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An Analysis of the Mutual Fund Industry: Mutual Fund Investors, Mutual Fund Managers and Mutual Fund Companies

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献给我的妈妈和爸爸

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Chapter 2

α :	Regression constant
β :	Regression coefficient
δ_k :	Regression coefficient of k^{th} piece in piecewise linear regressions
γ :	Regression coefficient vector of control variables
ε :	Residual from a regression model
$Adj.\,R^2$:	Adjusted coefficient of determination from a regression model
$D_{i,m}^{Asia}$:	Dummy variable that takes on the value 1 when fund *i* has an investment focus in Asia in month *m*, 0 otherwise
$D_{i,m}^{Int}$:	Dummy variable that takes on the value 1 when fund *i* is an internationally investing fund in month *m*, 0 otherwise
$EuroOF_{i,m}$:	Euro outflows of fund *i* in month *m*
$EuroIF_{i,m}$:	Euro inflows of fund *i* in month *m*
$ExR_{i,m}$:	Excess return of fund *i* in month *m* compared to the average return of all other funds in the same market segment and month
$FrontFee_{i,m}$:	Front-end load of fund *i* in month *m*
$IF_{i,m}$:	Growth rate of inflows of fund *i* in month *m*
$\ln Age_{i,m}$:	Natural logarithm of age (in months) of fund *i* at the end of month *m*
$\ln TNA_{i,m}$:	Natural logarithm of total net assets (in Euro) of fund *i* at the end of month *m*
$MgtFee_{i,t}$:	Management fees of fund *i* in year *t*

$NF_{i,m}$:	Growth rate of net flows of fund *i* in month *m*
$OF_{i,m}$:	Growth rate of outflows of fund *i* in month *m*
$P_{i,m}$:	Net asset value per share of fund *i* in month *m*
$Perf_{i,m}$:	Performance of fund *i* in month *m*
$R_{i,m}$:	Net return of fund *i* in month *m*
R^2:	Coefficient of determination from a regression model
$RT1_{i,m}$:	Proxy 1 for Rapid Trading of fund *i* in month *m*
$RT2_{i,m}$:	Proxy 2 for Rapid Trading of fund *i* in month *m*
$Seg\_NF_{i,m}$:	Growth rate of net flows of the segment which the fund *i* belongs to in month *m* (without fund *i*)
$SegRank^{1J}_{i,m}$:	The relative rank of the return of a fund *i* compared to the return of all other funds in the same market segment in the 12 months prior to month *m*
$Std^{1J}_{i,m}$:	Return standard deviation of a fund *i* in the last 12 months, i.e. from month *m-12* to the end of month *m-1*
$Tercile(1)_{i,m}$:	The bottom piece in the piecewise linear regression based on performance rank of fund *i* in month *m* among all funds which belong to the same segment like fund *i*
$Tercile(2)_{i,m}$:	The middle piece in the piecewise linear regression based on performance of fund *i* in month *m* among all funds which belong to the same segment like fund *i*
$Tercile(3)_{i,m}$:	The highest piece in the piecewise linear regression based on performance of fund *i* in month *m* among all funds which belong to the same segment like fund *i*
$TNA_{i,m}$:	Total net assets (in Euro) of fund *i* at the end of month *m*
Y:	A vector of control variables

Chapter 3

α :	Regression constant
β :	Regression coefficient
ε :	Residual from a regression model
$AverageTNA_t$:	The average of the TNA at the beginning of month *t* and the TNA at the end of month *t*
$Inflow_t$:	Inflows in a certain asset class in month *t*
$NCF_{i,t}$:	Net cash flow in asset class *i* in month *t*
$NegNF_{i,t}$:	Negative cash flows of asset class *i* in month *t*
$Outflow_t$:	Outflows in a certain asset class in month *t*
$PosNF_{i,t}$:	Positive cash flows of asset class *i* in month *t*
R_t^{neg} :	The average return earned on negative net cash flows in month *t*
$R^{overall}$:	The overall average return earned on \$1 net cash flows over the entire sample period, 1996-2009
R_t^{pos} :	The average return earned on positive net cash flows in month *t*
$r_{i,t}^h$:	*h*-month return on asset class *i* *h* months after *t*
R_t :	The average return earned on net cash flows in month *t*
$Turnover_i$:	Turnover ratio of asset class *i* in month *t*
T :	Number of months

Chapter 4

α :	Regression constant
β :	Regression coefficient

ε :	Residual from a regression model
Γ :	Regression coefficient matrix of the lagged index changes
ϕ :	Cumulative normal distribution
$CV\left(Manager_i\right)$:	Vector of control variables of manager *i*
D_i^{CFA} :	Dummy variable that takes on the value 1 when manager *i* has a CFA, 0 otherwise
D_i^{CPA} :	Dummy variable that takes on the value 1 when manager *i* has a CPA, 0 otherwise
D_i^{HY} :	Dummy variable that takes on the value 1 when fund *i* is an high yield fund in month *m*, 0 otherwise
$D_i^{OtherMaster}$:	Dummy variable that takes on the value 1 when manager *i* has a non-MBA master's degree, 0 otherwise
$D_i^{OtherDegree}$:	Dummy variable that takes on the value 1 when manager *i* has another post-graduate degree
$GMATDEV_i$:	Deviation between a manager's GMAT and the average GMAT of all managers employed by the fund family (both divided by 100)
$GMATRANK_i$:	GMAT rank of manager *i* across all managers employed by the same fund management company at the assignment date
$Expense\_ratio_{i,t}$:	Expense ratio of fund *i* in month *t*
$Exp_{i,t}$:	Experience of the manager of fund *i* in month *t*, measured in years
$\ln Age_{i,t}$:	Natural logarithm of age (in years) of fund *i* in month *t*
$\ln TNA_{i,t}$:	Natural logarithm of total net assets of fund *i* in year *t*

Chapter 5

$\alpha_{i,m}$:	Regression constant from a factor model for fund *i* in month *m*
$\varepsilon_{i,m}$:	Residual from a regression model for fund *i* in month *m*
ε_t^{bond}:	Residual from a regression model for bond index return change in day *t*
ε_t^{cds}:	Residual from a regression model for CDS index premium change in day *t*
$Activeshare_{i,t}$:	Asset weighted average of active share of all funds managed by the manager *i* in year *t*
$Age_{i,t}$:	Age of manager *i* in year *t*
$C\_4alpha\_gross_{i,t}$:	Asset weighted average of gross Carhart four factor alpha of all funds managed by manager *i* in year *t*
$Dummy\_gender$:	Dummy variable that takes on the value 1 when manager *i* is a male, 0 otherwise
$Dummy\_mba$:	Dummy variable that takes on the value 1 when manager *i* has a MBA degree, 0 otherwise
$Dummy\_other\_master$:	Dummy variable that takes on the value 1 when manager *i* has a non-MBA master's degree, 0 otherwise
$Dummy\_PhD$:	Dummy variable that takes on the value 1 when manager *i* has a PhD degree, 0 otherwise
$Dummy\_professional$:	Dummy variable that takes on the value 1 when manager *i* has a professional designation i.e. CFA, 0 otherwise
$Entrepreneur_{i,t}$:	Dummy variable that takes on the value 1 when manager *i* becomes entrepreneur in year *t*, and 0 otherwise
$Ex\_peer\_grossret_{i,t}$:	Asset weighted average excess peer group gross return of all funds managed by the manager *i* in year *t*

$FF\_3alpha\_gross_{i,t}$: Asset weighted average of gross Fama-French three factor alpha of all funds managed by the manager *i* in year *t*

$fraction\_of\_sole\_fund_{i,t}$: Fraction of sole managed funds of manager *i* in year *t*

$Gross\_Return_{i,t}$: Asset weighted average gross return of all funds managed by the manager *i* in year *t*

$Growth\_rate\_MF_t$: Growth rate of U.S. mutual fund market in year *t*

$Jensenalpha\_gross_{i,t}$: Asset weighted average of gross Jensen's one factor alpha of all funds managed by the manager *i* in year *t*

$\ln sumTNA_{i,t}$: Natural logarithm of sum of net assets of all funds managed by the manager *i* in year *t*

$Media\_Coverage_{i,t-1,t-n}$: Number of newspaper articles which mention fund manager *i* in the *n* years prior to *t*.

$Market\_return_t$: Market return in year *t*.

$No\_of\_funds_t$: Number of funds managed by manager *i* in year *t*

$No\_of\_IPO_t$: Number of IPOs in year *t*

$No\_of\_seg_{i,t}$: Number of different segments which funds managed by manager *i* belong to in year *t*

$Seg\_adj\_IR_{i,t}$: Asset weighted average of segment-adjusted investment restriction of permitted investment practices of all funds managed by the manager *i* in year *t*

$Seg\_adj\_STD_{i,t}$: Asset weighted average of segment-adjusted past annualized standard deviation of the fund return time series of all funds managed by the manager *i* in year *t*

$Seg\_adj\_Turnover_{i,t}$: Asset weighted average of segment-adjusted turnover ratio of all funds managed by the manager *i* in year *t*

$Seg\_adj\_Utilization_{i,t}$:	Asset weighted average of segment-adjusted utilization of permitted investment practices of all funds managed by the manager *i* in year *t*
$Style\_extremity_{i,t}$:	Asset weighted average style extremity of all funds managed by the manager *i* in year *t*
$Style\_extremity\_SMB_{i,t}$:	Asset weighted average SMB-style extremity of all funds managed by the manager *i* in year *t*
$Style\_extremity\_HML_{i,t}$:	Asset weighted average HML-style extremity of all funds managed by the manager *i* in year *t*
$Style\_extremity\_MOM_{i,t}$:	Asset weighted average Momentum-style extremity of all funds managed by the manager *i* in year *t*
$Style\_extremity_{i,t}$:	Asset weighted average style extremity of all funds managed by the manager *i* in year *t*
$Sum\_percentageFlow_{i,t}$:	Sum of percentage flows of all funds managed by the manager *i* in year *t*.
$Tenure_{i,t}$:	Tenure of manager *i* in the fund industry in year *t*
$Turnover_{i,t}$:	Turnover ratio of fund *i* in month *t*

LIST OF ABBREVIATIONS

ABBB:	Arellano/Bond-Bover/Blundell estimator
AMEX:	American stock exchange
AR:	Auto regression
BaFin:	Bundesanstalt für Finanzdienstleistungsaufsicht
BM:	Benchmark
BVI:	Bundesverband Investment und Asset Management e.V.
CDS:	Credit default swap
CEO:	Chief executive officer
CF:	Cash flow
CFA:	Chartered financial analyst
CIC:	Chartered investment counselor
CPA:	Certified public accountant
CRE:	Clustered robust standard error
CRSP:	Center for research in security prices
Dif:	Difference
ETF:	Exchange traded funds
Form N-SAR:	Form N, semi-annual report
GMAT:	Graduate management administration test
GMM:	Generalized method of moments
HY:	High yield
ICI:	Investment company institute
IG:	Investment grade
IPO:	Initial public offering
MBA:	Master of business administration
MSCI:	Morgan Stanley capital international
NASDAQ:	National association of securities dealers automated quotations
NAV:	Net asset value
Non-Prop:	Non-Proprietary brokers

NYSE:	New York stock exchange
OLS:	Ordinary least squares
PCSE:	Panel-corrected standard errors
PhD:	Doctor of Philosophy
Prop:	Proprietary brokers
SEC:	Securities and exchange commission
Syst.:	Simultaneous equation system
TNA:	Total net asset
U.S.:	United States
USD:	United States dollar
VAR:	Vector autoregressive

Chapter 1

General Introduction

1.1. Motivation and Background

In this dissertation I investigate the mutual fund industry, especially the three most important participants within this industry: mutual fund investors, mutual fund companies and mutual fund managers. Mutual fund investors are persons who purchase and redeem fund shares. Mutual fund companies are financial service providers which are responsible for fund administration, e.g. setting up the fund, bookkeeping, collecting fees and preparing annual reports, and they also hire mutual fund managers to manage funds. Mutual fund managers are professionals who are responsible for the portfolio management. They make the actual portfolio decisions, e.g. which stocks are bought and sold, and are therefore mainly responsible for the performance of mutual funds. These three main participants have already been the subject of investigation in the existing literature. The aim of this dissertation is to examine new research questions in terms of the three main participants in order to obtain a deeper understanding of the mutual fund industry.

For several decades, the mutual fund industry has been of interest to researchers. This interest has been intensified by the fast development of the mutual fund industry, especially in the 1980s and 1990s. Different groups of investors have contributed to this rapid growth:

private investors, businesses and institutional investors. For example, at the end of 2010 mutual funds accounted for about 50% of the retirement assets of all households in the U.S. More and more businesses and institutional investors are also investing in mutual funds, as for instance money market funds can be used as appropriate products to manage cash and short-term assets. Furthermore, due to the large amount of assets under management in the mutual fund industry, mutual funds have become the largest owner of financial securities in the U.S. Based on the ICI fact book 2011, at the end of 2010 mutual funds held 23% of U.S. corporate equity, 12% of U.S. and foreign corporate bonds, 11% of U.S. treasury and government agency securities, 29% of U.S. municipal securities and 45% of all commercial papers. Worldwide capital markets can be significantly influenced by mutual funds and especially by participants in the mutual fund industry. Therefore, investigations into the mutual fund industry are becoming more common.

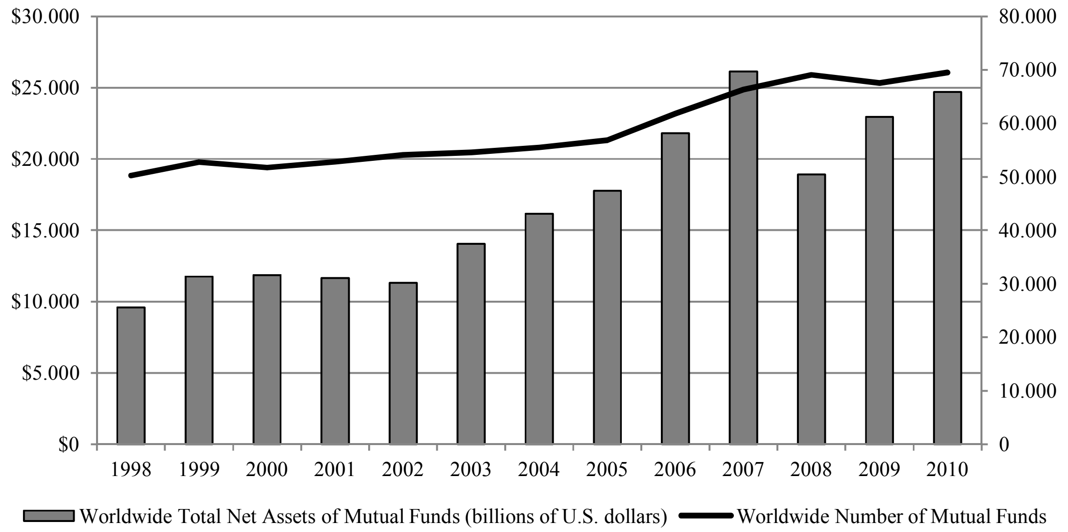
The rapid growth of the mutual fund industry can be explained by the various advantages mutual funds offer. By investing in mutual funds, investors can obtain better diversification opportunities. They can also acquire access to new asset classes and new securities which they are not able to invest in by themselves. Mutual funds also provide liquidity for investors. Mutual fund investors can purchase and redeem fund shares on a daily basis. Furthermore, there is no issuer risk associated with investing in mutual funds, since fund assets are legally separate. They are bankruptcy remote from the fund company and fund manager. We can observe the rapid growth of the mutual fund industry in Figure 1.1.

Figure 1.1 shows that the number of mutual funds increased from 50,266 in 1998 to 69,519 in 2010. Apart from the years during the global financial crisis, 2008 and 2009, total net assets have also been steadily increasing from 1998 to 2010. At the end of 2010 the number of funds increased by 38% as compared to 1998 and reached its record peak. The total net assets almost rebounded to the historical high in 2007.

The most important mutual fund market is the U.S. market. It accounts for about 50% of the worldwide mutual fund market. The German mutual fund market is relatively small, but it also experienced very fast development from 1980 to 2010. The development of the mutual fund markets in the U.S. and in Germany is shown in Figure 1.2.

Figure 1.1: Development of the worldwide mutual fund industry from 1998 to 2010

This figure shows the development of the worldwide mutual fund industry for the time period 1998 to 2010. The data of total net assets and number of funds are obtained from the ICI (Investment Company Institute).

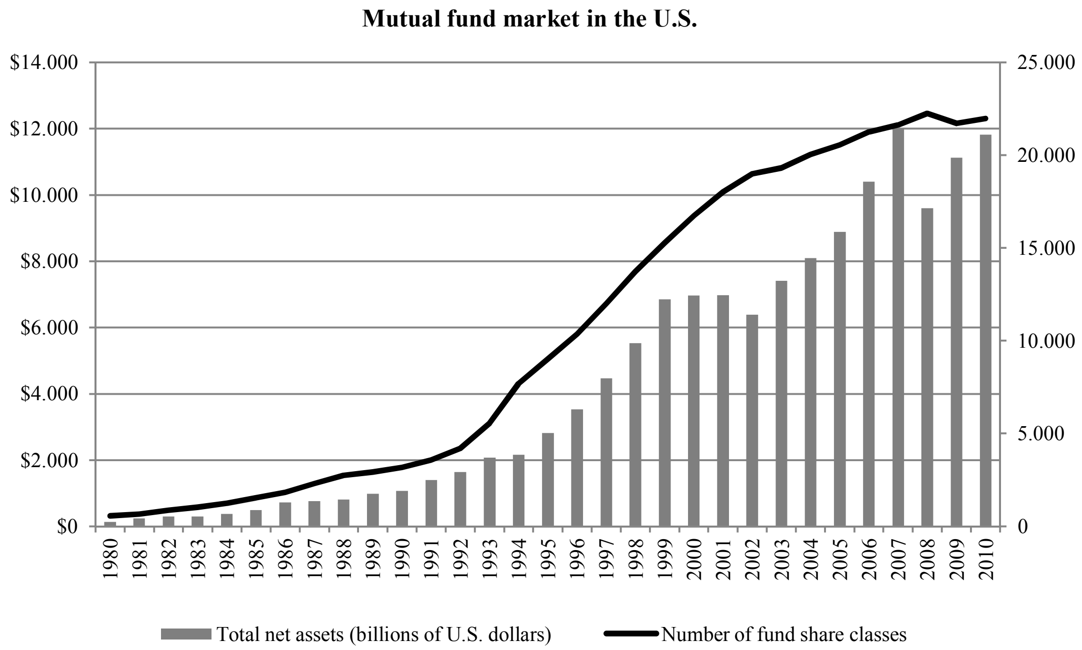


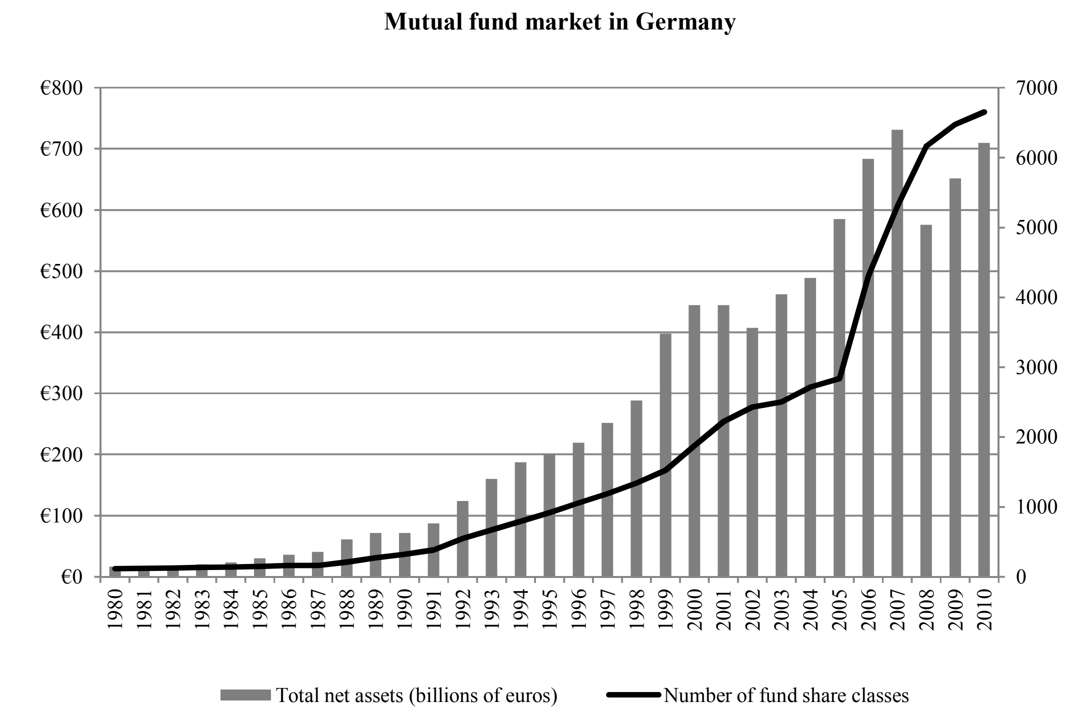
We can observe a similar development of both of these mutual fund markets in terms of total net assets and number of fund share classes. In the U.S. the assets of mutual funds increased from $135 billion in 1980 to $11,820 billion in 2010 with equity funds as the most important fund category. At end of 2010 almost 50% of mutual fund assets were invested in equity funds.

Due to the increasing interest in the mutual fund industry worldwide, it is especially important to investigate the different participants in the mutual fund industry: mutual fund investors, mutual fund companies, and mutual fund managers. In this context important questions arise: How do mutual fund investors behave when they trade mutual funds? Do they exhibit asset allocation ability in terms of mutual fund purchases? Do mutual fund companies allocate their fund managers in an efficient way in order to generate better performance for investors and higher profitability for themselves? What does the career path of a mutual fund manager look like?

Figure 1.2: Development of the mutual fund industry in the U.S. and in Germany from 1998 to 2010

This figure shows the development of the mutual fund industry in the U.S. and in Germany for the time period 1980 to 2010. The data of total net assets and number of funds are obtained from the ICI (Investment Company Institute) and BVI (Bundesverband Investment und Asset Management e.V.).





In the following section I will briefly describe the three participants in the mutual fund industry and my respective research findings.

1.2. Levels of Analysis

1.2.1. Mutual Fund Investors

A large number of papers investigate the determinants of purchases and redemptions of mutual fund investors. One of the most important factors is the past performance of mutual funds. Spitz (1970) finds a positive relationship between past performance and fund flows. Ippolito (1992) and Sirri and Tufano (1998) identify a convex performance flow relationship in the U.S. Since this convex relationship is well documented in different countries. e.g., Ber, Kempf and Ruenzi (2007) find similar evidence for the German mutual funds. This convex relationship suggests that mutual fund investors buy funds with the best performance ranks. However, they do not punish the funds with a bad past performance rank by redeeming them. Different studies have tried to explain this asymmetric relationship. Generally, there are two groups of explanations: rational and irrational.

Goetzmann and Peles (1997) explain the convex performance flow relationship with cognitive dissonance. They argue that investors who bought a fund that performs poorly do not want to admit their failure and thus continue to hold it. That is one reason why we do not observe punishment of bad performance. Ippolito (1992) explains the convexity with a rational argument: transaction costs. Transaction costs for mutual funds are important. Mutual fund investors face front-end and back-end loads when they purchase and redeem fund shares. Such transaction costs prevent investors from redeeming fund shares with bad performance.[1]

Another important strand of literature focuses on the ability of mutual fund investors to choose funds with superior future performance. Gruber (1996) and Zheng (1999) find evidence of a short-term smart money effect, which means that mutual fund investors are able to pick funds with superior short-term future performance. However, Sapp and Tiwari (2004) argue that this smart money effect is not due to superior picking abilities of

[1] Other rational explanations for the convex performance flow relationship can be found in Berk and Green (2004), Sirri and Tufano (1998), Huang, Wei and Yan (2007) and Lynch and Musto (2003).

investors and can rather be explained by stock momentum. Furthermore, Frazzini and Lamont (2008) find a long-term dumb money effect, which means that mutual fund investors record worse performance in the long-term due to repeated switching among different mutual funds. The timing ability of mutual fund investors is investigated by Friesen and Sapp (2007) and Braverman, Kandel and Wohl (2005). Both studies find evidence of poor timing ability among mutual fund investors.

1.2.2. Mutual Fund Companies

Mutual fund companies play a central role in the mutual fund industry. The goal of mutual fund companies is to maximize profits, which are mainly generated by fees charged on the assets under management. Mutual fund companies make important decisions, establish product policy, assign managers to funds, etc. These decisions can considerably influence fund performance, investor behavior and manager behavior.

Massa (2003) investigates the decisions of mutual fund companies regarding their product policies. He finds that in order to attract investors, mutual fund companies provide investors the option to switch across their funds for free. Khorana and Servaes (2004) examine the competition among mutual fund companies. They find that mutual fund companies gain a higher market share if they charge lower fees than their competitors. Furthermore, marketing and distribution fees have a positive influence on their market share. In addition, fund companies which provide a wide range of products can increase their market share.

Jain and Wu (2000) investigate fund advertising. They find that advertised funds do not have superior performance in the post-advertisement period, which means advertisements are non-informative and cannot help investors to identify funds with superior performance. However, they do find evidence of a positive impact of advertisement on individual fund flows. Advertised funds can attract investors' money more easily than funds without advertisement. Gallaher, Kaniel and Starks (2006) also examine advertisements in the mutual fund industry. However, the focus of their analyses lies on the fund company level. They find a convex relationship between company level flows and company level advertising expenditures. This implies that in order to obtain more flows through advertising, mutual fund companies should be one of the top advertisers as compared to other mutual fund companies.

Furthermore, mutual fund companies also make strategic decisions in terms of the fund management structure. Bär, Kempf and Ruenzi (2011) investigate the difference between team management and sole management of mutual funds. They find that once a fund management company chooses one type of management structure, this type is often applied to all funds managed by that company. They also investigate differences in terms of management behavior and performance, concluding that team management is characterized by a lower risk level than sole management. Team managed funds also show less style extremity than sole managed funds. Regarding the performance difference, they find weak evidence of a negative impact of team management on fund performance. However, the performance of team managed funds shows higher persistence as compared to sole managed funds. Massa, Reuter and Zitzewitz (2010) investigate named managers and anonymous managers. They argue that fund companies can benefit from the disclosure of manager names, since managers have a higher incentive to perform well when their names are associated with the funds. The name of a successful fund manager can also provide marketing benefits, which in turn can lead to higher inflows. However, these benefits are not free: If the named managers are successful, their bargaining power increases, which can allow them to get more rents from the fund management companies. Named managers are found to have more media coverage and high inflows, and the departure of such a manager can reduce fund inflows significantly.

1.2.3. Mutual Fund Managers

Mutual fund managers are responsible for portfolio management. An important strand of literature focuses on the impact of the fund managers' personal characteristics on fund performance. For example, Baks (2003) finds that the contribution of managers' qualities to the fund performance varies between 10% and 50%. Golec (1996), Chevalier and Ellison (1999a) and Ding and Wermers (2004) find that certain attributes, such as age, education and experience, have a significant impact on fund performance. Golec (1996) and Chevalier and Ellison (1999a) show that the age of fund managers has a negative influence on fund performance, while experience has a positive impact. Gottesman and Morey (2006) find that an MBA degree from one of the top MBA schools has a positive impact on fund performance.

The career path of fund managers is also investigated in the literature. Khorana (1996) finds that in cases of bad past and present performance, fund managers are more likely to be replaced. Chevalier and Ellison (1999b) show that younger managers are more careful and choose a lower level of unsystematic risk than older managers. They argue that the reason for this is that younger managers face greater employment risk than older managers. Becoming a hedge fund manager is also a potential career path of mutual fund managers. Deuskar, Pollet, Wang and Zheng (2011) show that the best mutual fund managers often stay in the mutual fund industry if the mutual fund companies provide them with the opportunity to manage hedge funds at the same time. However, many mutual fund managers with poor performance and high expense ratios tend to leave the mutual fund industry and join the hedge fund industry.

1.3. Main Research Questions and Main Results

The main research questions of this dissertation are:

1. Does rapid trading exist among German equity mutual fund investors? What are the determinants of rapid trading? Does rapid trading have a negative impact on mutual fund performance? (Chapter 2)

2. Do mutual fund investors, as a whole, have asset allocation abilities regarding their mutual fund investments? Are there differences in asset allocation ability among different mutual fund sales channels, especially between investors buying funds via non-proprietary and proprietary brokers? (Chapter 3)

3. Do fund companies allocate their fund managers to market segments in an efficient way, i.e. such that fund managers work in market segments in which their skills are rewarded best? (Chapter 4)

4. What are the characteristics and behavior of would-be entrepreneurs in the mutual fund industry? Do entrepreneurial fund managers change their behavior after they start their own firm? (Chapter 5)

I will use the remainder of this section to briefly summarize these chapters and their main results.

Chapter 2 (joint work with Stefan Ruenzi) is the first study to examine rapid trading among German equity mutual fund investors.[2] Rapid trading refers to the short-term trading behavior of mutual fund investors.

For this study we use proprietary data on monthly inflows and monthly outflows from a large German mutual fund company for all of its equity funds. We find a significant positive relationship between inflows and outflows in the same month, which we interpret as evidence of the existence of rapid trading among German equity mutual funds. The analysis of the determinants of rapid trading shows that this short-term trading behavior is particularly pronounced for small funds, risky funds, funds with low nominal prices, and international funds, i.e. funds with the strongest rapid trading show lottery-like characteristics. However, we find no evidence of market timing activities (time-zone arbitrage). Furthermore, contrary to the U.S. study O'Neal (2004), our research indicates that rapid trading is less pronounced for funds with high front-end loads. This indicates that rapid trading among German fund investors cannot be explained by brokers that push fund investors to rearrange their investments constantly in order to benefit from sales commissions. Rather, our results are consistent with the view that some investors use mutual funds for short-term, speculative purposes.

In terms of the impact of rapid trading on fund performance, we only find very weak evidence of a negative impact of rapid trading on fund performance before the mutual fund scandal in the U.S. in 2003. Regarding the period after the scandal there is no evidence of a

[2] This chapter was published in Springer/Kluwer Academic Publishers Book/Zeitschrift für Betriebswirtschaftschaft (Journal of Business Economics), Vol. 80 (9), September 2010, P. 883-920, Rapid Trading bei deutschen Aktienfonds: Evidenz aus einer großen deutschen Fondsgesellschaft, Jieyan Fang and Stefan Ruenzi (http://www.zfb-online.de/index.php?do=show&alloc=185&id=18720). I appreciate for the kind permission of Springer Science and Business Media.

negative impact. This suggests that the conduct guidelines of the BVI (Bundesverband of Investment und Asset Management e.V.) function properly and that at least the investigated fund company has taken appropriate measures in order to avoid the negative effects of rapid trading.

In Chapter 3, I investigate the asset allocation ability[3] of mutual fund investors at the aggregate level in the U.S. Specifically, I examine differences regarding the asset allocation ability among investors buying their shares via non-proprietary brokers, proprietary brokers, and direct channels. In order to conduct these analyses, I use data from the ICI (Investment Company Institute) that contain the total net assets and flows in different fund categories and via different mutual fund sales channels.

On aggregate, mutual fund investors do not seem to have superior asset allocation ability. The actual asset allocation performance is worse than a benchmark portfolio with constant asset allocation weights. This finding is stable based on a TNA portfolio as well as a flow portfolio. A possible explanation for this finding is the sentiment-driven behavior of mutual fund investors. On the one hand, Chalmers, Kaul and Phillips (2009) and Baker and Wurgler (2007) find a positive relationship between investor sentiment and equity fund flows. On the other hand, a negative relationship between investor sentiment and subsequent aggregate stock returns over multiyear horizons is shown by Brown and Cliff (2005). They argue that current high sentiment can lead to market overvaluations, which is followed by low cumulative long-term returns as market prices drop back to their fundamental value. Based on these findings we can argue that the observed underperformance of mutual fund investors could be explained by investor sentiment. The asset allocation decisions of mutual fund investors are influenced by investor sentiment. In high sentiment periods they invest in riskier asset classes, such as equity funds. Therefore, they suffer lower subsequent returns. In periods of low sentiment they prefer less risky asset classes, e.g. bond funds, and disinvest in equity funds. Therefore, fund investors miss the subsequent higher equity returns. The wrong shift among asset classes leads to a long-term underperformance as compared to the passive cash flow (CF) benchmark.

[3] Asset allocation ability is defined as the ability to allocate assets among major asset classes, i.e. stocks, bonds, money market securities.

Furthermore, I investigate the flows from different mutual fund sales channels separately. First, I find very different risk profiles among the various sales channels. In particular, the non-proprietary broker portfolio shows a significantly riskier profile than the proprietary broker portfolio. Second, I find that flows through non-proprietary brokers show significantly higher asset allocation performance than flows through proprietary brokers. This is consistent with the view that non-proprietary brokers are more likely to act on behalf of their customers, as opposed to proprietary brokers who represent their affiliated companies.

In Chapter 4 (joint work with Alexander Kempf and Monika Trapp) we study whether fund families efficiently allocate their fund managers to different market segments. Whether a fund manager can generate alpha depends both on her skill and on the efficiency of the market segment in which she is employed. We expect that in a fully efficient market even managers with extraordinary skills cannot generate systematic alphas. In an inefficient market, however, skilled managers can generate systematic alphas, while unskilled managers cannot. Thus, a fund family should allocate the managers with the highest skills to the least efficient market segments.

The questions above are crucial for fund companies, since the efficient allocation of fund managers directly influences the performance of the funds, flows into the funds and eventually profitability. To investigate manager allocation, we focus on the investment grade and high yield corporate bond fund market. In the first step, these two fund segments are ranked with respect to their efficiency. In the second step, we correlate fund performance to managerial skills. We find that managers with higher skills do indeed generate significantly higher alphas in the inefficient high yield segment. This indicates that managerial skills are more profitable in inefficient markets. In the final step, we investigate whether fund companies allocate their managers accordingly and assign their smartest managers to the inefficient high yield segment. Our results strongly show that fund companies indeed assign their smartest managers to the less efficient market segment. This indicates that fund companies allocate fund managers in an efficient way and exploit the comparative advantages of their managers.

Chapter 5 (joint work with Jerry Parwada and Stefan Ruenzi) is the first study to examine entrepreneurship in the mutual fund industry. The idea that entrepreneurs possess characteristics that differ from paid employees is featured in many theoretical models. In this study we provide evidence of the characteristics and the behavior of entrepreneurs suggested by theory, using the mutual fund industry as our laboratory. The advantage of using the mutual fund industry is that we can directly observe the characteristics and behavior of entrepreneurs in the mutual fund industry, since firm founders in the investment industry usually work as portfolio managers for another fund company first before starting their own firms. This allows us to provide the first comprehensive empirical tests of predictions derived from well-established theoretical models on entrepreneurial qualities. We find that would-be entrepreneurs are proactive, innovative and show signs of overconfidence. They use more active investment strategies and trade more frequently than non-entrepreneurial managers. They also use the permitted investment practices in a higher capacity than non-entrepreneurial managers. Would-be entrepreneurs are typically individuals with higher media coverage. Inconsistent with some models from the entrepreneurship literature, we do not find differences in risk taking between would-be entrepreneurs and non-entrepreneurial managers. Furthermore, would-be entrepreneurs do not perform better than non-entrepreneurial managers before starting their firm. In addition, we investigate how the behavior of fund managers changes after they start their own firms, i.e. once they switch from agent to principal. We observe a significant increase in risk and style extremity. In addition, the fraction of sole-managed funds decreases significantly, while the total number of funds managed increases. We also observe a slight performance decrease for managers after starting their own firms, which could be a consequence of overconfidence or of being distracted by now managing a company along with managing funds or of managing more funds at the same time.

Overall, the main contributions of the thesis are the following:

We examine rapid trading among German equity mutual fund investors. We find strong evidence for rapid trading. It is particularly pronounced for small funds, risky funds, funds with low nominal prices, and international funds. However, we find no evidence of market timing activities. Furthermore, unlike in the US, rapid trading is less pronounced for funds with high loads. This shows that rapid trading among German fund investors is not explained by churning due to brokers' advice. Rather, our results are consistent with the view that some investors use mutual funds for short-term, speculative purposes. The funds among which we observe the strongest rapid trading show lottery-like characteristics. Regarding fund performance, we find (at most) only very weak evidence for a negative impact of rapid trading on fund performance before the fund scandal of 2003, and no evidence afterwards.

The investigation of the asset allocation ability[4] of mutual fund investors at the aggregate level in the U.S. finds that mutual fund investors show poor asset allocation abilities. Furthermore, I find very strong evidence of better asset allocation abilities of investors buying their shares via non-proprietary brokers as compared to investors buying funds via proprietary brokers.

In our study regarding the fund manager allocation we find that managers with higher skills do in fact generate significantly higher alphas in the inefficient segment, which means managerial skills are more profitable in inefficient markets. Furthermore, we find strong evidence that fund companies indeed assign their smartest managers to the less efficient market segment. This indicates that fund companies do allocate fund managers in an efficient way and exploit the comparative advantages of managers.

We also examine entrepreneurship in the mutual fund industry. We find that would-be entrepreneurs are proactive and show signs of overconfidence. Funds managed by them deviate strongly from their benchmarks and trade more frequently. They have high reputation, as measured by media coverage. In terms of the differences in risk taking and performance between would-be entrepreneurs and non-entrepreneurial managers we do not find any evidence. The investigation regarding the behavior changes of fund managers after they start their own firms shows a slight performance decrease and a significant increase in risk and style extremity. Furthermore, the fraction of sole-managed funds decreases significantly, while the total number of funds managed increases.

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[4] Asset allocation ability is defined as the ability to allocate assets among major asset classes, i.e. stocks, bonds, money market securities.

Chapter 2

Rapid Trading Among German Equity Funds

2.1. Introduction

In 2003 the American fund industry was shaken by one of its worst scandals to date. The New York Attorney General, Elliott Spitzer, launched an investigation of several investment companies. The focus of interest was the explicitly illegal "late trading"[5] and "rapid trading" practices. Rapid trading is short-term trading in the fund shares by fund investors. In this case, buying and selling are usually only a few days apart. Rapid traders try to profit from short-term market movements. Rapid trading is therefore contrary to the basic idea of the fund concept, according to which funds represent a more long-term investment alternative for asset accumulation. This is the first study of rapid trading among German equity funds.

Rapid trading is critical for the following three reasons: (1) The associated high trading activity leads to high administrative costs and transaction costs for the fund, which must be paid by all investors. (2) The fund must maintain a relatively high cash position to satisfy

[5] Late trading refers to a situation in which the investment company allows certain preferred fund investors to trade fund shares at outdated prices. Thus, they can carry out quasi-arbitrage strategies at the expense of long-term fund investors (Zitzewitz 2006). Our study focuses only on rapid trading.

the liquidity needs of rapid traders. (3) The continuous inflows and outflows of funds make it difficult for the fund to implement a long-term investment policy.[6] Thus, rapid trading can lead to negative externalities in the form of performance losses for long-term fund investors (see Greene and Hodges (2002)).[7]

Therefore, shortly after the fund scandal in the United States, the German Federal Financial Supervisory Authority (BaFin) carried out a survey of late trading and rapid trading practices in German investment companies. Many companies have reported uncertainties in dealing with rapid trading practices (see Annual Report of the BaFin for 2003, p. 214). Therefore, the German Investment and Asset Management Organization (BVI) extended the conduct guidelines for its members which 'requires that actions should be taken to protect investors from the disadvantages induced by the short-term buying and selling of shares by other investors' ('The German Investment and Asset Management Organization '(BVI) Yearbook 2004, p. 30). However, there is no systematic study of rapid trading in Germany so far. Our work fills this gap and provides three main contributions: 1) We investigate whether there is evidence of rapid trading among German equity funds. 2) For the first time we consider several possible determinants of rapid trading and analyze several explanations for rapid trading. 3) We examine the consequences of rapid trading on fund performance. In this context, we can also examine whether appropriate measures were taken in Germany to reduce or prevent the potentially negative effects of rapid trading on performance.

To examine whether there is evidence of rapid trading in Germany, we use proprietary monthly data on inflows and outflows of all equity funds from a large German investment company for the period from January 1992 to December 2006. If fund investors do conduct rapid trading, we should observe simultaneously high inflows into and outflows out of the

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[6] The described negative effects do not occur if fund shares are traded on a stock exchange; however, in our sample period, stock exchanges are only of minor importance (see footnote 6).

[7] Fund companies are well aware of this problem, as reflected in their terms and conditions. In the terms and conditions of Fidelity in Section 10h, for example, "investment products are generally considered as a long-term investment and are also managed accordingly. Short-term investment or excessive trading of the fund shares is not recommended, because it affects the performance of the fund by interrupting portfolio management strategies and by causing higher costs."

affected fund.[8] We actually find a very strong positive correlation between inflows and outflows within the period. The volume of trading in funds is much higher than one would expect by just looking at net flow figures (= inflows - outflows). The volume of inflows and the volume of outflows are, in most years of our sample, higher by a multiple than the net flows. We interpret these results as a clear indication of the existence of rapid trading.

In the second step we develop an empirical proxy for rapid trading and analyze the characteristics of funds that are particularly affected by rapid trading. We find that our proxy for rapid trading is slightly lower in December and slightly higher in January than in other months. However, the differences are relatively small and rapid trading is consistently strong over the entire calendar year. Moreover, we can show that rapid trading is particularly strong for funds with low front-end load fees, small funds, risky funds and funds investing in international stocks, but not particularly pronounced for funds investing in Asia. The latter could be used for so-called time-zone arbitrage.[9] From this we can conclude that rapid trading cannot be explained by time-zone arbitrage in our sample.

Overall, our analysis suggests that rapid trading can be explained by the fact that certain funds are considered as speculative, short-term and lottery-like investments by investors. They are bought in the hope of quick profits and quickly sold again. Since in Germany equity funds are held largely by small investors, this result is consistent with recent results of Kumar (2009) and Han and Kumar (2009). These studies show that small investors prefer stocks with lottery-like characteristics.

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8 Strictly speaking, the simultaneous occurrence of high inflows and outflows is only a necessary condition for the short-term trading of a fund by the investors. It is also conceivable that certain funds have high inflows and outflows for some other reasons, while the respective investors are basically aligned with the long term investment. Our later results suggest that this interpretation, however, seems more unlikely. Therefore, we follow the procedure established in the literature (see, e.g., O'Neal (2004), Cashman, Deli, Nardari and Villupuram (2006)) and interpret the simultaneous presence of high inflows and outflows as a sign of rapid trading.

9 Time zone arbitrage is possible if the time of price determination for the fund in Germany is after the trading close of a foreign stock exchange where the fund invests. Then the tradable fund price on that day does not reflect all price-sensitive information that has become known after the foreign market closure. Therefore, these prices are outdated (so-called 'stale prices'). The quasi-arbitrage strategy can be operated by trading on these prices. For example, if there is very good news that became known after the closure of trading in Asia, then the time zone arbitrageur in Germany can invest in funds investing in Asia on the same day. The purchase will be billed at prices that do not reflect the new good news. The good information will be priced on the following day and the fund shares may be sold at a higher price. A detailed description of time zone arbitrage (also known as 'market timing') can be found in Frankel and Cunningham (2006). Time zone arbitrage is also examined, e.g., in Chalmers, Edelen and Kadlec (2001) and Greene and Hodges (2002).

In the last step, we investigate whether rapid trading leads to negative externalities in the form of reduced performance for long-term fund investors. Our results show a negative but very weak influence of rapid trading on performance in the period before the fund scandal became public in the U.S. in August 2003. Afterwards no influence is found. These results suggest that the conduct guidelines issued by BVI after the scandal in the U.S. are functioning properly. It seems that (at least in the anonymous fund company analyzed here) appropriate measures have been taken to prevent the potentially negative effects of rapid trading.

Our study contributes to the broad literature on the determinants of inflows to equity funds, which has so far focused mainly on the relationship between past performance and net flows. Studies with a focus on the U.S. market are Ippolito (1992), Chevalier and Ellison (1997) and Sirri and Tufano (1998). The relationship between past performance and net flows or market share in German equity funds is investigated in Krahnen, Schmid and Theissen (2006) and Ber, Kempf and Ruenzi (2007). While there are now some U.S. studies that look at inflows and outflows separately (see, e.g., Bergstresser and Poterba (2002), O'Neal (2004), Christoffersen, Evans and Musto (2005), Cashman, Deli, Nardari and Villupuram (2006)), there is no evidence for the German fund market so far. Rapid trading in the U.S. fund market is explicitly investigated by O'Neal (2004). He finds evidence of rapid trading among the 200 largest U.S. equity funds for the period from 1994 to 1998. However, he does not perform a systematic examination of the determinants of rapid trading, and does not consider the possible consequences of rapid trading on performance. Our study also differs from O'Neal's (2004) because our sample contains German equity funds and takes in a much longer sample period. Our paper contributes, as well, to the literature on the behavior of retail investors. This literature has so far focused mainly on the behavior of stock investors (see, e.g., Cohn, Lewellen, Lease and Schlarbaum (1975), Odean (1998a), Odean (1999), Barber and Odean (2000), Ivkovic, Sialm and Weisbenner (2007), Han and Kumar (2009), Goetzmann and Kumar (2008), Dorn, Huberman and Sengmueller (2008)). In this context it is particularly important to mention the study of Barber and Odean (2000), which shows that retail investors trade too much in stocks, which can also be interpreted as evidence of rapid trading among stocks.

Our study complements this evidence by showing that the unexpected high trading volumes can also be observed in mutual funds.

This study is structured as follows. In the following section, we present the data used. In Section 2.3 we present our results. Section 2.4 concludes.

2.2. Data and Methodology

We use data of German equity funds from 'The German Investment and Asset Management Organisation' (BVI), from the Hoppenstedt Fondsführer, as well as data obtained from an anonymous large German fund management company. The data from the anonymous fund company includes information on monthly inflows and outflows of all equity funds of the company for the period from January 1992 to December 2006. Therefore, this dataset covers all purchases and redemptions of fund shares through the fund company, which is also the typical trade channel for fund shares in Germany. Unfortunately, due to lack of data availability, we cannot make further distinctions among specific distribution channels (banks/saving banks, direct banks, investment companies, brokers and agents, etc.). We also do not consider the trading of fund shares on stock exchanges.[10] The dataset of the anonymous fund company provides additional information on the fund's assets and net returns (i.e., returns net of management fees). The front-end loads are calculated using data from the BVI. The anonymous fund company does not charge back-end load fees for their funds in our sample period. Based on the information in the database of the BVI, we assign each fund to one of four market segments: Domestic Equities, Domestic Equities Special, International Equities and International Equities Special.[11] We collect the management fees from the Hoppenstedt Fondfsführer.

[10] Based on data on trading volumes of the stock exchange in Hamburg we are able to compare the trading activity on the stock exchange and through the traditional trade channels (subscription and redemption of fund shares through the fund company). For those months in which both trading volumes of the stock exchange and flow data from the fund company exist, we found an average volume via the stock exchange of € 228,090 per month (median: € 55,502), while the sum of absolute inflows and outflows is on average 52,714,400 € (median: € 22,008,030). The magnitudes are in completely different dimensions. The stock exchange is not very important in our sample period. The correlation between trading volume and the sum of inflows and outflows is also very small and insignificant. This suggests that trades on the stock exchange are made by an investor clientele other than traders trading directly with the fund company

[11] The addition ‚special' is for funds that have a specific focus, e.g., funds focused on specific industries. In U.S. studies funds are often clustered by using the dimensions of Growth/Value and Large-Cap/Small-Cap. This classification has become common in Germany only recently and is not used in our sample period.

Descriptive statistics for the funds of the anonymous fund company are summarized in Panel A of Table 2.1.

Table 2.1: Descriptive statistics

This table presents summary statistics on equity funds of the anonymous fund company (Panel A), and on equity funds of the six largest German investment companies (Panel B). Data are obtained from the anonymous fund company, BVI, and Hoppenstedt Fondsführer. In Panel A the total number of observations is 8,777. In Panel B the total number of observations is 30,145.

Panel A: Descriptive statistics on equity funds of the anonymous fund company

Year	No. of funds	TNA per fund Mio. €	Age in year	Front-end load in %	Management fee p.a. in %	Total TNA in Mio. €	Market share in %	NF in %	IF in %	OF in %
1992	14	108.29	16.16	4.08	0.52	1,516	15.59	-0.39	1.38	1.78
1993	15	133.27	16.28	3.87	0.57	1,999	10.15	3.33	6.38	3.05
1994	18	241.33	15.02	4.27	0.57	4,344	17.47	3.28	5.86	2.57
1995	20	253.00	14.35	4.23	0.76	5,060	19.34	-1.65	1.49	3.14
1996	29	201.55	10.69	3.61	0.77	5,845	17.54	1.59	8.21	6.62
1997	35	226.11	10.22	3.57	0.68	7,914	13.18	1.80	7.50	5.69
1998	46	349.24	9.66	3.94	0.75	16,065	18.45	1.79	6.36	4.57
1999	52	429.29	9.76	3.66	0.78	22,323	12.68	1.40	9.27	7.88
2000	64	679.56	9.37	3.69	0.86	43,492	20.45	1.48	9.75	8.27
2001	71	502.31	9.19	3.59	0.90	35,664	20.58	-0.86	8.07	8.93
2002	79	353.63	9.30	3.54	1.08	27,937	24.23	-1.57	7.55	9.13
2003	98	270.56	9.45	3.67	1.24	26,515	20.23	-0.89	6.16	7.05
2004	90	374.13	10.25	3.77	1.34	33,672	24.71	-0.38	6.29	6.67
2005	118	309.09	9.87	4.00	1.35	36,473	21.04	0.58	8.03	7.45
2006	129	332.09	10.74	3.81	1.37	42,839	22.48	0.68	8.15	7.47

Panel B: Descriptive statistics on equity funds of the six largest German investment companies

Year	No. of funds	TNA per fund Mio. €	Age in year	Front-end load in %	Management feep.a. in %	Total TNA in Mio. €	Market share in %	NF in %
1992	47	152.36	17.34	4.29	0.62	7,161	73.63	0.04
1993	48	185.91	17.78	4.24	0.67	8,924	45.32	2.23
1994	57	260.60	16.38	4.39	0.74	14,854	59.75	2.64
1995	76	232.23	13.69	4.36	0.79	17,649	67.45	-0.97
1996	99	204.95	11.35	4.04	0.87	20,290	60.88	0.81
1997	119	241.85	10.80	3.91	0.82	28,780	47.94	1.88
1998	126	360.25	10.94	3.96	0.88	45,391	52.12	1.36
1999	174	463.99	9.87	3.67	0.93	80,734	45.88	1.00
2000	213	669.72	9.43	3.64	0.99	142,650	67.07	0.92
2001	253	519.46	8.95	3.53	1.06	131,423	75.85	-0.14
2002	297	340.13	8.71	3.51	1.20	101,019	87.60	-0.94
2003	336	258.54	9.06	3.62	1.19	86,870	66.28	-0.29
2004	269	367.94	10.34	3.72	1.26	98,977	72.62	-0.18
2005	289	339.82	10.75	3.81	1.29	98,208	56.65	-0.04
2006	313	360.34	11.57	3.75	---	112,786	59.19	-0.53

The number of funds increases from 14 in 1992 to 129 in 2006.[12] In the same period, the average TNA (total net assets) per fund increases from € 108.29 million to € 332.09 million, while the mean age of the fund decreases from over 16 years to less than 11 years. These figures reflect the rapid growth of the industry and the large number of newly established funds in this period. Front-end load fees are relatively constant in the sample period and are about 4%.[13] The management fees rise from 0.52% in 1992 to 1.37% in 2006. The total asset under management in the funds of the company increases from € 1.5 billion in 1992 to over € 40 billion. This represents a market share of up to nearly 25% based on the total market capitalization of all German equity funds. The average monthly growth rate of net flows (*NF)* varies between -1.65% and 3.33%. Looking at the growth rate of inflows (IF) and the growth rate of outflows (OF) separately, we can conclude that the net flows are neither driven only by purchases nor only by redemptions. For example, in 2006 the average monthly growth rate of net flows is 0.68%, which is calculated as the difference between the growth rate of inflows of 8.15% and the growth rate of outflows of 7.47%. Similar numerical relations are found in other years. The average monthly relative inflows and relative outflows, as well as the relative net flows over time, are shown in Figure 2.1.

It can be clearly seen that investors trade fund shares much more actively than one would expect by just looking at net flows. These figures suggest the existence of rapid trading in Germany. They are qualitatively consistent with the results for the U.S. fund market. However, the magnitude of rapid trading in Germany is greater than in the U.S. For example, Cashman, Deli, Nardari and Villupuram (2006) show that in the U.S. the average monthly relative net flow from 1997 to 2003 is 2%, while the average of relative inflows and outflows are 5.4% and 3.4%, respectively.

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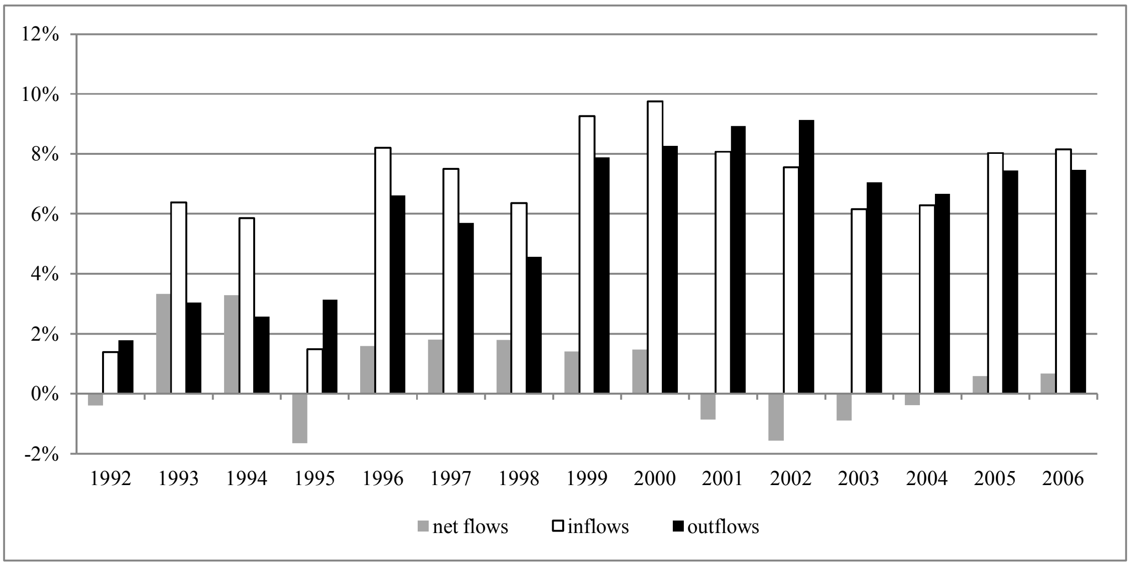
[12] Starting in 2002 multiple share classes are offered for some funds. These share classes are included as separate funds in our database. The share classes of a fund are based on the same portfolio, but they differ in fee structure. As we explicitly examine the influence of the different types of fees (Section 2.3.3) below, we use each share class as a separate observation, and refrain from aggregating them on the portfolio level.

[13] It is important to note that front-end load fees always represent the maximum sales charges payable. It is possible that some investors pay lower fees when they purchase funds through discount brokers or when they invest a very large amount in cases of a staggered front-end load fee structure. Since we only consider funds of one fund company, the front-end load fees could be a reasonable proxy to capture the differences in actual front-end load fees paid by investors. Thus we do not expect our following results to be skewed by possible existing differences between actual and maximum front-end load fees.

Figure 2.1: Average monthly relative net flows, relative inflows and relative outflows

This figure shows the monthly average of relative net flows, relative inflows and relative outflows in the years from 1992 to 2006. The data are obtained from the anonymous German fund company.



To ensure that the data of the anonymous fund company are representative for the German fund market, we collect additional data from five other large fund companies. These data are also available from the BVI. The expanded sample includes data from the six largest German fund companies.[14] The market share of equity fund assets managed by these companies covers up to 88% of the total equity fund assets in Germany. The descriptive statistics for this expanded sample are shown in Panel B of Table 2.1.[15] The magnitude of the individual variables shows no noticeable difference between the data of the anonymous fund company and the data of the expanded sample.

In addition, we compare the product structure of the anonymous fund company and the six largest fund companies by looking at the number and proportion of the funds in different fund categories. The corresponding results are shown in Table 2.2.

[14] They are Activest (since October 2006 Activest Pioneer), Cominvest/Adig, Deka, dit (since December 2006 merged with dbi to become Allianz Global Investors), DWS and Union Investment.

[15] Data on management fees in 2006 are not available for the enlarged sample.

Table 2.2: Types of funds of the anonymous fund company and the enlarged sample

This table presents the product range of the anonymous fund company and of the six largest fund companies. We calculate the number of funds and fraction of funds (in percent) in four fund categories: sector funds, country funds, index funds and other. The data are obtained from the anonymous fund company and BVI.

	No. of funds				Fraction of funds (in percent)			
	Sector funds	Country funds	Index funds	other	Sector funds	Country funds	Index funds	other
Anonymous fund company	40	99	2	28	23.67	58.58	1.18	16.57
Six largest mutual fund companies	106	298	29	56	21.68	60.94	5.93	11.45

The numbers indicate that most funds are international equity funds. At the anonymous fund company as well as the six largest fund companies the fraction of international equity funds is around 60%, followed by sector funds with a fraction of over 20%. Passive managed funds play no significant role in both groups. The fraction is below 10%.

Overall, Tables 2.1 and 2.2 show that the data of the anonymous large fund company are representative of equity funds and of the product range of a typical large German fund company. However, it is possible that smaller fund companies have a different product range. These companies, for example, often have a very specialized product range. Therefore we consider our following results only as being representative of rapid trading at large German fund companies. Even if we only consider the six largest companies, our results cover up to 88% of the total assets under management in equity funds.

2.3. Results

Before we turn to an examination of the existence, determinants and consequences of rapid trading in Sections 2.3.2 to 2.3.4, we first conduct a preliminary investigation of the widely documented relationship between past performance and fund net flows based on our sample in Section 2.3.1. On the one hand, this allows us to examine whether the known results on the determinants of fund net flows (e.g., Sirri and Tufano (1998), Ber, Kempf and Ruenzi (2007)) hold in our sample. On the other hand, we can compare the results based on the data from the anonymous fund company with the results based on data from the six largest German investment companies. Thus, we can analyze whether the behavior of fund investors of the anonymous fund company regarding net flow differs from the behavior of investors of the six largest German investment companies. If we cannot find significant evidence of any differences in investor behavior it is a strong indication not only that the fund characteristics do not differ significantly (see Section 2.2), but also that the investors of the anonymous fund company on aggregate are representative of investors of typical large German fund companies.

2.3.1. Performance Flow Relationship

One of the most important determinants of investment decisions of fund investors is the past fund performance (see, e.g., Capon, Fitzsimons and Prince (1996)). In the classic studies on the net flow performance relationship (see, e.g., Sirri and Tufano (1998)) net inflows (= inflows - outflows) are related to past performance and other control variables. Sirri and Tufano (1998) note that the absolute level of flows of funds of different sizes is not directly comparable. Therefore, we follow their suggestion and use relative net inflows of fund *i* in month *m*, which is calculated as follows:

$$NF_{i,m} = \frac{EuroIF_{i,m} - EuroOF_{i,m}}{TNA_{i,m-1}},$$

where $EuroIF_{i,m}$ ($EuroOF_{i,m}$) denotes the absolute inflows (outflows) in €. $TNA_{i,m-1}$ is the total net assets of fund i at the end of month m-1.

The literature on the determinants of net flows shows that the past performance of a fund has a positive influence. Funds with the best return ranks in their respective segment get significantly higher net flows as compared to other funds, while no significant differences can be observed for net flows in middle and poor performing funds. In order to capture the non-linear influence of past performance on relative net flows ($NF_{i,m}$), we estimate a piecewise linear regression. This method, suggested by Sirri and Tufano (1998), makes it possible to estimate the relationship between past performance and net flows for different performance parts as a closed, piecewise linear polygonal line. We estimate the slope of this relationship for the bottom, middle, and the best piece of past performance in one regression. Performance is defined as the relative rank of the return of a fund as compared to the return of all other funds in the same market segment in the previous year, i.e., in the last 12 months ending in month m-1, $SegRank^{1J}_{i,m-1}$.[16] We estimate the following model:

$$NF_{i,m} = \alpha + \sum_{k=1}^{3} \delta_k \cdot Tercile(k)_{i,m-1} + \gamma \cdot Y + \varepsilon_{i,m} \tag{2.1}$$

where $Tercile(1)_{i,m} = \min\left(0.33; SegRank^{1J}_{i,m-1}\right)$,

$Tercile(2)_{i,m} = \min\left(0.33; SegRank^{1J}_{i,m-1} - Tercile(1)_{i,m}\right)$

and $Tercile(3)_{i,m} = SegRank^{1J}_{i,m-1} - Tercile(1)_{i,m} - Tercile(2)_{i,m}$.

The vector Y contains other control variables, which are described in Table 2.3.

Table 2.3: Description of control variables

This table describes the control variables in model 2.1.

Variable	Description
$Std^{1J}_{i,m-1}$	Return standard deviation of a fund *i* in the last 12 months, i.e. from month *m-12* to end of month *m-1*
$FrontFee_{i,m-1}$	Front-end load of fund *i* in month *m-1* (in percent)
$\ln TNA_{i,m-1}$	The logarithm of assets of a fund *i* at the end of the month *m-1*
$MgtFee_{i,t-1}$	Management fee of a fund *i* in year *t-1* (There is no monthly data)
$NF_{i,m-1}$	Growth rate of net flows of a fund *i* in month *m-1* (or relative net flows)
$Seg-NF_{i,m}$	Growth rate of net flows of the segment which the fund *i* belongs to in month *m* (without fund *i*)
$\ln Age_{i,m-1}$	The logarithm of age (in months) of fund i at end of month m-1

These variables are also used in comparable studies as control variables, e.g., Sirri and Tufano (1998). The estimation results are presented in Table 2.4.

[16] Ranks are uniformly distributed between 0 and 1, where the best fund receives 1 and the worst fund receives 0. The rank of a fund is calculated according to the formula (absolute rank of a fund in its segment in a month -1) / (number of funds in the segment in a month - 1). The absolute rank is expressed in integers and is based on an ascending order, i.e., the worst fund has a rank of 1. The fourth worst fund in its segment with 20 funds, for example, has an absolute ranking of 4 and a segment rank of 0.1579 [=(4-1)/(20-1)]. Several studies have shown that net flows can be best explained by ranks based on returns (see Patel, Zeckhauser and Hendricks (1994), Myers (2001)).

Table 2.4: Performance flow relationship

This table presents the results of performance flow relationship in the two different samples, the anonymous fund company and the six largest German fund companies. We report regression results for four specifications: OLS, CRE, PCSE and ABBB. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

	1	2	3	4	5	6	7	8
	Anonymous fund company $NF_{i,m}$				Six largest German fund companies: $NF_{i,m}$			
	OLS	CRE	PCSE	ABBB	OLS	CRE	PCSE	ABBB
$Tercile(1)_{i,m-1}$	0.061***	0.061***	0.057***	0.038	0.024***	0.024***	0.021***	-0.129
$Tercile(2)_{i,m-1}$	-0.010	-0.010	-0.013	-0.041	0.010*	0.010	0.009	0.045
$Tercile(3)_{i,m-1}$	0.077***	0.077***	0.082***	0.150	0.052***	0.052***	0.055***	0.064
$NF_{i,m-1}$	0.331***	0.331***	0.334***	0.090**	0.250***	0.250***	0.253***	0.075***
$Std^{1,J}_{i,m-1}$	0.022	0.022	-0.014	0.060	0.005	0.005	-0.016	0.050
$FrontFee_{i,m-1}$	-0.020	-0.020	-0.027	-1.480	-0.010	-0.010	-0.008	0.576
$\ln TNA_{i,m-1}$	-0.001	-0.001	-0.001	0.005	0.001***	0.001*	0.001*	-0.006
$MgtFee_{i,t-1}$	1.030***	1.030**	0.967***	1.639	0.420***	0.420**	0.215	2.916
$Seg-NF_{i,m}$	0.153**	0.153**	0.346***	0.302	0.164***	0.164***	0.308***	1.023**
$\ln Age_{i,m-1}$	0.000	0.000	0.000	0.013	-0.000	-0.000	-0.000	0.000
$Constant$	-0.020	-0.020	-0.022*	-0.084	-0.021	-0.021***	-0.025***	-0.012
R^2	18.20%	18.20%	15.30%		9.10%	9.10%	8.00%	
$Adj.\ R^2$	16.20%				8.50%			
AR(1)-Test (p value)				0.000				0.002
AR(2)-Test (p value)				0.221				0.651
Sargan-Test (p value)				1.000				1.000
No. of obs.	8,172	8,172	8,172	8,172	29,088	29,088	29,088	29,088

We estimate the model first as a pooled OLS regression with time fixed effects (OLS, columns 1 and 5)[17] and also with fund level clustered robust standard errors (CRE, columns 2 and 6).[18] Since the model contains the lagged endogenous variable as an independent variable, there is a dynamic panel structure. Considering this data structure, we also use an estimation with panel-corrected standard errors (PCSE, see Beck and Katz (1995), columns 3 and 7) and the Arrelano/Bond-Bover/Blundell estimator (ABBB, Arellano and Bover (1995), Blundell and Bond (1998), columns 4 and 8).[19]

[17] The constants for single months are not reported in the table due to lack of space.

[18] We have also estimated all models with robust standard errors without clustering at fund level. The results (not explicitly reported) are very similar.

[19] Due to the long time series of our panel sample an estimate of ABBB method based on the maximum number of instruments is not possible. Therefore, we use only 10 lagged endogenous level variables (starting at t-3) in the differential equations and one lagged endogenous differential variable as instrumental variables. Alternatively, we can use the Arrelano/Bond (1991) estimator (so-called Difference GMM). The GMM moment conditions are based only on the differential equations and the lagged level variables are used as instruments. However, there are two problems using

The results in both samples show that investors prefer funds that perform well, indicated by the positive effect on net flows being in the best tercile. Moreover, in both cases there is a strong relationship between net flows and net flows in the previous month, which indicates a status-quo bias of fund investors (see Kempf and Ruenzi (2006)). The influence of management fees is positive in both samples, but not significant in all specifications. The positive relationship can be explained by the fund companies that are anxious to sell expensive funds and investors who do not fully consider management fees (Barber, Odean and Zheng (2005)). Furthermore, the influence of aggregate flows in the same market segment is highly significant and positive (with the exception of the specification ABBB) in both samples, while the other independent variables do not have a significant impact on net flows.

Overall, we can conclude from the results of this preliminary examination that the behavior of investors in the anonymous fund company does not, at least in the aggregate, differ explicitly from the behavior of investors in a large sample with the six largest German fund companies. This is not surprising, since the large fund companies under investigation (including the anonymous fund company) are all subsidiaries of large German banks or savings banks and distribute their funds mainly through those banks. Therefore, the composition of the clientele at all large fund companies is probably relatively similar. Therefore, we can assume that investors in the anonymous fund company are representative of a typical large German fund company.

the Arrelano/Bond (1991) estimator. First, by using the difference estimator we may lose the fund cross-sectional dimension of the data and the differentiation can reduce the signal-to-noise ratio (Griliches and Hausman, (1986)). Second, Alonso-Borrego and Arellano (1999) and Blundell and Bond (1998) show that lagged level variables are weak instruments when the variables are persistent. The difference estimator has a large bias in case of a limited sample and has low precision. As an alternative, the Arrelano/Bover-Blundell/Bond estimator (so-called system GMM) is proposed, where the GMM moment conditions are based on difference and level equations. The lagged level variables are used as instruments for the differential equations and the lagged difference variables as instruments for the level equations. Thus, the problem of weak instruments can be circumvented. However, it should be noted that the ABBB estimation method is not perfect in our context. Even though it takes into account the dynamic panel structure, it is actually designed for panel samples with a large number of funds and a short time period. Therefore, the efficiency gained by using ABBB might be ruined by the large number of instruments required. Thus, although none of the above estimation methods is perfect, we can expect stable results if all methods give similar results.

2.3.2. Evidence of Rapid Trading

Rapid trading is present when a significant number of investors buy and sell fund shares within a short-term period. Therefore, our empirical method is based on the idea suggested by O'Neal (2004) and Cashman, Deli, Nardari and Villupuram (2006) that rapid trading can be proved by a strong positive correlation between inflows in a month and outflows in the same month.[20] Without rapid trading, one would intuitively expect that high inflows are associated with low outflows and vice versa. The reason is that certain characteristics of a fund (e.g., good past performance) should lead to high inflows and low outflows simultaneously. If one only considers net flows, rapid trading cannot be observed, because high in- and outflows compensate for each other.

The relative inflows into fund i in month m, $IF_{i,m}$, and the relative outflows from fund i in month m, $OF_{i,m}$, are defined relative to the total net assets at the end of the previous month $t\text{-}1$ as:

$$IF_{i,m} = \frac{EuroIF_{i,m}}{TNA_{i,m-1}} \quad \text{and} \quad OF_{i,m} = \frac{EuroOF_{i,m}}{TNA_{i,m-1}}.$$

These two flow variables are defined as positive values, i.e., based on these definitions the relative net flows are calculated as the difference between relative inflows and relative outflows, $NF_{i,m} = IF_{i,m} - OF_{i,m}$. Our two basic models for the explanation of inflows and outflows are:

$$IF_{i,m} = f(OF_{i,m}, \ldots) \text{ and } OF_{i,m} = g(IF_{i,m}, \ldots).$$

In these models the inflows, $IF_{i,m}$, into a fund (outflows, $OF_{i,m}$, from a fund) i in month m as the dependent variable are explained by the corresponding outflows from (inflows into) the same fund in the same month. A significantly positive correlation is an indication of

[20] Strictly speaking, with this method we can only test the necessary condition for the existence of rapid trading. Indeed, it is also conceivable that such correlation between inflows and outflows in a month is not caused by rapid trading of certain investors, but by the influence of another factor that simultaneously leads to high inflows of certain investors and high outflows of other investors. Since we have no data on investor level, we cannot investigate this alternative hypothesis. However, our results in Section 2.3.3 suggest that this seems unlikely.

rapid trading. The "..." stands for other explanatory variables and are essentially identical to those in model (2.1). Our empirical models for the inflows and outflows are thus:

$$IF_{i,m} = \alpha + \beta \cdot OF_{i,m} + \sum_{k=1}^{3} \delta_k \cdot Tercile(k)_{i,m-1} + \gamma \cdot Y + \varepsilon_{i,m} \tag{2.2}$$

and

$$OF_{i,m} = \alpha + \beta \cdot IF_{i,m} + \sum_{k=1}^{3} \delta_k \cdot Tercile(k)_{i,m-1} + \gamma \cdot Y + \varepsilon_{i,m} \,. \tag{2.3}$$

The vector Y contains the control variables described in Table 2.3. However, we now replace $NF_{i,m-1}$ by the lagged values of the corresponding dependent variables $IF_{i,m-1}$ in model (2.2) and $OF_{i,m-1}$ in model (2.3).[21] The estimation results for these two models are presented in Table 2.5.

Since model 2.2 (2.3) uses the dependent variable of the model 2.3 (2.2) as an independent variable, we estimate these two equations simultaneously as a system (columns 5 and 10), in addition to those methods used in the estimation of model (2.1). Regardless of the methods chosen, our results show a strong dependence of inflows on outflows (columns 1 to 5) and vice versa (columns 6 to 10). The estimation for the impact of outflows on inflows in model (2.2) is always positive and statistically significant at the 1% level. There is a similar effect for the impact of inflows on outflows in the model (2.3). The effects are economically significant. Thus, the estimate of the impact of inflows on outflows is 0.39. This means that a fund that, for example, generates additional inflows of 10% of its volume in a month, suffers, ceteris paribus, in the same month additional outflows of 3.9% of its volume. A similar relation is found for the influence of outflows on inflows. Overall, based

[21] In an alternative specification, we include, in addition to the outflows $OF_{i,m}$ (inflows $IF_{i,m}$), the lagged outflows $OF_{i,m-1}$ (inflows $IF_{i,m-1}$) in model (2.2) (model (2.3)) as an explanatory variable. This does not change our main results. Furthermore, the influence of additional variables is economically very small and statistically not significant or only weakly significant. In addition, in unreported tests we also include the ratings and rating changes in the fund as explanatory variables. This also does not change our main results. We do not report these results, since our rating data are not survivorship-bias free and therefore the results of these control variables are difficult to interpret. All results not explicitly reported in the paper are available on request from the authors.

on O'Neal (2004) and Cashman, Deli, Nardari and Villupuram (2006) the pronounced correlation between inflows and outflows clearly indicates the existence of rapid trading.

Table 2.5: Relationship between inflows and outflows

This table presents the results of relationship between relative inflows and relative outflows based on the data of the anonymous German fund company. We report regression results for five specifications: OLS, CRE, PCSE, ABBB and Syst. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

	1	2	3	4	5	6	7	8	9	10
	Dependent Variable: $IF_{i,m}$					Dependent Variable: $OF_{i,m}$				
	OLS	CRE	PCSE	ABBB	Syst.	OLS	CRE	PCSE	ABBB	Syst.
$OF_{i,m}$	0.440***	0.440***	0.447***	0.710***	0.407***					
$IF_{i,m}$						0.386***	0.386***	0.392***	0.490***	0.310***
$Tercile(1)_{i,m-1}$	0.038***	0.038***	0.035**	0.091	0.035***	-0.060***	-0.060***	-0.059***	-0.043	-0.058***
$Tercile(2)_{i,m-1}$	-0.009	-0.009	-0.010	0.036	-0.009	0.004	0.004	0.008	-0.017	0.003
$Tercile(3)_{i,m-1}$	0.068***	0.068***	0.070***	0.067*	0.066***	-0.038***	-0.038***	-0.045***	-0.002	-0.028***
$IF_{i,m-1}$	0.437***	0.437***	0.436***	0.121**	0.451***					
$OF_{i,m-1}$						0.372***	0.372***	0.369***	0.121***	0.415***
$Std^{1,J}_{i,m-1}$	0.123***	0.123**	0.072*	0.778**	0.139***	0.197***	0.197***	0.180***	0.238	0.231***
$FrontFee_{i,m-1}$	-0.130**	-0.130*	-0.117	-1.586***	-0.149**	-0.230***	-0.230**	-0.196***	-0.791	-0.266***
$\ln TNA_{i,m-1}$	-0.001**	-0.001	-0.001	-0.025***	-0.001**	-0.001	-0.001	-0.001	0.001	-0.001
$MgtFee_{i,t-1}$	0.731***	0.731**	0.879***	0.416	0.708***	-0.720***	-0.720*	-0.337	0.971	-0.644***
$Seg-NF_{i,m}$	0.124**	0.124**	0.280***	-0.008	0.118**	-0.109**	-0.109**	-0.231***	-0.094	-0.095*
$\ln Age_{i,m-1}$	0.001	0.001	0.001	-0.016	0.001	0.001	0.001	0.001	-0.003	0.001
$Constant$	-0.011	-0.011	-0.009	0.361***	-0.008	0.032	0.032*	0.042***	0.078	0.036
R^2	60.44%	60.44%	58.89%		60.38%	55.76%	55.76%	53.77%		55.33%
$Adj.\ R^2$	59.50%					54.72%				
AR(1)-Test (p value)				0.000					0.000	
AR(2)-Test (p value)				0.194					0.118	
Sargan-Test (p value)				1.000					1.000	
No. of obs.	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172

Before we turn to the determinants of rapid trading, we first investigate whether rapid trading exists in sub-samples consisting of funds of a certain segment. To do so, we consider the estimation results for models (2.2) and (2.3) separately for the two largest categories, country funds and sector funds. The results without the estimations for control variables are shown in Table 2.6.

In both samples, we find clear evidence of a pronounced correlation between inflows and outflows in a period. The relationship is stronger for sector funds than for country funds. In both country funds and sector funds there is evidence of rapid trading.

Table 2.6: Relationship between inflows and outflows - sector funds & country funds

This table presents the results of the relationship between relative inflows and relative outflows for sector funds (Panel A) and country funds (Panel B) separately, based on the data of the anonymous German fund company. We report regression results for five specifications: OLS, CRE, PCSE, ABBB and Syst. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Panel A: Sector funds

	1	2	3	4	5	6	7	8	9	10
	Dependent variable: $IF_{i,m}$					Dependent variable: $OF_{i,m}$				
	OLS	CRE	PCSE	ABBB	Syst.	OLS	CRE	PCSE	ABBB	Syst.
$OF_{i,m}$	0.758***	0.758***	0.700***	0.844***	0.818***					
$IF_{i,m}$						0.657***	0.657***	0.590***	0.631***	0.684***
…	…	…	…	…	…	…	…	…	…	…
R^2	79.80%	79.80%	72.60%		60.40%	79.80%	79.80%	72.80%		55.30%
$Adj.\ R^2$	77.40%					77.40%				
AR(1)-Test (p value)				0.004					0.001	
AR(2)-Test (p value)				0.141					0.235	
Sargan-Test (p value)				1.000					1.000	
N	1,771	1,771	1,771	1,771	1,771	1,771	1,771	1,771	1,771	1,771

Panel B: Country funds

	Dependent variable: $IF_{i,m}$					Dependent variable: $OF_{i,m}$				
	OLS	CRE	PCSE	ABBB	Syst.	OLS	CRE	PCSE	ABBB	Syst.
$OF_{i,m}$	0.262***	0.262***	0.279***	0.441***	0.344***					
$IF_{i,m}$						0.250***	0.250***	0.261***	0.274***	0.242***
…	…	…	…	…	…	…	…	…	…	…
R^2	50.64%	50.64%	47.39%		50.23%	33.41%	33.41%	28.68%		33.40%
$Adj.\ R^2$	48.90%					31.10%				
AR(1)-Test (p value)				0.000					0.000	
AR(2)-Test (p value)				0.227					0.207	
Sargan-Test (p value)				1.000					1.000	
N	5,657	5,657	5,657	5,657	5,657	5,657	5,657	5,657	5,657	5,657

2.3.3. Determinants of Rapid Trading

In order to investigate the determinants of rapid trading, we first develop two proxies for rapid trading at individual fund level (Section 2.3.3.1). Then, we investigate whether rapid trading is strongly pronounced in certain calendar months (Section 2.3.3.2) and the main characteristics of funds that are particularly affected by rapid trading (Section 2.3.3.3). By carrying out these investigations, we can analyze alternative explanations for rapid trading in detail.

2.3.3.1. Proxies for Rapid Trading

We develop two proxies for rapid trading at individual fund level, $RT1_{i,m}$ and $RT2_{i,m}$. The first proxy is defined as the sum of euro inflows and euro outflows in a month divided by total net assets of the fund at the end of the previous month:

$$RT1_{i,m} = \frac{EuroIF_{i,m} + EuroOF_{i,m}}{TNA_{i,m-1}} = IF_{i,m} + OF_{i,m}\,. \tag{2.4}$$

This proxy captures the total absolute trade volume of the fund investors in relation to the fund's assets. By doing this, we prevent inflows and outflows from canceling each other.

A possible criticism of this measure is that $RT1_{i,m}$ can take on a large value even if only $IF_{i,m}$ or $OF_{i,m}$, is large, but not both simultaneously. The results from Figure 2.1 and Section 2.3.2 can prove that this case is indeed unlikely. However, in order to take this possibility into account, we define an alternative proxy for rapid trading as the minimum of relative inflows and relative outflows:

$$RT2_{i,m} = \frac{\min\left(EuroIF_{i,m}, EuroOF_{i,m}\right)}{TNA_{i,m-1}} = \min\left(IF_{i,m}, OF_{i,m}\right). \tag{2.5}$$

The average value of all funds is 14.20% for $RT1_{i,m}$ and 4.7% for $RT2_{i,m}$. The correlation of these two proxies is 0.91.

A direct measure of rapid trading is also the correlation between inflows and outflows of a fund over time (or alternatively, the estimate of β from the model (2.2) or (2.3)). However, since a certain minimum period is necessary for the calculation of this proxy, we do not use it in our regression analysis; if we did, we would exclude too many observations. It could also lead to biased results due to a possible survivorship bias. If this proxy (correlation between inflows and outflows) is calculated on an annual level, its correlation with the average value of $RT1_{i,m}$ ($RT2_{i,m}$) in the corresponding year is 0.54 (0.62) and significant at the 1% level.

2.3.3.2. Proxies for Rapid Trading over a Year

Ederington and Golubeva (2009) argue that, motivated either by tax reasons or by portfolio shifts, investors trade a lot in certain months of the year. Therefore, we first examine whether our proxies for rapid trading exhibit explicit time patterns within a calendar year. For this, we calculate the mean of our proxies for each month $\overline{RT1}_m = \frac{1}{n}\sum_{i=1}^{n} RT1_{i,m}$ and $\overline{RT2}_m = \frac{1}{n}\sum_{i=1}^{n} RT2_{i,m}$ over all funds in our sample. Then, we calculate the average of all $\overline{RT1}_m$ and $\overline{RT2}_m$ over all January values, February values, etc. The results are reported in Table 2.7.

Table 2.7: Rapid Trading in each calender month

This table presents the average values of two rapid trading proxies in different calendar months. Firstly, we calculate the average of these two proxies for each month for all funds in our sample. Then, we calculate the average of all averages over all January values, February values, etc.

Month	$\overline{RT1}_m$	$\overline{RT2}_m$	Month	$\overline{RT1}_m$	$\overline{RT2}_m$
January	0.147	0.045	July	0.125	0.041
February	0.126	0.038	August	0.115	0.035
March	0.133	0.042	September	0.109	0.035
April	0.126	0.038	October	0.126	0.041
May	0.123	0.040	November	0.126	0.038
June	0.118	0.039	December	0.113	0.033

The values show a similar magnitude over the year. The value for $\overline{RT1}_m$ ($\overline{RT2}_m$) varies between 0.11 (0.03) in December and 0.15 (0.05) in January. The majority of rapid trading cannot be explained by the fact that trades in fund shares are very pronounced in certain months and very little in other months.

The table shows, however, that our proxies for rapid trading are higher in January than in the other months. One possible explanation is that in January investors determine their investment strategy for the upcoming year and implement it accordingly. Therefore, the increased value in January is probably not due to rapid trading directly (i.e., the short-term purchase and redemption by the same investors), but the fact that some investors sell certain funds strongly as part of implementing their investment strategy, while other investors buy these funds strongly (see Ederington and Golubeva (2009)). The low value in December, however, is possibly related to the Christmas holidays. These effects will be considered in the following investigations by estimating our explanatory models for rapid trading with time-fixed effects. Thus for each month we estimate a single constant which corrects both differences in rapid trading among calendar months and over the years.

2.3.3.3. Determinants of Rapid Trading and Explanations

To get a first impression of the characteristics of funds that are affected by different magnitudes of rapid trading, we divide all funds based on $RT1_{i,m}$ and $RT2_{i,m}$, into ten deciles. The average characteristics of the funds in each decile are shown in Table 2.8.

Decile 1 contains the observations with the lowest values and Decile 10 contains the observations with the highest value of the respective proxy. In column 3, we compute the average values of $RT1_{i,m}$ (Panel A) and $RT2_{i,m}$ (Panel B) for each decile. We can clearly observe that the proxies have a strong cross-sectional variation. The proxy $RT1_{i,m}$ ($RT2_{i,m}$) varies between 1.48% (0.04%) in the lowest decile and 55.27% (21.74%) in the highest decile. In column 4, one can see the respective average values in the previous month for the funds in the corresponding decile. These values show that rapid trading is very persistent. The pattern is very similar to the values in column 3. Apparently, certain funds seem to be characterized by high values of the proxies, while other funds have consistently low values.

Table 2.8: Fund characteristics of rapid trading deciles

This table presents the average characteristics of funds in different deciles. We divide all observations based on $RT1_{i,m}$ (Panel A) and $RT2_{i,m}$, (Panel B) into ten deciles. Then we calculate the average characteristics of the funds in each decile. Decile 1 contains the observations with the lowest value of rapid trading proxies. Decile 10 contains the observations with the highest value of rapid trading proxies.

Panel A: Rapid trading deciles based on proxy $RT1_{i,m}$

1	2	3	4	5	6	7	8	9	10	11	12
Decile	No. of obs	RT1 in %	RT1 in % in previous month	FrontFee in %	MgtFee in %	SegRank	STD of fund returns in %	TNA in Mio.EUR	Age in year	Fraction of international funds in %	Fraction of passive managed funds in %
1	818	1.48	3.64	4.18	0.81	0.54	4.92	138.47	11.46	79.34	0.12
2	817	2.99	4.79	3.99	0.91	0.54	4.67	338.69	12.20	76.87	2.45
3	817	4.22	6.12	3.81	0.95	0.53	4.78	620.54	13.09	80.05	0.86
4	817	5.64	7.63	3.72	1.01	0.53	4.94	515.17	10.34	83.60	0.98
5	817	7.32	9.05	3.79	1.02	0.54	5.12	467.13	10.33	84.58	1.10
6	817	9.55	11.33	3.97	1.04	0.57	5.40	473.45	10.03	86.29	0.24
7	817	12.65	14.11	3.80	1.06	0.59	5.59	373.68	9.13	90.33	0.00
8	817	17.29	17.32	3.75	1.06	0.60	5.88	373.67	9.75	92.66	0.00
9	817	24.54	24.12	3.65	1.05	0.59	6.38	238.12	8.97	92.04	0.00
10	818	55.27	43.96	2.85	1.14	0.55	7.01	153.04	7.46	93.15	0.00

Panel B: Rapid trading deciles based on proxy $RT2_{i,m}$

1	2	3	4	5	6	7	8	9	10	11	12
Decile	No. of obs	RT2 in %	RT2 in % in previous month	FrontFee in %	MgtFee in %	SegRank	STD of fund returns in %	TNA in Mio.EUR	Age in year	Fraction of international funds in %	Fraction of passive managed funds in %
1	818	0.04	0.49	3.88	0.86	0.45	4.05	91.82	6.68	87.16	0.00
2	817	0.40	0.94	4.13	0.92	0.49	4.47	101.99	9.21	85.43	0.00
3	817	0.87	1.51	3.95	0.92	0.56	4.76	327.75	13.34	77.85	1.10
4	817	1.38	2.09	3.95	0.91	0.57	5.15	596.41	13.52	80.29	2.08
5	817	1.96	2.41	3.79	0.98	0.58	5.45	687.99	12.62	78.58	1.47
6	817	2.77	3.32	3.79	1.03	0.59	5.49	508.77	10.15	85.56	0.49
7	817	3.92	4.27	3.93	1.07	0.60	5.73	491.19	10.30	86.90	0.61
8	817	5.69	5.83	3.76	1.11	0.61	5.95	365.38	9.64	90.82	0.00
9	817	8.74	8.77	3.67	1.07	0.60	6.32	341.37	9.69	92.66	0.00
10	818	21.74	18.31	2.68	1.18	0.53	7.31	179.31	7.59	93.64	0.00

Other results from Table 2.8 indicate that funds with lower front-end load fees, funds with higher management fees and riskier funds are especially affected by rapid trading. Regarding past performance, fund size and fund age there are no or only small systematic differences. Finally, we find that the share of international equity funds in decile 10 is significantly higher than in decile 1 and that a few observations based on passively managed funds tend to be in the deciles with lower rapid trading. The average rapid trading based on proxy 1 (proxy 2) for active managed funds is 0.15 (0.05), whereas for passively managed funds it is only 0.05 (0.02). The difference is always significant at the 1% level. Therefore, passively managed funds appear to be less affected by rapid trading than actively managed funds. However, these results are only univariate. While they allow us to observe average characteristics of funds affected by different degrees of rapid trading, we cannot draw conclusions on possible explanations for rapid trading by using these results. Therefore, we investigate the determinants of rapid trading now by using the following multivariate model:

$$\begin{aligned} RT_{i,m} = {} & \alpha + \beta_1 \cdot RT_{i,m-1} + \beta_2 \cdot FrontFee_{i,m-1} + \beta_3 \cdot MgtFee_{i,t-1} + \beta_4 \cdot SegRank^{1J}_{i,m-1} \\ & + \beta_5 \cdot Std^{1J}_{i,m-1} + \beta_6 \cdot \ln TNA_{i,m-1} + \beta_7 \cdot \ln Age_{i,m-1} + \beta_8 \cdot D^{Int}_{i,m} + \varepsilon_{i,m} \ , \end{aligned} \tag{2.6}$$

where $RT_{i,m}$ can be interpreted as $RT1_{i,m}$ or $RT2_{i,m}$. $D^{Int}_{i,m}$ denotes a dummy variable that takes the value 1 when fund i is an international equity fund, and 0 otherwise. The remaining variables are defined above (see Table 2.3). The results for a pooled OLS regression with and without fund level clustered corrected robust standard errors, for PCSE and ABBB method (if possible)[22] are presented in Table 2.9.

The first results show a strong persistence of rapid trading over time. The estimate for the impact of lagged variables $RT_{i,m-1}$ is about 0.7 and always significant at the 1% level, independent of the choice of proxies and the specific estimation method.

[22] Since the ABBB method is based on differential equations, it cannot be applied in the case in which the models contain a fixed dummy variable that is constant over time, such as $D^{Int}_{i,m}$. Therefore, we only report estimation results for model (2.6) without $D^{Int}_{i,m}$.

Table 2.9: Determinants of rapid trading

This table presents the regression results of determinants of rapid trading based on $RT1_{i,m}$ (Panel A) and $RT2_{i,m}$. We report regression results for four specifications: OLS, CRE, PCSE and ABBB. Data are obtained from the anonymous German fund company. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Panel A: Proxy $RT1_{i,m}$ as the dependent variable

	1	2	3	4	5	6	7	8	9	10
	OLS			CRE			PCSE			ABBB
$RT1_{i,m-1}$	0.673***	0.673***	0.673***	0.673***	0.673***	0.673***	0.674***	0.674***	0.673***	0.299***
$FrontFee_{i,m-1}$	-0.643***	-0.637***	-0.625***	-0.643*	-0.637*	-0.625*	-0.574***	-0.570***	-0.565***	-5.858***
$MgtFee_{i,t-1}$	0.014	0.045	0.229	0.014	0.045	0.229	0.948*	0.967*	1.034**	11.961**
$SegRank^{1J}_{i,m-1}$	0.005	0.005	0.007	0.005	0.005	0.007	0.004	0.004	0.006	0.073*
$Std^{1J}_{i,m-1}$	0.634***	0.640***	0.635***	0.634***	0.640***	0.635***	0.491***	0.497***	0.496***	2.731*
$\ln TNA_{i,m-1}$	-0.003***	-0.003***	-0.003**	-0.003	-0.003	-0.003	-0.003**	-0.003**	-0.002**	-0.019*
$\ln Age_{i,m-1}$	0.002	0.002	0.003	0.002	0.002	0.003	0.003	0.003	0.003	0.012
$D^{Int}_{i,m}$	0.013***	0.014***	0.014***	0.013***	0.014***	0.014***	0.013***	0.013***	0.013***	
$D^{Asia}_{i,m}$		-0.004			-0.004			-0.005		
$P_{i,m-1}$			-0.00003**			-0.00003*			-0.00003***	-0.0004*
$Constant$	0.033	0.031	0.027	0.033	0.031	0.027	0.039**	0.037**	0.033*	0.315
R^2	55.74%	55.75%	55.77%	55.74%	55.75%	55.77%	53.19%	53.19%	53.22%	
Adj. R^2	54.71%	54.71%	54.73%							
AR(1)-Test (p value)										0.002
AR(2)-Test (p value)										0.409
Sargan-Test (p value)										1.000
No. of obs.	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172

Panel B: Proxy $RT2_{i,m}$ as the dependent variable

	1	2	3	4	5	6	7	8	9	10
	OLS			CRE			PCSE			ABBB
$RT2_{i,m-1}$	0.717***	0.717***	0.716***	0.717***	0.717***	0.716***	0.718***	0.717***	0.717***	0.344***
$FrontFee_{i,m-1}$	-0.289***	-0.286***	-0.281***	-0.289*	-0.286*	-0.281*	-0.265***	-0.262***	-0.261***	-2.606***
$MgtFee_{i,t-1}$	0.217	0.237	0.324*	0.217	0.237	0.324	0.541***	0.554***	0.582***	1.053
$SegRank^{1J}_{i,m-1}$	0.001	0.001	0.002	0.001	0.001	0.002	0.000	0.001	0.001	0.025
$Std^{1J}_{i,m-1}$	0.246***	0.250***	0.247***	0.246***	0.250***	0.247***	0.191***	0.195***	0.194***	1.176*
$\ln TNA_{i,m-1}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.013
$\ln Age_{i,m-1}$	0.002***	0.002***	0.002***	0.002*	0.002*	0.002*	0.002***	0.002***	0.002***	-0.002
$D^{Int}_{i,m}$	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.004***	0.005***	0.005***	
$D^{Asia}_{i,m}$		-0.003			-0.003			-0.003*		
$P_{i,m-1}$			-0.00002**			-0.00002**			-0.00002***	-0.0001
$Constant$	-0.004	-0.005	-0.007	-0.004	-0.005	-0.007	-0.005	-0.006	-0.008	0.256**
R^2	61.58%	61.59%	61.60%	61.58%	61.59%	61.60%	59.70%	59.71%	59.73%	
Adj. R^2	60.68%	60.69%	60.71%							
AR(1)-Test (p value)										0.015
AR(2)-Test (p value)										0.154
Sargan-Test (p value)										1.000
No. of Obs.	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172

Other results allow us to verify the following four possible explanations for rapid trading:

1. Our proxies do not capture rapid trading, but some funds are simply more visible to investors and thus investors are well aware when an investment decision has to be made. Such funds are then bought by investors more frequently than other funds. They are also more frequently sold if a sale decision has to be made (if the investor has the funds in his portfolio). Sirri and Tufano (1998) argue that especially large funds are visible for investors and thus are achieving brand recognition. In contrast, we find a significantly negative impact of fund size on our proxies for rapid trading, which means particularly visible funds do not seem to be affected. This shows that our results are probably not driven by the fact that some funds are traded more than others because they are more visible to investors.

2. Brokers push fund investors to rearrange their investments constantly in order to benefit from sales commissions: According to this explanation, we would expect strong rapid trading among funds with high front-end load fees that generally provide brokers a higher sales commission. In fact, O'Neal (2004) provides evidence that in the U.S. rapid trading is stronger among funds with higher front-end loads. We find, however, that rapid trading among funds with high front-end load fees is particularly weak. The influence of the front-end load fees is usually significantly negative. Therefore, our results show that brokers are not likely to be responsible for rapid trading. In fact, front-end load fees discourage the excessive trading of fund investors. The reason is that fee structures affect the fund selection of investors according to their holding period.[23] Rapid traders, i.e., investors with a short planned investment horizon and the associated higher trading frequency, prefer funds with the lowest possible sales charges, while long-term investors tend to choose funds with lower annual fees. Our results show that front-end load fees can be an effective tool for discouraging rapid trading. Since the distributors are mainly financed by front-end load fees and therefore try to sell funds with front-end load fees, these fees do not seem to play a major role in the explanation of rapid trading. Nevertheless, there might be significant differences between certain distribution channels (banks and

[23] For theoretical work on fee structures in mutual funds see Chordia (1996), Nanda, Narayanan and Warther (2000) and Ruenzi (2006), Section 2.2.

savings banks, direct banks, etc.). Since information on flows in certain sales channels is not available, we cannot examine the role of distribution in this paper.

3. Fund investors operate time zone arbitrage, and therefore buy and sell fund shares within a short time interval: Time zone arbitrage refers to the attempt to profit from funds investing in other time zones based on the predictability of price movements due to the earlier exchange closure. Time zone arbitrage is only possible with international equity funds. In fact, the influence of $D_{i,m}^{Int}$ that takes the value of 1 if the fund *i* has an investment focus in international stocks and 0 otherwise, is in all specifications positive and statistically significant at the 1% level, which means that rapid trading is stronger among international equity funds.[24] From the point of view of German investors time zone arbitrage makes sense for funds that invest in Asia stock markets, since the Asia stock markets close earlier than stock markets in Europe. Therefore, we expand model (2.6) by including an additional dummy variable $D_{i,m}^{Asia}$ that takes the value of 1 if the fund *i* has an investment focus in Asia and 0 otherwise. The results in Table 2.9 in columns 2, 5 and 8 do not show economically or statistically significant effects of this additional dummy variable, which means that funds which are prone to time zone arbitrage do not face a greater degree of rapid trading as compared to other international equity funds. This suggests that time zone arbitrage is responsible for just a small fraction of the observed rapid trading.

4. Mutual funds are considered by investors as short-term, speculative investments -- comparable to a lottery ticket. Therefore, they buy funds in the hope of quick success and sell them very quickly: Kumar (2009) shows that investors who mainly prefer lottery-type investments buy small and risky stocks on the stock market.[25] This is consistent with our results that fund risk has a positive and fund size has a negative impact on rapid trading. Kumar (2009) also shows that speculative investors prefer stocks with high idiosyncratic risk. Therefore, in additional regressions we include the idiosyncratic risk of the fund in the previous year as an explanatory variable. Its influence on rapid trading is indeed

[24] Alternatively, we also interact the $OF_{i,m}$ in model (2.2) and $IF_{i,m}$ in model (2.3) with $D_{i,m}^{Int}$ and include them in the respective models. The results (not explicitly reported) show that rapid trading can also be detected among domestic equity funds. However, it is about twice as strong among international equity funds.

[25] See also Budescu, Kuhn, Kramer and Johnson (2002) and Martin, Barron and Norton (2008).

significantly positive, but the idiosyncratic risk, particularly for international equity funds, is difficult to measure because there are often no appropriate benchmarks. Therefore, we do not include this variable in the reported results. In addition, we consider passively managed funds, which -- based on the lottery argument -- should be less affected by rapid trading. Consistent with the univariate results from Table 2.8, we find that the additional dummy variable for passive funds in model (2.6) has a significant negative influence on rapid trading (not explicitly reported). Kumar (2009) also finds that driven by speculative motives investors prefer stocks with a low nominal price because they are akin to a lottery ticket. If rapid trading is driven by speculative retail investors, we should see that rapid trading is also particularly pronounced for funds with a low price (Net Asset Value (NAV) per share). To analyze this, we expand model (2.6) by including the NAV of the fund at the end of the previous month, $P_{i,m-1}$. These results can be found in columns 3, 6, 9 and 10 of Table 2.9 The significant negative influence of this variable shows that rapid trading is indeed more pronounced for nominally cheap funds than for funds with higher NAV per share. Han and Kumar (2009) also find that small investors in the U.S. invest in foreign stocks especially for speculative reasons. Thus, our finding that especially international equity funds are affected by rapid trading is consistent with the view that rapid trading is driven by fund investors looking for speculative, lottery-like investments. This explanation is supported by the results of a new study by Ederington and Golubeva (2009). They find that in aggregate, inflows and outflows of U.S. mutual funds are on average particularly high if the expected volatility of the market is high.

Even though we can only demonstrate the existence of rapid trading indirectly due to lack of transaction data on individual investor level (Section 2.3.2), the results on the determinants of our proxies for rapid trading draw a fairly consistent picture: Funds that are strongly affected by rapid trading based on our proxies show exactly the characteristics of speculative investments, which are also observed among the stocks that are traded by short-term and speculative investors. However, this does not exclude the possibility that the same or other investors use other forms of investment such as stocks (see, e.g., Kumar, 2009), derivatives and structured products in order to make lottery-like investments.

2.3.4. Influence of Rapid Trading

We first examine the most important question from an investor's perspective, namely whether rapid trading has a negative influence on the performance of the fund. Then we briefly discuss the consequences of rapid trading from the point of view of a mutual fund company.

Based on the results from Greene and Hodges (2002), a negative impact on performance should be particularly induced by time zone arbitrage. This does not seem to play an important role among funds considered in this paper (Section 2.3.3). Therefore, we do not necessarily expect a particularly strong negative impact of rapid trading on fund performance. We choose a multivariate regression approach to analyze the impact of rapid trading on fund performance controlling for the influence of other fund characteristics on fund performance:

$$\begin{aligned} Perf_{i,m} = \alpha + \beta_1 \cdot RT_{i,m-1} + \beta_2 \cdot Perf_{i,m-1} + \beta_3 \cdot FrontFee_{i,m-1} + \beta_4 \cdot MgtFee_{i,t-1} \\ + \beta_5 \cdot \ln TNA_{i,m-1} + \beta_6 \cdot \ln Age_{i,m-1} + \varepsilon_{i,m}. \end{aligned} \tag{2.7}$$

As performance measures we use the net return of a fund, $R_{i,m}$, and the excess return of a fund as compared to the average return of all other funds in the same market segment and month, $ExR_{i,m}$.[26] The primarily interest lies in the independent variable, the rapid trading of the fund, $RT_{i,m-1}$. $RT_{i,m-1}$ represents one of our two proxies for rapid trading, $RT1_{i,m-1}$ or $RT2_{i,m-1}$. We use the lagged rapid trading measure in order to reduce the potential endogeneity problem. As control variables we use the past performance, $Perf_{i,m-1}$, the fund's age, $lnAge_{i,m-1}$, and the fee structure, $FrontFee_{i,m-1}$ and $MgtFee_{i,t-1}$. It is possible that funds facing strong rapid trading have higher average fund assets due to rapid trading than funds that are not affected by rapid trading. This could have an impact on the fund's performance due to economies of scale (Chen, Hong, Huang and Kubik (2004)), so we include the fund size, $lnTNA_{i,m-1}$, as a control variable.

[26] We use these simple return-based performance measures, since fund investors seem to be particularly interested in these simple measures and less interested in complex, risk-adjusted measures (Capon, Fitzsimons and Prince (1996)). Alternatively, we use Jensen's Alpha from a simple market model as a measure for risk-adjusted abnormal return $Perf_{i,m}$. The results (not explicitly reported here) are very similar. Similar statements are also obtained if we consider the abnormal returns compared to the average over all funds.

If rapid trading does have a serious adverse impact on fund performance, we should find a statistically and economically significant negative influence of $RT_{i,m-1}$ on $Perf_{i,m-1}$. The estimation results with time-fixed effects for a pooled OLS regression with and without clustered robust standard errors at the fund level, as well as with PCSE are presented in Table 2.10.[27]

The estimated coefficients for the impact of rapid trading in Panel A are consistently negative, but generally not statistically significant and economically small. Overall, it seems that rapid trading does not have serious consequences on the fund performance. The reasons could be either that rapid trading is not pronounced enough to pose a serious problem for the fund in our sample, or that the fund company has taken appropriate measures to prevent or at least reduce the negative effects on performance.

It is possible that funds do not have trouble dealing with a consistently high level of rapid trading, and that there is only a negative impact on performance by unexpected rapid trading. Therefore, we analyze the influence of unexpected rapid trading, (not explicitly reported): To do this, we first estimate the model (2.2) for inflows (contemporary outflows are not included as a control variable) and extract the respective $\varepsilon_{i,m}$. Then we estimate model (2.3) for the outflows (contemporaneous inflows are not included as a control variable) and again extract the respective $\varepsilon_{i,m}$. Finally, we define RT in this case as the sum of the two $\varepsilon_{i,m}$. The use of the so-defined unexpected rapid trading in model (2.7) gives virtually identical results.

[27] There is also a dynamic panel structure by including the previous performance in the regression model. However, we cannot use meaningful ABBB estimates in this case, because we cannot find a combination of instrumental variables, which is allowed for the total sample and the examined sub-periods (i.e., by using the appropriate combination of instrumental variables the AR (1) test should be rejected, and the AR (2)-test and the Sargan test should be accepted).

Table 2.10: Influence of rapid trading on fund performance

This table presents the regression results of the influence of rapid trading on fund performance based on $RT1_{i,m}$ and $RT2_{i,m}$. We examine the influence of rapid trading on the fund performance for three time periods: total sample period (1992/01-2006/12), period prior to the fund scandal in the U.S. (1992/01-2003/08) and period after the fund scandal in the U.S. (2003/09-2006/12). We report regression results for three specifications: OLS, CRE and PCSE. Data are obtained from the anonymous German fund company. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Panel A: Total sample period (1992/01-2006/12)

	1	2	3	4	5	6	7	8	9	10	11	12
	$RT1_{i,m-1}$						$RT2_{i,m-1}$					
	$R_{i,m}$			$ExR_{i,m}$			$R_{i,m}$			$ExR_{i,m}$		
	OLS	CRE	PCSE	OLS	CRE	PCSE	OLS	CRE	PCSE	OLS	CRE	PCSE
$RT1_{i,m-1}$	-0.003	-0.003	-0.007	-0.003	-0.003	-0.002						
$RT2_{i,m-1}$							-0.008	-0.008	-0.021	-0.009^{*}	-0.009	-0.006
$R_{i,m-1}$	0.080^{***}	0.080^{***}	0.134^{**}				0.079^{***}	0.079^{***}	0.134^{**}			
$ExR_{i,m-1}$				0.085^{***}	0.085^{***}	0.086^{**}				0.084^{***}	0.084^{***}	0.085^{**}
$FrontFee_{i,m-1}$	0.025	0.025	0.109^{*}	0.022	0.022	0.009	0.023	0.023	0.100^{*}	0.020	0.020	0.007
$\ln TNA_{i,m-1}$	-0.001^{***}	-0.001^{***}	-0.003^{***}	-0.001^{***}	-0.001^{***}	-0.001^{**}	-0.001^{***}	-0.001^{***}	-0.003^{***}	-0.001^{***}	-0.001^{***}	-0.001^{**}
$MgtFee_{i,t-1}$	0.088	0.088	0.738	0.076	0.076	-0.099	0.095	0.095	0.759	0.084	0.084	-0.095
$\ln Age_{i,m-1}$	0.001^{***}	0.001^{**}	0.003^{*}	0.001^{***}	0.001^{**}	0.001^{*}	0.001^{***}	0.001^{**}	0.003^{**}	0.002^{***}	0.002^{**}	0.001^{*}
$Constant$	0.016	0.016	0.014	0.014	0.014	0.007	0.016	0.016	0.014	0.014	0.014	0.007
R^2	63.37%	63.37%	2.71%	4.35%	4.35%	0.95%	63.37%	63.37%	2.75%	4.36%	4.36%	0.95%
$Adj.\ R^2$	62.53%			2.15%			62.53%			2.15%		
N	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172	8,172

Panel B: Period prior to the fund scandal in the U.S. (1992/01-2003/08)

	1	2	3	4	5	6	7	8	9	10	11	12
	$RT1_{i,m-1}$						$RT2_{i,m-1}$					
	$R_{i,m}$			$ExR_{i,m}$			$R_{i,m}$			$ExR_{i,m}$		
	OLS	CRE	PCSE	OLS	CRE	PCSE	OLS	CRE	PCSE	OLS	CRE	PCSE
$RT1_{i,m-1}$	-0.007^{**}	-0.007	-0.012	-0.006^{*}	-0.006	-0.005						
$RT2_{i,m-1}$							-0.016^{*}	-0.016	-0.037	-0.016^{**}	-0.016	-0.011
$R_{i,m-1}$	0.098^{***}	0.098^{***}	0.176^{**}				0.097^{***}	0.097^{***}	0.176^{**}			
$ExR_{i,m-1}$				0.106^{***}	0.106^{***}	0.106^{**}				0.106^{***}	0.106^{***}	0.105^{**}
$FrontFee_{i,m-1}$	-0.094^{*}	-0.094	-0.048	-0.095^{*}	-0.095	-0.078	-0.094^{*}	-0.094	-0.054	-0.096^{*}	-0.096	-0.078
$\ln TNA_{i,m-1}$	-0.001^{***}	-0.001^{***}	-0.004^{**}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.004^{**}	-0.001^{***}	-0.001^{***}	-0.001^{***}
$MgtFee_{i,t-1}$	-0.308	-0.308	0.065	-0.294	-0.294	-0.213	-0.293	-0.293	0.124	-0.276	-0.276	-0.200
$\ln Age_{i,m-1}$	0.001^{*}	0.001	0.003^{*}	0.001^{*}	0.001^{*}	0.001^{*}	0.001^{*}	0.001	0.003^{**}	0.002^{**}	0.002^{*}	0.001^{*}
$Constant$	0.038^{**}	0.038^{***}	0.034^{**}	0.013	0.013	0.016^{**}	0.037^{**}	0.037^{***}	0.032^{**}	0.012	0.012	0.016^{**}
R^2	65.45%	65.45%	3.78%	5.24%	5.24%	1.44%	65.45%	65.45%	3.84%	5.25%	5.25%	1.44%
$Adj.\ R^2$	64.40%			2.37%			64.40%			2.38%		
N	4,907	4,907	4,907	4,907	4,907	4,907	4,907	4,907	4,907	4,907	4,907	4,907

Panel C: Period after the fund scandal in the U.S. (2003/09-2006/12)

	1	2	3	4	5	6	7	8	9	10	11	12
	$RT1_{i,m-1}$						$RT2_{i,m-1}$					
	$R_{i,m}$			$ExR_{i,m}$			$R_{i,m}$			$ExR_{i,m}$		
	OLS	CRE	PCSE	OLS	CRE	PCSE	OLS	CRE	PCSE	OLS	CRE	PCSE
$RT1_{i,m-1}$	0.001	0.001	0.002	0.001	0.001	0.000						
$RT2_{i,m-1}$							0.000	0.000	-0.001	-0.001	-0.001	-0.002
$R_{i,m-1}$	0.017	0.017	-0.061				0.018	0.018	-0.061			
$ExR_{i,\mathrm{m-1}}$				0.012	0.012	0.015				0.012	0.012	0.015
$FrontFee_{i,m-1}$	0.101^{***}	0.101^{**}	0.169^{***}	0.100^{***}	0.100^{**}	0.104^{***}	0.098^{***}	0.098^{*}	0.163^{***}	0.097^{***}	0.097^{*}	0.100^{***}
$\ln TNA_{i,m-1}$	-0.001	-0.001	-0.001^{**}	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001^{**}	-0.001	-0.001	-0.001
$MgtFee_{i,t-1}$	0.241^{*}	0.241	0.576	0.213	0.213	0.244	0.248^{*}	0.248	0.595	0.222^{*}	0.222	0.254
$\ln Age_{i,m-1}$	0.001^{*}	0.001	0.001	0.001^{*}	0.001	0.001	0.001^{*}	0.001	0.001	0.001^{*}	0.001	0.001
$Constant$	0.051^{***}	0.051^{***}	0.008	-0.003	-0.003	-0.006	0.051^{***}	0.051^{***}	0.008	-0.003	-0.003	-0.006
R^2	53.71%	53.71%	1.13%	2.39%	2.39%	0.61%	53.71%	53.71%	1.12%	2.38%	2.38%	0.61%
$Adj.\ R^2$	53.06%			1.02%			53.06%			1.02%		
N	3,265	3,265	3,265	3,265	3,265	3,265	3,265	3,265	3,265	3,265	3,265	3,265

Since the problems of rapid trading have become a focus of interest, especially due to the fund scandal in the U.S. in August 2003, (it leads to adjusted conduct guidelines of the BVI in Germany, see Section 2.1), we consider the period before and after the scandal in the U.S. separately. The results for these sub-periods are given in Panels B and C of Table 2.10. The estimated coefficient of -0.007 (-0.016) for the influence of $RT1_{i,m}$ ($RT2_{i,m}$) in the period before the scandal is economically significant and suggests that a fund belonging to the decile with the highest rapid trading has a lower return by about 4.5% p.a. (4.2% p.a.) than a fund which belongs to the decile with the lowest rapid trading.[28] We can also find an economically significant difference for *RT1* that takes on less extreme values. If the value of *RT1* increases by about one standard deviation (0.1938), the fund's annual return declines by 1.6%.

However, the estimate is only on the 5% or 10% level significant in the OLS specification without robust standard errors. By using robust standard errors as well as the PCSE, the significance disappears. Even before the fund scandal there is no solid evidence for a negative impact of rapid trading on fund performance. For the period after the scandal (Panel C), there is no longer any effect. This suggests that at least the investigated fund

[28] The calculation of these values is based on current estimates of the impact of rapid trading in combination with the data from Table 2.8. Based on the results for $RT1_{i,m}$ ($RT2_{i,m}$), the difference in monthly return is (0.5527-0.0148)*(-0.007) = -0.0038 ((0.2174-0.0004) · (-0.016) =- 0.0035). The values mentioned above are annualised.

company has taken appropriate measures in order to avoid the negative effects of rapid trading. In fact, after the adjustment of the conduct guideline of the BVI in January 2004, many fund companies have included similar rules in their prospectuses, which prohibit rapid trading in fund shares and explicitly define appropriate countermeasures. They contain sentences such as, "all applications for purchase and/or exchange of shares of those investors to reject, who (...) should be regarded as frequent traders." (DWS) or "The Company reserves the right to reject subscription orders in whole or in part." (Alliance Global Investor).[29] These rules are similar for the anonymous fund company and other large German fund companies. Thus, the rules adopted by the anonymous fund company are also representative of the typical regulations implemented by the large German investment companies. Therefore, we can suppose that other large fund companies also effectively prevent the negative impact of rapid trading on fund performance. However, whether smaller fund companies are able to provide the necessary resources to implement effective measures to prevent negative effects of rapid trading is an open question.

Due to the lack of data availability, we can only consider performance at the fund level. The question of whether a specific investor benefits or is hurt when he carries out rapid trading, remains unanswered. Thus, we cannot draw reliable conclusions about whether rapid trading is an irrational phenomenon from the investor's point of view. The evidence of trading in stocks (e.g., Barber and Odean 2000) suggests, however, that the frequent trading of fund shares could be a sign of overconfidence: investors mistakenly believe that they possess the ability to obtain profits through short-term trading in fund shares. At least for stocks, Barber and Odean (2000) show that this hope is deceptive and high trading volume of private investors usually leads to a decrease in performance. Similar effects can also be expected by looking at funds. In any case, from a regulatory point of view, the relevant question here is whether there are negative externalities in the form of reduced performance for all investors in a fund if the fund is affected by rapid trading.

[29] Examples are already cited in footnote 3: terms and conditions of Fidelity ‚Fidelity actively monitoring the trading activities and reserves the right to reject any new purchase requests from people who are noticed because of short-term trading of shares or their trade was or can be disruptive.'(Section 10 h).

Besides the question of direct effects of rapid trading on performance, it is also interesting for fund companies to investigate how rapid trading affects the profitability of their funds. Since we have no data on internal profit contribution of individual funds, we can only make estimates. Rapid trading can have different effects on the profitability of the investment company: A positive effect could be the possible additional income from fees. Fund companies cannot benefit from front-end load fees, since they are traditionally received by distributors. Nevertheless, fund companies may benefit from annual management fees. These are paid by the rapid traders as long as they invest in the fund. When a fund attracts a clientele of rapid traders who would otherwise not invest in that fund, there is a positive effect on fee income. Possible negative effects are the reduced performance and the associated lower net flows. To estimate the overall effect on the fee income, we assume that a fund in the top performance tercile, which has a median magnitude of rapid trading (based on *RT1*), increases the rapid trading by one (three) standard deviations. This leads to a reduction of the management fee by € 388€ (€ 2361) per fund per year due to lower performance and concurrent additional revenue of € 25,705 (€ 77,115) per fund per year due to the rapid traders.[30] In addition to those explicit estimates of revenues and costs, rapid trading can also cause increased administrative costs that cannot be estimated. Overall, the effects of rapid trading appear to be relatively small at the fund company level.

2.4. Conclusion

This study analyzes rapid trading among German equity funds. Our analyses, which are based on data from one of Germany's largest fund companies, show for the first time that in Germany fund shares are traded surprisingly heavily. We document a pronounced positive correlation between monthly inflows and monthly outflows of funds that can be interpreted as a clear indication of the existence of rapid trading. The analysis of possible determinants

[30] In order to calculate the influence of rapid trading on net flows and fee income due to a performance decrease caused by rapid trading, we determine the performance consequences of a change of RT1 by 0.19 or 0.58 (one and three standard deviations of RT1) by using the estimated model (2.7). The next step is to determine the new performance ranking based on the newly determined performance (see footnote 13) and then based on the estimation of model (2.1) we can calculate the impact on net flows. Finally, we can determine the fee income by using an average management fee of 1.07% p.a.. The direct impact of a change in RT1 on net inflows (not via the channel of reduced performance) is determined as follows: we estimate an extended version of model (2.1) in which we add the delayed RT1 as an explanatory variable. The estimate of its influence is 0.037 and is significant at the 1% level. This allows us to determine the direct influence of a change in rapid trading on the net flows and on the fee income.

of rapid trading shows that small, risky and active funds, funds with low or no front-end load fees and international equity funds are particularly affected by rapid trading. Our results are consistent with the fact that many fund investors consider funds to be short-term and speculative investments with lottery characteristics. The trading activity of this investor group may at least partially explain rapid trading.

From the perspective of long-term investors rapid trading is especially problematic if there are negative externalities in the form of poorer performance. In fact, we find evidence of such negative influence of rapid trading on performance. However, the impact is relatively weak and cannot be proven to be stable for the period before the fund scandal in the U.S. After the fund scandal there is no more influence of rapid trading on performance. This indicates that appropriate measures were taken to reduce the harmful impact of rapid trading. The implementation of conduct guidelines of the BVI seems to be successful. Also, the self-regulation of the German fund industry seems to work. As the governance of mutual funds is only weakly developed in German investment law (as compared to the U.S.), self-regulation in this area is an important mechanism to ensure efficient functioning of the fund market.

In recent years, alternative investment opportunities, such as the trading of ETFs or traditional mutual funds on stock exchanges in Germany, have become more popular. It is conceivable that in the future rapid traders will increasingly rely on these alternative instruments or trading platforms. The low trading costs of ETFs are in favor of rapid trading. However, the result that rapid trading is conducted primarily among lottery funds is contradictory to more pronounced rapid trading among ETFs, since ETFs are passive index products with typically low idiosyncratic risk. Notwithstanding the above, rapid trading among ETFs and also trading of traditional equity funds on stock exchanges are less problematic, since secondary trading does not cause trading activity at the level of the fund company and, therefore, there is no negative external effect for fund investors.

Because sufficient data are not available, we can only investigate rapid trading indirectly on the basis of aggregated inflow and outflow data at the fund level obtained from a large mutual fund company. The comparison of the characteristics of funds from other fund companies shows that the funds used in this study are representative of a broader sample. Nevertheless, it is desirable that future literature repeat our investigation of rapid trading based on a larger sample, if possible based on daily data, or even using transaction data at the individual investor level. This could also examine whether the recognized methodology in the literature which is adapted in this study is suitable for the detection of rapid trading which is measured by the positive correlation of inflows and outflows.

Chapter 3

Smart or Dumb? Asset Allocation Ability of Mutual Fund Investors and the Role of Broker Advice

3.1. Introduction

Asset allocation policy is a dominant contributor to long-term portfolio performance.[31] Previous studies find that asset allocation policy explains about 90% of the variability of mutual fund returns across time and about 40% of the variation in returns across funds. Furthermore, on average nearly 100% of the return level is explained by asset allocation policy. Therefore, it is very important for investors to allocate their investments correctly among different asset classes. This study attempts to address the following two questions:

1. Do mutual fund investors, as a whole, have asset allocation ability among their mutual fund investments?

[31] There are a number of studies which show the importance of asset allocation decisions, e.g. Brinson, Hood and Beebower (1986), Brinson, Singer and Beebower (1991) and Ibbotson and Kaplan (2000).

2. Are there differences in asset allocation ability among investors buying funds via different mutual fund sales channels, especially between non-proprietary and proprietary brokers?

Data from the Investment Company Institute (ICI) shows that on average only 1% of overall mutual fund assets in the U.S. are invested in mutual funds with professional asset allocation decisions made by mutual fund managers.[32] This indicates that mutual fund investors prefer to make asset allocation decisions by themselves and not to delegate them to investment professionals. Therefore, in the context of the first question I examine whether mutual fund investors show any asset allocation ability among their mutual fund investments in aggregate. However, the first question ignores differences between diverse mutual fund sales channels: non-proprietary brokers, proprietary brokers and direct channels. Investors who buy mutual funds via non-proprietary brokers and proprietary brokers may get advice on their asset allocation from brokers. Depending on the type of brokers there might also be differences in the quality of advice. On the one hand, we can expect that non-proprietary brokers provide investors with more benefits than proprietary brokers, because they are not dependent on a parent company and can more easily provide their professional advice to investors without considering the interests of their parent company. On the other hand, proprietary brokers know the funds provided by their affiliated fund families in more detail than non-proprietary brokers. They can better leverage the resources embedded in the parent company and have an informational advantage over non-proprietary brokers. Therefore, they could also provide more benefits than non-proprietary brokers. Furthermore, answers to the second question can improve our understanding of the differences in service quality in terms of asset allocation ability between proprietary and non-proprietary brokers. Additionally, I compare these two types of brokers to direct channels where investors buy mutual funds and make their asset allocation decisions without the help of any intermediaries. Since Bergstresser, Chalmers and Tufano (2009) look at the difference in asset allocation performance between investors buying funds via brokers and investors buying funds via direct channels. I do not explicitly

[32] Funds with ICI investment objective "Flexible Portfolio" invest in stocks, bonds and money market securities. The portfolio can flexibly change its asset allocation weights depending on market conditions.

compare the direct channels to the aggregate broker channel in this study. Bergstresser, Chalmers and Tufano (2009) find that brokers do not deliver benefits in terms of asset allocation among mutual funds as compared to funds sold via direct channels. The authors of that study do not distinguish between non-proprietary brokers and proprietary brokers.

This study provides two main results: First, there is no evidence of superior asset allocation ability of mutual fund investors as a whole. They are not able to achieve better performance by allocating their mutual fund investments among different asset classes rather than investing in a passive benchmark portfolio. Second, I do find evidence of better asset allocation performance of money flows through non-proprietary brokers as compared to money flows through proprietary brokers. This result is consistent with evidence from studies on the insurance industry which show that non-proprietary agents are more effective in representing the interests of their clients and provide a higher quality of service than proprietary agents.[33]

This study is related to three strands of research. First, it contributes to the general mutual fund investor ability literature. The previous research in this area primarily focuses on the selection ability and timing ability of mutual fund investors. Gruber (1996) and Zheng (1999) find that mutual fund investors have selection ability, which they call smart money effect. They are able to choose funds with superior short-term performance. Sapp and Tiwari (2004), however, show that this smart money effect can be explained by stock momentum. Frazzini and Lamont (2008) reversely find a dumb money effect, which means that mutual fund investors reduce their wealth in the long-term by reallocating across different mutual funds. Friesen and Sapp (2007) focus on the timing ability of mutual fund investors at the fund level and find evidence of poor timing decisions. Braverman, Kandel and Wohl (2005) and Nesbitt (1995) analyze the timing ability of mutual fund investors at the asset class level. Both studies find evidence of poor timing abilities. Unlike those prior studies, my paper focuses on the asset allocation ability of mutual fund investors. I examine whether mutual fund investors allocate their money correctly across asset classes in order to earn a high performance. Second, this study fits into the literature investigating asset

[33] For example, Berger, Cummins and Weiss (1997) and Barrese, Doerpinghaus and Nelson (1995) find evidence that independent agents provide a higher quality of service than exclusive agents.

allocation decisions of mutual fund investors. Chalmers, Kaul and Phillips (2009) examine how economic conditions influence mutual fund investors' asset allocation decisions. They find that an anticipated improvement in economic conditions leads to cash flows out of relatively safe money market funds into riskier equity funds, and vice versa. Instead of reviewing the performance of actual asset allocation decisions they evaluate the benefits of a constructed flight-to-quality strategy.[34] The principal focus of that study is the analysis of factors which influence asset allocation decisions of mutual fund investors, but it does not provide an overall evaluation of the asset allocation ability of mutual fund investors. In other words, do mutual fund investors benefit from their actual asset allocation among mutual funds? The primary purpose of my research is to fill this gap by examining the performance of asset allocation decisions. Third, this paper builds on the literature regarding the role of the brokerage industry, which was examined in several recent studies. Bergstresser, Chalmers and Tufano (2009) look at the performance of mutual funds sold through brokers and compare it to the performance of mutual funds sold directly to investors. They find that brokers do not deliver benefits in terms of fund selection and asset allocation among mutual funds as compared to funds sold through direct channels. They do not distinguish between non-proprietary brokers and proprietary brokers. Christoffersen, Evans and Musto (2009) make additional comparisons between non-proprietary brokers and proprietary brokers. However, they focus on the impact of brokers' compensation and affiliation on equity fund flows and find evidence of differences between proprietary brokers and non-proprietary brokers regarding how they direct money flows to equity mutual funds. They also do not analyze the difference in asset allocation ability between non-proprietary and proprietary brokers. My paper is the first to investigate the difference in benefits delivered by these two types of brokers in terms of asset allocation among mutual funds.

The remainder of the paper is organized as follows. Section 3.2 describes the data and outlines the methodology. Section 3.3 presents the empirical results concerning asset

[34] Based on this flight-to-quality strategy, investors allocate 100% of their wealth to equity funds (money market funds) if economic conditions are expected to improve (worsen).

allocation ability. Additional analyses are reported in Section 3.4, and the conclusion is presented in Section 3.5.

3.2. Data and Methodology

3.2.1. Data

Monthly data of aggregate cash flows and total net assets from January 1996 to July 2009 are obtained from the ICI. The ICI is the national association of U.S. investment companies, including almost all mutual fund families as members. The data is divided into 33 categories according to the investment objectives of the funds, for example, aggressive growth, international equity, corporate-intermediate and taxable money market. Within each investment objective category, total net assets and cash flows are classified by method of sales: e.g. “proprietary sales force”, “non-proprietary sales force”, “direct market”. In “proprietary sales force” sales fund shares are sold primarily through a network of active brokers affiliated with the fund company. “Non-proprietary sales force” includes active brokers who have licensing agreements with the fund company. In “direct market” sales fund shares are sold mainly by the fund company without intermediaries. I examine the aggregate asset allocation ability of mutual fund investors by using aggregate flows and total net assets through all sales channels und consider them as the all fund portfolio. To compare non-proprietary brokers and proprietary brokers, I analyze net flows and total net assets of non-proprietary and proprietary brokers separately and treat them as two separate portfolios, namely the non-proprietary broker portfolio and the proprietary broker portfolio.

Within each investment objective category and each method of sales, cash flows are further categorized as new sales, redemptions, exchange sales and exchange redemptions. New sales and redemptions are money flows into and out of a fund family. Exchange sales and exchange redemptions are shifts of money from one fund to another within a fund family. Like Warther (1995) and Fant (1999) I define net flows of mutual funds as the sum of four components: new sales plus exchange sales minus redemptions minus exchange redemptions. In order to analyze the asset allocation decisions among different asset classes, I designate eight main asset classes and assign the investment objective categories to these asset classes. The eight asset classes are Domestic Equity, Foreign Equity, Hybrid, Taxable

Domestic Bond, Foreign Bond, Municipal Bond, Taxable Money Market and Municipal Money Market. My focus is to examine the asset allocation among the four main asset classes (Domestic Equity, Foreign Equity, Taxable Domestic Bond and Taxable Money Market)[35] which account for 85 percent of the aggregate assets in the U.S. mutual fund industry. Appendix A presents the classification of the 33 investment objectives into eight asset classes.

I follow Bergstresser, Chalmers and Tufano (2009) and use index returns as benchmarks to examine asset allocation ability instead of using aggregate fund returns. This allows me to exclude the potential selection ability of mutual fund investors. The indices for the Domestic Equity, Foreign Equity, Taxable Domestic Bond and Taxable Money Market asset classes are, respectively, the value-weighted CRSP index returns for the NYSE, AMEX, and NASDAQ stocks, the MSCI All Country World without U.S., the Barclays U.S. Aggregate Domestic Bond index[36], and the return on the 30-day Treasury bill.

3.2.2. Summary Statistics

Panel A of Table 3.1 presents mutual fund net cash flows and total net assets by asset class. Over the period from January 1996 to July 2009, the Taxable Money Market asset class captured the highest average monthly net cash flows ($10.94 billion), followed by Domestic Equity ($6.53 billion), Taxable Domestic Bond ($3.50 billion), and Foreign Equity ($3.27 billion). Over the entire mutual fund industry, net cash flows are on average positive over the sample period. The average monthly total net assets in the Domestic Equity asset class are $3,101.97 billion, followed by Taxable Money Market ($1,676.88 billion), Taxable Domestic Bond ($736.76 billion), and Foreign Equity ($675.28 billion).

Panel B of Table 3.1 shows mutual fund net cash flows and total net assets classified according to sales channel. The average monthly total net assets in the direct market are $1,917.71 billion, followed by non-proprietary sales force ($1,844.98 billion), and

[35] Hybrid funds already include funds' asset allocation decision. Therefore, I exclude this asset class. Municipal Bond and Municipal Money Market are often traded for tax reasons, so I also exclude them. For Foreign Bond there is no appropriate return index, which is the reason why I exclude it.
[36] This index used to be called the Lehman Aggregate Domestic Bond index.

proprietary sales force ($896.20 billion). While net cash flows are on average positive over the sample period, the proprietary broker channel, in contrast to other distribution channels, has negative net cash flows on average.

Table 3.1: Summary statistics

This table reports average monthly net flows and average monthly total net assets of mutual funds by asset class classification (Panel A) and by sales channel classification (Panel B) from January 1996 to July 2009. ICI data includes four flow categories: new sales, redemptions, exchange sales and exchange redemptions. New sales and redemptions are actual cash flows that enter or exit the fund family. Exchange sales and exchange redemptions are transfers of existing cash flows between funds in the same fund family. Net flows are calculated as: (new sales - redemption) + (exchange in – exchange out). Assets are net assets at the end of period. The funds are classified into eight asset classes: Domestic Equity, Foreign Equity, Hybrid, Domestic Bond, Foreign Bond, Municipal Bond, Taxable Money Market, Municipal Money Market. In Panel A I examine only the four major asset classes Domestic Equity, Foreign Equity, Domestic Bond and Taxable Money Market, which account for 85% of aggregate assets in the U.S. mutual fund industry. In Panel B I use the ICI categorization of distribution channels: non-proprietary sales force, proprietary sales force, direct market.

Panel A: Mutual fund net cash flows and total net assets by asset class classification

	Domestic Equity	Foreign Equity	Taxable Domestic Bond	Taxable Money Market
Mean Net flows ($ billions)	6.53	3.27	3.50	10.94
Mean Assets ($ billions)	3,101.97	675.28	736.76	1,676.88

Panel B: Mutual fund net cash flows and total net assets by sales channel classification

	Non-proprietary sales force	Proprietary sales force	Direct market
Mean Net flows($ billions)	4.19	-0.25	5.07
Mean Assets($ billions)	1,844.98	896.20	1,917.71

Table 3.2 presents the average asset allocation weights of all mutual funds, funds sold through non-proprietary brokers, funds sold through proprietary brokers and funds sold through the direct market channel.

Table 3.2: Average asset allocation weights of different portfolios

This table shows average asset allocation weights of all mutual funds, funds sold through non-proprietary brokers, funds sold through proprietary brokers, funds sold through the direct channel. I rescale aggregate portfolio weights under the assumption that these four asset classes represent the entire investment universe for these funds.

	Domestic Equity	Foreign Equity	Taxable Domestic Bond	Taxable Money Market
All Funds	50.70%	10.28%	11.89%	27.13%
Non-Proprietary	58.94%	16.79%	13.73%	10.54%
Proprietary	34.51%	6.50%	10.72%	48.28%
Direct Market	65.94%	9.15%	10.88%	14.03%

We can observe that money market funds make up a much higher proportion of assets in proprietary-sold funds (48.28%) than in non-proprietary-sold funds (10.54%) and direct-sold funds (14.03%). The weight of Foreign Equity is higher in the non-proprietary channel than in other channels. The total equity weight (Domestic and Foreign) is similar in the non-proprietary channel and direct market channel. The same holds for the sum of Domestic Bond and Money Market weights. This evidence suggests that the asset allocation of the proprietary broker channel has higher weights towards low-risk asset classes than the non-proprietary channel and the direct market channel. On the other hand, the non-proprietary channel and the direct channel show similar asset allocations among equity, bond and money market. The results regarding differences in asset allocation decisions between non-proprietary and proprietary brokers are consistent with the results of Venezia, Galai and Shapira (1999). They show that clients of non-proprietary and proprietary brokers differ. Clients who are less risk-averse choose the more expensive non-proprietary brokers while the more risk-averse clients prefer less expensive proprietary brokers. One possible explanation is that clients who are less risk-averse feel that they need help of their brokers due to the potentially more negative consequences of their riskier behavior. Therefore, they are willing to pay more for the possibly better quality of services provided by non-proprietary brokers. Another possible explanation is that non-proprietary brokers drive investors into riskier asset classes for some reasons. As we can see from the asset allocation weights, the proprietary broker channel investors bear lower risks by holding higher weights in low-risk asset classes as compared to the non-proprietary broker channel. Further evidence of the difference in risk levels between non-proprietary and proprietary brokers is shown in Section 3.4.

Having described the data, I now introduce the measurements used to examine asset allocation ability.

3.2.3. Measurement of Asset Allocation Ability

To examine the asset allocation ability of mutual fund investors, I first look at the returns that a hypothetical investor can earn by investing the same fractions of his wealth as the aggregate of all mutual fund investors in different asset classes. These returns are calculated on the basis of total net assets. Next, I examine the returns that investors obtain on new cash flows which they move into and out of mutual fund asset classes. While total net assets most likely include both past and recent decisions of mutual fund investors, new cash flows only reflect new investment decisions of investors.

Measurement based on total net assets

Similar to Bergstresser, Chalmers and Tufano (2009) I calculate the time series of portfolio returns using monthly rebalanced asset allocation weights for all fund portfolio, non-proprietary portfolio, proprietary portfolio and direct market portfolio. Asset allocation weights are portfolio weights based on the four asset classes included in my analysis (Domestic Equity, Foreign Equity, Taxable Domestic Bond and Taxable Money Market). They are based on the total net assets of different asset classes at the end of the previous month. I multiply aggregate portfolio weights with the respective index returns to calculate monthly portfolio returns. The monthly portfolio return is written as:

$$R_t = \sum_i \frac{TNA_{i,t-1}}{\sum_i TNA_{i,t-1}} \cdot r_{i,t}. \tag{3.1}$$

$TNA_{i,t-1}$ is total net asset of asset class i at the end of month $t-1$. $r_{i,t}$ is the return on asset class i in the month t.

I use the respective index returns, in order to isolate asset allocation ability from the fund picking ability which is not included in index returns. Next, I compare this time series to the return time series of the TNA (Total Net Asset) benchmark portfolio to examine the asset allocation ability of mutual fund investors as a whole. The TNA benchmark portfolio is a portfolio with constant weights in the four asset classes. The asset allocation weights of the TNA benchmark are calculated as the average weights of these four asset classes over the entire sample period. A higher average return of the all fund portfolio as compared to the TNA benchmark portfolio suggests that mutual fund investors, as a whole, have positive asset allocation abilities. They are able to modify the allocation of their assets in fund asset classes correctly and earn higher returns on their actual portfolio than returns on the passive TNA benchmark portfolio. By comparing the average return of the non-proprietary broker portfolio with the average return of the proprietary broker portfolio, I can examine whether investors buying funds via non-proprietary brokers have better asset allocation abilities than investors buying funds via proprietary brokers.

Measurement based on new cash flows

The second measurement of asset allocation ability is based on returns that investors earn on monthly new cash flows. Due to insufficient data on the exact holding period of mutual fund investors I assume four alternative holding periods for new cash flows: one year, two years, three years and four years ($h = 12, 24, 36, 48$). The overall return on new cash flows is calculated using two methods. Method 1 considers both the allocation across the entire time period (How do investors spread their investments across the sample period? e.g. \$1,000 in month 1, \$5,000 in month 2….) and the allocation within each month (How do investors allocate their investments within each month? e.g. in month 1, \$500 in Domestic Equity, \$200 in Foreign Equity, \$200 in Domestic Bond and \$100 in Money Market; in month 2, \$2,000 in Domestic Equity, \$1,250 in Foreign Equity, \$1,250 in Domestic Bond and \$500 in Money Market).

Following method 1, I first estimate the dollar gains on all net cash flows over the entire sample period. The net cash flows of an asset class in month t are multiplied by the return on that asset class in a subsequent period. This is summed up across all asset classes for all periods and divided by the sum of absolute net cash flows into all asset classes in all periods. This is the average return earned on \$1 net cash flows over the entire sample period and is written as[37]:

$$R^{overall} = \frac{\sum_i \sum_t NCF_{i,t-1} \cdot r_{i,t}^h}{\sum_i \sum_t \left| NCF_{i,t-1} \right|}. \tag{3.2}$$

$NCF_{i,t-1}$ is net cash flows in asset class i in month $t-1$. $r_{i,t,}^{h}$ is the h-month return on asset class i in the subsequent h months, where h can be 12, 24, 36 and 48. Assuming that the subsequent 12-month returns of Domestic Equity, Foreign Equity, Domestic Bond and

[37] Method 1 is introduced in Gruber (1996). It can also be written as weighted average of returns on positive and negative cash flows, which is shown in Appendix B.

Money Market are 8%, 9%, 5% and 4%, respectively, for month 1 and 2, the average return earned on \$1 net cash flows over the two months mentioned above is calculated as:

$$R^{overall} = \frac{\overbrace{500\cdot 0.08+200\cdot 0.09+200\cdot 0.05+100\cdot 0.04}^{Month\ 1}+\overbrace{2,000\cdot 0.08+1,250\cdot 0.09+1,250\cdot 0.05+500\cdot 0.04}^{Month\ 2}}{\overbrace{|500|+|200|+|200|+|100|}^{Month\ 1}+\overbrace{|2,000|+|1,250|+|1,250|+|500|}^{Month\ 2}}$$

$$= 7.12\% .$$

Nesbitt (1995) suggests that cash flows in one month may come from income earned in this month which is not available in other months. Hence, how investors spread their investments over time may be dependent on their cash availability and income rather than the active asset allocation decisions. To exclude the cash availability motivation and in order to focus on rebalancing decisions, I also use method 2 which focuses on rebalancing decisions within each month. I first estimate the return on net cash flows in month *t*. The dollars flowing into any asset class in month *t* are multiplied by the *h*-month return on that asset class in the subsequent period. This is summed up across all asset classes for month *t* and divided by the sum of absolute net cash flows into all asset classes in month *t*. This is the average return earned on net cash flows in month *t* and is formally defined as[38]:

$$R_t = \frac{\sum_i NCF_{i,t-1}\cdot r_{i,t}^h}{\sum_i \left|NCF_{i,t-1}\right|}. \tag{3.3}$$

I calculate the average return on net cash flows for each month and obtain a time series of cash flow portfolio returns. The overall return on net cash flows in method 2 is equal to the average of the return on net cash flows across the entire sample period. It is written as:

$$R^{overall} = \frac{\sum_{t=1}^{T} R_t}{T}. \tag{3.4}$$

[38] As with method 1, the return can also be written as a weighted average of returns on positive and negative cash flows in month t, which is shown in Appendix B.

T is the number of months. In contrast to method 1, the average value across the entire sample period ignores differences in total investment assets in different months. For the same example mentioned above, the overall return is calculated as:

$$R^{overall} = \frac{R_1 + R_2}{2} = \frac{\dfrac{\overbrace{500 \cdot 0.08 + 200 \cdot 0.09 + 200 \cdot 0.05 + 100 \cdot 0.04}^{Month\,1}}{\underbrace{|500| + |200| + |200| + |100|}_{}^{}\!\!\overbrace{}^{Month\,1}} + \dfrac{\overbrace{2{,}000 \cdot 0.08 + 1{,}250 \cdot 0.09 + 1{,}250 \cdot 0.05 + 500 \cdot 0.04}^{Month\,2}}{\overbrace{|2{,}000| + |1{,}250| + |1{,}250| + |500|}^{Month\,2}}}{2}$$

$$= 7.15\%.$$

As with total net assets, I also construct a CF (Cash Flow) benchmark portfolio. The CF benchmark has constant asset allocation weights over the entire sample period. Unlike the TNA benchmark portfolio, the weights of the four asset classes in the CF benchmark portfolio are calculated as weights of total net cash flows into the four asset classes over the entire time period (1996/01-2009/07).[39] The difference between the overall return of the all fund portfolio (non-proprietary portfolio/proprietary portfolio/direct market portfolio) and the return of the CF benchmark portfolio provides a measure of the asset allocation ability of mutual fund investors as a whole (investors buying funds via non-proprietary brokers/proprietary brokers/direct market). A positive difference indicates that mutual fund investors have asset allocation ability. They are able to earn a better performance based on their asset allocation decisions as compared to a passive CF benchmark. The difference between the overall return of the non-proprietary portfolio and the overall return of the proprietary portfolio measures the difference in asset allocation abilities between investors buying funds via non-proprietary brokers and investors buying funds via proprietary brokers. A positive difference indicates that mutual fund investors buying fund via non-proprietary brokers have better asset allocation abilities than investors buying fund via proprietary brokers.

[39] The asset allocation weights of the CF benchmark are: 26.23% for Domestic Equity, 13.25% for Foreign Equity, 15.29% for Taxable Domestic Bond and 45.23% for Taxable Money Market.

3.2.4. Significance Tests

Three significance tests are used for the mean of the performance measure and the mean of the performance differences: t-test, test with Bootstrap standard error and the nonparametric Wilcoxon signed rank test. The reason to use these three tests is that there is a overlapping problem with h-month returns (e.g. 6-month return). For example, for each month, I obtain a subsequent 6-month return based on net cash flows in that month. As a result, this time series consists of overlapping observations. The standard error of the normal t-test is then biased. The standard error provided by Hansen and Hodrick (1980) can correct this bias. However, this correction method does not perform well in samples with a small number of observations. Therefore, I use bootstrapped standard error to correct the bias. The nonparametric test is also more appropriate if the distribution of returns is non-normal. For this reason, I also use the Wilcoxon signed-rank test. I also use the Newey-West (1987, 1994) covariance matrix to adjust the autocorrelation. The results for Newey-West are not reported but are consistent with those based on other tests.

3.3. Empirical Results

3.3.1. Asset Allocation Ability of Aggregate Mutual Fund Investors

In this section I report the empirical results based on total net assets (3.3.1.1) and new cash flows (3.3.1.2).

3.3.1.1. Evidence from Total Net Assets

The standard deviation of portfolio returns and the risk-adjusted performance, measured by the Sharpe ratio, are calculated. The results are reported in Table 3.3.

Table 3.3: Sharpe ratio of different portfolios with four asset classes

This table presents average monthly return, average monthly excess return, standard deviation of monthly excess return and Sharpe ratio of different portfolios: the TNA benchmark portfolio and the all fund portfolio. Asset allocation weights are rebalanced on a monthly basis.

	TNA benchmark portfolio	All fund portfolio
Average monthly return	0.42%	0.41%
Average monthly excess return	0.14%	0.12%
Standard deviation of monthly return	2.96%	2.88%
Sharpe ratio	0.0469	0.0418

The average monthly excess returns of different portfolios shows that mutual fund investors do not show superior asset allocation ability. Average monthly excess returns of the passive TNA benchmark portfolio and the all fund portfolio are 0.14% and 0.12%, respectively. This difference is not statistically significant. The TNA benchmark and the all fund portfolio bear similar risk. The TNA benchmark portfolio has a higher Sharpe ratio (0.0469) than the all fund portfolio (0.0418) even though the difference is not statistically significant based on the test suggested by Jobson and Korkie (1981) and applying the correction pointed out by Memmel (2003).

3.3.1.2. Evidence from New Cash Flows

Using the two methods outlined in Section 3.2.3, I calculate the overall return on net new cash flows as well as a passive CF benchmark which has constant asset allocation weights over the entire sample period. Results based on method 1 are reported in Panel A of Table 3.4.

If we focus on the case of a holding period of 24 months the average dollar moved earns $0.0438 in the next 24 months, while the benchmark flow portfolio earns $0.0869 in the next 24 months. The difference between these values is -0.0431 and is statistically significant in three significance tests (t-test, test with Bootstrap standard error and the nonparametric Wilcoxon signed rank test). This negative difference indicates poor asset allocation abilities of mutual fund investors. For a holding period of 12 months the difference is negative and only statistically significant when using the Wilcoxon signed-rank test. In the case of a holding period of more than 12 months, the difference is always negative and statistically significant. Considering results for all holding periods, mutual fund investors, as a whole, have poor asset allocation abilities as compared to the passive CF benchmark. Furthermore, the longer the holding period, the stronger the evidence of poor asset allocation ability. This is consistent with results of Braverman, Kandel and Wohl (2005). They find a negative relationship between lagged flows and the return of fund categories. This negative relationship is significant when they look at long-term returns.

Table 3.4: Performance of net cash flow portfolios for all fund CF portfolio and the CF benchmark

This table presents overall returns based on monthly net cash flows. The sample period is from January 1996 to July 2009. In Panel A the overall return on new cash flows is calculated with method 1. To calculate the return on net flows, I first estimate the dollar gains on all net cash flows over the entire sample period. The net cash flows into an asset class in month t are multiplied by the return on that asset class in a subsequent period. This is summed up across all asset classes for all periods and divided by the sum of absolute net cash flows into all asset classes in all periods. In Panel B the overall return is calculated with method 2. This overall return is the equally weighted average of portfolio returns over the entire sample period. The portfolio return for month t is calculated as the sum of dollar gains across all asset classes for month t divided by the sum of absolute net cash flows into all asset classes in month t. Panel C presents Sharpe ratios of net cash flow portfolios based on method 2. In the case of a holding period of more than 12 months, for example 12 months, I first calculate asset allocation weights based on net cash flows in month t. Then I calculate monthly returns in the following 12 months (month t+1 to month t+12) based on asset allocation weights at the end of month t. Next, I calculate Sharpe ratios with these 12 monthly returns. I do that for each month and get a time series of Sharpe ratios. Based on the time series of Sharpe ratios I can test the significance of the Sharpe ratio difference. I use three tests: t-test, test with Bootstrap standard error and non-parametric test (Wilcoxon signed-rank test). Significance levels in parentheses are adjusted for bias caused by overlapping observations using the Bootstrap standard error. Significance levels in brackets are calculated by using the non-parametric test. Performance measures are *h*-month cumulative returns for *h* holding period (*h* = 12, 24, 36, 48). * indicates significance at 10%, ** at 5% and *** at 1% levels.

Panel A: Overall return calculated with method 1

No. of months	12m	24m	36m	48m
CF Benchmark	0.0382	0.0869	0.1318	0.1672
All Fund CF	0.0283	0.0438	0.0502	0.0649
Dif (All -CF BM)	**-0.0099** ()[***]	**-0.0431** **(***)[***]	**-0.0815** ***(***)[***]	**-0.1023** ***(***)[***]

Panel B: Overall return calculated with method 2

	12m	24m	36m	48m
CF Benchmark	0.0382	0.0869	0.1318	0.1672
All Fund CF	0.0398	0.0680	-0.0824	0.0872
Dif (All-CF BM)	**0.0016** ()[]	**-0.0188** **(**)[]	**-0.0493** ***(***)[***]	**-0.0800** ***(***)[***]

Panel C: Mean Sharpe ratio of net cash flow portfolios for all fund CF and the CF benchmark.

	12m	24m	36m	48m
CF Benchmark	0.1163	0.1041	0.0937	0.0774
All Fund CF	0.0133	-0.0278	-0.0807	-0.1317
Dif (All-CF BM)	**-0.1030** ***(***)[]	**-0.1318** ***(***)[***]	**-0.1743** ***(***)[***]	**-0.2091** ***(***)[***]

To examine whether investors' low overall returns are in part due to investors' cash availability, I use method 2 to calculate the overall return as an equally weighted average across the entire sample period. The results are presented in Panel B of Table 3.4. The evidence for underperformance becomes weaker and smaller. The performance difference between all funds CF and the CF benchmark is negative and significant in the case of a holding period with more than 12 months. For the holding period of 48 months the underperformance is 8%, compared with 10% when calculated by using method 1. In fact, the true level of investors' cash availability is unknown. If investments of mutual fund investors in different periods depend on their cash availability, the underperformance is 8%

in the case of a holding period of 48 months. If they are not driven by their cash availability, the underperformance is 10%. However, in either case poor asset allocation decisions are hurting investors' long-term investment success.

Panel C of Table 3.4 presents the risk adjusted performance, measured by the Sharpe ratio[40], of all funds CF and the CF benchmark. The results are consistent with the earlier findings. The mean Sharpe ratio of the all funds CF portfolio is significantly lower than the mean Sharpe ratio of the CF benchmark portfolio for all holding periods.

One potential explanation for the poor asset allocation ability is investor sentiment. On the one hand, Chalmers, Kaul and Phillips (2009) find evidence that sentiment models of investing can explain investors' asset allocation decisions. High sentiment leads to an increase in equity flows. Baker and Wurgler (2007) also show the positive relation between investor sentiment and equity fund flows.[41] On the other hand, Brown and Cliff (2005) show that future aggregate stock returns over multiyear horizons are negatively related to investor sentiment. They argue that current positive sentiment leads to market overvaluation, which is followed by low cumulative long-term returns as market prices drop back to their fundamental value. Frazzini and Lamont (2008) also find evidence that high sentiment predicts low future stock returns. Furthermore, Braverman, Kandel and Wohl (2005) find a negative relationship between lagged flows and long-term future performance in different mutual fund categories. They explain this negative relationship by investor sentiment and time-varying risk premiums.

Considering all the evidence mentioned above, the underperformance of all fund investors could be explained by investor sentiment. Investor sentiment influences asset allocation decisions of mutual fund investors. They invest in equity funds in the case of high sentiment and suffer lower subsequent returns. If mutual fund investors have low sentiment,

[40] I calculate Sharpe ratios of net cash flow portfolios based on method 2. In the case of a holding period of more than 12 months, for example 12 months, I first calculate asset allocation weights based on net cash flows in month t. Then I calculate monthly returns in the following 12 months (month t+1 to month t+12) based on asset allocation weights at the end of month t. Next, I calculate Sharpe ratios with these 12 monthly returns. I do that for each month to obtain a time series of Sharpe ratios. Based on the time series of Sharpe ratios I calculate the mean of Sharpe ratios.

[41] I also examine the influence of investor sentiment on the aggregate flows into different asset classes. I regress monthly net flows in $ and monthly normalized net flows of different asset classes on the Consumer Sentiment Index of the University of Michigan and find a significant positive influence of investor sentiment on equity flows.

they disinvest in equity funds and invest in bond funds. By doing this, they miss subsequent high equity returns. This “false” switching among asset classes can lead to the observed long-term underperformance as compared to the passive CF benchmark, which by construction is not affected by sentiment.

3.3.2. Asset Allocation Ability in Different Broker Channels

3.3.2.1. Evidence from Total Net Assets

Table 3.5 reports the standard deviation of portfolio returns and the risk adjusted performance, measured by the Sharpe ratio.

Table 3.5: Sharpe ratio of different sales channel portfolios with four asset classes

This table presents average monthly return, average monthly excess return, standard deviation of monthly excess return and Sharpe ratio of different portfolios: the TNA benchmark portfolio, the non-proprietary broker portfolio, the proprietary broker portfolio and the direct market portfolio. Asset allocation weights are rebalanced on a monthly basis.

	TNA benchmark portfolio	Non-proprietary broker portfolio	Proprietary broker portfolio	Direct market portfolio
Average monthly return	0.42%	0.42%	0.34%	0.45%
Average monthly excess return	0.14%	0.14%	0.05%	0.17%
Standard deviation of monthly return	2.96%	3.70%	1.93%	3.61%
Sharpe ratio	0.0469	0.0373	0.0275	0.0463

The difference between the average monthly excess return of non-proprietary brokers and proprietary brokers is positive (0.09%), indicating that non-proprietary brokers perform better than proprietary brokers even though this effect is not significant. The direct market channel has the highest average excess return (0.17%) but it is not significantly different from the TNA benchmark and the non-proprietary channel.

By comparing the standard deviation of the monthly excess returns we can find the same evidence as in Table 3.2. The risk level for the non-proprietary broker channel and the direct market channel is similar and significantly higher than the risk level of the TNA benchmark. Proprietary brokers bear the lowest risk, with a level that is significantly lower than the risk of non-proprietary brokers. These results are partially consistent with the findings of Bergstresser, Chalmers and Tufano (2009). They find that the aggregate broker channel delivers lower returns and has lower risk and lower return securities as compared to the direct market channel. In this paper I examine the benefits of brokers by separating non-proprietary brokers from proprietary brokers. Proprietary brokers behave in the way reported by as Bergstresser, Chalmers and Tufano (2009): lower return and lower risk. However, non-proprietary brokers are very different from proprietary brokers, bearing significantly higher risk. As mentioned in Section 3.2.2, this difference could be explained by the self-selection of mutual fund investors. Less risk-averse investors are willing to choose more expensive non-proprietary brokers for the superior services offered by them, in particular as these investors are more likely to require expert advice from brokers due to their riskier behavior. In contrast, more risk-averse investors prefer less expensive proprietary brokers.[42] Another possible explanation is that proprietary brokers drive investors towards riskier asset classes.

Furthermore, results based on the Sharpe ratio also show that there are differences between non-proprietary and proprietary brokers in terms of the benefits they provide to investors. Funds sold through non-proprietary brokers earn a better risk-adjusted asset allocation performance than funds sold through proprietary brokers. However, both broker channels show a lower Sharpe ratio than the TNA benchmark. The differences are significant at the 10% level based on the Jobson and Korkie (1981) test with Memmel (2003) correction.

3.3.2.2. Evidence from New Cash Flows

Table 3.6 reports results based on net cash flows for the non-proprietary broker channel, the proprietary broker channel and the direct market channel.

[42] This is consistent with findings of Venezia, Galai and Shapira (1999) in insurance literature.

Table 3.6: Performance of net cash flow portfolios for different sales channels, especially non-proprietary vs. proprietary brokers

This table presents overall returns based on monthly net cash flows. The sample period is from January 1996 to July 2009. In Panel A the overall return on new cash flows is calculated with method 1. To calculate the return on net flows, I first estimate the dollar gains on all net cash flows over the entire sample period. The net cash flows of one asset class in month t are multiplied by the return on that asset class in the subsequent period. This is summed up across all asset classes for all periods and divided by the sum of absolute net cash flows into all asset classes in all periods. In Panel B the overall return is calculated with method 2. This overall return is the equally weighted average of portfolio returns over the entire sample period The portfolio return for month t is calculated as the sum of dollar gains across all asset classes for month t divided by the sum of absolute net cash flows into all asset classes in month t. Panel C presents Sharpe ratios of net cash flow portfolios based on method 2. In the case of a holding period of more than 12 months, for example 12 months, I first calculate asset allocation weights based on net cash flows in month t. Then I calculate monthly returns in the following 12 months (month t+1 to month t+12) based on asset allocation weights at the end of month t. Next, I calculate Sharpe ratios with these 12 monthly returns. I do that for each month and obtain a time series of Sharpe ratios. Based on the time series of Sharpe ratios I can test the significance of Sharpe ratio differences. I use three tests: t-test, test with Bootstrap standard error and non-parametric test (Wilcoxon signed-rank test). Significance levels in parentheses are adjusted for bias caused by overlapping observations using the Bootstrap standard error. Significance levels in brackets are calculated by using the non-parametric test. Performance measures are *h*-month cumulative returns for *h* holding period (*h* = 12, 24, 36, 48). * indicates significance at 10%, ** at 5% and *** at 1% levels.

Panel A: Overall return calculated with method 1

	12m	24m	36m	48m
No. of months				
CF Benchmark	0.0382	0.0869	0.1318	0.1672
Non-proprietary brokers	0.0372	0.0436	0.0523	0.0790
Proprietary brokers	0.0093	0.0009	-0.0008	-0.0094
Direct Market	0.0408	0.0613	0.0663	0.0887
Dif (Non-Prop - Prop)	**0.0279** ***(***)[***]	**0.0427** ***(***)[***]	**0.0603** ***(**)[***]	**0.0885** ***(***)[***]
Dif (Non-Prop – CF BM)	-0.0010 ()[]	-0.0432 ***(***)[**]	-0.0795 ***(***)[***]	-0.0882 ***(***)[***]
Dif (Prop – CF BM)	-0.0289 ***(***)[***]	-0.0859 ***(***)[***]	-0.1397 ***(***)[***]	-0.1767 ***(***)[***]
Dif (Direct – CF BM)	0.0025 ()[]	-0.0255 *(*)[*]	-0.0655 ***(***)[***]	-0.0786 ***(***)[***]

Panel B: Overall return calculated with method 2

	12m	24m	36m	48m
CF Benchmark	0.0382	0.0869	0.1318	0.1672
Non-proprietary brokers	0.0513	0.0681	0.0935	0.1007
Proprietary brokers	0.0094	0.0064	-0.0003	0.0067
Direct Market	0.0474	0.0792	0.0962	0.1014
Dif (Non-Prop - Prop)	**0.0419** ***(***)[***]	**0.0616** ***(***)[***]	**0.0939** ***(***)[***]	**0.0940** ***(***)[***]
Dif (Non-Prop – CF BM)	0.0130 ()[]	-0.0188 *(*)[]	-0.0382 **(**)[**]	-0.0665 ***(***)[***]
Dif (Prop – CF BM)	-0.0288 ***(***)[***]	-0.0804 ***(***)[***]	-0.1321 ***(***)[***]	-0.1606 ***(***)[***]
Dif (Direct – CF BM)	0.0091 ()[**]	-0.0076 ()[]	-0.0356 **(***)[**]	-0.0659 ***(***)[***]

Panel C: Mean Sharpe ratio of net cash flow portfolios for different sales channels, especially non-proprietary vs. proprietary brokers

	12m	24m	36m	48m
CF Benchmark	0.1163	0.1041	0.0937	0.0774
Non-proprietary brokers	0.0398	0.0016	-0.0227	-0.0630
Proprietary brokers	-0.4330	-0.5186	-0.5664	-0.5669
Direct market	0.0286	0.0141	-0.0085	-0.0465
Dif (Non-Prop – Prop)	**0.4729** ***(***)[***]	**0.5202** ***(***)[***]	**0.5437** ***(***)[***]	**0.5039** ***(***)[***]
Dif (Non-Prop – CF BM)	-0.0764 *(*)[]	-0.1025 ***(***)[**]	-0.1163 ***(***)[***]	-0.1405 ***(***)[***]
Dif (Prop – CF BM)	-0.5493 ***(***)[***]	-0.6226 ***(***)[***]	-0.6600 ***(***)[***]	-0.6444 ***(***)[***]
Dif (Direct – CF BM)	-0.0877 **(**)[]	-0.0900 ***(***)[**]	-0.1022 ***(***)[***]	-0.1239 ***(***)[***]

The results are consistent with those based on total net assets. The non-proprietary broker channel shows significantly higher overall returns using alternative holding periods. In the case of a holding period of 12 months the average dollar cash flow in the non-proprietary broker channel earns $0.0372 over the next 12 months, whereas the average dollar cash flow in the proprietary broker channel only earns $0.0093 over the next 12 months. The difference is $0.0279, which is statistically significant in all significance tests and also economically meaningful. Due to asset allocation decisions, non-proprietary broker-sold funds earn 2.79% p.a. more than proprietary broker-sold funds. The raw returns calculated using method 2 in Panel B of Table 3.5 also show the same results: investors buying funds via non-proprietary brokers have better asset allocation abilities than investors buying funds via proprietary brokers.

However, no channel shows superior asset allocation ability as compared to the CF benchmark. In Panel A and Panel B of Table 3.6 the overall return differences between the proprietary broker channel and the CF benchmark are always negative and statistically significant for different holding periods. The differences between the non-proprietary broker channel (direct market channel) and the benchmark are not statistically significant or significantly negative depending on the holding period. Overall, the longer the holding period, the stronger is the evidence of poor aggregate asset allocation abilities.

The results of the Sharpe ratio analysis in Panel C of Table 3.6 also show strong evidence of a better asset allocation ability of non-proprietary brokers as compared to proprietary brokers. The Sharpe ratio differences between non-proprietary and proprietary brokers are always positive and statistically significant for all holding periods. The Sharpe ratio differences between the non-proprietary channel (the proprietary channel, the direct market channel) and the CF benchmark is always negative and in most cases statistically significant, which indicates that different sales channels do not show any superior asset allocation ability as compared to the CF benchmark.

3.4. Additional Analysis

Furthermore, I calculate the risk and performance of a portfolio consisting of asset allocation funds where asset allocation decisions are made by professional mutual fund managers.[43] The monthly return of the asset allocation fund portfolio is calculated as the equally weighted average of all asset allocation funds. Table 3.7 reports the average monthly portfolio return, the standard deviation of portfolio returns and the risk adjusted performance, measured by the Sharpe ratio.

Results in Table 3.7 show that asset allocation funds exhibit a slightly better performance and risk-adjusted performance than the TNA benchmark portfolio, although the difference is not statistically significant. This is consistent with the results of Comer (2006). He finds that asset allocation mutual funds show significantly positive market timing abilities. Looking at different sales channels, the asset allocation fund portfolio again shows the best asset allocation performance. It seems that professional mutual fund managers have better asset allocation abilities as compared to different mutual fund sales channels.

Table 3.7: Performance and risk of asset allocation fund portfolio and other portfolios with four asset classes

This table presents average monthly return, average monthly excess return, standard deviation of monthly excess return and Sharpe ratio of different portfolios: the TNA benchmark portfolio, the all fund portfolio, the non-proprietary broker portfolio, the proprietary broker portfolio, the direct market portfolio and the asset allocation fund portfolio. Asset allocation weights are rebalanced on a monthly basis. The monthly return of the asset allocation fund portfolio is calculated as an equally weighted average of all asset allocation funds.

	Asset allocation fund portfolio	TNA benchmark portfolio	All Fund portfolio	Non-proprietary broker portfolio	Proprietary broker portfolio	Direct market portfolio
Average monthly return	0.43%	0.42%	0.41%	0.42%	0.34%	0.45%
Average monthly excess return	0.15%	0.14%	0.12%	0.14%	0.05%	0.17%
Standard deviation of monthly return	3.14%	2.96%	2.88%	3.70%	1.93%	3.61%
Sharpe ratio	0.0471	0.0469	0.0418	0.0373	0.0275	0.0463

[43] Asset allocation funds are global flexible portfolio funds based on Lipper objective codes in the CRSP mutual fund database. Global flexible portfolio funds allocate investments across various asset classes, including domestic stocks, foreign stocks, bonds and money market instruments.

3.5. Conclusion

In this paper I find that mutual fund investors, as a whole, show poor asset allocation abilities. Over the long-term they attain lower raw and risk-adjusted return because of their allocation among mutual fund asset classes as compared to investing in a passive benchmark or in asset allocation funds.

Furthermore, I find very strong evidence of a better asset allocation ability of investors buying funds via non-proprietary brokers as compared to investors buying funds via proprietary brokers. Non-proprietary brokers are independent of an individual fund management company. They are free from strict regulations of a parent company, have access to a larger fund universe and are able to consult investors without consideration of their parent company. All of these advantages make it easier for non-proprietary brokers to act on behalf of investors, as opposed to proprietary brokers who represent their affiliated fund companies. Thus, non-proprietary brokers can provide a higher quality of service than proprietary brokers.

The results of this paper have important implications for mutual fund investors in terms of their asset allocation decisions. In order to earn a better asset allocation performance they should prefer a passive strategy rather than changing their asset allocation frequently. Alternatively they can delegate their asset allocation decisions to professional mutual fund managers by investing in asset allocation funds.[44] Furthermore, in terms of asset allocation ability investors can get better professional financial advice from non-proprietary brokers than from proprietary brokers.[45]

[44] Comer (2006) finds evidence of market timing ability of asset allocation funds, which results in a better performance as compared to a passive benchmark without timing ability.

[45] ICI research Fundamentals find that 60% of fund investors with ongoing advisory relationships get help from their advisors in terms of asset allocation. See ICI, Why Do Mutual Fund investors Use Professional Financial Advisers? (2007).

Chapter 4

Fund Manager Allocation

4.1. Introduction

This paper is the first to study whether fund families allocate their fund managers to market segments in an efficient way, i.e., such that fund managers work in market segments in which their skills are best rewarded. This question is vital since fund performance crucially depends on the fund manager on the one side (e.g., Baks (2003)), and determines the money inflow into the fund on the other side (e.g., Sirri and Tufano (1998)).[46] As a fund family typically charges a fixed percentage fee on its assets under management, the manager allocation ultimately determines the profitability of the fund family. To a certain degree, fund managers can choose the market segments in which they would like to work. However, we cannot separate managers' self-decisions from the allocation decisions of fund families. Based on their bargaining power we assume that fund families' decisions dominate the fund managers' decision regarding the selection of market segments.

Whether or not a fund manager is able to generate positive risk-adjusted excess returns depends simultaneously on her skills and on the efficiency of the market segment in which

[46] In the related literature there are several papers which analyze the impact of the CEO on firm performance. See, e.g., Pérez-González (2006), Hayes and Schaefer (1999), Denis and Denis (1995), Bertrand and Schoar (2003), and Malmendier and Tate (2009).

she is employed. In fully efficient markets, even highly skilled managers should be unable to generate systematic excess returns. If the market is less efficient, skilled managers can generate excess returns where unskilled managers cannot. Thus, a fund family should allocate its smartest managers to the least efficient market segments. We test this basic hypothesis by analyzing how fund families allocate their fund managers to different market segments. To do so, we first rank segments with respect to their efficiency, and show that managerial skills result in the highest rewards in the least efficient market segment. This finding suggests that it is optimal for the fund families to allocate their more highly skilled managers to less efficient market segments. We then show that fund families indeed allocate their managers in such a way and thus exploit the comparative advantages of their fund managers.

More specifically, we focus on the investment grade (IG) and the high yield (HY) corporate bond market. Empirical evidence provided by Longstaff, Mithal, and Neis (2005) suggests that liquidity frictions are more prevalent for bonds with a lower rating. These liquidity frictions might give rise to persisting market inefficiencies, as arbitrage strategies which diminish temporal inefficiencies rely on sufficient liquidity.[47] Hence, we expect the HY market to be less efficient than the IG market.[48] Therefore, it comes as no surprise that mutual funds exhibit a higher average performance in the HY bond market than in the IG bond market segment. This result holds for all models we use to measure performance. The average annualized alpha difference lies between 1.6% and 3.5% when we use the Fama and French (1993) five-factor model, between 1.6% and 2.6% for the model of Blake, Elton, and Gruber (1993), and between 1.5% and 4.9% for the Gebhardt, Hvidkjaer, and Swaminathan (2005) model.

In the second step, we relate fund performance to managerial skills. We measure the skill of a fund manager using the average matriculates' GMAT scores for the institution where a fund manager obtained her MBA degree. Gottesman and Morey (2006) develop two

[47] Such a link between liquidity and efficiency has been empirically documented for stock markets by Chordia, Roll, and Subrahmanyam (2008).

[48] We test this classification in a time-series analysis of the corporate bond market and the CDS market. A vector autoregressive (VAR) analysis shows that lagged index returns and CDS premium changes predict HY bond index return changes. In contrast, IG bond index return changes cannot be predicted by CDS premia and bond index return changes. This finding clearly shows that the HY bond market is less efficient that the IG bond market.

rationales why attending a top MBA program results in superior performance. First, they argue that the communal learning design of these programs results in "[…] better investment decision making […]" (p.179). Second, they suggest that the broader curriculum offered by these schools familiarizes students with a wider range of asset classes. Hence, managers who attended MBA programs at an institution with higher average matriculates' GMAT scores should exhibit a higher picking ability. This ability is especially profitable in inefficient markets with larger differences between over- and underpriced assets. Thus, a manager's higher GMAT score is likely to result in a higher alpha of the fund in the inefficient HY market. Our regression analysis clearly confirms this hypothesis, even after controlling for various other manager and fund characteristics. While higher GMAT scores do not affect performance in the efficient IG segment, managers with higher GMAT scores generate significantly higher alphas in the inefficient HY segment. Thus, managerial skill pays off more in inefficient markets.

In the final step, we analyze whether fund families allocate their managers accordingly and assign their smartest managers to the inefficient HY segment. To do so, we first rank the managers within each fund family. Looking at intra-firm GMAT ranking is sensible, since the fund family can more easily choose from the pool of managers within the company than cross-hire managers from different fund families. Thus, we hypothesize that the higher a manager's GMAT ranking is in comparison to her colleagues within the fund family, the more likely she is to be assigned to a HY fund. To test this hypothesis, we run a probit regression analysis. Our results strongly support the hypothesis that fund families assign their smartest managers to the least efficient market segment. This finding leads to our bottom line conclusion: Fund families allocate fund managers in an efficient way and exploit the comparative advantages of the managers.

Our paper is related to several strands of the literature: First, it contributes to the growing body of literature on decisions taken by fund families. For example, a fund family decides on its product policy (e.g., Mamaysky and Spiegel (2001), Massa (2003), Khorana and Servaes (2004)), the fees charged by their funds (e.g., Chordia (1996), Nanda, Narayanan, and Warther (2000)), the advertising strategy (e.g., Gallaher, Kaniel, and Starks (2006), Jain and Wu (2000)), the management approach (e.g., Bär, Kempf and Ruenzi (2011), Massa, Reuter, and Zitzewitz (2010)), and cross-subsidization between funds (e.g., Gaspar, Massa, and Matos (2006)). We contribute to this literature by showing how fund families allocate fund managers to different market segments. While other papers analyze hiring and firing of managers by fund families (e.g., Khorana (1996), Chevalier and Ellison (1999b)), to our knowledge ours is the first paper which addresses this allocation issue.

Second, this paper is complementary to the literature analyzing the impact of managerial characteristics on fund performance. Golec (1996) and Chevalier and Ellison (1999a) show that a manager's age negatively affects fund performance, whereas experience has a positive impact. The impact of an MBA degree on performance is mixed. Golec (1996) reports a positive impact, Gottesman and Morey (2006) also find a positive impact that depends on the quality of the MBA program, and Chevalier and Ellison (1999a) find no significant impact. We complement this literature by showing that a sound MBA education has a positive impact on performance only when the manager is investing in an inefficient market segment.

Third, our paper is related to studies which explore how managers are assigned. Only few papers analyze initial assignment: Fee and Hadlock (2003) show that the manager of a successful company is more likely to be hired as CEO by a competing company. Drazin and Rao (2002) analyze how fund families assign their already employed managers to newly founded funds. They find that related experience is a key characteristic of the managers assigned to such funds. We add to this literature by demonstrating that a manager's allocation to a given market segment is simultaneously driven by the manager's skill, and by the efficiency of the market segment.

The remainder of the paper is structured as follows. Section 4.2 describes the data which we use in this study. In Section 4.3, we compare HY funds' performance with IG funds' performance. We relate fund performance to managerial skills in Section 4.4. Section 4.5 analyzes how fund families assign their managers to the different market segments. Section 4.6 summarizes and presents the conclusion.

4.2. Data

Our main data source is the CRSP Survivor Bias Free U.S. Mutual Fund Database from which we obtain our data on funds and fund managers.[49] We focus on the fact sheets from the CRSP Mutual Fund CD as of January 2009. The fact sheet contains the name and a unique identifier number of the fund, the name of the managers responsible for the fund in January 2009, the name of the managing company, and the date that the managers assumed responsibility for the fund. The fund objective codes, monthly total net assets, monthly returns, expense ratios, and turnover ratios are also obtained from CRSP. All of this data is at fund share class level. We aggregate the data to the fund level based on the total net assets of different share classes, and perform our analysis at the fund level. We focus on funds with a single manager since it is not clear how the skills of single team members translate into the skills of a team. We also focus on funds where we were able to determine the institution where a fund manager obtained her MBA degree and the average matriculates' GMAT scores for the institution as described below.

We use Lipper objective code to identify the fund's objective. We only use funds classified either as Investment Grade (IG) corporate bond funds or as High Yield (HY) corporate bond funds. Compared to the Morningstar classification, our IG category corresponds to the "Corporate Bond – General" and "Corporate Bond – High Quality" categories, and HY to "Corporate Bond – High Yield".

For each fund, we take the time series of end-of-month fund net asset values, fund net returns, expense ratios, turnover ratios, and fund age for the sample period January 1999 to December 2007 from CRSP. We determine the fund's age using the date that the fund first was offered. We determine for each fund the monthly gross return by adding the total expense ratio. Since gross returns better reflect managerial ability, we henceforth focus on gross returns.[50]

[49] Source: CRSPTM, Center for Research in Security Prices, Graduate School of Business, The University of Chicago. Used with permission. All rights reserved. crsp.uchicago.edu. For a more detailed description of the CRSP database, see Carhart (1997) and Elton, Gruber, and Blake (2001).

[50] Clearly, from an investor's perspective, net returns are more interesting. However, our research objective is not whether HY managers deserve the higher fees they charge, but whether they are able to exploit bond market inefficiencies.

Table 4.1 shows the average characteristics of the 38 HY funds and the 93 IG funds in our sample.

Table 4.1: Summary statistics

We present summary statistics for all variables used in the analysis. The fund characteristics include the mean annualized gross and net return in percentage points, the mean expense and turnover ratios in percentage points per year, the assets under management in million USD, and the mean age in years. GMAT denotes the GMAT average across matriculates at the manager's MBA institution, averaged across all managers that have an MBA. Experience is measured as the difference between the current date and the beginning date of the manager's investment experience in years. Pre-fund experience denotes the difference between the date the manager first assumed responsibility of the fund, and the beginning date of the manager's investment experience in years. Since-fund experience is the difference between the current date and the date the manager first assumed responsibility for the fund in years. Averages are taken first over time for each fund, and then across funds.

	High Yield	Investment Grade	Difference (HY-IG)
Panel A: Fund Characteristics			
Gross Return [%/year]	5.96	5.84	0.12
Expense Ratio [%/year]	1.08	0.78	0.30***
Turnover Ratio [%/year]	84.83	162.33	-77.50***
Assets under Management [mn USD]	1,082.26	1,591.61	-509.34
Age [years]	10.38	10.35	0.03
Panel B: Manager Characteristics			
GMAT	674.59	661.72	12.87
Managers w/ other master [%]	7.32	1.08	6.24*
Managers w/ CFA [%]	56.10	56.90	-0.89
Managers w/ CPA [%]	7.32	2.15	5.17
Managers w/ other designation [%]	4.88	4.30	0.58
Experience[years]	17.42	20.65	-3.24***
Pre-Fund Experience[years]	10.66	14.33	-3.67***
Since-Fund Experience[years]	6.63	6.33	0.30**

As Panel A of Table 4.1 shows, HY funds yield higher gross annualized returns of 6.0% p.a. as compared to IG funds with 5.8% p.a. The expense ratios are also higher in the HY segment, which is consistent with higher costs of information gathering in the less efficient market segment. Interestingly, the higher expense ratios of HY funds do not correspond to higher turnover ratios. In fact, the turnover of HY funds is significantly smaller than the turnover of IG funds. This might reflect the higher costs of trading in the HY bond market segment due to lower liquidity as documented by Longstaff, Mithal, and Neis (2005).

On average, IG funds are larger than HY funds, but the difference is not statistically significant. The average age of HY funds and IG funds is almost identical.

Panel B of Table 4.1 reports characteristics of managers managing HY funds and IG funds. To obtain this information, we first verify the names of the managers by looking at the SEC filings, the fund management companies' websites, fund prospectuses, and other online resources. From the same sources, we then collect data on the managers' education: whether the manager obtained an MBA, a non-business master's degree, CFA, CPA, or another graduate degree, and the beginning date of their investment experience. For all managers with an MBA degree, we identify the average matriculates' GMAT score at the institution where the manager obtained her MBA from the websites mba.com, businessweek.com, entrepreneur.com, and the schools' websites. We compute the manager's experience as the difference between the current date and the beginning of the manager's investment experience.

With respect to the manager characteristics, we find that HY managers have attended business schools with higher average matriculates' GMAT scores. This ranking implies that highly skilled managers more frequently manage funds in the less efficient HY bond market segment. The majority of the fund managers holds a CFA degree, but only a few hold a non-MBA degree. Managers of HY funds appear to hold non-MBA degrees more frequently than managers of IG funds do.

Looking at the total experience shows that managers of HY funds are less experienced than managers of IG funds. This results from the fact that they have far less experience before taking on responsibility for the fund. In contrast, their experience since taking on the fund is significantly higher than the experience of IG fund managers. This difference suggests that fund families assign relatively inexperienced managers to HY funds, but employ them for a longer time.

4.3. Market Efficiency and Average Fund Performance of the Investment Grade and the High Yield Corporate Bond Market

We compare the performance of funds investing in the HY bond market segment and in the IG bond market segment. Given our earlier discussions of efficiency, we expect HY funds to generate higher alphas on average.

For each fund, we determine a time series of performance metrics, using three different factor models and two different conditioning models. Our factor models are the Fama and French (1993) five-factor model, the Gebhardt, Hvidkjaer, and Swaminathan (2005) model, and the Blake, Elton, and Gruber (1993) three-index model.[51] For each model, we determine alpha time series for a rolling window of 12 months once with constant betas, and once with conditional betas. The rationale for these two different conditioning models is that conditional betas allow us to capture dynamic strategies, where fund managers vary their factor loadings. As Ferson and Schadt (1996) show, conditional and constant beta models are likely to result in statistically and economically significant differences in fund performance.

This estimation procedure gives us a time series of six annualized alphas for each fund. Table 4.2 reports the average alpha for HY funds and IG funds as well as the corresponding standard deviations.

Table 4.2 shows that corporate bond funds generate positive alphas in most model specifications. This result suggests that neither the IG nor the HY bond market segments are fully efficient. The average outperformance of HY funds is between 1.6% p.a. when we use the Blake, Elton, and Gruber (1993) model and 3.9% p.a. for Fama and French (1993) model.[52] For all six models, the average alphas of HY funds are significantly higher than the average alphas of IG funds.[53] This finding supports our expectation that the HY bond market is less efficient than the IG bond market segment. The differences between the alphas are especially pronounced for the conditional beta models which take into account the time-varying factor loadings.

[51] Fama and French (1993) include the market risk premium, SMB, HML, the term premium and default premium. Gebhardt, Hvidkjaer and Swaminathan (2005) use only the term premium and default premium. Blake, Elton and Gruber (1993) three index model considers Lehman Brothers government/corporate bond index, the Lehman Brothers mortgage-based securities index and the Blume/Keim high-yield index.

[52] These values are somewhat lower than the alphas documented by Huij and Derwall (2008) for HY funds.

[53] From an investors' perspective focusing on net returns, the alphas in the investment grade segment cover roughly the total expense ratio. For the high yield segment the alphas are much larger than the total expense ratio.

Table 4.2: Average performance of corporate bond funds

We present summary statistics for the estimated alphas, using the factor models by Fama and French (1993), Gebhardt, Hvidkjaer, and Swaminathan (2005), and Blake, Elton, and Gruber (1993), each with constant betas and conditional betas. The alphas are determined by first estimating betas from the previous 12 monthly gross returns and then using these betas to determine alpha for the current monthly gross return. Estimation is performed via OLS, significance is determined using robust standard errors. ***, **, and * denote that the estimated alpha differs significantly from zero at the 1%, 5%, and 10% level. All values are annualized alphas in percentage points.

	High Yield	Investment Grade	Difference (HY-IG)
Panel A: Fama and French (1993) Model			
Constant Beta Model	2.281***	0.722***	1.559***
Standard Deviation	(0.277)	(0.109)	(0.246)
Conditional Beta Model	3.925***	0.451*	3.474***
Standard Deviation	(0.889)	(0.279)	(0.718)
Panel B: Gebhardt, Hvidkjaer, and Swaminathan (2005) Model			
Constant Beta Model	2.137***	0.558***	1.579***
Standard Deviation	(0.226)	(0.082)	(0.193)
Conditional Beta Model	3.410***	0.803***	2.608***
Standard Deviation	(0.605)	(0.284)	(0.588)
Panel C: Blake, Elton, and Gruber (1993) Model			
Constant Beta Model	1.615***	0.142**	1.474***
Standard Deviation	(0.224)	(0.063)	(0.175)
Conditional Beta Model	3.132	-1.754**	4.887**
Standard Deviation	(2.737)	(0.815)	(2.171)
Number of Observations	1,722	4,134	

4.4. Managerial Skill, Market Efficiency and Fund Performance

We first explore whether managerial skill has a positive impact on fund performance in general. To do so, we perform the following cross-sectional regression using all HY and IG funds in our sample:

$$\alpha_{i,t} = \beta_0 + \beta_1 GMAT_i + \beta_2 Exp_{i,t} + \beta_3 D_i^{\text{OtherMaster}} + \beta_4 D_i^{\text{CFA}} + \beta_5 D_i^{\text{CPA}} + \beta_6 D_i^{\text{OtherDegree}} \\ + \beta_7 \alpha_{i,t-1} + \beta_8 \ln\text{TNA}_{i,t-1} + \beta_9 \ln\text{Age}_{i,t-1} + \beta_{10}\text{Expense\_ratio}_{i,t-1} + \beta_{11}\text{Turnover}_{i,t-1} + \varepsilon_{i,t}, \tag{4.2}$$

where $\alpha_{i,t}$ is the alpha of fund i at date t and $GMAT_i$ is the GMAT score for the manager of fund i. We divide the GMAT score by 100 to obtain a more intuitive size of the coefficient estimate. We also include manager- and fund-control variables. The manager-control variables are the experience ($Exp_{i,t}$) of the manager of fund i at date t, measured in years, and dummy variables of whether the manager has a non-MBA master's degree ($D_i^{OtherMaster}$), CFA (D_i^{CFA}), CPA (D_i^{CPA}), or another post-graduate degree ($D_i^{OtherDegree}$). The fund-control variables are the lagged alpha ($\alpha_{i,t-1}$), the log of the assets under management ($lnTNA_{i,t-1}$), the log of the fund age ($lnAge_{i,t-1}$), the expense ratio ($Expense\_ratio_{i,t-1}$), and the turnover ratio ($Turnover_{i,t-1}$). The results of the regression analysis are given in Table 4.3.

Table 4.3: Impact of GMAT on alpha: overall analysis

We present the results of the regression in Equation (4.2) of impact of GMAT, manager and fund control variables on alphas. Alphas are determined as described in Table 4.3. The GMAT score is divided by 100 for ease of coefficient exposition. The remaining explanatory variables are as in Table 4.1. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using robust standard errors. All values are for annualized alphas in percentage points. The R^2 is also in percentage points.

	Fama-French Model		Gebhardt et al. Model		Blake et al. Model	
	Constant Beta	Conditional Beta	Constant Beta	Conditional Beta	Constant Beta	Conditional Beta
Constant	0.236	0.773	0.593	-1.845	-1.915	-14.684
GMAT	0.109	0.466	0.039	0.200	0.191	2.236
Manager Control Variables						
Experience	-0.002	-0.002	-0.002**	-0.002	0.001*	0.012
Non-MBA Master	-0.260	-1.032	-0.264	-0.343	-0.319	-5.321
CFA	-0.033	-0.007	-0.055	0.209	0.001	2.798
CPA	0.442	3.263	0.684	0.265	0.355	-2.679
Other Designation	-1.155	-7.393	-0.101	0.551	-1.198	28.134
Fund Control Variables						
Lagged alpha	0.101***	-0.015	0.143***	0.074***	0.079**	0.037
Log(Asset Value)	0.088	0.392*	0.063	0.195	0.015	-0.071
Log(Age)	-0.297	-1.433**	-0.234	0.042	-0.083	-2.212
Expense Ratio	1.687***	3.690***	1.606***	1.076	1.339***	6.741*
Turnover Ratio	0.111	-0.199	0.095*	0.183	-0.035	0.167
# Obs.	5,695	5,695	5,695	5,695	5,695	5,695
R^2	1.64	0.43	3.19	0.69	1.70	0.49

For the entire sample, GMAT does not significantly affect alpha, even though the individual coefficient estimates are positive. This result suggests that managers cannot translate their skill into higher performance in general – skill does not pay off. Our finding thus differs from the earlier results of Chevalier and Ellison (1999a) and Gottesman and Morey (2006), who show that attending a top school leads to overall better performance.

The impact of the manager control variables is small in economic and statistical terms. With respect to the fund characteristics, we find that the lagged alpha frequently has a significant positive impact on the current alpha. The positive autocorrelation coefficient implies short-term persistence of alpha, which has been documented by Kahn and Rudd (1995) for US fixed-income funds and Silva, Cortez, and Armada (2005) for European fixed-income funds. Also, a higher expense ratio coincides with higher alphas.

Second, we analyze whether skilled managers can generate a higher performance in less efficient markets. To do so, we extend Model (4.2), and interact the GMAT variable with a dummy variable D^{HY} which takes on the value one if the manager is running a HY fund, and the value zero if the manager is running an IG fund. Hence, our reference case is an IG fund manager. The model now reads:

$$\begin{aligned}\alpha_{i,t} = {} & \beta_0 + \beta_1 GMAT_i + \beta_2 GMAT_i \cdot D_i^{HY} + \beta_3 Exp_{i,t} + \beta_4 D_i^{\text{OtherMaster}} + \beta_5 D_i^{\text{CFA}} + \beta_6 D_i^{\text{CPA}} + \beta_7 D_i^{\text{OtherDegree}} \\ & + \beta_8 \alpha_{i,t-1} + \beta_9 \ln\text{TNA}_{i,t-1} + \beta_{10} \ln\text{Age}_{i,t-1} + \beta_{11} \text{Expense\_ratio}_{i,t-1} + \beta_{12} \text{Turnover}_{i,t-1} + \varepsilon_{i,t}.\end{aligned} \tag{4.3}$$

The variables are defined as in Model (4.2). Since the HY segment is less efficient than the IG segment (see Section 4.3), we expect that managers with high skills can demonstrate their skills better in the HY segment, leading to a positive coefficient for the GMAT score interacted with the high yield dummy. The results of the regression analysis are given in Table 4.4.

Table 4.4 shows that GMAT has a significant positive impact on alpha in the HY segment, but not in the IG segment. This finding suggests that managerial skill pays off only in the less efficient HY market. Therefore, fund families should assign their smartest managers to HY funds, since higher GMAT results in a better performance in this segment only. We test whether fund families behave sensibly in this respect in the next section.

Table 4.4: Impact of GMAT on alpha: segment specific analysis

We present the results of the regression in Equation (4.3) of GMAT on alpha, GMAT interacted with a dummy variable for the high-yield segment, and manager and fund control variables. Alphas are determined as described in Table 4.2. The GMAT score is divided by 100 for ease of coefficient exposition. The remaining explanatory variables are as in Table 4.1. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using robust standard errors. All values are for annualized alphas in percentage points. The R^2 is also in percentage points.

	Fama-French Model		Gebhardt et al. Model		Blake et al. Model	
	Constant Beta	Conditional Beta	Constant Beta	Conditional Beta	Constant Beta	Conditional Beta
Constant	2.441	5.447	2.748	2.975	-0.160	-9.221
GMAT	-0.063	0.101	-0.129	-0.177	0.054	1.807
GMAT *Dummy HY	0.003***	0.005***	0.002***	0.006**	0.002***	0.006
Manager Control Variables						
Experience	-0.003**	-0.045	-0.003***	-0.004	0.001	0.009
Non-MBA Master	-0.686	-1.933	-0.682	-1.277	-0.663	-6.376
CFA	-0.135	-0.222	-0.155	-0.014	-0.080	2.547
CPA	0.198	2.746	0.453	-0.268	0.162	-3.293
Other Designation	-2.077	-9.350*	-1.003	-0.461	-1.935	25.880
Fund Control Variables						
Lagged alpha	0.095***	-0.017	0.134***	0.070***	0.072*	0.037
Log(Asset Value)	-0.014	0.174	-0.038	-0.030	-0.068	-0.327
Log(Age)	-0.305	-1.449**	-0.243	0.028	-0.088	-2.227
Expense Ratio	0.894**	1.996**	0.839***	-0.679	0.705***	4.750
Turnover Ratio	0.238***	0.068	0.220***	0.460**	0.066	0.481
# Obs.	5,695	5,695	5,695	5,695	5,695	5,695
R^2	2.22	0.73	4.09	1.21	2.46	0.54

4.5. Manager Allocation

To test whether fund management companies rationally assign their managers to the different bond fund segments, we perform the following probit regression:

$$\Pr\left(D_i^{HY}=1\right)=\Phi\left(\beta_0+\beta_1 GMATRANK_i+\mathrm{CV}(\mathrm{Manager}_i)+\varepsilon_i\right). \tag{4.4}$$

D_i^{HY} is the dummy variable of whether the manager's assignment to a fund in our sample is within the HY segment. $GMATRANK_i$ is the manager's GMAT rank across all managers employed by the same fund management company at the assignment date. CV($\mathrm{Manager}_i$)

are manager-control variables, and Φ is the cumulative normal distribution. The results of the regression are given in Panel A of Table 4.5.

Table 4.5: Impact of GMAT on segment assignment

We present the results of the probit regressions in Equation (4.4) – (4.6) of the impact of GMAT and manager-control variables on manager's assignment. The dependent variable is the probability of a manager's being assigned to a HY fund. The explanatory variables are the manager's GMAT rank within the fund family at the assignment date in Panel A, the deviation of the manager's GMAT from the average GMAT within the fund family, both divided by 100, at the assignment date in Panel B, and the manager's GMAT score divided by 100 in Panel C, and manager control variables. The manager control variables are as in Table 4.1. ***, **, and * denote significance at the 1%, 5%, and 10% level. The pseudo-R^2 is in percentage points.

	Panel A: GMAT Rank within Fund Family		Panel B: Deviation from Average GMAT within Fund Family		Panel C: GMAT Level	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Constant	-0.339	-	-0.272	-	-1.782	-
GMAT	0.014*	0.005*	0.737**	0.254**	0.233	0.081
Manager Control Variables						
Experience	-0.002*	-0.001*	-0.002*	-0.001*	-0.002*	-0.001*
Non-MBA Master	0.751	0.288	0.754	0.289	0.774	0.297
CFA	0.057	0.020	0.055	0.019	0.052	0.018
CPA	0.401	0.150	0.393	0.146	0.412	0.154
Other Designation	-0.182	-0.060	-0.095	-0.032	-0.000	-0.000
# Obs.	130					
Pseudo-R^2	5.88		6.71		4.73	

Panel A of Table 4.5 shows that a higher GMAT rank makes it significantly more likely for a manager to be assigned to a HY fund. A manager which is one rank higher with respect to her GMAT is 0.5% more likely to be assigned to a HY fund.

In an alternative specification, we use the deviation between a manager's GMAT and the average GMAT of all managers employed by the fund family, $GMATDEV_i$, (both divided by 100) as the explanatory variable instead of the GMAT ranking:

$$\Pr\left(D_i^{HY}=1\right)=\Phi\left(\beta_0+\beta_1 GMATDEV_i+\text{CV}(\text{Manager}_i)+\varepsilon_i\right). \quad (4.5)$$

The results are shown in Panel B of Table 4.5. They also suggest that fund families assign their smartest managers to HY funds. The results are slightly stronger than the ones based on GMAT ranks. This difference suggests that the family not only considers the managers' ranking, but also bases its allocation decision on the level differences in GMAT.

In the final specification, we use the GMAT level as explanatory variable:

$$\Pr\left(D_i^{HY}=1\right)=\Phi\left(\beta_0+\beta_1 GMAT_i+\text{CV}(\text{Manager}_i)+\varepsilon_i\right). \tag{4.6}$$

The results reported in Panel C in Table 4.5 show that the GMAT level has no impact on the probability of being assigned to a HY fund. This finding suggests that it is not the absolute GMAT level of a manager, but rather the GMAT level relative to her colleagues, which matters for the fund family's allocation decision. The result is consistent with the view that fund families primarily choose from the pool of managers they already employ, and do not customarily hire new managers with higher GMAT to run their HY funds.

When looking at the control variables, the consistently negative impact of experience is striking. This result remains stable when looking at experience ranks instead of experience level: fund families seem to assign inexperienced managers to their HY funds. This finding raises the question whether experience-based manager allocation is as efficient as skill-based allocation. To check whether less experienced managers generate higher performance in the HY segment, we run an extended version of Equation (4.3). We interact experience with a dummy which takes on the value one if the fund belongs to the HY segment, and zero otherwise:

$$\begin{aligned}\alpha_{i,t}=&\beta_0+\beta_1 GMAT_i+\beta_2 GMAT_i\cdot D_i^{HY}+\beta_3 Exp_{i,t}+\beta_4 Exp_{i,t}\cdot D_i^{HY}\\&+\beta_5 D_i^{\text{OtherMaster}}+\beta_6 D_i^{\text{CFA}}+\beta_7 D_i^{\text{CPA}}+\beta_8 D_i^{\text{OtherDegree}}+\beta_9\alpha_{i,t-1}+\beta_{10}\text{lnTNA}_{i,t-1}\\&+\beta_{11}\text{lnAge}_{i,t-1}+\beta_{12}\text{Expense\_ratio}_{i,t-1}+\beta_{13}\text{Turnover}_{i,t-1}+\varepsilon_{i,t}\end{aligned} \tag{4.7}$$

The variables are defined as in Equation (4.2) and (4.3). If inexperience pays off in HY funds, we expect β_4 to be negative. The results of the regressions are reported in Table 4.6.

Table 4.6 clearly shows that experience has a negative impact on the performance of HY funds. This impact might be due to the overall negative effect of age, as documented by Chevalier and Ellison (1999a). However, we believe that experience in the HY segment might proxy for managers being more set in their ways. It is sensible that such inflexibility results in lower performance in the less efficient HY segment. Overall, we conclude that it is rational for fund families to assign less experienced managers to HY funds.

Table 4.6: Impact of GMAT and experience on alpha: segment specific analysis

We present the results of the regression in Equation (4.7) of impact of GMAT, experience, GMAT and experience interacted with a dummy variable for the high-yield segment, and manager and fund control variables on alpha. Alphas are determined as described in Table 4.2. The GMAT score is divided by 100 for ease of coefficient exposition. The remaining explanatory variables are as in Table 4.1. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using robust standard errors. All values are for annualized alphas in percentage points. The R^2 is also in percentage points

	Fama-French Model		Gebhardt et al. Model		Blake et al. Model	
	Constant Beta	Conditional Beta	Constant Beta	Conditional Beta	Constant Beta	Conditional Beta
Constant	0.736	1.975	0.773	0.529	0.060	-4.530
GMAT	-0.012	0.277	-0.082	-0.143	0.055	1.673
GMAT *Dummy HY	0.006***	0.016***	0.006***	0.007**	0.005***	0.025
Experience	0.010	-0.019	0.018*	0.037	-0.007	-0.046
Experience * Dummy HY	-0.009**	-0.033***	-0.012***	-0.005	-0.009***	-0.055
Manager Control Variables						
Non-MBA Master	-1.683**	-5.356**	-1.868***	-1.881	-1.404**	-10.320
CFA	-0.055	0.062	-0.075	0.030	-0.053	2.565
CPA	0.195	2.678	0.435	-0.232	0.088	-3.912
Other Designation	-1.637	-7.798	-0.532	-1.214	-1.712	26.679
Fund Control Variables						
Lagged alpha	0.095***	-0.019	0.133***	0.070***	0.069*	0.036
Log(Asset Value)	-0.017	0.155	-0.044	-0.026	-0.083	-0.448
Log(Age)	-0.211	-1.095	-0.146	0.070	-0.039	-2.068
Expense Ratio	0.842**	1.776*	0.785***	-0.684	0.659***	4.497
Turnover Ratio	0.210***	-0.027	0.190***	0.442**	0.056	0.469
# Obs.	5,695	5,695	5,695	5,695	5,695	5,695
R^2	2.26	0.94	4.23	1.18	2.78	0.60

4.6. Conclusion

In this paper, we show that fund families allocate their fund managers in an efficient way. They assign their smartest managers to the least efficient market segments where their skills pay most.

We come to this bottom line conclusion by studying US fund managers in the investment grade (IG) and the high yield (HY) corporate bond market. Our empirical study leads to four main results: (i) The HY bond market is less efficient than the IG bond market. (ii) The performance of a fund increases with the skill (measured by GMAT) of the fund manager only in the inefficient HY segment. In the more efficient IG market, skill does not matter. (iii) Fund families seem to be aware of this fact and assign their most skilled managers to the HY funds. (iv) Managerial experience harms the performance of HY funds and, consistent with this finding, fund families assign inexperienced managers to HY funds.

These manager allocation strategies are highly sensible since they increase HY fund alphas without decreasing IG fund alphas. Thus, average alpha in the fund family goes up and, as a consequence, the family attracts new money inflow and fee income. Manager allocation is thus a decision of similar importance to advertising and cross-subsidization. In these latter decisions, however, the fund family generates advantages for one manager at another manager's expense. Allocating the most highly skilled managers to the least efficient segment, on the other hand, does not put less highly skilled managers at a disadvantage.

Chapter 5

Entrepreneurship in the Mutual Fund Industry

5.1. Introduction

Determining which attributes characterize an entrepreneur is a perennial issue for economists, resulting in a large and growing body of literature. The idea that entrepreneurs possess characteristics that differentiate them from paid employees is featured in many theoretical models. These models argue that entrepreneurs differ from the rest of the population with respect to at least three characteristics: their risk-bearing tolerance, their skills and their overconfidence. Recent research finds that entrepreneurial success is persistent, meaning that entrepreneurs who started up a successful new venture also seem to be more effective in the timing and performance of their second and third businesses as compared to first-time entrepreneurs and those who have failed (Gompers, Kovner, Lerner and Scharfstein (2010)). However, the theorized qualities of successful entrepreneurs continue to elude academic researchers. A major cause of this gap in the literature is the inability of researchers to observe the behavior and performance of entrepreneurs prior to and after establishing firms. In other words, observing entrepreneurs at work is virtually impossible in most economic settings.

Establishing mutual fund companies is also a regularly chosen career path for fund managers in the mutual fund industry. In our dataset we can observe that more than 7% of all equity fund managers in the period of 1980-2009 choose this career path. However, this career path has been neglected until now in mutual fund research. In this paper we want to fill this gap with first empirical findings.

In the first part of paper we provide evidence on the characteristics and behavior of entrepreneurs suggested by theory, using the mutual fund industry as our laboratory. As firm founders in the investment industry usually work for another fund company first before starting on their own, we are able to observe their characteristics and behavior at the micro unit level. This allows us to provide the first comprehensive empirical tests of predictions derived from well established theoretical models on entrepreneurial qualities.

We target the following main theories. First, the notion of entrepreneurs as comparatively high risk bearers has repeatedly appeared in the cornerstone models of entrepreneurship (McClelland (1961), Lucas (1978), Kanbur (1979), and Kihlstrom and Laffont (1979)). Kihlstrom and Laffont (1979) show theoretically that the least risk-averse individuals in the population start firms. However, the risk-aversion of those individuals that will later become entrepreneurs has never been directly observed. Our dataset allows us to observe the behavior and risk-taking of future entrepreneurs while they are still employees. This enables us to directly compare them with those employees that do not become entrepreneurs, thereby delivering a direct test of differences in risk-aversion between the two groups.

Second, Lucas (1978) and Murphy, Shleifer and Vishny (1991) show that those individuals with the highest skill levels start firms, while individuals with lower human capital work for these entrepreneurs. Lazear (2003 and 2004) places attention on the influence of entrepreneurs' prior training and experiences. Having a background in a variety of roles increases an individual's probability of starting her own firm. We will examine how the skills and experience of a fund manager influence the probability that she will later start her own firm.

Third, it is already argued in Knight (1921) that it is not necessarily the true ability of a manager that determines whether or not she starts her own firm, but rather her belief in her own abilities. Bernardo and Welch (2001) show theoretically that individuals that are overconfident with respect to their own abilities are more likely to become entrepreneurs. We will examine whether there is any relationship between different proxies for managerial overconfidence and the probability of a manager becoming an entrepreneur.

Finally, Miller and Friesen (1978), Mintzberg (1973) and Lumpkin and Dess (1996) introduce proactiveness and innovativeness as dimensions of entrepreneurial orientation. Proactiveness means that entrepreneurs prefer to take initiatives. They also anticipate and pursue new opportunities. They are innovative individuals. We also examine proactiveness of would-be entrepreneurs by looking at proxies based on how actively and unconventionally they manage their funds.

In the second part of our paper we analyze the persistence of the behavior of entrepreneurial fund managers before and after they switch from agents to principals. We specifically examine the effects of this transition on managerial risk-taking, investment style and performance. On the one hand, risk taking might be more prevalent while managers are employed. After forming their own firms, risk-taking propensity is reduced by the additional personal financial and fiduciary risks they assume (e.g. Miner and Raju (2004)). On the other hand, entrepreneurial fund managers could become more risky as they are no longer constrained by employer-imposed investment restrictions.

Whether fund managers who become entrepreneurs switch to more conventional styles is also an open question. It is possible that entrepreneurs follow even more unconventional styles than before, because they are no longer restrained by employer-imposed restrictions that they might have been subject to before. On the other hand, they might now start to follow herd-like strategies in order to increase the probability of the survival of their firm.

In addition, performance could be improved due to increased effort, in particular as entrepreneurs now fully benefit from their success without having to split profits with a principal. They would also like to grandstand by providing superior performance so that they can attract investors more easily. Furthermore, they are now less restrained in their portfolio strategy and can implement their investment ideas unrestrained by family guidelines. However, given their much broader range of duties, they might not be able to fully focus on the management of their portfolio, which eventually leads to worse performance.

Our main findings in terms of the characteristics of entrepreneurial fund managers are broadly consistent with some models of entrepreneur, but not with others. Would-be entrepreneurs are individuals who are proactive, innovative and show signs of overconfidence. They follow more active investment strategies and trade more frequently as compared to non-entrepreneur managers. They are managers with high reputation, as measured by media coverage. They also use the permitted investment practices to a higher degree. However, they do not show superior past performance. Inconsistent with models in entrepreneurship literature, we cannot find differences in risk-taking between would-be entrepreneurs and non-entrepreneurial managers. This could be due to the very small number of entrepreneur managers as compared to the very large number of non-entrepreneur managers in our sample. Therefore, there is a significant amount of noise in the sample. But we do observe a significant increase in risk and in style extremity after entrepreneurial managers start their own firms. We also observe a slight performance decrease after starting their own firms, which could be a consequence of being distracted by now managing a company in addition to managing funds or managing more funds at the same time.

If we compare the number of funds managed by themselves, we can observe that after starting their own firms, entrepreneurial managers prefer team managed funds. The fraction of sole funds decreases significantly. However, the total number of funds managed increases. A reason for this change could be that entrepreneurs want to have control over their business. Therefore, they oversee fund management by managing many funds in teams.

To the best of our knowledge, our study is the first attempt to link the literature on the economics of entrepreneurship to mutual funds.[54] As such, this paper also contributes to the

[54] For an overview of the literature on the economics of entrepreneurship, see Parker (2004).

literature that focuses on the importance of fund managers' individual characteristics for performance. Recent studies have analyzed the relationship between performance and the career risks of fund managers. Khorana (1996) studies the relationship between fund returns and managerial replacement and documents that the probability of managerial turnover is negatively related to current and past returns. Chevalier and Ellison (1999b) examine managerial replacement in growth and growth-income funds and find that younger fund managers, exposed to greater employment risk, choose lower levels of unsystematic risk than older managers. Deuskar, Pollet, Wang and Zheng (2011) investigate mutual fund managers who join the hedge fund industry. They find that the mutual fund industry retains the best-performing managers by providing them with the opportunity to manage hedge funds at the same time. Mutual fund managers with poor performance and high expense ratios are more likely to leave the mutual fund industry and move entirely to the hedge fund industry. However, fund managers who leave paid employment to start new firms are not explicitly examined in these papers. The literature has largely ignored entrepreneurship as a career path open to fund managers, also neglecting to analyze how the incentives presented by such an option affect their behavior.

Our findings in terms of characteristics of fund managers who will become entrepreneurs bear implications for fund companies, as they allow these companies to estimate the probability that a manager, based on her personal characteristics and past career path, will leave and starts her own firm, thereby becoming a competitor. As fund companies can influence the career paths of their fund managers (e.g. through promotions and compensation packages) they can also influence the probability of a fund manager leaving to start on her own. Our results might also be interesting for investors who want to evaluate the chances that the manager whose fund they bought will actually stay the manager of this fund. Investors are concerned about incurring load fees when entering a fund managed by a particular manager only to find out that the manager leaves after a short while to start her own company.[55] Our results regarding the behavioral changes of entrepreneurial fund managers also have important implications for investors. If they like the investment style of

[55] There is also the possibility that the manager changes funds within the family, which happens quite regularly. However, this is less of a problem for an investor who wants to stay with a particular manager, as most fund families allow their investors to switch funds within the family at no charge (see, e.g., Siggelkow (2003)).

a particular manager and if this manager starts her own firm, the investors might consider following her to the new firm. However, they should be aware of the potential behavioral changes caused by the manager's new role.

The remainder of the paper is organized as follows. The next section introduces the data and methodology. Section 5.3 illustrates our empirical design and the included variables. In Section 5.4 we present empirical results, and the conclusion is contained in Section 5.5.

5.2. Constructing the Dataset

We utilize a unique hand-collected data set of approximately 1,215 entrepreneurs who started their own investment advisory firms between 1980 and 2009 as well as a control sample of 7,855 fund managers who remained employees.[56] To generate the initial list of fund managers that leave established investment companies to set up their own money management firms, we follow two procedures. With our first procedure, we collect the names of all mutual fund companies from the Center for Research in Security Prices (CRSP) survivor bias-free mutual fund database. Then, we identify the startup year and founder information of each mutual fund company that appear for the first time in the database in a specific year by looking at the websites of each company and other information sources, e.g. Morningstar Principia CDs, Lexis-Nexis and Factiva. Our second procedure follows the description in Parwada (2008). Relevant news articles were also searched for in the Lexis-Nexis, Factiva and ABI-Inform databases, supplemented with ADV Forms lodged by fund advisors when they register to practice through the Securities and Exchange Commission's Investment Advisor Public Disclosure. Start-ups and their founders were also identified in fund manager directories and Web sites of mutual fund companies.

In summary, two main advantages in terms of data quality are associated with our approach. Firstly, by identifying entrepreneurs at the point of departing their last employers and forming new firms, the dataset is free of survivorship bias. This is a relevant point, as many new firms close soon after commencing operations (Geroski (1995)) and are thus often

[56] We exclude from our control sample the managers who also manage or will manage hedge funds. The reason is that hedge fund managers could have similar characteristics to entrepreneurial managers. If they are contained in the control sample, our results could be biased.

under-represented in empirical studies based on the current (survived) firm population (e.g. Brockhaus and Horwitz (1980), and Cramer, Hartog, Jonker and Van Praag (2002)). Secondly, we can observe the behavior of would-be entrepreneurs right up to the decision to start on their own, thereby avoiding the problem of many empirical studies that derive results based on data on entrepreneurial behavior long after the occupational choice has been made (Cramer, Hartog, Jonker and Van Praag (2002)).

Table 5.1 summarizes the numbers of new startups and the numbers of entrepreneurs in the time period from 1980 to 2009.

Table 5.1: New startups and founders (1980-2009)

This table presents the total number of new fund companies and the total number of entrepreneurs in the time period 1980-2009. We also report the number of entrepreneurs who are fund managers and the number of entrepreneurs who are equity fund managers.

Number of new fund companies	703
Number of entrepreneurs	1,215
Number of entrepreneurs who are fund managers	688
Number of entrepreneurs who are equity fund managers	558

There are 703 new fund management companies in total, which have been established by 1,215 founders[57]. 688 of those are mutual fund managers who have a fund managing history in CRSP. Equity mutual fund managers make up more than 80% of all founders who are mutual fund managers. Therefore, we concentrate our analyses on the group of founders who manage equity funds. Our control sample consists of all equity fund managers that stay in paid employment. Our data might suffer from right censorship which means that we do not have information about the new startups after 2009. This can lead to a wrong classification of fund managers who will become entrepreneurs after 2009 as non-entrepreneurial managers. However, this right censorship works against finding any differences between entrepreneurs and non-entrepreneurs.

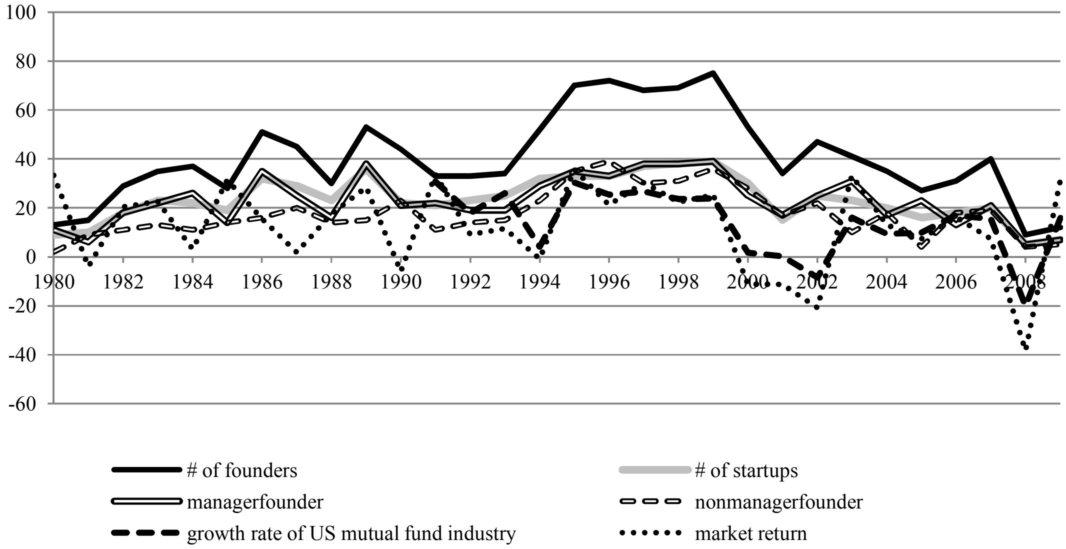
Figure 5.1 depicts the numbers of startups and founders from 1980 to 2009. There is a peak of new startups from 1994 to 2000. Each year there are more than 30 new mutual fund companies. The number of founders also has its highest level during 1994-2000. The graphs of the number of startups and founders have a very similar shape to the growth rate

[57] Founders who have more than one start-up in different years appear multiple times in the sample.

of the mutual fund industry (in percent)[58], which shows that an increase in the size of the mutual fund industry is paired with an increase in the number of startups.[59]

Figure 5.1: Number of startups and founders in different years

This figure depicts numbers of new fund companies and numbers of entrepreneurs in the time period 1980-2009. We split founders into two groups: manager founders who are fund managers and non-manager founders who are not fund managers. Additionally, we also add market return in percent for 1980-2009 from Kenneth French's website and the growth rate of the U.S. mutual fund industry in percent 1991-2009 from the ICI website.



We identify the control sample for our entrepreneurial fund managers primarily from the CRSP mutual fund database and Morningstar Direct Database. The CRSP database does not contain a complete manager history for each fund. Therefore, we use the Morningstar Direct Database to amend the manager history of each fund. We link the two databases by using the CUSIP number of each fund. We also compare the name and inception date of each fund in both databases to make sure that our matching is correct. We associate each fund manager in our entrepreneur and control samples with funds that she manages and obtain returns, total net assets, expense ratios and turnover ratios of these funds from the CRSP mutual fund database. Many funds have multiple share classes with different fee structures. We aggregate share class level data to fund level data. Except for total net assets, all portfolio characteristics are calculated as an asset-weighted average of different share classes. Portfolio total net assets are calculated as the sum of the total net assets of different

[58] We obtain the data of total assets in the US mutual fund industry from the ICI (Investment Company Institute) website.
[59] The correlation between the numbers of new startups and growth rates of the US mutual fund industry is 0.4797. The correlation between the numbers of new startups and lagged growth rates of the US mutual fund industry is 0.4881.

share classes. In order to collect manager characteristics, such as gender, education and date of birth, we use the Morningstar Principia CDs and Capital IQ which also include fund manager biographies. In total, we obtain manager biographies of the 7,855 equity fund managers that comprise our control group.

Table 5.2 presents descriptive statistics of the entrepreneur and control group. Generally, there are no great differences between these groups. The fraction of employed managers with an MBA (52%) is higher in the non-founder group than the one of entrepreneurs (49%). The fraction of founders with a Master's degree other than an MBA (19%) and with PhDs (11%) is higher than that of employed managers (17% and 5%, respectively).

Table 5.2: Founder characteristics vs. non-founder characteristics

This table presents personal characteristics of two groups: the founder group and non-founder group. We only include founders who are equity fund managers in our founder group. Our non-founder group consists of equity fund managers who do not establish their own firms.

	Founder	Non-founder managers
Number	556	7,855
Average date of birth	1,954	1,958
% founders/managers with Bachelor	99%	100%
% founders/managers with MBA	49%	52%
% founders/managers with other Master's	19%	17%
% founders/managers with PhD	11%	5%
% founders/managers with Professional degrees (e.g. CFA, CPA)	48%	50%
Male founders/managers	93%	87%

Furthermore, the data employed in this study to calculate fund performance are the Fama-French factors and the momentum factor obtained from Kenneth French's homepage.[60] We also use the active share data from Antti Petajisto's website.[61]

5.3. Empirical Design

We estimate the probability of identifying an entrepreneurial fund manager from our pooled sample consisting of all fund managers starting their own firm as well as from the control group of non-entrepreneurial managers using probit regression analysis. The dependent variable is $Entrepreneur_{it}$ which takes on the value one if the manager i starts her

[60] The data is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[61] The method used to calculate active share is described in Petajisto (2010) and Cremers and Petajisto (2009).

own firm in year *t*, and zero otherwise. Our model is specified to address five main groups of explanatory variables, which are managerial risk-taking, ability, manager personal characteristics, behavioral measures and reputation.

$$Entrepreneur_{i,t} = F\left(\begin{array}{l} Risk\ Measure \\ +\,Managerial\ Ability \\ +\,Manager\ Charateristics\ (Biological\ Charateristics,\ Experience) \\ +\,Behavioral\ Measures\ (Overconfidence,\ Activeness, \\ \qquad\qquad Utilization\ of\ \ Investment\ \ practics,\ Style\ Extremity) \\ +\,Reputation \\ +\,Control\ Variable \end{array}\right) \tag{5.1}$$

We discuss each group of explanatory variables in turn. If a manager manages different funds at the same time, we calculate the variables as an asset-weighted average of each fund, except TNA and flows, which are calculated as the sum of all funds managed by a certain manager.

First, for each fund linked to a manager in our sample we calculate a total risk measure (*STD*) using the segment-adjusted past standard deviation of the fund return time series in the previous year. Segment-adjusted standard deviation is calculated as the difference between standard deviation of a certain fund and the average standard deviation of all funds in the same segment. If the fund manager ran several funds before starting her own firm, we calculate the riskiness of her strategy by computing the value-weighted average of the individual fund risk measures.

A widely used proxy for managerial ability in the mutual fund industry is the manager's past performance. We employ different measures of fund performance in the previous year like raw returns, returns in excess to peer group returns, Jensen's alphas, Fama-French (1993) three-factor and Carhart (1997) four-factor alphas. In order to determine managers' ability, all performance measures are calculated based on gross returns.[62] If a manager has

[62] We also use net returns to calculate performance measures. The results are similar.

more than one fund, the performance of this manager is calculated as an asset-weighted average of all funds managed by this manager.

We assign the manager characteristics into two groups: sociodemographic characteristics and experience measures. Sociodemographic characteristics include age, gender and education of fund managers. The gender dummy variable takes on the value of one if a manager is male, and zero otherwise. We select dummy variables that take on the value of one if a manager has received a postgraduate university education (MBA degree, other Master's degree or PhD), and zero otherwise. Variations of this measure include an indicator of whether the managers have attained a professional qualification (CIC or CFA). The age of a fund manager is calculated as the difference between the current year and the year of birth of this manager. To measure variation in experience per Lazear (2004), we use total portfolio management experience, which is calculated as the difference between the first appearance year in our database and the current year. We conjecture that longer serving managers would have exposure to a greater range of tasks. Alternative indicators of the manager's experience are the number of funds managed by a fund manager and the number of segments to which funds managed by this manager belong.

Our behavioral measures include variables characterizing portfolio management: turnover ratio, active share, utilization of permitted investment practices and style extremity. If a manager has more than one fund, the variables of this manager in the previous year are calculated as asset-weighted average of all funds managed by this manager. Odean (1998b) shows that overconfident individuals trade too much. Therefore, a manager's asset-weighted segment-adjusted turnover ratio is used as a proxy of her overconfidence. We include active share[63] which is developed by Cremers and Petajisto (2009) to capture the proactiveness[64] and/or innovativeness of fund managers. Active share represents the share of portfolio holdings that differs from the benchmark index. It measures how far funds deviate from their benchmark index. Funds with higher active share pursue more active investment strategies. We also include proxies in terms of investment restrictions:

[63] The time period of active shares is 1990-2006. Therefore, the time period of regression analyses with the variable active share is 1990-2006. We also run all regressions without the variable active share. The results are similar.

[64] Miller and Friesen (1978), Mintzberg (1973) and Lumpkin and Dess (1996) suggest proactiveness and innovativeness as a dimension of an entrepreneurial orientation.

permitted investment activities and the utilization of the permitted investment activities. We follow Almazan, Brown, Carlson and Chapman (2004) and collect the answers to question 70 on Form N-SAR (Form N, Semi-Annual Report) for the period 1994 to 2010.[65] There are two questions in terms of 18 different investment activities: "Permitted by Investment Policies?" and "If permitted by investment policies, engaged in during the reporting period?" By using the answers to these questions we can calculate the investment constraints of portfolios which a fund manager must comply with and the utilization of the permitted investment activities. For example, portfolios with 17 (18) permitted investment practices produce 0.9444[=17/18] (1[=18/18]) as the investment restriction variable. The higher the score, the lower the investment restriction. If a manager engages in 15 out of 18 permitted investment practices, the score for utilization is 0.8333 (=15/18). In our analysis we include a measure of segment-adjusted investment restrictions and segment-adjusted utilization of the permitted investment activities.

In the next step, we examine whether managers follow very extreme or unconventional strategies before starting their own firms. Building on the methodology developed in Bär, Kempf and Ruenzi (2011), we measure the extremeness of the investment style of a fund based on the factor loadings on the four Carhart (1997) factors. This allows us to analyze how ‘unconventional’ the portfolio strategies of future founders are as compared to the other managers in the same market segment.

We also include the media coverage of fund managers in a certain year as a direct measure of the manager's reputation or visibility. In order to form this variable, we collect articles from 49 major newspapers in the U.S. using LexisNexis.[66] Our search of the newspaper articles is based on manager names. In order to reduce the number of articles which are not about a certain fund manager, we combine manager names with words like ‘equity’, ‘stock’, ‘portfolio’, ‘fund’ and ‘investment’ in our search queries. In total, we obtained approximately 165,000 newspaper articles for the time period 1973-2010.

[65] Question 70 on Form N-SAR can be found in Appendix C.
[66] Appendix D lists the newspapers we considered.

We incorporate a number of other control variables that are not directly related to managerial characteristics, but might influence entrepreneurial activity in general. We include the value-weighted CRSP index returns for the NYSE, AMEX, and NASDAQ stocks, annual counts of new IPOs and the growth rate of the mutual fund industry in the U.S.

5.4. Results

5.4.1. Managerial Characteristics of Entrepreneurs

In order to investigate managerial characteristics of entrepreneurs, we run the probit-regression (5.1) described in Section 5.3.1, incrementally including more independent variables. First, we focus on the ability and risk aspect of would-be entrepreneurs. The results are reported in Table 5.3.

We use different performance measures to determine the ability of managers: gross returns, excess peer group returns, Jensen's alphas, Fama-French three factor alphas and Carhart four factor alphas. Apart from the excess peer group return, other performance variables do not show any significant coefficients. We cannot find evidence of a true superior ability of would-be entrepreneurs as compared to non-entrepreneur managers. These results are not consistent with the theories of Lucas (1978), for example, who shows that the individuals with the highest skill become entrepreneurs. The risk measure (segment-adjusted STD) does not show a significant impact on the probability of becoming an entrepreneur. Apparently, there is no significant difference in terms of risk taking between would-be entrepreneurs and non-entrepreneur managers. This finding is not consistent with models of entrepreneurship[67] which show that entrepreneurs are less risk-averse than others. The reason for the insignificant results we obtained could be the still relatively small number of entrepreneur managers, which renders finding reliable estimates more difficult. The control variable annual count of new IPOs is positively correlated with entrepreneurial activity. In a time period with many new IPOs there are also many entrepreneurs who start their own mutual fund companies. The other control variables, total net assets managed, total flows

[67] See McClelland (1961), Lucas (1978), Kanbur (1979) and Kihlstrom and Laffont (1979).

received by fund managers, market return and growth rate of the mutual fund industry, do not show any significant impact.

Table 5.3: Performance and risk of would-be entrepreneurs

This table presents the results of probit regressions. The dependent variable $Entrepreneur_{i,t}$ is a dummy variable which is equal to 1 if manager *i* establishes her own firm in year *t*, and zero otherwise. Different performance measures are gross return, excess peer group return, Jensen's alpha, Fama-French three factor alpha and Carhart four factor alpha in the previous year. They are calculated as asset-weighted average of all funds managed by the manager. Seg_adj_STD indicates asset-weighted segment-adjusted standard deviation of all funds managed by the manager in the previous year. lnsumTNA is the natural logarithm of the sum of net assets of all funds managed by the manager in the previous year. Sum_percentageFlow is the sum of percentage flows of all funds managed by the manager in the previous year. The regression includes the value-weighted CRSP index returns for the NYSE, AMEX, and NASDAQ stocks, annual counts of new IPOs and the growth rate of the mutual fund industry in the U.S. in the previous year. * indicates significance at 10%, ** at 5%, and *** at 1% levels using standard errors clustered at the manager level.

	$Entrepreneur_{i,t}$				
$Gross\_return_{i,t-1}$	0.167 (0.137)				
$Ex\_Peer\_grossret_{i,t-1}$		**0.323**** **(0.145)**			
$Jensenalpha\_gross_{i,t-1}$			-1.615 (3.011)		
$FF\_3alpha\_gross_{i,t-1}$				-1.595 (2.814)	
$C\_4alpha\_gross_{i,t-1}$					-1.592 (2.518)
$seg\_adj\_STD_{i,t-1}$	-0.921 (2.701)	-1.413 (2.837)	-0.583 (2.770)	-0.577 (2.753)	-0.583 (2.757)
$\ln sumTNA_{i,t-1}$	0.005 (0.018)	0.006 (0.018)	0.007 (0.018)	0.007 (0.018)	0.008 (0.018)
$Sum\_percentageFlow_{i,t-1}$	-0.006 (0.007)	-0.006 (0.008)	-0.004 (0.006)	-0.004 (0.006)	-0.004 (0.006)
$Market\_return_{t-1}$	-0.254 (0.245)	-0.113 (0.216)	-0.131 (0.221)	-0.123 (0.221)	-0.128 (0.223)
$No\_of\_IPO_{t-1}$	**0.001***** **(0.000)**	**0.001***** **(0.000)**	**0.001***** **(0.000)**	**0.001***** **(0.000)**	**0.001***** **(0.000)**
$Growth\_rate\_MF_{t-1}$	0.187 (1.099)	0.094 (1.132)	-0.018 (1.139)	-0.004 (1.139)	-0.008 (1.141)
$Constant$	-3.216*** (0.142)	-3.212*** (0.142)	-3.213*** (0.142)	-3.216*** (0.141)	-3.216*** (0.141)
Pseudo R2	0.036	0.037	0.036	0.036	0.036
No. of observation	35,717	35,684	35,717	35,717	35,717

In the next step we analyze whether demographic characteristics, education and experience have an impact on the probability of becoming entrepreneurs.[68] Results are reported in Table 5.4.

[68] In the following analyses we just include one performance measure: gross return. By using different performance measures we obtain consistent results.

Table 5.4: Demographic characteristics, education and experience of would-be entrepreneurs

This table presents the results of probit regressions. The dependent variable $Entrepreneur_{i,t}$ is a dummy variable which is equal to 1 if manager *i* establishes her own firm in year *t*, otherwise zero. Gross_return is equal to net return plus expense ratio. It is calculated asset-weighted average of all funds managed by the manager in the previous year. Seg_adj_STD indicates the asset-weighted segment-adjusted standard deviation of all funds managed by the manager in the previous year. lnsumTNA is the natural logarithm of the sum of net assets of all funds managed by the manager in the previous year. Sum_percentageFlow is the sum of percentage flows of all funds managed by the manager in the previous year. Dummy_gender is equal to 1, if the manager is male. Dummy_mba, Dummy_other_master, Dummy_PhD and Dummy_professional are respectively equal to 1, if the manager has an MBA degree, another Master degree, a PhD degree or another professional degree, such as CFA or CPA. Tenure measures the length of portfolio management experience. No_of_funds is the number of funds managed by the fund manager in the previous year. No_of_seg indicates the number of segments to which funds managed by this manager in the previous year belong. The regression includes the value-weighted CRSP index returns for the NYSE, AMEX, and NASDAQ stocks, annual counts of new IPOs and the growth rate of the mutual fund industry in the U.S. in the previous year * indicates significance at 10%, ** at 5%, and *** at 1% levels using standard errors clustered at the manager level.

	$Entrepreneur_{i,t}$		
	(1)	(2)	(3)
$Gross\_return_{i,t-1}$	0.166	0.164	0.171
	(0.140)	(0.146)	(0.145)
$seg\_adj\_STD_{i,t-1}$	-0.987	-0.517	-0.517
	(2.806)	(2.878)	(2.874)
$\ln sumTNA_{i,t-1}$	0.003	0.007	0.003
	(0.019)	(0.019)	(0.019)
$Sum\_percentageFlow_{i,t-1}$	-0.007	-0.006	-0.006
	(0.008)	(0.007)	(0.008)
Age	-0.003	-0.006	-0.007
	(0.005)	(0.005)	(0.006)
$Dummy\_gender_i$	-0.070	-0.043	-0.047
	(0.106)	(0.109)	(0.109)
$Dummy\_mba_i$		0.139	0.139
		(0.085)	(0.085)
$Dummy\_other\_master_i$		-0.012	-0.010
		(0.115)	(0.115)
$Dummy\_PhD_i$		-0.152	-0.154
		(0.219)	(0.218)
$Dummy\_Professional_i$		**0.162****	**0.161****
		(0.077)	**(0.077)**
$Tenure$			0.005
			(0.007)
$No\_of\_funds_{i,t-1}$			-0.018
			(0.030)
$No\_of\_seg_{i,t-1}$			0.042
			(0.045)
$Market\_return_{t-1}$	-0.268	-0.246	-0.245
	(0.249)	(0.257)	(0.257)
$No\_of\_IPO_{t-1}$	**0.001*****	**0.001*****	**0.001*****
	(0.000)	**(0.000)**	**(0.000)**
$Growth\_rate\_MF_{t-1}$	0.265	-0.231	-0.255
	(1.232)	(1.265)	(1.262)
$Constant$	-2.978***	-3.063***	-3.035***
	(0.242)	(0.260)	(0.277)
Pseudo R2	0.036	0.048	0.049
No. of observation	30,990	30,966	30,966

In regression (1) of Table 5.4 we include age and gender. Both biological variables have no significant impact on entrepreneurial activity. Regression (2) reports the results regarding the impact of education. We only find evidence of a positive impact of the professional qualification dummy. This means that if, ceteris paribus, a manager has a professional designation (e.g. CFA, CPA), she is more likely to start her own firm. This is not the case if we look at other educational degrees like MBA, other Master's degrees or a PhD.

In regression (3) of Table 5.4 we include the proxies for experience: tenure in portfolio management, number of funds managed by the manager, and number of different segments to which managed funds belong. There is no evidence of an impact of our experience proxies. Apparently, the experience of portfolio managers does not increase the probability that they start their own firms.

We now turn to analyses of differences regarding would-be entrepreneurs' behavior and trading activity. We include additional variables like segment-adjusted turnover ratio, active share, utilization of permitted investment practices and style extremity. Table 5.5 presents the results.

Regression (1) of Table 5.5 includes the manager's segment-adjusted turnover ratio. This variable shows a very strong positive impact on the probability of later becoming an entrepreneur. This finding indicates that would-be entrepreneurs are very frequent traders. Based on Odean (1998)'s findings this could be evidence of entrepreneurs' overconfidence. However, turnover ratio is only a rough proxy for overconfidence and the results could also be simply an indication of a would-be entrepreneur being more active. In regression (2) we expand the model by including active share, which is introduced by Petajisto and Cremers (2009). We do find a significant impact of active share, confirming that would-be entrepreneurs are more active. They are more likely to deviate from their benchmark and use more active investment strategies. Regression (3) of Table 5.5 investigates the number and the utilization of permitted investment practices. Both variables are segment adjusted. We find a significant positive impact of utilization. This tells us that would-be entrepreneurs are managers who use the permitted activities to a higher degree than non-entrepreneur managers.[69] By including style extremity as explanatory variables, we also examine whether entrepreneurs follow very extreme or unconventional strategies before starting their own firms. Regression (4) shows that it is not the case. Style extremity does not have a significant influence.

Overall, we can observe a very active profile of would-be entrepreneurs. They trade frequently. They prefer to deviate substantially from their benchmark. They also use the permitted investment activities to a high degree.

Furthermore, a high reputation could be useful for a manager to attract investors once she starts her own company. Therefore, we now examine the impact of reputation on the probability of becoming entrepreneur. To determine reputation we add the variable media coverage. Media coverage of a fund manager refers to the number of newspaper articles which mention this fund manager. First, we examine the short-term media coverage by including media coverage in the previous year (Regression (1) of Table 5.6) and in the previous two years (Regression (2) of Table 5.6).

We find that managers who have significantly higher media coverage in the previous one and two years are more likely to start their own firms. The significantly higher media coverage that we observed for would-be entrepreneurs in the two years before they start their own firm could be due to two possible reasons. On the one hand, would-be entrepreneurs might receive more and more media coverage and become better known by investors, after which they decide to start their own firms. On the other hand, we can also argue that this positive impact means that would-be entrepreneurs plan to start their own firm two years prior to the new startup. Therefore, they try to gain recognition through appearances in newspaper articles in the two years prior to starting their firms. Both cases can lead to the significantly positive impact of media coverage we observes in Regression (1) and Regression (2) of Table 5.6.

In order to find out a more suitable reason, we examine the long-term media coverage by including the media coverage in the previous three years (Regression (3) of Table 5.6), and

[69] The impact of number of restrictions does not differ, meaning that would-be entrepreneurs are not more restricted than non-entrepreneurs; this might have been a reason to start a new firm.

in the previous four years (Regression (4) of Table 5.6). If the first explanation is true we should also observe the significant impact of long-term media coverage. Otherwise, the second explanation is more appropriate. The results of long-term media coverage support our second explanation and show that in the long-term (more than two years) there is no difference in terms of media coverage between would-be entrepreneurs and non-entrepreneurs. Apparently, would-be entrepreneurs are more likely to first have a plan to start their own firms, and then try to improve their reputation by significantly increasing their media coverage, as this could help their business in the future.

Table 5.5: Behavior and trading activity of would-be entrepreneurs

This table presents the results of probit regressions. The dependent variable $Entrepreneur_{i,t}$ is a dummy variable which is equal to 1 if manager *i* establishes her own firm in year *t*, otherwise zero. Gross_return is equal to net return plus expense ratio. It is calculated asset-weighted average of all funds managed by the manager in the previous year. Seg_adj_STD indicates the asset-weighted segment-adjusted standard deviation of all funds managed by the manager in the previous year. lnsumTNA is the natural logarithm of the sum of net assets of all funds managed by the manager in the previous year. Sum_percentageFlow is the sum of percentage flows of all funds managed by the manager in the previous year. Dummy_gender is equal to 1, if the manager is male. Dummy_mba, Dummy_other_master, Dummy_PhD and Dummy_professional are respectively equal to 1, if the manager has an MBA degree, another Master degree, a PhD degree or another professional degree, such as CFA or CPA. Tenure measures the length of portfolio management experience. No_of_funds is the number of funds managed by the fund manager in the previous year. $No\_of\_seg_{i,t}$ indicates the number of segments to which funds managed by this manager in the previous year belong. Seg_adj_Turnover is the asset weighted average of the segment adjusted turnover ratio in the previous year. Activeshare represents the asset weighted average of the shares of portfolio holdings that differ from the benchmark index. It is calculated as the asset-weighted average of all funds managed by this manager in the previous year. Seg_adj_IR indicates the asset-weighted average of the segment adjusted investment restrictions of all funds managed by this manager in the previous year. Seg_adj_Utilization means the asset-weighted average of the segment-adjusted utilization of the permitted investment practices of all funds managed by this manager in the previous year. Style_extremity captures the extremeness of the investment style based of the factor loadings on the four Carhart (1997) factors and is also calculated as asset-weighted average over all funds managed by the manager in the previous year. The regression includes the value-weighted CRSP index returns for the NYSE, AMEX, and NASDAQ stocks, annual counts of new IPOs and the growth rate of the mutual fund industry in the U.S. in the previous year * indicates significance at 10%, ** at 5%, and *** at 1% levels using standard errors clustered at the manager level.

	$Entrepreneur_{i,t}$			
	(1)	(2)	(3)	(4)
$Gross\_return_{i,t-1}$	0.160 (0.146)	0.170 (0.300)	0.279 (0.357)	0.283 (0.358)
$seg\_adj\_STD_{i,t-1}$	-1.423 (2.943)	-1.358 (3.288)	-3.857 (4.131)	-3.095 (4.549)
$\ln sumTNA_{i,t-1}$	0.007 (0.019)	-0.007 (0.025)	0.021 (0.031)	-0.024 (0.031)
$Sum\_percentageFlow_{i,t-1}$	-0.007 (0.008)	-0.014 (0.015)	-0.007 (0.009)	-0.008 (0.009)
Age	-0.007 (0.006)	-0.009 (0.007)	-0.003 (0.010)	-0.003 (0.010)
$Dummy\_gender_i$	-0.047 (0.109)	0.048 (0.148)	0.028 (0.180)	0.031 (0.180)
$Dummy\_mba_i$	0.143* (0.085)	0.171 (0.109)	0.111 (0.128)	0.106 (0.127)
$Dummy\_other\_master_i$	-0.008 (0.116)	0.003 (0.152)	-0.097 (0.191)	-0.095 (0.191)
$Dummy\_PhD_i$	-0.156 (0.219)	0.036 (0.239)	0.188 (0.244)	0.184 (0.243)
$Dummy\_Professional_i$	**0.169**** **(0.078)**	0.135 (0.094)	**0.217*** **(0.122)**	**0.216*** **(0.122)**
$Tenure$	0.006 (0.007)	0.008 (0.008)	0.005 (0.010)	0.005 (0.010)
$No\_of\_funds_{i,t-1}$	-0.019 (0.031)	-0.015 (0.033)	-0.019 (0.038)	-0.017 (0.037)
$No\_of\_seg_{i,t-1}$	0.040 (0.045)	0.056 (0.045)	0.063 (0.051)	0.063 (0.050)
$seg\_adj\_Turnover_{i,t-1}$	**0.072***** **(0.022)**	**0.100***** **(0.035)**	**0.081**** **(0.037)**	**0.083**** **(0.037)**
$Activeshare_{i,t-1}$		**0.675**** **(0.278)**	**0.583*** **(0.307)**	**0.607*** **(0.319)**
$seg\_adj\_IR_{i,t-1}$			0.349 (0.328)	0.341 (0.334)
$seg\_adj\_Utilization_{i,t-1}$			**0.565*** **(0.337)**	**0.561*** **(0.340)**
$Style\_Extremity_{i,t-1}$				-0.094 (0.108)
$Market\_return_{t-1}$	-0.245 (0.258)	-0.330 (0.385)	-0.805* (0.424)	-0.817* (0.426)
$No\_of\_IPO_{t-1}$	**0.001***** **(0.000)**	**0.001***** **(0.000)**	**0.001***** **(0.000)**	**0.001***** **(0.000)**
$Growth\_rate\_MF_{t-1}$	-0.311 (1.288)	1.403 (1.689)	2.699 (2.331)	2.681 (2.333)
$Constant$	-3.054*** (0.277)	-3.330*** (0.455)	-3.526*** (0.572)	-3.444*** (0.554)
Pseudo R2	0.054	0.059	0.078	0.079
No. of observation	30,766	14,620	10,677	10,677

Table 5.6: Media coverage of would-be entrepreneurs

This table presents the results of probit regressions. The dependent variable $Entrepreneur_{i,t}$ is a dummy variable which is equal to 1 if manager *i* establishes her own firm in year *t*, otherwise zero. Gross_return is equal to net return plus expense ratio. It is calculated asset-weighted average of all funds managed by the manager in the previous year. Seg_adj_STD indicates the asset-weighted segment-adjusted standard deviation of all funds managed by the manager in the previous year. lnsumTNA is the natural logarithm of the sum of net assets of all funds managed by the manager in the previous year. Sum_percentageFlow is the sum of percentage flows of all funds managed by the manager in the previous year. Dummy_gender is equal to 1, if the manager is male. Dummy_mba, Dummy_other_master, Dummy_PhD and Dummy_professional are respectively equal to 1, if the manager has an MBA degree, another Master degree, a PhD degree or another professional degree, such as CFA or CPA. Tenure measures the length of portfolio management experience. No_of_funds is the number of funds managed by the fund manager in the previous year. $No\_of\_seg_{i,t}$ indicates the number of segments to which funds managed by this manager in the previous year belong. Seg_adj_Turnover is the asset weighted average of the segment adjusted turnover ratio in the previous year. Activeshare represents the asset weighted average of the shares of portfolio holdings that differ from the benchmark index. It is calculated as the asset-weighted average of all funds managed by this manager in the previous year. Seg_adj_IR indicates the asset-weighted average of the segment adjusted investment restrictions of all funds managed by this manager in the previous year. Seg_adj_Utilization means the asset-weighted average of the segment-adjusted utilization of the permitted investment practices of all funds managed by this manager in the previous year. Style_extremity captures the extremeness of the investment style based of the factor loadings on the four Carhart (1997) factors and is also calculated as asset-weighted average over all funds managed by the manager in the previous year. $Media\_Coverage_{i,t-1;t-n}$ indicates the number of newspaper articles in the previous n years which mention manager i. The regression includes the value-weighted CRSP index returns for the NYSE, AMEX, and NASDAQ stocks, annual counts of new IPOs and the growth rate of the mutual fund industry in the U.S. in the previous year * indicates significance at 10%, ** at 5%, and *** at 1% levels using standard errors clustered at the manager level.

	$Entrepreneur_{i,t}$			
	(1)	(2)	(3)	(4)
$Gross\_return_{i,t-1}$	0.241	0.223	0.203	0.103
	(0.388)	(0.393)	(0.418)	(0.491)
$seg\_adj\_STD_{i,t-1}$	-3.838	-4.068	-3.384	-3.996
	(4.697)	(4.722)	(4.695)	(5.285)
$\ln sumTNA_{i,t-1}$	-0.044	-0.046	-0.034	-0.0129
	(0.030)	(0.030)	(0.031)	(0.033)
$Sum\_percentageFlow_{i,t-1}$	-0.014	-0.015	-0.016	-0.020
	(0.013)	(0.013)	(0.015)	(0.015)
Age	-0.005	-0.005	-0.007	-0.014
	(0.010)	(0.010)	(0.010)	(0.012)
$Dummy\_gender_i$	0.011	0.017	0.010	0.053
	(0.180)	(0.182)	(0.185)	(0.210)
$Dummy\_mba_i$	0.123	0.126	0.103	0.197
	(0.131)	(0.132)	(0.134)	(0.155)
$Dummy\_other\_master_i$	-0.077	-0.073	-0.061	-0.231
	(0.192)	(0.192)	(0.194)	(0.246)
$Dummy\_PhD_i$	-0.027	-0.026	-0.023	0.063
	(0.326)	(0.331)	(0.333)	(0.339)
$Dummy\_professional_i$	**0.279****	**0.286****	**0.268****	0.228
	(0.130)	**(0.131)**	**(0.134)**	(0.140)
$Tenure$	0.006	-0.001	-0.009	-0.011
	(0.011)	(0.012)	(0.014)	(0.015)
$No\_of\_funds_{i,t-1}$	-0.009	-0.011	-0.017	-0.019
	(0.024)	(0.026)	(0.030)	(0.034)
$No\_of\_seg_{i,t-1}$	0.060	0.060	0.078*	0.073
	(0.038)	(0.040)	(0.044)	(0.049)
$seg\_adj\_Turnover_{i,t-1}$	**0.086*****	**0.092*****	**0.088****	**0.131****
	(0.037)	**(0.041)**	**(0.041)**	**(0.064)**
$Activeshare_{i,t-1}$	**0.572***	**0.582****	**0.638***	0.531
	(0.324)	**(0.325)**	**(0.345)**	(0.352)
$seg\_adj\_IR_{i,t-1}$	0.294	0.299	0.423	0.218
	(0.344)	(0.347)	(0.369)	(0.383)
$seg\_adj\_Utilization_{i,t-1}$	**0.611***	**0.636***	**0.845***	**0.823****
	(0.357)	**(0.361)**	**(0.373)**	**(0.384)**
$Style\_Extremity_{i,t-1}$	-0.081	-0.082	-0.057	-0.079
	(0.110)	(0.111)	(0.111)	(0.131)
$Media\_Coverage_{i,t-1}$	**0.022****			
	(0.010)			
$Media\_Coverage_{i,t-1;t-2}$		**0.012****		
		(0.006)		
$Media\_Coverage_{i,t-1;t-3}$			0.001	
			(0.005)	
$Media\_Coverage_{i,t-1;t-4}$				-0.001
				(0.005)
Pseudo R2	0.084	0.087	0.087	0.094
No. of observation	10,290	9,397	8,469	7,406

5.4.2. Change in Behavior Due to the Transition from Agent to Principal

In this section, we investigate whether there is a time variation in the behavior of entrepreneurs prior to and after the new firm formation date. Specifically, we analyze how risk-taking, conventionalism of the portfolio strategy, performance, turnover ratio, active share, utilization of investment practices, total net asset managed and flows obtained all can change after fund managers start their own firm. First, we calculate the average value of proxies prior to and after the formation date by using all available yearly observations for each entrepreneur. Afterwards, we calculate the difference before and after starting the new firm for each entrepreneur. Then, we calculate the average of the differences across all entrepreneurs. As we have to aggregate and compare the behavior of identical managers prior to and after their startups, we can only perform our analyses with entrepreneurs who manage funds before as well as after they start their own firms. As the number of such entrepreneurs is very small, we limit our analyses to univariant analyses and restrict ourselves to indicative evidence. Table 5.7 presents the results.

After entrepreneurs start their own firm, active share and turnover ratio do not change significantly. However, we can observe a significant increase in total risk (by 0.0130) and idiosyncratic risk (by 0.0024) of the funds they managed. Additionally, they use more extreme strategies to manage their funds in their own companies. The overall style extremity increases by 0.1948. If we separate the overall style extremity into SMB, HML and MOM style extremity, we can observe an increase in all style extremity dimensions. Overall, entrepreneur managers become more aggressive after they start their own business.

Looking at different performance measures, we can observe a significant decrease in average one-year gross return and one-year excess peer group gross return. These results imply that after the establishment of their own firms, managers might not be able to fully concentrate on the portfolio management task due to their much broader range of duties. Overconfidence could be another potential explanation. Would-be entrepreneurs are overconfident and believe that they can do better if they are less constrained. Thus, they start their own firm and manage their own funds. However, it turns out that they are not performing better but rather worse than before. However, we cannot confirm the performance reduction if we look at 1-, 3- and 4-factor alphas. This latter finding should not be over-interpreted, as it might be due to lack of statistical power, as alphas are imperfect estimates.[70]

Additionally, we can also observe that after entrepreneurs start their own firms the fraction of sole managed funds is reduced by 11.79%. In the meantime, the total number of funds managed increases. Therefore, the sum of the proportional assets managed does not change significantly. Apparently, entrepreneur managers prefer to control more funds, which is possible with their own fund companies. Due to limited time and capacity they can only participate in managing funds by setting them up as team-managed funds.

Table 5.7: Average before vs. average after

This table presents the results of a before-and-after comparison. All characteristics are calculated as average of observations (manager-year) prior to and after startups. Difference is calculated as Before average characteristics minus After average characteristics for one manager. Then, we calculate the average across all managers and use the t-test to check whether the differences are significantly different from zero.

	No of entrepreneurs	Difference (before-after)
$Gross\_return$	94	**0.0844*****
Ex_peer_gross	94	**0.0175***
$Jensenalpha\_gross$	94	-0.0013
FF_3alpha_gross	94	0.0007
C_4alpha_gross	94	0.0007
STD	96	**-0.0130*****
seg_adj_STD	96	-0.0013
β^{market}	96	-0.0405
$\sigma(\varepsilon)$	96	**-0.0024****
$seg\_adj\_Turnover$	92	-0.1431
$Activeshare$	39	-0.0005
seg_adj_IR	62	0.0425
$seg\_adj\_Utilization$	62	0.0144
$Style\_extremity$	96	**-0.1948*****
$Style\_extremity\_SMB$	96	**-0.2182****
$Style\_extremity\_HML$ $Style\_extremity\_HML$	96	**-0.1628****
$Style\_extremity\_MOM$	96	**-0.1948*****
$fraction\_of\_sole\_funds$	107	**0.1179****
$Sum\_percentageFlow$	83	0.2011
$sumTNA$	107	-116.3178
$sum\_proportional\_TNA$	107	7.6955
No_of_funds	107	**-0.3264***

[70] This might also lead to an Error-In-Variable problem.

There are three major conclusions that we draw from the evidence presented in Table 5.7. First, after they start their own firms, entrepreneurs increase funds' total risk and idiosyncratic risk significantly and use more extreme investment strategies. Second, entrepreneurs manage more funds than before in total, but more team-managed funds instead of sole-managed funds. Third, we can also observe evidence of a performance decrease, which might be explained by market return mean reversion. There are no significant changes in assets managed, flows obtained, turnover ratios and active shares.

5.5. Conclusion

Our research investigates entrepreneurship in the mutual fund industry for the first time. We concentrate on characteristics of would-be entrepreneurs and behavioral changes after they start their own firms.

Conforming to the entrepreneur literature we find that entrepreneurs in the mutual fund industry are proactive, innovative and overconfident. They pursue active management strategies and trade more frequently as compared to non-entrepreneurial managers. They are managers with higher media coverage in the past, which helps them to start their own firms and attract investors. Inconsistent with predictions from the theoretical literature, we do not find evidence of high risk taking of would-be entrepreneurs as compared to non-entrepreneur managers. Investigations in terms of behavioral changes show that after entrepreneurs start their own firms they raise their risk levels significantly and use more extreme strategies. We also find a slight performance decrease after they start their own business. Additionally, they prefer team-managed funds instead of sole-managed funds and tend to manage a greater total number of funds.

Overall, these results are a first step in shedding more light on the characteristics, behavior and career path of entrepreneurial managers. The effect we document can be a starting point for a more thorough investigation of entrepreneurship as an alternative career path in the asset management industry.

Appendices

Appendix A: Classification of investment objectives into different asset classes

Asset classes	**Investment objectives**
Domestic Equity	Aggressive Growth, Growth, Sector, Growth and Income, Income Equity
Foreign Equity	Emerging Markets, Global Equity, International Equity, Regional Equity
Hybrid	Asset Allocation, Balanced, Flexible Portfolio, Income Mixed
Taxable Domestic Bond	Corporate-General, Corporate-Intermediate, Corporate-Short Term, High Yield, Government Bond-General, Government Bond-Intermediate, Government Bond-Short Term, Mortgaged Backed, Strategic Income
Foreign Bond	Global Bond-General, Global Bond-Short Term, Other World Bond
Municipal Bond	State Municipal Bond-General, State Municipal Bond-Short Term, National Municipal Bond-General, National Municipal Bond-Short Term
Taxable Money Market	Taxable Money Market-Government, Taxable Money Market-Non-Government
Municipal Money Market	National Tax-Exempt Money Market, State Tax-Exempt Money Market

Appendix B: Calculation of the overall return

Method 1 is described below. First, I estimate the return on all positive net cash flows. The dollars into any asset class in month *t* are multiplied by the return on that asset class in a subsequent period. This is summed across all asset classes for all periods and divided by total positive net cash flows to all asset classes in all periods. This is the average return earned on positive net cash flows over the entire sample period and is written as:

$$R^{pos} = \frac{\sum_i \sum_t PosNF_{i,t-1} \cdot r_{i,t}^h}{\sum_i \sum_t PosNF_{i,t-1}}. \tag{1}$$

$PosNF_{i,t-1}$ is positive net flows in asset class i in month t-1. $r_{i,t,}^{h}$ is the h-month return on asset class i in the subsequent h months. i represents only asset classes which have positive net cash flows in month t-1.

Second, I calculate the average return on negative net cash flows over the sample period by using the same procedure, except for the reversed sign. This is the return an investor gets by disinvesting (taking money out of an asset class) and is written as:

$$R^{neg} = -\frac{\sum_j \sum_t \left|NegNF_{j,t-1}\right| \cdot r_{j,t}^h}{\sum_j \sum_t \left|NegNF_{j,t-1}\right|}. \tag{2}$$

$NegNF_{i,t-1}$ is the negative net flows in asset class j in month t-1. $r_{j,t,}^{h}$ is the h-month return on asset class j in subsequent h months. j represents only asset classes which have negative net cash flows in month t-1.

The first method to calculate the overall return on new cash flows is a weighted average of returns on positive cash flows and negative cash flows. The weights are respectively the sum of positive cash flows and the sum of absolute negative cash flows divided by the sum of the two. This overall return is written as:

$$R^{overall} = R^{pos} \cdot \frac{\sum_i \sum_t PosNF_{i,t-1}}{\sum_i \sum_t PosNF_{i,t-1} + \sum_j \sum_t \left|NegNF_{j,t-1}\right|} + R^{neg} \cdot \frac{\sum_j \sum_t \left|NegNF_{j,t-1}\right|}{\sum_i \sum_t PosNF_{i,t-1} + \sum_j \sum_t \left|NegNF_{j,t-1}\right|},$$

where R^{pos} is given by (1) and R^{neg} by (2). For the entire sample period I obtain only one overall return.

Method 2 focuses on the asset allocation ability within each month. I first estimate the return on positive net cash flows in month t. The dollars into any asset class in month t are multiplied by the h-month return on that asset class in a subsequent period. This is summed up across all asset classes for month t and divided by the sum of positive net cash flows to all asset classes in month t. This is the average return earned on positive net cash flows in month t and is written as:

$$R_t^{pos} = \frac{\sum_i PosNF_{i,t-1} \cdot r_{i,t}^h}{\sum_i PosNF_{i,t-1}}.$$

The same procedure is followed for negative net cash flows. Again, the sign is reversed. This is the average return an investor gets by disinvesting in month t and is written as:

$$R_t^{neg} = -\frac{\sum_j \left|NegNF_{j,t-1}\right| \cdot r_{j,t}^h}{\sum_j \left|NegNF_{j,t-1}\right|}.$$

The return on new cash flows in month t is again defined as a weighted average of the return on positive cash flows in month t and negative cash flows in month t. The weights are the sum of positive net cash flows in month t and the sum of absolute negative net cash flows in month t respectively divided by the sum of the two. This return on new cash flows in month t is written as:

$$R_t^{overall} = R_t^{pos} \bullet \frac{\sum_i PosNF_{i,t-1}}{\sum_i PosNF_{i,t-1} + \sum_j \left|NegNF_{j,t-1}\right|} + R_t^{neg} \cdot \frac{\sum_j \left|NegNF_{j,t-1}\right|}{\sum_i PosNF_{i,t-1} + \sum_j \left|NegNF_{j,t-1}\right|}.$$

I calculate the return on cash flows for each month and get a time series of cash flow portfolio returns. The overall return on new cash flows in method 2 is equal to the average of the return on new cash flows across the entire sample period. The average value across the entire sample period ignores the difference in total investments in different months.

Appendix C: Question 70 on Form N-SAR

70. Investment practices
Answer "Y" (Yes) or "N" (No) to the following:

	Permitted by Investment Policies? Y/N	If permitted by investment policies, engaged in during the reporting period? Y/N
A. Writing or investing in repurchase agreements		
B. Writing or investing in options on equities		
C. Writing or investing in options on debt securities		
D. Writing or investing in options on stock indicies		
E. Writing or investing in interest rate futures		
F. Writing or investing in stock index futures		
G. Writing or investing in options on futures		
H. Writing or investing in options on stock index future		
I. Writing or investing in other commodity futures		
J. Investments in restricted securities		
K. Investments in shares of other investment companies		
L. Investments in securities of foreign issuers		
M. Currency exchange transactions		
N. Loaning portfolio securities		
O. Borrowing of money		
P. Purchases/sales by certain exempted affiliated persons		
Q. Margin purchases		
R. Short selling		

Appendix D: Newspapers for media coverage of fund managers

We include following newspapers to collect the media coverage of each fund manager:

Newspapers	
Atlanta Journal and Constitution	The Philadelphia Inquirer
Denver Post	The Plain Dealer
Houston Chronicle	The Star-Ledger (Newark, NJ)
Las Vegas Review-Journal	The Record (Bergen)
Minneapolis Star Tribune	The Boston Herald
New Orleans Times Picayune	Austin American-Statesman
New York Times	The Augusta Chronicle
Pittsburgh Post-Gazette	Tulsa World
Sacramento Bee	Salt Lake Tribune
San Antonio Express-News	Palm Beach Post
San Diego Union-Tribune	Richmond Times Dispatch
San Francisco Chronicle	Buffalo News
Seattle Post-Intelligencer	Dayton Daily News
St. Louis Post-Dispatch	Wisconsin State Journal
St. Petersburg Time	Birmingham News
Washington D.C. Post	The Providence Journal
USA Today	Arkansas Democrat-Gazette
Wall Street Journal	Tampa Tribune
Chicago Sun-Times	The Oklahoman
Daily News (New York)	The Virginian-Pilot
The Dallas Morning News	The Santa Fe New Mexican
The Kansas City Star	Phoenix New Times
New York Post	Fresno Bee
San Jose Mercury News (California)	Christian Science Monitor
The Oregonian	

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Lebenslauf

Studium

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Publikationen

03/2011	Entrepreneurship in the Mutual Fund Industry (mit Stefan Ruenzi und Jerry Parwada)
09/2010	Rapid Trading bei deutschen Aktienfonds: Evidenz aus einer großen deutschen Fondsgesellschaft (mit Stefan Ruenzi), in Zeitschrift für Betriebswirtschaft, Vol. 80(9), S.883-920
02/2010	Smart or Dumb? Asset Allocation Ability of Mutual Fund Investors and the Role of Broker Advice
02/2010	Fund Manager Allocation (mit Alexander Kempf und Monika Trapp)
11/2007	China Knigge-Business und Interkulturelle Kommunikation, Beck Wirtschaftsberater (mit Edith Diekmann, 1. Auflage November 2007)