratio is the average funds ratio between the minimum of aggregated sales or aggregated purchases of securities, divided by total net assets. Dividend yield is the previous 12 months of dividend payments for the CRSP index, divided by the index level with dividend at the end of the previous month. Nonprofessional AUM ratio is the proportion of equity that is held by household and non-profit organizations. All variables use the left y-axis, except the expense ratio and the nonprofessional AUM ratio.



survivorship bias. In this case we only include funds that exist over the estimation window. If disappearing funds have negative alphas, it is likely that the resulting average alpha is upward biased. It is, however, not clear how this affects the dynamics of alpha, as this would be the case in each period. The first method based on average returns, however, also gives biases. Because the universe changes over time, the resulting time-series of average mutual fund returns will have particular dynamics in the average beta. The reason is that when the equity market has a very good (poor) performance, it is more likely that mutual funds with low (high) betas perform badly, and hence these funds are more likely to be amongst the disappearing funds. At the same time new emerging mutual funds tend to follow successful styles[5]. This will strengthen the time-variation in the factor loadings for the average mutual fund return series. For the CRSP mutual fund database we find that if the lagged market return is positive, the average betas of surviving, disappearing, and emerging funds are 0.89, 0.65, and 0.82, respectively. In case the lagged market return is negative the betas of surviving, disappearing, and emerging funds are 0.95, 0.99, and 0.88, respectively. Hence disappearing funds have on average a worse beta than survivors given the market returns. And emerging funds have average betas that are higher (lower) than those of disappearing funds when the market returns have been positive (negative).

Given that the standard approach is to use static factor loadings for the estimation window[6], the underlying time-variation in factor loadings will lead to time-variation in the alphas that depend on the lagged factor returns. This in turn will affect the perceived dynamics in the average mutual fund alphas obtained from the average mutual fund return series.

4.3.2 A simple Monte Carlo experiment

We now proceed with a simple experiment to show that even in a very simple setting the survivorship bias-free approach of using average returns of all existing funds will lead to biases in the resulting average mutual fund alphas, due to the particular characteristics of disappearing

[5]Taylor (2003) also mentions that high beta funds are expected to be winning funds when the market goes up. Although he does not specifically study the betas of survivors and disappearing funds, most likely the winning funds are the survivors and the loser funds will be the disappearing funds.

[6]Commonly, the alpha and beta are estimated over multiple years, for example 3 years (see Carhart (1997), Elton et al. (1996), Elton et al. (2007), Goetzmann and Peles (1997), Gruber (1996), and Kim et al. (2008))

and emerging funds. We start with simulating returns from

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

where $r_{i,t}$ is the excess return of fund i in month t and $RMRF_t$ is the excess return on the market in month t. We generate returns for 1000 hypothetical funds, with betas drawn from the normal distribution with mean 0.89 and standard deviation 0.53. Mean and standard deviation are based on the sample characteristics of all mutual funds from 1962 to 2006. To generate excess market returns we draw from the normal distribution with a yearly mean 5.49 percent and a standard deviation of 15.26. Residuals are i.i.d. normal with zero mean and variance σ_i^2, where according to Brown et al. (1992), Hendricks et al. (1997), and ter Horst et al. (2001), σ_i^2 depends on the market beta of a fund as in

$$\sigma_i^2 = \omega(1-\beta_i)^2 \tag{4.2}$$

Here ω is set to 0.005 following Huij and Verbeek (2007). We generate the returns of 1000 funds for 50 years. Malkiel (1995) and Wermers (1997) show that non-survivor funds have lower returns than the survivor funds. To reflect this we let each year the five percent of the funds with the lowest returns disappear. These funds are replaced by new funds that have betas similar to the five percent highest return funds of past year. We repeat this experiment 1000 times and each time use 3-year rolling windows to estimate the average mutual fund alphas in two ways. The first is based on first computing the average mutual fund returns at each point in time and then computing the 3-year alphas for these series. The second estimates alphas and betas for each individual fund that exists for the 3-year estimation window and then averages over the individual alphas. Obviously in our experiment all mutual funds have zero alphas.

The results in Panel A of Table 4.2 show that average mutual fund alphas estimated by first computing average mutual fund returns are less precise than those based on estimating individual fund alphas. For the latter we find the MAE to be 0.00037 compared to 0.00711 when using average mutual fund returns. Similarly the RMSE is 0.00048 compared to 0.01266.

Table 4.2: Estimated Alpha

This table shows the results from a Monte Carlo simulation across 1000 runs. For each run we generate 1000 funds for 50 years, where the mutual fund returns are simulated from equation (4.1). We demonstrate the estimation error (MAE, RMSE), the annualized mean (in %) and the standard deviation of the estimated alphas (Panel A) and the dynamics of estimated alphas (Panel B). The "average returns" method takes average returns of funds and subsequently estimates the alpha of the average returns, whereas the "individual alphas" method estimates alphas of individual funds and subsequently takes the average of the individual alphas.

Panel A. The estimated alpha

	MAE	RMSE	mean	std
Average returns	0.00711	0.01266	0.01800	0.04330
Individual alphas	0.00037	0.00048	0.00360	0.00139

Panel B. The dynamics of estimated alpha

	MAE	RMSE	mean	std
Average returns	0.00926	0.01522	0.00240	0.05335
Individual alphas	0.00026	0.00033	0.00012	0.00104

Similar conclusions can be drawn from Panel B for changes in 3-year alphas, defined as the difference between the average alphas based on years t-2 to t and years t-3 to t-1. The RMSE, for example, is 0.01522 when first computing average mutual fund returns, and only 0.00033 when computing average mutual fund alphas from individual fund alphas. Similar conclusions are drawn when using non-overlapping alphas to compute changes in alphas.

Next, following the above-mentioned pattern in the betas of survivors, disappearing, and emerging funds, we regress the changes in 3-year alphas from our simulation experiment on the lagged changes in 3-year market returns. The results are shown in Table 4.3. In the first three columns we get the obvious result that if the universe does not change over time, it does not matter whether we first compute average returns and then compute alpha, or first compute individual mutual fund alphas and then compute average alpha. In this case the dynamics of alpha do not depend on the lagged changes in market returns. The last three columns, however, show that due to differences in how changes in the universe affect each method to compute the average alpha they no longer yield the same results. Now there is a significant positive loading on the lagged market return when computing alphas from average mutual fund returns, and the R-squared is 6.5 percent. Also the method based on individual alphas now has an R-squared of 5.1 percent, but the coefficient is much closer to zero[7]. Given the results in the first three

[7]We find that in 39 percent of the cases the loading on the lagged market return is significant when basing average alphas on individual alphas. Given that true alphas are zero we conjecture that we have so many significant

columns the relationship with the lagged market return comes solely from the mechanics behind changes in the fund universe.

Table 4.3: Monte Carlo simulation

This table shows the results from a Monte Carlo simulation across 1000 runs. For each run we generate 1000 funds for 50 years, where the mutual fund returns are simulated from equation (4.1). Columns 2 to 4 show the results when the fund universe does not change, whereas columns 5 to 7 show the results when every year the five percent lowest past return funds disappear and are replaced by new funds that have betas similar to the five percent highest past return funds. Then the 1-year changes in the estimated alphas from the methods ”average returns” and ”individual alphas” are regressed on the 1-year changes in the lagged market returns. The ”average returns” method takes average returns of funds and subsequently estimates the alpha of the average returns, whereas the ”individual alphas” method estimates alphas of individual funds and subsequently takes average of the alphas. We demonstrate the adjusted R^2, the loadings and the t-statistics in parentheses of the independent variable.

	Constant Universe			Changing Universe		
	Adj R^2	Intercept	Explanatory	Adj R^2	Intercept	Explanatory
A. The alpha of ”Average returns”						
Δmarket return	0.009	0.0000	0.0000	0.065	0.0002	0.0071
		(-0.001)	(0.018)		(0.163)	(1.990)
B. The alpha of ”Individual alphas”						
Δmarket return	0.009	0.0000	0.0000	0.051	0.0000	-0.0001
		(-0.001)	(0.018)		(0.264)	(-1.640)

4.3.3 Which factors to use?

Cremers et al. (2008) observe that the Fama and French model generates significant non-zero alphas for passive indices such as the S&P 500 and the Russell 2000. They show that these alphas come especially from the Fama and French factors giving disproportionate weights to small-value stocks. The reason behind this is as follows. SMB and HML are constructed from the equally weighted return difference between small and large-cap stock portfolios, and value and growth portfolios, respectively. Since there is significantly more market capitalization in large-cap and low book-to-market portfolios, SMB and HML give more weight to small-cap and value portfolios, which historically outperform other stocks. Additionally the market factor from French’s data library is a downward-biased benchmark for U.S. stocks because it also consists of non-U.S. firms, closed-end funds and REITs that underperform U.S. stocks. Furthermore, Huij and Verbeek (2009) show that the Fama and French factors ignore transaction

coefficients due to a few outliers dominating the regression results amongst many near-zero values.

costs, trade impact and trading restrictions. These arguments together suggest that the Fama and French factors may not be the most appropriate factors to compute mutual fund alphas. To mitigate the factor premium biases, Cremers et al. propose to use the S&P 500 index (market), the Russel 2000 index minus the S&P 500 index (size), and the Russell 3000 Value index minus the Russel 3000 Growth index (value-growth). For further comparison between these factors and the Fama and French factors we refer the reader to Cremers et al.

To illustrate the importance for the analysis of the average mutual fund alphas, in Table 4.4 we show the results from regressing mutual fund returns on the Fama and French factors (panel A) or alternatively on the factors proposed by Cremers et al. (panel B). We see striking differences in the perceived exposures to the size and value-growth factors. When we use each fund's full life history to compute the loadings on the risk factors, and subsequently compute averages over all funds, the loading on HML, for example, is an insignificant 0.044 (suggesting an average tilt towards value stocks), whereas the loading on the difference between the Russell 3000 Value and Growth indices is significant at -0.152 (suggesting an average tilt to growth stocks). Similarly the SMB loading is an insignificant 0.163, whilst the loading on the difference between the Russell 2000 and S&P 500 indices is significant at 0.345 suggesting a much larger average tilt towards small stocks. When we take average returns of all funds, and subsequently estimate the loadings on the risk factors, we also find that the loadings on the Cremers et al. factors indicate a higher tilt to small and growth stocks. These results are consistent with the holdings-based analysis of mutual funds by Chan et al. (2002), and Kacperczyk et al. (2005), i.e. that mutual funds on average tilt to small-growth stocks. Although we do not intend to choose side in the debate which factors to use we will center our discussion around the results for the Cremers et al. factors, but also report and discuss the results for the Fama and French factors. It will turn out that most of our conclusions are robust to this choice.

4.3.4 Four series of average alphas

To summarize the methodology, we will have four time-series of alphas. The first choice is between averaging over individual mutual fund alphas, or first computing average mutual fund

Table 4.4: The Premium Bias

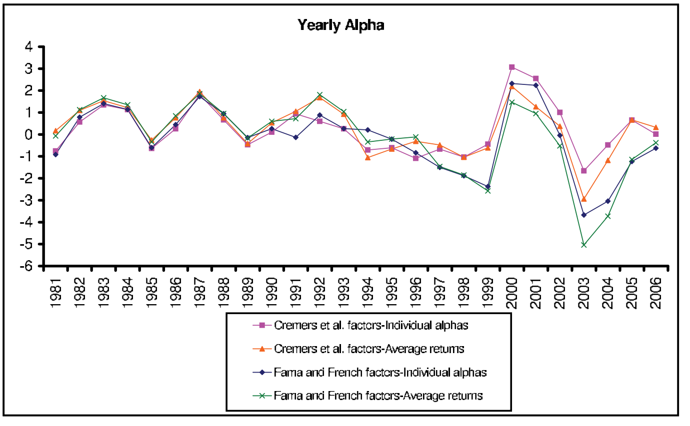
Mutual funds returns from 1979 to 2006 are analyzed by the Fama and French (1993) factors (Panel A) as well as the Cremers et al. (2008) factors (Panel B). The ”average returns” method takes average returns of funds and subsequently estimates the alpha of the average returns, whereas the ”individual alphas” method estimates alphas of individual funds and subsequently takes average of the alphas. We show the adjusted R^2, the loadings and the t-statistics of each factor.

	Individual alphas			Average returns		
	Adj R^2	Loading	t-statistic	Adj R^2	Loading	t-statistic
A. The Fama and French factors						
alpha	0.755	-0.102	-0.758	0.893	0.011	0.183
RMRF		0.889	19.119		0.679	43.054
SMB		0.163	1.357		0.141	6.945
HML		0.044	1.139		-0.025	-1.037
B. The Cremers et al. factors						
alpha	0.765	-0.010	-0.472	0.877	0.043	0.660
RMRF		0.866	28.302		0.650	40.166
SMB		0.345	5.836		0.265	13.498
HML		-0.152	-2.065		-0.119	-4.851

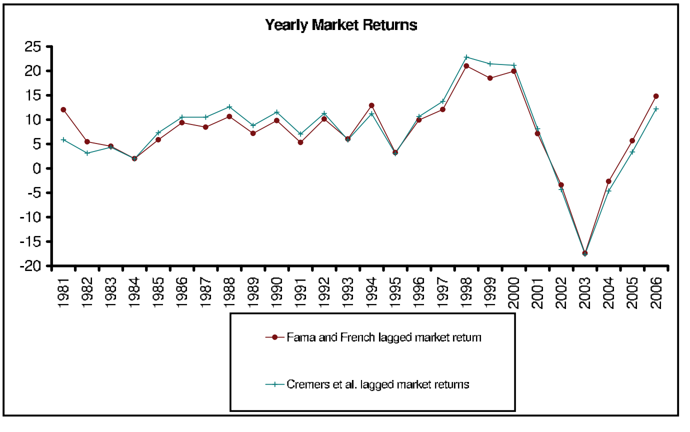
returns and then computing the alpha. The second choice is between using the Fama and French factors, and the Cremers et al. factors. In each case we use 3-year rolling windows. The resulting time-series of average alphas are shown in Figure 4.2, and Table 4.5 shows the average value of these alphas and their standard deviation. We see that on the one hand the alpha series have similar dynamics, but on the other hand they are quite different at times. For example for the period 2001-2003 the Fama and French alpha obtained from average mutual fund returns is -5.04 percent whereas the Cremers et al. alpha obtained from individual mutual fund alphas is -1.66 percent. Notable is that the market return for the 2000-2002 period is -17.64 percent explaining at least part of this difference: Alphas obtained from average mutual fund returns tend to be downward biased after negative market returns. And small growth stocks usually perform poorly during or shortly after large market downturns leading to a downward bias in Fama and French alphas because the loading on small growth is underestimated.

Figure 4.2: The Values of Alpha and Market Return Over Time

Figure (a) displays the yearly average alpha of mutual funds over time. The square line and the triangle line show the estimated Cremers et al. (2008) alphas based on individual mutual fund alphas and based on first computing average returns, respectively. The diamond line and the cross line show corresponding versions using the Fama and French factors. Figure (b) shows the lagged market returns that are proxied by Cremers et al. (2008) as well as Fama and French (1993) factors.



(a) Yearly Alpha



(b) Yearly Market Return

Table 4.5: The Sample Statistics of Alpha

This table shows the annualized mean and standard deviation of 3-year alphas that are estimated from the Fama and French (1993) factors or the Cremers et al. (2008) factors, using either individual mutual fund alphas or first compute average mutual fund returns and then compute alphas using these returns. The 3-year alpha is updated yearly, and.the mutual funds returns span from 1979 to 2006. Panel A and B provide results for the level of alpha and the dynamics (changes) of alphas, respectively.

Panel A. Alpha levels

		Cremers et al.	Fama and French
Individual alphas	mean	0.248	-0.176
	std	1.135	1.505
Average returns	mean	0.291	-0.135
	std	1.160	1.701

Panel B. The dynamics of alpha

		Cremers et al.	Fama and French
Individual alphas	mean	0.031	0.012
	std	1.284	1.562
Average returns	mean	0.006	-0.013
	std	1.332	1.635

Using the Dickey-Fuller test in Table 4.6, we find that the average mutual fund alpha is non-stationary. Hence when we run regressions of alphas on explanatory variables we prefer to look at changes (dynamics) in alphas and changes (dynamics) in these explanatory variables (see equation (4.3)), to avoid spurious inference. Additionally we use Newey-West standard errors to solve another issue that the annual dynamics in the 3-year alphas are auto-correlated and have time-varying volatility.

$$\Delta\alpha_t = \gamma_1 + \gamma_2 \Delta V_t + \varepsilon_t, \tag{4.3}$$

where $\Delta\alpha_t$ denotes the 1-year change in the 3-year alphas that are estimated from the three-factor model. ΔV_t is the dynamic of the explanatory variable.

4.4 Results

We now proceed with the key results. Which variables can explain the dynamics in average alphas? Table 4.7 summarizes the results. In the discussion we will focus on the results obtained by using individual fund alphas and the factors used by Cremers et al. (2008). But we also make

Table 4.6: The Dickey-Fuller Test

This table shows the p-values from the Dickey-Fuller test for the alphas that are estimated from the Fama and French (1993) factors or the Cremers et al. (2008) factors, using either individual mutual fund alphas or first compute average mutual fund returns and then compute alphas using these returns. By assuming a significance level of 5 percent, a p-value below 0.05 indicates that the test rejects the null hypothesis of non-stationarity. The mutual funds returns in our sample span from 1979 to 2006.

		p value	
		Cremers et al.	Fama and French
Individual alphas	Level	0.0658	0.0796
	First level difference	0.0011	0.0001
Average returns	Level	0.0596	0.2298
	First level difference	0.0001	0.0000

a direct comparison with the three alternatives.

We start with the skilled and unskilled ratios introduced by Barras et al. (2009). As expected we find that an increase in the skilled ratio leads to an increase in the average alpha, whereas an increase in the unskilled ratio leads to a decrease in the average alpha. In the latter case the loading is -1.47, indicating that an increase of 10 percent in the unskilled ratio leads to a decrease of 0.15 percent in the average alpha. The regression R-squared, however, is quite small at 2.9 percent and the t-statistic is marginally significant at -1.94. The loading on the skilled coefficient is even insignificant. As we discussed in Section 4.2 we believe that it is more logical to combine both ratios. The difference between the two skilled ratios is highly significant with a t-stat of 2.49 and a regression R-squared of 19.0 percent. Hence a substantial portion of the dynamics in the average alpha can be explained by this average skill measure. Also in the results based on the alternatives to compute the average alpha we see that the difference between the skilled and unskilled ratios is always highly significant and superior to using only the skilled or only the unskilled ratio.

Next, an increase in the average expense ratio significantly lowers the average alpha. The t-statistic is -2.0 and the R-squared 5.0 percent. Given that the expense ratio increases over time (see also French (2008)), this partially explains why average net alphas are declining over time. The results for the alternative methods to compute average alphas are even stronger, with higher t-statistics and/or higher R-squared.

Moving our attention to the turnover results we see that over the 1979-2006 sample on

Table 4.7: Univariate regression

This table shows what variables explain the dynamics of average alphas. We demonstrate the results for the average alphas that are estimated from the Fama and French (1993) factors or the Cremers et al. (2008) factors, using either individual mutual fund alphas or first compute average mutual fund returns and then compute alphas using these returns. Skilled ratio and unskilled ratio are the proportion of skilled funds and unskilled funds, respectively, that are estimated by the same methodology as Barras et al. (2009). Expense ratio is the average funds ratio between all expenses (e.g. 12b-1 fee, management fee, administrative fee) and total net assets. Turnover ratio is the average funds ratio between the minimum of aggregated sales or aggregated purchases of securities, divided by total net assets. Market return is the excess return of Cremers et al. market factor or Fama and French market factor. Dividend yield is the previous 12 months of dividend payments for the CRSP index, divided by the index level with dividend at the end of the previous month. Nonprofessional AUM ratio is the proportion of equity that is held by household and non-profit organizations. Mutual/hedge fund ratio is the ratio between the number of mutual funds and the number of hedge funds. We show the adjusted R^2, the loadings and the t-statistics in parentheses of each explanatory variable. This table demonstrates the results from 1979 to 2006. * denotes a period from 1992 to 2006, for which the mutual/hedge fund ratio is available.

	Cremers et al. factors				Fama and French factors			
	Individual alphas		Average returns		Individual alphas		Average returns	
	Adj R^2	Loading	Adj R^2	Loading	Adj R^2	Loading	Adj R^2	Loading
Δskilled ratio	0.020	0.962	-0.007	0.750	0.123	2.297	0.078	2.049
		(0.887)		(0.684)		(1.797)		(1.586)
Δunskilled ratio	0.029	-1.466	0.056	-1.784	0.097	-1.574	0.069	-1.474
		(-1.940)		(-2.655)		(-1.977)		(-2.258)
Δ(skilled - unskilled)	0.190	2.014	0.159	1.947	0.249	1.807	0.181	1.656
		(2.491)		(2.769)		(2.975)		(3.322)
Δexpense ratio	0.050	-0.688	0.108	-1.025	0.050	-0.944	0.091	-1.188
		(-1.997)		(-2.432)		(-2.338)		(-2.466)
Δ(turnover*cost/skilled ratio)	0.307	-1.537	0.307	-1.594	0.250	-2.334	0.257	-2.476
		(-4.325)		(-3.275)		(-2.603)		(-3.381)
Δ(turnover*skilled ratio/cost)	0.042	0.004	0.054	0.004	0.096	0.004	0.042	0.003
		(0.892)		(1.119)		(1.662)		(1.410)
Δmarket return	0.050	0.054	0.130	0.077	0.111	0.082	0.156	0.098
		(1.386)		(1.834)		(2.063)		(2.180)
Δdividend yield	-0.026	-0.895	-0.041	-0.355	-0.035	-0.767	-0.043	-0.264
		(-0.573)		(-0.226)		(-0.383)		(-0.125)
Δnonprofessional AUM ratio	-0.042	0.748	-0.040	1.313	-0.044	0.007	-0.042	0.963
		(0.188)		(0.329)		(0.001)		(0.212)
Δmutual/hedge fund*	0.359	0.406	0.211	0.345	0.338	0.526	0.236	0.485
		(2.734)		(1.963)		(2.711)		(2.188)

average higher turnover hurts alpha given the highly significant negative loading on [turnover x costs]/[skilled ratio], and the insignificant loading on [turnover x skilled ratio]/[costs]. Apparently there are not enough skilled funds in the universe (relative to unskilled funds) to make a higher average turnover have a positive impact on average alpha. Hence more turnover and higher trading costs reduce alpha. This finding supports French (2008) who also finds that an investor on average would increase average annual return by 67 basis points when following a passive strategy. And turnover hurts even more when the skilled ratio declines. This is the strongest variable, explaining 30.7 percent of the variation in alphas. The t-statistic is highly significant at -4.33. This conclusion holds also for the alternative methods to compute average alpha.

The role of the next variable, the lagged change in the market return, is more difficult to interpret. As we mention before there are various mechanisms at work causing differences between the results for the different methods to compute average alpha. The results in Table 4.7 also show this. The change in the market return is the only variable for which the results markedly differ across the different methods. Using the Fama and French factors the loading is twice significant, whereas using the Cremers et al. (2008) factors the loading is insignificant. We believe that an important reason is that with these factors we more closely match the true size/value-growth characteristics, which reduces the dependence of alphas on the business cycle and hence market returns. Also the explanatory power is higher when computing the average alphas from the average mutual fund returns, than when computing the average alphas from the (surviving) individual fund alphas. We believe that this is primarily caused by funds on average adjusting their loadings towards the winning factors by (i) disappearing funds having more likely made the wrong factor bets; (ii) newly emerging funds more likely following recently successful styles; (iii) and existing funds adjusting their loadings towards successful styles.

We find that the next two variables, the (change in the) dividend yield and the ratio of equity hold by household and non-profit organisations, are not significant factors in explaining changes in the average alpha. The t-statistics are close to zero and the adjusted R-squared even negative. This applies to all methods used to compute average alphas.

Finally we find for the 1992-2006 period that it is important for average alpha for mutual funds that the number of hedge funds has increased. The t-statistic is 2.73 and the adjusted R-squared is 35.9 percent[8]. The results are somewhat weaker but still significant when using the average mutual fund return to compute the average alpha. As a robustness check we also produce results for the number of hedge funds in 1994 to 2004 as mentioned in Naik et al. (2007), where they use Lipper TASS, HFR, CISDM, and MSCI. We find that the conclusion remains the same.

4.5 Conclusion

We study the dynamics in average mutual fund alphas. Our first contribution shows that different methods to compute average alphas can lead to substantial variation in the results. Two choices need to be made. Choice one is whether to compute first the average return each month taken over all mutual funds in the universe in that month and then estimate alpha for the resulting return series, or to first compute individual mutual fund alphas for funds in the universe for the entire estimation window and then take the average over these alphas. The second choice is whether to use the Fama and French factors or the index factors recently advocated by Cremers et al. (2008). Illustrative for the differences that can arise is that from 1979 to 2006 the average Fama and French alphas have a negative mean whereas those from Cremers et al. are positive. We also show in a simple experiment that when the universe changes mostly due to losing funds disappearing and emerging funds tending towards the winning styles, that first computing individual alphas is more accurate then first computing average returns over all mutual funds. The latter is biased due to a dependence on lagged market returns, which results from time-variation in the average beta taken over all funds.

Our second contribution is to show what explains the dynamics in alpha beyond the skilled and unskilled measures of Barras et al. (2009). We find that the average turnover ratio times

[8]For comparison, in the 1992-2006 period the R-squared is 39.2 percent for the skilled-unskilled ratio, 17.9 percent for the expense ratio, and 54.5 percent for the turnover ratio. Hence the relative number of hedge funds is almost as important as the skilled-unskilled ratio.

trading costs divided by the skilled ratio is most successful in explaining alphas. The rationale is that the average mutual fund is not skilled enough resulting in more turnover simply increasing transaction costs and hence reducing alpha. Also the hiring of successful mutual funds by hedge funds is an important factor, and finally the average expense ratio has been rising which reduces alpha.

Chapter 5

Mutual Fund Style Timing Skills and Alpha

5.1 Introduction

Style timing is the challenge to follow a particular style at the right time. A mutual fund manager can, for example, have a tilt towards high beta stocks when he believes the market will go up. Studies on style timing focus primarily on two questions. First, do mutual funds have style timing skills? Second, if there are some style timers, how to identify them ex-ante? Both questions are not easy to answer due to estimation errors in the style exposures, see Jagannathan and Korajczyk (1986). A related problem is the negative correlation between alpha and timing skills, see Kon (1983), Henriksson (1984), Jagannathan and Korajczyk (1986) and Bollen and Busse (2001). This results in a poor ex-post performance when selecting mutual funds on style timing. In this study, we provide a method to alleviate the biases. This method selects funds by using the full return history (the ex-ante period from the inception of a fund until the point we stand), daily returns, and include alpha and all three timing skills: market timing, size timing, and value-growth timing. With this approach we are able to show that style timing skills exist and those mutual funds can be successfully identified ex-ante. In particular we find that investing each month in the top decile of mutual funds selected with our approach yields an excess return of 8.01 percent per annum with a Sharpe ratio of 0.476. In comparison, selecting only on alpha yields an excess return of 5.10 percent per annum with a Sharpe ratio of 0.234. Also selecting funds on just one style timing skills leads to inferior performance. Moreover, selecting on alpha and all three style timing skills using only one quarter of daily data instead of all the available data up to that point yields an excess return of 4.75 percent per annum with a Sharpe ratio of 0.253. And finally, selecting on alpha and all three style timing skills using monthly data instead of daily data only yields an excess return of 2.68 percent per annum with a Sharpe ratio of 0.122. Hence all three dimensions are important: (i) Use as much history as possible; (ii) use daily data, and (iii) select simultaneously on alpha and three style timing skills.

Several solutions have been proposed in the literature to identify style timers. First, Bollen and Busse (2001) show that market timing exposures are more accurately estimated with daily instead of monthly data. Second, Chance and Hemler (2001) use explicit recommendations executed in customer accounts (i.e. they observe the positions that are taken by market timers from customer statements). Third, Jiang et al. (2007) use fund holdings. Finally, Friesen and Sapp (2007) use cash flow data. Evidence on successful style timing studies is mixed, with Bollen and Busse (2001), Chance and Hemler (2001) and Jiang et al. (2007) showing successful market timers do exist, whilst Friesen and Sapp (2007) do not find any evidence of market timing skills. Non-return data is often hard to get and usually only available in low frequency. In this study we therefore focus on daily return data. The advantage of daily return data is that intra-month shifts in styles can be picked up more accurately than with monthly data.

Previous studies usually only study one style timing skill at a time. Bollen and Busse (2001), for example, study market timing, and Swinkels and Tjong-A-Tjoe (2007) study market timing, size timing and value timing separately[1]. Bollen and Busse (2001) conclude that mutual funds demonstrate significant market timing skill more often by using higher frequency data. And Swinkels and Tjong-A-Tjoe (2007) find evidence that mutual funds are able to time the market and value-growth, but only find weak evidence that they can time size. In this study we show

[1]Chan et al. (2002) do look simultaneously at all timing skills, but they analyze timing skills for the average mutual fund, not for individual mutual funds.

that when using return data only, the best way to select mutual funds is to select simultaneously on alpha and all style timing skills. These skills are best estimated using daily data and the full fund's history (the ex-ante period from the inception of a fund until the point we stand).

We provide two complimentary analyses to support our main conclusions. First, we use bootstrap analysis in order to illustrate which method provides the most accurate estimation results for alpha and the level of style timing. The advantage of using a bootstrap for this is that we know the true outcomes for each fund. The results show that this way (selecting funds on the full return history, daily returns and include alpha and all three timing skills) the fund loadings are estimated the most accurately. Estimation accuracy decreases when selecting funds on a single timing skill, with monthly data and/or a shorter estimation window. Selecting mutual funds on one characteristic only, for example market timing, results in a large positive estimation error on the market timing skills, negative biases towards alpha and other timing skills, and fails to choose the best funds (the funds that should be selected given that we know the true values).

Second, we show empirically that the ex-post performance of the top decile based on all characteristics is superior to top deciles selected on a subset of the characteristics. And we can also show that the top decile has statistically significant ex-post style timing skills. Hence style timers exist and our method manages to successfully identify these style timers. Moreover, we find that the top decile funds have fund characteristics (e.g. age, expense ratio, and fund size) that are close to average characteristics of all funds. Hence, it is hard to identify style timers from their fund characteristics. Similar to the finding of Jiang et al. (2007) and Bae and Yi (2008), we find that most of the successful style timers are small growth funds.

The remainder of this study is organized as follows. First, Section 5.2 describes the data and explains the methodology both for the bootstrap and the empirical analysis. Section 5.3 shows the bootstrap results, whereas Section 5.4 presents the empirical evidence. Next, Section 5.5 shows some robustness checks. Finally Section 5.6 concludes.

5.2 Data and Methodology

Bollen and Busse (2001, 2004) study daily returns of 230 mutual funds from 1985 to 1995. In this paper we also use daily data from a more recent period and larger cross-section data. Daily returns of 11,225 equity mutual funds are extracted from the CRSP Mutual Fund Survivorship-bias Free Database that is available from 1998 to 2006. We include funds that are classified as small company growth, aggressive growth, growth, income, growth & income or maximum capital gains. The choice of the selected fund types is similar to that of Carhart (1997) and Pastor and Stambaugh (2002). The information about the fund classification is provided by Wiesenberger, Micropal/Investment Company Data, Inc. and S&P.

We also extract daily returns on the Fama and French factors, i.e. the market factor (RMRF), the size factor (SMB) and the value-growth factor (HML), from Kenneth French's data library. The daily SMB and HML factors are constructed in the same way as the monthly SMB and HML (see Fama and French (1993)). The excess market return (RMRF) is based on the returns from all NYSE, AMEX and NASDAQ stocks, and the risk-free rate. To proxy the risk-free rate, we use the one-month Treasury bill rate from Ibbotson and Associates. All returns are returns in excess of the risk-free rate. Swinkels and Tjong-A-Tjoe (2007) also extract daily data from the CRSP database to investigate a style timing skill of mutual funds. To check the quality of the daily CRSP data we aggregate them to monthly returns to compare with the monthly CRSP returns. We find that the monthly returns that are aggregated from CRSP daily returns and the CRSP monthly returns have a correlation of 0.98.

In Section 5.2.1 we explain which model is used to estimate the style timing skills and how we select the style timers. This paper implements bootstrap analysis to investigate how to minimize the problem of estimation bias when selecting mutual funds on their style timing skills. Section 5.2.2 shows the methodology for the bootstrap analysis. Finally, we show in Section 5.2.3 how we estimate the ex-post skills and the ex-post performance of the selected funds.

5.2.1 Estimation of style timing skills and selecting style timers

A fund manager with style timing skills can anticipate the style factor returns and hence adjust the exposures to the style factors accordingly. To identify style timers we will use equation (5.1),

$$r_{i,t} = \alpha_i + \beta_{1,i}RMRF_t + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}RMRF_t^+ + \beta_{5,i}SMB_t^+ + \beta_{6,i}HML_t^+ + \varepsilon_{i,t}, \tag{5.1}$$

where $r_{i,t}$ is the excess return of mutual fund i in day t, and $RMRF_t$, SMB_t and HML_t are the daily Fama and French (1993) factor returns. $RMRF_t^+$, SMB_t^+ and HML_t^+ are equal to $max(0, RMRF_t)$, $max(0, SMB_t)$ and $max(0, HML_t)$, respectively.

Existing studies often use only part of this model. Henriksson and Merton (1981), for example, test the existence of market timing skills by excluding a fund's exposures to the size and value factors ($\beta_{2,i}$=$\beta_{3,i}$=0), and a fund's size and value timing skills ($\beta_{5,i}$=$\beta_{6,i}$=0) from equation (5.1).

For comparison, we do not only identify funds that have four skills (market timing, size timing, value timing and alpha), but also funds that only have one of them. Suppose we want to select funds on alpha. Then we use equation (5.1) and exclude $\beta_{4,i}RMRF_t^+$, $\beta_{5,i}SMB_t^+$ and $\beta_{6,i}HML_t^+$ to identify the funds. And if we want to select funds on market timing skill, we drop $\beta_{5,i}SMB_t^+$ and $\beta_{6,i}HML_t^+$ from equation (5.1) (see eg. Bollen and Busse (2001) and Swinkels and Tjong-A-Tjoe (2007)).

To select funds based on all or one of alpha and three timing skills, we estimate the ex-ante parameters of the relevant restricted version of equation (5.1), and then rank funds on the ex-ante coefficients. The ex-ante period is either the full-life history available up to the point where we estimate the timing skills, the most recent three years or the most recent quarter. Next, we select the funds with the highest skill(s) in the top decile and rebalance it every month. When we select funds on just a single skill, the methodology is straightforward. When, for example, we select market timers, we rank funds each month on the ex-ante estimated $\beta_{4,i}$. When, however, we select funds on more than one skill, we implement the following method. Suppose we select funds that have alpha, market timing skill, size timing skill and value timing skill, and there are 100 funds. First, we rank the 100 funds on the ex-ante estimated α_i's. The fund with the highest (lowest) α_i gets alpha-rank 1 (100). Similarly we rank the 100 funds on the ex-ante coefficients for market timing ($\beta_{4,i}$), size timing ($\beta_{5,i}$), and value-growth timing ($\beta_{6,i}$). Then, for each fund, we sum the four rankings, and subsequently rank all funds based on this sum. Hence, the funds in the top decile have the highest combination of alpha and three style timing skills. Bollen and Busse (2004) rank mutual funds on their alpha and market timing skill in a different way. They select the top decile of funds based on the sum of α_i and $\beta_{4,i}RMRF_t^+$. We have also tested this methodology to select funds on alpha and three timing skills. An important finding is that this method puts much more emphasis on alpha. Our ranking method has a more balanced distribution among alpha and timing skills. We will mention results using the Bollen and Busse (2004) methodology for comparison in the text when discussing our results.

5.2.2 Bootstrap

The advantage of a bootstrap analysis is that we know what the true values are. In this study we use bootstrap analysis in order to compare which method provides the most accurate estimation of style timing skills. Also we can illustrate the direction of the estimation biases. The bootstrap analysis is set up in the same way as Kosowski et al. (2006) and Kosowski et al. (2007). The simulated returns are bootstrapped from the empirical data so that the simulated returns are representative for the empirical data. For each mutual fund we estimate and save the loadings (α_i, $\beta_{1,i}$, $\beta_{2,i}$, $\beta_{3,i}$, $\beta_{4,i}$, $\beta_{5,i}$ and $\beta_{6,i}$) and the time-series of residuals ($\varepsilon_{i,t}$) from equation (5.1). Next, we draw the residuals that we save before with replacements ($\varepsilon_{i,t_e}, t_e = s_1, s_2, \ldots, s_T\}$), where $s_1, s_2, \ldots, s_T$ is the reordering imposed by the bootstrap. Hence, the simulated returns are generated according to equation (5.2).

$$\begin{aligned} r_{i,t} = {} & \alpha_i + \beta_{1,i}RMRF_t + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \\ & \beta_{4,i}RMRF_t^+ + \beta_{5,i}SMB_t^+ + \beta_{6,i}HML_t^+ + \varepsilon_{i,t_e}, \end{aligned} \tag{5.2}$$

Bollen and Busse (2001) conclude that testing market timing skills of mutual funds by using daily data is more powerful than that using monthly data. In this paper, we also make a comparison between the daily and monthly frequency. To generate monthly returns, we accumulate the generated daily returns in the corresponding month. For each method of selecting funds, we estimate ex-ante skills of funds and rank them on their ex-ante skills and select funds that are in the top 10 percent (see Section 5.2.1). Since we know the true alphas and style timing exposures of all funds, we can study the bias from each methodology by determining the Mean Squared Errors (MSE) and the mean estimation error. The mean error indicates whether a certain method of selecting funds tends to overestimate or underestimate a certain skill.

5.2.3 Empirical analysis of ex-post timing skills and performances

After we select funds on all or one of the alpha and three timing skills, we estimate the ex-post style timing skills of the selected funds in the top decile portfolio every month by taking the average daily returns of the selected funds and then using equation (5.1) to estimate the ex-post skills in the one month ex-post period. Finally we take the average of all ex-post timing coefficients over time. This methodology follows Bollen and Busse (2004). According to Bollen and Busse (2004), this methodology is better than concatenating all ex-post returns and estimate the funds' skills at once. The explanation is based on the difference between unconditional and conditional performance measures. Ferson and Schadt (1996) show that fund performance looks better when it is evaluated on a conditional model, where they use macro-economics variables such as dividend yield, term spread, and default spread. The method of estimating the ex-post timing skills every month can be seen as a non-parametric implementation of a conditional model. We would like to refer the readers to Bollen and Busse (2004) for the detailed explanation. Besides estimating the ex-post timing skills, we also observe the ex-post annual returns and Sharpe ratio of the selected funds.

5.3 Bootstrap results

Section 5.3.1 shows the results from the bootstrap analysis, in particular that fund selection based on all criteria has lower estimation errors in the alpha and style timing coefficients than the corresponding estimation errors when selecting funds on a subset of criteria. In Section 5.3.2 we show that the estimation errors of the skills are worse when the estimation window is shorter and the data frequency is lower.

5.3.1 Selecting funds on a subset of characteristics

In this section we show the biases in the estimated loadings of the mutual funds that are selected in the top decile. This will illustrate the importance of selecting mutual funds on all criteria, not just on alpha or a single timing skill. The results in this section are based on the bootstrap methodology explained in Section 5.2.2 and the general approach on selecting the top decile of mutual funds described in Section 5.2.1.

Table 5.1 shows the key results when each month selecting the top decile of mutual funds based on one or more criteria, after estimating the relevant mutual fund loadings using all available daily data up to the moment of selection. In this experiment we know the true fund loadings, and hence we can compute the Mean Squared Error (MSE) by comparing the estimated loadings with the true loadings.

We first note that including all criteria simultaneously results in the lowest MSEs, meaning that the true characteristics of the funds we select in that case are closest to the characteristics we believed we were selecting. For example, the MSE for alpha is 0.005 when selecting on all criteria (row labelled α, RMRF$^+$, SMB$^+$, HML$^+$ in panel A in Table 5.1), compared to 0.521 when selecting only on alpha. Similarly the MSE for RMRF$^+$ is 0.005 when selecting on all criteria compared to 0.818 when selecting only on market timing. In Section 5.5 we demonstrate that these results are still robust when the simulated returns are generated from different models.

Second, panel B illustrates the main reason behind the higher MSEs when selecting only on one criterion. The estimated loading on the characteristic of our interest is upward biased. For

Table 5.1: Estimation errors in loadings of top decile mutual funds

This table shows the mean squared errors (panel A), mean errors (panel B) and average true loadings (panel C) for the top decile of mutual funds selected on one or more criteria based on daily data and the full return history (the ex-ante period from the inception of a fund until the point we stand). The first column shows each time on which criteria the mutual funds are selected. Each time α, RMRF, SMB and HML are always included in the model. If mutual funds are selected on a particular timing skill then this style is also included in the model. Selecting on all timing skills and alpha will result in the model in equation (5.1). In the simulation we know the true loadings of each selected mutual fund and hence we can compare the estimated fund loadings with the true loadings. The analysis is based on mutual funds data over the period 1998 to 2006.

Model	α	$RMRF^+$	SMB^+	HML^+
Panel A: Mean Squared Errors (x100)				
α	0.521			
$RMRF^+$	0.080	0.818		
SMB^+	0.104		2.257	
HML^+	0.073			2.759
$RMRF^+$, SMB^+, HML^+	0.196	0.028	0.544	0.259
α, $RMRF^+$, SMB^+, HML^+	0.005	0.005	0.219	0.060
Panel B: Mean error				
α	0.070			
$RMRF^+$	-0.012	0.083		
SMB^+	-0.011		0.129	
HML^+	-0.004			0.144
$RMRF^+$, SMB^+, HML^+	-0.033	0.015	0.055	0.031
α, $RMRF^+$, SMB^+, HML^+	-0.004	0.003	0.038	0.016
Panel C: Average true loadings				
α	-0.018	0.027	0.036	0.057
$RMRF^+$	-0.066	0.095	0.031	0.072
SMB^+	-0.055	0.020	0.130	0.055
HML^+	-0.064	0.057	0.042	0.127
$RMRF^+$, SMB^+, HML^+	-0.072	0.060	0.095	0.083
α, $RMRF^+$, SMB^+, HML^+	-0.046	0.034	0.083	0.071

example when selecting only on 3-factor alpha the estimated 3-factor alpha is 0.070 percent per day higher than the true 6-factor alpha. In fact the true 6-factor alpha in that case is on average -0.018 percent per day (row labelled α in Panel C of Table 5.1) but we estimated it to be 0.052 percent per day (the difference between 0.070 and 0.018).

Third, panel C shows that, despite the bias in selecting funds for which we overestimated the loadings, we do manage to select better-than-average funds on the selected criteria. The average true alpha, and market, size and value timing coefficients are -0.016, 0.014, 0.018 and 0.014, respectively. When selecting on market timing skills, for example, the average true market timing skill is 0.095 compared to 0.014 for the average mutual fund.

Fourth, Table 5.1 also illustrates that we have a disappointing loading on criteria which we do not select on. When selecting on market timing skills only, for example, the true alpha is -0.066 percent per day, compared to -0.018 percent per day when selecting on alpha. On the other hand when selecting only on alpha the loading on market timing is 0.027 compared to the 0.095 loading when selecting on market timing.

All the aforementioned conclusions are confirmed when re-doing the bootstrap analysis with cross-correlation or time-series dependence in the residuals in equation (5.2); see Kosowski et al. (2006) for details on these alternative ways to conduct the bootstrap.

5.3.2 Impact of data frequency and estimation window

The results in Table 5.1 are based on using for each fund its full return history (the ex-ante period from the inception of a fund until the point we stand). To illustrate the impact of this choice on the estimation errors we reproduce panel A in Table 5.1 for the popular 3-year estimation window as well as the quarterly window advocated in Bollen and Busse (2001). The results are presented in Table 5.2.

The results in Table 5.2 first of all confirm the pattern that MSEs decline when estimating simultaneously alpha and all three style timing skills. Second the results rapidly deteriorate the shorter the time window used to estimate the parameters. For example when selecting on all skills using quarterly estimation windows the MSEs are 0.716, 1.857, 7.062 and 16.478 for

Table 5.2: The Impact of Estimation Window

This table shows the mean squared errors that are scaled by 100 for the top decile of mutual funds selected on one or more criteria based on 3 year estimation windows (panel A) and 1 quarter windows (panel B) of daily data. The first column shows each time on which criteria the mutual funds are selected. Each time α, RMRF, SMB and HML are always included in the model. If mutual funds are selected on a particular timing skill then this style is also included in the model. Selecting on all timing skills and alpha will result in the model in equation (5.1). In the simulation we know the true loadings of each selected mutual fund and hence we can compare the estimated fund loadings with the true loadings. The analysis is based on mutual funds data over the period 1998 to 2006.

Model	α	$RMRF^+$	SMB^+	HML^+
Panel A: 3 year				
α	0.474			
$RMRF^+$	0.095	1.072		
SMB^+	0.125		3.467	
HML^+	0.076			4.994
$RMRF^+$, SMB^+, HML^+	0.258	0.068	0.763	0.663
α, $RMRF^+$, SMB^+, HML^+	0.020	0.024	0.331	0.428
Panel B: 1 quarter				
α	2.064			
$RMRF^+$	2.396	22.302		
SMB^+	2.557		64.995	
HML^+	2.302			125.816
$RMRF^+$, SMB^+, HML^+	4.796	4.055	16.960	30.773
α, $RMRF^+$, SMB^+, HML^+	0.716	1.857	7.062	16.478

alpha, market timing, size timing and value-growth timing, respectively. In Table 5.1 panel A the corresponding values were much lower at 0.005, 0.005, 0.219, and 0.060, respectively.

Of course in our bootstrap set-up the parameters are held constant, and hence longer estimation windows should be beneficial. In case timing skills change over time shorter time windows could do better. These results, however, show the dramatic increase in estimation errors for short time windows. Furthermore we will later show in the empirical results that also for the actual data it is better to use the longest available estimation windows, with the exception of estimating alphas for which we corroborate the findings of Bollen and Busse (2001) that they are better estimated using a shorter time window.

In unreported results we also find that when the shorter estimation window is used, the estimated loading on the characteristic of our interest is more upward biased than is the case with the longer estimation window. At the same time the estimated loadings of the characteristics that we do not select on is more downward biased. For example, when selecting market timers based on the full return history of each fund, the estimated market timing loading is 0.083 higher than the true market timing skill. And the estimated alpha is 0.012 percent per day lower than the true alpha. However, when we estimate market timing with quarterly estimation windows, the estimated loading is 0.443 higher than the true market timing loading. The estimated alpha in this case is 0.154 percent per day lower than the true alpha. Hence, the problem of the negative correlation between alpha and timing skills (see Kon (1983), Henriksson (1984), Jagannathan and Korajczyk (1986) and Bollen and Busse (2001)) is more pronounced when the estimation window is shorter.

Additionally, when we select on market timing using the full return history, 3-year windows and the quarterly windows, the average true loading of market timing skills are 0.095 (see Table 5.1), 0.089 and 0.047 (these two numbers are not reported in the table), respectively. Hence, if we use a shorter estimation window, the selected funds will be further away from selecting the funds that should be selected when we know the true values.

The results in Table 5.1 are based on daily returns. For comparison the results in panel A are reproduced for monthly returns with the same data generated process, see Table 5.3. Again we see that MSEs decline when estimating all skills simultaneously. Furthermore the results are clearly worse for monthly data. Selecting, for example, on market timing only the MSE increases from 0.818 for daily data to 22.433 for monthly data. It shows that using lower frequency return loses some efficiency in the estimation and is less powerful to test timing skill (see also Bollen and Busse (2001).

Moreover, by using monthly data, we will select funds that are further away from selecting the funds that should be selected when we know the true values. For example, in this case monthly data select funds with average true market timing of 0.028, whilst the daily data select funds with average market timing of 0.095 (see Table 5.1). Hence it is really important to use daily data for accurately estimating and identifying style timers. When, for example, there is a reversal in a factor return within the month and the portfolio manager anticipates this, using daily data can identify his skill more accurately.

Table 5.3: The Impact of Data Frequency

This table shows the mean squared errors (panel A), mean errors (panel B) and average true loadings (panel C) for the top decile of mutual funds selected on one or more criteria based on daily data and the full return history (the ex-ante period from the inception of a fund until the point we stand). The first column shows each time on which criteria the mutual funds are selected. Each time α, RMRF, SMB and HML are always included in the model. If mutual funds are selected on a particular timing skill then this style is also included in the model. Selecting on all timing skills and alpha will result in the model in equation (5.1). In the simulation we know the true loadings of each selected mutual fund and hence we can compare the estimated fund loadings with the true loadings. The analysis is based on mutual funds data over the period 1998 to 2006.

Model	α	$RMRF^+$	SMB^+	HML^+
Panel A: Mean Squared Errors (x100)				
α	0.172			
$RMRF^+$	0.021	22.433		
SMB^+	0.050		30.414	
HML^+	0.026			31.618
$RMRF^+$, SMB^+, HML^+	0.087	5.118	5.605	5.059
α, $RMRF^+$, SMB^+, HML^+	0.069	1.533	5.484	2.707
Panel B: Mean error				
α	0.040			
$RMRF^+$	-0.008	0.461		
SMB^+	-0.001		0.489	
HML^+	0.008			0.538
$RMRF^+$, SMB^+, HML^+	-0.015	0.208	0.193	0.193
α, $RMRF^+$, SMB^+, HML^+	0.007	0.102	0.178	0.111
Panel C: Average true loadings				
α	0.011	0.011	0.008	-0.001
$RMRF^+$	-0.042	0.028	0.054	0.052
SMB^+	-0.037	0.026	0.059	0.046
HML^+	-0.051	0.028	0.068	0.077
$RMRF^+$, SMB^+, HML^+	-0.050	0.029	0.069	0.066
α, $RMRF^+$, SMB^+, HML^+	-0.028	0.020	0.052	0.049

5.4 Empirical results

In this section we present the empirical results where we select the top decile of mutual funds based on one or more characteristics. Subsequently we estimate the ex-post exposures to style timing. These results are presented in Section 5.4.1. Next, in Section 5.4.2, we also show the ex-post performance of the top decile of mutual funds when selecting these on one or more characteristics.

5.4.1 Ex-post style timing exposures

Each month we form the top decile of mutual funds based on the loadings on alpha, market timing, size timing, value-growth timing or a combination of these. Subsequently we use the daily returns in the subsequent month to estimate the ex-post loading on the selected characteristic(s). The average loadings taken over all months and the corresponding t-values are presented in Table 5.4.

Panel A in Table 5.4 shows the main results. When selecting simultaneously on all three style timing skills (row with α, $RMRF^+$, SMB^+, HML^+) the ex-post loadings on market timing and size timing are statistically significant at the 5 percent and 10 percent significance level, respectively. Hence style timing exists and persists, and additionally we can also identify the successful style timers.

The other panels in Table 5.4 illustrate that identifying the successful style timers is more difficult with less data. In all cases the loadings on the style timing factors become less significant or even not significant at all. For example when using monthly data and selecting on market timing (Panel D, row $RMRF^+$) the loading on $RMRF^+$ is 0.025 with an insignificant t-value of 1.56. In panel A we see, however, that when selecting the market timers with daily data the loading on $RMRF^+$ is 0.072 with a t-value of 3.29.

It is noteworthy that when selecting mutual funds on alpha the results do improve when using one quarter of daily data, confirming the findings of Bollen and Busse (2004). The alpha is 0.017 percent per day with a significant t-value of 2.18 using three months, whereas it is 0.010

Table 5.4: Ex-post style timing exposures

This table shows the adjusted R^2 and the ex-post skills of the top decile mutual funds that are selected on one or more criteria. We rebalance the portfolio monthly and then estimate the ex-post skill monthly from the average daily returns of selected funds. Subsequently, we take average of all ex-post skill over time. Panel A, B and C use daily data over full return history (the ex-ante period from the inception of a fund until the point we stand), 3 year and 1 quarter estimation window, respectively. And panel D use monthly data. The first column shows each time on which criteria the mutual funds are selected. The t-statistics of the estimation are shown in parentheses. The analysis is based on mutual funds data over the period 1998 to 2006.

Model	Adj R^2	α		$RMRF^+$		SMB^+		HML^+	
Panel A: Full-life history									
α	0.938	0.010	(1.36)						
$RMRF^+$	0.928	-0.024	(-1.93)	0.072	(3.29)				
SMB^+	0.952	-0.002	(-0.42)			0.038	(1.66)		
HML^+	0.906	-0.003	(-0.37)					0.077	(1.84)
$RMRF^+$, SMB^+, HML^+	0.956	-0.024	(-3.20)	0.046	(2.95)	0.053	(2.10)	0.019	(0.68)
α, $RMRF^+$, SMB^+, HML^+	0.965	-0.002	(-0.28)	0.039	(2.29)	0.036	(1.78)	0.004	(0.16)
Panel B: 3 year									
α	0.919	0.014	(1.92)						
$RMRF^+$	0.921	-0.021	(-1.61)	0.063	(2.65)				
SMB^+	0.918	0.002	(0.22)			0.038	(1.22)		
HML^+	0.891	-0.004	(-0.52)					0.113	(2.43)
$RMRF^+$, SMB^+, HML^+	0.933	-0.021	(-2.13)	0.050	(2.57)	0.039	(1.14)	0.050	(1.31)
α, $RMRF^+$, SMB^+, HML^+	0.951	0.002	(0.26)	0.035	(1.70)	0.029	(1.03)	0.019	(0.51)
Panel C: 1 quarter									
α	0.901	0.017	(2.18)						
$RMRF^+$	0.910	-0.003	(-0.20)	0.051	(2.11)				
SMB^+	0.892	0.005	(0.50)			0.002	(0.04)		
HML^+	0.886	0.001	(0.08)					0.054	(1.26)
$RMRF^+$, SMB^+, HML^+	0.915	-0.002	(-0.13)	0.049	(2.31)	0.017	(0.60)	0.023	(0.57)
α, $RMRF^+$, SMB^+, HML^+	0.933	0.013	(1.18)	0.052	(1.82)	0.023	(0.73)	-0.013	(-0.35)
Panel D: monthly data									
α	0.952	0.011	(1.42)						
$RMRF^+$	0.954	-0.009	(-0.98)	0.025	(1.56)				
SMB^+	0.954	0.016	(1.54)			-0.019	(-0.72)		
HML^+	0.961	0.018	(1.51)					0.029	(0.72)
$RMRF^+$, SMB^+, HML^+	0.960	0.010	(0.78)	0.066	(2.72)	0.000	(0.01)	0.019	(0.52)
α, $RMRF^+$, SMB^+, HML^+	0.955	0.023	(1.51)	0.065	(2.38)	-0.008	(-0.23)	0.028	(0.70)

percent per day with an insignificant t-value of 1.36 using the full return history for each fund.

5.4.2 Ex-post performance of the selected funds

Each month we form the top decile of mutual funds based on the estimated loadings of alpha, market timing, size timing, value-growth timing or a combination of these. From the resulting ex-post daily returns we can compute the average (annualised) returns and the Sharpe ratio. Table 5.5 shows the results when selecting on a single or a combination of skills, the results for different estimation windows and the results for the daily and monthly frequency.

The most important result from Table 5.5 is that when selecting mutual funds based on all skills with the loadings on these skills estimated using daily data for the full return history or the ex-ante period from the inception of a fund until the point we stand (Panel A, row α, RMRF^{+}, SMB^{+}, HML^{+}) we obtain the highest annualised return at 8.01 percent per annum and the highest Sharpe ratio of 0.476. These results are superior compared to the average return and Sharpe ratio of all mutual funds over the same period, which are equal to 3.65 percent and 0.213, respectively. Hence the approach that most accurately estimates the loadings is also the most successful in selecting mutual funds. We can also conclude that selecting mutual funds that are good on alpha and three timing skills improves upon selecting mutual funds that are very good on one characteristic and worse on the other characteristics.

As already mentioned in Section 5.4.1 we, like Bollen and Busse (2004), find that when selecting only on alpha we better use only 1 quarter of daily data to estimate the alphas. The first row of Panel C shows that in that case the annualised return is 7.07 percent per annum with a Sharpe ratio of 0.347. Hence it appears that style timing skills are best estimated over the longest possible estimation period, whereas for alpha we should use a very recent and short estimation period. Bollen and Busse (2004) explain that the alpha has short persistence because when a fund has higher alpha, many investors allocate their money in the fund. But this capital inflow will erode the alpha of this fund. Such a short estimation period, however, is insufficient to identify style timing abilities. First of all it might well be that in a 3-month period a factor mainly shows positive returns, making it impossible to identify style timing. Second, it will

Table 5.5: Ex-post performance of the selected funds

This table shows the ex-post return and sharpe ratio of the top decile mutual funds that are selected on one or more criteria. Panel A, B and C use daily data over full-life (the ex-ante period from the inception of a fund until the point we stand), 3 year and 1 quarter estimation window, respectively. And panel D use monthly data. The first column shows each time on which criteria the mutual funds are selected. The analysis is based on mutual funds data over the period 1998 to 2006.

Model	Excess Return	Sharpe ratio
Panel A: Full-life history		
α	5.101	0.234
$RMRF^+$	1.413	0.063
SMB^+	6.936	0.443
HML^+	3.958	0.218
$RMRF^+$, SMB^+, HML^+	6.578	0.395
α, $RMRF^+$, SMB^+, HML^+	8.014	0.476
Panel B: 3 year		
α	6.608	0.309
$RMRF^+$	1.415	0.063
SMB^+	6.588	0.402
HML^+	4.259	0.228
$RMRF^+$, SMB^+, HML^+	6.098	0.351
α, $RMRF^+$, SMB^+, HML^+	7.868	0.461
Panel C: 1 quarter		
α	7.070	0.347
$RMRF^+$	0.870	0.038
SMB^+	3.009	0.167
HML^+	2.350	0.118
$RMRF^+$, SMB^+, HML^+	1.309	0.070
α, $RMRF^+$, SMB^+, HML^+	4.750	0.253
Panel D: monthly data		
α	4.716	0.207
$RMRF^+$	1.194	0.063
SMB^+	3.031	0.147
HML^+	4.430	0.195
$RMRF^+$, SMB^+, HML^+	2.227	0.111
α, $RMRF^+$, SMB^+, HML^+	2.682	0.122

be hard to distinguish skill from luck. These problems are alleviated when looking at longer estimation periods. Given that alphas should be estimated on a short period and style timing skills over a longer period it is not surprising that choosing the middle ground with a 3-year estimation window is also doing well when selecting on all skills, see the final row in Panel B. The annualised return is 7.87 percent with a Sharpe ratio of 0.461, close to our best result.

Selecting mutual funds on fund loadings estimated with monthly data (Panel D) clearly leads to inferior results. We already noted the very poor MSEs in Table 5.3 for the style timing skills, and this clearly translates in poor selection skills. In unreported results, we repeat the analysis for monthly data (Table 5.5 Panel D) over 1962 to 2006. In this analysis we do see that selecting on all skills is the second best to selecting only on alpha. It shows that the style timings are identified the best by daily data rather than monthly data as monthly data overlook intra-month timing (see Bollen and Busse (2001)). And subsequently, selecting on alpha with monthly data will look the best strategy.

We also computed the corresponding results when selecting the top decile with the Bollen and Busse (2004) method, i.e. summing alpha and the timing terms in equation (5.1) rather than adding rankings. Unreported results show that in this case selecting on all four skills results in an annualised return of 5.35 percent and a Sharpe ratio of 0.235. The reason for the lower performance lies in the much larger weight on alpha in the Bollen and Busse (2004) methodology. We compute the overlap of the selected top deciles with those selected on a single skill and observe that their methodology selects 88.5 percent, 22.7 percent, 18.6 percent and 20.0 percent the same funds as those selected on only alpha, market timing, size timing and value timing, respectively. In our case the corresponding numbers are 31.1 percent, 34.4 percent, 50.1 percent and 40.2 percent, respectively, showing we spread more evenly over the different skills. Finally we also computed the corresponding results when selecting the top decile based on t-values of the loadings, rather than the loadings themselves. Obviously when we can perfectly estimate the loadings, it will be better to select mutual funds on those loadings provided they show persistence. In the case, however, where estimation errors are very high with a positive estimation error for the characteristic(s) on which the top decile of mutual funds is selected, t-values might be more reliable in identifying true style timers. In that case ranking on coefficients may more often than not select the wrong funds. For example, in Table 5.5 when selecting market timers using daily data for the full return history (row 2 in Panel A) the average return is 1.41 percent per annum with a Sharpe ratio of 0.063. Producing the same result be selecting market timers on the t-value on the loading on RMRF$^+$ the average return is 3.21 percent per annum with a Sharpe ratio of 0.168. Still, when applying our recommended method of selecting funds on alpha and all three timing skills simultaneously, ranking on t-values gives a return of 6.31 percent per annum and a Sharpe of 0.384, well short of the 8.01 percent and 0.476 Sharpe when ranking on loadings.

5.4.3 Fund characteristics of the selected funds

In Section 5.4.2 we find that the best approach is to select mutual funds simultaneously on alpha and all timing skills, identified using daily data over the largest possible window. In this section we look at the characteristics of the top decile of funds selected in this way. The results are presented in Table 5.6. Age is reported in months from CRSP monthly summary. Expense ratio is the ratio between all expenses (e.g. 12b-1 fee, management fee, administrative fee) and total net assets. Size is the fund's total net assets that is reported in millions of U.S. dollars. Turnover ratio is the minimum of aggregated sales or aggregated purchases of securities, divided by total net assets. Volatility is standard deviation of monthly returns. The exposures to the Fama and French factors are estimated using 3 years of monthly data.

First of all we note that the average characteristics of the selected funds do not show large deviations from the overall average, especially when putting the small differences in perspective to the differences between the top and bottom 10 percent funds selected on a single characteristic. The selected funds are similar in age, expense ratio, turnover and volatility. Second, we do see that the selected funds have on average a market beta that at 1.02 is slightly higher than that of all funds at 0.97. A plausible explanation is that one of our criteria is to select on market timing skills. Given that the market goes up more frequently than it declines, successful timers should have more often a higher beta than a lower beta. Third, the selected funds to have a tilt towards small growth stocks, with both the loading on SMB and HML higher than that of the average mutual fund. To investigate this further we also look at the average investment objectives of the mutual funds in the selected decile, see Table 5.7.

Table 5.6: Fund characteristics of the selected funds

The second column shows the characteristics of the top decile mutual funds that are selected on alpha and three timing skills (market, size and value), and daily returns over the full-life history (the ex-ante period from the inception of a fund until the point we stand). For comparison, the third, fourth and fifth columns show the characteristics of average mutual funds, the highest 10%, and the lowest 10% of the characteristics values. Age is reported in months from CRSP monthly summary. Expense ratio is the ratio between all expenses (e.g. 12b-1 fee, management fee, administrative fee) and total net assets. Size is the fund's total net assets that is reported in millions of U.S. dollars. Turnover ratio is the minimum of aggregated sales or aggregated purchases of securities, divided by total net assets. Volatility is standard deviation of monthly returns. The exposures to the Fama and French factors are estimated from 3-year period.

	selected funds	average	max 10%	min 10%
age	101.63	110.80	344.38	45.32
expense ratio	1.53	1.47	2.65	0.51
size	155.33	203.70	1571.24	0.51
turnover ratio	1.01	0.96	3.51	0.07
volatility	5.16	4.72	8.99	2.06
exposure RMRF	1.02	0.97	1.42	0.46
exposure SMB	0.32	0.18	0.89	-0.28
exposure HML	0.19	0.06	0.76	-0.79

Table 5.7: The proportion of the selected investment objective

Mutual funds are selected based on alpha and three timing skills that are estimated from daily returns over the funds' full-life history (the ex-ante period from the inception of a fund until the point we stand). This table demonstrates the proportion of each investment objective that is selected in the top decile portfolio. The information about the investment objective of a fund is provided by Wiesenberger, Micropal/Investment Company Data, Inc. and S&P. "mean" and "std" denote the average and the standard deviation of the proportions over time, respectively.

	Aggressive Growth	Growth	Growth and Income	Income	Small Growth
mean	0.226	0.225	0.078	0.005	0.465
std	0.155	0.037	0.028	0.008	0.170

The results show that on average more than 46 percent of the selected funds are classified as small growth. This outcome is consistent with Jiang et al. (2007) who find, using fund holdings, that market timers tilt towards small-cap stocks, and Bae and Yi (2008) who show with return-based analysis that growth funds time the market more actively than value funds. Additionally, Chen et al. (2000) find that growth-oriented funds have better skills than income-oriented funds.

5.5 Robustness checks

In Section 5.3, we discussed the results when the simulated returns assuming equation (5.1) is the true data generating process. In this section, we replicate the same analysis for alternative data generating processes to show that our results in Section 5.3 are not purely driven by the specific data generating process. First, we generate returns from equation (5.2) by excluding the style timing skills ($\beta_{4,i}$=$\beta_{5,i}$=$\beta_{6,i}$=0). Hence the mutual funds only have a true alpha, but they do not have any timing skills. The results are presented in Table 5.8 Part I.

Table 5.8: Different return generating process

In Part I, II, III and IV, the simulated returns are generated from equation (5.2) by excluding $\beta_{4,i}RMRF_t^+$, $\beta_{5,i}SMB_t^+$ and $\beta_{6,i}HML_t^+$; $\beta_{5,i}SMB_t^+$ and $\beta_{6,i}HML_t^+$; $\beta_{4,i}RMRF_t^+$ and $\beta_{6,i}HML_t^+$; $\beta_{4,i}RMRF_t^+$ and $\beta_{5,i}SMB_t^+$, respectively. And mutual funds have true alphas. This table shows the mean squared errors (panel A), mean errors (panel B) and average true loadings (panel C) for the top decile of mutual funds selected on one or more criteria based on daily data and the full return history (the ex-ante period from the inception of a fund until the point we stand). The first column shows each time on which criteria the mutual funds are selected. Each time α, RMRF, SMB and HML are always included in the model. If mutual funds are selected on a particular timing skill then this style is also included in the model. Selecting on all timing skills and alpha will result in the model in equation (5.1). In the simulation we know the true loadings of each selected mutual fund and hence we can compare the estimated fund loadings with the true loadings. The analysis is based on mutual funds data over the period 1998 to 2006.

Part I. There are only true alphas

Model	α	RMRF$^+$	SMB$^+$	HML$^+$
Panel A: Mean Squared Errors (x100)				
α	0.133			
RMRF$^+$	0.231	0.951		
SMB$^+$	0.266		3.120	
HML$^+$	0.228			2.647
RMRF$^+$, SMB$^+$, HML$^+$	0.375	0.070	1.104	0.413
α, RMRF$^+$, SMB$^+$, HML$^+$	0.006	0.008	0.346	0.069
Panel B: Mean error				
α	0.031			
RMRF$^+$	-0.043	0.088		
SMB$^+$	-0.044		0.159	
HML$^+$	-0.042			0.143
RMRF$^+$, SMB$^+$, HML$^+$	-0.054	0.025	0.093	0.053
α, RMRF$^+$, SMB$^+$, HML$^+$	-0.005	0.007	0.054	0.019
Panel C: Average true loadings				
α	0.015	0.000	0.000	0.000
RMRF$^+$	-0.002	0.000	0.000	0.000
SMB$^+$	-0.002	0.000	0.000	0.000
HML$^+$	-0.002	0.000	0.000	0.000
RMRF$^+$, SMB$^+$, HML$^+$	-0.003	0.000	0.000	0.000
α, RMRF$^+$, SMB$^+$, HML$^+$	0.008	0.000	0.000	0.000

Table 5.8 continued

Part II. There are only true alphas and market timing skills

Model	α	$RMRF^+$	SMB^+	HML^+
Panel A: Mean Squared Errors (x100)				
α	0.317			
$RMRF^+$	0.100	0.464		
SMB^+	0.133		3.483	
HML^+	0.083			4.490
$RMRF^+$, SMB^+, HML^+	0.256	0.006	0.930	0.561
α, $RMRF^+$	0.048	0.021		
α, $RMRF^+$, SMB^+, HML^+	0.010	0.043	0.499	0.299
Panel B: Mean error				
α	0.053			
$RMRF^+$	-0.025	0.054		
SMB^+	-0.022		0.170	
HML^+	-0.009			0.199
$RMRF^+$, SMB^+, HML^+	-0.042	0.000	0.084	0.066
α, $RMRF^+$	0.020	0.008		
α, $RMRF^+$, SMB^+, HML^+	-0.009	-0.020	0.067	0.052
Panel C: Average true loadings				
α	-0.004	0.043	0.000	0.000
$RMRF^+$	-0.055	0.121	0.000	0.000
SMB^+	-0.024	0.051	0.000	0.000
HML^+	-0.045	0.099	0.000	0.000
$RMRF^+$, SMB^+, HML^+	-0.039	0.082	0.000	0.000
α, $RMRF^+$	-0.014	0.055	0.000	0.000
α, $RMRF^+$, SMB^+, HML^+	-0.013	0.043	0.000	0.000

Table 5.8 continued

Part III. There are only true alphas and size timing skills

Model	α	$RMRF^+$	SMB^+	HML^+
Panel A: Mean Squared Errors (x100)				
α	0.229			
$RMRF^+$	0.136	1.017		
SMB^+	0.157		1.857	
HML^+	0.143			2.798
$RMRF^+$, SMB^+, HML^+	0.269	0.073	0.578	0.378
α, SMB^+	0.031		0.107	
α, $RMRF^+$, SMB^+, HML^+	0.005	0.020	0.108	0.119
Panel B: Mean error				
α	0.044			
$RMRF^+$	-0.029	0.092		
SMB^+	-0.030		0.108	
HML^+	-0.028			0.149
$RMRF^+$, SMB^+, HML^+	-0.044	0.026	0.055	0.051
α, SMB^+	0.016		0.026	
α, $RMRF^+$, SMB^+, HML^+	-0.003	0.013	0.018	0.031
Panel C: Average true loadings				
α	0.004	0.000	0.047	0.000
$RMRF^+$	-0.016	0.000	0.056	0.000
SMB^+	-0.039	0.000	0.152	0.000
HML^+	-0.015	0.000	0.056	0.000
$RMRF^+$, SMB^+, HML^+	-0.031	0.000	0.114	0.000
α, SMB^+	-0.009	0.000	0.078	0.000
α, $RMRF^+$, SMB^+, HML^+	-0.010	0.000	0.068	0.000

Table 5.8 continued

Part IV. There are only true alphas and value timing skills

Model	α	$RMRF^+$	SMB^+	HML^+
Panel A: Mean Squared Errors (x100)				
α	0.337			
$RMRF^+$	0.077	1.644		
SMB^+	0.166		3.368	
HML^+	0.108			1.371
$RMRF^+$, SMB^+, HML^+	0.264	0.125	0.947	0.167
α, HML^+	0.046			0.056
α, $RMRF^+$, SMB^+, HML^+	0.011	0.082	0.455	0.105
Panel B: Mean error				
α	0.055			
$RMRF^+$	-0.014	0.124		
SMB^+	-0.026		0.168	
HML^+	-0.024			0.086
$RMRF^+$, SMB^+, HML^+	-0.043	0.035	0.083	0.010
α, HML^+	0.019			0.014
α, $RMRF^+$, SMB^+, HML^+	-0.008	0.028	0.064	-0.028
Panel C: Average true loadings				
α	-0.004	0.000	0.000	0.082
$RMRF^+$	-0.037	0.000	0.000	0.153
SMB^+	-0.018	0.000	0.000	0.071
HML^+	-0.043	0.000	0.000	0.184
$RMRF^+$, SMB^+, HML^+	-0.031	0.000	0.000	0.123
α, HML^+	-0.011	0.000	0.000	0.089
α, $RMRF^+$, SMB^+, HML^+	-0.010	0.000	0.000	0.068

Just like in Table 5.1 we find that the MSE of alpha is lowest when also including the three style timing skills in the estimation. The MSE is 0.006 compared to 0.133 when only considering alpha. Reason is that when selecting only on alpha the estimated alphas suggest the top decile of funds selected on alpha have an average alpha of 4.6 percent per annum. The true value, however, is 1.5 percent. In contrast when also including the three style timing skills the estimated alpha of the top decile is 0.3 percent per annum compared to 0.8 percent for the true value. It illustrates that in the Fama and French model, without style timing factors, the alpha error distribution is much larger allowing the top decile to overstate alpha by a larger margin. Of course from an investor point of view we would still prefer to get the alpha of 1.5 percent per annum. The difference with Table 5.1 is that in the presence of true timing skills the better alpha we had in Table 5.1 when only selecting on alpha was more than offset by the often negative true exposure to the three style timing skills. Of course that is not possible in this case, as all true style timing skills are set to zero. Here we only see in column 1 of Table 5.8 Part I, Panel B that we have a negative bias in the estimated style timing exposures, just like we had in Table 5.1.

Of course we have seen in Section 5.4.2 that selecting funds on alpha and all three timing skills results in higher out-sample performance than selecting funds only on a subset of criteria. This indicates that both alpha and style timing skills exist, and the data generating process underlying the results in Table 5.8 Part I is different from the true data generating process as it ignores style timing skills.

Similarly, in Table 5.8 Part II, III and IV, we generate returns such that mutual funds only have market timing skill, size timing skill and value timing skill, respectively. To do so the mutual fund returns in Table 5.8 Part II, III and IV are generated from equation (5.2) by excluding size timing skill and value timing skill ($\beta_{5,i}$=$\beta_{6,i}$=0), market timing skill and value timing skill ($\beta_{4,i}$=$\beta_{6,i}$=0), and market timing skill and size timing skill ($\beta_{4,i}$=$\beta_{5,i}$=0), respectively. In Table 5.8 Part II, mutual funds only have true alpha and market timing skills. When we select funds on just these two skills (see row α $RMRF_t^+$), the MSE of the estimated alpha and market timing skills is 0.048 and 0.021, respectively. Whereas this is better than the MSE for alpha when selecting only on alpha at 0.317 or when selecting on timing skills for which the true level is zero, we again see that selecting on all skills simultaneously is a good alternative. For alpha the MSE is lower at 0.010 and for the market timing coefficient $\beta_{4,i}$ the MSE is higher at 0.043.

In Table 5.8 Part III, with mutual funds having selection skills (alpha) and size timing skills ($\beta_{5,i}$) again also including in this case the non-existing skills of market timing and value-growth timing leads to acceptable results. The MSE for alpha is lower at 0.005 compared to 0.031 when using the true model, and the MSE for $\beta_{5,i}$ is similar at 0.108 compared to 0.107 for the true model.

Finally in Table 5.8 Part IV we look at the data generating process that assumes mutual funds have true alphas and value-growth timing skills but no market timing and size timing skills. Also here using the true model gives low MSEs at 0.046 for alpha and 0.056 for the value-growth timing parameter, but the full model including all timing skills can compete with a lower MSE for alpha at 0.011 and a higher MSE for value-growth timing at 0.105.

Hence even when using a restricted model for the data generating process, the full model still gives acceptable results [2]. In contrast, in Table 5.1 we have seen that if the full model is the data generating process, estimation biases are quite large when estimating restricted models. As a result the best approach is to always use the full model, as also vindicated by the empirical results in Table 5.5.

5.6 Conclusion

The selection of mutual funds on their Fama and French 3-factor alpha has so far been more popular in the literature than selection of mutual funds on their ability to time the market, the size factor and the value-growth premium. The reason is that it is difficult to identify successful style timers due to estimation errors.

In this study we first of all show that to measure style timing, daily data are important because intra-month switches between styles can be more accurately modelled. Second, we find that style timing skills are much more persistent than alpha and hence should be estimated preferably with the full fund return history available at each point in time. Finally we show that the simultaneous selection of mutual funds on alpha and all three timing skills is very important. The reason is that using only a subset - usually mutual funds are selected on only one skill - increases the estimation errors with a positive estimation error on the characteristic the mutual funds are selected on and a negative loading on the other timing skills.

Hence our main conclusion is to always use the entire available return history, daily returns, and simultaneously estimate alpha and all three timing skills. With a bootstrap we show this leads to the smallest estimation errors. And the empirical data show this leads to selecting top deciles of mutual funds with the highest annualized returns and Sharpe ratio. This illustrates that style timers do exist and that we are able to identify successful style timers using only return data.

[2] The conclusions are still similar when we assume that mutual funds have zero alphas instead of true non-zero alphas.

Chapter 6

Summary and Conclusion

This dissertation aims to analyze the performance of mutual funds. This chapter summarizes the research questions and the results of the analyses from Chapter 2 to Chapter 5.

Chapter 2 analyzes the persistence of mutual fund performance[1]. In this study we consider time-varying exposures in our proposed conditional Fama and French (1993) model. The important aspect of our conditional model is the conditioning information that contains the sign and magnitude of the past year factor returns, as well as the dispersion in the exposures of individual mutual funds. By using our model for the analysis, we find that the performance of mutual funds persists. Furthermore, we demonstrate that our model has the largest explanatory power for the return differential between winner and loser funds, among other models in our study. Additionally, from a bootstrap analysis we show that the Carhart (1997) model underestimates persistence, whereas the Fama and French (1993) model overestimates persistence. The main reason is that the return differential between winner and loser funds has systematic time-variation in the exposures to the Fama and French (1993) factors, which are not considered properly in those models.

Chapter 3 studies whether mutual fund characteristics predict the risk-adjusted returns (alphas) of mutual funds, and additionally whether using fund characteristics in addition to past information of risk-adjusted returns to select funds can create an investment strategy that is

[1]This chapter is based on Budiono and Martens (2009c).

significantly better than an investment strategy that uses only past information of risk-adjusted returns[2]. We find that past alpha, turnover ratio, and ability (or the risk-adjusted fund performance from the time a fund exists until the moment we want to predict future performance) of mutual funds can significantly predict future alpha. By using the information of the three mentioned variables in our strategy (the predicted alpha strategy), we find that it produces a net excess return of 8 percent per year, whereas selecting funds only on their past information of risk-adjusted returns produces 7 percent per year. Adjusting for systematic risks, and then additionally using fund characteristics increases yearly alpha from 0.8 percent to 1.7 percent. From an economic point of view, this strategy is also more interesting as it requires less turnover.

Chapter 4 analyzes the dynamics of average mutual funds alpha and investigates why it varies over time[3]. Additionally, we critically look at different ways to estimate average fund alpha. The commonly used method is either calculating the average returns across funds and subsequently estimating alpha, or estimating individual fund alpha and subsequently calculating the average of individual fund alphas. We demonstrate that both methods lead to biases that are related to the changes of fund universe over time. Moreover, we also look at different factors to evaluate the mutual fund alpha. Cremers et al. (2008) argue that the Fama and French (1993) factors give disproportionate weight to small-value stocks, and they further propose index-based factors. Our main conclusions about which variables explain the dynamics of alpha are robust to the different ways to estimate alpha. However, we find that the lagged market return has a substantial explanatory power for Fama and French alpha, which is attributed to the biases cited by Cremers et al. Moreover, we show that turnover times cost divided by the skilled ratio is the most important variable to explain the dynamics of average alpha. It shows that having high turnover while the average mutual fund is not skilled simply hurts the average fund performance because there is higher costs that are not compensated by the good performance. Furthermore, the difference between skilled and unskilled fund ratio, the average expense ratio, and the ratio between the number of mutual funds and hedge funds also explain the dynamics of average

[2]This chapter is based on Budiono and Martens (2009b).
[3]This chapter is based on Budiono et al. (2009).

alpha, although the last variable is only available in a shorter period.

Finally, from Chapter 5 we investigate whether mutual funds have style timing skills and how to identify style timers ex-ante[4]. We find that selecting mutual funds based on only alpha or a single style timing skill (e.g. market timing) leads to biased results, both overestimating the loading on the item you select on and underestimating loadings on the characteristics you do not select on. As a result ex-post performance of the top decile selected on a particular characteristic is often weak. By estimating for each fund simultaneously both alpha and style timing skills over its complete ex-ante available history and using high frequency returns we achieve two important results. First, the estimated alphas and style timing loadings of the top decile are estimated more accurately. Second, the ex-post performance of the top decile is superior to that of deciles selected on a subset of characteristics, using monthly data or a shorter estimation window. Hence, style timers do exist and it is possible to identify them ex-ante.

After all, there are several points that we can learn about mutual fund performance from this dissertation. First, to analyze the persistence of mutual fund performance, it is important to consider the time-variation of the exposures. Failing to consider the time-varying exposures results in overestimating or underestimating the persistence. Second, the performance of a mutual fund is predictable from its characteristics and past performance. Additionally, this information can be used to improve upon the funds selection and the ex-post performance of the portfolio. Third, the average turnover ratio that is adjusted by the skilled ratio and trading costs, the difference between skilled and unskilled fund ratio, and the average expense ratio explain the variation of the average mutual funds alpha over time. Fourth, to identify successful style timers using only return data, there are three ingredients to minimize the estimation errors: (i) use the entire available return history, (ii) use daily returns, and (iii) simultaneously estimate alpha and all three timing skills.

[4]This chapter is based on Budiono and Martens (2009a).

Samenvatting en Conclusie (Summary and Conclusion in Dutch)

Deze dissertatie stelt zich tot doel om empirisch onderzoek te verrichten naar de performance van beleggingsfondsen. In dit hoofdstuk worden de onderzoeksvraag en de resultaten uit de analyses van Hoofdstuk 2 tot en met Hoofdstuk 5 samengevat.

Hoofdstuk 2 analyseert de performance persistentie van beleggingsfondsen[5]. In deze studie nemen we tijdsvariërende gevoeligheden in aanmerking in het conditioneel Fama en French (1993) model dat wij voorstellen. Het belangrijke aspect van ons conditioneel model is de conditionele informatie dat zowel het teken als de hoogte bevat van de factorrendementen van het voorafgaande jaar, evenals de dispersie in gevoeligheden van individuele beleggingsfondsen. Door gebruikmaking van ons model bij de analyse, vinden we dat de performance van beleggingsfondsen persistent zijn. Bovendien laten we zien dat ons model, in vergelijking met andere modellen in onze studie, de grootste verklaringskracht heeft voor de rendementsspreiding tussen winnaars fondsen en verliezers fondsen. Daarbovenop laten we door middel van een bootstrap analyse zien dat het Carhart (1997) model persistentie onderschat, terwijl het Fama en French (1993) model persistentie overschat. De belangrijkste reden hiervan is dat de rendementsspreiding tussen winnaars fondsen en verliezers fondsen systematische tijdsvariatie bevat in de gevoeligheid tot de Fama en French (1993) factoren, welke niet op de juiste manier behandeld worden in deze modellen.

Hoofdstuk 3 onderzoekt of eigenschappen van beleggingsfondsen de voor risico gecor-

[5]Dit hoofdstuk is gebaseerd op Budiono en Martens (2009c).

rigeerde rendementen (alfa's) van deze fondsen kunnen voorspellen. Daarnaast wordt onderzocht of, voor de selectie van fondsen, het gebruikmaken van de fondseigenschappen naast het gebruiken van historische informatie van de voor risico gecorrigeerde rendementen, een strategie kan opleveren die significant beter is dan een beleggingsstrategie puur gebaseerd op historische informatie van de voor risico gecorrigeerde rendementen[6]. We vinden dat historische alfa, de omzetratio en de bekwaamheid (de voor risico gecorrigeerde fonds performance vanaf het begin van het bestaan van de fonds tot op het moment waarop we de toekomstige performance willen voorspellen) van beleggingsfondsen toekomstige alfa's significant kunnen voorspellen. Door het gebruikmaken van de informatie over de drie genoemde variabelen in onze strategie (de voorspelde alfa strategie), vinden wij dat dit een netto rendement van 8 procent per jaar genereert bovenop het risicovrije rendement, terwijl een fondsselectie strategie, enkel gebaseerd op historische informatie van de voor risico gecorrigeerde rendementen, 7 procent per jaar oplevert. Corrigeren voor systematisch risico en vervolgens gebruikmaken van fondseigenschappen verhoogt de jaarlijkse alfa van 0,8 procent naar 1,7 procent. Vanuit een economisch perspectief gezien is deze strategie tevens interessanter omdat het een lagere omzet vereist.

Hoodstuk 4 analyseert de dynamiek in de gemiddelde alfa van beleggingsfondsen en onderzoekt waarom het tijdsvariërend is[7]. Tevens wordt er kritisch gekeken naar verschillende manieren waarop een gemiddelde alfa voor alle beleggingsfondsen kan worden geschat. De gebruikelijke methoden kenmerken zich enerzijds door het gemiddelde rendement over fondsen te berekenen en vervolgens de alfa te schatten, of anderzijds door individuele beleggingsfondsalfa's te schatten en vervolgens hier het gemiddelde van te nemen. We laten zien dat beide methoden leiden tot afwijkingen die gerelateerd zijn aan veranderingen door de tijd heen van het beleggingsfonds universum. Daarbovenop kijken we ook naar verschillende factoren om beleggingsfondsalfa's te evalueren. Cremers et al. (2008) demonstreren dat de Fama en French (1993) factoren een disproportioneel gewicht toekennen aan kleine, waarde aandelen en stellen het gebruik van op index gebaseerde factoren voor. Onze belangrijkste conclusies met be-

[6] Dit hoofdstuk is gebaseerd op Budiono en Martens (2009b).
[7] Dit hoofdstuk is gebaseerd op Budiono et al. (2009).

trekking tot welke variabelen de dynamiek in alfa verklaren, zijn robuust voor de verschillende manieren waarop alfa kan worden geschat. Echter, wij vinden dat het vertraagde marktrendement een substantiële verklaringskracht heeft voor de Fama en French alfa, hetgeen is toe te kennen aan de afwijkingen genoemd in Cremers et al. Daarnaast laten we zien dat omzet vermenigvuldigd met kosten gedeeld door de bekwaamheidsratio de meest belangrijke variabele is om de dynamiek van de gemiddelde alfa te verklaren. Het laat zien dat het hebben van een hoge omzet, terwijl het gemiddelde beleggingsfonds onbekwaam is, simpelweg de gemiddelde fonds performance schaadt omdat er hogere kosten zijn die niet worden gecompenseerd door een goede performance. Verder zijn de ratio tussen de bekwaam- en onbekwaamheid, de gemiddelde kosten ratio en de ratio tussen het aantal beleggingsfondsen en hedgefondsen ook variabelen die de dynamiek van de gemiddelde alfa verklaren, hoewel de laatstgenoemde variabele alleen beschikbaar is voor een kortere periode.

Tenslotte, onderzoeken we in Hoofdstuk 5 of beleggingsfondsen over stijltiming vaardigheden beschikken en hoe stijltimers kunnen worden geïdentificeerd ex ante[8]. We vinden dat het selecteren van beleggingsfondsen alleen gebaseerd op alfa of een enkele stijltiming vaardigheid (bijvoorbeeld markttiming) leidt tot afwijkende resultaten: er is zowel overschatting van de lading van hetgeen waarop geselecteerd wordt alsmede onderschatting van de ladingen van de karakteristieken waarop niet geselecteerd wordt. Dit resulteert in een zwakke ex post performance van het top deciel van fondsen waarop geselecteerd is. Bij het voor elk fonds schatten van tegelijkertijd de alfa en de stijltiming vaardigheid, over de op voorhand compleet beschikbare historie en gebruikmakend van hoge frequentie rendementen, bereiken we twee belangrijke resultaten. Ten eerste worden de alfa's en stijltiming ladingen van het top deciel nauwkeuriger geschat. En twee, de ex post performance van het top deciel is superieur aan dat van decielen geselecteerd op een deel van mogelijke karakteristieken, wanneer gebruik wordt gemaakt van maandelijkse data of een kortere schattingsperiode. Stijltimers bestaan dus wel degelijk en het is mogelijk om ze op voorhand te identificeren.

Concluderend zijn er een aantal punten dat we kunnen leren van deze dissertatie met be-

[8]Dit hoofdstuk is gebaseerd op Budiono en Martens (2009a).

trekking tot de performance van beleggingsfondsen. Allereerst is het belangrijk om bij de analyse van de persistentie van de performance van beleggingsfondsen, tijdsvariërende gevoeligheden in ogenschouw te nemen. Het negeren van de mogelijkheid tot tijdsvariërende gevoeligheden leiden tot over- of onderschatting van de persistentie. Ten tweede is de performance van een beleggingsfonds te voorspellen aan de hand van haar karakteristieken en historische performance. En deze informatie kan ook gebruikt worden bij de verbetering van fondsselectie en de ex post performance van een portefeuille. Daarnaast verklaren de gemiddelde omzet ratio gecorrigeerd voor de bekwaamheidsratio en transactiekosten, de ratio tussen bekwame en onbekwame fondsen, en de gemiddelde kosten ratio de variatie van de gemiddelde beleggingsfondsalfa door de tijd heen. Als laatste, om succesvolle stijltimers te identificeren door enkel het gebruik van rendementsdata, zijn er drie ingrediënten om de schattingsfouten te minimaliseren: (i) gebruik de volledige beschikbare historie van rendementen, (ii) maak gebruik van dagrendementen, en (iii) schat alfa en alle drie de timingvaardigheden tegelijkertijd.

Bibliography

Bae, K.-H. and J. Yi, 2008. The impact of the short-short rule repeal on the timing ability of mutual funds. Journal of Business Finance and Accounting 35, 969–997.

Barras, L., O. Scaillet, and R. Wermers, 2009. False discoveries in mutual fund performance: Measuring luck in estimated alphas. Journal of Finance, Forthcoming.

Becker, C., W. Ferson, D. H. Myers, and M. J. Schill, 1999. Conditional market timing with benchmark investors. Journal of Financial Economics 52, 119–148.

Berk, J. B. and R. C. Green, 2004. Mutual fund flows and performance in rational markets. Journal of Political Economy 112, 1269–1295.

Black, F., M. C. Jensen, and M. Scholes, 1972. The capital asset pricing model: Some empirical tests. Studies in the Theory of Capital Markets.

Blake, C. R., E. J. Elton, and M. J. Gruber, 1993. The performance of bond mutual funds. Journal of Business 66, 371–403.

Bollen, N. P. B. and J. A. Busse, 2001. On the timing ability of mutual fund managers. Journal of Finance 56, 1075–1094.

Bollen, N. P. B. and J. A. Busse, 2004. Short-term persistence in mutual fund performance. The Review of Financial Studies 18, 569–597.

Boudoukh, J., M. Richardson, M. Subrahmanyam, and R. F. Whitelaw, 2002. Stale prices and strategies for trading mutual funds. Financial Analyst Journal 58, 53–71.

Brown, S. J., W. Goetzmann, R. G. Ibbotson, and S. A. Ross, 1992. Survivorship bias in performance studies. Review of Financial Studies 5, 553–580.

Brown, S. J. and W. N. Goetzmann, 1995. Performance persistence. Journal of Finance 50, 679–698.

Budiono, D. P. and M. Martens, 2009a. Mutual fund style timing skills and alpha. Working Paper.

Budiono, D. P. and M. Martens, 2009b. Mutual funds selection based on fund characteristics. Journal of Financial Research, Forthcoming.

Budiono, D. P. and M. Martens, 2009c. Persistence in mutual fund performance and time-varying risk exposures. Working Paper.

Budiono, D. P., M. Martens, and M. Verbeek, 2009. The dynamics of mutual funds alpha. Working Paper.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Chan, L. K., H.-L. Chen, and J. Lakonishok, 2002. On mutual fund investment styles. Review of Financial Studies 15, 1407–1437.

Chance, D. M. and M. L. Hemler, 2001. The performance of professional market timers: Daily evidence from executed strategies. Journal of Financial Economics 62, 377–411.

Chen, H.-L., N. Jegadeesh, and R. Wermers, 2000. The value of active mutual fund management: An examination of stockholdings and trades of fund managers. Journal of Finance and Quantitative Analysis 35, 343–368.

Chen, J., H. Hong, M. Huang, and J. D. Kubik, 2004. Does fund size erode mutual fund performance ? The role of liquidity and organization. American Economic Review 94, 1276–1302.

Coggin, T. D., F. J. Fabozzi, and S. Rahman, 1993. The investment performance of U.S. equity pension fund managers: An empirical investigation. Journal of Finance 48, 1039–1055.

Cooper, M. J., H. Gulen, and P. R. Rau, 2005. Changing names with style: Mutual fund name changes and their effects on fund flows. Journal of Finance 60, 2825–2858.

Cremers, M., A. Petajisto, and E. Zitzewitz, 2008. Should benchmark indices have alpha ? Revisiting performance evaluation. SSRN Working Paper.

Daniel, K. and S. Titman, 1999. Market efficiency in an irrational world. Financial Analysts Journal 55, 28–40.

Elton, E. J., M. J. Gruber, and C. R. Blake, 1996. The persistence of risk-adjusted mutual fund performance. Journal of Business 69, 133–157.

Elton, E. J., M. J. Gruber, and C. R. Blake, 2003. Incentive fees and mutual funds. Journal of Finance 58, 779–804.

Elton, E. J., M. J. Gruber, and C. R. Blake, 2007. Participant reaction and the performance of funds offered by 401(k) plans. Journal of Financial Intermediation 16, 249–271.

Elton, E. J., M. J. Gruber, and J. A. Busse, 2004. Are investors rational ? Choices among index funds. Journal of Finance 59, 261–288.

Elton, E. J., M. J. Gruber, S. Das, and M. Hlavka, 2004. Efficiency with costly information: A reinterpretation of evidence from managed portfolios. Review of Financial Studies 6, 1–22.

Fama, E. F. and K. R. French, 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fama, E. F. and K. R. French, 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F. and K. R. French, 2008. Mutual fund performance. Working Paper.

Fama, E. F. and J. D. MacBeth, 1973. Risk, returns, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Ferson, W. E. and C. R. Harvey, 1999. Conditioning variables and the cross section of stock returns. Journal of Finance 54, 1325–1360.

Ferson, W. E. and R. W. Schadt, 1996. Measuring fund strategy and performance in changing economic conditions. Journal of Finance 51, 425–461.

French, K. R., 2008. Presidential address: The cost of active investing. Journal of Finance 63, 1537–1573.

Friesen, G. C. and T. R. Sapp, 2007. Mutual fund flows and investor returns: An empirical examination of fund investor timing ability. Journal of Banking and Finance 31, 2796–2816.

Ghysels, E., 1998. On stable factor structures in the pricing of risk: Do time-varying betas help or hurt? Journal of Finance 53, 549–573.

Goetzmann, W. N. and R. G. Ibbotson, 1994. Do winners repeat? Journal of Portfolio Management 20, 9–18.

Goetzmann, W. N. and N. Peles, 1997. Cognitive dissonance and mutual fund investors. Journal of Financial Research 20, 145–158.

Grinblatt, M. and S. Titman, 1989. Mutual fund performance: An analysis of quarterly portfolio holdings. Journal of Business 62, 393–416.

Grinblatt, M. and S. Titman, 1994. A study of monthly mutual fund returns and performance evaluation techniques. Journal of Financial and Quantitative Analysis 29, 419–444.

Grinold, R., 1989. The fundamental law of active management. Journal of Portfolio Management 15, 30–37.

Gruber, M. J., 1996. Another puzzle: The growth in actively managed mutual funds. Journal of Finance 51, 783–810.

Grundy, B. D. and J. S. Martin, 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. The Review of Financial Studies 14, 29–78.

Hendricks, D., J. Patel, and R. Zeckhauser, 1993. Hot hands in mutual funds: Short-run persistence of relative performance 1974-1988. Journal of Finance 48, 93–130.

Hendricks, D., J. Patel, and R. Zeckhauser, 1997. The J-shape of performance persistence given survivorship bias. The Review of Economics and Statistics 79, 161–166.

Henriksson, R. D., 1984. Market timing and mutual fund performance: An empirical investigation. Journal of Business 57, 73–96.

Henriksson, R. D. and R. C. Merton, 1981. On market timing and investment performance. II. statistical procedures for evaluating forecasting skills. Journal of Business 54, 513–533.

Huij, J., M. Martens, and T. Post, 2007. Return persistence, risk dynamics and momentum exposures of equity and bond mutual funds. SSRN Working Paper Series.

Huij, J. and M. Verbeek, 2007. Cross-sectional learning and short-run persistence in mutual fund performance. Journal of Banking and Finance 31, 973–997.

Huij, J. and M. Verbeek, 2009. On the use of multifactor models to evaluate mutual fund performance. Financial Management Spring, 75–102.

Ippolito, R. A., 1989. Efficiency with costly information: A study of mutual fund performance, 1965-1984. The Quarterly Journal of Economics 104, 1–23.

Jagannathan, R. and R. A. Korajczyk, 1986. Assessing the market training performance of managed portfolios. Journal of Business 59, 217–235.

Jensen, M. C., 1968. The performance of mutual funds in the period 1945-1964. Journal of Finance 23, 389–416.

Jensen, M. C., 1969. Risk, the pricing of capital assets, and the evaluation of investment portfolios. Journal of Finance 54, 953–980.

Jiang, G. J., T. Yao, and T. Yu, 2007. Do mutual funds time the market ? Evidence from portfolio holdings. Journal of Financial Economics 86, 724–758.

Jones, C. S. and J. Shanken, 2005. Mutual fund performance with learning across funds. Journal of Financial Economics 78, 507–552.

Kacperczyk, M., C. Sialm, and L. Zheng, 2005. On the industry concentration of actively managed equity mutual funds. Journal of Finance 60, 1983–2011.

Kim, S., A. Klein, and J. Rosenfeld, 2008. Return performance surrounding reverse stock splits: Can investors profit? Financial Management 37, 173 – 192.

Kon, S. J., 1983. The market-timing performance of mutual fund managers. Journal of Business 56, 323–347.

Kon, S. J. and F. C. Jen, 1978. Estimation of time-varying systematic risk and performance for mutual fund portfolios: An application of switching regression. Journal of Finance 33, 457–475.

Korkie, R. M. and H. J. Turtle, 2002. What's a portfolio manager worth ? Journal of Portfolio Management 28, 65–73.

Kosowski, R., N. Y. Naik, and M. Teo, 2007. Do hedge funds deliver alpha? A Bayesian and bootstrap analysis. Journal of Financial Economics 84, 229–264.

Kosowski, R., A. Timmermann, R. Wermers, and H. White, 2006. Can mutual fund "stars" really pick stocks? New evidence from a bootstrap analysis. Journal of Finance 61, 2551–2596.

Lhabitant, F.-S. and M. Learned, 2002. Hedge fund diversification: How much is enough. FAME Research Paper 52, 1–44.

Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. Review of Economics and Statistics 47, 13–37.

Livingston, M. and E. S. O'Neal, 1998. The cost of mutual fund distribution fees. Journal of Financial Research 21, 205–218.

Malkiel, B. G., 1995. Return from investing in equity mutual funds 1971 to 1991. Journal of Finance 50, 549–572.

Malkiel, B. G., 2003. Passive investment strategies and efficient markets. European Financial Management 9, 1–10.

Malkiel, B. G., 2005. Reflections on the efficient market hypothesis: 30 years later. Financial Review 40, 1–9.

Naik, N. Y., T. Ramadorai, and M. Stromqvist, 2007. Capacity constraints and hedge fund strategy returns. European Financial Management 13, 239–256.

Odean, T., 1999. Do investors trade too much? American Economic Review 89, 1279–1298.

Pastor, L. and R. F. Stambaugh, 2002. Mutual fund performance and seemingly unrelated assets. Journal of Financial Economics 63, 315–349.

Rouwenhorst, K. G., 2004. The origins of mutual funds. Yale ICF Working Paper 04-48, 1–31.

Sharpe, W. F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance 19, 425–442.

Sharpe, W. F., 1966. Mutual fund performance. Journal of Business 39, 119–138.

Statman, M., 1987. How many stocks make a diversified portfolio. Journal of Financial and Quantitative Analysis 22, 353–363.

Swinkels, L. and L. Tjong-A-Tjoe, 2007. Can mutual funds time investment styles. Journal of Asset Management 8, 123–132.

Taylor, J., 2003. Risk-taking behavior in mutual fund tournaments. Journal of Economic Behavior and Organization 50, 373–383.

ter Horst, J. R., T. E. Nijman, and M. Verbeek, 2001. Eliminating look-ahead bias in evaluating persistence in mutual fund performance. Journal of Empirical Finance 8, 345–373.

Tole, T. M., 1982. You can't diversify without diversifying. Journal of Portfolio Management 8, 5–11.

Wermers, R., 1997. Momentum investment strategies of mutual funds, performance persistence, and survivorship bias. Working Paper.

Wermers, R., 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, trasactions costs, and expenses. Journal of Finance 55, 1655–1695.

Wilson, T. C., 1998. Portfolio credit risk. FRBNY Economic Policy Review October, 71–82.

Biography

Diana Patricia Budiono was born on April 27^{th} 1981 in Surabaya, Indonesia. She studied her Bachelor Degree in Industrial Engineering at Petra Christian University Indonesia, and graduated with *cum laude* in 2003. Soon after the graduation, she continued a Master Degree in Financial Engineering at the University of Twente, The Netherlands. In the final year of her Master studies, she joined ING Bank in Amsterdam as an intern. After receiving the M.Sc., she directly started her Ph.D. in 2005 at the Department of Finance in Erasmus University, The Netherlands. She has presented her research at international conferences, such as in Imperial College London, EURO Working Group on Financial Modeling, and the Southern Finance Association. The article at the basis of Chapter 3 in her dissertation has been accepted for publication in the Journal of Financial Research. Next to her research, she supervises Master theses at Erasmus University. Her research interest includes portfolio management, performance and risk analysis, asset management, mutual funds, and asset pricing.

Erasmus Research Institute of Management - ERIM

THE ANALYSIS OF MUTUAL FUND PERFORMANCE: EVIDENCE FROM U.S. EQUITY MUTUAL FUNDS

We study the mutual fund performance for about 45 years. There are several key points that we can withdraw from this dissertation. First, to study the persistence of mutual fund performance, it is important to consider time-varying exposures because when they are ignored, the persistence will be overestimated or underestimated. Second, the popular investment strategy in literature is to use only past performance to select mutual funds. We find that an investor can select superior funds by additionally using fund characteristics (fund turnover ratio and ability). Importantly, this strategy also requires less turnover, which is more appealing from the economic point of view. Third, the average alpha of mutual funds is an indication of whether it pays off to invest in actively managed funds. We show that a substantial part of the variation in the average alpha can be explained by the average expense ratio, the ratio between skilled and unskilled funds, and combining the average turnover ratio with the skilled ratio and trading costs. The latter demonstrates that average turnover hurts the average funds performance due to there not being enough skilled funds. Fourth, selecting mutual funds on only alpha or a single style timing skill leads to overestimating the loading on the selected characteristic and underestimating the loadings on the other characteristics. By estimating for each fund simultaneously alpha and style timing skills over its complete ex-ante available history based on daily returns we achieve two important results, namely the estimated alphas and style timing loadings of the top decile funds are estimated more accurately; and the ex-post performance of the top decile is superior to that of deciles selected on a subset of characteristics, using monthly data or a shorter estimation window.

ERIM

The Erasmus Research Institute of Management (ERIM) is the Research School (Onderzoekschool) in the field of management of the Erasmus University Rotterdam. The founding participants of ERIM are Rotterdam School of Management (RSM), and the Erasmus School of Economics (ESE). ERIM was founded in 1999 and is officially accredited by the Royal Netherlands Academy of Arts and Sciences (KNAW). The research undertaken by ERIM is focused on the management of the firm in its environment, its intra- and interfirm relations, and its business processes in their interdependent connections.

The objective of ERIM is to carry out first rate research in management, and to offer an advanced doctoral programme in Research in Management. Within ERIM, over three hundred senior researchers and PhD candidates are active in the different research programmes. From a variety of academic backgrounds and expertises, the ERIM community is united in striving for excellence and working at the forefront of creating new business knowledge.

ERIM PhD Series
Research in Management

Erasmus Research Institute of Management - **ERIM**
Rotterdam School of Management (RSM)
Erasmus School of Economics (ESE)
P.O. Box 1738, 3000 DR Rotterdam
The Netherlands

Tel. +31 10 408 11 82
Fax +31 10 408 96 40
E-mail info@erim.eur.nl
Internet www.erim.eur.nl

Design & layout: B&T Ontwerp en advies (www.b-en-t.nl) Print: Haveka (www.haveka.nl)