Quantitatives Controlling

Hrsg.: Carsten Homburg

Ute Bonenkamp

Combining Technical and Fundamental Trading Strategies

Profits, Market Reactions, and Use by Professional Investors

GABLER

RESEARCH

Ute Bonenkamp

Combining Technical and Fundamental Trading Strategies

GABLER RESEARCH

Quantitatives Controlling

Herausgegeben von Professor Dr. Carsten Homburg,
Universität zu Köln

Die Schriftenreihe dient als Forum für hervorragende Forschungsergebnisse auf dem Gebiet des Controlling. Ihr liegt ein weites Controllingverständnis zugrunde, das über Problemstellungen der traditionellen internen Unternehmensrechnung hinaus geht und beispielsweise auch Aspekte der Verhaltenssteuerung einschließt.

Der Schwerpunkt der Reihe liegt auf quantitativen Analysen aktueller Controllingfragen. Hierbei werden formal-analytische ebenso wie empirisch ausgerichtete Arbeiten in Betracht gezogen.

Ute Bonenkamp

Combining Technical and Fundamental Trading Strategies

Profits, Market Reactions, and Use by Professional Investors

With a preface by Prof. Dr. Carsten Homburg

GABLER

RESEARCH

Bibliographic information published by the Deutsche Nationalbibliothek
The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available in the Internet at http://dnb.d-nb.de.

Dissertation University of Cologne, 2010

1st Edition 2010

Editorial Office: Ute Wrasmann | Stefanie Loyal

Gabler Verlag ist eine Marke von Springer Fachmedien.
Springer Fachmedien ist Teil der Fachverlagsgruppe Springer Science+Business Media.
www.gabler.de

Umschlaggestaltung: KünkelLopka Medienentwicklung, Heidelberg
Printed on acid-free paper
Printed in Germany

ISBN 978-3-8349-2597-8

Geleitwort

Die vorliegende Dissertationsschrift basiert auf der Grundidee, Aktien mit besonderem Kurspotential herauszufiltern. Prinzipiell bieten sich hierzu zwei Strategien an, die auf unterschiedlichen Prämissen fußen: die technische und die fundamentale Anlage. Die technische Anlage setzt auf die Fortsetzung bestehender Trends und verfolgt einen kurz- bis mittelfristigen Anlagehorizont. Die fundamentale Anlage hingegen zielt darauf ab, unterbewertete Aktien zu finden, um mittel- bis langfristig an deren Kursentwicklung hin zum fairen Preis zu partizipieren.

In der Arbeit werden beide Anlagestrategien mit der Absicht kombiniert, komplementäre Effekte in Bezug auf die resultierenden Renditen zu erreichen. Hierzu wird exemplarisch auf zwei zentrale Strategien zurückgegriffen: die technische Momentumstrategie und die fundamentale Cashflowstrategie. Das heißt, Aktien mit hoher vergangener Rendite und hohen operativen Cashflows werden gekauft und Aktien mit geringer vergangener Rendite und geringen operativen Cashflows werden (leer)verkauft. Die Dissertationsschrift untersucht empirisch, inwieweit eine kombinierte Strategie zum Erfolg führt.

Insbesondere wird empirisch gezeigt, dass eine Strategie, die auf hohen vergangenen Renditen und hohen operativen Cashflows basiert, eine signifikant positive risikoadjustierte Rendite (Überrendite) abwirft, die die Überrenditen „reiner" Momentum- und Cashflowstrategien übersteigt. Ebenso wirft eine Anlage in Aktien mit geringen vergangenen Renditen und geringen Cashflows signifikant negative risikoadjustierte Renditen ab. Diese risikoadjustieren Renditen widersprechen der Effizienz der Märkte und führen somit zu der Frage, welche inadäquaten Reaktionen des Marktes verantwortlich waren. Diesem Problem widmet sich die Arbeit ebenfalls.

Weiterhin wird in der Dissertation der Frage nachgegangen, warum die zu erzielenden Überrenditen nicht durch Handel auf diese Effekte verschwinden und ob Akteure an den Kapitalmärkten entsprechend dieser Effekte investieren. Insbesondere sollten professionelle Anleger die Effekte kennen und versuchen sie auszunutzen.

Das Ergebnis, dass eine Kombinationsstrategie erfolgreicher ist als reine Momentum- und Cashflowstrategien wird Investoren in der Praxis dazu ermuntern, ihre Anlageentscheidungen auf beide Informationsquellen zu stützen, bzw. sogar die hier untersuchte spezifische Anlagestrategie umzusetzen. Für Akademiker bedeuten die Ergebnisse, dass vergangene Renditen und Cashflows beide dazu beitragen, zukünftige Renditen zu prognostizieren, so dass in Prognosemodellen stets beide Variablen berücksichtigt werden sollten.

Zusammenfassend leistet die Arbeit zahlreiche neue Überlegungen und erzielt Ergebnisse, die für Praxis und Forschung gleichermaßen von Interesse sind. Die Arbeit besticht auch durch ihre klare Struktur und das überzeugende empirische Handwerk. Ihr ist deshalb eine gute Aufnahme in der Controlling-Community zu wünschen.

Prof. Dr. Carsten Homburg

Vorwort

Die vorliegende Arbeit entstand während meiner Tätigkeit als wissenschaftliche Mitarbeiterin am Controllingseminar der Universität zu Köln. Nach erfolgreichem Abschluss meiner Dissertation möchte ich die folgenden Zeilen dazu nutzen, den Personen herzlich zu danken, die zum Gelingen der Arbeit beigetragen haben.

Meinem Doktorvater und akademischen Lehrer, Herrn Prof. Dr. Carsten Homburg, danke ich für seine vielfältige Unterstützung. Er hat den Anstoß für diese Arbeit gegeben und in zahlreichen Diskussionen meine Ideen hinterfragt, unterstützt und vorangebracht. Besonders motiviert hat mich das Vertrauen, welches er mir entgegengebracht hat, indem er mir große Freiheiten bei der Erstellung meiner Arbeit eingeräumt hat. Weiterhin danke ich dem Förderverein des Controllingseminars. Allein die finanziellen Mittel des Fördervereins haben meine Reisen zu internationalen wissenschaftlichen Konferenzen und auch den Zugriff auf das empirische Datenmaterial möglich gemacht.

Mein weiterer Dank gilt Herrn Prof. Dr. Alexander Kempf für die Übernahme des Zweitgutachtens sowie für sehr lehrreiche Diskussionen in angenehmer Atmosphäre. Ich weiß sehr zu schätzen, wie viel Zeit er sich für mich genommen hat und wie stark er sich in die Forschungsarbeit eingebracht hat. Weiterhin danke ich ihm für die Zurverfügungstellung der Investmentfondsdatenbank. In diesem Zusammenhang gilt zudem Tanja Thiele großer Dank für die hervorragende Vorarbeit, die sie bei der Aufbereitung dieser Datenbank geleistet hat. Herrn Prof. Dr. Ludwig Kuntz danke ich sehr für den Vorsitz bei meiner Disputation.

Weiterhin danke ich meinen Lehrstuhlkollegen Daniel Baumgarten, Max Berens, Marcus Berghäuser, Ulf Brüggemann, Tanja Klettke, Michael Lorenz, Sebastian Gell, Dominika Gödde, Stefan Henschke, Julia Nasev und Philipp Plank. Wir hatten eine wunderschöne gemeinsame Zeit am Lehrstuhl, während der die gegenseitige Unterstützung immer an erster Stelle stand. Besonders bedanken möchte ich mich bei Michael Lorenz. Unsere Zusammenarbeit im Grundstudium hätte ich mir nicht besser wünschen können und seine Unterstützung während der Endphase meiner Dissertation war einmalig. Weiterer Dank gilt den studentischen Hilfskräften des Lehrstuhls, die unermüdlich ihre Hilfe angeboten haben und durch so viele große und kleine Dinge einen sehr wichtigen Beitrag zu meiner Dissertation geleistet haben. Mein besonderer Dank gilt Elisabeth Eich, der guten Seele des Seminars. Sie schafft mit ihrer unvergleichlichen Art mit so viel Herz und Kraft eine wunderbare Atmosphäre am Lehrstuhl, in der man sich nur wohlfühlen kann. Ihr Verständnis und ihre Unterstützung waren einmalig und unbezahlbar.

Weiterhin danke ich Herrn Jochen Menge, der die Arbeit sprachlich auf Herz und Nieren geprüft hat. Außerdem Dank an meinen Freundeskreis, der immer an mich geglaubt und mich unterstützt hat.

Privat gilt mein besonderer Dank meinem Freund Tobias. Er hat meine Arbeit mit Engelsgeduld sowohl fachlich als auch sprachlich vorangebracht. Viel wichtiger war jedoch, dass er es geschafft hat, mir Ruhe und auch die oft nötige Sicherheit zu geben. Hierfür kann ich ihm gar nicht genug danken. Weiterhin danke ich meiner Familie: meinen Eltern Heiko und Hannelore Bonenkamp, meinen Großeltern Jakob und Anneliese Kürten, meiner Schwester Eva Lange und ihrem Mann Markus. Eure Liebe und Unterstützung und auch Euer Verständnis waren der Grundstein für mein Studium und meine Dissertation. Ohne Euch wäre nichts davon möglich gewesen! Schließlich danke ich meinem Neffen Jakob und meiner Nichte Annika für viele glückliche Stunden fernab von der Welt der Universität und für die Erinnerung an die Dinge, die wirklich wichtig sind.

Ute Bonenkamp

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AMEX	American Stock Exchange
AMH	Adaptive Market Hypothesis
bp	basis points
CRSP	Center for Research in Security Prices
CSI	Compustat Item
e.g.	exempli gratia (for example)
EMH	Efficient Market Hypothesis
EP	Evaluation Period
etc.	et cetera
et al.	et alii (and others)
excl.	excluding
exp.	expected
FMB	Fama MacBeth
G	Growth
G&I	Growth & Income
G7	Group of Seven
I	Income
ICI	Investment Company Industry
i.e.	id est (that is)
Inc.	Incorporated
incl.	including
IP	Investment Period
MBA	Master of Business Administration
mfs1%	mutual fund sample 1 % which includes only stocks that are at least included in 1 % of the mutual funds at the given time point
mfs3%	mutual fund sample 3 % which includes only stocks that are at least included in 3 % of the mutual funds at the given time point
mio.	million
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
OR	Overreaction
p.	page
pp.	pages

p.a.	per annum
p.m.	per month
p.q.	per quarter
regr	regression
SC&AG	Small Cap & Aggressive Growth
SEC	Securities and Exchange Commission
S&P 500	Standard & Poor's 500
UR	Underreaction
US	United States
Vol.	Volume

List of Symbols

Latin Symbols

$abnreturn_{i(j)}$	abnormal return of stock *i* or (fund)portfolio *j*
$abnreturn^{Combi}$	*abnreturn* of the combination portfolio *Combi55*
$abnreturn^{Combi+}$	mean *abnreturn* of stocks with $abnreturn_i > 0$ in portfolio *Combi55*
$abnreturn^{Combi-}$	mean *abnreturn* of stocks with $abnreturn_i \leq 0$ in portfolio *Combi55*
$abnreturn^{Mom}$	*abnreturn* of portfolio *Mom5*
$abnreturn^{Mom+}$	mean *abnreturn* of stocks with $abnreturn_i > 0$ in portfolio *Mom5*
$abnreturn^{Mom-}$	mean *abnreturn* of stocks with $abnreturn_i \leq 0$ in portfolio *Mom5*
$abnreturn_j^{+}$	mean positive abnormal return of (fund)portfolio *j*
$abnreturn_j^{-}$	mean negative abnormal return of (fund)portfolio *j*
acc_i	accruals of firm *i*, computed using the cash flow statement approach
$accdec_i$	deciles of acc_i
$accruals_i$	accruals of firm *i*, computed using the balance sheet approach
ad	day of the earnings announcement
$adj.R^2$	adjusted coefficient of determination
$alpha_j$	Fama French 3-factor alpha of portfolio *j*
ap	three-days earnings announcement period
$attention_i$	investor attention stock *i* has attracted during the past seven months
bm	benchmark
$btom_i$	book-to-market of firm *i*
ca_i	current assets of firm *i*
$cashflow_i$	operating cash flow per average assets computed by the balance sheet approach of firm *i*
cfo_i	quarterly operating cash flow per average assets of firm *i*, using the operating cash flow from the cash flow statement
$cfodec_i$	decile in terms of cfo_i
$Cfo1$	portfolio of stocks belonging to the 20 % with lowest cfo_i

$Cfo5$	portfolio of stocks belonging to the 20 % with highest cfo_i
$CfoFund_j$	measure of fund j's cash flow strategy
$CfoFundDec_j$	deciles in terms of $CfoFund_j$
cl_i	current liabilities of firm i
$combi_i$	combination characteristic of firm i
$Combi11$	portfolio of stocks at the same time belonging to the 20 % with lowest cfo_i and with lowest mom_i
$Combi55$	portfolio of stocks at the same time belonging to the 20 % with highest cfo_i and with highest mom_i
$CombiFund_j$	measure of fund j's combination strategy
$CombiFundDec_j$	deciles in terms of $CombiFund_j$
$cost_j$	costs of fund j
d	(end of) day d
D_i^{att}	Dummy Variable indicating if stock i attracts high investor attention
D_j^{G}	Dummy Variable for the fund investment objective "Growth"
$D_j^{G\&I}$	Dummy Variable for the fund investment objective "Growth & Income"
$D_j^{SC\&AG}$	Dummy Variable for the fund investment objective "Small Cap & Aggressive Growth"
D_i^{+}	Dummy Variable, indicating positive future abnormal returns of stock i
$days_i$	number of trading days of stock i
dep_i	depreciation of firm i
$difference_j$	difference between (abnormal) returns of portfolio j and (abnormal) returns of the whole sample
$dmturnover_i$	demeaned turnover of stock i
$earn_i$	operating income of firm i
ew	equally weighted
$fundreturn_j$	return of fund j
$fundsize_j$	size of fund j
$grossreturn_j$	gross return of fund j
HML	value benchmark factor
i	index for a stock or firm

I_i	illiquidity of stock i, defined as in Amihud (2002)
$idio_i$	idiosyncratic risk of stock i
$inflow_j$	inflow into fund j
j	index for a stock portfolio or mutual fund portfolio
L_i	liquidity of stock i, defined as in Korajczyk and Sadka (2008)
$\ln(x)$	natural logarithm of variable x
m	(end of) month m
mom_i	momentum, past compounded six-month stock return of stock i, measured with a one-month lag
$momdec_i$	decile in terms of mom_i
$Mom1$	portfolio of stocks belonging to the 20 % with lowest mom_i
$Mom5$	portfolio of stocks belonging to the 20 % with highest mom_i
$MomFund_j$	measure of fund j's momentum strategy
$MomFund_j^{pass}$	*MomFund* that would occur if the fund manager did not trade since the last report
$MomFundDec_j$	deciles in terms of $MomFund_j$
n	number of observations
$n_{i,j}$	number of stock i in fund portfolio j
N_j	total number of stocks in portfolio j
$netreturn_j$	net return of fund j
p_i	price of stock i
p_j^+	picking ratio of stocks with $abnreturn_i > 0$ in portfolio j
p_j^-	picking ratio of stocks with $abnreturn_i \leq 0$ in portfolio j
p^{Combi+}	picking ratio of stocks with $abnreturn_i > 0$ in portfolio *Combi55*
p^{Combi-}	picking ratio of stocks with $abnreturn_i \leq 0$ in portfolio *Combi55*
p^{Mom+}	picking ratio of stocks with $abnreturn_i > 0$ in portfolio *Mom5*
p^{Mom-}	picking ratio of stocks with $abnreturn_i \leq 0$ in portfolio *Mom5*
p25	lower quartile
p50	median
p75	upper quartile
$picking_j$	picking ratio of stocks with $abnreturn_i > 0$ in fund portfolio j

$prevreturn_j$	previous yearly return of fund j
q	(end of) quarter q
r^f	riskless rate
$return_i$	return of stock i
$return_i^e$	expected return of stock i
$return_i^{bm}$	buy-and-hold return of the characteristic-based benchmark portfolio which consists of stocks belonging to the same quintiles in terms of size and book to market as stock i
$RMRF$	market benchmark factor
$shares_i$	number of shares outstanding of stock i
$size_i$	market capitalization of stock i
SMB	size benchmark factor
std_i	debt included in current liabilities of firm i
$Strategy_j$	proxy variable for different investment strategies of fund j
sue_i	standardized unexpected earnings of stock i
$suedec_i$	decile in terms of sue_i
t	(end of) period t, proxy for different time variables (y, q, m, d)
tna_j	total net assets of fund j
tp_i	income taxes payable of firm i
$turnover_{i(j)}$	turnover of stock i or (fund)portfolio j
v	error term, residual of a regression
vw	value weighted
$volume_i$	trading volume in shares of stock i
$volume\$_i$	trading volume in dollars of stock i
$w_{i,j}$	portfolio weight of stock i in portfolio j
$w_{i,j}^{pass}$	portfolio weights of stock i that would have been valid if fund j had not traded since the last fund report
X_i	variables relevant for pricing of stock i
X_i^e	rational forecast of X_i
y	(end of) year y
z	proxy for different explanatory variables

Greek Symbols

α	regression coefficient or intercept
$\hat{\alpha}$	estimated value of regression coefficient or intercept
α^*	pricing coefficient in Sloan (1996)
$\hat{\alpha}^*$	estimated value of the pricing coefficient in Sloan (1996)
β	regression coefficient or intercept
$\hat{\beta}$	estimated value of regression coefficient or intercept
β^l	loading on factor l
$\Delta active_j$	active strategy change of fund j
$\Delta active_j^{Cfo}$	active change of fund j's cash flow strategy $CfoFund_j$
$\Delta active_j^{Combi}$	active change of fund j's combination strategy $CombiFund_j$
$\Delta active_j^{Mom}$	active change of fund j's momentum strategy $MomFund_j$
$\Delta passive_j$	passive strategy change of fund j
$\Delta passive_j^{Cfo}$	passive change of fund j's cash flow strategy $CfoFund_j$
$\Delta passive_j^{Combi}$	passive change of fund j's combination strategy $CombiFund_j$
$\Delta passive_j^{Mom}$	passive change of fund j's momentum strategy $MomFund_j$
$\Delta total_j$	total strategy change of fund j
$\Delta total_j^{Cfo}$	total change of fund j's cash flow strategy $CfoFund_j$
$\Delta total_j^{Combi}$	total change of fund j's combination strategy $CombiFund_j$
$\Delta total_j^{Mom}$	total change of fund j's momentum strategy $MomFund_j$
Δx	change in variable x
ε	error term, residual of a regression
γ	regression coefficient or intercept
$\hat{\gamma}$	estimated value of regression coefficient or intercept
γ^*	pricing coefficient in Sloan (1996)
$\hat{\gamma}^*$	estimated value of pricing coefficient in Sloan (1996)
θ	set of information
τ	running time index

Further Symbols

$\varnothing x$	mean of variable x
$	Dollar
#	item number
*** (**, *, ^^^, ^^)	significance at the 1 %- (5 %-, 10 %-, 15 %-, 20 %-) level

1 Introduction

1.1 Motivation and Research Questions

The financial crisis in 2008 and 2009 has once again demonstrated that capital markets are important for the functioning of the economy in the industrial world. Stock markets represent one important part of the capital markets. Their importance is, for instance, reflected in numerous books and studies about different aspects of stock markets. This thesis deals with three of these aspects, namely investment trading strategies, the reactions of market participants, as well as the trading and success of institutional investors. I will describe these aspects shortly in the following. These descriptions will lead over to the three research questions I address in this thesis.

At first, I analyze stock market trading strategies. Stock trading is the central function of stock markets. Via stocks, entrepreneurs are provided with equity capital and investors are enabled to invest in different firms. Investors are interested in finding stocks that yield the highest returns. Therefore, they often engage professional investors, who choose the investments for them. Professional investors have become a wide-spread profession. Accordingly, there are not only innumerable academic studies on the topic of trading strategies, but there are a lot of experiences of practitioners available, too.

Generally speaking, there are two ways of selecting stocks, namely technical and fundamental trading. Technical trading means investing according to past changes in stock price. The main aim of technical trading strategies is to detect price trends and to participate in them. In order to identify these price trends, past price movements are analyzed and evaluated. Fundamental trading, in contrast, means trading according to fundamental information, for example from companies' financial statements. This fundamental information is utilized to determine whether a stock is undervalued or not. Accordingly, fundamental traders invest in stocks that they assess to be undervalued and aim to participate in the upward price movement towards the stocks' fair value.

This thesis examines both methods of investing − technical and fundamental trading − and then focuses on the potentials of combining them. Though, in practice, most experienced investors do intuitively base their investment decisions on a combination of both methods of some sort, the theoretical basis as well as the results of such strategies have rarely been analyzed in the academic literature. With this thesis, I aim to fill a part of this research gap by analyzing the combination of a technical and a fundamental trading strategy. In accordance with this aim, the first and central research question of this thesis is:

1. *Is trading based on technical* ***and*** *fundamental information more profitable than trading based on only one of the two types of information?*

I examine this question by analyzing a trading strategy that combines the technical momentum and the fundamental operating cash flow strategy. Of course, the analysis of a combination of these two specific strategies does not necessarily allow conclusions about all types of technical and fundamental strategies. Since I analyze momentum and operating cash flows throughout my whole thesis, this limitation applies to all three research questions I investigate and should be kept in mind. However, momentum is the most widely discussed technical trading strategy in the academic literature and cash flows are central in the evaluation of stocks. Accordingly, the analysis of these two key figures should allow considerable insights into technical and fundamental trading and their combination. Additionally, the combination of momentum and operating cash flows has not been analyzed in the academic literature before.

The outcome of combinations of technical and fundamental trading is highly relevant for practical investors as well as for academics. Surveys show that investors in practice do not restrain themselves to one of the two sources of information, so that an analysis of a combination strategy can encourage them to stick to this investment principle. Moreover – and probably more importantly – investors will be interested in implementing the specific momentum and operating cash flow combination strategy I analyze in my thesis. For academics, it is important to know whether both types of information possess incremental ability to predict future returns. If one type of information subsumes the other, future research can neglect the other one. If, on the contrary, both types of information have incremental predictive power, future studies about stock price prediction should include both of them. The latter case would lead to a further interesting field of research about the differences in information contents of technical and fundamental information and about their interaction.

In academic studies, profits of trading strategies are met with skepticism. In efficient markets, such profits based on publicly available information should not exist. In particular, the question arises whether the profits found are due to a mismeasurement of risk or whether the market does not correctly price the information at hand. Assuming mispricing, there are two possible explanations: market overreaction, implying that the trading profits are based on a price movement away from fair value, or market underreaction, meaning that the profits result from the correction of an initially too weak market reaction. In the existing literature, profits of technical trading strategies are explained by both over- and underreaction. Returns of accounting-based anomalies, in contrast, are mainly attributed to market reactions that are too weak or too slow. Against the background of these competing explanations, the market reactions underlying the profits of a strategy that combines both types of information are of special interest. This leads to my second research question:

2. *What kind of market (mis)behavior leads to the profitability of technical and fundamental strategies and of a strategy that combines both types of information?*

I examine this second question using the specific momentum, cash flow, and combination strategies that are central in my thesis.

The second research question is a core question of research in finance, since it addresses the efficiency of markets and the process of stock price building. Understanding the reactions of market participants poses a challenge to academics in this field. Exploring these reactions is an extremely difficult task, since the way investors think is not easily observable. To overcome this problem, I analyze stock price developments and draw possible conclusions about investors' over- or underreaction from them. Such analyses do not suffice to prove certain market behavior, but they can be seen as a step further towards a better understanding of stock market dynamics.

The assumption of market mispricing leads to the question whether professional investors trade on such mispricing. Since anomalies are discussed in academic studies that professional investors probably know, such trading should be extremely likely. This leads to my third research question:

3. *Do professional investors trade on technical or fundamental information or both and are they successful if they do so?*

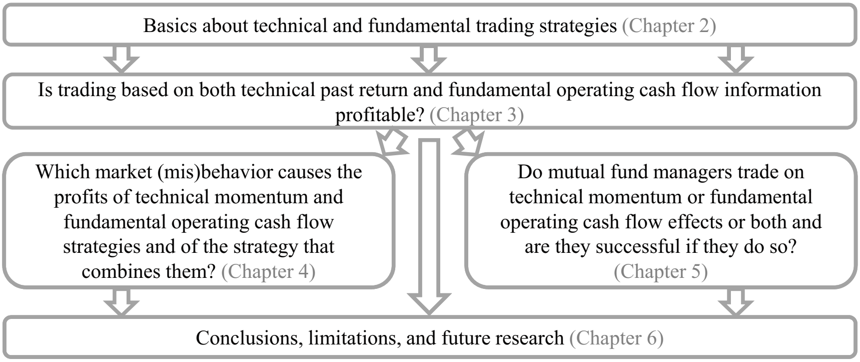
In order to find an answer to this third question, I again use the momentum, cash flow, and combination strategies. Moreover, I use mutual fund managers as representatives for professional investors.

The third research question is of interest for academics as well as practical investors. It gives academics further insights into the trading behavior of professional investors and determinants of their performance. In addition, it leads to further research questions. If, for example, professional investors trade on the anomalies, we must ask ourselves why the profitability of these anomalies does not vanish due to this trading. If they do not trade on it, this might be one reason for the persistence of the anomalies. On the other hand, the latter case might raise the question whether professional investors have reasons not to trade on them. Moreover, the results of the third analysis are of interest for practical investors who think about implementing the combination strategy. If mutual fund managers are successful when buying high momentum and high cash flow stocks, this strategy will also be highly interesting for other investors.

1.2 Structure of the Thesis

Figure 1.1 illustrates the structure of this thesis.

Figure 1.1: Structure of the Thesis

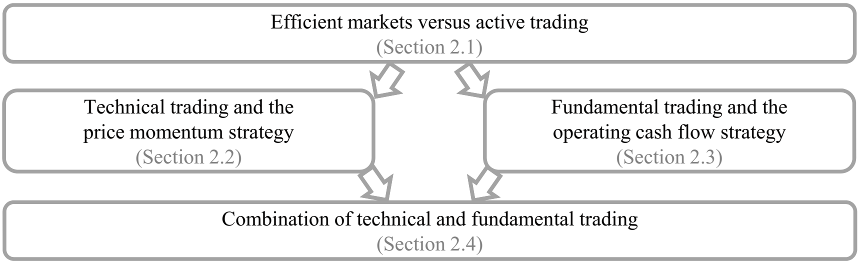


In chapter 2, I discuss the basics of the efficiency of markets and of trading strategies that rely on technical or fundamental information. In anticipation of the combination strategy in chapter 3, chapter 2 focuses, in particular, on the technical price momentum and the fundamental operating cash flow strategy. Chapter 3 is the centerpiece of this thesis, dealing with the first research question. In chapter 3, I empirically analyze a combination trading strategy that makes use of both, technical and fundamental information, investing in stocks with high past returns and high operating cash flows. Moreover, I decompose the strategies' returns and rule out alternative explanations for the results. Lastly, I check whether the strategies are implementable in practice. Chapter 4 is closely related to chapter 3. In chapter 4, I investigate research question number two, that is, the market behavior which leads to the profits of the momentum, the operating cash flow, and the combination strategy. I conduct several empirical tests that give clues about the market reactions which might have caused the effects. I do not only analyze the effects in total, but also consider the long and short portfolios of the trading strategies separately, which allows for further insights. In chapter 5, I cover the third research question. I analyze whether mutual fund managers, as one important group of professional investors, invest according to the momentum, the operating cash flow, and the combination strategy and whether they are successful if they do so. In chapter 6, I conclude, present limitations, and give propositions for future research.

2 Basics about Technical and Fundamental Trading

This chapter provides the basic knowledge for the rest of my thesis. Section 2.1 summarizes the hypothesis of efficient markets and demonstrates its links to my thesis. Sections 2.2 and 2.3 introduce technical and fundamental trading, focusing especially on the price momentum and the operating cash flow strategy. Section 2.4 serves as a bridge to the following chapters, discussing combinations of technical and fundamental trading. Figure 2.1 illustrates the structure of this chapter.

Figure 2.1: Structure of Chapter 2



2.1 Efficient Markets versus Active Trading

The efficient market hypothesis (EMH) has been developed by Eugene F. Fama and Paul A. Samuelson in the 1960s.[1] The central message of the EMH is: "A market in which prices always 'fully reflect' available information is called 'efficient'."[2] Depending on the set of available information θ_t that is supposed to be fully impounded in prices, Fama (1970) differentiates between three forms of market efficiency. In weakly efficient markets, historical prices are incorporated in the current price. In markets which are semi-strong efficient, past prices and other publicly information are priced correctly. The strong form of market efficiency even claims that prices fully reflect private information.

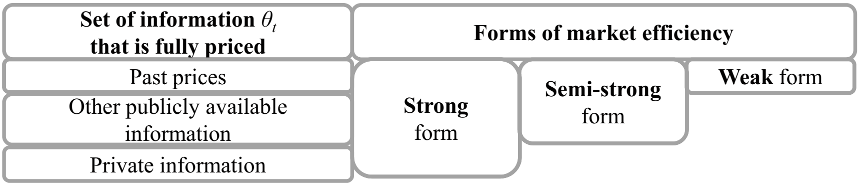
---

1 The article of Samuelson (1965) is titled "Proof that Properly Anticipated Prices Fluctuate Randomly." Fama published a series of seminal papers: Fama (1963), Fama (1965a), Fama (1965b), and finally the most widely cited article Fama (1970) "Efficient Capital Markets: A Review of Theory and Empirical Work" published in the Journal of Finance.

2 Fama (1970), p. 383.

Figure 2.2 illustrates this differentiation, using the information in Fama (1970), p. 383.

Figure 2.2: Forms of Market Efficiency



Market efficiency is crucial for the profits of active investing as clarified by Jensen (1978): "A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t. By economic profits, we mean the risk adjusted returns net of all costs."[3] Accordingly, the difference between actual returns and returns that are expected based on the given set of information should equal zero in efficient markets, making active investments useless.

In contrast, many academic studies find so-called "anomalous" trading strategies that are based on past prices, publicly available information, or private information and yield abnormal returns. The weak form of market efficiency is challenged by short-term reversals, medium-term momentum, and long-term return reversals as reported by Jegadeesh (1990), Jegadeesh and Titman (1993), and De Bondt and Thaler (1985). Also seasonal patterns in returns as the January effect, documented by Keim (1983), and the finding of Gibbons and Hess (1981) that returns are lower on Mondays stand in contrast to the weak form. The semi-strong form of market efficiency is challenged by all types of accounting-based anomalies, like the post earnings announcement drift of Ball and Brown (1968), the accrual anomaly of Sloan (1996), and Sloan's operating cash flow effect, which is central in this thesis. Also anomalies referring to market reactions to stock splits and dividends reported by Grinblatt, Masulis, and Titman (1984), or to analysts' forecast revisions documented by Stickel (1991), or to Initial Public Offerings found by Ritter (1984) are not in line with the semi-strong form of market efficiency. Lastly, any study that detects profits of insider trading, as, for example, Givoly and Palmon (1985) questions the strong form of market efficiency.

The mentioned successful trading strategies indicate – but do not prove – that the stock market is not efficient. Abnormal returns to trading strategies in empirical studies do not suffice to prove market inefficiency because it is difficult to determine whether returns are expected or abnormal. Campbell, Lo, and MacKinlay (1997) phrase this problem as follows: "First, any test of efficiency must assume an equilibrium model that defines normal security

---

3 Jensen (1978), p. 3.

returns. If efficiency is rejected, this could be because the market is truly inefficient or because an incorrect equilibrium model has been assumed. This joint hypothesis problem means that market efficiency as such can never be rejected."[4] Accordingly, any abnormal return found could be due to higher risks that are not adequately captured by the technique used to compute abnormal returns.

Possible explanations for the existence of anomalies are given by behavioral finance studies which assume that market participants do not always act rationally. Barberis and Thaler (2003) put it as follows: "Behavioral finance argues that some financial phenomena can plausibly be understood by using models in which some agents are not fully rational."[5] Academic studies differentiate between several biases.[6] For instance, Edwards (1968) defines the conservatism bias which means that people are too slow in changing their opinions which can lead to underreaction to new information. Similarly, anchoring means that people use a starting point when forming estimates and then they "anchor" too much on it, resulting in a too slow adjustment. The confirmation bias describes that people only seek information that confirms their view. Similarly, the status quo bias means that people prefer to leave things as they are.[7] Moreover, people are on average overconfident and overly optimistic in their acting.[8] Furthermore, they put a greater weight on more recent or salient events when taking decisions, which is named availability bias.

A relatively new idea in the literature is the Adaptive Market Hypothesis (AMH) presented by Lo (2004). The AMH tries to reconcile the EMH with the ideas of behavioral critics.[9] It assumes that markets evolve dynamically and that they are predictable at any moment, providing profit opportunities. Investors arbitrage these opportunities away. By their trading, new price patterns emerge, offering new chances to make profits. These will be discovered as well, and so on. The AMH uses many concepts of biological sciences and Lo (2008) assumes that perhaps it will be necessary to learn from other fields of research in order to really understand markets one day.[10] One example for such interdisciplinary research is the field of "neurofinance" which makes use of medical sciences. Academics in neurofinance investigate

---

4 Campbell, Lo, and MacKinlay (1997), p. 24. Similarly, Fama (1991) states: "Thus, market efficiency per se is not testable. It must be tested jointly with some model of equilibrium, an asset-pricing model." Fama (1991), pp. 1575-1576.

5 Barberis and Thaler (2003), p. 1054.

6 Overviews on the different biases are given by Tversky and Kahneman (1974), Montier (2002), pp. 1-28 and by Barberis and Thaler (2003), pp. 1063-1073. Some of the following explanations are also taken from these studies. Therefore, I do not cite them again in this paragraph, but only give citations for other studies I refer to.

7 For more information on the status quo bias; see, e.g., Samuelson and Zeckhauser (1988).

8 Studies about overconfidence and optimism are, for instance, Lichtenstein and Fischhoff (1977), Weinstein (1980), as well as Griffin and Tversky (1992).

9 See Lo (2004), p. 15.

10 See Lo (2008), pp. 5-7.

physiological characteristics, such as brain and hormonal activities, and draw conclusions about market participants' trading behavior from them.[11]

The subject of market efficiency will be prevalent throughout my whole thesis. The success of the fundamental, technical, and combination strategies as shown in chapter 1 contradicts the EMH. The success of the pure momentum strategy even challenges the weak form of market efficiency. As explained before, such trading profits do not prove market inefficiency, but they strongly hint at it.[12] This leads me to the question which type of market participants' "misbehavior" could lead to these profits. I come to this aspect in chapter 1, where I examine investors' over- and underreaction as possible behavioral explanations. Another open question evolving from the found returns to the trading strategies is why existing anomalies are not arbitraged away. Chapter 5 discusses this question, analyzing whether professional investors (successfully) trade on the momentum, operating cash flow, and combination effect.

2.2 Technical Trading Strategies

2.2.1 Technical Trading at a Glance

Numerous different factors influence the value of firms. It is very complex to observe and analyze all these factors and some of them are even unobservable. To cope with this complexity, advocates of technical trading recommend observing past price movements and trading volumes instead of these factors when taking investment decisions. Accordingly, Murphy (1999) states: "The technician believes that anything that can possibly affect the price – fundamentally, politically, psychologically, or otherwise – is actually reflected in the price of that market. It follows, therefore, that a study of price action is all that is required."[13] Murphy (1999) labels this premise the „cornerstone of technical analysis."[14] The second premise of technical trading is that prices move in trends, meaning that a trend will more likely continue than reverse. The third premise is that history repeats itself, implying that a study of the past is helpful in understanding the future.[15] Based on these premises, technical traders apply certain trading rules that are based on past price movements and volumes. Basically, they use either charts or the mathematical analysis of the time series of past prices

---

11 For example, Tseng (2006) gives an overview on behavioral finance, neuro-finance, and traditional finance. Two prominent examples for neurofinance studies are Kuhnen and Knutson (2005) as well as Lo and Repin (2002).

12 As explained before, the abnormal performances could be due to higher risks that are not adequately captured by the techniques I use to compute abnormal returns. I do not enlarge upon this problem and rely on two techniques that are currently state of the art, i.e., 3-factor alphas and benchmark adjusted abnormal returns. The precise computation is explained in section 3.2.1.

13 Murphy (1999), p. 2.

14 Murphy (1999), p. 2.

15 Regarding the premises of technical trading; see, e.g., Murphy (1999), pp. 3-7 or Khatlawala (2008), pp. 15-18.

and volume to come to an investment decision. Some prominent examples of techniques of technical trading are candlesticks, support and resistance, or the relative strength strategy, which underlies the price momentum strategy described in section 2.2.2. All in all, there are numerous techniques of technical trading. The description and analysis of all of these techniques goes beyond the scope of this thesis.[16]

Opponents of technical trading criticize its lack of theoretical background. Malkiel (2007) puts it like this: „Technical analysis is anathema to the academic world.“[17] Despite these critics, technical trading strategies are the subject of many academic studies, and some of them find that the strategies are indeed successful. Table 2.1 gives an overview of studies about technical trading strategies.

Table 2.1: Studies on Technical Trading

Study	Fama, Eugene F. and Marshall E. Blume. 1966. Filter Rules and Stock-Market Trading. *Journal of Business* 39 (1): 226-241.
Strategy	Fama and Blume (1966) analyze 42 filter rules using the Dow Jones Industrial Average from 1956 to 1962.
Result	After deduction of transaction costs, the stocks picked by the filter rules are not significantly more successful than the average stock.
Study	Levy, Robert A. 1967. Relative Strength As a Criterion for Investment Selection. *Journal of Finance* 22 (4): 595-610.
Strategy	Levy (1967) tests the relative strength strategy which picks stocks with high relative past returns in the past 4 or 26 weeks. He uses a sample of 200 NYSE stocks between 1960 and 1965.
Result	If relative strength is based on 26 weeks, it is profitable, also after trading costs.
Study	Jensen, Michael C. and George A. Benington. 1970. Random Walks and Technical Theories: Some Additional Evidence. *Journal of Finance* 25 (2): 469-482.
Strategy	Jensen and Benington (1970) reexamine the relative strength strategy of Levy (1967) using 29 subsamples of 200 NYSE stocks between 1926 and 1966.
Result	The relative strength strategy does not yield abnormal profits. Jensen and Benington (1970) ascribe the results of Levy (1967) to data snooping.
Study	Levy, Robert A. 1971. The Predictive Significance of Five-Point Chart Patterns. *Journal of Business* 44 (3): 316-323.
Strategy	Levy (1971) examines 32 formation charting rules using 548 NYSE stocks between 1964 and 1969.
Result	The charting rules are not profitable after deduction of trading costs.
Study	Brock, William, Josef Lakonishok, and Blake LeBaron. 1992. Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *Journal of Finance* 47 (5): 1731-1764.
Strategy	Brock, Lakonishok, and LeBaron (1992) test strategies based on combined moving averages and trading range break using the Dow Jones Industrial Average between 1897 and 1986.
Result	The strategies are profitable. However, Brock, Lakonishok, and LeBaron (1992) do not consider trading costs.

16 For an overview of the methods of technical analysis; see, e.g., Murphy (1999), pp. 35-47, Edwards, Magee, and Bassetti (2007), pp. 55-73, Malkiel (2007), pp. 126-149, or Jones (2007), pp. 435-447.

17 Malkiel (2007), p. 127.

Study	Sullivan, Ryan, Allan Timmermann, and Halbert White. 1999. Data-Snooping, Technical Trading Rule Performance, and the Bootstrap. *Journal of Finance* 54 (5): 1647-1691.
Strategy	Sullivan, Timmermann, and White (1999) reexamine and expand the trading rules utilized by Brock, Lakonishok, and LeBaron (1992) using the Dow Jones Index and the S&P 500. The investment period is from 1987 to 1996 for the Dow Jones and 1984 to 1996 for the S&P 500. Moreover, they control for data snooping biases.
Result	The strategies of Brock, Lakonishok, and LeBaron (1992) yield abnormal returns, also after controlling for data snooping. However, the returns cannot be replicated in an out of sample test.
Study	Lo, Andrew W., Harry Mamaysky, and Jiang Wang. 2000. Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation. *Journal of Finance* 55 (4): 1705-1765.
Strategy	Lo, Mamaysky, and Wang (2000) investigate ten different chart formations they draw from empirical return observations. They use all NYSE, AMEX, and NASDAQ stocks between 1962 and 1996.
Result	Some formations can support investors in their investment decisions, but it remains unclear whether they outperform systematically.

2.2.2 The Price Momentum Strategy − Jegadeesh and Titman (1993)

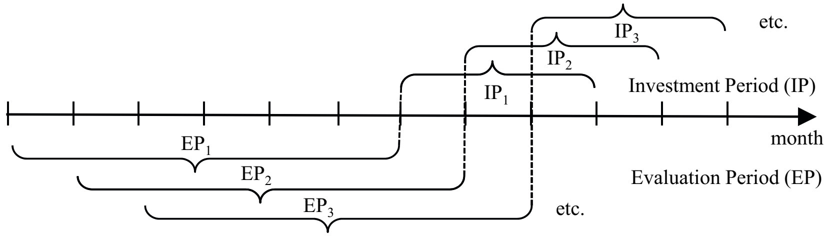
The technical trading strategy that is central in this thesis is the price momentum strategy, which is based on the findings of Jegadeesh (1990) and Jegadeesh and Titman (1993). The main reason for my focus on the price momentum strategy is its prominence and simplicity. In this section, I will summarize the central findings of Jegadeesh and Titman (1993), which is the landmark paper for the momentum effect.

Jegadeesh and Titman (1993) investigate all stocks for which CRSP (Centre for Research in Security Prices) offers daily data from 1965 to 1989. Every month, they sort these stocks according to their returns in the past evaluation period. As evaluation periods, Jegadeesh and Titman (1993) use the past 3, 6, 9, or 12 months. They buy the 10 % stocks with highest past returns and sell the 10 % stocks with lowest past returns during the evaluation period. Portfolios are equally weighted and held for the investment period, i.e., the following 3, 6, 9, or 12 months.[18] Figure 2.3 illustrates the portfolio formation of Jegadeesh and Titman (1993) when the evaluation period has a length of 6 months and the investment period endures 3 months.[19]

[18] Additionally Jegadeesh and Titman (1993) implement all strategies with a one-month lag between EP and IP; see Jegadeesh and Titman (1993), p. 70. I only present the results without lag.

[19] For more information on the portfolio formation; see Jegadeesh and Titman (1993), p. 68.

Figure 2.3: Momentum Portfolio Formation in Jegadeesh and Titman (1993)



Jegadeesh and Titman (1993) find that the momentum strategy is highly profitable. For the constellation of 6 months evaluation period and 3 months investment period, the long position earns 1.71 % per month. The short position yields 0.87 % per month, leading to a monthly hedge portfolio return of 0.84 %. Table 2.2 gives an overview of the returns earned for the different evaluation and investment periods.

Table 2.2: Momentum Portfolio Returns of Jegadeesh and Titman (1993)

		IP = 3	IP = 6	IP = 9	IP = 12
EP = 3	long	1.40 ***	1.49 ***	1.52 ***	1.56 ***
EP = 3	short	1.08 **	0.91 *	0.92 *	0.87 *
EP = 3	hedge	0.32	0.58 **	0.61 ***	0.69 ***
EP = 6	long	1.71 ***	1.74 ***	1.74 ***	1.66 ***
EP = 6	short	0.87 *	0.79	0.72	0.80 *
EP = 6	hedge	0.84 **	0.95 ***	1.02 ***	0.86 ***
EP = 9	long	1.86 ***	1.86 ***	1.76 ***	1.64 ***
EP = 9	short	0.77	0.65	0.71	0.82 *
EP = 9	hedge	1.09 ***	1.21 ***	1.05 ***	0.82 ***
EP = 12	long	1.92 ***	1.79 ***	1.86 ***	1.55 ***
EP = 12	short	0.60	0.65	0.75	0.87 *
EP = 12	hedge	1.31 ***	1.14 ***	0.93 ***	0.68 **

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level; based on a two-tailed test.

Moreover, Jegadeesh and Titman (1993) show that the strategy remains profitable when it is restricted to size- and beta-based subsamples or to several subperiods.[20] The consideration of transaction costs does not erode the performance, either.[21] Lastly, Jegadeesh and Titman (1993) probe the causes for the found momentum returns. Their findings indicate that the returns are not due to higher systematic risk, as the stocks' beta and size are not extraordinarily high. They are also not due to serial dependence of a common risk factor, because the serial covariance of the used market index is negative. Rather, the returns stem

[20] See Jegadeesh and Titman (1993), pp. 76-77.
[21] See Jegadeesh and Titman (1993), p. 77.

from serial dependence in the idiosyncratic component of returns. This serial dependence is not due to a lagged reaction to market returns, precluding the lead-lag effect of Lo and MacKinlay (1990). In contrast, the results indicate underreaction to firm-specific news as a possible source of the momentum profits.[22] This conclusion is supported by the finding that the returns around the two earnings announcements following portfolio building are significantly higher for winner than for loser stocks. This stock price correction during the arrival of new information indicates that market participants underreacted to firm specific information, before.[23]

Innumerable studies have followed the paper of Jegadeesh and Titman (1993), inter alia analyzing the success and implementability of the momentum trading strategy and searching for possible reasons for the momentum effect. Until today, no absolute explanation has been found for this effect, which even contradicts the weak form of market efficiency. I will give a short synopsis of these follow-up papers in the following, but this list is by no means intended to be exhaustive.

First, there are many studies sustaining the profitability of the momentum strategy in other countries than the US. Rouwenhorst (1998) demonstrates the profits for different European countries, Schiereck, De Bondt, and Weber (1999) for Germany and Chui, Titman, and Wei (2000) for several Asian countries.

As momentum profits contradict the efficient market hypothesis, there are studies searching for reasons for the mispricing. In this regard, I differentiate between three different types of studies and present examples for each type: The first type explains the effect by market participants' "misbehavior". The second type sticks to market efficiency, finding rational arguments for the effect. The third and last type asks the question whether the trading profits really exist or whether they vanish when transaction costs are deducted.

The most prominent examples for studies giving behavioral explanations are Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), as well as Hong and Stein (1999). Daniel, Hirshleifer, and Subrahmanyam (1998) mainly attribute the momentum effect to investors' overreaction, which is mainly due to the investors' biased self-attribution and overconfidence. These biases lead to a too strong reaction to news that confirms investors' previous attitudes. Barberis, Shleifer, and Vishny (1998) as well as Hong and Stein (1999) both attribute momentum returns to a combination of investors' under- and overreaction. In Barberis, Shleifer, and Vishny (1998) this combination is due to a biased

22 For details of this decomposition of returns; see Jegadeesh and Titman (1993), pp. 71-72.

23 See Jegadeesh and Titman (1993), pp. 86-89. See also section 4.4 of this dissertation, in which I also analyze returns around subsequent earnings announcements.

assessment of different types of information. In Hong and Stein (1999), an interaction of two types of investors leads to an underreaction at the beginning and an overreaction afterwards.[24]

Two articles published in 2002 belong to the second type of studies that find rational explanations for the effect. Chordia and Shivakumar (2002) investigate the influence of macroeconomic variables on price momentum. They show that past return loser stocks and past return winner stocks react to macroeconomic variables in a different way. A model that considers these macroeconomic variables predicts the higher returns of past winner and the lower returns of past loser stocks during up markets. All in all, the results of Chordia and Shivakumar (2002) question the influence of stock specific characteristics on momentum returns. This makes a behavioral explanation for the effect difficult. Johnson (2002) attributes the momentum effect to growth rate risks. Past return winners are assumed to have experienced positive changes in growth rate. The higher the growth rate, the higher the growth rate risk. This risk has to be compensated for by the market, leading to the momentum returns found.

Two studies asking whether momentum profits suffice to cover their trading costs were published in 2004. These studies yield mixed results, casting doubt on the profitability of the momentum strategy. Lesmond, Schill, and Zhou (2004) claim that momentum profits are only "illusory", being completely absorbed by transaction costs. In contrast, Korajczyk and Sadka (2004) show that up to US$ 5 billion may be invested in momentum portfolios before profit opportunities vanish due to transaction costs.

2.3 Fundamental Trading Strategies

2.3.1 Fundamental Trading at a Glance

The central aim of fundamental trading strategies is to determine whether a stock is priced below its fair value. This fair value is supposed to be the discounted value of all future cash flows investors expect to receive from the stock. In order to predict these future cash flows, fundamental analysts consult and analyze the available fundamental information, as for example macroeconomic factors or information from financial statements. On the basis of this fundamental information, they assess whether a stock is over- or undervalued. Accordingly, they advise buying a stock if they assume that it is undervalued and selling it if the contrary is the case. The assumption underlying this trading is that stock prices deviate at times from their fair value, but they move back to it slowly.[25]

---

[24] I will come back to these behavioral models in chapter 1 of this thesis.

[25] For further details about the basic assumptions of fundamental trading described in this paragraph; see, e.g., Malkiel (2007), p. 110, Alexander, Sharpe, and Bailey (2001), p. 285, or Ou and Penman (1989), p. 296.

One way of determining a stock's fair value is through company valuation models. The literature knows several valuation models. Examples are the dividend discount model, the discounted cash flow model, or the residual income model.[26] Another way to determine a company's fair value is the multiple approach. The main advantage of this approach is that it does not require forecasting future cash flows. It uses stock prices of other stocks with similar characteristics as a standard of comparison and derives a company's fair value from them.[27]

Another more simple way to arrive at investment advice via fundamental analysis is the study of one or several ratios from the firms' financial statements. This approach is ultimately based on the same assumption as the valuation methods, as it also implicitly deduces future cash flows and the stock's fair value from the ratios. Nevertheless, it does not determine a specific fair value but directly derives a possible under- or overvaluation.[28] The investment according to relative operating cash flows used in this thesis is one example of this approach. It assumes a stock to be undervalued if the relation between operating cash flows and average assets is high and vice versa. Table 2.3 summarizes some empirical studies about the success of fundamental trading strategies. Referring to Frankel and Lee (1998), it gives one example of the first approach of investing according to a company's fair value that is derived from a company valuation model. The other studies mentioned are examples for investments according to single or several ratios from the financial statements.

Table 2.3: Studies on the Value Relevance of Fundamental Information

Study	Ball, Ray and Philip Brown. 1968. An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research* 6 (2): 159-178.
Strategy	Ball and Brown (1968) investigate the relation between accounting earnings and future returns. Their sample consists of all NYSE stocks between 1957 and 1965.
Result	Published earnings are highly value relevant. The study of Ball and Brown (1968) is the first study documenting the post earnings announcement drift.
Study	Ou, Jane A. and Stephen H. Penman. 1989. Financial Statement Analysis and the Prediction of Stock Returns. *Journal of Accounting and Economics* 11 (4): 295-329.
Strategy	Ou and Penman (1989) condensate 68 different accounting ratios into one key figure that is intended to predict future earnings. They use all stocks from NYSE or AMEX and some additional utilities and financial firms for which financial statement information is available from Compustat. Their investment period spans from 1973 to 1983.
Result	The analyzed trading strategy is profitable, also after adjustments for the size effect.
Study	Holthausen, Robert W. and David F. Larcker. 1992. The Prediction of Stock Returns Using Financial Statement Information. *Journal of Accounting and Economics* 15 (2/3): 373-411.
Strategy	Holthausen and Larcker (1992) condensate 60 of the 68 accounting ratios of Ou and Penman (1989) into one key figure that is now intended to directly predict future abnormal returns. They analyze NYSE, AMEX, and over the counter firms between 1978 and 1988.
Result	The trading strategy turns out to be even more profitable than that of Ou and Penman (1989).

[26] For a survey of these and other valuation models; see, e.g., Drukarczyk and Schüler (2007) or Penman (2007).
[27] The multiple approach is also discussed in Drukarczyk and Schüler (2007) and Penman (2007).
[28] See, e.g., Alexander, Sharpe, and Bailey (2001), p. 285.

Study	Lev, Baruch and S. Ramu Thiagarajan. 1993. Fundamental Information Analysis. *Journal of Accounting Research* 31 (2): 190-215.
Strategy	Lev and Thiagarajan (1993) test the predictive ability of 12 accounting signals analysts consider as value relevant for future returns via a regression-based approach. Moreover, they check whether this ability depends on macroeconomic conditions. Their sample comprises all stocks with sufficient information in Compustat and the investment period spans from 1974 to 1988.
Result	Most of the analyzed accounting signals have predictive ability for future returns in addition to current earnings. Their influence is stronger if it is conditioned on macroeconomic states.
Study	Abarbanell, Jeffery S. and Brian J. Bushee. 1998. Abnormal Returns to a Fundamental Analysis Strategy. *The Accounting Review* 73 (1): 19-45.
Strategy	Abarbanell and Bushee (1998) form investment portfolios, making use of the accounting signals that Lev and Thiagarajan (1993) have shown to be value relevant in their regression-based approach. They investigate the period between 1974 and 1993 using all stocks from NYSE and AMEX.
Result	The implemented trading strategy turns out to be highly profitable. Moreover, the returns are associated with higher future earnings indicating that they are not due to higher risks.
Study	Frankel, Richard and Charles M. C. Lee. 1998. Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns. *Journal of Accounting and Economics* 25 (3): 283-319
Strategy	Frankel and Lee (1998) examine whether estimations of firm value based on the residual income valuation model have predictive power for future returns. Their sample includes all NYSE, AMEX, and NASDAQ firms in the years 1975 to 1993.
Result	Estimates of fair value from the residual income model can be used to predict future returns, especially over long horizons up to three years.

2.3.2 The Operating Cash Flow Strategy − Sloan (1996)

The fundamental trading strategy I focus on in this thesis is the operating cash flow strategy, which buys stocks with high and sells stocks with low operating cash flows. This strategy is based on the findings of Sloan (1996), whose paper is a landmark in the financial accounting literature. I will present this study in the following. Afterwards I will present some – but by no means all – studies that followed Sloan (1996).

The central finding of Sloan (1996) is that market participants do not seem to differentiate between the cash flow and the accrual component of earnings when pricing stocks. This fixation on earnings leads to an overvaluation of stocks with high accruals and low operating cash flows and to an undervaluation of stocks with low accruals and high operating cash flows. This mispricing is traced back to the different persistence of these two earnings components.

Sloan (1996) analyzes all AMEX and NYSE firms between 1962 and 1991. First, he conducts two forecasting equations displayed in equations 2.1 and 2.2:

$$earnings_{y+1} = \alpha_0 + \alpha_1 \cdot earnings_y + v_{y+1} \qquad 2.1$$

$$earnings_{y+1} = \gamma_0 + \gamma_1 \cdot accruals_y + \gamma_2 \cdot cashflow_y + v_{y+1} \qquad 2.2$$

with:

$$earnings_{y+1} = \frac{operating\ income_{y+1}}{\varnothing\, total\ assets_{y+1}}$$

$$accruals_y = \frac{(\Delta ca_y - \Delta cash_y) - \left(\Delta cl_y - \Delta std_y - \Delta tp_y\right) - dep_y}{\varnothing\, total\ assets_y}$$

$$cashflow_y = \frac{operating\ income_y}{\varnothing\, total\ assets_y} - accruals_y$$

Compustat items (CSI):

$operating\ income_y$	=	operating income at the end of year y, CSI #178
$\varnothing\, total\ assets_y$	=	average total assets during year y, CSI #6
Δca_y	=	change in current assets during year y, CSI #4
$\Delta cash_y$	=	change in cash during year y, CSI #1
Δcl_y	=	change in current liabilities during year y, CSI #5
Δstd_y	=	change in debt included in current liabilities during year y, CSI #34
Δtp_y	=	change in income taxes payable during year y, CSI #71
dep_y	=	depreciation at the end of year y, CSI #14

In regression 2.1 Sloan (1996) regresses earnings of the following year on current earnings and finds a persistence coefficient of $\hat{\alpha}_1 = 0.841$. In regression 2.2 he regresses future earnings on current accruals and operating cash flows and finds a persistence coefficient of $\hat{\gamma}_1 = 0.765$ for current accruals and of $\hat{\gamma}_2 = 0.855$ for current operating cash flows. The coefficient of cash flows is significantly higher than that of accruals, which means that operating cash flows are significantly more persistent than accruals.[29]

The basis for Sloan's second step is the following model 2.3, which satisfies the condition of efficient markets.

$$\left(return_{y+1} - return^e_{y+1} | \theta_y\right) = \beta \cdot \left(X_{y+1} - X^e_{y+1}\right) + \varepsilon_{y+1} \qquad 2.3$$

with:

$return_{y+1}$	=	stock return during year y+1
$return^e_{y+1}$	=	expected return during year y+1
θ_y	=	set of information given at the end of year y
β	=	response coefficient
X_{y+1}	=	variables relevant for stock pricing during year y+1
X^e_{y+1}	=	rational forecast of X_{y+1}

29 See Sloan (1996), pp. 299-300.

Model 2.3 implies that only changes in X_{y+1} that are not anticipated can be correlated with unexpected returns. In Sloan (1996) the variables X_{y+1} that are supposed to be price relevant are earnings, accruals, and cash flows. As expected return, he uses the value weighted return of a portfolio of stocks with the same size. Accordingly, Sloan (1996) conducts two pricing equations 2.4 and 2.5. In these regressions, he combines model 2.3 with equations 2.1 and 2.2 and regresses future unexpected returns on current unexpected earnings and earnings components:

$$\left(return_{y+1} - return^{e}_{y+1} \mid \theta_y\right) = \beta \cdot \left(earnings_{y+1} - \underbrace{(\alpha_0 + \alpha_1^{*} \cdot earnings_y)}_{expected\ earnings} \right) + \varepsilon_{y+1} \qquad 2.4$$

$$\begin{aligned} &\left(return_{y+1} - return^{e}_{y+1} \mid \theta_y\right) \\ &= \beta \cdot \left(earnings_{y+1} - \underbrace{(\gamma_0 + \gamma_1^{*} \cdot accruals_y + \gamma_2^{*} \cdot cashflow_y)}_{expected\ earnings} \right) + \varepsilon_{y+1} \end{aligned} \qquad 2.5$$

These pricing equations reveal the stock market reaction to information contained in current earnings and earnings components about future earnings. The results indicate that the market prices earnings correctly, but does not consider the differing persistence of accruals and cash flows: The coefficient of earnings in the regression on future unexpected stock returns is $\hat{\alpha}_1^{*} = 0.840$, which is extremely close to the persistence coefficient of $\hat{\alpha}_1 = 0.841$ in the forecasting equation. This implies that the market correctly prices annual earnings. In contrast, the pricing coefficient of accruals is $\hat{\gamma}_1^{*} = 0.911$, which is significantly higher than the forecasting coefficient of $\hat{\gamma}_1 = 0.765$. Accordingly, the weight the market puts on accruals seems to be too high. For operating cash flows, the contrary is the case: Whereas the persistence coefficient in the forecasting equation amounts to $\hat{\gamma}_2 = 0.855$, the coefficient in the pricing equation is significantly lower with a value of $\hat{\gamma}_2^{*} = 0.747$. This signifies that the market underestimates the greater persistence of operating cash flows.[30]

Following these results, Sloan (1996) conducts a portfolio test investing in the 10 % stocks with lowest accruals and going short in the 10 % stocks with highest accruals. The long portfolio yields size-adjusted returns of 4.9 % p.a. and a Jensen alpha of 3.9 % p.a.[31] Also regressions of future returns on current accruals confirm the results, yielding a significantly negative coefficient when accruals are the only explaining variable and future yearly returns

30 See Sloan (1996), pp. 304-305. The methodology is taken from Mishkin (1983), pp. 9-27.

31 Jensen Alpha corrects for market risks; see Jensen (1968). For the returns to the other accrual portfolios and the returns in the two following years; see Sloan (1996), p. 307.

are the dependent variable.[32] Lastly, Sloan (1996) shows that a considerable portion of the positive returns of low accrual stocks occur during the following earnings announcement. In contrast, the negative returns to the short portfolio do not occur during the following announcement period, indicating that bad news is more likely to be preempted in prices and does not surprise the market during the earnings announcement.[33]

The literature following Sloan (1996) has mainly concentrated on the accrual effect and has disregarded the operating cash flow effect for a long time. That is why I will exemplarily present some studies analyzing the accrual effect in the following. Similar to my proceeding in section 2.2.2, I differentiate between studies concluding market mispricing, those that find rational arguments, and studies analyzing profits after trading costs.

Sloan's earnings fixation hypothesis is the main explanation which assumes that the accrual effect is due to market mispricing. Completely in line with Sloan (1996) is Xie (2001). He shows that abnormal accruals, i.e., accruals that are most likely manipulated by managers, represent the less persistent and the most mispriced portion of accruals. Similarly, also Richardson et al. (2005) show that accruals of lower reliability are more mispriced. In contrast, Zhang (2007) contradicts this explanation. He demonstrates that investors incorrectly price the growth information that is contained in accruals.

A rational explanation of the accrual effect is proposed by Khan (2008). He introduces a four-factor model motivated by the Intertemporal Capital Asset Pricing Model.[34] When he applies this model, he does not find any significant outperformance of low accrual stocks, any more.

Concerning the implementability of the accrual strategy, Lev and Nissim (2006) and Mashruwala, Rajgopal, and Shevlin (2006) find that extreme accrual stocks are often small and infrequently traded and thus cause high trading costs, impeding the exploitation of the anomaly.

Lastly, some follow-up studies also analyze the mispricing of operating cash flows: Hackel, Livnat, and Rai (2000) present a trading strategy which is based on free cash flows and yields abnormal returns. Dechow, Richardson, and Sloan (2008) document that it is mainly the change in the cash balance that is mispriced.

Moreover, there are some studies that analyze both, the accrual and the operating cash flow anomaly. They document that the two anomalies are not the same phenomena. Houge and Loughran (2000) demonstrate that the accrual and the cash flow anomaly derive from

---

32 For the further results of the other conducted return regressions; see Sloan (1996), p. 310.
33 For the whole investigation of earnings announcement periods; see Sloan (1996), pp. 309-314.
34 The Intertemporal Capital Asset Pricing Model has been introduced by Merton (1973).

different stocks with different characteristics.[35] Barone and Magilke (2009) as well as Drake, Myers, and Myers (2009) also show that the accrual and the cash flow effect are distinct. Moreover, Livnat and López-Espinosa (2008) prove that quarterly operating cash flows predict future returns better than quarterly accruals.

2.4 Combination of Technical and Fundamental Trading

2.4.1 Potential of Combining Fundamental and Technical Trading

Sections 2.2 and 2.3 illustrate that technical and fundamental trading are different in several respects: Whereas they both have the same aim of determining in which direction prices are going to move, they choose different ways to achieve that aim: Whereas technical traders study the effect of market movements, fundamental traders analyzes its cause.[36] Moreover, the two types of trading have different theoretical backgrounds: Technical trading fully relies on past prices and volumes, assuming that these comprise the necessary information. In contrast, fundamental trading is based on theoretical models of computing a stock's fair value. Correspondingly, advocates of the two types of trading also see market participants differently. Malkiel (2007) expresses this as follows: "Most chartists believe that the market is only 10 % logical and 90 % psychological. […] Fundamental analysts take the opposite tack, believing that the market is 90 % logical and only 10 % psychological."[37] Lastly, the two strategies also typically have different investment horizons. Technical trading mainly strives for exploiting short- to medium term trends, whereas most fundamental investments have a medium- to long term investment horizon. The fact that believers in technical trading are often just called "traders" in contrast to fundamentalists who are called "investors," exemplifies this difference.[38]

According to these different characteristics, most common textbooks also have different chapters for technical and fundamental trading.[39] This strict separation does not adequately reflect reality. Surveys show that practitioners do not constrain themselves to one of the two strategies. Taylor and Allen (1992) find that foreign exchange dealers use both fundamental and technical data in their work and Oberlechner (2001) demonstrates the same for the European foreign exchange market and financial journalists in Frankfurt. These findings for the foreign exchange market are confirmed by the statement of Stuart Walton, a successful professional investor. When asked in an interview "And how do you find these good

[35] Houge and Loughran (2000), p. 165.
[36] See Murphy (1999), p. 5.
[37] Malkiel (2007), p. 101.
[38] See, e.g., Malkiel (2007), p. 104. I am not going to differentiate between "investors" and "traders" in this thesis.
[39] See, e.g., chapters 15 and 16 of Jones (2007).

companies?” he replies: “I look for companies that have been blessed by the market. They may be blessed because of a long string of quarters they’ve made (quarters in which the company’s reported earnings reached or exceeded expectations).” And on the later question: “What tells you – to use your word – that a stock is ‘blessed’?” he replies: “It’s a combination of things. The fundamentals of the stock are only 25 % of it. […] Another 25 % is technical.”[40] Finally, also some textbooks acknowledge that traders in practice do use both techniques. For example, Edwards, Magee, and Bassetti (2007) state that a “pure fundamentalist is a very rare bird.”[41]

Against the background of the evidence for combined trading in reality, it is highly interesting to empirically analyze the success and characteristics of a trading strategy that combines technical and fundamental elements. This thesis covers this subject by analyzing a trading strategy that combines technical past return and fundamental operating cash flow information. Especially the disparity of the two techniques is a motivation for such an analysis. The disparity indicates that both sets of information are complements in predicting returns and that a meaningful combination should offer additional profit opportunities. In other words: if both approaches recommend buying a certain stock even though they have come to this recommendation in completely different ways, the stock is much more likely to outperform. Of course, one should not randomly combine any technical and fundamental technique, but rather look for a combination that makes sense economically. The idea behind a combination of past returns and operating cash flows is presented in section 3.1.

2.4.2 Related Literature

Surprisingly, until today there have been only few academic studies analyzing combinations of technical and fundamental trading. A study explicitly addressing this subject is Bettman, Sault, and Schultz (2009). They run multivariate regressions of future stock prices on past accounting and market data. Their model works better when fundamental and technical data are included as explanatory variables instead of only one of the two groups.

Also Figelman (2007) combines technical with fundamental information. She analyzes whether the momentum effect depends on profitability or earnings quality. She provides evidence that companies with poor past returns and high return on equity tend to manipulate their earnings. Their future returns are worse than the returns of stocks with poor past returns and low return on equity.

---

40 Schwager (2003), p. 15.
41 Edwards, Magee, and Bassetti (2007), p. 4.

Moreover, Chan, Jegadeesh, and Lakonishok (1996) test in their study, whether price and earnings momentum are the same phenomena. They find that the two effects are distinct, since they both predict future returns, even after controlling for each other. Their conclusion is that the price momentum effect is not only due to the market's underreaction to past earnings news.

In addition, there are some studies analyzing whether several variables are complements or substitutes in predicting future returns. If these variables include technical and fundamental data, these studies also analyze the value of combination strategies, even if they do not directly address this issue. Among these studies are Kraft (2001) and Fama and French (2008). Surprisingly, neither of the two studies includes operating cash flows in their models.

Lastly, there are papers which combine the momentum effect with other variables. Examples for these studies are Lee and Swaminathan (2000), as well as Sagi and Seasholes (2007).

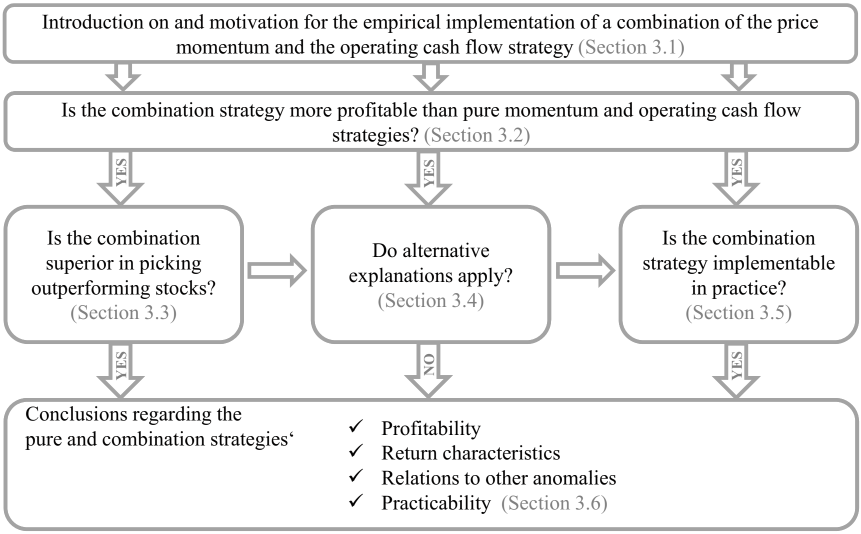
Lee and Swaminathan (2000) combine two types of technical information. They analyze the impact of trading volume on price momentum and find that analyzing trading volume can help to predict the magnitude and persistence of the price momentum effect. Moreover, trading volume seems to provide an important link between momentum and value strategies. Lastly, Sagi and Seasholes (2007) provide a real option model and show that return autocorrelation depends on firm-specific attributes. Their empirical study supports the hypotheses derived from their model: The traditional momentum strategy, i.e., buying winners and selling losers, works better for firms with high revenue growth volatility, low costs, or valuable growth options.

To conclude, there is still a lot of room for further research in the intersection of technical and fundamental analysis. I contribute to this field by thoroughly investigating a trading strategy which combines the technical momentum strategy with the fundamental information of operating cash flows. I do not only address the strategies' returns, but also the return characteristics and portfolio composition. This analysis is presented in detail in chapter 1.

3 Combination of Momentum and Operating Cash Flow Strategies

In section 2.4, I have discussed the potentials of combining technical and fundamental trading. In the following, I empirically implement, test, and analyze a combination trading strategy. This combination strategy combines the technical price momentum strategy presented in section 2.2.2 and the fundamental operating cash flow strategy illustrated in section 2.3.2. Figure 3.1 describes the structure of this chapter, which is the centerpiece of this thesis and provides the basis for chapters 1 and 5.[42]

Figure 3.1: Structure of Chapter 3



3.1 Idea and Motivation

My basic motivation for combining fundamental and technical trading is to better understand the characteristics of these two different ways of investing and to explore the potential of combining them. The idea behind the specific combination of momentum and operating cash flows is as follows:

Pure momentum strategies invest according to past returns. In the long position they buy past return winners, assuming that the past price upturn is going to continue. Of course, not every

[42] This chapter is based on the paper: Bonenkamp, Ute, Carsten Homburg, and Alexander Kempf. 2009. Fundamental Information in Technical Trading Strategies. Even though I have written this paper together with Prof. Carsten Homburg and Prof. Alexander Kempf, I will use the first person throughout this chapter in order to ensure consistency with the other chapters.

price upturn will equally likely endure and investors would like to know for which stocks this will be the case. This is where the combination with operating cash flows comes in. I use operating cash flows to pick those past price upturns which will more probably endure in the future. The rationale is that price upturns which are accompanied by high operating cash flows should be more likely fundamentally justified and not be the outcome of noise trading or pricing pressure. If the underlying fundamental good news has not yet been fully incorporated into the current price, the past upturn should endure. Following this consideration, I build a combination portfolio which consists of stocks with high past returns that are accompanied by high operating cash flows. For this combination portfolio, I expect a greater ratio of stocks that outperform during the investment period. The ratio of outperforming stocks in the pure momentum portfolio should be lower because this portfolio comprises **all** stocks with high past price upturns, thus also comprising upturns which merely result from pricing pressure and should be more prone to reversal. The consideration for the short position is similar: Past price downturns are more probably economically justified if they are accompanied by low/negative operating cash flows. Therefore, stocks with both low past returns and low operating cash flows should on average yield lower future returns than all stocks with low past returns in a pure short momentum portfolio.

Why are operating cash flows especially suitable for the refinement? First, operating cash flows are given in financial statements, which are easily available to investors as soon as they are published. Furthermore, information from financial statements does not reflect any stock market effects, making it a good complement to momentum market information. Among the variety of information given in financial statements, the operating cash flow is a good indicator of a firm's overall well-being and its available funds for future investments. Thus, operating cash flows should reflect whether the past price upturn has been justified or not. Lastly, operating cash flows are less prone to manipulation by managers than alternative measures like accruals or earnings.[43] This is underlined by the fact that Dechow and Dichev (2002) even use operating cash flows as benchmark to assess the quality of accruals. The cash flows' reliability is important in the combination strategy, because a reliable measure of firm performance is more suitable to assess past price movements.

The main reason for choosing price momentum as technical strategy is its prominence and simplicity. The simple sorting according to past returns is straightforward and easily imaginable, facilitating the understanding of the combination strategy.

---

[43] Though, e.g., Roychowdhury (2006) provides evidence of earnings management via real activities that affect operating cash flows, manipulations of earnings via accruals are much more prevalent. This prevalence is reflected in the earnings management literature which mainly analyzes (the discretionary part of) accruals, as, e.g., Jones (1991), Dechow, Sloan, and Sweeney (1995), or Kothari, Leone, and Wasley (2005).

My examination of the pure and combination strategies yields the following insights: First, it reveals to what extent past returns and operating cash flows are complements in predicting future returns. Second, it unveils differing return extremities of the two trading strategies. Third, I examine the relations to other well-known anomalies. Lastly, my empirical results have practical implications, suggesting that investors should account for past returns and operating cash flows when trading stocks.

3.2 Profits of the Pure and Combination Strategies

3.2.1 Methodology and Sample

Methodology

I build 35 portfolios to assess the profits of pure momentum, pure operating cash flow, and combination strategies. When building the portfolios, I use two sorting criteria: past returns (*mom*) and operating cash flows (*cfo*). *Mom* is the past compounded six-month stock return, measured with a one-month lag to exclude possible short-term reversal effects, and is calculated every month *m*.[44]

$$mom_{i,m} = \prod_{\tau=-6}^{-1}(1 + return_{i,m+\tau}) - 1 \qquad 3.1$$

Cfo is the company's quarterly operating cash flow (CSI #Q108) per average total assets (CSI #Q44) and is given every quarter *q*.

$$cfo_{i,q} = \frac{quarterly\,operating\,cash\,flow_{i,q}}{\varnothing total\,assets_{i,q}} \qquad 3.2$$

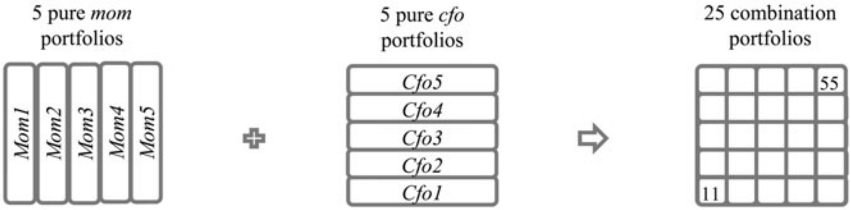
Every quarter, I sort the whole universe of stocks according to their *mom* and assign them into five quintile portfolios *Mom1* to *Mom5*. I assign the top 20 % of stocks to portfolio *Mom5*, and the bottom 20 % to portfolio *Mom1*. Second, I independently sort all companies according to their operating cash flow into the quintile portfolios *Cfo1* to *Cfo5*. *Cfo5* comprises the 20 % stocks with highest *cfo*, *Cfo1* the 20 % with lowest *cfo*. Then I build 25 combination portfolios *Combi11* to *Combi55*. These portfolios consist of the intersections of the two independent sortings. Accordingly, portfolio *Combi11* comprises those stocks that belong to the 20 % with lowest *mom* (portfolio *Mom1*) and to the 20 % with lowest *cfo* (portfolio *Cfo1*) at the same

---

[44] Jegadeesh (1990) presents negative short-term serial correlation in stock returns. Jegadeesh and Titman (1995) examine the relation between bid-ask spreads and short-term reversals. Lo and MacKinlay (1990) show that short-term contrarian profits may also be due to lead-lag effects between different stocks. My results do not depend on the one-month lag. I get very similar results when measuring momentum without a time lag.

time. The portfolio I mainly focus on is *Combi55*. It includes all companies belonging to the top 20 % with respect to their *mom* (*Mom5*) and to the top 20 % with respect to their *cfo* (*Cfo5*) at the same time. Figure 3.2 illustrates the double sorting procedure.

Figure 3.2: Portfolio Sorting Procedure



I assign the stocks to the 35 portfolios every quarter at the end of March, June, September, and December and hold the stocks for the ensuing three months. The allocation of stocks to portfolios in terms of *mom* is simple. It refers to the six-month period before portfolio formation with a one-month lag. The allocation of stocks according to their *cfo* is more complicated because of reporting lags and different fiscal quarter ends. First, quarterly reports on average become publicly available 44.7 days after fiscal quarter end.[45] I insert a three-month lag between fiscal quarter end and portfolio formation in order to ensure the availability of cash flow information at the time of investment.[46] Second, it is appropriate to compare quarterly data belonging to the same fiscal quarter. This is not necessarily the same calendar quarter due to differing fiscal year ends.[47] I consider this by only referring to cash flow information from the same fiscal quarter when sorting stocks according to *cfo*. For the portfolio formation at the end of March, I only use data from the fourth fiscal quarter, at the end of June those of the second et cetera. The shortcoming of this procedure is that for companies whose fiscal year does not end in December, the lag between fiscal quarter end and portfolio formation is longer than three months.[48] In my sample, this is the case for 37.63 % of the observations.[49] Figure 3.3 summarizes the time structure of the trading strategies.

45 See Easton and Zmijewski (1993), p. 121.

46 Additionally I replicate the analysis only using stocks for which I have the exact earnings publication date and for which I thus certainly now that the cash flow information is publicly available. This analysis yields similar results.

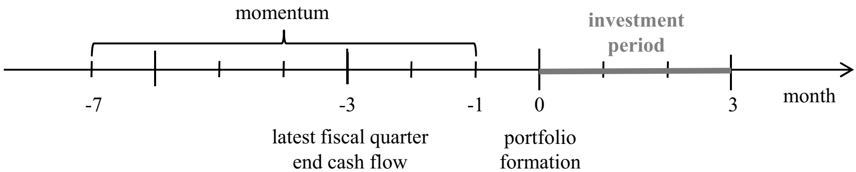
47 Rangan and Sloan (1998) describe the difficulties in comparing financial information from different fiscal quarters and years resulting from the integral approach to quarterly reporting.

48 If, for example, a company's fiscal year ends in September, cash flow information that is supposed to be published in September is used as investment criterion at the end of March of the following year.

49 Nevertheless, my results are not driven by this shortcoming. When I repeat my analyses using only stocks with fiscal year end December, this does not qualitatively change my results.

Figure 3.3: Time Structure of the Trading Strategies

measurement momentum	latest fiscal quarter end cash flow	fiscal quarter cash flow	portfolio formation	investment period
Sep – Feb	Dec 31	IV	March 31	April – June
Dec – May	March 31	I	June 30	July – Sep
March – Aug	June 30	II	Sep 30	Oct – Dec
June – Nov	Sep 30	III	Dec 31	Jan – March



The stocks in my portfolios are initially equally weighted.[50] To assess the trading strategy's success, I use two different measures of risk-adjusted returns: $abnreturn$ and $alpha$.[51]

To compute a firm's monthly abnormal return during month m $abnreturn_{i,m}$ I compute the difference between its return and the value-weighted return of all firms belonging to the same quintiles in terms of size and book-to-market.[52]

$$abnreturn_{i,m} = return_{i,m} - return_{i,m}^{bm} \tag{3.3}$$

with:

$return_{i,m}$ = return of stock i during month m

$return_{i,m}^{bm}$ = value weighted buy-and-hold return during month m of the characteristic-based benchmark portfolio which consists of stocks that belong to the same quintiles in terms of size and book to market as stock i at the beginning of month m.[53]

---

50 When I replicate the analysis using value-weighted portfolios, I obtain very similar results.

51 I furthermore compute normal returns which are not adjusted for risk, leading to the same conclusions. For the sake of brevity, I do not present the results for normal returns here.

52 See Fama and French (1992), pp. 451-452.

53 I obtain size and book-to-market decile breakpoints and portfolio returns from Kenneth R. French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. If the book value of equity is not given for a certain point of time, I use the last given previous book value.

To calculate the portfolios' monthly 3-factor alphas, I regress the monthly time series of portfolio returns on the monthly Fama French factors market (*RMRF*), firm size (*SMB*), and value (*HML*):[54]

$$return_{j,m} - r_m^f = \alpha_j + \beta_j^{Market} \cdot RMRF_m + \beta_j^{Size} \cdot SMB_m + \beta_j^{Value} \cdot HML_m + \varepsilon_{j,m} \qquad 3.4$$

with:

$return_{j,m}$	=	return of portfolio *j* during month *m*
r_m^f	=	riskless rate during month *m*
$RMRF_m$	=	market benchmark factor during month *m*
SMB_m	=	size benchmark factor during month *m*
HML_m	=	value benchmark factor during month *m*
β_j^l	=	loading of portfolio *j* on factor *l*

Using the estimated factor loadings from regression 3.4, I calculate monthly 3-factor alphas $alpha_{j,m}$ for each portfolio *j*.

$$alpha_{j,m} = return_{j,m} - r_m^f - \hat{\beta}_j^{Market} \cdot RMRF_m - \hat{\beta}_j^{Size} \cdot SMB_m - \hat{\beta}_j^{Value} \cdot HML_m \qquad 3.5$$

If a firm delists during the three-month investment period, I follow Beaver, McNichols, and Price (2007):[55] If CRSP gives the delisting return, I use this delisting return. In other cases, I use the mean delisting return of all companies with the same first digit of the delisting code provided by CRSP. For the remaining holding period, I assume an investment into the value-weighted market portfolio from CRSP.

My first approach to assess the portfolios' profits is a comparison of mean monthly $abnreturn_{j,m}$ and $alpha_{j,m}$ earned by the different portfolios. I especially focus on portfolios *Cfo5*, *Mom5*, and *Combi55*. Portfolio *Cfo5* consists of the 20 % stocks with the highest *cfo*, thus representing a pure long-only cash flow strategy. Portfolio *Mom5* comprises the 20 % stocks with highest *mom* and represents a pure long-only momentum strategy without any consideration of fundamental information. Accordingly, *Mom5* is the benchmark to assess whether the refinement of the momentum strategy is worthwhile. *Combi55*, finally, is the portfolio my strategy recommends investing in, comprising stocks with highest past returns and operating cash flows. To test whether portfolio *Combi55* is more profitable than *Mom5*, I use the time series of monthly portfolio *abnreturns* and *alphas*. In order to decide whether

[54] *RMRF* is computed as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks minus the one-month Treasury bill rate. *SMB* and *HML* denote return differences between portfolios formed on size and book-to-market. A description of the exact calculation as well as the data are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[55] See Beaver, McNichols, and Price (2007), pp. 344-348.

these risk-adjusted returns significantly differ from zero, I conduct two-sided t-tests with Newey and West (1987) standard errors that control for possible time-series dependence.

Besides the comparison of portfolio returns, I conduct regressions to evaluate the strategies' success. The pure strategies will only perform well if operating cash flows and past returns predict future returns during the investment period. To test this condition, I run regressions with the future stock return on the left hand side and momentum or operating cash flow as explanatory variables. First, I only insert one of the two variables to test their separate predictive ability. The combination strategy is expected to perform well if past returns and operating cash flows are **complementary** pieces of information for predicting stock returns. To test this condition, I insert both variables as explanatory variables in the regression. For momentum and operating cash flow I use deciles scaled from zero to one (*momdec* and *cfodec*) instead of the actual values *mom* and *cfo*.[56] By means of this approach, the beta coefficients can be interpreted as the return difference between stocks in the tenth and the first deciles in terms of *mom* or *cfo*. In regression 3.9, I additionally insert the natural logarithm of firm size (*size*), and book-to-market (*btom*) as control variables, because they are known predictors of future returns.[57] I leave out market beta because it has no significant explanatory power for expected returns after accounting for size and book-to-market.[58]

I conduct two types of regressions: Fama-MacBeth regressions following Fama and MacBeth (1973) and Ordinary Least Squares (OLS) Regressions with standard errors that are clustered by firm and time recommended by Petersen (2009).

In the Fama-MacBeth approach I run regressions for each point of time *t*. Then I compute the mean estimated coefficients aggregated across time.[59] By calculating regressions for every point of time, this approach only uses cross-sectional information for the estimation of the coefficients. The standard errors are calculated by using the time-series of the estimated coefficients. Thus, standard errors account for the "time effect", i.e., correlation across different firms at one point of time.[60] Petersen (2009) demonstrates the necessity of also controlling for correlations between residuals across time for a given firm, which he calls "firm effect."[61] He advises to run regressions with standard errors that are clustered in both dimensions, firm and time. Following this advice, I also estimate the regressions using pooled ordinary least squares regressions and standard errors that are clustered by firm and time. I run

56 I obtain very similar results when using the actual values *mom* and *cfo* instead of deciles.
57 For the size effect, see Banz (1981). Graham and Dodd (1934) are considered as the founders of value investing due to their work "Security Analysis".
58 See Daniel and Titman (1997).
59 See Fama and MacBeth (1973).
60 Petersen (2009) calls this cross-sectional dependence "time effect"; see Petersen (2009), p. 436.
61 See Petersen (2009), p. 436.

the following regressions 3.6 to 3.9. As dependent variable I choose non-overlapping compounded future three-month returns, corresponding to the quarterly portfolio rebalancing of my trading strategy, and future monthly stock returns. Since I control for size and book to market in regression 3.9, I use normal returns as dependent variable. As cash flows and book values are only available every quarter, I use their values three times in the monthly regressions.[62]

$$return_{i,t+1} = \alpha + \beta^{mom} \cdot momdec_{i,t} + \varepsilon_{i,t+1} \tag{3.6}$$

$$return_{i,t+1} = \alpha + \beta^{cfo} \cdot cfodec_{i,t} + \varepsilon_{i,t+1} \tag{3.7}$$

$$return_{i,t+1} = \alpha + \beta^{mom} \cdot momdec_{i,t} + \beta^{cfo} \cdot cfodec_{i,t} + \varepsilon_{i,t+1} \tag{3.8}$$

$$\begin{aligned} return_{i,t+1} = {} & \alpha + \beta^{mom} \cdot momdec_{i,t} + \beta^{cfo} \cdot cfodec_{i,t} + \beta^{size} \cdot \ln\left(size\right)_{i,t} \\ & + \beta^{btom} \cdot \ln\left(btom\right)_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{3.9}$$

with:

t	=	proxy variable for period t, t stands for month m in the monthly regressions and for quarter q in the quarterly regressions.
$return_{i,t+1}$	=	return of stock i during period t+1
$momdec_{i,t}$	=	decile in terms of *mom* of stock i at the end of period t $momdec_{i,t} \in \{0, \frac{1}{9}, \frac{2}{9}, \ldots, 1\}$
$cfodec_{i,t}$	=	decile in terms of *cfo* of stock i at the end of period t $cfodec_{i,t} \in \{0, \frac{1}{9}, \frac{2}{9}, \ldots, 1\}$
$\ln(size)_{i,t}$	=	natural logarithm of the market value of stock i at the end of period t
$\ln(btom)_{i,t}$	=	natural logarithm of book-to-market of stock i at the end of period t
β^{l}	=	loading on variable l

Sample

I use the merged CRSP and Compustat databases, taking monthly returns of all NYSE, AMEX, and NASDAQ companies as well as information on quarterly operating cash flows. The investigation spans the period from March 1989 to December 2007. I exclude the 1 % extreme outliers in terms of current *return*, *mom*, and *cfo*. This leaves me in total with 1,100,451 monthly returns and 366,817 quarterly observations of the financial statements. Table 3.1 presents descriptive statistics for my sample.

62 Exemplarily, I list the formulas for the OLS regressions. For the Fama-MacBeth approach, an additional time superscript would be necessary because of the cross-sectional regressions that are conducted per period in this approach.

Table 3.1: Descriptive Statistics of the Main Variables

	n	mean	p 25	p 50	p 75
cfo (in %)	366,817	0.74	-1.16	1.36	3.68
mom (in %)	366,817	5.82	-17.07	1.92	21.71
size (in million US$)	347,894	1,896	33.65	144.49	679.26
btom (in %)	347,894	74.65	30.89	53.22	87.30
return (in % p.m.)	1,100,451	1.18	-7.22	0	7.5
abnreturn (in % p.m.)	1,100,451	0.04	-8.02	-0.89	6.21

The mean quarterly ratio of operating cash flows to average assets is 0.74 %. Mean past compounded six-month-returns mom have a mean of 5.82 % and exhibit a high dispersion with a lower quartile of -17.07 % and an upper quartile of 21.71 %. *Mom* and *cfo* are positively correlated with a mean Spearman correlation coefficient of 0.1387. Due to data availability of book values I have only 347,894 observations for the quarterly regression 3.9. I report descriptive statistics for *size* and *btom* for this subsample. Mean market value is 1,896 million US$ and the mean relation between book and market value is 74.65 %. The mean monthly raw return in my sample is 1.18 %, implying a return of 15.12 % p.a. The mean monthly abnormal return is close to zero with a value of 0.04 %.

3.2.2 Empirical Results and Discussion

First, I compare the risk-adjusted returns earned by the 35 portfolios. Table 3.2 presents mean monthly abnormal returns *abnreturn* in Panel A and mean monthly 3-factor alphas *alpha* in Panel B. The given levels of significance are based on two-tailed tests using Newey and West (1987) standard errors with a lag of 6 months to account for possible time-series dependence.

Table 3.2: Risk-Adjusted Performance of the Trading Strategies

Panel A Mean *abnreturn* (in % p.m.)

		low *mom*				high *mom*	
		Mom1	*Mom2*	*Mom3*	*Mom4*	*Mom5*	pure *cfo*
high *cfo*	*Cfo5*	0.25	0.35 ***	0.41 ***	0.52 ***	1.16 ***	0.58 ***
	Cfo4	-0.35	0.13	0.12	0.15	0.87 ***	0.21 ***
	Cfo3	-0.46 *	-0.22 *	-0.12	0.07	0.61 ***	-0.01
	Cfo2	-0.65 *	-0.37 **	-0.26 **	-0.26 **	0.46 ***	-0.25 *
low *cfo*	*Cfo1*	-0.70 *	-0.55 **	-0.45 **	-0.14	0.43	-0.35
pure *mom*		-0.46	-0.14	-0.03	0.10	0.73 ***	

Panel B Mean *alpha* (in % p.m.)

	low *mom*				high *mom*	
	Mom1	*Mom2*	*Mom3*	*Mom4*	*Mom5*	pure *cfo*
high *cfo* *Cfo5*	-0.07	0.35 **	0.55 ***	0.69 ***	1.20 ***	0.62 ***
Cfo4	-0.54 **	0.18	0.34 ***	0.43 ***	1.00 ***	0.35 ***
Cfo3	-0.65 **	-0.15	0.12	0.35 ***	0.80 ***	0.13 *
Cfo2	-0.93 ***	-0.36 **	-0.06	-0.04	0.53 ***	-0.23 *
low *cfo* *Cfo1*	-1.14 **	-0.71 **	-0.43 *	-0.10	0.24	-0.59 **
pure *mom*	-0.79 ***	-0.15	0.14 **	0.33 ***	0.80 ***	

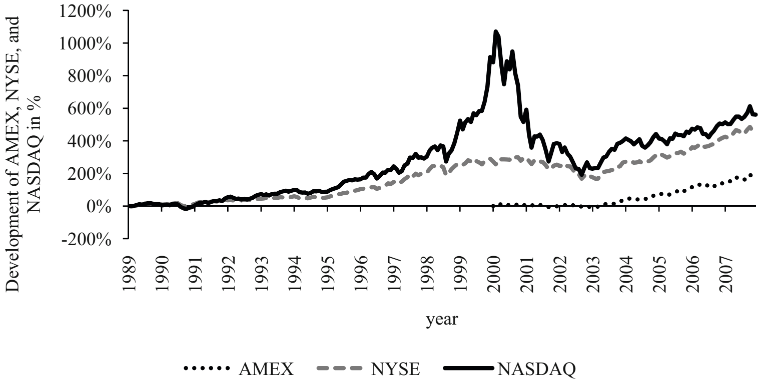
*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

Table 3.2 provides evidence that an investor can increase profits by simultaneously taking *mom* and *cfo* into account. This basic result holds irrespective of the performance measure used. Within each momentum quintile trading profits increase with the operating cash flow of the stocks. The same is true within each cash flow quintile: the higher the momentum of the stocks, the higher the performance. Therefore, the combination strategy (*Combi55*), which selects stocks with high *mom* and high *cfo*, yields the maximum profit. Its average *abnreturn* is 1.16 % p.m. and its *alpha* is 1.20 % p.m. Both are highly significant. If the investor follows a pure momentum strategy or a pure cash flow strategy, the profit is significantly lower. The pure momentum portfolio *Mom5* yields an *abnreturn* of 0.73 % and an *alpha* of 0.80 % p.m. The respective numbers for the pure cash flow strategy are 0.58 % and 0.62 % p.m. The differences in performance between the combination strategy and the pure strategies are significant at the 1 %-level. The difference in *abnreturn* between portfolios *Combi55* and *Mom5* is 0.43 % p.m. and exhibits a t-value of 5.00. In terms of *alpha*, the difference is 0.40 % p.m. with a t-value of 4.51. The comparison of portfolios *Combi55* and *Cfo5* yields similar results with a difference of 0.58 % p.m. (*abnreturn*) and a t-value of 3.53, and 0.58 % p.m. (*alpha*) with a t-value of 4.69, respectively.

The statistical significance of the presented returns suggests that the strategies' success is stable over time. Nevertheless, the profits could depend on states or movements of the market. This is what I am going to analyze in the following. The market movements during my investigation period are visible in Figure 3.4 where I visualize the development of NYSE, AMEX, and NASDAQ between 1989 and 2007.[63]

[63] The data for the illustration is taken from http://de.finance.yahoo.com.

Figure 3.4: NYSE, AMEX, and NASDAQ between 1989 and 2007



The indices have risen considerably in the 19 years of the investigation period. In December 2007, they are about six times more worth than in January 1989. Mostly the three indices commove together. Only in 1999 and 2000 they diverge extremely due to the internet bubble which is reflected in the jump and the ensuing drop of the NASDAQ Composite Index. All in all, there is an upward movement until the end of 1999. After that, the market declines until the end of 2002. In 2003 the trend changes again and markets rise again steadily until the end of 2007. The different market movements during the investment period allow me to test the trading strategies' profits under different market conditions.

Figure 3.5 shows monthly risk-adjusted returns to portfolios *Combi55*, *Mom5*, and *Cfo5* on a year-by-year basis. Figure A presents mean *abnreturns* and Figure B mean *alphas* in % p.m.

Figure 3.5: Performance of the Long Positions on a Year-by-Year Basis

Figure A: Mean *abnreturn* (in % p.m.)

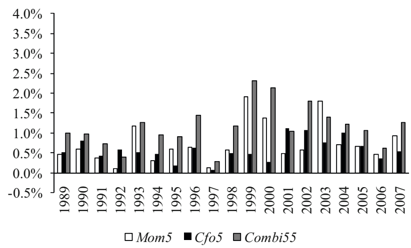
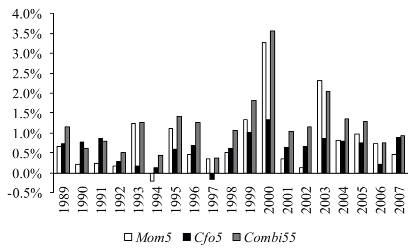


Figure B: Mean *alpha* (in % p.m.)



The success of the combination strategy is extremely stable. Portfolio *Combi55* outperforms the pure momentum and the pure cash flow strategy in almost all years – no matter which performance measure I use. Only in 2003 portfolio *Mom5* beats the combination strategy. This could be attributable to the exceptional market trend in this year. In 2003, the market made the transition from the bear market in the previous years to a bull market. Such an environment would be especially suitable for the momentum strategy, if prices gathered especially high momentum in such turning markets.[64] Fundamental information would be less important in such a changing environment. Consequently, one misses some of the exceptional upturn by requiring the additional criterion of high operating cash flows in this year. The pure cash flow strategy beats the combination strategy in two years – 1992 and 2001 in terms of *abnreturn*, and 1990 and 1991 when using *alpha*. In all other years, the combination strategy is superior to both pure ones, strengthening the overall result that it makes sense to pick stocks based on *mom* and *cfo* at the same time, independently from the respective market state.

In the short position, the combination strategy is also superior to the two pure ones, as it yields lower risk-adjusted returns. Portfolio *Combi11* yields risk-adjusted returns of *abnreturn* = -0.70 % and *alpha* = -1.14 % p.m. However, these returns are only significantly lower than those of the pure portfolios *Mom1* and *Cfo1* when *alpha* is used as measure of risk-adjusted returns. The difference in *alpha* of -0.35 % p.m. between *Combi11* and *Mom1* yields a t-value of -2.03 and the difference between *Combi11* and *Cfo1* of -0.55 % p.m. yields a t-value of -2.67. The differences of -0.24 % p.m. and -0.35 % p.m. in terms of *abnreturn* are only different from zero on the 15 % level with t-values of -1.51 and -1.49. Figure 3.6 shows risk-adjusted returns to the portfolios *Mom1*, *Cfo1*, and *Combi11* on a year-by-year basis.

Figure 3.6: Performance of the Short Positions on a Year-by-Year Basis

Figure A: Mean *abnreturn* (in % p.m.)

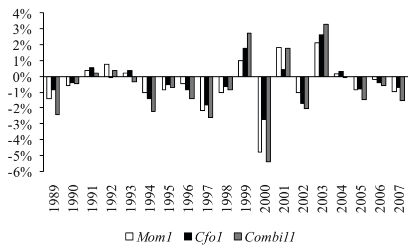
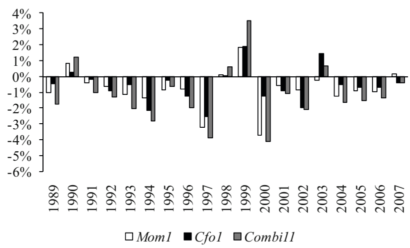


Figure B: Mean *alpha* (in % p.m.)



The most noticeable year for portfolio *Combi11* is 1999, where the portfolio yields higher *abnreturns* and *alphas* than the two pure strategies. I trace this back to the high portion of NASDAQ stocks in portfolio *Combi11*. For the whole sample, about 10 % of the stocks

[64] Until now, there is to my knowledge no paper examining the influence of regime switching on momentum profits. There are only studies investigating the dependence of momentum profits on market states, as, e.g., Cooper, Gutierrez Jr., and Hameed (2004) as well as Siganos and Chelley-Steeley (2006).

belong to AMEX, 30 % to NYSE, and 60 % to NASDAQ. The distribution in the long combination portfolio *Combi55* is similar with ratios of 8 %, 28 %, and 64 %. In portfolio *Combi11*, also 10 % of the stocks belong to AMEX, but only 8 % to NYSE, so that an enormous ratio of 82 % of the stocks belongs to NASDAQ. The NASDAQ Composite Index and the other stocks diverged strongly in 1999 and 2000 as visible in Figure 3.4. In 1999, the NASDAQ Composite Index outperformed. This outperformance might have contributed to the high returns of portfolio *Combi11* during that year. In 2000, in contrast, the NASDAQ underwent a sharp drop, which was one important reason for the failure of portfolio *Combi11* in 2000. From 2001 on, the exchanges again commove together. All in all, the year-by-year analysis confirms that the profits of the combination strategy are extremely stable and robust to different market conditions, especially in the long position.

The results of the regression-based analysis also support the superiority of the combination strategy as presented in Table 3.3. Panel A lists the results of the OLS regressions with clustered standard errors and Panel B gives the results of the Fama-MacBeth approach.

Table 3.3: Determinants of Future Returns

Panel A: OLS Regression with Adjusted Standard Errors

regr		$\hat{\alpha}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{cfo}$	$\hat{\beta}^{size}$	$\hat{\beta}^{btom}$
3.6	$return_{m+1}$	0.06	1.38 ***			
3.6	$return_{q+1}$	2.02	3.31 ***			
3.7	$return_{m+1}$	-0.09		1.63 ***		
3.7	$return_{q+1}$	2.11		3.13 ***		
3.8	$return_{m+1}$	-0.60	1.19 ***	1.47 ***		
3.8	$return_{q+1}$	0.85	2.93 **	2.73 ***		
3.9	$return_{m+1}$	-0.52	1.15 ***	1.38 ***	0.06	0.45 ***
3.9	$return_{q+1}$	4.08	3.81 ***	3.51 ***	-0.62 **	1.36 **

Panel B: Fama-MacBeth Regression

regr		$\hat{\alpha}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{cfo}$	$\hat{\beta}^{size}$	$\hat{\beta}^{btom}$
3.6	$return_{m+1}$	0.05	1.43 ***			
3.6	$return_{q+1}$	2.18	3.13 **			
3.7	$return_{m+1}$	-0.04		1.57 ***		
3.7	$return_{q+1}$	2.22		3.05 ***		
3.8	$return_{m+1}$	-0.54	1.23 ***	1.36 ***		
3.8	$return_{q+1}$	1.11	2.67 **	2.60 ***		
3.9	$return_{m+1}$	-0.61	1.16 ***	1.25 ***	0.07	0.23 ***
3.9	$return_{q+1}$	3.68	3.41 ***	3.32 ***	-0.57 ***	0.65

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test. Standard errors of the OLS regressions are clustered by stock and by time.

The estimated coefficients of regressions 3.6 and 3.7 show that both momentum and operating cash flows **separately** have a highly significant impact on future stock returns. This is in line with previous literature, as, e.g., with Livnat and Zarowin (1990), Sloan (1996), and Jegadeesh and Titman (1993). In addition, the results of regressions 3.8 and 3.9 furthermore underline that the two variables are indeed **complements** in predicting future returns. The predictive power of both variables remains significant when I include both variables in the regression. Furthermore, the coefficients do not change a lot when inserting the respective other variable. In the OLS regressions the influence of *momdec* changes from $\hat{\beta}^{mom} = 1.38$ to $\hat{\beta}^{mom} = 1.19$ in the monthly and from $\hat{\beta}^{mom} = 3.31$ to $\hat{\beta}^{mom} = 2.93$ in the quarterly regressions when I insert *cfodec*. Similarly, the influence of *cfodec* only moderately decreases from $\hat{\beta}^{cfo} = 1.63$ to $\hat{\beta}^{cfo} = 1.47$ and from $\hat{\beta}^{cfo} = 3.13$ to $\hat{\beta}^{cfo} = 2.73$ when controlling for *momdec*. These moderate decreases show that *momdec* and *cfodec* are not highly correlated, thus acting more as complements than as substitutes. This result also holds when I additionally control for size and book-to-market in regression 3.9. Furthermore, it applies to returns over the next month as well as to returns over the next quarter. The results also do not change qualitatively when I use OLS regressions with adjusted standard errors instead of the Fama-MacBeth approach. These results support the profits found in the comparison of strategy returns in Table 3.2, underlining that a trading strategy which combines past return and past operating cash flow information is highly valuable.

3.3 Decomposition of the Outperformance

3.3.1 Introduction and Methodology

The outperformance of the combination strategy over the pure strategies might result from two sources. First, it might result from a greater probability of picking stocks with positive outperformance. The second possible source is a conditionally better performance of the stocks picked. According to the central idea of combining the two criteria, high operating cash flows are intended to increase the probability that an observed past price upturn is due to real fundamental information and should therefore more probably endure in the future.[65] If the criterion of high operating cash flows indeed works that way, the outperformance of the combination strategy should be due to picking a greater ratio of outperforming stocks in portfolio *Combi55* than in portfolio *Mom5*. Conditional returns, in contrast, should not necessarily be higher in the combination. In the following, I am going to analyze whether this is indeed the case. In particular, I am going to focus on the long position of the trading strategies.

65 This central idea is described in section 3.1.

In a preliminary analysis, I investigate quarterly abnormal returns which comply with the quarterly rebalancing of the investment portfolios. Every quarter at the beginning of a new investment, I calculate which portion of the stocks in the different portfolios yields positive compounded *abnreturns* in the following three months. I name this picking ratio $p^{+}_{j,q}$ of portfolio j, at the end of quarter q, i.e., at the beginning of quarter q+1:

$$p^{+}_{j,q} = \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^{+}_{i,q+1} = \sum_{i=1}^{N_{j,q}} \frac{1}{N_{j,q}} \cdot D^{+}_{i,q+1} \qquad 3.10$$

with:

$w_{i,j,q}$	=	portfolio weight of stock i in portfolio j at the end of quarter q
$N_{j,q}$	=	number of stocks in portfolio j at the end of quarter q
$D^{+}_{i,q+1}$	=	Dummy Variable; $D^{+}_{i,q+1}$ = 1 if $abnreturn_{i,q+1} > 0$, otherwise $D^{+}_{i,q+1} = 0$
$abnreturn_{i,q+1}$	=	*abnreturn* of stock i during quarter q+1

Then I determine mean positive and negative compounded quarterly abnormal returns $abnreturn^{+}_{j,q+1}$ and $abnreturn^{-}_{j,q+1}$ of portfolio j.

$$\begin{aligned} abnreturn^{+}_{j,q+1} &= \frac{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^{+}_{i,q+1} \cdot abnreturn_{i,q+1}}{\sum_{i=1}^{N} w_{i,j,q} \cdot D^{+}_{i,q+1}} \\ abnreturn^{-}_{j,q+1} &= \frac{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot (1-D^{+}_{i,q+1}) \cdot abnreturn_{i,q+1}}{\sum_{i=1}^{N} w_{i,j,q} \cdot (1-D^{+}_{i,q+1})} \end{aligned} \qquad 3.11$$

Using these conditional returns allows me to analyze the extremity of the gained profits that have led to the total mean *abnreturn*. The abnormal return of portfolio j in quarter q+1 $abnreturn_{j,q+1}$ can be computed using the picking rate $p^{+}_{j,q}$ and $abnreturn^{+}_{j,q+1}$ and $abnreturn^{-}_{j,q+1}$:

$$
\begin{aligned}
abnreturn_{j,q+1} &= \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot abnreturn_{i,q+1} \\
&= \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^{+}_{i,q+1} \cdot abnreturn_{i,q+1} + \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot (1 - D^{+}_{i,q+1}) \cdot abnreturn_{i,q+1} \\
&= \underbrace{(\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^{+}_{i,q+1})}_{p^{+}_{j,q}} \cdot \underbrace{\frac{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^{+}_{i,q+1} \cdot abnreturn_{i,q+1}}{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^{+}_{i,q+1}}}_{abnreturn^{+}_{j,q+1}} \\
&\quad + \underbrace{(\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot (1 - D^{+}_{i,q+1}))}_{p^{-}_{j,q}} \cdot \underbrace{\frac{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot (1 - D^{+}_{i,q+1}) \cdot abnreturn_{i,q+1}}{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot (1 - D^{+}_{i,q+1})}}_{abnreturn^{-}_{j,q+1}} \\
&= p^{+}_{j,q} \cdot abnreturn^{+}_{j,q+1} + (1 - p^{+}_{j,q}) \cdot abnreturn^{-}_{j,q+1} \\
&= p^{+}_{j,q} \cdot abnreturn^{+}_{j,q+1} + p^{-}_{j,q} \cdot abnreturn^{-}_{j,q+1}
\end{aligned}
\qquad 3.12
$$

with:

$abnreturn_{j,q+1}$	=	mean abnormal return of portfolio *j* during quarter *q*+1
$p^{+}_{j,q}$	=	ratio of stocks in portfolio *j* picked at the end of quarter *q* with $abnreturn_{i,q+1} > 0$ during quarter *q*+1
$p^{-}_{j,q}$	=	1- $p^{+}_{j,q}$
	=	ratio of stocks in portfolio *j* picked at the end of quarter *q* with $abnreturn_{i,q+1} \leq 0$ during quarter *q*+1

In my second analysis, I change from the quarterly to the monthly basis and focus on the level of outperformance of the gained profits. This monthly basis corresponds to the returns and the outperformance I report in Panel A of Table 3.2. Every month, I determine the ratio of stocks that yield positive abnormal returns in the following month and the conditional positive and negative monthly abnormal returns, respectively.[66] Using these monthly data, I decompose the **out**performance of portfolio *Combi55* compared to the portfolios *Mom5* and *Cfo5*. I determine which part of the outperformance can be attributed to the greater probability of choosing stocks with positive *abnreturns* (stock picking effect), and which part can be attributed to higher conditional abnormal returns (conditional performance effect). I decompose the performance difference each month, calculate the two different performance contributions, and then aggregate them over time.

[66] Basically, the same formulas apply as described in equations 3.10 to 3.12, only I use monthly instead of quarterly data.

I describe this procedure using the performance difference between portfolio *Combi55* and *Mom5* as an example. The performance difference between these two strategies can be written as:[67]

$$
\begin{aligned}
& abnreturn_{m+1}^{Combi} - abnreturn_{m+1}^{Mom} \\
&= \left[p_m^{Combi+} \cdot abnreturn_{m+1}^{Combi+} + p_m^{Combi-} \cdot abnreturn_{m+1}^{Combi-} \right] \\
&\qquad - \left[p_m^{Mom+} \cdot abnreturn_{m+1}^{Mom+} + p_m^{Mom-} \cdot abnreturn_{m+1}^{Mom-} \right] \\
&= \left[p_m^{Combi+} - p_m^{Mom+} \right] \cdot \left[abnreturn_{m+1}^{Mom+} - abnreturn_{m+1}^{Mom-} \right] \\
&\qquad + p_m^{Mom+} \cdot \left[abnreturn_{m+1}^{Combi+} - abnreturn_{m+1}^{Mom+} \right] \\
&\qquad + p_m^{Mom-} \cdot \left[abnreturn_{m+1}^{Combi-} - abnreturn_{m+1}^{Mom-} \right] \\
&\qquad + \left[p_m^{Combi+} - p_m^{Mom+} \right] \cdot \left[abnreturn_{m+1}^{Combi+} - abnreturn_{m+1}^{Mom+} \right] \\
&\qquad + \left[p_m^{Combi-} - p_m^{Mom-} \right] \cdot \left[abnreturn_{m+1}^{Combi-} - abnreturn_{m+1}^{Mom-} \right]
\end{aligned}
\qquad (3.13)
$$

with:

$abnreturn_{m+1}^{Combi}$	=	$abnreturn$ of the combination portfolio *Combi55* during month m+1
$abnreturn_{m+1}^{Combi+}$	=	mean $abnreturn$ of stocks with $abnreturn_{i,m+1} > 0$ in portfolio *Combi55* during month m+1
$abnreturn_{m+1}^{Combi-}$	=	mean $abnreturn$ of stocks with $abnreturn_{i,m+1} \leq 0$ in portfolio *Combi55* during month m+1
p_m^{Combi+}	=	ratio of stocks picked at the end of month m with $abnreturn_{i,m+1} > 0$ in portfolio *Combi55*
p_m^{Combi-}	=	1- p_m^{Combi+}
	=	ratio of stocks picked at the end of month m with $abnreturn_{i,m+1} \leq 0$ in portfolio *Combi55*
Mom	=	the superscript *Mom* denotes the same variables for the pure momentum portfolio *Mom5*, respectively.

$\left[p_m^{Combi+} - p_m^{Mom+} \right] \cdot \left[abnreturn_{m+1}^{Mom+} - abnreturn_{m+1}^{Mom-} \right]$ is the contribution of the better ability to pick outperforming stocks. The different conditional performance levels are $\left\{ p_m^{Mom+} \cdot \left[abnreturn_{m+1}^{Combi+} - abnreturn_{m+1}^{Mom+} \right] + p_m^{Mom-} \cdot \left[abnreturn_{m+1}^{Combi-} - abnreturn_{m+1}^{Mom-} \right] \right\}$. The remaining part is the cross product and cannot be attributed to either of the two sources. To assess the significance of the different sources of the outperformance, I use Newey West standard errors with a lag of 6 months to control for possible time-series dependence.

67 For the ease of exposition, I leave out the portfolio subscript j.

3.3.2 Empirical Results and Discussion

The preliminary analysis of quarterly returns shows that the strategies differ in their picking ability and return extremeness. Table 3.4 lists the results of the quarterly analysis.

Table 3.4: Decomposition of the Quarterly Outperformance

Portfolio	mean picking ratio of outperforming stocks p^{+}	mean quarterly positive abnormal return $abnret^{+}$	mean quarterly negative abnormal return $abnret^{-}$
Combi55	53.37	+21.81	-17.43
Mom5	50.67	+22.46	-18.52
Cfo5	50.62	+20.01	-17.10

In the pure momentum strategy, on average 50.67 % of the stocks chosen deliver mean positive abnormal returns in the following quarter. A similar ratio of 50.62 % is obtained for the pure cash flow strategy. The proportion is significantly higher when applying the combination strategy. 53.37 % of all stocks held in portfolio *Combi55* deliver mean positive abnormal returns in the following quarter. The differences between the proportion in portfolio *Combi55* and in the pure portfolios *Mom5* and *Cfo5* are 2.7 % and 2.75 % and are highly statistically significant with t-values of 6.89 and 4.20 based on Newey West standard errors with a lag of 2 quarters.

Comparing conditional mean positive and negative abnormal returns of the strategies shows that the strategies differ with respect to the performance extremeness of the stocks chosen. The momentum strategy is the most extreme strategy. The average negative abnormal return is -18.52 % p.q. and the average positive return is 22.46 % p.q. The pure cash flow strategy is less extreme. It avoids high negative abnormal returns but gets only fairly low positive abnormal returns. The average numbers are -17.10 % p.q. and 20.01 % p.q., respectively. The combination strategy takes the middle position. The average negative abnormal return of the combination strategy is -17.43 % and the average positive abnormal return is 21.81 % p.q.

Now I come to my second analysis where I decompose the outperformance of the combination strategy using monthly returns. The results of this analysis are listed in Table 3.5.

Table 3.5: Decomposition of the Monthly Outperformance

	Overall Outperformance	Stock Picking Effect	Conditional Performance Effect		Cross Product
Combi55 versus *Mom5*	0.424***	0.394*** 93%	0.044 10%		-0.014*** -3%
			abnreturn$^+$	*abnreturn*$^-$	
			-0.199***	0.243***	
Combi55 versus *Cfo5*	0.579***	0.425*** 73%	0.112 20%		0.042** 7%
			abnreturn$^+$	*abnreturn*$^-$	
			0.281***	-0.168***	

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

The results in Table 3.5 show that the combination strategy outperforms the pure momentum strategy almost solely due to its superior ability to select stocks with positive performance. From the total abnormal return difference of 0.424 % p.m., 0.394 % (i.e., a ratio of 93 %) can be attributed to the better ability to pick outperforming stocks. This result supports the idea that incorporating cash flow information into the momentum strategy increases the probability of choosing stocks with continuing price trends. In contrast, the contribution of the differences in conditional performance is close to zero and not statistically significant. Additionally I decompose the contribution of conditional performance into the parts that stem from differing positive and negative abnormal returns. This analysis confirms the finding of the preliminary analysis. The contribution of *abnreturn*$^+$ on the outperformance of *Combi55* is significantly negative, as mean positive abnormal returns are higher in *Mom5* than in *Combi55*. In contrast, the contribution of *abnreturn*$^-$ on the outperformance is significantly positive reflecting the less negative returns in *Combi55*. These two effects compensate one another so that the total conditional performance effect of 0.044 % p.m. is not significantly different from zero.

The results are slightly different when I decompose the performance difference between the combination strategy and the pure cash flow strategy. Still, the greater ability to pick outperforming stocks of the combination strategy is responsible for a large fraction of 73 % of the outperformance, but now the higher conditional performance level also contributes 20 % of the outperformance. This contribution is mainly due to the positive influence of higher positive abnormal returns in *Combi55* than in *Cfo5* which outweighs the negative effect of larger *abnreturn*$^-$ in *Combi55*.

3.4 Alternative Explanations for the Combination Effect

There are potential alternative explanations for the performance of the combination strategy. Especially extremity of momentum and operating cash flows, other accounting-based anomalies, or idiosyncratic risk could be the underlying reason. In this section, I rule out these competing explanations.

3.4.1 Extremity of Momentum and Operating Cash Flows

The first possible objection is that the higher performance of the combination portfolio might simply result from the fact that the stocks in the combination portfolio (*Combi55*) exhibit more extreme *mom* **or** *cfo* than the stocks in the pure momentum portfolio *Mom5* and in the pure cash flow portfolio *Cfo5*. Given the positive impact of *mom* and *cfo* on future returns presented in Table 3.2 and Table 3.3 this could lead to the higher performance of the combination strategy. To rule out this possibility, I compute the mean *mom* and mean *cfo* of the various portfolios during portfolio formation and report the results in Table 3.6.

Table 3.6: Past Returns and Operating Cash Flows in the Portfolios

Panel A: Mean *mom* in %

		low *mom* *Mom1*	*Mom2*	*Mom3*	*Mom4*	high *mom* *Mom5*	pure *cfo*
high *cfo*	*Cfo5*	-33.99	-12.15	1.66	17.28	57.26	10.81
	Cfo4	-33.24	-11.81	2.12	16.75	52.95	7.97
	Cfo3	-34.40	-11.69	1.92	16.42	53.56	5.65
	Cfo2	-37.60	-12.61	1.75	17.51	60.17	3.33
low cfo	*Cfo1*	-40.35	-14.30	1.45	19.19	73.25	1.36
pure *mom*		-36.83	-12.49	1.81	17.27	59.43	

Panel B: Mean *cfo* in %

		low *mom* *Mom1*	*Mom2*	*Mom3*	*Mom4*	high *mom* *Mom5*	pure *cfo*
high *cfo*	*Cfo5*	7.73	7.33	7.15	7.18	7.49	7.36
	Cfo4	3.20	3.17	3.14	3.17	3.20	3.17
	Cfo3	1.37	1.38	1.41	1.41	1.39	1.39
	Cfo2	-0.73	-0.54	-0.45	-0.49	-0.64	-0.57
low *cfo*	*Cfo1*	-8.16	-7.38	-7.04	-7.03	-7.81	-7.62
pure *mom*		-1.00	0.75	1.34	1.56	1.07	

Table 3.6 shows that neither *mom* nor *cfo* is extremely high in the combination portfolio (*Combi55*). The mean *mom* in portfolio *Combi55* is even slightly lower than the *mom* in the pure momentum portfolio *Mom5*, and the mean *cfo* of the combination portfolio is about equal

to that of the pure cash flow portfolio *Cfo5*. The mean *cfo* of 7.49 % in portfolio *Combi55* is not significantly different from the mean of 7.36 % in *Cfo5*.

To conclude, the superiority of the combination strategy does not result from choosing stocks with extreme momentum **or** cash flow, but from choosing stocks with high momentum **and** high operating cash flow at the same time.

3.4.2 Earnings Surprises, Accrual Anomaly, and Idiosyncratic Risk

A second caveat is that past returns and operating cash flows might just be proxies for other factors that I have not taken into account yet. As known, for example, from Ball and Brown (1968) and Bernard and Thomas (1989), earnings surprises predict future returns. This phenomenon is also known as the "Post Earnings Announcement Drift" in the academic literature. To my knowledge, no study has analyzed yet whether the post earnings announcement drift and the operating cash flow anomaly are distinct.[68] In this regard, it could be the case that the stocks with high *cfo* at the same time have high earnings surprises and that actually the high earnings surprises positively influence future returns. In contrast, there are already some studies analyzing whether the momentum effect and the post earnings announcement drift are the same phenomena. These studies come to different conclusions. Some state that the two phenomena are the same, whereas others find that they only partly overlap.[69]

Second, Sloan (1996) and Xie (2001) show that accruals and abnormal accruals are predictors of future returns. Accruals and operating cash flows are highly negatively correlated.[70] Thus, the high *cfo* in portfolio *Combi55* could just proxy for the low accruals of those stocks which in reality lead to the portfolio's profits instead of the high *cfo*.

Third, there is a debate in the scientific literature, whether and in which way idiosyncratic risk predicts future returns. Previous studies, as for example Lehmann (1990) as well as Xu and Malkiel (2004) find a positive impact of idiosyncratic risk on future returns. In contrast, Ang et al. (2006) and Ang et al. (2009) find a strong negative relation between idiosyncratic risk and future returns in all G7 countries and in the US. Fu (2009) points out that idiosyncratic risk is extremely time-varying and that the present risk should not be used as proxy for the expected idiosyncratic, which is one possible explanation for the differing results.

---

68 Collins and Hribar (2000) show the distinctiveness of the accrual anomaly and the post earnings announcement drift, but do not analyze operating cash flows.

69 For example, Chan, Jegadeesh, and Lakonishok (1996) come to the conclusion that the two effects are distinct. Leippold and Lohre (2009) also find that they are distinct in the US and have different outcomes for other countries. The findings of Jackson and Johnson (2006) and Chordia and Shivakumar (2006) indicate, on the contrary, that momentum and the post earnings announcement drift are the same phenomena.

70 The negative correlation between accruals and cash flows and their changes is documented by Dechow (1994), pp. 17-21 and Sloan (1996) pp. 295-314.

To control for the impact of earnings surprises, accruals, and idiosyncratic risk, I extend regressions 3.8 and 3.9 and include deciles of accruals (*acc*), deciles of standardized unexpected earnings (*sue*) and idiosyncratic risk (*idio*) as additional control variables.

I define *acc* using the quarterly cash flow statement following, for example, Collins and Hribar (2000). This approach avoids problems of the balance sheet approach.[71]

$$acc_{i,q} = \frac{earn_{i,q}}{\varnothing total\ assets_{i,q}} - cfo_{i,q} \qquad 3.14$$

with:

$earn_{i,q}$ = quarterly operating income of firm *i* at the end of quarter *q*, CSI #Q8

$cfo_{i,q}$ = operating cash flow per average total assets as defined in equation 3.2

I compute *sue* in analogy to Bernard, Thomas, and Wahlen (1997), p. 101, using the market capitalization to deflate the earnings surprise. Another frequently used denominator for *sue* is the standard deviation of past earnings surprises. I decide for the market capitalization in order not to lose too many observations due to the requirement of several past quarterly earnings observations. This should not alter the conclusions as pointed out by Bernard and Thomas (1990), p. 333.

$$sue_{i,q} = \frac{earn_{i,q} - earn_{i,q-4}}{size_{i,q}} \qquad 3.15$$

with:

$size_{i,q}$ = market capitalization of firm *i* at the end of quarter *q*, CSI #61 · CSI #14

In analogy to *mom* and *cfo*, I do not include the actual values of *acc* and *sue*, but deciles defined from zero to one (*accdec* and *suedec*). Again, the insertion of the actual values does not alter my conclusions.

I estimate idiosyncratic risk following Fu (2009): For each stock and each month, I regress daily excess stock returns, i.e., the stock return minus the daily interest rate, on the three daily Fama French factors, market, size, and value.[72] The idiosyncratic volatility is the standard deviation of the regression residuals. Also following Fu (2009), I require a minimum of 15 trading days in a month with given daily return and a non-zero trading volume and transform the daily standard deviation to a monthly figure by multiplying by the square root of the

---

71 For a description of these problems; see Hribar and Collins (2002).

72 Again, I obtain the series of daily Fama French factors from Kenneth R. French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

number of trading days in that month.[73] I label this monthly return residual *idio* and insert it as control variable in the return regression.

When I require values for all control variables, I still have 284,727 observations. Table 3.7 presents descriptive statistics for the newly inserted control variables accruals, earnings surprises, and idiosyncratic risk.

Table 3.7: Descriptive Statistics of the Control Variables

	n	mean	p 25	p 50	p 75
acc (in %)	284,727	-1.304	-2.047	-0.933	-0.443
sue (in %)	284,727	-0.126	-0.407	-0.073	0.212
idio (in % p.m.)	284,727	13.919	12.458	14.127	15.493

When including all control variables, I obtain the following regression 3.16:[74]

$$\begin{aligned} return_{i,t+1} &= \alpha + \beta^{mom} \cdot momdec_{i,t} + \beta^{cfo} \cdot cfodec_{i,t} + \beta^{size} \cdot \ln\left(size\right)_{i,t} \\ &\quad + \beta^{bm} \cdot \ln\left(btom\right)_{i,t} + \beta^{acc} \cdot accdec_{i,t} + \beta^{sue} \cdot suedec_{i,t} + \beta^{idio} \cdot idio_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{3.16}$$

with:

t = proxy variable for the end of period t, t stands for month m in the monthly regressions and for quarter q in the quarterly regressions.

$accdec_{i,t}$ = decile in terms of *acc* of stock i measured at the end of period t $accdec_{i,t} \in \{0, \frac{1}{9}, \frac{2}{9}, \ldots, 1\}$

$suedec_{i,t}$ = decile in terms of *sue* of stock i measured at the end of period t $suedec_{i,t} \in \{0, \frac{1}{9}, \frac{2}{9}, \ldots, 1\}$

$idio_{i,t}$ = idiosyncratic volatility of stock i at the end of period t

The other variables are the same as in equation 3.9.

Again, I report results for regressions with one-month returns and compounded three-month returns as dependent variables. Furthermore, I again estimate both OLS regressions with standard errors clustered by time and stock and Fama-Mac Beth regressions. In addition, Table 3.8 once more reports the results of the basic regressions 3.8 and 3.9 for an easier comparison of results.

73 See Fu (2009), p. 26.

74 Of course, financial statement variables are only given quarterly. In the monthly regressions, I use the respective quarterly values three times.

Table 3.8: Impact of Earnings Surprises, Accruals, and Idiosyncratic Risk

Panel A: OLS Regression with Adjusted Standard Errors

regr		$\hat{\alpha}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{cfo}$	$\hat{\beta}^{size}$	$\hat{\beta}^{btom}$	$\hat{\beta}^{acc}$	$\hat{\beta}^{sue}$	$\hat{\beta}^{idio}$
3.8	$return_{m+1}$	-0.60	1.19 ***	1.47 ***					
3.8	$return_{q+1}$	0.85	2.93 **	2.73 ***					
3.9	$return_{m+1}$	-0.52	1.15 ***	1.38 ***	0.06	0.45 ***			
3.9	$return_{q+1}$	4.08	3.81 ***	3.51 ***	-0.62 **	1.36 **			
3.16	$return_{m+1}$	-0.54	0.89 **	1.81 ***	-0.04	0.42 ***	0.88 ***	0.47 ***	-0.82
3.16	$return_{q+1}$	2.50	3.16 ***	3.10 *	-0.54 **	1.42 ***	-0.03	2.83 ***	6.06

Panel B: Fama-MacBeth Regression

regr		$\hat{\alpha}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{cfo}$	$\hat{\beta}^{size}$	$\hat{\beta}^{btom}$	$\hat{\beta}^{acc}$	$\hat{\beta}^{sue}$	$\hat{\beta}^{idio}$
3.8	$return_{m+1}$	-0.54	1.23 ***	1.36 ***					
3.8	$return_{q+1}$	1.11	2.67 **	2.60 ***					
3.9	$return_{m+1}$	-0.61	1.16 ***	1.25 ***	0.07	0.23 ***			
3.9	$return_{q+1}$	3.68	3.41 ***	3.32 ***	-0.57 ***	0.65			
3.16	$return_{m+1}$	0.45	0.82 ***	1.40 ***	-0.09 *	0.16 *	0.57 ***	0.50 ***	-4.72 ***
3.16	$return_{q+1}$	4.57 *	2.59 ***	2.43 *	-0.64 ***	0.58	-0.55	2.85 ***	-4.90 *

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test. Standard errors of the OLS regressions are clustered by stock and by time.

The coefficients of both operating cash flow and momentum remain significantly positive even after controlling for all the other factors. In the monthly OLS regression 3.16, the estimated coefficient of momentum implies a return difference of 0.89 % p.m. between the first and the tenth momentum decile when holding all the other variables constant. The coefficient of the operating cash flow implies a difference of 1.81 % between the two extreme operating cash flow deciles. The differences between extreme deciles based on compounded three months returns are 3.16 % for momentum and 3.10 % for operating cash flow, respectively. Accruals have a significant impact only on future one-month returns and no influence on future quarterly returns. As expected, earnings surprises have a significant positive impact on returns in the following month and in the following quarter. Idiosyncratic risk only has a significantly negative impact on returns in the following month when I estimate the regressions using the Fama-MacBeth approach. In all other cases, I do not find any significant influence of *idio* on future returns. This finding fits the contradicting results in previous literature. All in all, the results for *momdec* and *cfodec* do not depend on the estimation procedure. Both the coefficients and the significance levels of the estimations for *momdec* and *cfodec* only change slightly when switching from the OLS regression approach to Fama-MacBeth.

The only finding that comes as a surprise is the positive influence of accruals on returns in the following month. This positive sign contradicts the findings of Sloan (1996), who finds a significant negative impact. However, Sloan (1996) did not include operating cash flows in his regressions. When I re-run the regression and leave out the operating cash flow as explanatory variable in regression 3.17, the coefficient of *accdec* becomes negative again, as listed in Table 3.9.

$$\begin{aligned} return_{i,t+1} &= \alpha + \beta^{mom} \cdot momdec_{i,t} + \beta^{size} \cdot \ln\left(size\right)_{i,t} + \beta^{bm} \cdot \ln\left(btom\right)_{i,t} \\ &+ \beta^{acc} \cdot accdec_{i,t} + \beta^{sue} \cdot suedec_{i,t} + \beta^{idio} \cdot idio_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{3.17}$$

Table 3.9: Test of the Accrual Effect

Panel A: OLS Regression with Adjusted Standard Errors

regr		$\hat{\alpha}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{size}$	$\hat{\beta}^{btom}$	$\hat{\beta}^{acc}$	$\hat{\beta}^{sue}$	$\hat{\beta}^{idio}$
3.17	$return_{m+1}$	0.58	0.98 **	0.02	0.45 ***	-0.33 ***	0.88 ***	-1.35
3.17	$return_{q+1}$	4.39 *	3.32 ***	-0.45 *	1.48 ***	-2.07 ***	3.49 ***	5.11

Panel B: Fama-MacBeth Approach

regr		$\hat{\alpha}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{size}$	$\hat{\beta}^{btom}$	$\hat{\beta}^{acc}$	$\hat{\beta}^{sue}$	$\hat{\beta}^{idio}$
3.17	$return_{m+1}$	1.30 ***	0.91 ***	-0.05	0.19 **	-0.39 ***	0.84 ***	-5.31 ***
3.17	$return_{q+1}$	6.06 ***	2.84 ***	-0.58 ***	0.63	-2.15 ***	3.40 ***	-6.09 *

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test. Standard errors of the OLS regressions are clustered by stock and by time.

When leaving out operating cash flows as explanatory variable, the results confirm the negative influence of accruals on future returns. This finding suggests that in the short term, accruals are just an inverse proxy for operating cash flows, which in truth drive future returns. This is in line with Livnat and López-Espinosa (2008). In their study, quarterly accruals also lose their influence on future returns if quarterly operating cash flows are included in the regression.[75] Accordingly, their conclusion is "For most industries, investment managers and financial analysts should focus on operating cash flows more than on accruals."[76]

To conclude this section, the momentum and operating cash flow effects are not the earnings surprise, the accrual anomaly, or idiosyncratic risk in disguise. They still predict future returns after controlling for the other known factors.

---

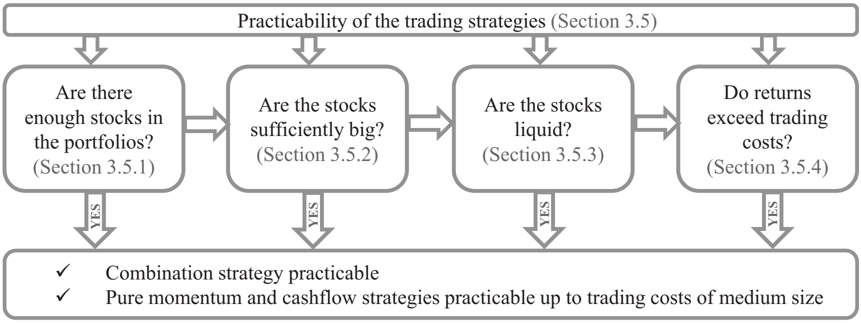
[75] See Livnat and López-Espinosa (2008), p. 73.

[76] Livnat and López-Espinosa (2008), p. 67.

3.5 Practicability of the Trading Strategies

Several factors might prevent investors from implementing the combination strategy. First, there might be only few stocks meeting both conditions (high momentum and high operating cash flows) at the same time. Second, the stocks selected by the combination strategy might be very small, making it difficult to trade them. Similarly, the stocks' illiquidity could endanger the strategies' profitability. Lastly, the turnover of the strategy might be so high that returns do not suffice to cover transaction costs. I address these potential problems in this section. Figure 3.7 illustrates the structure of this section.

Figure 3.7: Structure of Section 3.5



3.5.1 Portfolio Size

First, I check the size of the portfolios underlying the trading strategies. If, for example, only a small number of stocks fulfilled the investment criteria of high *mom* and high *cfo*, the combination strategy would be exposed to high idiosyncratic risk. To check the size of the portfolio underlying the combination strategy, I calculate the distribution of stocks across all portfolios every quarter. By construction, each quintile portfolio based on a pure strategy includes 20 % of the stocks.[77] For the 25 combination portfolios, I would expect a fraction of 1/25 = 4 % in each portfolio if *mom* and *cfo* were independent. The actual fractions depend on the correlation between the stocks' *mom* and *cfo*. The mean fractions in % of the whole sample are presented in Table 3.10.

[77] Some fractions are not exactly 20 % due to multiple observations with the same values which are therefore allocated in the same quintile.

Table 3.10: Portfolio Size

		low *mom*				high *mom*	pure *cfo*
		Mom1	*Mom2*	*Mom3*	*Mom4*	*Mom5*	
high *cfo*	*Cfo5*	3.05	3.70	3.93	4.39	4.92	19.99
	Cfo4	2.84	3.90	4.56	4.70	3.99	20.00
	Cfo3	3.22	4.20	4.58	4.46	3.54	20.00
	Cfo2	4.37	4.37	4.03	3.65	3.58	20.00
low *cfo*	*Cfo1*	6.55	3.80	2.89	2.80	3.96	20.01
pure *mom*		20.03	19.98	20.00	20.00	19.99	

Altogether, the fractions support the positive correlation between *mom* and *cfo*, with higher values in portfolios with high *mom* and high *cfo* and with low *mom* and low *cfo*. Portfolio *Combi11* comprises the highest fraction of stocks with a value of 6.55 %, reflecting that stocks with very low cash flows also experience extreme price drops. In contrast, there are only few stocks belonging to the fourth quintile in terms of *mom* and to the first quintile in terms of operating cash flows. *Combi41* only comprises 2.80 % of the stocks. The portfolio underlying the combination strategy, *Combi55,* includes on average 4.92 % of my sample stocks. The minimum fraction for this portfolio is 3.63 %, which corresponds to a minimum number of 195 stocks in the portfolio underlying the combination strategy. This suggests that a sufficient number of firms comply with both criteria, making the combination strategy investable.

Even though the number of stocks in *Combi55* is sufficiently high, it is, by construction, lower than in the two pure long portfolios *Mom5* and *Cfo5*. On average, portfolio *Combi55* comprises only 24.6 % of the stocks included in the pure portfolios *Mom5* and *Cfo5*. In an additional analysis, I find that this lower number of stocks is not the underlying reason for the higher profits of portfolio *Combi55*. A hundred times, I randomly draw 24.6 % of the stocks in portfolio *Mom5* and portfolio *Cfo5* each quarter. Then I compute mean monthly abnormal returns and alphas to these randomly drawn subportfolios. In all hundred cases, the abnormal returns and alphas earned by portfolio *Combi55* significantly exceed those of the randomly picked pure momentum and pure cash flow subportfolios. Therefore, the smaller number of stocks in portfolio *Combi55* is not the underlying reason for the higher profits yielded by the combination strategy.

3.5.2 Stock Size

Another important criterion for the implementability of the combination strategy is the size of the stocks in portfolio *Combi55*. If the combination portfolio only consisted of small stocks, it would be very difficult to earn the reported profits in reality. I address this potential problem by testing the strategy for subsamples of stocks. That is, I rebuild my pure momentum, pure cash flow, and combination portfolios *Mom5*, *Cfo5*, and *Combi55* only for stocks belonging to the 50 % smallest, 50 % biggest, and the 25 % biggest stocks in terms of their market capitalization. I describe the size subsamples in Panel A of Table 3.11 and mean monthly 3-factor alphas and abnormal returns to the portfolios in Panel B of Table 3.11.

Table 3.11: Stock Size

Panel A: Description of Size Subsamples

			market capitalization (mio.US $)		
		n	mean	median	minimum
whole sample	all stocks	366,817	1,852	139	0.08
small stocks	50 % smallest stocks	179,438	57	31	0.08
big stocks	50 % biggest stocks	187,379	3,572	641	28
very big stocks	25 % biggest stocks	94,345	6,733	1,864	146

Panel B: Portfolio Returns in the Size Subsamples

					market capitalization (mio. US $)		
portfolio		*alpha*	*abnreturn*	n	mean	median	minimum
Mom5	whole sample	0.80 ***	0.73 ***	73,329	1,804	186	0.12
	small stocks	0.75 ***	0.58 ***	31,870	64	36	0.12
	big stocks	0.73 ***	0.76 ***	41,459	3,142	606	28
	very big stocks	0.61 ***	0.53 ***	20,459	5,990	1,705	146
Cfo5	whole sample	0.62 ***	0.58 ***	73,333	2,760	206	0.15
	small stocks	0.74 ***	0.58 ***	30,549	57	38	0.15
	big stocks	0.49 ***	0.55 ***	42,784	4,690	732	28
	very big stocks	0.47 ***	0.47 ***	23,066	8,369	1,896	147
Combi55	whole sample	1.20 ***	1.16 ***	18,085	2,838	267	0.25
	small stocks	1.34 ***	1.17 ***	6,616	66	38	0.25
	big stocks	1.04 ***	1.09 ***	11,469	4,437	710	28
	very big stocks	0.92 ***	0.84 ***	6,110	7,983	1,784	147

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

Profits decrease slightly when I limit the sample to stocks with high market capitalization. However, even when I restrict the sample to stocks belonging to the 25 % with the highest market capitalization, all three strategies are still significantly successful. Portfolio *Combi55* still yields a 3-factor alpha of 0.92 % and an abnormal return of 0.84 % p.m. Moreover, portfolio *Combi55* is more successful than portfolios *Mom5* and *Cfo5* in all samples. I conclude from this, that stock size does slightly reduce but not impede the successful implementation of the combination strategy.

3.5.3 Stock Liquidity

Another potential objection to the combination strategy is that stocks with high momentum and high operating cash flow might be illiquid. If this was the case, the stocks would be very difficult to buy and sell, hindering the realization of the computed profits.[78] In order to check for this potential problem when implementing the strategy I calculate two liquidity measures for each stock and then aggregate them to mean liquidity measures for each portfolio. The first measure is turnover as defined by Korajczyk and Sadka (2008). It relates the monthly trading volume to shares outstanding:[79] The higher a stock's trading volume is in relation to its number of shares outstanding, the more liquid it is.

$$L_{i,m} = \frac{\sum_{d=1}^{days_{i,m}} volume_{i,d}}{shares_{i,m}} \tag{3.18}$$

with:

$days_{i,m}$ = number of trading days for stock *i* during month *m*

$shares_{i,m}$ = number of shares of stock *i* outstanding at the end of month *m*

$volume_{i,d}$ = trading volume in shares of stock *i* on day *d*

The higher $L_{i,m}$, the higher is the liquidity of stock *i* during month *m*.

The second measure captures illiquidity, as defined by Amihud (2002).[80] It calculates the absolute return per unit of trade volume in dollars multiplied by 10^6. This measure assumes that a strong stock price reaction to a certain trading volume is a sign of illiquidity. On the contrary, the stock price of highly liquid stocks should not react strongly, even in response to a high trading volume. Put shortly: The more a stock price reacts to a certain trading volume, the more illiquid it is.

$$I_{i,m} = \frac{1}{days_{i,m}} \cdot \sum_{d=1}^{days_{i,m}} \frac{\left|return_{i,d}\right|}{volume\$_{i,d}} \cdot 10^6 \tag{3.19}$$

with:

$return_{i,d}$ = return of stock *i* on day *d*

$volume\$_{i,d}$ = trading volume in dollars of stock *i* on day *d*

The higher $I_{i,m}$, the more illiquid is stock *i* during month *m*.

---

78 Moreover, Pástor and Stambaugh (2003) show that market wide liquidity is important for asset pricing and Sadka (2006) demonstrates that parts of momentum returns can be attributed to the variable part of liquidity risk. These studies also indicate that an investigation of liquidity is worthwhile.

79 For details, see Korajczyk and Sadka (2008), p. 49.

80 For details, see Amihud (2002), p. 37.

I present mean values for the two measures in Table 3.12.

Table 3.12: Portfolio Liquidity

Panel A: Liquidity Measure of Korajczyk and Sadka (2008)

		low *mom*				high *mom*	pure *cfo*
		Mom1	*Mom2*	*Mom3*	*Mom4*	*Mom5*	
high *cfo*	*Cfo5*	0.150	0.110	0.104	0.111	0.178	0.132
	Cfo4	0.137	0.098	0.083	0.093	0.146	0.109
	Cfo3	0.123	0.088	0.078	0.086	0.136	0.099
	Cfo2	0.119	0.084	0.079	0.090	0.145	0.103
low *cfo*	*Cfo1*	0.136	0.106	0.111	0.131	0.193	0.137
pure *mom*		0.132	0.097	0.089	0.100	0.161	

Panel B: Illiquidity Measure of Amihud (2002)

		low *mom*				high *mom*	pure *cfo*
		Mom1	*Mom2*	*Mom3*	*Mom4*	*Mom5*	
high *cfo*	*Cfo5*	0.267	0.301	0.284	0.230	0.202	0.250
	Cfo4	0.247	0.258	0.228	0.196	0.186	0.219
	Cfo3	0.270	0.283	0.242	0.217	0.203	0.240
	Cfo2	0.329	0.389	0.343	0.296	0.256	0.324
low *cfo*	*Cfo1*	0.335	0.394	0.379	0.345	0.241	0.331
pure *mom*		0.292	0.318	0.281	0.242	0.214	

Both measures indicate that the stocks in the combination portfolio *Combi55* are more liquid than the average stock. According to Korajczyk and Sadka's liquidity measure, the portfolio of the combination strategy is the second most liquid of all portfolios. Amihud's illiquidity measure shows a similar picture. In Panel B, the portfolio of the combination strategy is the third most liquid portfolio. In comparison with the portfolios based on the pure strategies, the portfolio of the combination strategy invests in more liquid stocks. Thus, low liquidity seems to be no obstacle to implementing the combination strategy.

3.5.4 Success after Trading Costs

Since the combination strategy uses two criteria for stock selection, its turnover is higher than that of the pure strategies. Therefore, the outperformance (before costs) of the combination strategy might be absorbed by higher transaction costs. I present the mean portfolio turnover ratios of the different portfolios in % in Table 3.13.

Table 3.13: Portfolio Turnover Ratios

		low *mom*				high *mom*	pure *cfo*
		Mom1	*Mom2*	*Mom3*	*Mom4*	*Mom5*	
high *cfo*	*Cfo5*	89.2	91.3	91.0	88.9	81.1	66.8
	Cfo4	91.2	91.9	90.0	88.6	88.1	70.8
	Cfo3	89.2	90.7	89.2	89.0	89.1	70.7
	Cfo2	85.3	90.2	91.2	92.2	89.1	70.4
low *cfo*	*Cfo1*	72.5	89.7	93.4	93.3	82.5	56.2
pure *mom*		56.0	72.5	73.3	72.0	58.9	

Table 3.13 confirms the conjecture: The turnover is lower for pure strategies than for combination strategies. In addition, the table shows that more extreme realizations of momentum and operating cash flow are more likely to persist. Within the 25 combination portfolios, the most extreme portfolios (*Combi11, Combi55*) have the lowest turnover ratios. The same is true for the extreme pure momentum portfolios (*Mom1*, *Mom5*) and the extreme pure cash flow portfolios (*Cfo1, Cfo5*).

To calculate the impact of transaction costs, I take into account the costs when setting up the portfolio for the first time, the portfolio adjustment costs every quarter, and the costs of closing the portfolios at the end of December 2007. I assume round-trip transaction costs between 50 and 300 basis points. These costs would occur if every stock in a portfolio was replaced. I report the after-cost performance of the combination strategy, the pure momentum strategy, and the pure cash flow strategy in Table 3.14. Performance is again measured as abnormal return *abnreturn* in Panel A and 3-factor alpha *alpha* in Panel B.

Table 3.14: Performance after Trading Costs

Panel A: Abnormal Return *abnreturn* in % p.m.

Trading Costs	*Combi55*	*Mom5*	*Cfo5*	*Combi55 - Mom5*	*Combi55 - Cfo5*
0 bp	1.16 ***	0.73 ***	0.58 ***	0.42 ***	0.58 ***
50 bp	1.02 ***	0.63 ***	0.47 ***	0.39 ***	0.55 ***
100 bp	0.89 ***	0.54 ***	0.36 ***	0.35 ***	0.53 ***
150 bp	0.75 ***	0.44 ***	0.24 ***	0.32 ***	0.51 ***
200 bp	0.62 ***	0.34 ***	0.13 **	0.28 ***	0.48 ***
250 bp	0.48 ***	0.24 *	0.02	0.24 ***	0.46 ***
300 bp	0.35 ***	0.14	-0.09	0.21 **	0.44 ***

Panel B: 3-Factor Alpha *alpha* in % p.m.

Trading Costs	*Combi55*	*Mom5*	*Cfo5*	*Combi55 - Mom5*	*Combi55 - Cfo5*
0 bp	1.20 ***	0.80 ***	0.62 ***	0.40 ***	0.58 ***
50 bp	1.07 ***	0.70 ***	0.51 ***	0.37 ***	0.56 ***
100 bp	0.93 ***	0.60 ***	0.40 ***	0.33 ***	0.53 ***
150 bp	0.80 ***	0.50 ***	0.29 ***	0.30 ***	0.51 ***
200 bp	0.66 ***	0.40 **	0.18 **	0.26 ***	0.48 ***
250 bp	0.52 ***	0.30 *	0.06	0.22 ***	0.46 ***
300 bp	0.39 **	0.20	-0.05	0.19 **	0.44 ***

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

Even with high transaction costs, the combination strategy delivers significantly positive performance, no matter how I measure the performance. In contrast, the pure strategies no longer deliver significant profits when transaction costs are high. This finding is in line with previous research on the performance of the momentum strategy.[81] Furthermore, it casts doubt on the profitability of the operating cash flow strategy. The results underline the superiority of the combination strategy. Despite its higher turnover, portfolio *Combi55* delivers significantly higher after-cost performance than the pure strategies. All in all, I conclude from these findings that the combination strategy can be successfully implemented.

3.6 Summary and Conclusion

The main result of this chapter is that past returns and operating cash flows are complements in predicting future returns. I implement a trading strategy that combines these two pieces of information, investing in stocks with high past returns and high operating cash flows at the same time. The empirical results underline that the two types of information are complements in predicting future returns: The combination portfolio *Combi55* clearly outperforms a pure momentum strategy and a pure cash flow strategy. This holds true not only on average but also in 18 out of 19 single years.

A return decomposition reveals that the outperformance stems from a greater probability of picking outperforming stocks in the combination portfolio than in the pure momentum and cash flow portfolios. This fits the idea that the two criteria are suitable to pick stocks with enduring price trends. Moreover, the decomposition discloses the different characteristics of the abnormal returns earned by the two strategies. Abnormal returns earned by the pure momentum strategy are both very positive and very negative, leading to a positive mean abnormal return. In contrast, abnormal returns of the pure cash flow strategy are much less

[81] See, e.g., Lesmond, Schill, and Zhou (2004).

extreme. The combination strategy takes the middle position with medium positive and negative abnormal returns.

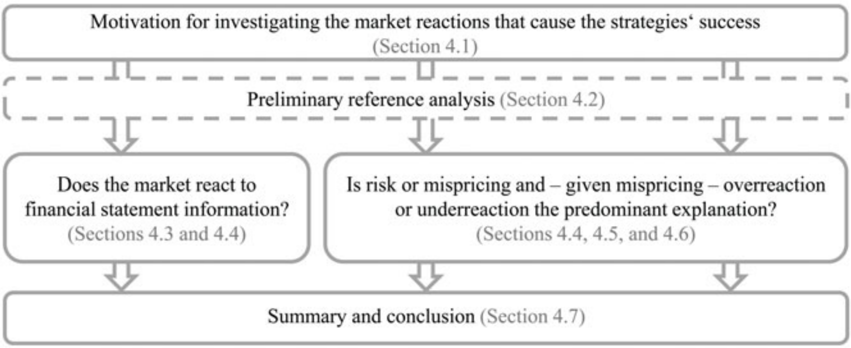
Further analyses confirm that the combination effect is neither due to extreme realizations of the two criteria nor to other known predictors of future returns, as earnings surprises, accruals, or idiosyncratic risk. Rather, both past returns and operating cash flows have their own impact on future returns, leading to the success of the combination strategy. The trading strategy's success contradicts market efficiency. The central question is whether the risk-adjustment misses hidden risks in the combination, justifying the higher future returns or whether the market does not completely process the given information. If the risk adjustment is assumed to be appropriate, the question remains in which way market participants fail in processing the given information. Is the effect due to a market overreaction or due to market participants reacting too slowly to a given piece of information, leading to a drift that causes the returns? Chapter 1 addresses this question more closely, investigating the market participants' behavior and information processing. Of course, also chapter 1 cannot fully explain the way investors react. This is simply too challenging a task.

Another possible explanation for the success of the combination strategy is that the returns cannot be arbitraged away due to market restrictions. In this regard, section 3.5 checks the implementability of the pure and combination strategies. I do not find any obstacles to a successful implementation of the trading strategy: A sufficient number of stocks meet the selection criteria, and the stocks are more liquid than the average stock in my sample. Moreover, the performance of the strategy remains significant even when I account for round-trip transaction costs of 300 basis points. Obviously, this makes the strategy highly interesting for investors, which leads me to the question whether professional investors exploit these return opportunities by following the combination strategy. Chapter 5 addresses this question by analyzing the trading behavior and returns of mutual funds in the US.

4 A Closer Look at the Market Reactions

In this chapter, I take a closer look at the market reactions which are the underlying reasons for the anomalous returns found in chapter 1. Therefore, I carry out several different analyses. I address two questions. First, I ask whether the market really reacts to financial statement information. Second, I aim at determining the predominant reason for the momentum, cash flow, and combination strategies' anomalous returns. Possible reasons are risk, market participants' overreaction, or underreaction. Figure 4.1 illustrates the structure of this chapter.

Figure 4.1: Structure of Chapter 1



4.1 Introduction and Motivation

Profits of trading strategies that rely on public information pose a challenge to the academic literature. As pointed out in section 2.1, such profits contradict market efficiency, but the inefficiency of markets cannot be proven due to the joint hypothesis problem. Academics try to understand the market reactions that cause "anomalous" success of trading strategies. For this reason, they gather empirical evidence and draw possible conclusions concerning market behavior in order to contribute to a better understanding of the market.[82] Previous studies offer a variety of tests that can be used to disentangle market behavior. I make use of this "toolbox," conducting several examinations on the market reactions that lead to the price momentum, the operating cash flow, and the combination effect. In particular, I focus on the following aspects:

First, I address the question whether market participants respond to information from financial statements. This question is of particular interest within the scope of my thesis, because of the differences between the strategies I analyze. Whereas the price momentum strategy does not

[82] Examples for these studies will be mentioned in the course of this chapter.

depend on financial statement information, the opposite is the case for the operating cash flow strategy. Accordingly, the analysis of reactions to financial statements should yield different results for the two effects. Moreover, the question is whether the outcome for the combination strategy is a mixture of the two separate strategies. Sections 4.3 and 4.4 deal with this first question. Note that this question does not yet address the differentiation between risk and mispricing. Any price reaction to financial statement information can be both: irrational or economically justified, for example by a changed assessment of risk.

The question of risk versus market mispricing is the second aspect I address. This aspect is a central issue in the finance literature and – as already pointed out – cannot be finally answered. Assuming that markets are not efficient, the resulting question is, what kind of market misbehavior leads to the abnormal returns. In particular, studies ask whether the market reacts too strongly or too weakly. The concepts of overreaction and underreaction are prevalent and widely analyzed in the academic literature. For instance, Barberis, Shleifer, and Vishny (1998) state: "Recent empirical research in finance has uncovered two families of pervasive regularities: underreaction of stock prices […], and overreaction of stock prices […]."[83] Michaely, Thaler, and Womack (1995) put the main problem in a nutshell: "We hope future research will help us understand why the market appears to overreact in some circumstances and underreact in others."[84]

The analysis of over- and underreaction is of special interest for my specific trading strategies because previous literature finds different explanations for the price momentum effect than for accounting-based anomalies. Returns to the price momentum strategy are both attributed to over- and underreaction.[85] For example, De Long et al. (1990) as well as Lee and Swaminathan (2000) state that at least a portion of the price momentum effect is due to overreaction. In contrast, Jegadeesh and Titman (1993), Chan, Jegadeesh, and Lakonishok (1996), as well as Barberis, Shleifer, and Vishny (1998) mainly attribute the momentum effect to market participants' underreaction to firm-specific information. The behavioral models of Daniel, Hirshleifer, and Subrahmanyam (1998) as well as Hong and Stein (1999) show that these two competing explanations are not mutually exclusive. Daniel, Hirshleifer, and Subrahmanyam (1998) differentiate between different types of information. They assume that market participants overreact to private and underreact to public information. Hong and Stein (1999) distinguish two different types of investors, namely news watchers and momentum traders. News watchers gather private information and trade according to it. The private information only slowly disseminates, leading to initial underreaction. The momentum

83 Barberis, Shleifer, and Vishny (1998), p. 309.
84 Michaely, Thaler, and Womack (1995), p. 606.
85 See Lee and Swaminathan (2000), p. 2018.

traders, in contrast, only observe the price movements that result from the news watchers' trades and trade on these movements. Their trading finally leads to stock price overreaction.

In contrast to the mixed explanations for the technical momentum effect, previous studies almost exclusively explain anomalies that are based on fundamental information by market underreaction. Familiar examples for these studies are Bernard and Thomas (1989), Bernard and Thomas (1990), as well as Kama (2009). Against the background of the differing explanations for the price momentum and fundamental anomalies, the question is whether I will also find differences between the two strategies and which will be the outcome for the combination strategy. Moreover, any evidence of systematic market over- or underreaction indicates at the same time that markets are not efficient. Accordingly, the aspects of risk versus mispricing and overreaction versus underreaction are closely connected.

All in all, the anomalous returns to the momentum, the cash flow, and the combination strategy will presumably be due to a mixture of risk, overreaction, and underreaction. The examinations in sections 4.4 to 4.6 aim at identifying which influencing factor is mainly responsible for the profits.

Throughout the whole chapter, I conduct two different types of analysis: First, I study the total momentum and cash flow effects. Therefore, I analyze the dependence of future (abnormal) returns on cash flows and past returns by conducting regressions. This is the classical approach, since most studies aim at understanding full anomalous effects and therefore analyze the whole sample of stocks. My second type of analysis investigates abnormal returns to the long portfolios *Mom5*, *Cfo5*, and *Combi55* as well as to the short portfolios *Mom1*, *Cfo1*, and *Combi11*. The advantage of this approach in comparison to regressions is that it does not consider return differences which net out the effects of the long and short portfolios. Rather, the isolated analysis of the portfolios allows for examining to what extent the explanations apply to the long and short position of the effects. Moreover, it is more illustrative and application oriented, since it refers to real portfolios. At last, the portfolio analysis considers the combination effect directly, which is not possible by means of regressions.

4.2 Preliminary Analysis: Reference Trading Strategy

Due to five data requirements, the sample I will use in this chapter is significantly smaller than that utilized in chapter 3. In the following, I first present the requirements and corresponding sample reductions. Then I reestimate the trading strategies' success for this restricted sample. Thus, I ensure that the results still hold for the smaller sample and provide an adequate benchmark for the following analyses.

The sample restrictions mostly result from the investigation of earnings announcement returns in section 4.4. In order to ensure comparability, I will use this sample throughout this whole fourth chapter. The five sample requirements are the following:

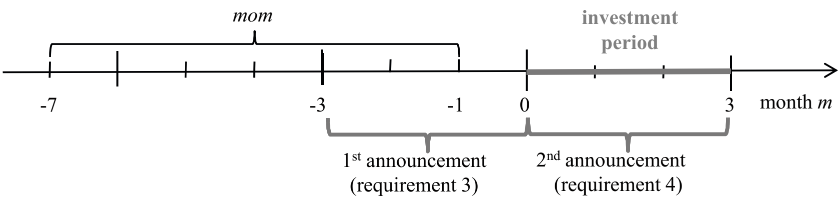
1. The companies' fiscal year has to end in December. This ensures a homogenous temporal structure and is the most severe restriction.
2. The earnings announcement date has to be available.
3. The operating cash flow that is crucial for the investment decision has to be published three months after the fiscal quarter end at the latest, meaning before the start of investment.
4. The following earnings announcement has to take place during the investment period.
5. The three-day return during the following earnings announcement has to be available.

The application of these restrictions results in 207,123 remaining observations, which is equivalent to 56.5 % of the sample used in section 3.2. Table 4.1 summarizes the data requirements and corresponding sample reductions. Figure 4.2 illustrates sample requirements 3 and 4.

Table 4.1: Sample Requirements and Reductions

	Data Requirement	n before	n afterwards
1	Fiscal year end December	366,817	236,122
2	Earnings announcement date available	236,122	221,027
3	Publication of cash flows which are used for the investment between m = -3 and m = 0	221,027	212,692
4	Publication of cash flows of the following quarter between m = 0 and m = 3	212,692	208,168
5	Announcement period return available for the 2nd announcement	208,168	207,123

Figure 4.2: Visualization of Sample Requirements 3 and 4



In the following, I calculate the quarterly return regressions 3.6 to 3.9 presented and explained in section 3.2.1 on page 30 for this restricted sample.[86]

Second, I conduct the same regressions using future quarterly abnormal returns as dependent variable. Abnormal returns are primarily studied in the following investigations. They are adjusted for risk and should therefore reflect market under- or overreactions better. Hence, I also use them in this preliminary analysis, which is intended to offer a standard of comparison for the following investigations. Abnormal returns are adjusted for book to market and size. Therefore, I do not include size and book to market in these regressions. Thus, I obtain the following three equations:[87]

$$abnreturn_{i,q+1} = \alpha + \beta^{mom} \cdot momdec_{i,q} + \varepsilon_{i,q+1} \quad 4.1$$

$$abnreturn_{i,q+1} = \alpha + \beta^{cfo} \cdot cfodec_{i,q} + \varepsilon_{i,q+1} \quad 4.2$$

$$abnreturn_{i,q+1} = \alpha + \beta^{mom} \cdot momdec_{i,q} + \beta^{cfo} \cdot cfodec_{i,q} + \varepsilon_{i,q+1} \quad 4.3$$

All regressions lead to similar results. Panel A of Table 4.2 lists the results of regressions on future returns and Panel B those of regressions on future abnormal returns.

Table 4.2: Determinants of Future Returns in the Restricted Sample

Panel A: Determinants of Future Quarterly Returns

regr		$\hat{\alpha}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{cfo}$	$\hat{\beta}^{size}$	$\hat{\beta}^{btom}$
3.6	OLS	1.79	3.59 ***			
	FMB	2.18	3.22 **			
3.7	OLS	1.80		3.58 ***		
	FMB	2.16		3.25 ***		
3.8	OLS	0.46	3.13 **	3.12 ***		
	FMB	1.01	2.75 **	2.81 ***		
3.9	OLS	3.84	4.02 ***	4.07 ***	-0.62 **	1.27 *
	FMB	3.96	3.40 ***	3.70 ***	-0.63 ***	0.36

[86] Moreover, I replicate the regressions including the control variables accruals, earnings surprises and idiosyncratic risk from section 3.4.2. This inclusion does not qualitatively alter my results. Therefore, I only present the results of the above listed regressions for the sake of brevity.

[87] I again, list the equations for the OLS regressions. The Fama MacBeth approach would need additional time subscripts for the regression coefficients.

Panel B: Determinants of Future Quarterly Abnormal Returns

regr		$\hat{\alpha}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{cfo}$
4.1	OLS	-2.01 **	4.14 ***	
	FMB	-1.73 **	3.76 ***	
4.2	OLS	-1.77 **		3.66 ***
	FMB	-1.52 **		3.33 ***
4.3	OLS	-3.34 ***	3.68 ***	3.13 ***
	FMB	-2.92 ***	3.29 ***	2.84 ***

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test. Standard errors of the OLS regressions are clustered by stock and by time.

The results of chapter 3 also hold true in this restricted sample. For example, FMB regression 4.3 shows that abnormal quarterly returns to the 10 % stocks with highest momentum are 3.29 percentage points higher than quarterly abnormal returns to the 10 % stocks with the lowest past return if cash flows are held constant. The respective abnormal return difference for operating cash flows is 2.84 percentage points. All in all, the estimated coefficients are slightly higher than in section 3.2.2, especially for the operating cash flow effect. This could be due to the on average more recent publication of operating cash flows in this sample. Unlike in chapter 1, I now analyze only stocks with fiscal year end December, meaning that the maximum lag between fiscal quarter end and beginning of the investment period is three months. In chapter 3, in contrast, this lag is at least three months and longer for earlier fiscal year ends. These longer lags might weaken the influence of operating cash flows on future returns.

As standard of comparison for my second type of analysis where I examine the long and short portfolios, I compute mean monthly normal and abnormal returns and alphas for the portfolios *Mom5*, *Cfo5*, and *Combi55* as well as *Mom1*, *Cfo1*, and *Combi11* for the restricted sample. The results are listed in Table 4.3.

Table 4.3: Monthly Portfolio Returns to the Long and Short Portfolios

	return	*abnreturn*	*alpha*
Mom5	1.87 ***	0.80 ***	0.87 ***
Cfo5	1.79 ***	0.69 ***	0.72 ***
Combi55	2.32 ***	1.28 ***	1.33 ***
Mom1	0.74	-0.42	-0.79 ***
Cfo1	0.83	-0.25	-0.51 *
Combi11	0.56	-0.59	-1.03 **

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

The results confirm the findings of the regressions. All three long portfolios are successful in the restricted sample with slightly higher profits than in the unrestricted sample. All three short portfolios yield much lower profits than their long counterparts. The returns and their significance are similar to those presented in section 3.2.2. To conclude this preliminary analysis: All three strategies also work in the smaller sample that is used in this chapter.

4.3 Market Reactions in the Short Term

4.3.1 Introduction and Methodology

In this section, I investigate the short-term returns of the trading strategies. Particularly, I address the question whether and how the market responds to earnings announcement news. This comprises the first market reaction during the month of the announcement and the subsequent information processing during the following months.

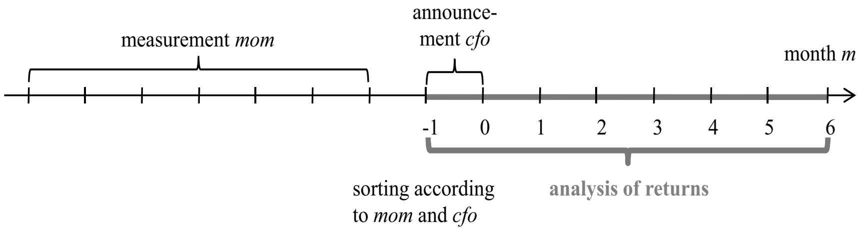
The operating cash flow strategy offers the ideal setting for this analysis, because it is based on the publication of cash flow news. Therefore, I expect to find a strong market reaction for the cash flow strategy at the time when earnings and cash flows are announced. Moreover, returns to the cash flow strategy should diminish gradually the more the cash flow information is processed by the market. The momentum strategy provides a suitable counterpart for this analysis as it does not directly depend on the release of new earnings information. Accordingly, the returns to the momentum strategy should not depend on the time when earnings are announced. However, the momentum effect should also decrease over time when the drive of the initial momentum ceases.

I use a time structure which is different from that underlying the investment strategy in chapter 1 and in section 4.2. There, I insert a three-month lag between fiscal quarter end and portfolio building to make sure that the cash flow information is publicly available.[88] In the following, I analyze stock returns already at the beginning of the month in which the cash flow will actually be published. Then I evaluate stock returns of this publishing month and the following 6 months. The momentum variable, which is used for the sorting into the momentum portfolios, is again measured with one month lag to the analysis of returns, i.e., to the month of the earnings announcement. The sorting according to operating cash flows is conducted at the beginning of the announcement month and is based on all operating cash flows of the respective fiscal quarter. Figure 4.3 illustrates the time structure.

---

[88] See Figure 3.3 on p. 30.

Figure 4.3: Time Structure of the Analysis of Short-Term Returns



It should be noted that this time structure does not meet the requirements of an implementable trading strategy. It rather assumes perfect foresight. If an investor wanted to earn the abnormal returns I find in this analysis, he would need to know already at the beginning of the publication month that the respective company is going to publish its cash flow during that respective month. He would also need to know all cash flows that will be announced in this fiscal quarter in order to be able to sort the stocks into the cash flow deciles at the beginning of that month. This assumption of perfect foresight is appropriate in this section because, in distinction from chapter 1, I do not calculate returns to an implementable trading strategy, now. I rather analyze the timing and the characteristics of market reactions ex post.

Using the sorting into cash flow and momentum deciles, I first conduct three different regressions 4.4 to 4.6. In regressions 4.4 and 4.5, I separately regress abnormal stock returns during the months 0 to 6 on momentum and cash flow deciles at the end of month $m = -1$. In regression 4.6, I include *momdec* and *cfodec* at the same time.[89] By means of this regression approach, I analyze the whole momentum and cash flow effects, because all stocks are included in the regressions. Moreover, regression 4.6 allows assessing the net influences of momentum and cash flows, as it controls for the respective other effect.[90]

$$abnreturn_{i,m+\tau} = \alpha + \beta^{mom} \cdot momdec_{i,m-1} + \varepsilon_{i,m+\tau} \qquad 4.4$$

$$abnreturn_{i,m+\tau} = \alpha + \beta^{cfo} \cdot cfodec_{i,m-1} + \varepsilon_{i,m+\tau} \qquad 4.5$$

$$abnreturn_{i,m+\tau} = \alpha + \beta^{mom} \cdot momdec_{i,m-1} + \beta^{cfo} \cdot cfodec_{i,m-1} + \varepsilon_{i,m+\tau} \qquad 4.6$$

89 Moreover, I again replicate the regressions including the control variables accruals, earnings surprises, and idiosyncratic risk from section 3.4.2. This inclusion does not qualitatively alter my results. Therefore, I only present the results regressions listed above for the sake of brevity.

90 In this analysis, I only use OLS regressions with standard errors that are clustered by firm and time. I do not use the Fama-MacBeth technique because the variables belong to different months. More precisely, $m = -1$ represents the month of the earnings announcement and thus different calendar months for different firms. Accordingly, it is not adequate to estimate single regressions per month and to aggregate the beta coefficients afterwards.

$\tau \in \{0,1,2,\ldots,6\}$

In a second step, I examine the long and short positions of the momentum, cash flow, and combination strategy. I compute monthly abnormal returns to portfolios *Mom5*, *Cfo5*, and *Combi55* as well as *Mom1*, *Cfo1*, and *Combi11* of the earnings announcement month and the following 6 months.

4.3.2 Empirical Results and Discussion

The results confirm that the market reacts to cash flow news. Figure 4.4 illustrates the regression coefficients $\hat{\beta}^{mom}$ and $\hat{\beta}^{cfo}$ for regression 4.6 where both, *momdec* and *cfodec* are included as explaining variables. Table 4.4 lists the results of all three regressions 4.4 to 4.6

Figure 4.4: Short-Term Development of the Predictive Ability of Past Returns and Operating Cash Flows for Future Abnormal Returns

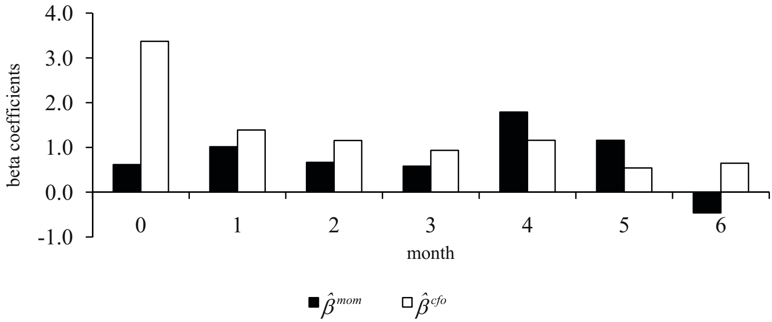


Table 4.4: Short-Term Development of the Predictive Ability of Past Returns and Operating Cash Flows for Future Abnormal Returns

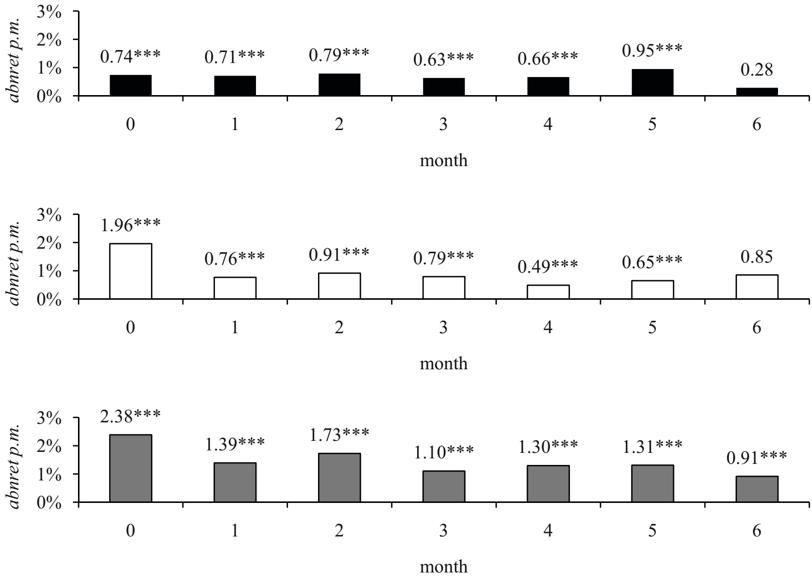
regr		month $m+\tau$						
		$\tau=0$	$\tau=1$	$\tau=2$	$\tau=3$	$\tau=4$	$\tau=5$	$\tau=6$
4.4	$\hat{\beta}^{mom}$	1.05 *	1.20 **	0.81	0.70	1.93 ***	1.23 **	-0.39
4.5	$\hat{\beta}^{cfo}$	3.45 ***	1.52 ***	1.24 ***	1.01 **	1.38 ***	0.68	0.59
4.6	$\hat{\beta}^{mom}$	0.62	1.02 *	0.67	0.58	1.79 ***	1.16 ***	-0.46
4.6	$\hat{\beta}^{cfo}$	3.37 ***	1.39 ***	1.16 ***	0.93 **	1.16 ***	0.54	0.65

***(**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test with standard errors that are clustered by stock and by time.

So far, the empirical results imply that the market reacts to the announcement of cash flows. The cash flow effect is extremely high in the month of the earnings announcement with a regression coefficient of $\hat{\beta}^{cfo} = 3.37$ in regression 4.6. This coefficient implies a difference in abnormal returns of 3.37 % between stocks in the first and the tenth cash flow decile during the announcement month, holding *momdec* constant. In the following months, the influence of cash flows on future abnormal returns decreases. This matches the expectation that the market processes the cash flow information as time passes by. However, this process takes time. $\hat{\beta}^{cfo}$ does not lose significance until the fifth month after the earnings announcement. The momentum coefficient $\hat{\beta}^{mom}$, in contrast, is not particularly high during the month of the earnings announcement complying with the fact that the momentum effect is not based on the announcement. However, I do not find the expected decrease of the influence of past returns on future returns in the first six months. $\hat{\beta}^{mom}$ reaches its maximum value of 1.79 not before the fourth month after the sorting into momentum deciles. A comparison of regression 4.6 with regressions 4.4 and 4.5 moreover shows that the two effects partly overlap. Both $\hat{\beta}^{mom}$ and $\hat{\beta}^{cfo}$ decrease slightly when the respective other variable is included in regression 4.6.

Now I turn to the long positions of the effects, i.e., I analyze portfolios *Mom5*, *Cfo5*, and *Combi55*. Figure 4.5 illustrates the short-term development of monthly abnormal returns in the three long portfolios.

Figure 4.5: Short-Term Development of Abnormal Returns in the Long Portfolios (■ *Mom5*, □ *Cfo5*, and ■ *Combi55*)

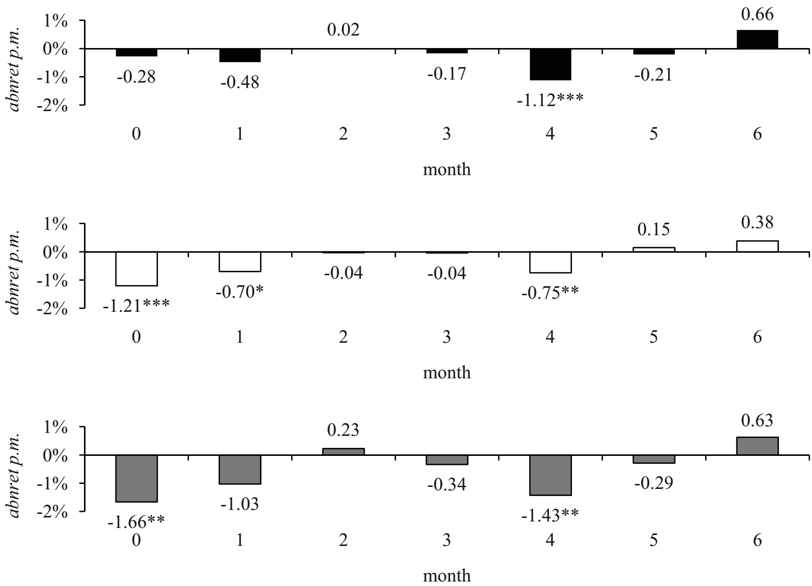


***(**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test with standard errors that are clustered by stock and by time.

The development of portfolio abnormal returns in the long portfolios supports the regression results. Abnormal returns to portfolio *Cfo5* are by far the highest in the month of the earnings announcement with a value of 1.96 % p.m. After that, they decrease. Abnormal returns to portfolio *Mom5* show a similar development as $\hat{\beta}^{mom}$ before. They are not extremely high in the month of the earnings announcement, do not show a clear trend, and lose significance in month 6. Furthermore, all abnormal portfolio returns in months zero to five are lower than the respective regression coefficients. This implies that the abnormal return difference between the first and the tenth decile is higher than abnormal returns to stocks belonging to the fifth quintile. All in all, the conclusions regarding the whole effects also hold when only the long portfolios are analyzed. Concerning the combination portfolio *Combi55*, the development of abnormal returns is similar to that of the long cash flow portfolio *Cfo5*: Highest returns are earned in the month of the earnings announcement and abnormal returns decrease slightly afterwards, reflecting the gradual processing of the cash flow information. In portfolio *Combi55*, this development takes place on a higher level than in *Cfo5*. This indicates that the combination portfolio seems to benefit not only from the slow processing of the cash flow information, but also from the drive of the momentum effect.

Now, I turn to the short portfolios, i.e., stocks with low operating cash flows and/or low past returns. Figure 4.6 illustrates the short-term development of abnormal returns in these portfolios.

Figure 4.6: Short-Term Development of Abnormal Returns in the Short Portfolios (■ *Mom1*, □ *Cfo1*, and ▩ *Combi11*)



***(**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test with standard errors that are clustered by stock and by time.

The analysis of the short portfolio also confirms the regression results. During the month of the earnings announcement, the market reacts strongly to the cash flow news, which is bad news this time. This reaction leads to high negative abnormal returns in portfolio *Cfo1* in month 0. This strong reaction declines in the following months. Compared to the long portfolios, the bad information is more quickly processed. In the fifth month after the announcement, stocks in portfolio *Cfo1* yield a positive, but not significant return of 0.15 %, again. The returns to the short momentum portfolio are not extremely negative in the earnings announcement month, as expected. They do not show a clear trend and reach the largest negative value of -1.12 % not before the fourth month after the earnings announcement.

Portfolio *Combi11* “benefits” from both effects, earning the largest negative abnormal returns. In this portfolio, the market reaction in the month of the announcement of the low cash flows is extremely high, leading to a negative abnormal return of -1.66 % p.m. However, the negative abnormal returns are only significant in months zero and four. Also in the combination portfolio, the negative response to bad news does not last very long. In month six after the announcement, the stocks in *Combi11* again yield on average positive – though not statistically significant – abnormal returns.

All in all, the market, indeed, strongly reacts to cash flow information. This response leads to considerable differences between the timely sequences of momentum and cash flow portfolio returns. The combination portfolios capture both effects – the extreme cash flow reaction and the momentum drift. Altogether, positive news seems to take more time to be incorporated into the price than bad news, since the anomalous returns in the long portfolios last longer than in the short portfolios. This finding indicates that a separate investigation of long and short portfolios in the following sections should be worthwhile.

4.4 Returns Surrounding Earnings Announcements

4.4.1 Introduction and Methodology

This section analyzes the returns around the earnings announcement that follows the building of the momentum, operating cash flow, and combination portfolios. In particular, I examine to what extent the returns earned by these portfolios are clustered around the earnings announcement that occurs during the investment period.

This analysis addresses the differentiation between risk and mispricing and the question whether market over- or underreaction is the primary reason for the anomalous returns of the strategies. Bernard, Thomas, and Wahlen (1997) analyze returns around subsequent earnings announcements in order to disentangle risk from mispricing. They argue that “if a security is mispriced, corrections will occur around subsequent information releases, because the new information causes traders to re-examine their prior (incorrect) beliefs.”[91] Extreme earnings announcement returns indicate that market participants are surprised by the new accounting information. They adjust their valuation of the stock according to the new information. This adjustment reflects initial mispricing and not risk. Prices will be traded upward if the new accounting numbers are a positive surprise, revealing that the stock has been undervalued before. This result would indicate that the earned profits are (partly) due to an initial underreaction and an upward correction at the time of the following earnings announcement. In contrast, extremely negative earnings announcement returns suggest a correction of a prior

91 Bernard, Thomas, and Wahlen (1997), p. 95.

overestimation. Following this argument, Jegadeesh and Titman (1993) analyze earnings announcement returns and state that these will be positive if the market initially reacted too weakly to information about future earnings.[92] Indeed, they find positive announcement returns for their hedge momentum portfolios. Similarly, Sloan (1996) studies earnings announcement returns to prove that the abnormal returns to the extremely low accruals portfolio represent a "delayed response to predictable changes in future earnings."[93] In his empirical investigation, he finds positive announcement returns for low accrual stocks and concludes that the market initially reacted too weakly to these low accruals.[94]

Because of the findings of Jegadeesh and Titman (1993) and Sloan (1996), I expect to find abnormal returns around the earnings announcement, both for the long momentum and for the operating cash flow portfolios. Moreover, I will analyze the announcement returns in the combination portfolio. A hypothesis about whether announcement returns in the combination portfolio will be higher or lower than in the pure portfolios is difficult. In section 4.3.2, I demonstrated that the abnormal returns during the earnings announcement month are more extreme in the combination portfolios than in the pure cash flow portfolios. I found abnormal returns of 2.38 % for *Combi55* and -1.66 % for *Combi11* during the month of the earnings announcement compared to 1.96 % for portfolio *Cfo5* and -1.21 % for *Cfo1*. However, this stronger initial reaction can be interpreted in two ways. On the one hand, it may indicate that the market reacted more strongly to the first cash flow news in the combination portfolios than in the pure cash flow portfolios. In this case, the reaction to the next cash flow announcement should be weaker in the combination, since the underreaction that has to be corrected should be smaller. On the other hand, the actual cash flow surprise of the stocks in portfolio *Combi55* (*Combi11*) could also be greater than that of the stocks in portfolio *Cfo5* (*Cfo1*). For this reason, the higher returns in the combination could also be due to this greater surprise. In this case, they would not necessarily imply a weaker underreaction, at all. Accordingly, the result for the combination portfolio, especially in comparison with the pure cash flow portfolios, is an open empirical question.

I measure earnings announcement returns as follows. The earnings announcement period *ap* endures three trading days, beginning two days prior to the day of the earnings announcement

---

92 See Jegadeesh and Titman (1993), pp. 86-89 and section 2.2.2 of this thesis.
93 Sloan (1996), p. 292.
94 See Sloan (1996), p. 312 and section 2.3.2 of this thesis.

ad.[95] I compute compounded normal and abnormal returns of stock *i* during the earnings announcement period $return_{i,ap}$ and $abnreturn_{i,ap}$:[96]

$$return_{i,ap} = \prod_{\tau=-2}^{0}\left(1+return_{i,ad+\tau}\right)-1 \qquad 4.7$$

$$abnreturn_{i,ap} = \left[\prod_{\tau=-2}^{0}\left(1+return_{i,ad+\tau}\right)-1\right]-\left[\prod_{\tau=-2}^{0}\left(1+return_{i,ad+\tau}^{bm}\right)-1)\right] \qquad 4.8$$

with:

ad	=	day of the earnings announcement
$return_{i,ap}$	=	stock return of stock *i* during the announcement period *ap*
$abnreturn_{i,ap}$	=	abnormal stock return of stock *i* during the announcement period
$return_{i,d}^{bm}$	=	value weighted daily return of the characteristic-based benchmark portfolio which consists of stocks belonging to the same quintiles in terms of size and book to market as stock *i*

The descriptive statistics of $return_{ap}$ and $abnreturn_{ap}$ are listed in Table 4.5.

Table 4.5: Descriptive Statistics of Announcement Period Returns

	mean	p 25	p 50	p 75
$return_{ap}$ (in %)	0.53 ***	0.09	0.41	0.92
$abnreturn_{ap}$ (in %)	0.43 ***	0.23	0.35	0.63

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

It is striking that the mean abnormal earnings announcement return for the whole sample is significantly positive with a value of Ø$abnreturn_{ap}$ = 0.43 %. This finding is in line with prior literature. Due to the greater amount of information the market receives at the time of an earnings announcement, stock returns during the announcement period are higher and more volatile than during non-announcement periods. This is, for example, shown by Chambers and Penman (1984).[97] The amount of the announcement returns I find is also comparable to

95 This definition is analogous to prior literature; see Jegadeesh and Titman (1993), p. 87, Sloan (1996), p. 309, or Bernard, Thomas, and Wahlen (1997), p. 103. One advantage of the computation of abnormal returns over this brief interval of three days is that the errors in capturing risks should be minimized; see Bernard, Thomas, and Wahlen (1997), p. 96.

96 When I replicate the analyses using cumulative (abnormal) returns, I obtain similar results.

97 Chari, Jagannathan, and Ofer (1988) furthermore show that the effect is especially high for small firms. Ball and Kothari (1991) find that the abnormal returns remain even when they control for increases of risk during earnings announcements.

previous literature. Sloan (1996) reports mean returns for four consecutive announcement periods of 1.68 %, which corresponds to about 0.42 % per announcement.[98]

In order to analyze announcement returns of the cash flow, momentum, and combination strategies, I first conduct similar regressions as in the previous sections. This time I regress future normal and abnormal announcement returns $return_{ap}$ and $abnreturn_{ap}$ on the strategy variables *momdec* and *cfodec*, as well as on *momdec* and *cfodec* at the same time.[99] That is, I reestimate regressions 3.6 to 3.8, now with $return_{ap}$ or $abnreturn_{ap}$ as dependent variable.[100] The time structure is illustrated in Figure 4.2 on p. 60. I assign the stocks to momentum and cash flow deciles at the beginning of the investment period ($m = 0$). The assignment is based on *mom* which is measured between $m = -7$ and $m = -1$ and on *cfo* which is announced between $m = -3$ and $m = 0$. The following earnings announcement period during which I measure $return_{ap}$ and $abnreturn_{ap}$ occurs sometime during the investment period, i.e., between $m = 0$ and $m = 3$.

In my second examination, I turn to the long and short portfolios *Mom5*, *Cfo5*, and *Combi55*, as well as *Mom1*, *Cfo1*, and *Combi11* and compute their mean $return_{ap}$ and $abnreturn_{ap}$. To evaluate these returns, I compare them to their respective means in the whole sample presented in Table 4.5. This comparison is necessary, since the mean abnormal announcement return is positive in the whole sample. Therefore, I compute the mean *difference* between announcement returns in the portfolios and the mean announcement returns in the whole sample as noted in equation 4.9.

$$difference_{j,ap} = (abn)return_{j,ap} - (abn)return_{sample,ap} \qquad 4.9$$

4.4.2 Empirical Results and Discussion

The regression results confirm that both, past returns and operating cash flows, predict returns during the next earnings announcement significantly.

Table 4.6 lists the estimated regression coefficients, again for OLS and FMB regressions. Panel A presents the results for regressions with future announcement returns $return_{ap}$ as

98 See Sloan (1996), p. 313 and section 2.3.2 of this thesis.

99 Using the regression-based approach, I follow for instance Bartov, Radhakrishnan, and Krinsky (2000) who regress announcement period returns on earnings surprises. Jegadeesh and Titman (1993) and Sloan (1996), in contrast, do not conduct regressions of earnings announcement returns. They only analyze announcement returns of their portfolios.

100 Moreover, I again replicate the regressions including the control variables accruals, earnings surprises and idiosyncratic risk from section 3.4.2. This inclusion does not qualitatively alter my results. Therefore, I only present the results of the above listed regressions for the sake of brevity.

dependent variable. The dependent variable in Panel B is future abnormal announcement returns *abnreturn*$_{ap}$.

Table 4.6: Determinants of Announcement Period Returns

Panel A: Determinants of Future Raw Announcement Returns *return*$_{ap}$

regr	$\hat{\alpha}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{cfo}$
OLS	0.40 **	0.30 **	
FMB	0.35 **	0.41 ***	
OLS	0.39 ***		0.34 ***
FMB	0.36 ***		0.39 ***
OLS	0.28	0.26 **	0.30 ***
FMB	0.18	0.36 ***	0.37 ***

Panel B: Determinants of Future Abnormal Announcement Returns *abnreturn*$_{ap}$

regr	$\hat{\alpha}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{cfo}$
OLS	0.30 ***	0.29 **	
FMB	0.23 ***	0.40 ***	
OLS	0.29 ***		0.30 ***
FMB	0.25 ***		0.36 ***
OLS	0.18	0.25 *	0.27 ***
FMB	0.08	0.36 ***	0.33 ***

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test. Standard errors of the OLS regressions are clustered by stock and by time.

The results of all regressions are similar, regardless of whether normal or abnormal announcement period returns are the dependent variable or whether I use the Fama-MacBeth or the Petersen approach for the estimation. Both *momdec* and *cfodec* have a significantly positive influence on the returns occurring during the following earnings announcement. The higher the past return or operating cash flow of a stock, the higher are the returns during the following earnings announcement. For example, the coefficient of *momdec* is $\hat{\beta}^{mom} = 0.36$ in the Fama-MacBeth regression that incorporates both coefficients. This means that the difference in abnormal three-day announcement period returns between the tenth and the first momentum decile is 0.36 percentage points when *cfodec* is held constant. The difference between the first and the tenth cash flow decile is 0.33, respectively. These return differences are fairly high underlining the exceptional market reaction during earnings announcements. For example, the difference of 0.33 percentage points per three days at a rough estimate corresponds to an abnormal return difference of 31.5 % per year when I assume 250 trading days per year. The predictive abilities of the two variables overlap to a small extent, as both coefficients $\hat{\beta}^{mom}$ and $\hat{\beta}^{cfo}$ decrease slightly when the respective other variable is included in the regression.

All in all, I conclude from the results that initial underreaction is part of the reason for both, the momentum and the operating cash flow effect. The higher the past returns and/or the operating cash flow, the more positively surprised the market is during the next earnings announcement, leading to an upward price correction. Put it the other way around: The lower the past return and/or operating cash flow, the less positively surprised is the market during the next announcement, leading to a downward or a smaller upward correction.

The second approach that analyzes the actually occurring announcement returns for stocks in portfolios *Mom5*, *Cfo5*, and *Combi55* leads to similar conclusions. Conclusions for the short portfolios *Mom1*, *Cfo1*, and *Combi11* are different, as outlined in the following.

Table 4.7 lists mean normal and abnormal returns ($Øreturn_{ap}$ and $Øabnreturn_{ap}$) of the long portfolios that occur during the earnings announcement period that follows portfolio building. Moreover, it gives the *difference* between these (abnormal) announcement returns and the mean (abnormal) announcement returns of the whole sample. All values are given in %.

Table 4.7: Earnings Announcement Returns in the Long Portfolios

	$return_{ap}$	$abnreturn_{ap}$
Mom5	0.85 ***	0.76 ***
Ø difference	0.31 ***	0.33 ***
Cfo5	0.81 ***	0.72 ***
Ø difference	0.28 ***	0.29 ***
Combi55	1.05 ***	0.97 ***
Ø difference	0.52 ***	0.53 ***

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

Mean normal and abnormal returns that occur during the announcement period are significantly positive for all three long portfolios, indicating an initial underreaction. However, significantly positive $Øabnreturn_{ap}$ only suffice to show that an upward price correction takes place during the earnings announcement which is, on average, also given for the whole sample.[101] I test whether this correction is especially high in the long portfolios *Mom5*, *Cfo5*, and *Combi55* by comparing mean abnormal announcement returns in these portfolios with those of the whole sample. As listed in the rows *Ødifference* in Table 4.7,

[101] Remember that the mean announcement return of the whole sample is $Øreturn_{ap}$ = 0.53 and the mean abnormal return $Øabnreturn_{ap}$ = 0.43 as listed in Table 4.5 on page 72.

abnormal announcement returns in all three long portfolios are significantly higher than their sample average. I conclude from this, that market participants are indeed particularly positively surprised by the subsequent earnings announcements of stocks with high past returns and/or high operating cash flows. For these stocks, the upward price correction during the announcement which follows the initial announcement of cash flows and the measurement of momentum is significantly higher than for the average stock. Accordingly, market participants seem to correct their prior underreaction upward when they receive the new accounting information for these high cash flow/high momentum stocks.

Whereas the results prove upward corrections in all three portfolios, they do not reveal large differences between the three portfolios. The amount of announcement returns is similar in the two pure portfolios *Mom5* and *Cfo5*. Announcement returns are higher in the combination portfolio *Combi55*, but this does not come as a surprise, since the investment return in the combination portfolio is higher, too. All in all, I do not conclude a stronger or weaker initial underreaction in one of the three long portfolios from the results.

Now I analyze the same numbers for the three short portfolios *Mom1*, *Cfo1*, and *Combi11*. The interpretation of announcement period returns in the short portfolios is different from that in the long portfolios. Initially, the stocks in the short portfolios had low cash flows and/or low returns, meaning negative news. If the market initially reacted too weakly to this negative news, I would expect a negative return during the following announcement period. This negative announcement return would then show that the market corrects the initially too weak reaction to the bad news. If the market, in contrast, initially overreacted to the bad news, I would expect a subsequent positive announcement period return which corrects the initial overreaction. Table 4.8 lists the results.

Table 4.8: Earnings Announcement Returns in the Short Portfolios

	$return_{ap}$	$abnreturn_{ap}$
Mom1	0.41***	0.33***
Ø difference	-0.12	-0.10
Cfo1	0.45***	0.38***
Ø difference	-0.09	-0.05
Combi11	0.37*	0.32**
Ø difference	-0.16	-0.11

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

Announcement period returns and abnormal returns are significantly positive in all three short portfolios. This upward price correction suggests that an initial overreaction is corrected. However, the comparison of the announcement period returns of the stocks in these portfolios with those of the whole sample reveals that the upward correction for the short portfolios does not significantly differ from that in the whole sample. I conclude from this finding that market participants do not underreact to negative cash flow information or negative information that is incorporated in low past returns.[102] The significantly positive announcement returns in all six cases rather suggest initial overreaction. This result is in line with Sloan's investigation of announcement period returns of low and high accrual stocks. He finds that the positive returns to low accruals stocks largely occur around the earnings announcement in the following year, whereas the negative returns to high accrual stocks are not clustered during the future yearly earnings announcement. He concludes from this finding that bad news is more likely to be preempted by the stock market.[103]

My conclusion from this analysis is that the returns to the long portfolios which consist of stocks with high past returns and/or high operating cash flows can, to a great extent, be attributed to initial market underreaction on the information that is contained in high past returns and high operating cash flows. This underreaction is at least partly corrected during the next earnings announcement, leading to a big part of the returns earned by the portfolios during the investment period. Moreover, announcement returns are similar for all three long portfolios, not indicating stronger or weaker underreactions in one of them. By contrast, the positive announcement returns to the short portfolios that consist of stocks with low past returns and/or operating cash flows indicate an initial reaction to bad news that is too strong. However, these announcement period returns are not higher than in the whole sample, so that I do not draw too many inferences from them.

Furthermore, the abnormal announcement returns I find for the three-day announcement period are too high to be explained by risk. Especially the correction that takes place in the long portfolios strongly indicates initial mispricing and not a sudden increase of risk.

4.5 Influence of Investor Attention

4.5.1 Introduction and Methodology

In this section, I investigate the influence of investor attention on the momentum, the operating cash flow, and the combination effect. Similar to the previous section, this analysis also addresses the question of whether the effects are due to a market reaction that is too strong or too weak. The relation between investor attention and market over- and

[102] Note that corresponding to the positive announcement returns in the short portfolios, the announcement period raw and abnormal returns of the long portfolios are this time higher than the corresponding regression coefficients listed in Table 4.6. For example, portfolio *Cfo5* earns an abnormal return of 0.72 % during the announcement period, whereas the respective coefficient for cash flows from the FMB regression is 0.36.

[103] See Sloan (1996), pp. 313-314.

underreaction is, for example, explained by Hou, Peng, and Xiong (2009). They argue that investor attention plays a dual role. If attention for a stock is low, investors will more probably miss or not completely incorporate important information, leading to stock price underreaction. Accordingly, underreaction should decrease with investor attention. The contrary will be the case if investor attention is high. Market participants can only overreact to firm-specific information if they pay attention to a stock. Accordingly, overreaction should increase with investor attention.[104] Transferred to anomaly-based trading strategies, this means that returns to anomalies that are mainly due to overreaction should be higher for stocks attracting **high** investor attention. In contrast, returns to strategies which are mainly caused by underreaction, should be higher for stocks with **low** investor attention.

Hou, Peng, and Xiong (2009) find that returns to the momentum strategy are higher for stocks with high investor attention. In contrast, the success of a trading strategy that aims to exploit the post earnings announcement drift is higher for stocks with low attention. The authors conclude from their findings that the price momentum effect can mainly be attributed to overreaction, whereas earnings momentum primarily stems from underreaction.

In order to measure investor attention in the cross-section, Hou, Peng, and Xiong (2009) use a stock's trading volume. The rationale behind this measure is the following: If a stock is traded actively, investors should pay attention to it. If, in contrast, a stock does not attract investor attention, it will not be actively traded. The relation between the price momentum effect and trading volume has also been analyzed by Lee and Swaminathan (2000). They show that trading volume provides a link between momentum and value strategies and that trading volume predicts the magnitude and persistence of price momentum. In particular, the momentum effect is higher for high volume firms. Moreover, high volume winners and low volume losers exhibit faster reversals. Lee and Swaminathan (2000) develop a "momentum life cycle" which uses trading volume to determine in which state of this cycle a stock is at present. The momentum of stocks which are in the early stage will more probably persist, whereas the momentum of stocks in the late stage will presumably reverse sooner.[105]

In the following, I conduct a similar analysis as Hou, Peng, and Xiong (2009). I analyze whether the momentum, operating cash flow, and combination strategies' success depends on investor attention. However, my analysis differs from Hou, Peng, and Xiong (2009) in several ways. Unlike them, I analyze the momentum, the cash flow and the combination effect, not momentum and the post-earnings-announcement drift. Moreover, I do not only focus on the whole effects when interpreting my results, but I also thoroughly investigate and interpret the long and short portfolios individually.

---

[104] For a more detailed explanation; see Hou, Peng, and Xiong (2009), pp. 1-2.
[105] For a more detailed explanation; see Lee and Swaminathan (2000), pp. 2063-2065.

In order to measure attention, I follow Hou, Peng, and Xiong (2009) using the stocks' turnover, which is defined as follows:

$$turnover_{i,m} = \frac{volume_{i,m}}{shares_{i,m}} \qquad 4.10$$

with:

$turnover_{i,m}$ = turnover of stock *i* during month *m*

$volume_{i,m}$ = trading volume in shares of stock *i* during month *m*

$shares_{i,m}$ = number of shares of stock *i* outstanding at the end of month *m*

The trading volume of NASDAQ stocks is on average higher than the trading volume of AMEX and NYSE stocks because of the different organization of the exchanges.[106] In order to make trading volumes comparable across exchanges, I follow Chen, Hong, and Stein (2002) and use demeaned trading volumes.[107] That is, I use either the difference between the stock's *turnover* and the mean *turnover* of all AMEX and NYSE stocks, or the difference between the stock's *turnover* and the mean *turnover* of all NASDAQ stocks in the given month, depending the exchange of stock *i*.

$$dmturnover_{i,m} = turnover_{i,m} - \varnothing turnover_{exchange_i,m} \qquad 4.11$$

with:

$dmturnover_{i,m}$ = demeaned turnover of stock *i* during month *m*

$\varnothing turnover_{exchange_i,m}$ = mean turnover of stocks belonging to AMEX or NYSE or to NASDAQ during month *m*

At the end of every month *m*, I use the mean *dmturnover* during the last seven months to decide whether a stock has attracted high or low attention. I choose the last seven months, because they correspond to the six-month period during which I measure momentum including the one-month lag.[108]

$$attention_{i,m} = \frac{1}{7} \cdot \sum_{\tau=-6}^{0} dmturnover_{i,m+\tau} \qquad 4.12$$

with:

$attention_{i,m}$ = mean *dmturnover* during the last seven months, determined at the end of month *m*

---

106 See, e.g., Lee and Swaminathan (2000), p. 2021 or Chen, Hong, and Stein (2002), p. 181.

107 See Chen, Hong, and Stein (2002), p. 181.

108 Lee and Swaminathan (2000) also use the mean turnover during the portfolio formation period; see Lee and Swaminathan (2000), p. 2022. Hou, Peng, and Xiong (2009) use the average turnover over the prior year; see Hou, Peng, and Xiong (2009), p. 9.

Then I compute a dummy variable D^{att} that denotes whether a stock attracts high investor attention or not, dependent on the relation to the median.

$$\begin{aligned} D^{att}_{i,m} &= 1 \;\; if \;\; attention_{i,m} > p50\,(attention_m) \\ D^{att}_{i,m} &= 0 \;\; if \;\; attention_{i,m} \leq p50\,(attention_m) \end{aligned} \qquad 4.13$$

with:

$p50\,(attention_m)$ = median of the distribution of all stocks' *attention*, determined at the end of month *m*

In my first analysis, I conduct regressions to test whether the momentum or the operating cash flow effect is higher for stocks belonging to the 50 % stocks that attract the highest attention. I interact the momentum and the cash flow deciles with D^{att} and additionally incorporate D^{att} alone to control for the influence of attention on future returns. As dependent variable, I use future quarterly abnormal returns.[109] This leads to the following regression equations for which I conduct FMB and OLS regressions:[110]

$$abnreturn_{i,q+1} = \alpha \;+ D^{att}_{i,q} + \beta^{mom} \cdot momdec_{i,q} + \beta^{Dmom} \cdot D^{att}_{i,q} \cdot momdec_{i,q} + \varepsilon_{i,q+1} \qquad 4.14$$

$$abnreturn_{i,q+1} = \alpha \;+ D^{att}_{i,q} + \beta^{cfo} \cdot cfodec_{i,q} + \beta^{Dcfo} \cdot D^{att}_{i,q} \cdot cfodec_{i,q} + \varepsilon_{i,q+1} \qquad 4.15$$

$$\begin{aligned} abnreturn_{i,q+1} = \alpha \;&+ D^{att}_{i,q} + \beta^{mom} \cdot momdec_{i,q} + \beta^{Dmom} \cdot D^{att}_{i,q} \cdot momdec_{i,q} \\ &+ \beta^{cfo} \cdot cfodec_{i,q} + \beta^{Dcfo} \cdot D^{att}_{i,q} \cdot cfodec_{i,q} + \varepsilon_{i,q+1} \end{aligned} \qquad 4.16$$

In regression 4.14, β^{mom} captures the influence of momentum on future abnormal returns for low attention stocks. β^{Dmom} measures the incremental influence of momentum for high attention stocks. D^{att} expresses the amount by which the abnormal returns of high attention stocks exceed those of low attention stocks, independently from momentum. The interpretation of the coefficients of the other two regressions is analogical.

After the regression analysis, I examine whether the profits of the long and short momentum, cash flow, and combination portfolios depend on investor attention. Therefore, I compute abnormal returns and 3-factor alphas to the portfolios, separately for the 50 % stocks attracting lowest and for the 50 % stocks attracting highest investor attention, i.e., the stocks with lowest and highest turnover. Then I take differences between the returns to low and high turnover stocks and test whether these differences significantly differ from zero, using a t-test based on Newey and West (1987) standard errors with a lag of 6 months.

---

109 Note that I determine *attention* for every month *m*, but I only use it in the regression every quarter. For this reason, the subscript changes from *m* to *q*.

110 Again, I also estimate the regressions including all control variables as in regression 3.16 in section 3.4.2. This modification does not qualitatively change my results.

4.5.2 Empirical Results and Discussion

The regression analysis does not reveal any significant influence of investor attention on the predictive ability of momentum or cash flows for future abnormal returns. Table 4.9 lists the results of regressions 4.14 to 4.16:

Table 4.9: Analysis of Investor Attention

	$\hat{\alpha}$	$\hat{D}^{att}$	$\hat{\beta}^{mom}$	$\hat{\beta}^{Dmom}$	$\hat{\beta}^{cfo}$	$\hat{\beta}^{Dcfo}$
OLS	-1.42**	-1.16	3.56***	1.12		
FMB	-1.07	-1.38*	3.09***	1.37		
OLS	-1.14*	-1.27			2.95***	1.42
FMB	-0.95	-1.08			2.71***	1.15
OLS	-2.44***	-1.82	3.16***	1.02	2.47***	1.31
FMB	-2.00**	-1.86*	2.71**	1.24	2.28***	1.02

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test. Standard errors of the OLS regressions are clustered by stock and by time.

$\hat{\beta}^{Dmom}$ and $\hat{\beta}^{Dcfo}$ are both positive but not significantly different from zero. The exceptionless positive values suggest a stronger predictive power for past returns and operating cash flows in the case of high turnover stocks, but they are not statistically significant on conventional levels. The results for the momentum effect are different from those of Hou, Peng, and Xiong (2009) who find significant hedge momentum portfolio return differences between high and low turnover stocks. However, the comparability to their study is limited since they do not conduct regressions and regroup their momentum portfolios monthly whereas I rearrange my portfolios quarterly. The negative value of $\hat{D}^{att}$ shows that stocks with high turnover yield on average lower future abnormal returns. However, this result is also only weakly statistically significant in two of the four regressions and not significant in the other cases.

Before turning to the results of the portfolio analysis, I give a first impression on how much attention the stocks in the momentum and cash flow portfolios attract. Therefore, I list the mean ratios of stocks that belong to the 50 % stocks with highest trading volume in Table 4.10.

Table 4.10: Ratios of Stocks Attracting High Investor Attention

portfolio	n	ratio of high attention stocks
whole sample	207,123	50.0
Mom5	41,387	61.0
Cfo5	41,395	54.4
Combi55	10,692	64.4
Mom1	41,471	54.1
Cfo1	41,454	52.4
Combi11	14,028	52.9

All six long and short portfolios comprise a ratio of high-attention stocks that is higher than 50 %. Ratios in the three long portfolios are slightly higher than in the short portfolios with values from 54.4 % in *Cfo5* to 64.4 % in *Combi55*. This finding indicates that stocks with good news are traded more heavily. In the following, I analyze whether these high turnover stocks are responsible for the larger part of the anomalous returns of the long and short portfolios than stocks which attract lower investor attention.

The portfolio analysis allows a more differentiated examination of the effects than the regressions. Its results suggest stock market overreaction for the short portfolios and are mixed for the long portfolios. Table 4.11 reports mean monthly returns, abnormal returns, and alphas for the long portfolios *Mom5*, *Cfo5*, and *Combi55*, when the sample is divided into high and low attention stocks.

Table 4.11: Returns to the Long Portfolios Dependent on Investor Attention

		high *attention*	low *attention*	high − low
Mom5	*abnreturn*	0.71 ***	0.96 ***	-0.24
	alpha	0.65 ***	1.23 ***	-0.57 ***
Cfo5	*abnreturn*	0.59 ***	0.80 ***	-0.21
	alpha	0.45 ***	1.01 ***	-0.57 ***
Combi55	*abnreturn*	1.23 ***	1.47 ***	-0.25
	alpha	1.17 ***	1.67 ***	-0.50 *

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

In all cases, portfolio returns are higher for stocks with low investor attention, i.e., with low turnover. Accordingly, investor attention seems to reduce the returns that can be earned by buying stocks with high past returns and/or high operating cash flows. Following the line of reasoning of Hou, Peng, and Xiong (2009), this finding indicates that anomalous returns which can be earned by buying these stocks should rather be due to investor underreaction than to overreaction. However, I do not attach too much importance to this result, since the difference between high and low attention returns is only statistically significant in three of the six analyzed cases.

Results are clearer when analyzing the short portfolios. The returns and return differences for portfolios *Mom1*, *Cfo1*, and *Combi11* are listed in Table 4.12.

Table 4.12: Returns to the Short Portfolios Dependent on Investor Attention

		high *attention*	low *attention*	high − low
Mom1	*abnreturn*	-0.78 *	-0.06	-0.72 ***
	alpha	-1.33 ***	-0.18	-1.16 ***
Cfo1	*abnreturn*	-0.53	0.08	-0.61 **
	alpha	-1.02 ***	0.08	-1.09 ***
Combi11	*abnreturn*	-1.07 **	-0.06	-1.01 ***
	alpha	-1.70 ***	-0.31	-1.39 ***

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

Again, for all cases, returns are higher for the subsample of stocks that attract lower investor attention. This time, the differences between low and high attention stocks are highly statistically significant in all six cases. Unlike for the long portfolios, the lower – or more negative – returns of high attention stocks indicate for the short portfolios, that overreaction is the driving force behind the anomalous returns. If market participants pay attention to a stock, their reaction to bad information is too strong, leading to negative anomalous returns in the short portfolios. The overreaction is especially high for stocks in portfolio *Combi11*. For these stocks, the market seems to overreact to both: the bad cash flow news and the bad news contained in low past returns. If, in contrast, the market only pays little attention to a stock, it does not exaggeratedly react to bad information, since abnormal returns and alphas to these portfolios are not even significantly lower than zero. Following the arguments of Hou, Peng, and Xiong (2009), I conclude from these results that the anomalous negative returns to the short momentum, cash flow, and combination portfolios are largely due to a market reaction to bad news that is too strong.

4.6 Market Reactions in the Long Term

4.6.1 Introduction and Methodology

As last analysis of this fourth chapter, I take a closer look at the market reactions in the long term. In section 4.3, I examined returns during the six months after the initial cash flow announcement. I close this chapter by conducting the same analysis for the following one and a half years, that is months 7 to 24 after the initial earnings announcement.

By analyzing the long-term effects, I mainly address the questions whether the two effects are due to risk or mispricing and, in particular, whether a market overreaction is the predominant reason for the effects. If the initial market reaction was too strong and the abnormal returns earned by the investment strategy were due to a market overreaction, this overreaction would be corrected afterwards. In this case, I would expect a reversal in the long term.[111] If, in contrast, the initial effect resulted out of market underreaction, the following price correction towards the fair value should weaken by the time and vanish at last. In this case, I expect no reversal. Since the occurrence of long-term reversals strongly indicates market overreaction, it will also rule out the possibility that risk is the underlying reason for the abnormal returns. Previous studies analyzing return reversals are, for instance, De Bondt and Thaler (1985), De Bondt and Thaler (1987), Chopra, Lakonishok, and Ritter (1992), Lee and Swaminathan (2000), as well as Jegadeesh and Titman (2001).

I use the same methodology as in section 4.3. First, I regress momentum and cash flow deciles *momdec* and *cfodec* on future monthly abnormal returns, but this time of the months 7 to 24 after the earnings announcement. The regressions are given in equations 4.17 to 4.19.

$$abnreturn_{i,m+\tau} = \alpha + \beta^{mom} \cdot momdec_{i,m-1} + \varepsilon_{i,m+\tau} \quad 4.17$$

$$abnreturn_{i,m+\tau} = \alpha + \beta^{cfo} \cdot cfodec_{i,m-1} + \varepsilon_{i,m+\tau} \quad 4.18$$

$$abnreturn_{i,m+\tau} = \alpha + \beta^{mom} \cdot momdec_{i,m-1} + \beta^{cfo} \cdot cfodec_{i,m-1} + \varepsilon_{i,m+\tau} \quad 4.19$$

$$\tau \in \{7,8,9,\ldots,24\}$$

Second, I again calculate mean abnormal monthly returns that occur during the months 7 to 24 of the stocks that have been sorted into portfolios *Mom5*, *Cfo5*, and *Combi55* as well as into *Mom1*, *Cfo1*, and *Combi11* at the beginning of the earnings announcement month.[112]

4.6.2 Empirical Results and Discussion

The regression results show different pictures for the momentum and the operating cash flow effect in the long term. Figure 4.7 illustrates the development of $\hat{\beta}^{mom}$ and $\hat{\beta}^{cfo}$ during months 7 to 24. Table 4.13 lists the corresponding numbers and levels of significance.

---

[111] For example De Bondt and Thaler (1985), De Bondt and Thaler (1987), and Chopra, Lakonishok, and Ritter (1992) explain long-term reversals by investor overreaction.

[112] In an additional analysis, I repeat the investigation restricting my sample only to those stocks which survive until the 24th month in order to see whether my results are driven by stocks that are delisted during the investigation period. My conclusions do not change when I only analyze surviving stocks.

Figure 4.7: Long-Term Development of the Predictive Ability of Past Returns and Operating Cash Flows for Future Abnormal Returns

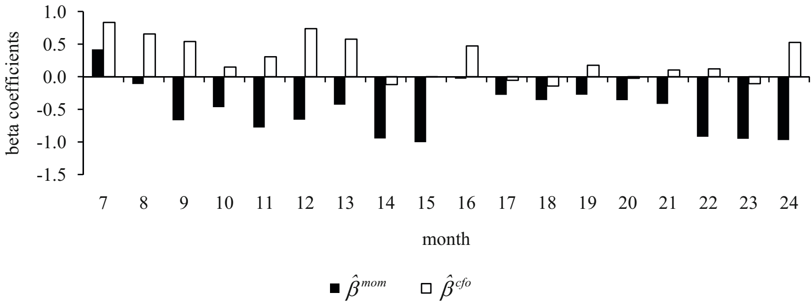


Table 4.13: Long-Term Development of the Predictive Ability of Past Returns and Operating Cash Flows for Future Abnormal Returns

regr		month $m+\tau$								
		$\tau=7$	$\tau=8$	$\tau=9$	$\tau=10$	$\tau=11$	$\tau=12$	$\tau=13$	$\tau=14$	$\tau=15$
4.17	$\hat{\beta}^{mom}$	0.52	-0.03	-0.60	-0.45	-0.74**	-0.57	-0.36	-0.96**	-1.01***
4.18	$\hat{\beta}^{cfo}$	0.88**	0.64	0.46	0.09	0.22	0.66*	0.53	-0.23	-0.12
4.19	$\hat{\beta}^{mom}$	0.42	-0.11	-0.67	-0.47	-0.78**	-0.66*	-0.43	-0.95**	-1.00***
4.19	$\hat{\beta}^{cfo}$	0.83**	0.66	0.54	0.15	0.31	0.74*	0.58	-0.12	0.00

regr		month $m+\tau$								
		$\tau=16$	$\tau=17$	$\tau=18$	$\tau=19$	$\tau=20$	$\tau=21$	$\tau=22$	$\tau=23$	$\tau=24$
4.17	$\hat{\beta}^{mom}$	0.02	-0.28	-0.37	-0.26	-0.36	-0.41	-0.91***	-0.96***	-0.91***
4.18	$\hat{\beta}^{cfo}$	0.47	-0.09	-0.18	0.15	-0.06	0.06	0.02	-0.21	0.42
4.19	$\hat{\beta}^{mom}$	-0.03	-0.28	-0.36	-0.28	-0.36	-0.42	-0.92***	-0.95***	-0.97***
4.19	$\hat{\beta}^{cfo}$	0.47	-0.05	-0.14	0.18	-0.02	0.10	0.12	-0.11	0.53

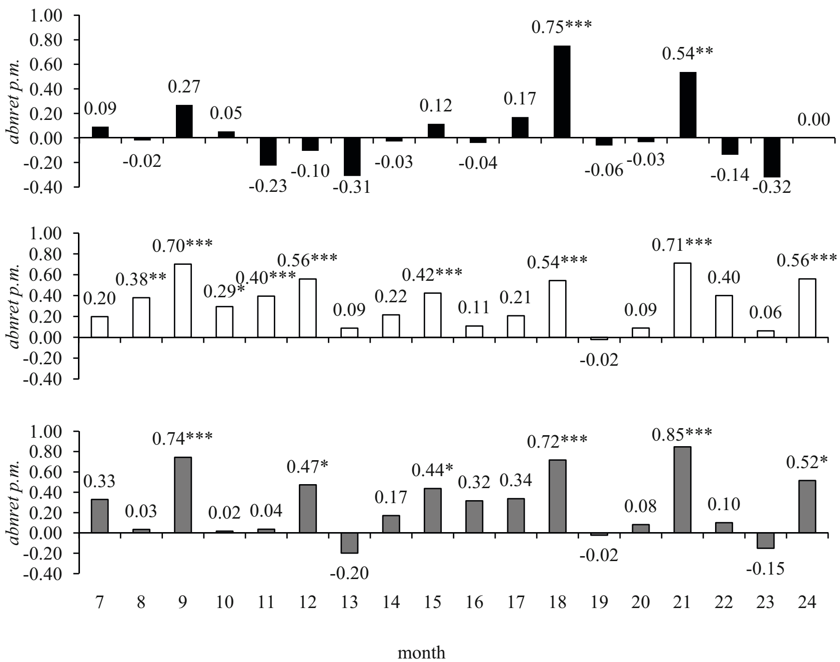
***(**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test with standard errors that are clustered by stock and by time.

The estimated coefficients for the momentum effect $\hat{\beta}^{mom}$ turn negative, starting from the eighth month after the initial earnings announcement. This negative impact becomes stronger by the time and is statistically significant in the months 11, 12, 14, 15, 22, 23, and 24 in regression 4.19. The market indeed appears to initially react too strongly to past returns and this overreaction is corrected later on, leading to the reversal.

The operating cash flow effect reveals a different picture, since it lasts longer than the momentum effect. $\hat{\beta}^{cfo}$ is still significantly higher than zero in the seventh month after the initial cash flow announcement. After that, the coefficients are still positive, but no longer statistically significant, except in month twelve, in which it reaches a weak significance at the 10 % level. This development indicates that the market does not fully incorporate operating cash flows when they are announced. Over time the market corrects its initial underreaction so that the initial cash flow more and more loses its predictive power for future returns.

When I now turn to the long portfolios and do not analyze all stocks but only those with the highest past returns and/or highest operating cash flows, the differences between the two strategies is less obvious. The returns of all three long portfolios do not reverse significantly in the long run, as illustrated in Figure 4.8.

Figure 4.8: Long-Term Development of Abnormal Returns in the Long Portfolios (■ *Mom5*, □ *Cfo5*, and ▩ *Combi55*)



***(**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test and standard errors that are clustered by month.

Portfolio *Mom5* is no longer profitable in the long term, alternately yielding positive and negative mostly insignificant abnormal returns. But in contrast to the regression results, momentum portfolio returns do not reverse in the long run. Whereas the relation between past and future returns reverses, indicating initial overreaction, this is not the case for the isolated long position. Here the predictive power of high past returns diminishes without any reversal taking place. This missing reversal suggests that the market does not strongly overreact to high past returns.

In contrast to the long momentum portfolio, the long cash flow portfolio remains profitable for a long time. In most of the months, abnormal returns to portfolio *Cfo5* are significantly positive. Moreover, it is striking, that the returns are especially high every three months. This could be because a high portion of the firms releases new quarterly earnings and cash flow numbers every three months. Accordingly, the positive abnormal returns in these months could indicate that the market is positively surprised by the announced numbers of the stocks in portfolio *Cfo5*. This regularity in abnormal returns also makes a risk-based explanation of the returns unlikely. If risk was the underlying reason, the portfolio would constantly yield significant positive abnormal returns. The abnormal returns occurring during future announcement months rather suggest market underreaction.

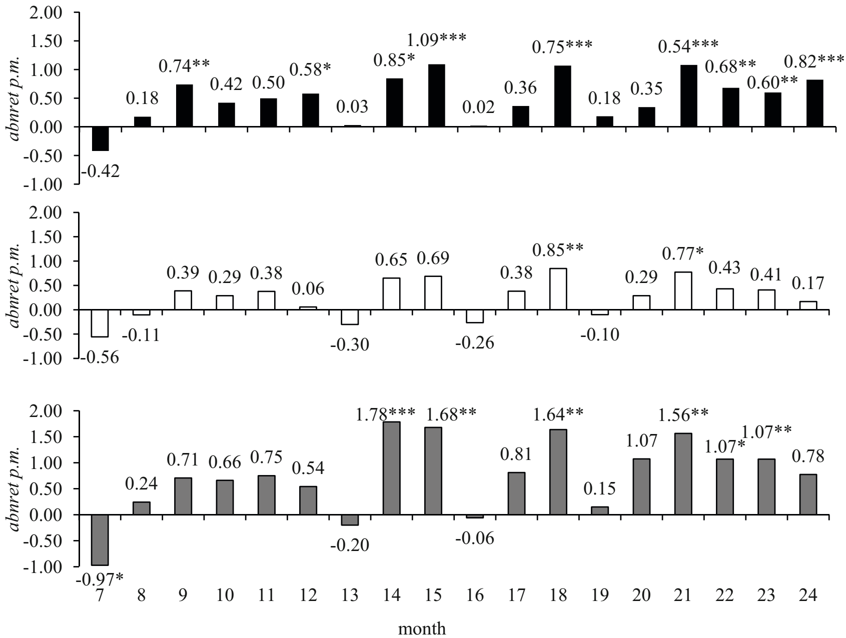
The longer profitability of the cash flow strategy compared to the momentum strategy underlines the different time horizons of technical and fundamental strategies that are discussed in chapter 2. The long-term orientation of fundamental strategies is underlined by the longer profitability of the cash flow strategy. In contrast, the short-term horizon of technical trading is reflected in the shorter profitability of the momentum strategy.

The long-term returns to portfolio *Combi55* are in between the two pure portfolios. They are also higher every three months, similar to *Cfo5*, but all in all, long-term returns to portfolio *Combi55* are not higher than those to *Cfo5*, any more. In this long-term analysis the stock return momentum does not yield additional drive, any more. Moreover, there is no reversal in the returns to *Combi55* and also less reversal than in *Mom5*. This supports the notion that the combination picks past price upturns which are not due to pure pricing pressures or speculation, i.e., overreaction.[113]

Long-term returns to the short portfolios *Mom1*, *Cfo1*, and *Combi11* show a different picture, as illustrated in Figure 4.9:

113 This idea underlying the combination strategy is described in section 3.1.

Figure 4.9: Long-Term Development of Abnormal Returns in the Short Portfolios
(■ *Mom1*, □ *Cfo1*, and ■ *Combi11*)



***(**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test and standard errors that are clustered by month.

The isolated analysis of the short momentum portfolio indicates that the reversal for the whole momentum effect found in the regressions primarily stems from the short portfolio *Mom1*. For the stocks of this portfolio, I find positive returns in the long run, which are significantly different from zero in 9 of the 18 investigated months. Accordingly, the market seems to correct the initially too negative reaction, i.e., overreaction, in the long term. Long-term returns to stocks in portfolio *Cfo1*, in contrast, do not exhibit any reversal at all. Except in two months, they are neither significantly positive nor significantly negative, thus indicating neither over- nor underreaction. The stocks in portfolio *Combi11* also show a tendency to reverse. The magnitude of reversal is higher even though statistically slightly less significant than in portfolio *Mom1*. Therefore, I conclude that the market initially reacts too strongly to the bad information contained in low operating cash flows and low returns. This overreaction is corrected in the long run.

In sum, the results of the long-term analysis indicate that the whole momentum effect is partly due to overreaction, as the influence of past on future returns reverses in the long term. This reversal can mainly be attributed to the stocks with low past returns contained in portfolio *Mom1*. The operating cash flow effect does not seem to be based on overreaction at all, as it shows no sign of reversal – neither in the regression nor in the portfolio analysis. The combination portfolio only shows signs of reversal and thus initial overreaction in the short portfolio *Combi11*.

4.7 Summary and Conclusion

The closer look at the market reactions in this chapter allows for several insights.

Section 4.3 shows that the market reacts strongly to cash flow announcements, but only slowly incorporates the cash flow information into prices. Moreover, it depicts that good news seem to be incorporated more slowly in stock prices than bad news, as abnormal returns of the long portfolios last longer than of the short portfolios.[114] This asymmetry already indicates that an isolated analysis of long and short portfolios is necessary. Sections 4.4 to 4.6 address the question whether market mispricing and − if mispricing − market over- or underreaction is the primary reason for the anomalous effects. In section 4.4, I find a strong positive influence of past returns and operating cash flows on future earnings announcement returns, indicating that the effects should be due to an initially too weak market response and not due to risk. The portfolio analysis furthermore reveals that announcement period returns are especially high for all three long portfolios, suggesting that the anomalous returns of these portfolios result out of the upward correction of initial market underreaction. In contrast, announcement returns to the short portfolios are not particularly high, so that underreaction does not seem to be the underlying reason for these portfolios. Section 4.5 investigates the dependence of the effects on investor attention. I do not find any dependence for the whole momentum and cash flow effects. But when I investigate long and short portfolios separately, I come to different conclusions. There are weak hints that the returns to the long portfolios are based on market underreaction, since they are significantly higher for low attention stocks in three of six cases. The results for the short portfolios are clearer. For these short portfolios, the negative abnormal returns are significantly more extreme for high attention stocks in all six cases, indicating stock price overreaction. The analysis of long-term returns in section 4.6 leads to similar conclusions: Return reversals indicate that the market initially reacts too strongly to

[114] This finding resembles the study of Basu (1997) who shows that negative returns are more strongly related to earnings than positive returns. Assuming market efficiency, Basu (1997) concludes from this that bad news, measured as negative returns, is more quickly incorporated into earnings than good news, measured as positive returns. This concept is known as the asymmetric timeliness of earnings or conditional conservatism in the accounting literature. Basu's interpretation depends on the assumption that stock prices immediately reflect news in a correct way and that earnings follow stock prices. In my analysis, I investigate the other direction, i.e., the influence information about earnings or cash flows has on stock prices and I do not assume market efficiency. I also find asymmetry between good and bad news.

the bad news of the stocks in portfolios *Mom1* and *Combi11*. Such reversals can be found neither for portfolio *Cfo1*, nor for the three long portfolios. When analyzing the whole effects, I find long-term reversal for the momentum effect, but not for cash flows. Figure 4.10 summarizes the findings of this chapter. It sums up whether market underreaction (UR) or overreaction (OR) seems to be the predominant reason for the anomalies.

Figure 4.10: Summary of Findings in Chapter 4

	Section 4.4	Section 4.5	Section 4.6	
	UR if returns around subsequent earnings announcements are extremely high	OR if the effect is stronger for high attention firms, UR otherwise	OR if effect reverses in the long term	predominant effect
momentum effect	UR	–	OR	mixture
Mom5	UR	rather UR	no OR	UR
Mom1	no UR	OR	OR	OR
cash flow effect	UR	–	–	rather UR
Cfo5	UR	rather UR	no OR	UR
Cfo1	no UR	OR	–	rather OR
Combi55	UR	rather UR	no OR	UR
Combi11	no UR	OR	OR	OR

The returns to the long portfolios seem to stem primarily from market reactions that are too weak. This can be seen most clearly in portfolio *Combi55*. In contrast, the anomalous returns to the short portfolios seem to be based on overreaction. This is especially distinct for the short momentum and combination portfolios. The collection of evidence does not prove the existence of market over- or underreaction. However, the results of the different tests lead to similar conclusions, supporting the inferences.

These inferences are not easy to reconcile with the behavioral models of Hong and Stein (1999) and of Daniel, Hirshleifer, and Subrahmanyam (1998) which allow for both, over- and underreaction.[115] A compatibility with Hong and Stein (1999) is particularly difficult. It would be given if stocks in the long and short portfolios were in different momentum states and thus traded by different types of investors. Stocks in the long portfolios would have to be in the early momentum stage, in which news traders gathered private information, leading to stock price underreaction. The stocks in the short portfolios, however, would have to be in the later stage with momentum traders trading on the initial price movement, leading to stock price overreaction. Since it is questionable why the stocks in the long and short portfolios should be in different stages, the model of Hong and Stein (1999) does not comply with my results.

[115] See section 4.1 of this thesis for a description of these two models.

Daniel, Hirshleifer, and Subrahmanyam (1998) assume in their model that investors overreact to private and underreact to public information. For a compatibility with my results, bad news would have to be mostly private and good news mostly public. However, since the bad news about low cash flows in portfolios *Cfo1* and *Combi11* is definitely public and since I also find manifestations of overreaction for these stocks, the compatibility to Daniel, Hirshleifer, and Subrahmanyam (1998) is also limited. All in all, my results suggest that investors are rather over-confident when they receive bad news, leading to an overreaction to this bad news. In contrast, they might underlie the conservatism bias and be skeptic when receiving positive (cash flow) news. This skepticism may lead them to react too hesitantly to this positive news, resulting in the stock price underreaction I find for the long portfolios.

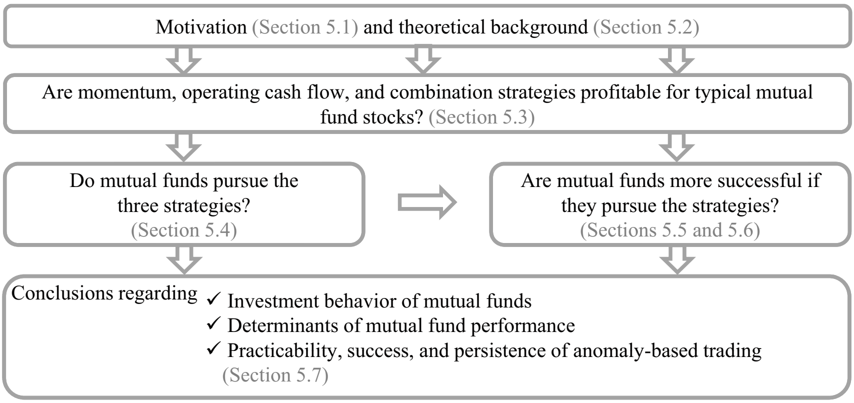
One limitation is that I only shortly address the distinction between risk and mispricing throughout the whole fourth chapter. In this regard, further research can definitely conduct further investigations. Similarly, I do not decide on whether markets are efficient or not. In this regard, Fama (1998) points out that if anomalies split randomly between underreaction and overreaction, they do not contradict market efficiency.[116] However, since I find more overreaction in the short and underreaction in the long portfolios, my data do not confirm the condition “randomly”. As a lesson learned, further research should not only focus on the total anomalous effects. It should rather analyze the long and short portfolios with extreme characterizations separately. My investigations show that there are different effects at hand in the long and short positions so that one single analysis of the effects in total does not reveal the full impacts.

116 See Fama (1998), p. 284.

5 Fundamental and Technical Trading by Mutual Funds

In this chapter, I investigate momentum, operating cash flow, and combination strategies of mutual funds, which are one important group of professional investors. Figure 5.1 describes the structure of this chapter.

Figure 5.1: Structure of Chapter 5



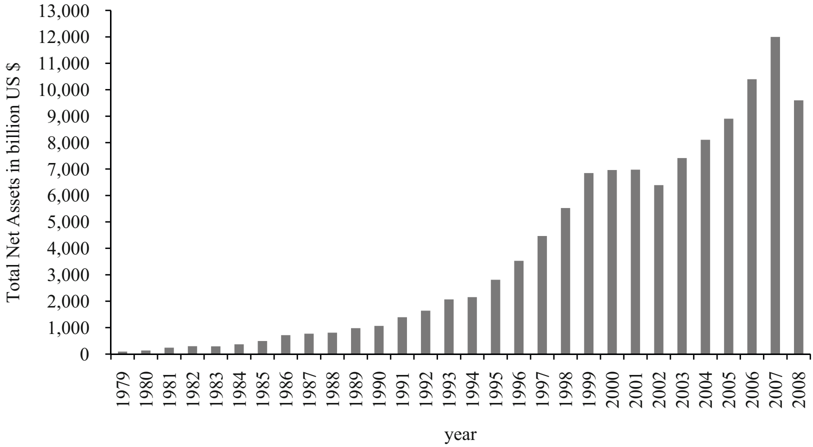
5.1 Introduction and Motivation

The most simple and impressive motivation for any investigation of mutual funds is the rising importance of mutual funds in the US stock market. In the last 30 years, the assets under management increased in almost every year. Whereas in 1979 mutual fund managers managed US$ 94.51 billion, in 2007 this figure had risen to US$ 11,999 billion. Due to the present financial crisis, this figure dropped to US$ 9,601 billion in 2008. The importance of the mutual fund industry is also reflected by the composition of the US retirement market. At the end of 2008, mutual funds accounted for 22 %, i.e., US$ 3,100 billion, of this market segment.[117]

Figure 5.2 illustrates the assets under management in the mutual fund industry between 1979 and 2008 based on the numbers given in the ICI Investment Company Fact Book (2009), p. 110.

[117] See ICI Investment Company Factbook 2009, p. 100.

Figure 5.2: Assets Under Management in the US Mutual Fund Industry



The first aspect I analyze is the trading behavior of this important group of professional investors, testing their pursuit of the momentum, cash flow, and combination strategy. One might argue that professional investors should know the scientific literature and should therefore trade on the anomalies which are reported there. Second, my analysis looks at the determinants of mutual fund performance. So far, the academic literature has mainly studied the influence of fund characteristics on future fund returns.[118] Studies investigating the influence of specific investment strategies are rare.[119] My analysis of the influence of the momentum, the cash flow, and the combination strategy on fund returns in this thesis aims at contributing to this line of literature.

The questions resulting from the existence of market anomalies provide further motivation for my analysis. Researchers and market participants puzzle about the practicability of anomaly-based trading strategies, their success after transaction costs, and the anomaly persistence. These puzzles are difficult to resolve. One obstacle is that research studies mostly analyze hypothetical trading strategies using empirical data, as I did in chapter 1. This procedure makes it difficult to finally decide on the practicability of trading strategies. Another problem is that empirical studies have to find estimates of transaction costs when they evaluate the after cost performance of these strategies. Of course, it is never sure whether these estimates of transaction costs are correct. The sample I will use in my mutual fund analysis allows me to circumvent these problems because it provides real mutual fund holdings and mutual fund

118 Section 5.2.2 gives an overview of these characteristics.

119 Examples for these studies are Grinblatt, Titman, and Wermers (1995), Ali et al. (2008a), and Ali et al. (2008b).

returns after actual trading costs: That is, the data automatically account for the strategies' practicability because they reflect realized mutual fund portfolio holdings instead of hypothetical ones.[120] Moreover, the assessment of returns after trading costs does not depend on the measure of costs used because the given fund returns are net of actually incurred trading costs. My analysis furthermore allows conclusions regarding anomaly persistence. If fund managers, as one important group of professional investors, do not trade on the analyzed anomalies, this might be one reason for their persistent success.[121]

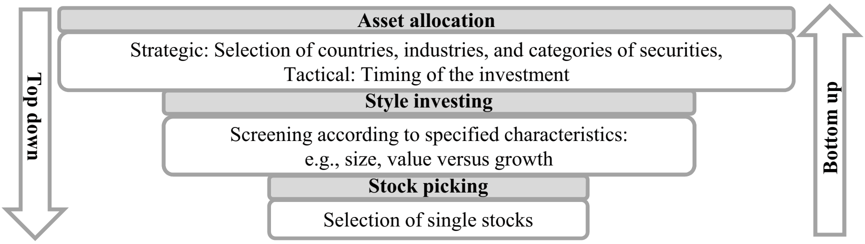
5.2 Framework for the Mutual Fund Analysis

This section summarizes previous literature that is linked to my analysis. First, it describes the asset allocation process of mutual funds in section 5.2.1. Section 5.2.2 presents factors that have been identified to influence fund performance. In section 5.2.3, I present two studies investigating mutual funds' momentum and accrual trading strategies.

5.2.1 Asset Allocation of Mutual Funds

The asset allocation process of mutual funds provides a framework for any analysis of mutual fund investment strategies. This process can be divided into different steps as described by Reilly and Brown (2003) and Zimmermann (2006) and illustrated in Figure 5.3.[122]

Figure 5.3: Asset Allocation of Mutual Funds



Mutual fund managers are not the only ones to decide on the asset allocation. First, there are legal restrictions to which fund managers have to adhere.[123] Second, mutual fund investment companies decide on the main aims of a certain fund recording them in the fund's policy

---

[120] For an overview on factors affecting the implementability of stock market trading strategies, see Bushee and Smith Raedy (2006).

[121] Ali et al. (2008a) also give the last two arguments in their investigation of mutual fund accrual strategies.

[122] For more detailed information; see, e.g., Reilly and Brown (2003), pp. 660-920 or Zimmermann (2006), pp. 245-284.

[123] For an overview of the legal restrictions in the mutual fund industry, see Almazan et al. (2004) and the information on the SEC website.

statement.[124] Third, also the internal research department recommends certain investments to fund managers. In this regard, the asset allocation is the outcome of inputs, guidelines, and decisions of different parties.

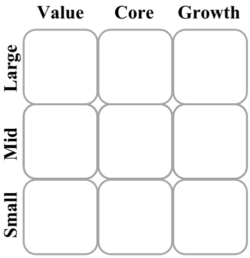
The allocation process can be implemented by a bottom-up or top-down approach. The bottom-up approach starts with the most specific step of picking certain stocks and afterwards aggregating them in the portfolio. The top-down approach works the other way around, starting with the most general step – the strategic asset allocation. The strategic asset allocation determines, in which economies, industries, and types of securities a mutual fund invests, and it has a big impact on fund performance. Ibbotson and Kaplan (2000) attribute 40 % of the return differences between balanced funds to differences in the strategic asset allocation. Closely related to these strategic decisions is the timing of the asset allocation process. If fund managers, for example, expect a stock market depression, they will invest less in stocks and more in cash or bonds for this period.

Style investing is the next way to compose a fund portfolio. Because of the huge number of stocks, it is impossible for fund managers to analyze and evaluate every single stock. Consequently, they screen the stock universe according to stock characteristics and invest according to this screening − depending on the style they assess to be most promising. The most prominent style criteria are company size leading to “Small Cap” and “Large Cap” styles and the relation of book- to market value providing the basis for “Value” and “Growth” styles. These styles have become explicitly present to fund investors after the introduction of the Morningstar Style Box in 1992. This box assigns style categories to funds and displays them in a simple image. It helps investors to assess a given fund style independent of its name or category. Figure 5.4 displays the Morningstar Style Box, giving a compact overview of the mutual fund styles and the corresponding characteristics. It is based on the information in the fact sheet of Morningstar Inc. (2004).

---

124 The precision of these guidelines differs a lot. They can prescribe investments exclusively in stocks of one specific country or stipulate the investment of a certain proportion of assets in small stocks. The maximum deviation from the benchmark portfolio can also be stated.

Figure 5.4: Morningstar Style Box



Value	weight	**Growth**
price to exp. earnings	50%	long-term exp. earnings growth
price-to-book	12.5%	historical earnings growth
price-to-sales	12.5%	sales growth
price-to-cash flow	12.5%	cash flow growth
dividend yield	12.5%	book value growth

Large	top 70% of market capitalization
Mid	middle 20% of market capitalization
Small	lowest 10% of market capitalization

Computer programs make a simple implementation of style investing at low cost possible. One disadvantage of style investing is that it can lead to less diversification because stocks of the same style often exhibit similar characteristics and high return correlations.[125] To mitigate this problem, fund mangers additionally search for single stocks that they judge as undervalued. This is what is meant by stock picking in Figure 5.3. Here, fund managers use for example fundamental analysis or information from managers to identify potentially successful investments.

I classify the momentum, operating cash flow, and combination strategies as mixtures of style investing and stock picking. They are based on a simple sorting of stocks according to past returns and/or operating cash flows, which is a common technique of style investing.[126] Furthermore, the strategies exhibit features of stock picking. This applies especially to the combination strategy, which I introduced in chapter 1 and which strives at picking single stocks whose past price upturn is economically justified.

5.2.2 Determinants of Mutual Fund Performance

Many studies analyze the determinants of mutual fund performance. I will focus on those determinants that have attracted most attention in the academic literature, namely fund size, costs, turnover, past returns, and inflow.[127] Other factors presented in these studies are mutual fund managers' characteristics, as education, age, tenure, and gender and the impact of a team approach.

---

[125] Damodaran (2003) – to mention just one study on this topic – alludes to this problem; see Damodaran (2003) pp. 242-243.

[126] Accordingly, Carhart (1997) has introduced the momentum factor to adjust fund returns for momentum "style".

[127] I will get back to these factors later on in my empirical analysis of mutual fund performance in section 0, using them as control variables in the multivariate regressions.

The first determinant is fund size. Chen et al. (2004), as well as Ferreira, Miguel, and Ramos (2009), find a negative relationship between fund size and returns. The major reasons Chen et al. (2004) give for this relation are liquidity, limited investment ideas, and hierarchical costs: The number of different stocks held by a fund increases with the amount of assets the fund has under management. This makes it more difficult to concentrate on liquid stocks. Similarly, a larger fund will on average trade a higher number of the same stock, thus provoking a higher price impact that reduces fund returns. Moreover, fund managers do not have unlimited investment ideas from which to choose. It becomes more difficult for them to pick outperforming stocks as the assets under management rise.[128] Employing more fund managers for a single fund would mitigate this problem but would also lead to more complex decision-making processes and hierarchical costs. In teams it is more difficult to achieve acceptance for investment ideas that are based on "soft" facts, such as private information received from managers in personal conversations. Such soft information is more easily processed in small funds with one single fund manager, allowing higher fund returns.[129]

In contrast to Chen et al. (2004), Grinblatt and Titman (1994) as well as Prather, Bertin, and Henker (2004) do not find a significant relation between fund size and future fund returns. Otten and Bams (2002) even find a positive influence. Possible reasons for this positive relationship are economies of scale and more research resources in larger mutual funds.[130] The differing findings could be due to different underlying samples. Whereas the first-mentioned studies investigate the US fund market, Otten and Bams (2002) use European mutual funds and argue that there are still economies of scale in the European fund market. Ferreira, Miguel, and Ramos (2009) conduct a cross-country study.

The second influencing factor is fund costs. Costs comprise internal and external costs. Internal costs are paid directly to the mutual fund and comprehend one-time loads and ongoing fees. External costs are charged by outsiders and comprise trading costs as, for example, commissions paid to brokers. Ongoing fees and trading costs add up to the total expense ratio that directly reduces mutual fund returns. Whether fund costs influence fund returns is an important question that is also related to the question of market efficiency and to the model of Grossman and Stiglitz (1980). They argue that if investors are compensated for the costs they spend for information processing, the market is still efficient. If fund fees, therefore, lead to higher research quality, funds with higher fees will earn higher fund gross returns. This positive relation should vanish when fund returns net of fees are examined. Consequently, there should be a positive impact of fees on gross returns, and no impact on net

---

128 Berk and Green (2004) develop a rational model fitting this line of argument.

129 This idea of higher hierarchy costs goes back to Stein (2002) and is picked up by Chen et al. (2004).

130 Latzko (1999) shows the existence of economies of scale in mutual fund administration.

returns, which are net of charged costs if the model of Grossman and Stiglitz (1980) applies.[131]

Empirical findings about the influence of fund costs on fund returns are mixed, depending on the analyzed cost component and return measure. Ippolito (1989) finds that fund expenses are compensated by higher gross fund returns, complying with the model of Grossman and Stiglitz (1980). In the study of Droms and Walker (1996) expenses are even positively related to fund net returns and loads do not have a significant impact on fund net returns. Similarly, Grinblatt and Titman (1994) detect a positive impact of total expenses on fund net returns, also leading to the conclusion that investors seem to profit if they reward successful fund investors by paying higher fees. Golec (1996) detects a positive impact of fees on fund net returns, but also a negative impact of administrative expenses. Studies contradicting the aforementioned are Elton et al. (1993), Malkiel (1995), as well as Prather, Bertin, and Henker (2004), who find a negative impact of the total expense ratio on returns. Lastly, loads do not have a significant influence in the study of Prather, Bertin, and Henker (2004).

The third determinant is fund turnover. Turnover and fund costs are closely related, as higher turnover leads to higher trading costs and therefore to lower fund net returns. On the other hand, a high turnover can also be a sign of promising trade activities of skilled fund managers, enhancing fund returns. Therefore, the underlying economic question is similar to the one of fund costs, i.e., whether the trading of skilled fund managers is profitable. Empirical results concerning this question are mixed. Elton et al. (1993) find a negative influence of turnover on fund returns, whereas Ippolito (1989), Droms and Walker (1996), Prather, Bertin, and Henker (2004), as well as Chen et al. (2004) do not detect any significant relationship. Grinblatt and Titman (1994) find higher fund returns of high turnover funds. Finally, Wermers (2000) shows that stocks that are held by high turnover funds yield higher returns than stocks held by low turnover funds. This finding suggests a better stock picking ability of fund managers who rearrange their portfolios more actively.

Another factor closely related to the stock picking ability of mutual fund managers is fund return persistence. If some fund managers are more skilled in picking successful stocks, their good performance in the past will persist in the future. Earlier studies confirm the existence of fund return persistence, as, for example, Hendricks, Patel, and Zeckhauser (1993), Brown and Goetzmann (1995), as well as Chen et al. (2004). Otten and Bams (2002) confirm return persistence for the European fund market. However, fund return persistence seems to be only a short-time phenomenon as analyzed by Bollen and Busse (2005). They show that persistence only exists if fund returns are evaluated several times a year. Malkiel (1995) does

---

[131] See, e.g., Ippolito (1989), pp. 2-3.

not find any persistence from 1980 on and Carhart (1997) states that long-term return persistence in mutual fund performance is not due to a better stock picking ability of fund managers. According to Carhart (1997), it should rather be attributed to mutual fund momentum strategies.

One reason for the weakness of return persistence is the influence of inflows into the fund. High past returns lead to higher future inflows and these inflows reduce future fund returns due to limited investment ideas and purely liquidity motivated trading. This mechanism is pointed out by Berk and Green (2004) as well as Alexander, Cici, and Gibson (2007). Accordingly, fund inflow is another determinant of fund performance.

Other studies analyze the influence of fund manager characteristics on fund returns. One example is fund manager education. All in all, better-qualified fund managers are more successful. Golec (1996) finds that fund managers succeed if they have passed an MBA degree course. Chevalier and Ellison (1999) show that managers who attended undergraduate institutions of higher quality, earn higher fund returns. Similarly, Gottesman and Morey (2006) demonstrate that a fund manager is more successful if he has passed an MBA program of higher quality and reputation. The same studies also investigate the influence of the fund managers' age and tenure on fund performance. Older fund managers obtain lower fund returns than their younger counterparts.[132] Tenure has a contrary influence, as fund managers with a longer tenure earn higher fund returns.[133]

The impact of mutual fund managers' gender on fund performance has also been the subject of academic studies. Bliss and Potter (2002), Atkinson, Baird, and Frye (2003), as well as Niessen and Ruenzi (2009) find that there is no difference in risk-adjusted performance between female and male fund managers. Also the fact whether a single manager or a team manages a fund has been subject of academic studies. Prather and Middleton (2002) do not find any influence of a team approach on fund performance. Bär, Kempf, and Ruenzi (2005) detect a slightly inferior performance of team-managed funds. Bär, Niessen, and Ruenzi (2007) demonstrate that diversity in terms of education and tenure has a positive impact on fund performance, whereas performance is negatively affected by diversity in gender.[134]

All in all, (as shown by Baks (2003)) the influence of fund characteristics on fund performance is stronger than that of manager characteristics.

---

132 See Golec (1996) as well as Chevalier and Ellison (1999).

133 See Golec (1996), Chevalier and Ellison (1999), as well as Gottesman and Morey (2006).

134 Bär, Niessen, and Ruenzi (2007) differentiate between "informational diversity" and "social category diversity"; see Bär, Niessen, and Ruenzi (2007), p. 2.

5.2.3 Mutual Fund Momentum and Accrual Strategies

In this section, I sum up the results of two studies that are most closely related to my mutual fund investigation. This description links the more general survey on mutual funds in the previous sections with my own empirical analysis in sections 5.3 to 5.6.

Grinblatt, Titman, and Wermers (1995): "Momentum Investment Strategies, Portfolio Performance and Herding: A Study of Mutual Fund Behavior" analyze the success of mutual fund momentum strategies. Ali et al. (2008a): "Do Mutual Funds Profit from the Accruals Anomaly?" investigate mutual fund strategies that are based on the accruals anomaly. I will here concentrate on the specific findings of these studies and not on their methodology, which will be dealt with in sections 5.3 to 5.6, where I use some of their methodology in my empirical investigation.

Grinblatt, Titman, and Wermers (1995) demonstrate that mutual funds invest according to the momentum strategy. In their sample, 76.8 % of the analyzed mutual funds buy winner stocks and/or sell loser stocks. Furthermore, Grinblatt, Titman, and Wermers (1995) show that it is funds with the investment objectives "Aggressive Growth" or "Growth" that most heavily follow the momentum strategy. They find that funds which follow the momentum strategy are also significantly more successful than those following a contrarian strategy. In their sample, an increase of 1 % in momentum investment increases performance by 1.27 % per year. Especially the buying of past winners influences fund performance. Finally, Grinblatt, Titman, and Wermers (1995) demonstrate that it is in fact the tendency to buy past winner stocks and not the herding of funds into the same stocks which increases fund returns.

Ali et al. (2008a) analyze mutual fund accrual strategies. The accrual strategy is related to the operating cash flow strategy, because accruals and operating cash flows add to operating income. Sloan (1996) demonstrates both anomalies and supposes that the market seems to overestimate accruals and to underestimate cash flows when building prices, resulting in the cash flow and the accrual anomaly.[135] Trading on the accrual anomaly means buying stocks with low and selling stocks with high accruals. Ali et al. (2008a) find that though the accrual anomaly is well known, mutual funds on average do not pursue accrual strategies. Relatively few funds tilt their portfolios to low accrual stocks, but those indeed earn higher fund returns, i.e., a significantly positive 3-factor alpha of 2.83 % per year. However, Ali et al. (2008a) demonstrate that these low accrual funds also have some disadvantages. They tend to be smaller and to hold more concentrated portfolios and their fund returns and inflows are more volatile than those of the average fund. Finally, Ali et al. (2008a) conclude that the limited interest of fund managers to accruals is one reason for the persistence of the accrual anomaly.

---

[135] See Sloan (1996) and section 2.3.2 of this thesis.

5.3 Stock Universe of Mutual Funds

In this section, I analyze whether in general the momentum, operating cash flow, and combination strategies can be beneficial for mutual funds. In a first step, I investigate the characteristics of stocks which are typical investments of mutual fund managers. In this regard, previous literature shows that mutual funds prefer stocks with certain characteristics as, for example, high visibility and low transaction costs.[136] If stocks in the combination portfolio were, for example, highly invisible, they would be out of question for mutual fund investments, which would hinder the exploitation of the combination strategy. Therefore, I investigate in the second step whether the returns of the strategies persist if I restrict my stock sample to those stocks that are typically held by mutual funds.[137] Furthermore, the restriction procedure itself will provide additional insights to what extent mutual funds hold stocks with high past returns and/or high operating cash flows.

5.3.1 Methodology

To restrict the stock universe to "typical" mutual fund stocks, I use mutual fund holdings from June 1989 to December 2003 that are given in the Thomson Financial Mutual Fund Database.[138] Every quarter, I determine for every stock the number of funds it is held by. Then I build three different samples: first, an unrestricted sample including every stock in the investigated period.[139] Second, mutual fund sample 1 % (mfs1%), which comprises only those stocks that are at least included in 1 % of the mutual funds at the given point of time. This corresponds to a mean number of 7 different mutual funds (= 0.01 · 40,617 fund quarters/58 quarters) by which a stock has to be held. The third and smallest sample is mutual fund sample 3 % (mfs3%). To be included in mfs3% at a certain time point, a stock has to be held by at least 3 % of the mutual funds, which is on average 21 funds. These requirements are quite strict. The whole stock sample without any restriction comprises 292,503 stock quarter observations, mfs1% comprises 101,110, and mfs3% is limited to 41,879 stock quarter observations. This underlines that mutual funds tend to concentrate on the same stocks.

As a first step, I investigate whether there are differences between stocks that are typically held by mutual funds and those that are not. Falkenstein (1996) finds that mutual funds prefer stocks with high visibility, high liquidity, and low idiosyncratic risk. To test whether this

---

136 See Falkenstein (1996).

137 I demonstrate in section 3.5.3 that stocks in the combination portfolio are more liquid than the average stock and that the combination strategy also works when stocks with low market capitalization are excluded. These results indicate that the strategies should also work when I restrict the sample to "typical" mutual fund stocks.

138 For further information and descriptions of the mutual fund sample, see section 5.4.1.

139 Note that this unrestricted sample is smaller than the sample in section 3.2. Now I only analyze the years 1989 to 2003 for which I have mutual fund holdings information.

finding also holds for my sample, I analyze the stocks' market capitalization, stock price, idiosyncratic risk, and liquidity. I compute means of these characteristics, separately for stocks that belong to mutual fund sample 1 % and are therefore held by at least 1 % of the funds and for stocks which are held by **less** than 1 % of the mutual funds at a given point of time. I call the latter group "neglected stocks". I measure idiosyncratic risk as proposed by Fu (2009) and as described in section 3.4.2. To measure liquidity, I utilize the liquidity measure *L* of Korajczyk and Sadka (2008) and the illiquidity measure *I* of Amihud (2002), both explained in section 3.5.3 of this dissertation. Lastly, I also compute mean *mom* and mean *cfo* for the stocks of these two groups. To test whether the two groups differ with respect to these variables, I compute the difference between the two means and utilize a two-tailed t-test with Newey West standard errors with a lag of 6 months in order to decide whether this difference is distinct from zero.

As a second step, I study the development of the number of stocks in the pure momentum and cash flow and in the combination portfolios when moving from the whole sample to mutual fund sample 1 % and mutual fund sample 3 %. This proceeding allows me to identify those portfolios that lose most stocks when I restrict the sample to "typical mutual fund stocks."

Third, I implement the momentum, cash flow, and combination strategies based on all three samples. For the unrestricted sample, I implement it in the same manner as described in section 3.2.1. For the two other samples, I use the assignment to the quintiles of the unrestricted sample, but include only those stocks in the portfolios that are held by at least 1 % or 3 % of the mutual funds.

5.3.2 Empirical Results and Discussion

First I present the test whether there are differences between stocks that are at least held by 1 % of the mutual funds and those that are held by less than 1 %.

Table 5.1: Stock Characteristics of Typical Mutual Fund Stocks

	mfs1%		neglected stocks	difference
total number of observations	101,110		191,393	
Ø market capitalization (mio. US $)	3,918	>	136	3,782 ***
Ø stock price (US $)	50.85	>	9.16	41.70 ***
Ø idiosyncratic risk *idio* (% p.m.)	10.09	<	19.56	-9.47 ***
Ø Illiquidity Measure *I*	0.071	<	0.589	-0.519 ***
Ø Liquidity Measure *L*	0.133	>	0.086	0.048 ***
Ø operating cash flow *cfo* (in %)	2.35	>	-0.17	2.52 ***
Ø past returns *mom* (in %)	9.32	>	3.95	5.37 ***

*** denotes significance at the 1 %- level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

My results show that stocks which are neglected by mutual funds are on average significantly smaller, exhibit smaller stock prices, and higher idiosyncratic risk. Furthermore they are significantly less liquid exhibiting a higher value of Amihud's illiquidity measure *I* and a lower value of Koraczyk and Sadka's liquidity measure *L*. These results are in line with Falkenstein (1996) and underline the preference of fund managers for stocks which can easily be traded at low cost. In addition, I compute the mean *cfo* and *mom* of the stocks of both samples. I find that stocks which are neglected by mutual funds earn negative operating cash flows which are significantly lower than those of stocks mutual funds prefer. Similarly, neglected stocks have lower past returns than stocks which are held by mutual funds. This finding is in line with the results of my second test, in which I analyze the development of the ratios of stocks in the 10 pure and in the 25 combination portfolios when moving from the unrestricted sample to mfs1% and to mfs3%. Table 5.2 presents the results of this analysis.[140]

Table 5.2: Stock Ratios in the Investment Portfolios for Different Samples

1st row	unrestricted sample	292,503 stock quarters
2nd row	mutual fund sample 1 % (mfs1%)	101,110 stock quarters
3rd row	mutual fund sample 3 % (mfs3%)	41,879 stock quarters

		low *mom* *Mom1*	*Mom2*	*Mom3*	*Mom4*	high *mom* *Mom5*	pure *cfo*
high *cfo*	*Cfo5*	3.0	3.8	4.0	4.4	4.8	20.0
		2.2	4.2	5.3	6.4	6.1	24.2
		1.9	4.2	6.1	7.4	6.7	26.2
	Cfo4	2.8	3.9	4.7	4.8	3.9	20.0
		2.3	5.1	6.9	7.4	5.2	27.0
		1.8	5.3	7.9	8.9	5.8	29.8
	Cfo3	3.2	4.2	4.6	4.5	3.6	20.0
		2.4	4.6	6.1	6.1	4.1	23.4
		1.7	4.6	6.5	6.7	4.4	23.9
	Cfo2	4.6	4.3	3.8	3.6	3.7	20.0
		2.4	3.7	3.9	3.9	3.4	17.3
		1.4	2.9	3.7	4.0	2.9	15.0
	Cfo1	6.5	3.9	2.9	2.8	4.0	20.0
		1.5	1.6	1.6	1.7	1.9	8.1
low *cfo*		0.6	0.9	1.2	1.3	1.2	5.1
pure *mom*		20.0	20.0	20.0	20.0	20.0	
		10.9	19.2	23.8	25.5	20.8	
		7.4	17.9	25.4	28.3	21.1	

By construction, the ratios in the pure momentum and cash flow quintiles are 20 % in the unrestricted sample. The restriction of the sample to "typical mutual fund stocks" shows that mutual funds more often hold stocks with moderately high past returns and operating cash

[140] Note that the sample of neglected stocks is the difference between the unrestricted sample and mfs1%.

flows. In mfs1%, 27 % of the stocks belong to *Cfo4*, in mfs3% this ratio is 29.8 %. Similarly, 25.5 % of the stocks of mfs1% belong to quintile *Mom4*, the respective ratio in mfs3% is 28.3 %. The combination portfolios' ratios show a similar picture. The portfolios in the upper right corner comprise higher stock ratios the more the sample is restricted to typical mutual fund stocks. In contrast, the ratios towards the lower left corner decrease due to the restriction. For example, the ratio of 6.5 % in portfolio *Combi11* is highest when the sample is not restricted, which shows that low past returns are often accompanied by low operating cash flows. This ratio decreases sharply from 6.5 % to 1.5 % in mfs1% and even to the minimum ratio of 0.6 % in mfs3%. This decline shows that mutual funds avoid stocks with low past returns and low operating cash flows. Neither do they mostly concentrate on stocks with extremely high past returns and operating cash flows. Instead, funds focus on the second quintile with the highest ratio of stocks in portfolio *Combi44* of 7.4 % in mfs1% and 8.9 % in mfs3%.

To summarize the first step of this analysis: Mutual funds concentrate on a relatively low number of different stocks. They prefer stocks which can easily be traded at low cost and avoid stocks with low past returns and low operating cash flows. Nevertheless, they do not pursue extreme momentum and cash flow strategies, as they prefer stocks with only moderately high past returns and operating cash flows.[141]

In the second step, I analyze whether the trading strategies are still profitable when I exclude stocks that are held by **less** than 1 % or 3 % of the mutual funds. I present monthly 3-factor alphas in % for the unrestricted sample and then for the two restricted ones in Table 5.3.

Table 5.3: Portfolio 3-Factor Alphas for Different Samples

Panel A: Unrestricted Sample (n=292,503)

		low *mom* *Mom1*	*Mom2*	*Mom3*	*Mom4*	high *mom* *Mom5*	pure *cfo*
high *cfo*	*Cfo5*	-0.09	0.29 *	0.55 ***	0.68 ***	1.27 ***	0.62 ***
	Cfo4	-0.61 **	0.12	0.27 ***	0.42 ***	1.02 ***	0.32 ***
	Cfo3	-0.69 *	-0.22	0.06	0.34 **	0.86 ***	0.11
	Cfo2	-0.95 **	-0.41 **	-0.07	-0.04	0.56 ***	-0.25
low *cfo*	*Cfo1*	-1.12 *	-0.83 **	-0.46 *	-0.01	0.31	-0.60 *
pure *mom*		-0.83 **	-0.22	0.12	0.34 ***	0.84 ***	

141 Mutual fund holdings will be more closely analyzed in section 5.4.2, where I also consider the portfolio weights of the stocks held and not only if a stock is included in a fund portfolio or not.

Panel B: Mutual Fund Sample 1 % (n=101,110)

		low *mom* Mom1	Mom2	Mom3	Mom4	high mom Mom5	pure *cfo*
high *cfo*	*Cfo5*	-0.29	0.04	0.38 **	0.42 ***	0.88 ***	0.40 ***
	Cfo4	-1.05 ***	-0.17	0.15	0.21	0.58 ***	0.12
	Cfo3	-1.53 ***	-0.58 ***	-0.17	0.05	0.55 ***	-0.16
	Cfo2	-1.88 ***	-0.75 ***	-0.56 ***	-0.52 ***	0.23	-0.60 ***
low *cfo*	*Cfo1*	-2.35 ***	-1.70 ***	-0.91 ***	-0.35 *	-0.14	-0.99 ***
pure *mom*		-1.45 ***	-0.46 ***	-0.06	0.08	0.52 ***	

Panel C: Mutual Fund Sample 3 % (n=41,879)

		low *mom* Mom1	Mom2	Mom3	Mom4	high *mom* Mom5	pure *cfo*
high *cfo*	*Cfo5*	0.15	-0.10	0.32 *	0.24	0.77 ***	0.35 **
	Cfo4	-0.80	0.04	-0.13	0.08	0.37	0.06
	Cfo3	-2.04 ***	-0.41 *	-0.13	-0.11	0.39 *	-0.17 *
	Cfo2	-1.89 ***	-0.82 ***	-0.77 ***	-0.52 ***	0.17	-0.64 ***
low *cfo*	*Cfo1*	-2.49 ***	-1.10 ***	-0.51	-0.21	-1.01 ***	-1.04 ***
pure *mom*		-1.24 ***	-0.34	-0.13	-0.03	0.40 **	

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 6 months.

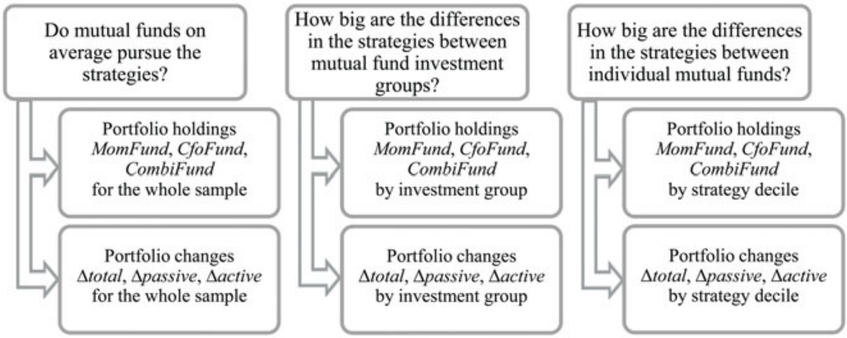
The attained alphas decrease the more the sample is restricted to typical mutual fund stocks. Thus, a considerable portion of the strategies' abnormal returns in the unrestricted sample stems from stocks that are only held by less than 1 % or 3 % of the mutual funds in the sample. It becomes more difficult to earn positive 3-factor alphas, the more the sample is restricted to "typical mutual fund stocks." In the unrestricted sample it suffices to invest in the extreme 40 % stocks in terms of momentum or cash flow to earn a significant positive alpha. In mfs3%, in contrast, only an investment in the extreme 20 % of stocks renders a significantly positive alpha. This indicates that stocks which are held by mutual funds are more correctly priced than the average stock. However, the sorting of the returns works in all three samples: The alpha earned during the investment period is higher, the higher the past returns in the preceding months were. The same applies to operating cash flows. Furthermore, the combination is more profitable than the pure strategies in all three samples, too.

To summarize, even if the stock universe is restricted to stocks that are held by mutual funds, it is more profitable to implement a combination strategy rather than pure momentum or cash flow strategies. Thus, mutual fund managers should have the chance to exploit the combination strategy's return opportunities. In order to achieve a significantly positive alpha in their asset spectrum, it is necessary to invest in stocks with considerable high past returns and operating cash flows. The results in Table 5.2 show that mutual fund managers do not seem to invest in such an extreme way. The following section analyzes mutual fund investments in more detail.

5.4 Pursuit of the Trading Strategies

In this section, I more closely examine to what extent mutual funds pursue the momentum strategy, the operating cash flow strategy, or both. In detail, I investigate whether mutual funds as a whole, certain mutual fund investment groups, as well as single mutual funds follow the strategies. Figure 5.5 displays the analyzed questions and names the variables I will use in the empirical analysis in italics. These variables will be explained in section 5.4.1.

Figure 5.5: Structure of Section 5.4



5.4.1 Methodology and Sample

Methodology − Analysis of Portfolio Holdings

In order to determine whether a fund tilts its portfolio to high momentum and/or high cash flow stocks, I first utilize portfolio **holdings** at a certain point of time. I use information on quarterly mutual fund holdings at the end of March, June, September, and December. I assume all reported holdings to be valid at quarter end, even if some funds occasionally report their holdings earlier. During my investigation period, which endures from June 1989 to December 2003, funds were only obliged to report their holdings to the SEC semiannually.[142] Some funds voluntarily reported their holdings more often. I use both − obligatory and voluntary fund reports in my analysis. I determine subsamples of stock holdings for which I have information about past returns and operating cash flows for each fund report. On

[142] Since May 2004 – which is already after my investigation period – the SEC has switched to obligatory quarterly reports.

average, I have data for 87.8 % of the whole fund stock holdings. For every stock i of this subsample j, I compute fund portfolio weights $w_{i,j,q}$, which are valid at the end of quarter q:[143]

$$w_{i,j,q} = \frac{n_{i,j,q} \cdot p_{i,q}}{\sum_{i=1}^{N_{j,q}} n_{i,j,q} \cdot p_{i,q}} \qquad 5.1$$

with:

$N_{j,q}$ = number of stocks in fund portfolio j at the end of quarter q

$w_{i,j,q}$ = portfolio weight of stock i in fund portfolio j at the end of quarter q

$p_{i,q}$ = price of stock i at the end of quarter q

$n_{i,j,q}$ = number of stock i in fund portfolio j at the end of quarter q

I determine for every stock i in every quarter q to which decile it belongs in terms of past returns (*mom*) and operating cash flows (*cfo*). The only difference to the definition of the deciles *momdec* and *cfodec* in section 3.2 is that they now take values from 1 to 10 instead of 0 to 1. Despite this different standardization, I name these deciles *momdec* and *cfodec*, too. Using the approach of Ali et al. (2008a), I calculate *MomFund* and *CfoFund*, which capture how much a fund manager tilts his portfolio to stocks with high momentum or operating cash flow stocks. *MomFund* is the sum of *momdec* of all firms in each quarterly fund portfolio, weighted according to the stocks' portfolio weight. *CfoFund* is defined in the same manner.

$$MomFund_{j,q} = \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot momdec_{i,q} \qquad 5.2$$

$$CfoFund_{j,q} = \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot cfodec_{i,q} \qquad 5.3$$

with:

$momdec_{i,q}$ = decile in terms of past compounded six month returns (*mom*) of stock i at the end of quarter q; $momdec_{i,q} \in \{1, 2, \dots, 10\}$

$cfodec_{i,q}$ = decile in terms of operating cash flows per average assets (*cfo*) of stock i at the end of quarter q; $cfodec_{i,q} \in \{1, 2, \dots, 10\}$

I assign the stocks' *momdec* and *cfodec* to the funds' portfolio weight as follows: In analogy to the trading strategy in section 3.2, I include a minimum three-month lag between fiscal quarter end and the report date of mutual fund holdings so that the cash flow information should be available to fund managers. For the computation of *momdec*, I consider a one-month lag. That means, for example, that in order to compute *momdec* for the holdings a fund reports at the end of December, I use the compounded past 6-month return from June to

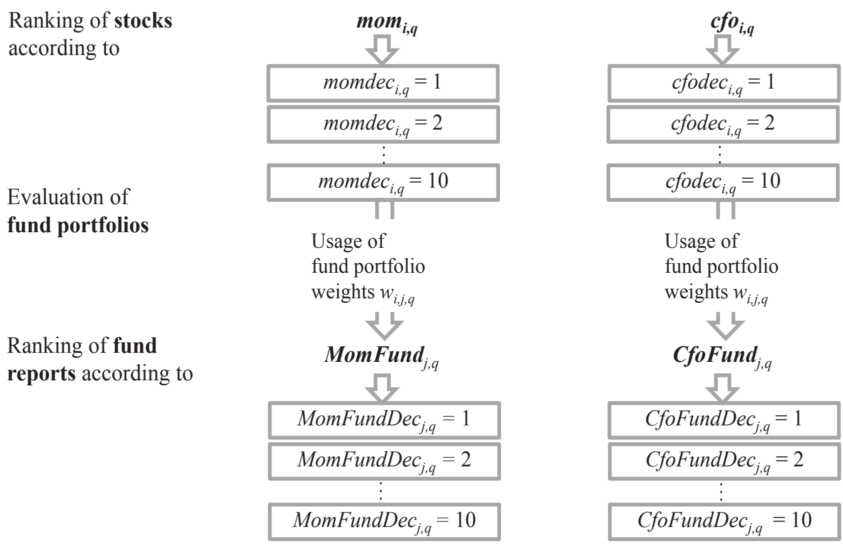
[143] In the following I will not differentiate between the whole fund portfolio and the subsample of stocks I have momentum and cash flow information about. I will only speak about the fund portfolio j, meaning the stocks I can characterize in terms of their past returns and cash flows.

November. To determine *cfodec*, I use the respective cash flow information from the third fiscal quarter that should have been published by the end of September at the latest.

I build decile groups in order to distinguish between funds that follow the strategies and those that do not. Every quarter I sort all fund reports according to their *MomFund* and assign them to one of ten decile groups named *MomFundDec* in ascending order. These groups obtain values from 1 to 10 and the first decile contains the 10 % fund reports with lowest values of *MomFund.* The 10 % funds that tilt their portfolios the most to high momentum stocks are assigned to the tenth decile, receiving a value of 10 (*MomFundDec* = 10). For *CfoFund* I proceed in the same way so that in the end every fund report belongs to one of ten deciles in terms of their momentum (*MomFundDec*) and operating cash flow strategy (*CfoFundDec*).

Figure 5.6 illustrates the computation of the fund holding-based measures.

Figure 5.6: Analysis of Mutual Fund Holdings



I am not only interested in the funds' separate momentum and cash flow strategies, but also in whether funds also follow both strategies at the same time. To capture this, I define the variable *CombiFund*. In analogy to *MomFund* and *CfoFund*, *CombiFund* is the sum of *combi* of all firms in each quarterly fund portfolio, weighted according to the stocks' portfolio weight. The variable *combi* denotes whether a stock has high past returns and high operating cash flows at the same time. It is defined as the mean of *momdec* and *cfodec*, which have been assigned to the respective fund report, and thus also takes values from 1 to 10. The computation of *CombiFund* is described in equation 5.4:

$$CombiFund_{j,q} = \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot combi_{i,q} \tag{5.4}$$

with:

$$combi_{i,q} = \frac{momdec_{i,q} + cfodec_{i,q}}{2} \text{; } combi_{i,q} \in \{1, 1.5, 2, 2.5, ..., 10\}$$

In the end, *CombiFund* is the mean of *MomFund* and *CfoFund*.

$$\begin{aligned} CombiFund_{j,q} &= \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot combi_{i,q} = \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot \frac{momdec_{i,q} + cfodec_{i,q}}{2} \\ &= \frac{1}{2} \cdot \left[\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot momdec_{i,q} + \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot cfodec_{i,q} \right] \\ &= \frac{1}{2} \cdot \left[MomFund_{j,q} + CfoFund_{j,q} \right] \end{aligned}$$

Accordingly, *CombiFund* measures strictly speaking to what extent a fund follows the momentum and the operating cash flow strategy at the same time. On average, following both strategies at the same time goes along with buying stocks that have both, high past returns and high operating cash flows, which implies pursuing the combination strategy analyzed in chapter 1. However, a high value of *CombiFund* does not necessarily mean that a fund holds stocks which simultaneously exhibit high cash flows and high past returns. For example, a fund can also have a high value of *CombiFund* if it holds 50 % stocks with very high *mom* and medium *cfo* and 50 % stocks with high *cfo* and medium *mom*. Such a strategy does not comply with the actual combination strategy of buying stocks with high *mom* **and** high *cfo* at the same time I analyze in chapter 1. Accordingly, the definition of the combination strategy in the following differs from that in chapter 1 which cannot be used here exactly in the same way since I now analyze whole mutual fund portfolios. However, regarding the abnormal returns to the 25 combination portfolios in Table 3.2, I would recommend increasing *momdec* and *cfodec*, and an increase of *momdec* by 2 would be as valuable as an increase of *momdec* and *cfodec* by 1. Accordingly, defining the combination strategy for mutual funds via *CombiFund* as described above seems to be an adequate way to capture this basic idea. Despite this difference to chapter 1, I will speak of the “combination strategy” when evaluating *CombiFund* in the following sections, too.

Methodology − Analysis of Portfolio Changes

MomFund, *CfoFund*, and *CombiFund* capture to which extent a fund holds stocks with high past returns and/or high operating cash flows. In addition to the **holding** of stocks, I examine how actively a fund **trades** to tilt its portfolio to high or low momentum stocks.[144] By this means, I aim to measure whether the pursuance of a given strategy is intended. Therefore, I calculate the difference between the funds' *MomFund* in the next and the present fund report:[145]

$$\Delta total_{j,q+1}^{Mom} = MomFund_{j,q+1} - MomFund_{j,q} \tag{5.5}$$

If $\Delta total_{j,q+1}^{Mom}$ is significantly higher than zero, this signifies that the exposure of fund j to the momentum strategy increases during quarter q+1.

I split this total difference between future and present holdings ($\Delta total$) into two parts: Part one ($\Delta passive$) represents the difference that would have resulted only due to stock price changes, that is, if all positions had been passively held since the last report. Part two ($\Delta active$) captures the active portfolio adjustments towards high/low momentum stocks net of changes that are due to stock price changes.[146] To split $\Delta total$, I compute $MomFund^{pass}$, which is the value of *MomFund* that would have been valid in the next report, if all positions had been passively held. In order to compute $MomFund^{pass}$, I first calculate the weights $w_{i,j,q+1}^{pass}$ that would have been valid at the end of quarter q+1 if the fund had not traded since the last fund report at the end of quarter q. Then I calculate $MomFund^{pass}$ using $w_{i,j,q+1}^{pass}$ and the momentum deciles $momdec_{i,q+1}$ to which the stocks belong at the time q+1 of the following fund report.

$$w_{i,j,q+1}^{pass} = \frac{w_{i,j,q} \cdot (1 + return_{i,q+1})}{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot (1 + return_{i,q+1})} \tag{5.6}$$

$$MomFund_{j,q+1}^{pass} = \sum_{i=1}^{N_{j,q}} w_{i,j,q+1}^{pass} \cdot momdec_{i,q+1} \tag{5.7}$$

$return_{i,q+1}$ = return of stock i during quarter q+1

Using $MomFund_{j,q+1}^{pass}$, I determine the passive change of the momentum strategy $\Delta passive_{j,q+1}^{Mom}$ during quarter q+1:

$$\Delta passive_{j,q+1}^{Mom} = MomFund_{j,q+1}^{pass} - MomFund_{j,q} \tag{5.8}$$

---

144 In the following I demonstrate the procedure using *MomFund* as example. The approach for *CfoFund* and *CombiFund* is the same.

145 I give the equations for the case when the next fund report is published in the next quarter. If the next report is only published 6 months later, the subscripts have to be exchanged from quarterly to half-yearly.

146 Ali et al. (2008a) also analyze $\Delta active$ in order to measure the intended accrual strategies of mutual funds; see Ali et al. (2008a), pp. 14-15. Nevertheless, they neither analyze $\Delta total$ nor $\Delta passive$, which both permit further insights in my analysis.

If $\Delta passive_{j,q+1}^{Mom}$ is significantly higher than zero, the fund exposure to the momentum strategy would have increased significantly if the fund manager had not changed portfolio weights during quarter q+1.

Furthermore, I compute $\Delta active_{j,q+1}^{Mom}$, which is the active change of the fund's momentum strategy during quarter q+1. Accordingly, a positive value of $\Delta active_{j,q+1}^{Mom}$ signifies that the exposure of fund j to the momentum strategy increases due to active portfolio changes during quarter q+1.

$$\Delta active_{j,q+1}^{Mom} = MomFund_{j,q+1} - MomFund_{j,q+1}^{pass} \tag{5.9}$$

Of course, $\Delta total_{j,q+1}^{Mom}$ is the sum of $\Delta passive_{j,q+1}^{Mom}$ and $\Delta active_{j,q+1}^{Mom}$:

$$\begin{aligned}
\Delta total_{j,q+1}^{Mom} &= MomFund_{j,q+1} - MomFund_{j,q} \\
&= MomFund_{j,q+1} - MomFund_{j,q} + MomFund_{j,q+1}^{pass} - MomFund_{j,q+1}^{pass} \\
&= \underbrace{MomFund_{j,q+1}^{pass} - MomFund_{j,q}}_{\Delta passive_{j,q+1}^{Mom}} + \underbrace{MomFund_{j,q+1} - MomFund_{j,q+1}^{pass}}_{\Delta active_{j,q+1}^{Mom}} \\
&= \Delta passive_{j,q+1}^{Mom} + \Delta active_{j,q+1}^{Mom}
\end{aligned}$$

In section 5.4.2, I utilize portfolio changes $\Delta total_{j,q+1}^{Mom}$, $\Delta passive_{j,q+1}^{Mom}$, and $\Delta active_{j,q+1}^{Mom}$ to assess whether a fund holds high momentum stocks on purpose or just by chance. In the same manner I also compute and analyze the trading-based measures of the cash flow and the combination strategy, $\Delta total_{j,q+1}^{Cfo}$, $\Delta passive_{j,q+1}^{Cfo}$, $\Delta active_{j,q+1}^{Cfo}$, as well as $\Delta total_{j,q+1}^{Combi}$, $\Delta passive_{j,q+1}^{Combi}$, and $\Delta active_{j,q+1}^{Combi}$.

Sample

I use fund returns, fees, and fund turnover given in the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database.[147] Mutual fund holdings and total net assets are taken from the Thomson Financial Mutual Fund Database as in section 5.3. The sample period spans from June 1989 to December 2003. I use all fund reports that are available on Thompson and contain new fund holdings. The two databases have been merged as described in Appendix A of Kempf, Ruenzi, and Thiele (2009).

---

[147] Formerly, databases included only funds that survived during the investment period, whereas funds that disappeared were mostly purged. The constriction to surviving funds led to a bias in academic studies, as, for example, analyzed by Brown et al. (1992). This bias is now averted by studying both, funds that survived and those that have "died" in the survivorship bias free Thomson database.

Indexfunds, bondfunds, international funds, and balanced funds are excluded from the sample, as I focus on actively managed equity funds only. Furthermore, those fund quarters are excluded for which I only have information about past returns and operating cash flows for less than 75 % of the reported stock holdings. Funds are classified into four categories according to their self-declared investment objectives following Pástor and Stambaugh (2002). I differentiate between the objectives “Small Cap & Aggressive Growth” (SC&AG), “Growth” (G), “Growth & Income” (G&I), and “Income” (I).

The selection criteria lead to a sample consisting of 37,522 quarterly fund reports from 1,943 different funds, which is comparable to the sample sizes of other studies.[148] The number of observations increases during the investigation period. Whereas the sample comprises only 250 different funds and 496 quarterly reports in 1989, it increases to 1,220 funds and 3,767 fund reports in 2003. I present the characteristics of the mutual fund sample in Table 5.4.[149]

Table 5.4: Descriptive Statistics of Mutual Funds by Fund Objective

	n	Ø *tna* [million $]	Ø *turnover* [% p.a.]	Ø number of different stocks
Small Cap & Aggressive Growth (SC&AG)	10,110	527	86.6	114
Growth (G)	16,707	891	86.3	70
Growth & Income (G&I)	8,750	1,208	56.9	79
Income (I)	1,955	1,001	56.2	62
Whole Sample	37,522	864	77.3	81.2

Mutual funds with objective Growth represent the biggest group with a total of 16,707 quarterly reports, whereas Income funds only account for 1,955 different reports. In the groups of Growth & Income and Income funds, assets are held by a lower number of funds. Funds of these groups manage the highest assets. On average, their total net assets amount to US$ 1,208 million and US$ 1,001 million. The more growth-oriented a fund is, the more it trades. The mean turnover rate of Small Cap & Aggressive Growth funds amounts to 86.6 % in contrast to a rate of only 56.2 % for Income funds. This finding indicates that investing in stocks with potential for growth requires more trading than picking income stocks. The mean number of different stocks per fund portfolio is lowest for Income funds with 62 different stocks, whereas it amounts to 114 stocks for Small Cap & Aggressive Growth funds.

[148] For example, Wermers (2000) investigates 1,788 distinct funds in a period of 20 years.

[149] The characteristics are similar to those of previous studies; see, e.g., Wermers (2000) or Kempf, Ruenzi, and Thiele (2009).

5.4.2 Empirical Results and Discussion

In this section, I present the empirical results about the strength of the mutual funds' momentum, operating cash flow, and combination strategies. I begin by analyzing the most aggregated level, asking whether the entirety of mutual funds on average follows the strategies. Then I turn to a less aggregated level, investigating whether certain mutual fund investment groups follow the strategies more intensely. After that, I turn to the less aggregated level, analyzing to what extent individual funds differ in their employment of the strategies. As a last step of this section, I critically judge the quality of the measure of the combination strategy, *CombiFund*.

Analysis of the Whole Mutual Fund Sample

As first step, I examine to what extent mutual funds as a whole follow the momentum strategy, the cash flow strategy, and both. Therefore I compute the mean values of *MomFund*, *CfoFund*, and *CombiFund* for the whole mutual fund sample. They are 6.575 for *MomFund*, 6.766 for *CfoFund*, and 6.671 for *CombiFund* and thus all three clearly exceed the equally-weighted mean of *mom*, *cfo*, and *combi* of all stocks, which is 5.5 if I use the equally-weighted market as standard of comparison.[150] This indicates that funds in general seem to tilt their portfolios to high momentum and cash flow stocks.

If I use the value-weighted market as standard of comparison, conclusions are different. The value weighted means of *momdec*, *cfodec*, and *combi* of all stocks are Ø $momdec^{vw} = 6.437$, Ø $cfodec^{vw} = 6.878$, and Ø $combi^{vw} = 6.657$. These means exceed their equally weighted counterparts, indicating that stocks with higher market capitalization on average exhibit both higher past returns and higher operating cash flows than stocks with lower market capitalization. The comparison of the mean values for the mutual fund sample to the value-weighted means leads to the following conclusions: Mutual funds on average still hold stocks with higher past returns than they would if they held the value-weighted market index. In contrast, stocks with low operating cash flows are more strongly represented in mutual fund portfolios than in the value-weighted market portfolio, which shows that fund managers tilt their portfolios to low cash flow stocks in comparison to the value weighted market. In terms of the combination of high past returns and cash flows, the two effects cancel each other out so that the mutual fund portfolios on average do not differ significantly from the value-weighted market in terms of combination stocks. Table 5.5 summarizes these findings.

---

150 Ali et al. (2008a) also compare their accrual investing measure to the equally-weighted mean of 5.5; see Ali et al. (2008a), p. 12.

Table 5.5: Mutual Fund Investment Strategies for the Whole Sample

	momdec	*cfodec*	*combi*
Ø fund value	6.575	6.766	6.671
Ø market value^{ew}	5.5	5.5	5.5
Ø difference	+1.075 ***	+1.266 ***	+1.171 ***
Ø fund value	6.575	6.766	6.671
Ø market value^{vw}	6.437	6.878	6.657
Ø difference	+0.138 ***	-0.112 ***	+0.014

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 2 quarters.

The equally- and value-weighted means also have to be kept in mind when reading the following sections. If, for example, a fund has a value of *MomFund* that is significantly higher than 6.437, this indicates that the fund tilts its portfolio to high momentum stocks.

Beside the analysis of portfolio holdings, I also examine portfolio changes from one fund report to the next. This examination confirms my previous findings about momentum- and cash flow strategies of the whole sample. Portfolio changes $\Delta total$, $\Delta active$, and $\Delta passive$ for the whole sample are listed in Table 5.6.

Table 5.6: Mutual Fund Investment Strategy Changes for the Whole Sample

	MomFund	*CfoFund*	*CombiFund*
$\Delta total$	-0.039	-0.007	-0.023
$\Delta passive$	-0.130 *	-0.009	-0.069 *
$\Delta active$	0.091 ***	0.001	0.046 ***

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 2 quarters.

$\Delta total$ is not significantly different from zero for all three strategies. This is not surprising because total changes should even out for the whole sample if mutual funds do not systematically increase their exposure to momentum (or cash flow) over time. A closer analysis of passive and active changes allows for additional insights. If funds did not change their portfolios from one report to the other, the mean fund exposure to momentum would decrease significantly. *MomFund* would decrease by $\Delta passive^{Mom} = -0.130$. Mutual funds avoid this decline by buying stocks with higher and/or selling stocks with lower past returns, actively raising *MomFund* by $\Delta active^{Mom} = 0.091$. Concerning operating cash flows, there is much less movement in active and passive changes. All three Δ^{Cfo} take much lower values than their momentum counterparts and are not significantly different from zero. Concerning the combination strategy, the active increase of *MomFund* is strong enough to also cause an active increase of *CombiFund* by $\Delta active^{Combi} = 0.046$.

To sum up: Mutual funds on average do follow the momentum strategy.[151] However, the data do not conclusively support the thesis that they also pursue operating cash flow and combination strategies.

Analysis of Mutual Fund Investment Groups

The mean values of *MomFund*, *CfoFund*, and *CombiFund* by mutual fund investment groups are listed in Table 5.7. In the last two rows of Table 5.7, I list again mean values for the whole fund sample and the value-weighted mean of *momdec* and *cfodec* for all stocks in the market as standard of comparison.[152]

Table 5.7: Mutual Fund Investment Strategies by Fund Objective

	Ø *MomFund*	Ø *CfoFund*	Ø *CombiFund*
Small Cap & Aggressive Growth (SC&AG)	6.685	6.548	6.616
Growth (G)	6.605	6.853	6.729
Growth & Income (G&I)	6.438	6.833	6.636
Income (I)	6.315	6.731	6.523
Whole Sample	6.575	6.766	6.671
Ø market value^{vw}	6.437	6.878	6.657

Growth oriented funds follow the momentum strategy more intensely. The mean values of *MomFund* of funds with investment objective Small Cap & Aggressive Growth and Growth are 6.685 and 6.605 and are significantly higher than the value the funds would have if they held the value-weighted market portfolio. The dependence of the momentum strategy on the funds' growth orientation is in line with Grinblatt, Titman, and Wermers (1995) and reflects that high past returns ceteris paribus lead to a higher market value compared to the book value, which is a typical characteristic of growth stocks.[153] In contrast, the strength of the cash flow strategy does not depend on the funds' growth orientation. In addition, funds of all investment groups have a lower exposure to the cash flow strategy than they would have if they held the value-weighted market. The combination strategy of course occupies a position in the middle, only increasing slightly with the funds' orientation towards growth.

151 This is in line with previous literature, as, e.g., Grinblatt, Titman, and Wermers (1995).

152 Note that in Table 5.5 to Table 5.8 the mean values of *CombiFund* are the mean of *MomFund* and *CfoFund*. Despite this, I report the values to give a complete picture and the levels of significance.

153 The Morning Star Style Box (Figure 5.4, p. 106) displays typical growth stocks characteristics.

The analysis of active and passive portfolio changes by investment objective does not alter these conclusions as listed in Table 5.8.

Table 5.8: Mutual Fund Investment Strategy Changes by Fund Objective

		MomFund	*CfoFund*	*CombiFund*
Small Cap & Aggressive Growth (SC&AG)	$\Delta total$	-0.033	0.001	-0.016
	$\Delta passive$	-0.183 ***	0.010	-0.086 ***
	$\Delta active$	0.150 ***	-0.010	0.070 ***
Growth (G)	$\Delta total$	-0.045	-0.007	-0.026
	$\Delta passive$	-0.152 **	-0.011	-0.082 **
	$\Delta active$	0.107 ***	0.005	0.056 ***
Growth & Income (G&I)	$\Delta total$	-0.051	-0.008	-0.029
	$\Delta passive$	-0.079	-0.018	-0.049
	$\Delta active$	0.029 ***	0.011 **	0.020 ***
Income (I)	$\Delta total$	-0.031	-0.012	-0.022
	$\Delta passive$	-0.002	-0.020	-0.011
	$\Delta active$	-0.029 ***	0.007	-0.011 *

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 2 quarters.

In the growth-oriented groups, weights in high momentum stocks are actively increased, since $\Delta active^{Mom}$ for Small Cap & Aggressive Growth, Growth, as well as Growth & Income funds are significantly higher than zero. This active trading also leads to an increase in the combination strategy for these groups. Funds with objective Small Cap & Aggressive Growth actively increase their exposure the most. In contrast, Income funds actively trade against momentum and therefore also against the combination strategy. The values of $\Delta active^{Mom}$ and $\Delta active^{Combi}$ for Income Funds are significantly negative. Active trading towards high cash flow stocks is only significant for Growth & Income funds. But even in this group, the active buying of high cash flow stocks only takes a moderate value of $\Delta active^{Cfo} = 0.011$.

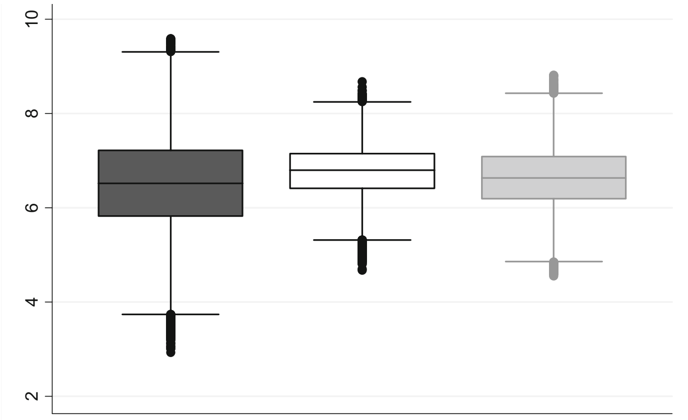
Accordingly, the answer to the second research question about the differences in the pursuit of the strategy among mutual fund investment groups is that growth-oriented funds follow the momentum strategy more actively. Similarly, also the combination strategy is actively pursued by these funds. In contrast, only funds with investment objective Growth & Income seem to weakly change their portfolios towards high operating cash flow stocks.

Now I come to the less aggregated level and analyze the pursuit of the three strategies by individual mutual funds.

Analysis of Individual Mutual Fund Reports

The question whether single mutual funds differ in their pursuit of the three strategies is important for the later analysis of the strategies' success. Only if funds differ in their momentum, cash flow, and combination strategies, will it be possible to detect differences in their fund returns which can be assigned to these strategies. To get a first impression of the dispersion of *MomFund*, *CfoFund*, and *CombiFund*, I draw boxplots for the three variables in Figure 5.7. The band inside the boxes represents the median. The top and the bottom of the boxes represent the upper and lower quartiles of the distributions. The so-called "whiskers" outside the box mark the 1.5 interquartile intervals. The outliers outside this range are plotted with dots.

Figure 5.7: Dispersion of Mutual Fund Strategies
(■ *MomFund*, □ *CfoFund*, and ■ *CombiFund*)



The boxplots show that funds differ much more in terms of their momentum than of their operating cash flow strategies. The dispersion of *MomFund* is nearly twice as high as that of *CfoFund* with a standard deviation of 1.04 for *MomFund* compared to 0.55 for *CfoFund*. By construction, the dispersion of *CombiFund* lies in the middle.

This first impression is confirmed by my second analysis in which I analyze the ten decile groups − *MomFundDec*, *CfoFundDec*, and *CombiFundDec* − comprising the first, second, etc. 10 % of reports of funds that follow the three strategies the most in a given quarter. Then I compute the mean values of quarterly mean *MomFund*, *CfoFund*, and *CombiFund* by decile group and present them in Table 5.9.[154] Moreover I list the difference between the tenth and the first strategy deciles and the mean difference between two consequent deciles. Lastly, I list again the value-weighted mean of *momdec* and *cfodec* for all stocks in the market as standard of comparison.

Table 5.9: Mutual Fund Investment Strategies by Strategy Decile

Strategy Decile	Ø *MomFund*	Ø *CfoFund*	Ø *CombiFund*
1	5.343	5.790	5.803
2	5.819	6.219	6.159
3	6.073	6.432	6.343
4	6.272	6.596	6.486
5	6.454	6.736	6.616
6	6.636	6.869	6.738
7	6.834	6.995	6.863
8	7.064	7.131	7.004
9	7.354	7.296	7.184
10	7.925	7.608	7.524
difference 10-1	2.582 ***	1.818 ***	1.721 ***
Ø difference	0.287	0.202	0.191
Ø market value^{vw}	6.437	6.878	6.657

*** denotes significance at the 1 %- level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 2 quarters.

When comparing the values for the funds with the value-weighted market, funds in the strategy deciles *MomFundDec* 5 to 10 exhibit higher values of *MomFund* than they would if they held the value-weighted market portfolio. For the cash flow strategy, this is only the case for funds in the upper four deciles *CfoFundDec* 7 to 10, and for the combination strategy in the upper five deciles *CombiFundDec* 6 to 10.

The most striking feature is, again, that the dispersion of *MomFund* is much higher than that of the other two strategies *CfoFund* and *CombiFund*. On average, *MomFund* increases by 0.287 from one decile to the next, whereas *CfoFund* and *CombiFund* only increase by 0.202 and 0.191. The difference between the first and the tenth decile is statistically significant for all three strategies, but highest for the momentum strategy in comparison to both, the cash flow and the combination strategy. The difference in terms of momentum of 2.582 is significantly higher than the differences of 1.818 and 1.721 for the cash flow and the

[154] Note that I illustrate "raw" values without taking means by strategy deciles in Figure 5.7, so that *CombiFund* is by construction the mean of *MomFund* and *CfoFund*. This does not apply to the numbers in the strategy deciles in Table 5.9. Here the mean of *CombiFund* is not the mean of *MomFund* and *CfoFund* in the same row because the three columns are based on different sortings. The first column is sorted according to *MomFund*, the second according to *CfoFund*, and the third according to *CombiFund*. Consequently, the decile rows contain different fund reports with independent means. The same applies to Table 5.12.

combination strategy. The respective Newey West t-values are 11.75 for the comparison of momentum with cash flow and 18.48 for that of momentum with the combination.

The higher dispersion of *MomFund* in comparison to *CfoFund* leads to the question, how well a change in *CombiFund* indeed captures a change in both strategies. As *MomFund* has a considerably higher dispersion, it will more strongly influence the variation of *CombiFund* than *CfoFund*. To analyze this question more closely, I compute the correlations between the three strategy variables *MomFund*, *CfoFund*, and *CombiFund* and report their means in Table 5.10.

Table 5.10: Correlation between Mutual Fund Investment Strategy Measures

	MomFund	*CfoFund*	*CombiFund*
MomFund	1.00	0.20	0.85
CfoFund		1.00	0.67
CombiFund			1.00

As expected, *CombiFund* is more strongly driven by *MomFund* with a mean correlation coefficient of 0.85. The dependency of *CombiFund* from the cash flow strategy is lower with a coefficient of 0.67. The correlation between the funds' momentum and cash flow strategies amounts to 0.20, already indicating that mutual funds hardly ever hold high momentum and operating cash flow stocks at the same time. Table 5.11 underlines the high correlation between *MomFund* and *CombiFund*. It reports mean ratios of fund reports in % by *MomFundDec* and *CombiFundDec*.

Table 5.11: Ratios of Fund Reports in Mutual Fund Investment Strategy Deciles

		CombiFundDec									
		1	2	3	4	5	6	7	8	9	10
MomFundDec	1	60.6	22.5	9.6	4.2	2.1	0.8	0.3	0.0	0.0	0.0
	2	21.1	31.6	23.3	12.0	6.2	3.6	1.7	0.5	0.1	0.0
	3	9.3	20.3	24.0	21.5	12.5	7.3	3.5	1.3	0.5	0.0
	4	4.4	10.7	17.9	21.4	19.9	13.9	7.6	3.2	1.1	0.1
	5	2.5	6.7	10.3	16.4	19.9	19.9	14.2	7.4	2.3	0.5
	6	1.4	4.1	7.4	11.2	17.0	20.5	19.5	12.5	5.6	0.9
	7	0.8	2.4	4.6	6.6	11.2	15.6	21.7	22.6	11.9	2.6
	8	0.3	1.1	2.1	4.1	5.8	10.9	17.7	25.9	24.0	8.1
	9	0.1	0.4	0.8	1.9	4.4	6.2	10.4	19.2	33.7	22.9
	10	0.0	0.2	0.2	0.5	1.0	1.6	3.5	7.5	21.0	64.7

The correlation between *MomFund* and *CombiFund* is mostly present in the extreme deciles. For example, 60.6 % of fund reports belonging to the first *MomFund* decile also belong to the first *CombiFund* decile. The respective ratio for the tenth deciles is 64.7 %. On the other hand, the distribution also shows that the two strategy variables do not completely measure the same thing. That means *CombiFund* still also measures the strength of the pursuit of the cash flow strategy, which makes it still worthwhile to analyze *CombiFund* in the following sections. Nevertheless, the stronger dependence of *CombiFund* on *MomFund* has to be kept in mind when reading the following sections. Whenever I assess the combination strategy, these results are more strongly driven by the pursuit of the momentum rather than of the cash flow strategy.

As pointed out before, the strategy variables *MomFund*, *CfoFund*, and *CombiFund* rely on portfolio holdings and therefore do not necessarily reflect intended trades. To extend my analysis, I use a second type of measures, this time relying on portfolio **changes**. By analyzing changes, I test whether the strategies identified by fund holdings are intended. If, for example, funds in the tenth decile of *MomFund* in fact aim at tilting their portfolios to high momentum stocks, they should actively buy high momentum stocks and sell low momentum stocks. Consequently they should have a high positive $\Delta active^{Mom}$. The results of this analysis are presented in Table 5.12, which lists mean values of $\Delta total$, $\Delta active$, and $\Delta passive$ by strategy deciles. For ease of exposition, I condense deciles 4 to 7 into one row.

Table 5.12: Mutual Fund Investment Strategy Changes by Strategy Decile

Strategy Decile		*MomFund*	*CfoFund*	*CombiFund*
1	Δ*total*	0.534 ***	0.395 ***	0.308 ***
	Δ*active*	-0.097 ***	0.028 ***	-0.050 ***
	Δ*passive*	0.632 ***	0.368 ***	0.358 ***
2	Δ*total*	0.270 ***	0.177 ***	0.155 ***
	Δ*active*	-0.034 ***	0.015 ***	-0.009
	Δ*passive*	0.304 ***	0.162 ***	0.164 ***
3	Δ*total*	0.166 **	0.106 ***	0.064 *
	Δ*active*	-0.007	0.020 ***	-0.008
	Δ*passive*	0.173 **	0.086 ***	0.071 *
4 to 7	Δ*total*	-0.068	-0.021	-0.033
	Δ*active*	0.060 ***	0.005	0.039 ***
	Δ*passive*	-0.128 *	-0.026 *	-0.072 *
8	Δ*total*	-0.270 ***	-0.120 ***	-0.142 ***
	Δ*active*	0.148 ***	-0.016 *	0.087 ***
	Δ*passive*	-0.419 ***	-0.105 ***	-0.229 ***
9	Δ*total*	-0.336 ***	-0.185 ***	-0.177 ***
	Δ*active*	0.239 ***	-0.011	0.114 ***
	Δ*passive*	-0.575 ***	-0.174 ***	-0.291 ***
10	Δ*total*	-0.473 ***	-0.353 ***	-0.300 ***
	Δ*active*	0.433 ***	-0.043 ***	0.172 ***
	Δ*passive*	-0.905 ***	-0.310 ***	-0.472 ***

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 2 quarters.

Funds belonging to the fourth or a higher momentum decile actively buy high momentum stocks. The most active buyers of high momentum stocks are the funds in momentum decile 10 with a value of $\Delta active^{Mom} = 0.433$. This figure has to be evaluated in conjunction with the large negative value of $\Delta passive^{Mom} = -0.905$ in this decile that results from the variability of momentum: Extreme winners of the last period will not necessarily also be the extreme winners of the next. If funds in the tenth momentum decile passively held their stocks, *MomFund* would decrease by $\Delta passive^{Mom} = -0.905$ from one fund report to the next, which would lead to an inclusion in the seventh or eighth *MomFundDec*. This descent is avoided by active buys of high and/or sells of low momentum stocks, resulting in a more moderate decrease of *MomFund* by $\Delta total^{Mom} = -0.473$. Concerning momentum, there are two conclusions to be drawn from Table 5.12: The more a fund tilts its portfolio to high momentum stocks, a) the more trading is needed to maintain this momentum strategy as $\Delta passive^{Mom}$ becomes more negative by momentum decile and b) the more it trades to maintain this high momentum value, as $\Delta active^{Mom}$ increases by momentum decile. Taking these two findings together, I conclude that funds in the higher momentum deciles seem to pursue the momentum strategy intentionally even though their value of *MomFund* decreases slightly in total.

With regard to the operating cash flow strategy, conclusions are different. First, Table 5.12 shows the lower variation in operating cash flows than in momentum. Especially the values of $\Delta passive^{Cfo}$ are much lower than for the momentum strategy, indicating that the operating cash flow is a more persistent stock characteristic than momentum. Similarly to *MomFund*, also the values of *CfoFund* have a tendency to the mean. Second, funds in the lowest cash flow deciles actively buy high cash flow stocks, whereas those in the high deciles trade contrariwise, actively decreasing their value of *CfoFund*. This is the opposite of my findings for the momentum strategy and indicates that funds which hold high cash flow stocks do not seem to do so on purpose. Therefore, it seems to be difficult to differentiate between funds that follow the cash flow strategy and funds that do not. This outcome should be kept in mind during the analyses in the following sections.

Regarding the combination strategy, the results resemble those of the momentum strategy, reflecting the strong dependence: Funds holding the highest combination stocks seem to do so on purpose, as they actively trade to maintain their high value of *CombiFund*, since $\Delta active^{Combi} = 0.172$ in the tenth *CombiFundDec* is the highest value of all deciles. In contrast, funds in the lower deciles in terms of *CombiFund* actively trade to maintain these low values, as $\Delta active^{Combi} = -0.050$. Nevertheless, in total, funds in the low deciles exhibit slight increases whereas funds in the high deciles feature slight decreases of *CombiFund*. In sum, the following of the combination strategy appears to be intended. These results provide some justification for differentiating among funds more or less following the combination strategy. However, the findings for the funds' combination strategy are strongly driven by their momentum strategy. This limitation is also confirmed by the trading based measures. $\Delta active^{Mom}$ more strongly influences $\Delta active^{Combi}$ than $\Delta active^{Cfo}$, as visible from the correlations in Table 5.13.

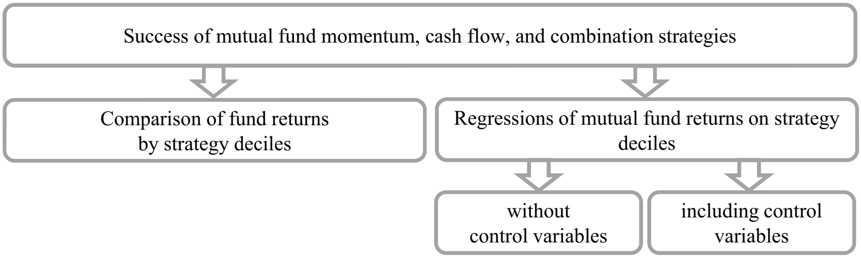
Table 5.13: Correlation between Mutual Fund Investment Strategy Changes

	$\Delta active^{Mom}$	$\Delta active^{Cfo}$	$\Delta active^{Combi}$
$\Delta active^{Mom}$	1.00	0.07	0.86
$\Delta active^{Cfo}$		1.00	0.56
$\Delta active^{Combi}$			1.00

5.5 Success of the Trading Strategies

Figure 5.8 illustrates the analyses I conduct in this section in order to investigate the success of the momentum, cash flow, and combination strategies in mutual fund portfolios. First, I compare fund returns by momentum, cash flow, and combination strategy deciles. After that, I conduct regressions of fund returns on the strategy measures with and without inclusion of further control variables.

Figure 5.8: Structure of Section 5.5



Against the background of the findings in section 5.4, it is most reasonable to search for return differences between funds that follow the momentum strategy and funds that do not. Funds mostly differ with respect to their momentum strategies and this seems to be on purpose, so it is here that differences in returns can be mostly expected. However, note that even though the dispersion of *MomFund* is higher than that of *CfoFund* and *CombiFund*, it is much lower than in the artificially constructed portfolios in sections 3.2 and 5.3. There, portfolio *Mom5* only comprises stocks from quintile 5, i.e., deciles 9 and 10, thus having a mean *MomFund* of 9.5. The mean *MomFund* of portfolio *Mom4* is 7.5 and so on. Consequently, the difference in the pursuit of the momentum strategy between the fourth and the fifth quintiles in the artificially constructed portfolios is 2 and nearly as high as the difference of 2.582 between *MomFund* in the first and the tenth deciles of the grouping of real mutual fund portfolio holdings presented in Table 5.9. These figures illustrate that much lower return differences should be expected when comparing mutual fund returns in comparison to the return differences in the artificially constructed portfolios in sections 3.2 and 5.3.

Regarding the operating cash flow strategy, it is questionable whether there will be return differences between funds in the first and tenth *CfoFund*-deciles at all. Here the difference between the two extreme fund deciles in “fund exposure” to high operating cash flows is 1.818 as listed in Table 5.9. This difference is even less than the difference between two consecutive quintiles in the artificial portfolios. Moreover, funds holding high cash flow stocks do not seem to do so on purpose, and therefore do not actively pursue a cash flow strategy as found out in section 5.4.2. This is another reason why it might be difficult to find any returns to that strategy.

Finding return differences between funds that follow the combination strategy and funds that do not may be possible due to the medium dispersion in *CombiFund*. However, such return differences will be driven to a large part by the pursuit of the momentum strategy as described in section 5.4.2. This makes it difficult to attribute the success to the combination. One has to keep these limitations in mind when interpreting the results of the following analysis of the success of mutual funds' trading strategies.

5.5.1 Methodology and Sample

Methodology – Fund Return Measures and Comparison by Strategy Deciles

I calculate four different measures to assess mutual fund performance: *netreturn*, *grossreturn*, *abnreturn*, and *alpha*. These measures differ in the underlying portfolios and in their risk-adjustment.

The usage of fund net returns *netreturn*, follows, for example, Ali et al. (2008a) and Wermers (2000). *Netreturns* are net of real transaction costs and reflect the returns that are actually earned by mutual fund investors. *Netreturn* is monthly available in the CRSP mutual fund database.[155] I use compounded three-month net returns to assess the quarterly *netreturn* of the fund:

$$netreturn_{j,q} = \prod_{m=1}^{3}\left(1 + netreturn_{j,m}\right) - 1 \qquad 5.10$$

$netreturn_{j,m}$ is the given fund *netreturn* in month *m* and *m* is the first, second, and third month of quarter *q*

Second, I compute *grossreturn* based on the given fund stock holdings in the Thomson database. *Grossreturns* are also used by Wermers (2000) in his decomposition of mutual fund performance. In comparison to *netreturn*, *grossreturn* reflects returns that are earned only by the funds' stock holdings and not the holdings of cash and bonds. Moreover, costs have not been subtracted yet.

155 To be more precise, CRSP provides *netreturn* for each share class of one mutual fund. Different share classes refer to the same underlying stock portfolios, but have different fee and expense structures. I compute *netreturn* as the mean *netreturn* of the underlying share classes, weighted by the total net assets of the respective share class.

$$grossreturn_{j,q} = \sum_{i=1}^{N_{j,q-1}} w_{i,j,q-1} \cdot return_{i,q} \tag{5.11}$$

with:

$N_{j,q-1}$ = number of stocks in portfolio *j* at the end of quarter *q*-1

$w_{i,j,q-1}$ = weight of stock *i* in portfolio *j* at the end of quarter *q*-1

$return_{i,q}$ = return of stock *i* during quarter *q*

I utilize *abnreturn* and *alpha* as return measures which adjust for the funds' exposure to risk. *Abnreturn* only refers to the funds' stock holdings analogous to *grossreturn*. *Alpha* refers to the whole fund portfolio, analogous to *netreturn*. Equation 5.12 displays the calculation of *abnreturn*.

$$abnreturn_{j,q} = \sum_{i=1}^{N_{j,q-1}} w_{i,j,q-1} \cdot (return_{i,q} - return_{i,q}^{bm}) \tag{5.12}$$

with:

$return_{i,q}^{bm}$ = value-weighted quarter *q* buy-and-hold return of the characteristic-based benchmark portfolio which consists of stocks belonging to the same quintiles in terms of size and book to market as stock *i* at the beginning of quarter *q*.[156]

Wermers (2000) uses *abnreturn* to measure the fund managers' stock picking ability.[157] The usage of *abnreturn* as risk-adjusted return follows Daniel et al. (1997). They argue that decomposing performance by using benchmark returns more precisely adjusts for investment style than computing alphas.[158]

To give a complete picture, I also compute the funds' 3-factor alphas, following inter alia Ali et al. (2008a). I calculate quarterly Fama French 3-factor alphas $alpha$, which are corrected for the funds' loading on the market, size, and value.[159] I estimate the funds' factor loadings using monthly *netreturns* and the three Fama French factors.[160]

$$netreturn_{j,m} - r_m^f = \alpha_j + \beta_j^{Market} \cdot RMRF_m + \beta_j^{Size} \cdot SMB_m + \beta_j^{Value} \cdot HML_m + \varepsilon_{j,m} \tag{5.13}$$

156 Note that this procedure is analogous to the computation of abnormal stock returns in section 3.2.1.

157 Wermers (2000) names it "characteristic selectivity measure"; see Wermers (2000), p. 1667. Wermers (2000) uses stocks with similar size, book to market, and momentum as benchmark portfolio. I do not adjust for momentum in order to leave the influence of momentum in the fund returns.

158 See Daniel et al. (1997), p. 1036.

159 Carhart (1997) introduces a 4 factor alpha, which additionally adjusts for the fund's momentum style. I use the 3-factor alpha, as I intend to measure the influence of momentum on fund returns.

160 The Fama French factors are obtained from Kenneth R. French's data library on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

with:

$netreturn_{j,m}$	=	net return of fund portfolio j during month m
r_m^f	=	riskless rate in month m
$RMRF_m$	=	market benchmark factor in month m
SMB_m	=	size benchmark factor in month m
HML_m	=	value benchmark factor in month m
β_j^l	=	loading of fund portfolio j on factor l

Using the estimated factor loadings from regression 3.4, I calculate monthly 3-factor alphas $\hat{\alpha}_{j,m}$ for each fund j.

$$\hat{\alpha}_{j,m} = netreturn_{j,m} - r_m^f - \hat{\beta}_j^{Market} \cdot RMRF_m - \hat{\beta}_j^{Size} \cdot SMB_m - \hat{\beta}_j^{Value} \cdot HML_m \tag{5.14}$$

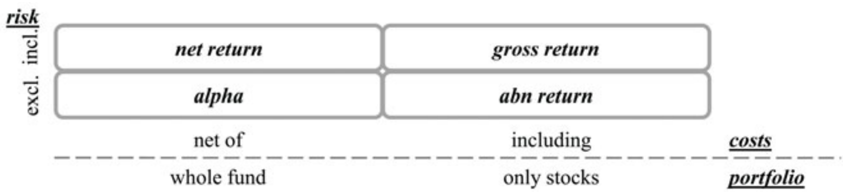
Quarterly 3-factor alphas $alpha_{j,q}$ are then computed as the three-months cumulated monthly 3-factor alphas:

$$alpha_{j,q} = \prod_{m=1}^{3}\left(1+\hat{\alpha}_{j,m}\right)-1 \tag{5.15}$$

m is the first, second, and third month of quarter q.

Figure 5.9 summarizes the characteristics of the four return measures in terms of risk- and cost- adjustment, and the underlying portfolios.

Figure 5.9: Characteristics of Fund Return Measures



My first approach to decide on the strategies' success is a comparison of fund returns by strategy deciles *MomFundDec*, *CfoFundDec*, and *CombiFundDec*. If mutual funds' momentum strategies are successful, returns of funds belonging to the 10 % that mostly tilt their portfolios to high momentum stocks, should exceed the returns of funds belonging to *MomFundDec* = 1. The same should apply to funds belonging to *CombiFundDec* = 10 and to *CfoFundDec* = 10. I evaluate the significance of fund return differences by using Newey West (1987) standard errors with a lag of 2 quarters to control for potential time-series dependence.

Methodology − Fund Return Regressions

I use Fama-MacBeth regressions as a second approach to decide if the strategies are successful. Fama-MacBeth regressions are also used by Grinblatt and Titman (1994), Edelen (1999), Chen et al. (2004), as well as Ali et al. (2008b) in their analyses of determinants of mutual fund returns.[161] I regress fund returns on the lagged strategy variables every quarter and use the means of the estimated coefficients. I conduct four different regressions in two blocks. In block A, only the strategy variables are included as explaining variables. In block B, I additionally include several control variables.

In the first regression 5.16, I use *MomFund* as the explanatory variable. *CfoFund* is the explanatory variable in regression 5.17. In regression 5.18, I include *MomFund* and *CfoFund* simultaneously. I do not regress fundreturns on *CombiFund* because this would not yield further insights: *CombiFund* measures the mean of *MomFund* and *CfoFund*. Accordingly, increases of *MomFund* and *CfoFund* raise *CombiFund*. If, therefore, both *MomFund* and *CfoFund* have incremental power to predict future *fundreturns* in regression 5.18, a simultaneous pursuit of both strategies will be even more successful, indicating the success of the combination strategy and making regressions on *CombiFund* superfluous. Equations 5.16 to 5.18 display the regressions of block A:

$$fundreturn_{j,q+1} = \alpha_q + \beta_q^{Mom} \cdot MomFund_{j,q} + \varepsilon_{j,q+1} \tag{5.16}$$

$$fundreturn_{j,q+1} = \alpha_q + \beta_q^{Cfo} \cdot CfoFund_{j,q} + \varepsilon_{j,q+1} \tag{5.17}$$

and

$$fundreturn_{j,q+1} = \alpha_q + \beta_q^{Mom} \cdot MomFund_{j,q} + \beta_q^{Cfo} \cdot CfoFund_{j,q} + \varepsilon_{j,q+1} \tag{5.18}$$

with:

$fundreturn_{j,q+1} = netreturn_{j,q+1}$, $grossreturn_{j,q+1}$, $abnreturn_{j,q+1}$, or $alpha_{j,q+1}$

Remember that $fundreturn_{j,q+1}$ measures the fund's return in quarter q+1, whereas the strategy measures depend on the weights of the beginning of that quarter.[162] Accordingly, for example, $MomFund_{j,q}$ depends on portfolio holdings which are reported at the end of March and the $fund\,return_{j,q+1}$ on the left side is the fund *j*'s return in the quarter following the fund report, i.e., April to June.

The regression-based approach enables me to control for the influences of further determinants of mutual fund returns. In section 5.2.2, I presented the determinants of fund performance analyzed in the academic literature. In my empirical analysis, I cannot include all

161 I have also conducted OLS regressions with standard errors clustered by fund and time following Petersen (2009). These regressions yield similar coefficients with in most cases lower statistical significance.

162 See equations 5.2 to 5.3.

of these variables as controls due to data restrictions. I account for *fundsize*, *costs*, *turnover*, previous returns (*prevreturns*), and *inflow* in my multivariate regressions and leave out the fund manager characteristics. This is in line with Baks (2003), who shows that fund characteristics are more important for fund performance than manager characteristics.[163]

I include *fundsize*, which is measured as the natural logarithm of the fund's total net assets in million US$. Second, I include *cost*, namely the fund's yearly expense ratio in % including 12b-1-fees measured as the fraction of the assets held by investors.[164] Third, *turnover* is included, meaning the fund's turnover in % p.a. as a proxy for the fund's trading activity. *inflow* is the fourth control variable and is computed as in Sirri and Tufano (1998).

$$inflow_{j,q} = \frac{tna_{j,q} - tna_{j,q-1} \cdot (1 + netreturn_{j,q})}{tna_{j,q-1}} \qquad 5.19$$

$tna_{j,q}$ = total net assets of fund *j* at the end of quarter *q*

To capture fund performance persistence, I include the previous yearly fund return *prevreturn* in %.[165]

$$prevreturn_{j,q} = \prod_{\tau=-5}^{-2} \left(1 + netreturn_{j,q+\tau}\right) - 1 \qquad 5.20$$

Moreover, I include dummy variables to account for differences in returns between fund objectives.[166] $D^{SC\&AG}$ takes the value 1 if the fund belongs to the group "Small Cap & Aggressive Growth", otherwise it is zero. D^{G} takes the value 1 if it belongs to "Growth", and $D^{G\&I}$ is 1 if the fund's objective is "Growth & Income". The fourth group "Income" serves as the basic group.

Regression 5.21 represents the regressions of block B, where *Strategy* stands for the strategy variables *MomFund*, *CfoFund*, or both. That is, I conduct the same regressions as in block A presented in equations 5.16 to 5.18 only this time including the control variables.

---

163 Furthermore, I presume that fund manager characteristics are not highly correlated with my measures *MomFund*, *CfoFund*, and *CombiFund* which capture the strength of the three investigated strategies. Therefore, the omission of these variables in my multivariate regressions should not alter my conclusions concerning the success of the trading strategies.

164 12b-1 fees mean an annual marketing or distribution fee. They get their name from the SEC rule that authorizes a fund to invoice them; see the SEC Investment Company Act of 1940, p. 45.

165 I use the previous yearly returns with one quarter additional lag, in order to avoid an overlap with the measurement of *MomFund*, so that $prevreturn_{j,q}$ is the compounded return during quarters *q*-5 to *q*-2.

166 The slight diversity of fund returns among fund groups will be analyzed for my sample in the descriptive statistics presented in Table 5.14.

$$\begin{aligned} fundreturn_{j,q+1} = {} & \alpha_q + \beta_q^{Strategy} \cdot Strategy_{j,q} + \beta_q^{fundsize} \cdot fundsize_{j,q} + \beta_q^{cost} \cdot cost_{j,q} \\ & + \beta_q^{turnover} \cdot turnover_{j,q} + \beta_q^{inflow} \cdot inflow_{j,q} + \beta_q^{prevreturn} \cdot prevreturn_{j,q} \\ & + \beta_q^{SC\&AG} \cdot D_{j,q}^{SC\&AG} + \beta_q^{G} \cdot D_{j,q}^{G} + \beta_q^{G\&I} \cdot D_{j,q}^{G\&I} + \varepsilon_{j,q+1} \end{aligned} \quad 5.21$$

with all variables as described in detail in the text above.

Sample

In this section, my sample differs slightly from that of the previous section 5.4 since I need information about future fund returns now. This requirement leads, for example, to an exclusion of all reports published in December 2003. Moreover, I drop the upper and bottom 0.5 % fund reports with extreme fund returns to mitigate the influence of outliers. The resulting sample is slightly lower than that in the previous section 5.4 with 36,378 fund quarters instead of 37,522. Nevertheless, the sample's characteristics do not change significantly, so that I refer to Table 5.4 for the descriptive statistics on the fund characteristics. I present means quarterly returns of the different return measures for the whole sample and the five investment groups in Table 5.14.

Table 5.14: Mutual Fund Returns by Fund Objective

	n	Ø *grossreturn* [% p.q.]	Ø *netreturn* [% p.q.]	Ø *abnreturn* [% p.q.]	Ø *alpha* [% p.q.]
Small Cap & Aggressive Growth (SC&AG)	9,741	3.75	3.51	0.33	-0.05
Growth (G)	16,227	3.23	2.81	0.06	-0.18
Growth & Income (G&I)	1,894	3.00	2.49	-0.25	-0.18
Income (I)	8,516	3.10	2.69	-0.12	-0.14
Whole Sample	36,378	3.28	2.91	0.03	-0.16

Grossreturns are of course higher than *netreturns* because costs are not subtracted and they solely reflect returns from stock holdings and not from cash or bonds. The resulting return difference is 0.37 percentage points and statistically significant (Newey West t-value = 3.78). Mean *abnreturns* exceed mean *alphas* by 0.19 percentage points, which is not statistically significant (Newey West t-value = 1.33). Comparing fund groups, returns of funds with objective Small Cap & Aggressive Growth are slightly higher, also when they are adjusted for size and value effects. However, return differences between fund investment groups are not statistically significant.

In the regressions of block B, which include the whole battery of control variables, my sample shrinks to 33,374 observations. This restriction only has a negligible effect on fund returns. Table 5.15 lists descriptive statistics for the control variables used.

Table 5.15: Mutual Fund Characteristics in the Restricted Sample

	n	*Ø tna* [million $]	*Ø cost* [% p.a.]	*Ø turnover* [% p.a.]	*Ø inflow* [% p.q.]	*Ø prevreturn* [% p.a.]
Small Cap & Aggressive Growth (SC&AG)	8,815	556	1.45	87.78	29.72	11.43
Growth (G)	14,895	943	1.33	90.72	30.14	11.39
Growth & Income (G&I)	1,773	1,049	1.23	57.56	5.40	9.91
Income (I)	7,891	1,266	1.25	57.05	22.33	10.48
Whole Sample	33,374	914	1.33	79.45	25.00	11.23

The characteristics are similar to those of the full sample described in Table 5.4. Beyond that, it is striking that Growth & Income funds have the lowest inflows. Their total net assets on average only grow by 5.4 %, while the mean quarterly inflow amounts to 25 %.

5.5.2 Empirical Results and Discussion

Comparison of Fund Returns by Strategy Deciles

To give a first overview on fund returns by strategy deciles, I plot quarterly *grossreturn* and *alpha* by the strategy deciles of all three strategies in Figure 5.10. By choosing these two measures, I present one figure for returns which are computed based on stock holdings and are not adjusted for risk (*grossreturns*) and one figure for risk-adjusted returns that refer to the whole fund portfolio and are given in the CRSP returns database (*alpha*).

Figure 5.10: Quarterly Fund Performance by Strategy Deciles

Figure A: Quarterly *grossreturn* by ■ *MomFundDec*, □ *CfoFundDec,* and ■ *CombiFundDec*

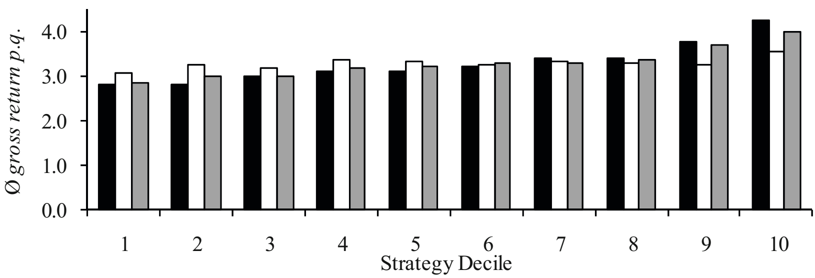
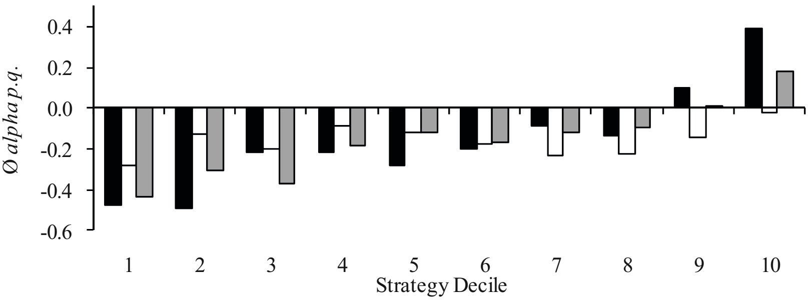


Figure B: Quarterly *alpha* by ■ *MomFundDec*, □ *CfoFundDec,* and ■ *CombiFundDec*



Both figures illustrate the superiority of the momentum strategy, the medium success of the combination, and the only weak dependence of future fund returns on *CfoFund*.

In the following, I give the precise numbers and levels of significance of fund returns in the strategy deciles. I start with the momentum strategy in Table 5.16. The first column gives the respective strategy decile, the second to fifth columns list mean fund returns. The row "difference 10-1" gives the return difference between funds belonging to the tenth and the first strategy decile and row "t-value difference" the corresponding t-value.

Table 5.16: Mutual Fund Returns by Momentum Strategy Decile

MomFundDec	Ø *grossreturn* [% p.q.]	Ø *netreturn* [% p.q.]	Ø *abnreturn* [% p.q.]	Ø *alpha* [% p.q.]
1	2.79 **	2.41 **	-0.31	-0.48 **
2	2.78 **	2.42 **	-0.33	-0.49 **
3	2.99 ***	2.71 ***	-0.12	-0.22
4	3.11 ***	2.73 ***	-0.04	-0.22
5	3.09 ***	2.72 ***	-0.09	-0.28 *
6	3.21 ***	2.87 ***	-0.03	-0.20
7	3.41 ***	3.04 ***	0.08	-0.09
8	3.39 ***	3.02 ***	-0.03	-0.13
9	3.77 ***	3.36 ***	0.35	0.10
10	4.23 ***	3.81 ***	0.82	0.39
difference 10-1	1.44	1.40	1.13	0.87 **
(t-value difference)	(1.36)	(1.49)	(1.37)	(2.22)

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 2 quarters.

Fund returns increase with the strength of the momentum strategy, independently of the fund return measure used. The return difference between funds in the tenth and the first momentum decile is economically significant. It starts from a quarterly *alpha* that is 0.87 percentage points higher to a difference in *grossreturns* of 1.44 percentage points per quarter.

Nevertheless, the statistical significance is not clear-cut with a maximum t-value of 2.22 when analyzing *alpha*. Similarly, the risk-adjusted returns in the 10^{th} momentum decile reach economically significant, but statistically insignificant values.

As expected, results regarding the success of the operating cash flow strategy are different, as listed in Table 5.17.

Table 5.17: Mutual Fund Returns by Operating Cash Flow Strategy Decile

CfoFundDec	Ø *grossreturn* [% p.q.]	Ø *netreturn* [% p.q.]	Ø *abnreturn* [% p.q.]	Ø *alpha* [% p.q.]
1	3.06 ***	2.82 ***	-0.19	-0.28
2	3.25 ***	3.01 ***	-0.01	-0.13
3	3.17 ***	2.87 ***	-0.14	-0.20
4	3.35 ***	3.05 ***	0.13	-0.09
5	3.32 ***	2.96 ***	0.01	-0.12
6	3.25 ***	2.83 ***	0.05	-0.18
7	3.31 ***	2.94 ***	0.02	-0.23
8	3.28 ***	2.82 ***	0.06	-0.23
9	3.25 ***	2.80 ***	0.02	-0.14
10	3.54 ***	3.01 ***	0.34	-0.02
difference 10-1	0.48	0.19	0.53 *	0.26
(t-value difference)	(0.74)	(0.34)	(1.94)	(0.86)

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 2 quarters.

The comparison of returns by cash flow deciles shows that the cash flow strategy is not particularly successful. Although returns of funds in the tenth cash flow strategy decile are higher than those in the first, the return difference is only weakly statistically significant when *abnreturns* are analyzed. The analysis of the medium strategy deciles confirms that fund returns do not increase with rising *CfoFundDec*. From *CfoFundDec* 2 to 9, fund returns do not show a clear trend. These findings comply with my conclusion in section 5.4.2, namely that mutual funds do not differ significantly in their operating cash flow strategies. Accordingly, it is not surprising that the corresponding returns do not differ significantly, either. Moreover, again, risk-adjusted returns are not statistically significant in the 10^{th} cash flow strategy decile.

The results of comparing fund returns by *CombiFundDec* can already be predicted from Table 5.16 and Table 5.17. As an increase of *CfoFund* does not raise *fundreturns*, increasing *MomFund* less in exchange for a simultaneous increase of *CfoFund* does not seem promising. However, this is exactly, what a sorting according to *CombiFund* does. The mean value of *MomFund* in the tenth *CombiFundDec* will be lower than in the tenth *MomFundDec*. In return, the mean *CfoFund* will be higher. This exchange should in the end lead to lower future *fundreturns* in the tenth *CombiFundDec* than in the tenth *MomFundDec*.

The results presented in Table 5.18 confirm the assumptions. Fund returns increase with the strength of the combination strategy, but the dependence is weaker than in the momentum strategy. Return differences between the two extreme deciles are not highly statistically significant, but economically considerable, with values from 0.62 % *alpha* to 1.13 % *grossreturn* per quarter.

Table 5.18: Mutual Fund Returns by Combination Strategy Decile

CombiFundDec	Ø *grossreturn* [% p.q.]	Ø *netreturn* [% p.q.]	Ø *abnreturn* [% p.q.]	Ø *alpha* [% p.q.]
1	2.84 **	2.51 **	-0.37	-0.43 *
2	2.97 ***	2.70 ***	-0.18	-0.31
3	3.00 ***	2.63 ***	-0.20	-0.37 *
4	3.17 ***	2.84 ***	0.01	-0.19
5	3.21 ***	2.92 ***	0.02	-0.12
6	3.29 ***	2.97 ***	-0.03	-0.17
7	3.27 ***	2.93 ***	0.03	-0.12
8	3.34 ***	2.99 ***	0.05	-0.09
9	3.70 ***	3.14 ***	0.33	0.01
10	3.98 ***	3.47 ***	0.64	0.18
difference 10-1	1.13	0.95	1.01	0.62 *
(t-value difference)	(1.25)	(1.15)	(1.58)	(1.77)

*** (**, *) denotes significance at the 1 %- (5 %-, 10 %-) level based on a two-tailed test using Newey and West (1987) standard errors with a lag of 2 quarters.

To sum up the results of this comparison of returns: Mutual funds that follow the momentum strategy are more successful than those that do not. This is not true for the operating cash flow strategy, since funds do not differ much in terms of their operating cash flow strategies. The missing impact of the cash flow strategy on future fund returns moreover leads to an inferior performance of the combination strategy in comparison to the pure momentum strategy in my mutual fund sample.

Fund Return Regressions

As a second test, I use regressions to measure the strategies' influence on fund returns. In contrast to the analyses of returns in the strategy deciles, regression coefficients measure the difference in future fund returns per one unit change of the strategy variables *MomFund* and *CfoFund* so that they better control for the different dispersions of the variables. Moreover, regressions allow controlling for further determinants of fund returns. Table 5.19 lists the results of regressions 5.16 to 5.18 where I do not include any control variables, yet.

Table 5.19: Determinants of Mutual Fund Returns

fund return	$\hat{\alpha}$	$\hat{\beta}^{MomFund}$	$\hat{\beta}^{CfoFund}$	Ø adj. R^2
grossreturn	-0.56	0.56 ^^		16.1
netreturn	-0.77	0.54 ^^		14.2
abnreturn	-2.96 ^^^	0.45 ^^^		10.5
alpha	-2.33 **	0.32 *		6.7
grossreturn	1.77		0.23	7.5
netreturn	2.65		0.04	6.6
abnreturn	-1.60 *		0.24 *	2.2
alpha	-0.90		0.11	2.2
grossreturn	-0.64	0.55 ^^	0.04	21.4
netreturn	0.35	0.54 ^^^	-0.16	18.7
abnreturn	-3.80 *	0.43 ^^	0.14	12.4
alpha	-2.21 *	0.35 **	-0.05	8.5

*** (**, *, ^^^, ^^) denotes significance at the 1 %- (5 %-, 10 %-, 15 %-, 20 %-) level.

Results confirm the comparison by strategy deciles in terms of the amount and significance of the estimated coefficients. An increase of *MomFund* by 1 leads to an increase of fund *grossreturns* by 0.56 percentage points per quarter. The momentum strategy's impact on fund performance is lowest but most stable when mutual fund *alphas* are analyzed with a t-value of t = 1.94 and $\hat{\beta}^{MomFund} = 0.32$. The other coefficients are not significant at conventional levels, confirming the results of the previous analysis. *CfoFund* does not have a significant impact on future fund *grossreturns*, *netreturns*, and *alphas*.[167] Finally, the results to regression 5.18 where *MomFund* **and** *CfoFund* are included as explaining variables, do not show any benefits from overweighting high cash flow stocks in addition to following the momentum strategy. All four $\hat{\beta}^{CfoFund}$ are far away from being significantly positive. Furthermore, *CfoFund* does not subsume any of the influence of *MomFund* on future fund returns, as all four estimated coefficients $\hat{\beta}^{MomFund}$ are nearly the same as in regression 5.16. This indicates that it is not beneficial to simultaneously strengthen the momentum and the cash flow strategy in this mutual fund sample. Moreover, it underlines that the success of the combination strategy found in Table 5.18 mainly stems from the overweighting of high momentum stocks in the mutual fund combination portfolios.

The results of the multivariate regression 5.21, where I add the control variables presented in section 5.5.2, confirm these conclusions. Table 5.20 lists the results for the strategy variables *MomFund* and *CfoFund*.

[167] Only the t-value for the regression on *abnreturns* denotes statistical significance. Nevertheless, as the t-values of the other three regressions are very low and far away from indicating statistical significance, I do not attach much importance on this single regression.

Table 5.20: Determinants of Mutual Fund Returns Including Control Variables

fund return	$\hat{\alpha}$	$\hat{\beta}^{MomFund}$	$\hat{\beta}^{CfoFund}$	Ø adj R^2
grossreturn	-0.63	0.57 *		33.4
netreturn	-0.76	0.53 *		32.7
abnreturn	-2.85 ^^^	0.42 ^^^		22.2
alpha	-1.97 **	0.33 **		15.8
grossreturn	1.69		0.20	30.2
netreturn	2.13		0.08	30.0
abnreturn	-1.73 ^^		0.22 ^^	17.9
alpha	-0.65		0.12	13.7
grossreturn	-0.75	0.56 *	0.04	37.1
netreturn	-0.03	0.53 *	-0.10	35.8
abnreturn	-3.67 *	0.41 ^^^	0.14	23.9
alpha	-2.08 ^^^	0.35 **	0.01	17.2

*** (**, *, ^^^, ^^) denotes significance at the 1 %- (5 %-, 10 %-, 15 %-, 20 %-) level.

The influences of the strategy variables on future fund returns do not significantly change when I include the control variables. The influence of *MomFund* is still weakly significant. This result also holds, when I additionally insert *CfoFund* in the third regression. *CfoFund*, in contrast, still does not have any significant influence on future *grossreturns*, *netreturns*, and *alpha*. The coefficients neither exhibit significance alone, nor when computed together with *MomFund*. However, the coefficients are with one exception all positive.

To sum up: The effects I find in the regressions of the first block withstand the inclusion of further control variables. They are neither subsumed nor heavily altered by the inclusion of *fundsize*, *cost*, *turnover*, *inflow*, *prevreturn*, or fund investment group.

In Table 5.21, I present the estimated coefficients of the inserted control variables for the regression when both *MomFund* and *CfoFund* are included as explaining variables.[168]

Table 5.21: Further Determinants of Mutual Fund Returns

Panel A: Fund Characteristics

fundreturn	$\hat{\beta}^{fundsize}$	$\hat{\beta}^{cost}$	$\hat{\beta}^{turnover}$	$\hat{\beta}^{inflow}$	$\hat{\beta}^{prevreturn}$
grossreturn	-0.03 ^^^	0.02	0.000	-0.01 ***	0.02 *
netreturn	-0.04 *	-0.18 ***	0.001 ^^	-0.01 ***	0.03 **
abnreturn	-0.01	0.03	0.000	-0.01 ***	0.02 ^^^
alpha	-0.04 ***	-0.22 ***	0.000	-0.01 ***	0.03 ***

168 For the sake of brevity, I only present the results of the third regression. The results for the other two regressions, in which *MomFund* or *CfoFund* is included alone, are qualitatively the same.

Panel B: Fund Objectives

fundreturn	$\hat{\beta}^{SC\&AG}$	$\hat{\beta}^{G}$	$\hat{\beta}^{G\&I}$
grossreturn	1.05 **	0.35 *	-0.20 ^^^
netreturn	1.11 **	0.32 ^^^	-0.31 **
abnreturn	0.68 ***	0.27 *	-0.17 ^^
alpha	0.16	-0.02	-0.07

*** (**, *, ^^^, ^^) denotes significance at the 1 %- (5 %-, 10 %-, 15 %-, 20 %-) level.

In accordance with most previous studies, *fundsize* has a negative influence on fund returns, indicating limited investment ideas and diseconomies of scale for mutual funds. The influence of costs by definition depends on the analyzed fund return variable. In my sample, costs do not have any influence on *grossreturns* and *abnreturns*, which both still include fund costs. This indicates that higher costs are not a sign of better skills of the mutual fund manager. The influence on *netreturn* and *alpha* is significantly negative, underlining that the investors' higher costs do not pay off. The influence of *turnover* on fund returns is negligible. The influence I find for fund *inflow* is consistent with previous literature. Higher inflows significantly decrease fund returns. An increase of inflow by 1 percentage point leads to a slight decrease of quarterly fund returns of about 0.01 percentage points. This relation is significant at the 1 % level and suggests liquidity-motivated trading and that mutual fund managers are short of investment ideas. Also consistent with previous studies, I find short-term persistence in mutual fund returns. The coefficient of *prevreturn* is significantly positive. Moreover, the influences of *prevreturn* and *MomFund* do not subsume each other. Therefore, short-term fund return persistence is not only due to the mutual funds' momentum strategies in my sample. This is different from the findings of Carhart (1997) for the long term and is for instance in line with Ferreira, Miguel, and Ramos (2009).

The results for the investment objective dummies confirm the descriptive statistics in Table 5.14, but now with statistically significant differences between the investment groups. Small Cap & Aggressive Growth funds earn significantly higher returns than Income funds and the same applies to funds with objective Growth. In contrast, Growth & Income funds are slightly less successful than Income funds. Fund *alphas* differ less between the investment groups. This result suggests that the Fama French procedure more adequately corrects for the influences of size and value strategies of mutual funds than the characteristic adjustment in the computation of *netreturn*.

5.6 Decomposition of Mutual Fund Returns

Section 3.3 describes the different characteristics of abnormal returns earned by momentum, cash flow, and combination strategies. Abnormal returns to pure momentum strategies are much more extreme than those to operating cash flow strategies. The combination strategy takes the middle position in terms of abnormal return extremity and succeeds by picking a high ratio of outperforming stocks. In this section, I test whether these characteristics also apply to mutual fund portfolios. Especially I test whether funds most actively following the combination strategy, also exhibit superior stock picking abilities. However, similar to the previous section 0, also this examination has to be judged against the background that actually funds do not tend to extremely tilt their portfolios to high cash flow or combination stocks.

5.6.1 Methodology and Sample

Methodology

The calculation of the ratio of outperforming stocks in a fund portfolio *j* that is picked at the end of quarter *q* $picking_{j,q}$ is similar to that in section 3.3 and described in equation 5.22:

$$picking_{j,q} = \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^{+}_{i,q+1} \qquad 5.22$$

with:

$w_{i,j,q}$ = portfolio weight of stock *i* in fund *j* at the end of quarter *q*

$D^{+}_{i,q+1}$ = Dummy Variable; $D^{+}_{i,q+1} = 1$ if $abnreturn_{i,q+1} > 0$, otherwise $D^{+}_{i,q+1} = 0$

$abnreturn_{i,q+1}$ = abnormal return of stock *i* during quarter *q*+1

For each fund report, I summate the portfolio weights $w_{i,j,q}$ in stocks which outperform in the following quarter *q*+1. The higher the total weight in outperforming stocks, the higher is the stock picking ability $picking_{j,q}$ of fund *j* at the beginning of quarter *q*+1.

The second component of $abnreturn_{j,q+1}$ of fund *j* in quarter *q*+1, is the level of the stocks' out- or underperformance. The mean *abnreturn* of fund *j* in quarter *q*+1 can be computed by using conditional mean positive and negative abnormal returns $abnreturn^{+}_{j,q+1}$ and $abnreturn^{-}_{j,q+1}$ as displayed in equation 5.23.

$$\begin{aligned} abnreturn_{j,q+1} &= \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot abnreturn_{i,q+1} \\ abnreturn_{j,q+1} &= \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^{+}_{i,q+1} \cdot abnreturn_{i,q+1} + \sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot (1 - D^{+}_{i,q+1}) \cdot abnreturn_{i,q+1} \end{aligned} \qquad 5.23$$

$$abnreturn_{j,q+1} = (\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^+_{i,q+1}) \cdot \underbrace{\frac{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^+_{i,q+1} \cdot abnreturn_{i,q+1}}{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot D^+_{i,q+1}}}_{abnreturn^+_{j,q+1}}$$

$$+(\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot (1-D^+_{i,q+1})) \cdot \underbrace{\frac{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot (1-D^+_{i,q+1}) \cdot abnreturn_{i,q+1}}{\sum_{i=1}^{N_{j,q}} w_{i,j,q} \cdot (1-D^+_{i,q+1})}}_{abnreturn^-_{j,q+1}}$$

$$abnreturn_{j,q+1} = picking_{j,q} \cdot abnreturn^+_{j,q+1} + (1-picking_{j,q}) \cdot abnreturn^-_{j,q+1}$$

with:

$abnreturn_{j,q+1}$	=	abnormal return of fund *j* during quarter *q*+1
$abnreturn^{+(-)}_{j,q+1}$	=	mean positive (negative) abnormal return of fund *j* in quarter *q*+1

I use $picking_{j,q}$ to measure the fund managers' ability to choose outperforming stocks. In order to test whether the strategies increase the stock picking ability, I conduct the same regressions as presented in equations 5.16 to 5.18, only using $picking_{j,q}$ as dependent variable instead of fund returns. Furthermore, I also control for potential other influencing factors. As the influencing factors on stock picking have − to my knowledge − not been investigated yet, there are no widely acknowledged control variables at hand. Stock picking and fund performance are closely related. Accordingly, I assume that the factors influencing fund returns also have a potential influence on $picking_{j,q}$ and include the same control variables as in regression 5.21, namely *fundsize*, *cost*, *turnover*, *inflow*, *prevreturn*, and dummies representing the mutual fund investment groups.

I also analyze the strategies' influence on mean positive and negative abnormal returns by choosing $abnreturn^+_{j,q+1}$ and $abnreturn^-_{j,q+1}$ as dependent variables in the regressions. Mean positive abnormal returns $abnreturn^+_{j,q+1}$ are those returns that would have been earned on average if the fund had exclusively held outperforming stocks. Mean negative abnormal returns $abnreturn^-_{j,q+1}$ are the abnormal returns that would have been earned if the fund had had a picking rate of $picking_{j,q} = 0$ %.

Equation 5.24 summarizes the conducted regressions.[169]

$$\begin{aligned} z_{j,q(+1)} = {} & \alpha_q + \beta_q^{Strategy} \cdot Strategy_{j,q} + \beta_q^{fundsize} \cdot fundsize_{j,q} + \beta_q^{cost} \cdot cost_{j,q} \\ & + \beta_q^{turnover} \cdot turnover_{j,q} + \beta_q^{inflow} \cdot inflow_{j,q} + \beta_q^{prevreturn} \cdot prevreturn_{j,q} \\ & + \beta_q^{SC\&AG} \cdot D_{j,q}^{SC\&AG} + \beta_q^{G} \cdot D_{j,q}^{G} + \beta_q^{G\&I} \cdot D_{j,q}^{G\&I} + \varepsilon_{j,q(+1)} \end{aligned} \qquad 5.24$$

with:
$z = picking_{j,q}, abnreturn^{+}_{j,q+1}$, or $abnreturn^{-}_{j,q+1}$

and all other variables as described in detail in section 5.5.1.

Sample

Table 5.22 lists mean picking rates and positive and negative abnormal returns of the whole sample and by mutual fund objective.

Table 5.22: Picking Rates and Abnormal Returns by Fund Objective

	n	Ø *picking* [%]	Ø *abnreturn*$^{+}$ [% p.q.]	Ø *abnreturn*$^{-}$ [% p.q.]
Small Cap & Aggressive Growth (SC&AG)	9,741	49.27	17.31	-16.14
Growth (G)	16,227	49.38	12.73	-12.33
Growth & Income (G&I)	1,894	48.49	9.94	-9.96
Income (I)	8,516	49.10	10.82	-10.69
Whole Sample	36,378	49.16	13.11	-12.63

The mean picking rate is slightly below 50 % with a value of 49.16 %. Small Cap & Aggressive Growth funds hold the most extreme stocks which yield the largest positive and negative abnormal returns of on average 17.31 % and -16.14 % p.q. Growth & Income funds, in contrast, exhibit the lowest return dispersion with mean *abnreturn*$^{+}$ = 9.94 % and mean *abnreturn*$^{-}$ = -9.96 % p.q. and they also have the lowest picking rate of 48.49 %.

5.6.2 Empirical Results and Discussion

Despite the low dispersion in *CfoFund*, the results of regression 5.24 reveal a significantly positive influence of *CfoFund* on *picking*, as listed in Table 5.23.

[169] Note that even though $picking_{j,q}$ has the subscript q, it is not determined before quarter q+1 since it depends on the abnormal returns during quarter q+1. Accordingly $picking_{j,q}$ is determined after the explaining variables so that the causal relation should be in the right direction.

Table 5.23: Determinants of Fund Performance Components

z	$\hat{\alpha}$		$\hat{\beta}^{MomFund}$		$\hat{\beta}^{CfoFund}$		Ø adj. R^2
picking	42.53	***	0.88	*			19.4
abnreturn$^+$	8.37	***	0.43	^^^			36.3
abnreturn$^-$	-9.38	***	-0.18				39.9
picking	40.01	***			1.20	***	16.7
abnreturn$^+$	17.24	***			-1.02	***	34.2
abnreturn$^-$	-15.13	***			0.77	***	37.7
picking	36.43	***	0.73	^^^	1.05	***	21.5
abnreturn$^+$	14.88	***	0.63	**	-1.12	***	38.7
abnreturn$^-$	-14.26	***	-0.34	*	0.84	***	41.9

*** (**, *, ^^^) denotes significance at the 1 %- (5 %-, 10 %-, 15 %-) level.

A more intense pursuit of both strategies leads to significantly greater picking rates. An increase of *MomFund* by 1 increases *picking* by 0.88 percentage points. The influence of *CfoFund* is higher, with an increase of 1.20 percentage points in *picking* per unit *CfoFund*. The benefits of using both criteria in a combination strategy can be seen in the third regression: Holding *CfoFund* constant, an increase of *MomFund* by 1 still raises the picking rate by 0.73 percentage points. The intensification of the cash flow strategy by one for a given level of *MomFund* increases *picking* by 1.05 percentage points. These results are in line with the conclusions drawn from the artificially constructed portfolios in section 3.3: The usage of both criteria, past returns and operating cash flows, enables managers to pick outperforming stocks, this time despite the low dispersion of *CfoFund*.

Before turning to the regression coefficients on conditional returns, I shortly review the results of the artificially constructed portfolios in section 3.4. There, the momentum strategy was the most extreme strategy, yielding the highest positive and negative abnormal returns, whereas the cash flow strategy had significantly lower positive and less negative abnormal returns. The combination strategy took the middle position, avoiding extreme returns due to the cash flow criterion while earning high returns based on the momentum criterion. This constellation in conjunction with the greater picking ability led to higher returns to the combination strategy.

When I now analyze mutual fund portfolios, I find similar results but with a different outcome: Again, high cash flow stocks avoid stocks that yield extreme returns. The higher the value of *CfoFund*, the lower the mean positive abnormal returns ($\hat{\beta}^{CfoFund} < 0$, when $z = abnret^{+}_{j,q+1}$) and the less extreme the negative abnormal returns ($\hat{\beta}^{CfoFund} > 0$, when $z = abnret^{-}_{j,q+1}$). In contrast, an increase in *MomFund* leads to significantly higher positive abnormal returns ($\hat{\beta}^{MomFund} > 0,$ when $z = abnreturn^{+}_{j,q+1}$). This means that the pure momentum strategy succeeds in picking highly outperforming stocks. Moreover, fund managers seem to be quite successful in avoiding highly underperforming stocks when following the momentum strategy, as $\hat{\beta}^{MomFund}$ takes on a fairly low value of -0.34 for *MomFund* when $z = abnret^{-}_{j,q+1}$. The same results apply to the third regression, which includes *MomFund* and *CfoFund* at the same time. All in all, the fact that the momentum strategy is worse able to pick stocks but at the same time yields higher conditional returns makes it more successful than the combination strategy. This final outcome for mutual fund portfolios and returns differs from that of the artificially constructed portfolios in section 3.3.

The influences of the control variables on *picking*, *abnreturn*$^{+}$, and *abnreturn*$^{-}$ are presented in Table 5.24. I list the results of the third regressions, which include *MomFund* and *CfoFund* and exhibit the highest adjusted R^2.

Table 5.24: Further Determinants of Fund Performance Components

z	$\hat{\beta}^{fundsize}$	$\hat{\beta}^{cost}$	$\hat{\beta}^{turnover}$	$\hat{\beta}^{inflow}$	$\hat{\beta}^{prevreturn}$
picking	0.03	0.08	0.001	-0.02 ***	0.03 ^^^
abnreturn^{+}	-0.11 ***	0.27 ***	0.003 ***	-0.01 ***	0.00
abnreturn^{-}	0.05 ***	-0.26 ***	-0.003 ***	0.00	0.00

z	$\hat{\beta}^{SC\&AG}$	$\hat{\beta}^{G}$	$\hat{\beta}^{G\&I}$
picking	0.88 ^^^	0.54 ^^^	-0.498 ^^
abnreturn^{+}	4.36 ***	1.29 ***	-0.818 ***
abnreturn^{-}	-3.38 ***	-1.00 ***	0.561 ***

*** (**, *, ^^^, ^^) denotes significance at the 1 %- (5 %-, 10 %-, 15 %-, 20 %-) level.

The stock picking ability only depends on *inflow*, previous returns *prevreturn*, and the investment objective. A high inflow in the previous quarter lessens the stock picking ability in the following quarter. This fits the explanation that limited investment ideas of mutual fund managers and liquidity motivated trading play an important role. A higher *prevreturn* increases the ratio of outperforming stocks, indicating short-term persistence in the skill of mutual fund managers. Finally, growth-oriented fund managers seem to have greater stock picking abilities than those of Income funds.

Mean positive and negative abnormal returns depend on *fundsize*, *cost*, *turnover*, and investment objective. Bigger *fundsize* causes lower positive and higher negative abnormal returns. The higher negative coefficient on *abnreturn*$^{+}$ explains the negative impact on total *abnreturn*, listed in Table 5.21. Fund *cost* and *turnover* affect returns inversely. They increase positive and decrease negative abnormal returns, adding to the dispersion of returns. These opposing influences explain the insignificant influence on *abnreturns* found in regression 5.21 and listed in Table 5.21. The coefficients of the dummy variables for the investment objectives confirm the first impression of the descriptive statistics in Table 5.22. Funds with objective Small Cap & Aggressive Growth and Growth exhibit a higher difference between positive and negative abnormal returns than funds with objective Income, as indicated by the positive coefficients on *abnreturn*$^+$ and the negative for *abnreturn*$^-$. In contrast, the negative coefficient for *abnreturn*$^+$ and the positive one for *abnreturn*$^-$ in the case of Growth & Income funds reflect the lower dispersion of returns in this group.

5.7 Summary and Conclusion

The main aspects I analyze in my investigation of mutual fund portfolios and returns are mutual fund investment behavior and determinants of their performance. Furthermore, my analysis allows conclusions regarding the practicability and persistence of anomaly based trading. My empirical results lead to the following conclusions:

Concerning mutual fund investment behavior, I find that mutual funds tend to concentrate on the same stocks. They prefer stocks which can be traded easily and at low cost. Only 14.3 % of the stocks in my sample are held by at least 3 % of the mutual funds. Phrased the other way around: 85.7 % of the stock universe is only held by less than 3 % of the mutual funds. Second, I find that mutual fund managers follow momentum strategies. On average, they tend to hold stocks with high past returns and actively trade to maintain their positions in high momentum stocks. When comparing the strategies of different funds, I find a considerable dispersion in their degree of following the momentum strategy. In contrast, fund managers on average do not tilt their portfolios to high operating cash flow stocks. Funds holding stocks with high operating cash flows do not seem to do so intentionally, as they do not trade to maintain these positions. Furthermore, funds do not considerably differ in their degree of following the operating cash flow strategy. The pursuit of the combination strategy I measure is more heavily influenced by the pursuit of the momentum than of the operating cash flow strategy. Moreover, it is only moderately followed by mutual funds. The dispersion of the pursuit of the combination strategy between single funds is low.

Regarding mutual fund performance, I find that pursuing the momentum strategy significantly increases fund returns. Such an influence cannot be confirmed for the operating cash flow and the combination strategy. This may be explained by the facts that the cash flow strategy is only weakly followed by mutual funds, that funds do not differ enough in their cash flow strategies, and that managers do not actively trade to maintain their high cash flow positions. Pursuing the combination strategy only increases fund returns slightly and this relation is mainly driven by the pursuit of the momentum strategy. A decomposition of fund returns allows for further insights. Here, high past returns and high operating cash flows both significantly contribute to the ability to pick outperforming stocks. Moreover, high operating cash flow stocks level off the extremes of mutual fund returns.

On the question of market anomalies, I draw the following conclusions:

I do not find extreme realizations of any of the three investigated anomaly-based strategies which would prove their implementability. However, the implementability is not disproved either, as the absence of such extreme strategies could be either due to restrictions or just because fund managers do not want to follow the strategies in an extreme manner. Concerning the success after actual trading costs, I find that momentum profits are sufficient to cover transaction costs. Results for the combination strategy are weaker. My fund sample and results do not allow conclusions regarding the operating cash flow strategy. Concerning the puzzle about anomaly persistence, it can be said that fund managers do not trade on the cash flow anomaly. As they account for a big group of professional investors, this could contribute to its persistence. The reason for the persistence of the momentum effect seems to be the opposite. As mutual funds actively buy high momentum stocks, the herding into these stocks could fuel the initial momentum effect. Similarly, funds sell low momentum stocks, which might fortify their downward trend.

6 Concluding Remarks

6.1 Summary of Results

Throughout this thesis, I investigate different aspects of combining fundamental and technical information in trading strategies. I demonstrate the benefits of combining these two types of information in one trading strategy and analyze the market reactions that cause these benefits. I furthermore examine if professional investors pursue the strategies – separately or in combination – and whether they are more successful if they do so. In my analysis, I use past returns and operating cash flows as examples for technical and fundamental information.

In chapter 2, I first present the basics of the efficiency of markets and fundamental and technical trading. In addition, I discuss the potential of combining these two types of trading. Such a combination is central in the empirical investigations of the following chapters 3 to 5. These investigations provide the following insights:

In chapter 3, I address the first research question, which is: "*Is trading based on technical and fundamental information more profitable than trading based on only one of the two types of information?*" For this purpose, I implement a trading strategy that invests in stocks which exhibit high past returns and high operating cash flows at the same time. The empirical analysis shows that combining these two signals is significantly more profitable than using one of the two signals alone. The higher investment returns of the combination strategy are due to a greater probability of picking outperforming stocks when using both signals. Accordingly, high operating cash flows seem to indicate that past price upturns will continue. In addition, the combination of the two signals enables investors to pick stocks with highest future profitability, since the stocks with high past returns and high operating cash flows will also earn the highest operating cash flows in the future. The outperformance of the combination strategy is extremely stable and is not eroded when transaction costs are included. Lastly, it cannot be explained by other factors that are known to predict future returns, as, for example, accruals, earnings surprises, or idiosyncratic risk. For academics, this result indicates that future return prediction models should include both indicators – past returns and operating cash flows. Moreover, I show that the two types of information contain different characteristics, since stocks with high past returns yield more extreme future returns than high cash flow stocks. These differences between the two types of information suggest that future research on their differences and interaction might be fruitful. In practice, investors may be interested in implementing the specific momentum/cash flow combination trading strategy. This should be possible, since I do not find any obstacles to a successful implementation. All in all, the answer to the first research question is:

"*Yes*, *trading based on technical past return* ***and*** *on fundamental operating cash flow information is more profitable than trading on one of the two characteristics alone*."

In chapter 4, I analyze the second research question: "*What kind of market (mis)behavior leads to the profitability of technical and fundamental strategies and of a strategy that combines both types of information?*" In order to answer this question, I conduct several investigations to figure out whether the abnormal returns earned by the momentum, cash flow, and combination strategies are more probably due to a too strong or to a too weak market reaction. Namely, I investigate the short-term return development, returns during earnings announcements, the influence of investor attention, and the long-term return development. The tests lead to similar conclusions. In particular, I find mixed results for the momentum effect and only weak indicators that underreaction might be the cause for the cash flow effect when analyzing the effects in total. A further separate examination of the long and short portfolios allows for further insights. My results for the long portfolios suggest that the positive abnormal returns earned by high cash flow stocks as well as by stocks that have both high past returns and high cash flows are due to an initial market underreaction. For stocks with high past returns, the tests also indicate underreaction, but the results are slightly weaker. In contrast, the abnormal negative returns to stocks with low past returns as well as to stocks with both low past returns and low operating cash flows seem to be due to market reactions that are too strong. The results for all low cash flow stocks also indicate initial overreaction as underlying reason, but they are weaker than the results for the other two short portfolios. All in all, my answer to research question two is:

"*Market participants initially underreact to good news, whereas they overreact to bad news. These inadequate reactions lead to positive abnormal returns of stocks with high past returns and/or high operating cash flows and to negative abnormal returns of stocks with low past returns and/or low operating cash flows*."

This result signifies in particular that further research should not only focus on the whole anomalous effects when investigating market reactions. It should rather analyze long and short portfolios separately, since my results suggest that there are different effects at work in these portfolios.

I address the third research question in chapter 5. The third research question is: "*Do professional investors trade on technical or fundamental information or both and are they successful if they do so?*" Again, I focus on the momentum, operating cash flow, and combination strategies, which are central in my thesis. Additionally, I use mutual fund portfolio holdings as well as portfolio changes. To decide on the strategies' success, I utilize mutual fund returns. I find that institutional investors, namely mutual fund managers, trade on the momentum effect. These trades are rewarded by higher fund returns. However, fund managers do not choose high cash flow stocks when building their portfolios. Since cash flow strategies are not pursued by funds, my mutual fund investigation cannot draw any conclusion about their profitability. The results for the combination strategy lie in between. They indicate weak pursuit and success of the combination strategy, which largely stem from high momentum stocks. However, high cash flow stocks in mutual fund portfolios at least increase the ratio of outperforming stocks. All in all, my answer to the third research question is:

"*Mutual fund managers follow technical momentum strategies successfully. In contrast, they only weakly pursue a strategy that combines technical momentum and fundamental operating cash flow information and this combination strategy only yields little success. A purely fundamental cash flow strategy is not pursued by mutual funds at all.*"

The finding that this important group of professional investors does not excessively buy high cash flow stocks could be one reason for the persistence of the cash flow anomaly. Moreover, it could encourage investors in practice to pay more attention to operating cash flows when taking their investment decisions.

6.2 Limitations and Propositions for Future Research

My examinations offer a wide range of important insights, but they are also subject to some limitations. These limitations, on the other hand, offer possibilities for future research.

The main limitation of chapter 3 is that I analyze a simulated trading strategy. Even though I have addressed numerous possible obstacles to implementing the strategy, one can never be sure that no other limitation impedes the implementation. The finding of chapter 5 that fund managers do not excessively buy high cash flow stocks suggests, for instance, that there might be some reasons for not buying them. In this regard, future research could conduct surveys, asking professional investors why they do not buy high cash flow stocks. In addition, other future research opportunities arise out of my analysis. One question is whether the stocks in the combination portfolio have one or several other characteristics in common which could be the reason for their high profits. Moreover, it would be interesting to know whether cash flow information is especially helpful for improving the momentum strategy in certain industries.

Chapter 4 is subject to the most severe limitations, since I address the most difficult question in this chapter. I do not prove over- or underreaction in chapter 4, but I find several indicators that suggest my conclusions. Moreover, the different tests lead to similar conclusions supporting my findings. Proof is extremely difficult to find, since data about how investors think and about their reasons to trade are not easily available. Anyhow, future research could conduct further additional investigations of the momentum and/or cash flow effect or the same analyses for other fundamental and technical strategies and reveal whether these lead to the same conclusions. However, even if over- and/or underreaction could be unambiguously proven, a new question would emerge. Namely, it would be interesting to know **why** market participants over- or underreact to certain types of information. This question is even more challenging and provides a wide range of future research opportunities. Lastly, an unobserved risk factor could be the underlying reason for the success of the combination strategy. In this regard, future research will probably develop new procedures to adjust stock returns for the risks the stocks bear. These new procedures should then be used to retest whether the abnormal returns I find are indeed due to market mispricing or whether they are in truth due to higher risks. In any event, future studies on this topic should investigate the long and short positions separately when trying to explain the profits of anomaly-based trading strategies.

One limitation of the investigation of mutual fund portfolios and returns in chapter 5 is that the assignment of portfolio holdings to portfolio returns is far from perfect. I only have information about mutual fund portfolios at the end of a quarter which I assign to the fund returns earned in the following three months. During these months, the fund manager may already have changed his portfolio, making the assignment obsolete. In this regard, the available databases will certainly improve in the future so that they will make a more precise assignment of fund portfolio holdings to the corresponding fund return possible. Another weakness of chapter 5 is that I do not exactly measure the strength of mutual funds' combination strategies. I rather measure to what extent funds follow momentum and cash flow strategies at the same time. This results in a stronger dependence of the measured combination strategy on momentum than on cash flows due to the higher dispersion of mutual funds' momentum strategies. This higher dependence on momentum, in turn, complicates inferences about the combination. Furthermore, I do not draw conclusions about the reasons why fund managers do not excessively buy high cash flow stocks. On the one hand, they might simply miss profit opportunities, but on the other, they might also have reasons for this decision. As already pointed out, a survey could explain their motives.

One last limitation applies to all three investigations. In my whole thesis, I investigate the combination of high momentum and high cash flow stocks. For this reason, my conclusions do not necessarily apply to all technical and fundamental trading strategies. In this regard, future research can additionally analyze other technical and fundamental trading strategies and assess whether my conclusions also hold for them. So far, I can conclude that past returns and operating cash flows include different information. Therefore, both information should be used when evaluating and trading stocks. Trading strategies that use both sources of information are more profitable, mostly because the market underreacts to good and overreacts to bad news. Professional investors, however, seem to concentrate only on past return information and less on information about operating cash flows. They could benefit by using both sources of information.

References

Abarbanell, Jeffery S. and Brian J. Bushee. 1998. Abnormal Returns to a Fundamental Analysis Strategy. *The Accounting Review* 73 (1): 19-45.

Alexander, Gordon J., Gjergji Cici, and Scott Gibson. 2007. Does Motivation Matter When Assessing Trade Performance? An Analysis of Mutual Funds. *Review of Financial Studies* 20 (1): 125-150.

Alexander, Gordon J., William F. Sharpe, and Jeffery V. Bailey. 2001. Fundamentals of Investments. 3rd edition. Upper Saddle River, New Jersey: Prentice Hall.

Ali, Ashiq, Xuanjuan Chen, Tong Yao, and Tong Yu. 2008. Do Mutual Funds Profit from the Accruals Anomaly? *Journal of Accounting Research* 46 (1): 1-26.

---. 2008. Profiting from the Post Earnings Announcement Drift: Mutual Fund Trades, Market Frictions, and Market Efficiency. *Working Paper*. School of Management, University of Texas at Dallas. http://ssrn.com/abstract=1108717. Accessed: 4th October 2009.

Almazan, Andres, Keith C. Brown, Murray Carlson, and David A. Chapman. 2004. Why Constrain Your Mutual Fund Manager? *Journal of Financial Economics* 73 (2): 289-321.

Amihud, Yakov. 2002. Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets* 5 (1): 31-56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. 2006. The Cross-Section of Volatility and Expected Returns. *Journal of Finance* 61 (1): 259-299.

---. 2009. High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence. *Journal of Financial Economics* 91 (1): 1-23.

Atkinson, Stanley M., Samantha B. Baird, and Melissa B. Frye. 2003. Do Female Mutual Fund Managers Manage Differently? *Journal of Financial Research* 26 (1): 1-18.

Baks, Klaas P. 2003. On the Performance of Mutual Fund Managers. *Working Paper*. Goizueta Business School, Emory University at Atlanta. http://www.goizueta.emory.edu/faculty/KlaasBaks/Documents/manager_000.pdf. Accessed: 14th December 2009.

Ball, Ray and Philip Brown. 1968. An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research* 6 (2): 159-178.

Ball, Ray and S. P. Kothari. 1991. Security Returns Around Earnings Announcements. *The Accounting Review* 66 (4): 718-738.

Banz, Rolf W. 1981. The Relationship Between Return and Market Value of Common Stocks. *Journal of Financial Economics* 9 (1): 3-18.

Bär, Michaela, Alexander Kempf, and Stefan Ruenzi. 2005. Team Management and Mutual Funds. *Working Paper*. Graduate School of Risk Management, University of Cologne. http://www.cfr-cologne.de/download/workingpaper/cfr-05-10.pdf. Accessed: 1st October 2009.

Bär, Michaela, Alexandra Niessen, and Stefan Ruenzi. 2007. The Impact of Work Group Diversity on Performance: Large Sample Evidence from the Mutual Fund Industry. *Working Paper*. Centre for Financial Research, University of Cologne and University of Mannheim. http://www.cfr-cologne.de/download/workingpaper/cfr-07-16.pdf. Accessed: 14th December 2009.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny. 1998. A Model of Investor Sentiment. *Journal of Financial Economics* 49 (3): 307-343.

Barberis, Nicholas and Richard H. Thaler. 2003. A Survey of Behavioral Finance. In: *Handbook of the Economics of Finance*, ed. George M. Constantinides, Milton Harris, and René M. Stulz, Vol. 1, Part 2:1053-1128. Amsterdam: Elsevier.

Barone, Gerhard J. and Matthew J. Magilke. 2009. An Examination of the Effects of Investor Sophistication on the Pricing of Accruals and Cash Flows. *Journal of Accounting, Auditing & Finance* 24 (3): 385-414.

Bartov, Eli, Suresh Radhakrishnan, and Itzhak Krinsky. 2000. Investor Sophistication and Patterns in Stock Returns After Earnings Announcements. *The Accounting Review* 75 (1): 43-63.

Basu, Sudipta. 1997. The Conservatism Principle and the Asymmetric Timeliness of Earnings. *Journal of Accounting and Economics* 24 (1): 3-37.

Beaver, William H., Maureen McNichols, and Richard Price. 2007. Delisting Returns and Their Effect on Accounting-Based Market Anomalies. *Journal of Accounting and Economics* 43 (2/3): 341-368.

Berk, Jonathan B. and Richard C. Green. 2004. Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy* 112 (6): 1269-1295.

Bernard, Victor L. and Jacob K. Thomas. 1989. Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? *Journal of Accounting Research* 27 (Supplement): 1-36.

---. 1990. Evidence That Stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings. *Journal of Accounting and Economics* 13 (4): 305-340.

Bernard, Victor L., Jacob K. Thomas, and James Wahlen. 1997. Accounting-Based Stock Price Anomalies: Separating Market Inefficiencies from Risk. *Contemporary Accounting Research* 14 (2): 89-136.

Bettman, Jenni L., Stephen J. Sault, and Emma L. Schultz. 2009. Fundamental and Technical Analysis: Substitutes or Complements? *Accounting and Finance* 49 (1): 21-36.

Bliss, Richard T. and Mark E. Potter. 2002. Mutual Fund Managers: Does Gender Matter? *Journal of Business and Economic Studies* 8 (1): 1-15.

Bollen, Nicolas P. B. and Jeffrey A. Busse. 2005. Short-Term Persistence in Mutual Fund Performance. *Review of Financial Studies* 18 (2): 569-597.

Bonenkamp, Ute, Carsten Homburg, and Alexander Kempf. 2009. Fundamental Information in Technical Trading Strategies. University of Cologne. http://www.cfr-cologne.de/download/workingpaper/cfr-08-12.pdf. Accessed: 19th December 2009.

Brock, William, Josef Lakonishok, and Blake LeBaron. 1992. Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *Journal of Finance* 47 (5): 1731-1764.

Brown, Stephen J., William Goetzmann, Roger G. Ibbotson, and Stephen A. Ross. 1992. Survivorship Bias in Performance Studies. *Review of Financial Studies* 5 (4): 553-580.

Brown, Stephen J. and William N. Goetzmann. 1995. Performance Persistence. *Journal of Finance* 50 (2): 679-698.

Bushee, Brian J. and Jana Smith Raedy. 2006. Factors Affecting the Implementability of Stock Market Trading Strategies. *Working Paper*. The Wharton School, University of Pennsylvania. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=384500. Accessed: 14th December 2009.

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay. 1997. The Econometrics of Financial Markets. Princeton, New Jersey: Princeton University Press.

Carhart, Mark M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* 52 (1): 57-82.

Chambers, Anne E. and Stephen H. Penman. 1984. Timeliness of Reporting and the Stock Price Reaction to Earnings Announcements. *Journal of Accounting Research* 22 (1): 21-47.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok. 1996. Momentum Strategies. *Journal of Finance* 51 (5): 1681-1713.

Chari, Varadarajan V., Ravi Jagannathan, and Aharon R. Ofer. 1988. Seasonalities in Security Returns: The Case of Earnings Announcements. *Journal of Financial Economics* 21 (1): 101-121.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey D. Kubik. 2004. Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization. *American Economic Review* 94 (5): 1276-1302.

Chen, Joseph, Harrison Hong, and Jeremy C. Stein. 2002. Breadth of Ownership and Stock Returns. *Journal of Financial Economics* 66 (2/3): 171-205.

Chevalier, Judith and Glenn Ellison. 1999. Are Some Mutual Fund Managers Better Than Others? Cross-Sectional Patterns in Behavior and Performance. *Journal of Finance* 54 (3): 875-899.

Chopra, Navin, Josef Lakonishok, and Jay R. Ritter. 1992. Measuring Abnormal Performance: Do Stocks Overreact? *Journal of Financial Economics* 31 (2): 235-268.

Chordia, Tarun and Lakshmanan Shivakumar. 2002. Momentum, Business Cycle, and Time-Varying Expected Returns. *Journal of Finance* 57 (2): 985-1019.

---. 2006. Earnings and Price Momentum. *Journal of Financial Economics* 80 (3): 627-656.

Chui, Andy C. W., Sheridan Titman, and K. C. John Wei. 2000. Momentum, Legal Systems and Ownership Structure: An Analysis of Asian Stock Markets. *Working Paper*. Hong Kong Polytechnic University. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=265848. Accessed: 16th September 2009.

Collins, Daniel W. and Paul Hribar. 2000. Earnings-Based and Accrual-Based Market Anomalies: One Effect or Two? *Journal of Accounting and Economics* 29 (1): 101-123.

Cooper, Michael J., Roberto C. Gutierrez Jr., and Allaudeen Hameed. 2004. Market States and Momentum. *Journal of Finance* 59 (3): 1345-1365.

Damodaran, Aswath. 2003. Investment Philosophies: Successful Strategies and the Investors Who Made Them Work. New York: John Wiley & Sons.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers. 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. *Journal of Finance* 52 (3): 1035-1058.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. 1998. Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance* 53 (6): 1839-1885.

Daniel, Kent and Sheridan Titman. 1997. Evidence on the Characteristics of Cross Sectional Variation in Stock Returns. *Journal of Finance* 52 (1): 1-33.

De Bondt, Werner F. M. and Richard H. Thaler. 1985. Does the Stock Market Overreact? *Journal of Finance* 40 (3): 793-805.

---. 1987. Further Evidence on Investor Overreaction and Stock Market Seasonality. *Journal of Finance* 42 (3): 557-581.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann. 1990. Positive Feedback Investment Strategies and Destabilizing Rational Speculation. *Journal of Finance* 45 (2): 379-395.

Dechow, Patricia M. 1994. Accounting Earnings and Cash Flows As Measures of Firm Performance: The Role of Accounting Accruals. *Journal of Accounting and Economics* 18 (1): 3-42.

Dechow, Patricia M. and Ilia D. Dichev. 2002. The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors. *The Accounting Review* 77 (4): 35-59.

Dechow, Patricia M., Scott A. Richardson, and Richard G. Sloan. 2008. The Persistence and Pricing of the Cash Component of Earnings. *Journal of Accounting Research* 46 (3): 537-566.

Dechow, Patricia M., Richard G. Sloan, and Amy P. Sweeney. 1995. Detecting Earnings Management. *The Accounting Review* 70 (2): 193-225.

Drake, Michael S., James N. Myers, and Linda A. Myers. 2009. Disclosure Quality and the Mispricing of Accruals and Cash Flow. *Journal of Accounting, Auditing & Finance* 24 (3): 355-385.

Droms, William G. and David A. Walker. 1996. Mutual Fund Investment Performance. *The Quarterly Review of Economics and Finance* 36 (3): 347-363.

Drukarczyk, Jochen and Andreas Schüler. 2007. Unternehmensbewertung. 5th edition. München: Vahlen.

Easton, Peter D. and Mark E. Zmijewski. 1993. SEC Form 10K/10Q Reports and Annual Reports to Shareholders: Reporting Lags and Squared Market Model Prediction Errors. *Journal of Accounting Research* 31 (1): 113-129.

Edelen, Roger M. 1999. Investor Flows and the Assessed Performance of Open-End Mutual Funds. *Journal of Financial Economics* 53 (3): 439-466.

Edwards, Robert D., John Magee, and W.H.C. Bassetti. 2007. Technical Analysis of Stock Trends. 9th edition. Boca Raton, Florida et al.: CRC Press.

Edwards, W. 1968. Conservatism in Human Information Processing. In: *Formal Representation of Human Judgment*, ed. Benjamin Kleinmutz. New York: Wiley.

Elton, Edwin J., Martin J. Gruber, Sanjiv Das, and Matthew Hlavka. 1993. Efficiency with Costly Information: A Reinterpretation of Evidence from Managed Portfolios. *Review of Financial Studies* 6 (1): 1-22.

Falkenstein, Eric G. 1996. Preferences for Stock Characteristics As Revealed by Mutual Fund Portfolio Holdings. *Journal of Finance* 51 (1): 111-135.

Fama, Eugene F. 1963. Mandelbrot and the Stable Paretian Hypothesis. *Journal of Business* 36 (4): 420-429.

---. 1965. The Behavior of Stock-Market Prices. *Journal of Business* 38 (1): 34-105.

---. 1965. Random Walks in Stock Market Prices. *Financial Analysts Journal* 21 (5): 55-59.

---. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance* 25 (2): 383-417.

---. 1991. Efficient Capital Markets II. *Journal of Finance* 46 (5): 1575-1617.

---. 1998. Market Efficiency, Long-Term Returns and Behavioral Finance. *Journal of Financial Economics* 49 (3): 283-306.

Fama, Eugene F. and Marshall E. Blume. 1966. Filter Rules and Stock-Market Trading. *Journal of Business* 39 (1): 226-241.

Fama, Eugene F. and Kenneth R. French. 1992. The Cross-Section of Expected Stock Returns. *Journal of Finance* 47 (2): 427-465.

---. 2008. Dissecting Anomalies. *Journal of Finance* 63 (4): 1653-1678.

Fama, Eugene F. and James D. MacBeth. 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81 (3): 607-636.

Ferreira, Miguel A., António F. Miguel, and Sofia B. Ramos. 2009. The Determinants of Mutual Fund Performance: A Cross-Country Study. *Working Paper*. ISCTE Business School, Universitario de Lisboa. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=947098&rec=1&srcabs=75871. Accessed: 15th December 2009.

Figelman, Ilya. 2007. Interaction of Stock Return Momentum with Earnings Measures. *Financial Analysts Journal* 63 (3): 71-78.

Frankel, Richard and Charles M. C. Lee. 1998. Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns. *Journal of Accounting and Economics* 25 (3): 283-319.

Fu, Fangjian. 2009. Idiosyncratic Risk and the Cross-Section of Expected Stock Returns. *Journal of Financial Economics* 91 (1): 24-37.

Gibbons, Michael R. and Patrick Hess. 1981. Day of the Week Effects and Asset Returns. *Journal of Business* 54 (4): 579-596.

Givoly, Dan and Dan Palmon. 1985. Insider Trading and the Exploitation of Inside Information: Some Empirical Evidence. *Journal of Business* 58 (1): 69-87.

Golec, Joseph H. 1996. The Effects of Mutual Fund Managers' Characteristics on Their Portfolio Performance, Risk and Fees. *Financial Services Review* 5 (2): 133-148.

Gottesman, Aron A. and Matthew R. Morey. 2006. Manager Education and Mutual Fund Performance. *Journal of Empirical Finance* 13 (2): 145-182.

Graham, Benjamin and David L. Dodd. 1934. Security Analysis: Principles and Techniques. New York et al.: Mc Graw Hill.

Griffin, Dale and Amos Tversky. 1992. The Weighing of Evidence and the Determinants of Confidence. *Cognitive Psychology* 24 (3): 411-435.

Grinblatt, Mark S., Ronald W. Masulis, and Sheridan Titman. 1984. The Valuation Effects of Stock Splits and Stock Dividends. *Journal of Financial Economics* 13 (4): 461-490.

Grinblatt, Mark S. and Sheridan Titman. 1994. A Study of Monthly Mutual Fund Returns and Performance Evaluation Techniques. *Journal of Financial and Quantitative Analysis* 29 (3): 419-444.

Grinblatt, Mark S., Sheridan Titman, and Russ Wermers. 1995. Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior. *American Economic Review* 85 (5): 1088-1105.

Grossman, Sanford J. and Joseph E. Stiglitz. 1980. On the Impossibility of Informationally Efficient Markets. *American Economic Review* 70 (3): 393-408.

Hackel, Kenneth S., Joshua Livnat, and Atul Rai. 2000. A Free Cash Flow Investment Anomaly. *Journal of Accounting, Auditing & Finance* 15 (1): 1-24.

Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser. 1993. Hot Hands in Mutual Funds: Short-Run Persistence of Relative Performance, 1974-1988. *Journal of Finance* 48 (1): 93-130.

Holthausen, Robert W. and David F. Larcker. 1992. The Prediction of Stock Returns Using Financial Statement Information. *Journal of Accounting and Economics* 15 (2/3): 373-411.

Hong, Harrison and Jeremy C. Stein. 1999. A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *Journal of Finance* 54 (6): 2143-2184.

Hou, Kewei, Lin Peng, and Wei Xiong. 2009. A Tale of Two Anomalies: The Implications of Investor Attention for Price and Earnings Momentum. *Working Paper*. Fisher College of Business, Ohio State University. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=976394. Accessed: 23rd September 2009.

Houge, Todd and Tim Loughran. 2000. Cash Flow Is King? Cognitive Errors by Investors. *Journal of Psychology and Financial Markets* 1 (3/4): 161-175.

Hribar, Paul and Daniel W. Collins. 2002. Errors in Estimating Accruals: Implications for Empirical Research. *Journal of Accounting Research* 40 (1): 105-134.

Ibbotson, Roger G. and Paul D. Kaplan. 2000. Does Asset Allocation Policy Explain 40, 90, or 100 Percent of Performance? *Financial Analysts Journal* 56 (1): 26-33.

ICI. 2009. Investment Company Fact Book. http://www.icifactbook.org. Accessed: 19th December 2009.

Ippolito, Richard A. 1989. Efficiency with Costly Information: A Study of Mutual Fund Performance, 1965-1984. *The Quarterly Journal of Economics* 104 (1): 1-23.

Jackson, Andrew and Timothy Johnson. 2006. Unifying Underreaction Anomalies. *Journal of Business* 79: 75-114.

Jegadeesh, Narasimhan. 1990. Evidence of Predictable Behavior of Security Returns. *Journal of Finance* 45 (3): 881-898.

Jegadeesh, Narasimhan and Sheridan Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance* 48 (1): 65-91.

---. 1995. Short-Horizon Return Reversals and the Bid-Ask Spread. *Journal of Financial Intermediation* 4 (2): 116-132.

---. 2001. Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *Journal of Finance* 56 (2): 699-720.

Jensen, Michael C. 1968. The Performance of Mutual Funds in the Period 1945-1964. *Journal of Finance* 23 (2): 389-416.

---. 1978. Some Anomalous Evidence Regarding Market Efficiency. *Journal of Financial Economics* 6 (2/3): 95-101.

Jensen, Michael C. and George A. Benington. 1970. Random Walks and Technical Theories: Some Additional Evidence. *Journal of Finance* 25 (2): 469-482.

Johnson, Timothy C. 2002. Rational Momentum Effects. *Journal of Finance* 57 (2): 585-608.

Jones, Charles P. 2007. Investments: Analysis and Management. 10th edition. Hoboken, New Jersey: John Wiley & Sons.

Jones, Jennifer J. 1991. Earnings Management During Import Relief Investigations. *Journal of Accounting Research* 29 (2): 193-228.

Kama, Itay. 2009. On the Market Reaction to Revenue and Earnings Surprises. *Journal of Business Finance & Accounting* 36 (1/2): 31-50.

Keim, Donald B. 1983. Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence. *Journal of Financial Economics* 12 (1): 13-32.

Kempf, Alexander, Stefan Ruenzi, and Tanja Thiele. 2009. Employment Risk, Compensation Incentives, and Managerial Risk Taking: Evidence from the Mutual Fund Industry. *Journal of Financial Economics* 92 (1): 92-108.

Khan, Mozaffar. 2008. Are Accruals Mispriced? Evidence from Tests of an Intertemporal Capital Asset Pricing Model. *Journal of Accounting and Economics* 45 (1): 55-77.

Khatlawala, Rajiv D. 2008. How to Profit from Technical Analysis. New Delhi: Vision Books Pvt. Ltd.

Korajczyk, Robert A. and Ronnie Sadka. 2004. Are Momentum Profits Robust to Trading Costs? *Journal of Finance* 59 (3): 1039-1082.

---. 2008. Pricing the Commonality Across Alternative Measures of Liquidity. *Journal of Financial Economics* 87 (1): 45-72.

Kothari, S. P., Andrew J. Leone, and Charles E. Wasley. 2005. Performance Matched Discretionary Accrual Measures. *Journal of Accounting and Economics* 39 (1): 163-197.

Kraft, Arthur G. 2001. Accounting-Based and Market-Based Trading Strategies. Dissertation, University of Chicago.

Kuhnen, Camelia M. and Brian Knutson. 2005. The Neural Basis of Financial Risk Taking. *Neuron* 47 (5): 763-770.

Latzko, David A. 1999. Economies of Scale in Mutual Fund Administration. *Journal of Financial Research* 22 (3): 331-339.

Lee, Charles M. C. and Bhaskaran Swaminathan. 2000. Price Momentum and Trading Volume. *Journal of Finance* 55 (5): 2017-2069.

Lehmann, Bruce N. 1990. Residual Risk Revisited. *Journal of Econometrics* 45 (1/2): 71-97.

Leippold, Markus and Harald Lohre. 2009. International Price and Earnings Momentum. Imperial College London and University of Zürich. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1102689. Accessed: 25th January 2010.

Lesmond, David A., Michael J. Schill, and Chunsheng Zhou. 2004. The Illusory Nature of Momentum Profits. *Journal of Financial Economics* 71 (2): 349-380.

Lev, Baruch and Doron Nissim. 2006. The Persistence of the Accrual Anomaly. *Contemporary Accounting Research* 23 (1): 193-226.

Lev, Baruch and S. Ramu Thiagarajan. 1993. Fundamental Information Analysis. *Journal of Accounting Research* 31 (2): 190-215.

Levy, Robert A. 1967. Relative Strength As a Criterion for Investment Selection. *Journal of Finance* 22 (4): 595-610.

---. 1971. The Predictive Significance of Five-Point Chart Patterns. *Journal of Business* 44 (3): 316-323.

Lichtenstein, Sarah and Baruch Fischhoff. 1977. Do Those Who Know More Also Know More about How Much They Know? *Organizational Behavior and Human Performance* 20 (2): 159-183.

Livnat, Joshua and Germán López-Espinosa. 2008. Quarterly Accruals or Cash Flows in Portfolio Construction? *Financial Analysts Journal* 64 (3): 67-79.

Livnat, Joshua and Paul Zarowin. 1990. The Incremental Information Content of Cash-Flow Components. *Journal of Accounting and Economics* 13 (1): 25-46.

Lo, Andrew W. 2004. The Adaptive Markets Hypothesis - Market Efficiency from an Evolutionary Perspective. *Journal of Portfolio Management* 30 (Sep 2004 Anniversary Issue): 15-29.

---. 2008. Efficient Markets Hypothesis. In: *The New Palgrave: A Dictionary of Economics*, ed. Steven N. Durlauf and Lawrence E. Blume. 2nd edition. New York: Palgrave McMillan.

Lo, Andrew W. and A. Craig MacKinlay. 1990. When Are Contrarian Profits Due to Stock Market Overreaction? *Review of Financial Studies* 3 (2): 175-205.

Lo, Andrew W., Harry Mamaysky, and Jiang Wang. 2000. Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation. *Journal of Finance* 55 (4): 1705-1765.

Lo, Andrew W. and Dmitry V. Repin. 2002. The Psychophysiology of Real-Time Financial Risk Processing. *Journal of Cognitive Neuroscience* 14 (3): 323-339.

Malkiel, Burton G. 1995. Returns from Investing in Equity Mutual Funds 1971 to 1991. *Journal of Finance* 50 (2): 549-573.

---. 2007. A Random Walk Down Wall Street: The Time-Tested Strategy for Successful Investing. 9th edition. New York: W.W. Norton & Company, Inc.

Mashruwala, Christina, Shivaram Rajgopal, and Terry Shevlin. 2006. Why Is the Accrual Anomaly Not Arbitraged Away? The Role of Idiosyncratic Risk and Transaction Costs. *Journal of Accounting and Economics* 42 (1/2): 3-33.

Merton, Robert C. 1973. An Intertemporal Capital Asset Pricing Model. *Econometrica* 41 (5): 867-887.

Michaely, Roni, Richard H. Thaler, and Kent L. Womack. 1995. Price Reactions to Dividend Initiations and Omissions: Overreaction or Drift? *Journal of Finance* 50 (2): 573-608.

Mishkin, Frederic S. 1983. A Rational Expectations Approach to Macroeconometrics. Chicago: University of Chicago Press.

Montier, James. 2002. Behavioural Finance: Insights into Irrational Minds and Markets. Chichester et al.: John Wiley & Sons.

Morningstar Inc. 2004. Fact Sheet: The Morningstar Style Box ™. http://corporate.morningstar.com/bf/documents/MethodologyDocuments/FactSheets/MorningstarStyleBox_FactSheet_.pdf. Accessed: 19th December 2009.

Murphy, John J. 1999. Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications. Completetely updated and expand. edition. Paramus, New Jersey et al.: Prentice Hall.

Newey, Whitney K. and Kenneth D. West. 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55 (3): 703-708.

Niessen, Alexandra and Stefan Ruenzi. 2009. Sex Matters: Gender Differences in the Mutual Fund Industry. *Working Paper*. Centre for Financial Research, University of Cologne and University of Mannheim. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1343490. Accessed: 19th December 2009.

Oberlechner, Thomas. 2001. Importance of Technical and Fundamental Analysis in the European Foreign Exchange Market. *International Journal of Finance and Economics* 6 (1): 81-93.

Otten, Roger and Dennis Bams. 2002. European Mutual Fund Performance. *European Financial Management* 8 (1): 75-101.

Ou, Jane A. and Stephen H. Penman. 1989. Financial Statement Analysis and the Prediction of Stock Returns. *Journal of Accounting and Economics* 11 (4): 295-329.

Pástor, Lubos and Robert F. Stambaugh. 2002. Mutual Fund Performance and Seemingly Unrelated Assets. *Journal of Financial Economics* 63 (3): 315-349.

---. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111 (3): 642-685.

Penman, Stephen H. 2007. Financial Statement Analysis and Security Valuation. 3rd edition. Boston et al.: Mc Graw-Hill.

Petersen, Mitchell A. 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies* 22 (1): 435-480.

Prather, Larry J. and Karen L. Middleton. 2002. Are N+1 Heads Better Than One? The Case of Mutual Fund Managers. *Journal of Economic Behavior & Organization* 47 (1): 103-120.

Prather, Laurie, William J. Bertin, and Thomas Henker. 2004. Mutual Fund Characteristics, Managerial Attributes, and Fund Performance. *Review of Financial Economics* 13 (4): 305-326.

Rangan, Srinivasan and Richard G. Sloan. 1998. Implications of the Integral Approach to Quarterly Reporting for the Post-Earnings-Announcement Drift. *The Accounting Review* 73 (3): 353-371.

Reilly, Frank K. and Keith C. Brown. 2003. Investment Analysis and Portfolio Management. 7th edition. Mason, Ohio et al.: South-Western.

Richardson, Scott A., Richard G. Sloan, Mark T. Soliman, and Irem Tuna. 2005. Accrual Reliability, Earnings Persistence and Stock Prices. *Journal of Accounting and Economics* 39 (3): 437-485.

Ritter, Jay R. 1984. The "Hot Issue" Market of 1980. *Journal of Business* 57 (2): 215-40.

Rouwenhorst, K. Geert. 1998. International Momentum Strategies. *Journal of Finance* 53 (1): 267-284.

Roychowdhury, Sugata. 2006. Earnings Management Through Real Activities Manipulation. *Journal of Accounting and Economics* 42 (3): 335-370.

Sadka, Ronnie. 2006. Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk. *Journal of Financial Economics* 80 (2): 309-349.

Sagi, Jacob S. and Mark S. Seasholes. 2007. Firm-Specific Attributes and the Cross-Section of Momentum. *Journal of Financial Economics* 84 (2): 389-434.

Samuelson, Paul A. 1965. Proof That Properly Anticipated Prices Fluctuate Randomly. *Industrial Management Review* 6 (2): 41-49.

Samuelson, William and Richard Zeckhauser. 1988. Status Quo Bias in Decision Making. *Journal of Risk and Uncertainty* 1 (1): 7-59.

Schiereck, Dirk, Werner De Bondt, and Martin Weber. 1999. Contrarian and Momentum Strategies in Germany. *Financial Analysts Journal* 55 (6): 104-116.

Schwager, Jack D. 2003. Stock Market Wizards: Interviews with America's Top Stock Traders. 1st edition. New York: HarperCollins Publishers Inc.

SEC. 1940. Investment Company Act 1940. http://www.sec.gov/about/laws/ica40.pdf. Accessed: 20th December 2009.

Siganos, Antonios and Patricia Chelley-Steeley. 2006. Momentum Profits Following Bull and Bear Markets. *Journal of Asset Management* 6 (5): 381-388.

Sirri, Erik R. and Peter Tufano. 1998. Costly Search and Mutual Fund Flows. *Journal of Finance* 53 (5): 1589-1622.

Sloan, Richard G. 1996. Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings? *The Accounting Review* 71 (3): 289-315.

Stein, Jeremy C. 2002. Information Production and Capital Allocation: Decentralized Versus Hierarchical Firms. *Journal of Finance* 57 (5): 1891-1921.

Stickel, Scott E. 1991. Common Stock Returns Surrounding Earnings Forecast Revisions: More Puzzling Evidence. *The Accounting Review* 66 (2): 402-416.

Sullivan, Ryan, Allan Timmermann, and Halbert White. 1999. Data-Snooping, Technical Trading Rule Performance, and the Bootstrap. *Journal of Finance* 54 (5): 1647-1691.

Taylor, Mark P. and Helen Allen. 1992. The Use of Technical Analysis in the Foreign Exchange Market. *Journal of International Money and Finance* 11 (3): 304-314.

Tseng, K.C. 2006. Behavioral Finance, Bounded Rationality, Neuro-Finance, and Traditional Finance. *Investment Management and Financial Innovations* 3 (4): 7-18.

Tversky, Amos and Daniel Kahneman. 1974. Judgment under Uncertainty: Heuristics and Biases. *Science* 185 (4157): 1124-1131.

Weinstein, Neil D. 1980. Unrealistic Optimism About Future Life Events. *Journal of Personality and Social Psychology* 39 (5): 806-820.

Wermers, Russ. 2000. Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses. *Journal of Finance* 55 (4): 1655-1695.

Xie, Hong. 2001. The Mispricing of Abnormal Accruals. *The Accounting Review* 76 (3): 357-373.

Xu, Yexiao and Burton G. Malkiel. 2004. Idiosyncratic Risk and Security Returns. *Working Paper*. School of Management, The University of Texas at Dallas. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=255303. Accessed: 10th August 2009.

Zhang, X. Frank. 2007. Accruals, Investment, and the Accrual Anomaly. *The Accounting Review* 82 (5): 1333-1363.

Zimmermann, Heinz. 2006. Finance Compact. 2nd edition. Zürich: Verlag Neue Züricher Zeitung.