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Titel der Masterarbeit

Determinants of Momentum Strategy:

Liquidity, Sustainability or Industry?

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Wien, am 20.04.2015 Stefan Rößler

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List of Variables and Parameters

$A_{i,t}$ = ask price of security i at time t

α_i = abnormal risk-adjusted return of an risky asset

α_P = abnormal risk-adjusted return of the portfolio

$B_{i,t}$ = bid price of security i at time t

BE/ME = book-to-equity divided by market equity

β_{HML} = exposure to value firms

β_M = systematic risk exposure to the market portfolio

β_{MOM} = exposure to momentum

β_{SMB} = exposure to small firms

$c_{i,t}$ = illiquidity cost of security i at time t

D_{iy} = number of days at which data is available of stock i in year y

$ES_{i,t}$ = effective half spread of security i at time t

$e_{i,t}$ = firm-specific component of return of security i at time t

ϵ_t = standard error at time t

$f_{k,t}$ = return of the factor-mimicking portfolio k

HML_t = return through value firms at time t

$ILLIQ_{iy}$ = Amihud illiquidity measure

J = length of formation period in months

K = length of holding period in months

λ_t = risk premium of the LAPM

M = number of industries

$M_{i,t}$ = mid price of security i at time t

MOM_t = return through momentum firms at time t

μ_t = expected return on security i

N = number of observations

$\theta_{i,m}$ = stock i’s sensitivity to the return on industry m

p_t = stock price at time t

ϕ_t = information until time t

$S_{i,t}$ = bid-ask spread of security i at time t

SMB_t = return through small firms at time t

SR_t	=	portfolio's sharp ratio at time t
SRI	=	socially responsible investment
$R_{I,t}$	=	return of industry portfolio I at time t
R_{iyd}	=	return of stock i on day d in year y
$r_{f,t}$	=	risk-free rate at time t
$r_{i,t}$	=	security i's return at time t
$r_{M,t}$	=	market return at time t
$r_{p,t}$	=	portfolio return at time t
$\sigma_{i,M}$	=	covariance between the asset return and market return
σ_M^2	=	variance of the market return
σ_P	=	standard deviation of portfolio returns
$\rho_{i,j}$	=	correlation coefficient of returns of asset i and asset j
$QS_{i,t}$	=	quoted spread of security i at time t
$V_{i,t}$	=	transaction price of security i at time t
$VOLD_{i,y}$	=	daily traded volume of security i in USD
$w_{i,t}$	=	weight of asset I at time t
x_t	=	logarithm of price p at time t
$z_{m,t}$	=	industry portfolio returns orthogonal to return on factor-mimicking portfolio

1 Introduction

The term momentum has been brought up about 20 years ago in the context of finance and has been a phenomenon since then. But where does the term momentum come from? In physics or more precise in classical mechanics momentum p describes the product of mass m and velocity v, $p = m * v$. Hence, momentum is a vector quantity, which possesses a direction and a magnitude. Furthermore, momentum is a conserved quantity that can not change in a closed system (often illustrated through Newton's cradle), i.e. if no external force affects momentum. Metaphorically speaking, it takes a lot of force to generate momentum and the same time it takes a lot of force to stop momentum. This can be easily derived from Newton's first law of motion.[1]

In finance, momentum is the phenomenon that securities which have performed well relative to peers ('winners') continue to outperform and securities that have performed relatively poorly ('losers') tend to continue to underperform.[2] Accordingly, the idea of momentum investing is that securities which exhibit a tendency in price movements are likely to keep this trend. Hence, similarities to momentum in physics can be found and profitability of momentum strategy seems to be intuitive. However, stocks in financial markets clearly don't move in a closed system and stock price persistence is far from conserved momentum demonstrated by Newton's cradle. Moreover, stock prices not only deal with external forces like business cycles, but also financial theory is built on the assumption that stock prices follow random walks. Thus, also the crucial hypothesis of market efficiency is based on the presumption that current stock prices fully reflect available information. Accordingly, no profit should be generated through the observation of historic stock price patterns. Therefore, the occurrence of momentum profits is an anomaly traditional financial theory struggles with.

[1] Source: http://lightandmatter.com/lm/, Chapter 14; Newton's cradle, named after Sir Isaac Newton, is a device that demonstrates conservation of momentum and energy via a series of swinging spheres.

[2] Asness, Frazzini, Israel and Moskowitz (2014)

Nevertheless, since its inception by academics Jegadeesh and Titman (1993), momentum grew in popularity. Since momentum has been investigated by academics across markets, countries, industries and asset classes with robust results, it became an established investment strategy. As a consequence, even large funds like iShares MSCI USA momentum Factor ETF invest according to this strategy. Although traditional assumption from financial literature struggles with the anomaly of momentum, it has been included in modern asset pricing models like the Carhart-four-factor model. While other factors of this asset pricing model are based on fundamentals, momentum is an impact factor that observes stock price trends. Another established factor from the 4-factor model is the assumption that value stocks (firms with high book-to-market ratio) outperform growth stocks (firms with low book-to-market ratio). An indisputable evidence of return premia from value and momentum factor has been found in empirical studies.[3] Furthermore, a negative correlation between both strategies has been observed, which is the reason why momentum became an eligible factor in modern asset pricing models.

Since evidence of momentum profitability is undoubted and became an established investment strategy, it is interesting that financial literature struggles until today to explain the existence of momentum. Hence, the purpose of this thesis is to investigate driving forces of momentum in stock prices. In traditional momentum literature several factors are named and tested on its influence on momentum profitability. The importance of traditional factors like markets, firm size, industry and seasonality are analyzed in a qualitative and quantitative way. In addition to traditional momentum factors, the effect of liquidity on momentum profits is investigated, as liquidity patterns of securities are gaining importance in financial markets. Therefore, this factor is introduced in modern asset pricing models like the LAPM of Acharya and Pedersen (1994). Correspondingly, liquidity also might impact the profitability of the momentum strategy. Finally, the upcoming trend of sustainable investing is integrated in the momentum approach. The concept of 'Socially Responsible Investing' (SRI) is nothing new, but grew in popularity as well as assets under management

[3]Asness, Moskowitz and Pedersen (2013)

especially among institutional investors during the last decade. Hence, thanks to the increasing number of research studies, the awareness of investors regarding the sustainability of companies' business is growing. As the trend of sustainable investing is increasing, sustainability research agencies are also becoming more important. In addition, academics claim that sustainability ratings accredited by the agencies impact asset pricing as well as stock price returns. Since ratings incorporate risks relating to environmental, social and corporate governance issues, this might impact the business and stock price of companies. Thus, price movements of sustainable securities might be more persistent and hence drive momentum profits. Mentioned factors are analyzed in the context of momentum literature and further factors are tested on the results of an empirical study.

The thesis is organized as follows: Section 2 reviews findings from traditional momentum literature and presents momentum strategy as well as factors that are assumed to explain momentum. Section 3 introduces efficient market hypothesis, asset pricing models and its issues with the phenomenon of momentum. Section 4 provides a decomposition of profits from momentum strategy and evaluates the importance of the components. In section 5, the factor liquidity, its measures and its impact on asset pricing and momentum are presented. In section 6, the momentum strategy is applied to different subsamples of securities and on two periods. In addition, the most important determinants of momentum profits are analyzed for their impact. Section 7 concludes the thesis.

2 Momentum Strategy in Literature Review

In addition to value and growth, momentum strategy is one of the most popular investment strategies, which is at the same time discussed controversially. While other strategies are based on various financial figures, momentum is the tendency of investments to exhibit persistence in their relative performance.[4] Among others, Jegadeesh and Titman (1993) report about abnormal returns from investing in securities, which most recently outperform others. Although there exist various models in the world of financial markets, momentum is a phenomenon, which is barely captured. Explanations range from questioning efficient market hypothesis to behavioral finance.

In this section the principles of momentum strategy are introduced and results of different studies are presented. Furthermore, the focus is on potential drivers of momentum returns and distinctions when analyzing profitability of momentum strategies. These factors are introduced in this chapter and will also be investigated in the empirical study in chapter 6.

2.1 Momentum Approach

Financial literature defines stock price momentum as a current trend of stock price patterns. Hence, persistence of stock prices is the fundamental presumption when dealing with momentum. Accordingly, momentum literature claims that investors are able to generate excess returns by buying stocks which performed well in recent months and selling stocks which exhibited losses recently. This hypothesis is based on the assumption that stock price movements stay persistent and continue to yield gains or losses depending on historic performance. Jegadeesh and Titman (1993) found abnormal returns in momentum strategies, investing (divesting) in companies performing well (bad) during last 3 to 12 months. Since they were the first researchers analyzing momentum in stock prices, their approach is used as a reference point.

[4] Berger, Israel and Moskowitz (2009)

While evidence of profitability of momentum strategy exists, other literature proving that contrarian strategies generate abnormal returns by stock price reversals should be mentioned.[5] De Bondt and Thaler (1984) show that companies, that were performing poor over a horizon of about 3-5 years, earn higher average returns over the next months compared to securities which outperformed over the same time horizon. Furthermore, there is evidence of short-term price reversals, reporting that stocks performing worse during the recent month experience price reversals and on average outperform securities with higher returns over the last month. Apparently, there is more than one pattern of price movements in empirical research, i.e. momentum and stock price reversals. Hence, it is important to distinguish different time horizons of stock price observation as well as holding periods in the portfolio. Since the topic of this study is momentum, the focus will be on the time horizons when momentum strategy is profitable.

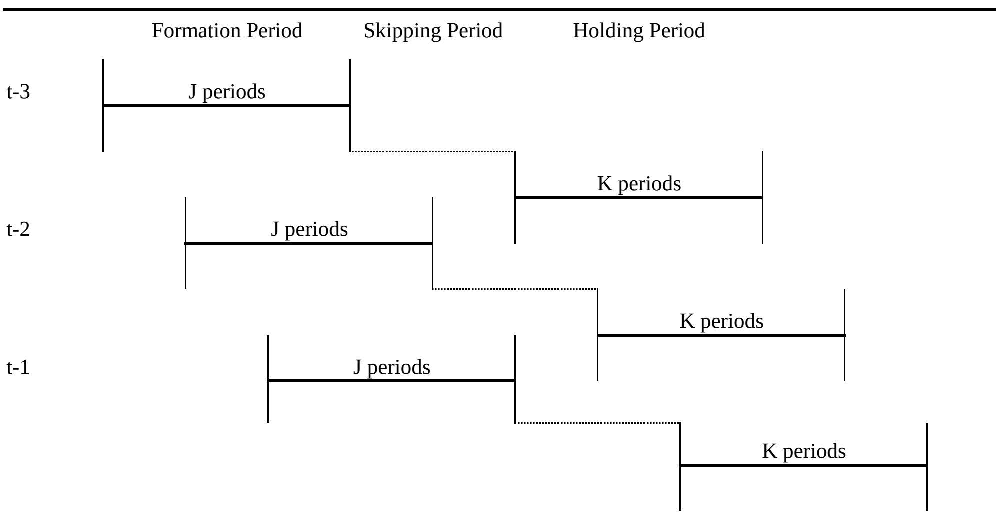
Jegadeesh and Titman (1993) found that price continuations of stocks with high returns in the previous 3 to 12 months generate profits over the following 3 to 12 months as well. Various papers investigate different time horizons, confirming profitability of momentum strategy with a formation period of three months to one year. For that reason, at the beginning of each month, a wide range of securities is analyzed regarding their recent stock price developments. Stock price performance of an analyzed universe of companies ranks the securities according to a simple buy-and-hold strategy over the observed time horizon of 3 to 12 months. In addition, it is common in momentum literature to skip the most recent month. This skipping period is for the sake of mentioned stock price reversals after one month. Lo and MacKinlay (1990), Asness (1994) as well as Grinblatt and Moskowitz (1999) report about stock price reversals according to liquidity or microstructure reasons.

Alongside variations in the formation period, there are differences in profitability according to the holding period of securities in the portfolio. In the work of Je-

[5] Contrarian strategy: An investment style that goes against prevailing market trends by buying assets that are performing poorly and then selling when they perform well. Source: http://www.investopedia.com/terms/c/contrarian.asp

gadeesh and Titman (1993) holding periods from 3 to 12 months were investigated. Further studies confirm profitability of similar holding periods as in Rouwenhorst (1998) or Grinblatt and Moskowitz (1999). In addition, Jegadeesh and Titman (1993) determine returns of momentum portfolios over a time horizon of 36 months after the formation period. The findings show that profits decline after 12 months. Moreover, profits generated for the first 12 months by momentum strategy, are diminished. This supports findings from De Bondt and Thaler (1984) and Conrad and Kaul (1998) which show that price reversals occur over a long-time horizon. Negative profits of short-term stock price reversals over one month are avoided by the skipping period.

Figure 1: Structure of momentum portfolio



This figure provides an overview of the structure of a Momentum portfolio with a formation period of J months, a skipping period and a holding period of K months.

Taking into account formation period, holding period and skipping period every month securities are ranked into deciles based on their J-month return, where J equals 3, 6, 9 or 12 months. Stocks that perform best (worst) during the J months go into the 'winner'-portfolio ('loser'-portfolio) and will be hold for K month, where K equals 3, 6, 9 or 12 months.[6] As portfolios are restructured every month and holding periods vary from 3 to 12 months there are overlaps in holding periods. Hence, in time t portfolios following a K month holding period structure, consist out of K parts with positions from investments in $t-K$ to $t-1$. Overlapping periods support the power of the test of momentum returns.[7]

Momentum literature distinguishes between two different approaches for the portfolio formation. While Jegadeesh and Titman (1993) suggest the approach of ranking stocks into deciles, Conrad and Kaul (1998) and Lewellen (2002) propose a 'Weighted Relative Strength Strategy' ('WRRS'). In the decile method, securities are ranked into deciles according to their stock price performance. Best 10 percent performing stocks go to decile P10 ('winners') and worst performing stocks to decile P1 ('losers'). Accordingly, a relative strength portfolio is built, buying securities from decile P10 and selling stocks short from decile P1. Hence, only stocks with extreme price movements, i.e. best and worst 10 percent of stocks, are taken into account for the momentum profit of the relative strength portfolio. Now, relative strength portfolio must be weighted to measure its performance. Stocks within these portfolios can be equally-weighted or weighted according to market capitalization of the security. Hong and Stein (1999) found that profitability of the momentum strategy declines tremendously the higher the market capitalization of a companies. Taking this in consideration, weightings of stocks in the portfolio matter in terms of profitability. Hence, most studies use equally-weighted portfolios to analyze profits of momentum strategy to prevent the bias of value weighted portfolios.

Although empirical studies in the literature of momentum mainly use the equally-weighted portfolio approach of Jegadeesh and Titman (1993), technical explanations of momentum returns in terms of (auto-)correlation consequently base on the 'WRSS'. Within this strategy not only most extreme moving stocks are considered for the relative strength portfolio. Moreover, stocks are weighted in the portfolio

[6] E.g. Rouwenhorst (1998)

[7] Jegadeesh and Titman (1993)

according to their performance during the formation period, i.e. recent J-months. Accordingly, stock weight in the portfolio at time t is

$$w_{i,t} = \frac{1}{N}\left[r^k_{i,t-1} - r^k_{m,t-1}\right]$$

where $r^k_{i,t-1}$ equals k-month's return of asset i in $t-1$, $r^k_{m,t-1}$ equals corresponding return on the equally-weighted index and N is the total number of stocks. As the sign of the weight can be either positive or negative, the portfolio invests in stocks with highest past returns and sells stocks performing worst. Any observed stock is considered for the relative strength portfolio with a weight either positive or negative depending on past returns being above or below average.[8]

Furthermore, all of the weights $w_{i,t}$ sum up to zero, which implies a zero cost portfolio strategy by construction:[9]

$$\sum_{i=1}^{N} w^k_{i,t-1} = 0 \quad \forall k.$$

The approach of 'WRSS' is reviewed in section 4 when the (auto-)correlation hypothesis of the momentum strategy is derived. At this point the decile approach is followed and its results from several empirical studies are investigated. According to that approach studies like those of Jegadeesh and Titman (1993) or Rouwenhorst (1998) generate 16 portfolios, which are analyzed over different time horizons and different markets. Majority of these 16 strategies have resulted in significant abnormal returns. The data and results, pertaining to profitability of these momentum strategies, are presented in the next subsection.

2.2 Data and Empirical Results

Literature provides several studies investigating the approach of Jegadeesh and Titman (1993) and proving significance of abnormal returns of momentum strategy in different markets. Jegadeesh and Titman (1993)use data of stocks from NYSE, AMEX and Nasdaq for the period from 1965 to 1998 where daily returns are avail-

[8] Lewellen (2002)

[9] Conrad and Kaul (1998)

able. Conrad and Kaul (1998) found that the reason for profitability of contrarian strategy through long time reversals, is due to the inclusion of low priced stocks. For that reason, companies with a stock price below USD 5 and market capitalization which would rank the company at the lowest decile in NYSE, are excluded. Nevertheless, Jegadeesh and Titman (1993) found that returns do not differ with or without low-priced stocks for the investigated time horizon, except in Januaries. Further studies determine profitability of momentum strategy in international markets (Griffin et al. (2004)), European market (Rouwenhorst (1998)) and emerging markets (Rouwenhorst (1999)).

In the studies of Jegadeesh and Titman (1993), a very long time horizon is considered and they find a monthly return of 1.23 percent for the relative strength portfolio (P10-P1) with formation period of 6 months and holding period of 6 months for period between 1965 and 1998. Additionally t-statistics of 6.48 support those returns are reliably different from 0.[10] For each of the other 15 strategies of holding and formation periods, both varying from 3 to 12 months, Jegadeesh and Titman (1993) find further abnormal monthly returns. All of the 16 strategies are analyzed with and without a skipping period of 1 week. Except for the 3-month/3-month strategy without skipping period, returns are statistically significant.[11]

In his study, Rouwenhorst (1998) analyzes the European market using data from 12 different countries for a time horizon between 1978 and 1995. Data sample captures 60 to 90 percent of total market capitalization and all stock prices are converted to Deutsche Marks (DM). Applying the approach of Jegadeesh and Titman (1993), 16 portfolios were investigated with and without skipping period and formation/holding periods from 3 to 12 months. His findings show highest monthly returns for holding periods from 3 to 6 months, irrespective of the formation period and declining but positive returns for longer holding periods. 'Winner'-portfolio outperforms the 'loser'-portfolio each month by over 1 percent in each combination of formation and holding period. However, the highest return of 1.45 percent per month is generated

[10] Jegadeesh and Titman (1993)
[11] Jegadeesh and Titman (1993)

with a formation period of 9 months, a holding period of 3 months and 1 month of skipping period.

The international market study of Griffin et al. (2004) relies on American data from NYSE and AMEX and further contains listed firms from 39 countries with data available on Datastream International. Due to availabilities, US market data starts in 1976 while other countries are covered as of 1987. The study of Griffin et al. (2004) does not cover all of 16 portfolio combinations, but the focus lies on the most common 6-month/6-month approach with a one-month skipping period. For the observed time period, 'winner'-portfolios outperform 'loser'-portfolios as well as the considered market indices. The US market 'winner'-portfolio generates a return of USD 142 in 2000 from investing USD 1 in 1975 while market index and 'loser'-portfolio only return USD 33.87 and USD 7.27 respectively. In all of the other markets, considered in the study of Griffin et al. (2004), even higher returns are observed, which might be due to lower capitalization of the sample companies, i.e. Asia and Americas excluding the United States.

Apparently, evidence of abnormal returns from momentum strategies in different markets, can be found over the last decades. Besides analyzing returns from momentum strategies for different time periods and different stock markets, researchers like Jegadeesh and Titman, Moskowitz, Grinblatt and Rouwenhorst were searching for impact of firm size, industry or seasonality. Their findings will be presented in the following sub-section.

2.3 Markets, Industries, Size and Seasonality

Results of the previous chapter showed evidence of the profitability of momentum strategies and indicate that differences in abnormal returns over different markets exist. Besides markets several studies analyze further factors to identify the driver of stock price momentum. In this subsection various factors are introduced which are also part of the momentum analysis of the empirical study of this thesis.

Both studies of Griffin et al. (2004) and Rouwenhorst (1998) suggest that differences in returns of momentum correlate with market capitalization of companies in relevant markets. 'Winner'-portfolios in Asia and Americas excl. US outperform the market indices by far. Moreover, also the 'loser'-portfolios outperform the market indices. Both findings suggest that this outcome relates to firms with lower capitalization in these markets.[12] In analyzed European countries half of 2190 stocks are from the biggest countries such as Great Britain, France and Germany, implying that firms have higher market capitalization than firms in smaller European countries.[13] One might also argue that firms' information of low capitalized companies becomes public later.[14] Furthermore, firms with low market capitalization are less liquid and hence their stocks are more difficult to trade. Hence, using the 6-month/6-month approach of Jegadeesh and Titman (1993) and removing firms with low market capitalization, Hong and Stein (1999) determined that profitability of momentum strategy declines sharply with growing market capitilization. For that reason, one can find several investigations in momentum literature which compare size and market.

In the study of Rouwenhorst (1998) the influence of market and company size is analyzed by creating country-neutral relative strength portfolios and size-neutral relative strength portfolios respectively. For the country-neutral portfolio a relative strength portfolio is generated. For each of the 12 countries, investigated by Rouwenhorst, the 6-month/6-month approach of Jegadeesh and Titman (1993) is applied. Results differ for the 12 markets with positive returns between 0.0064 per month in Switzerland and 0.0132 per month in Spain. Now, a country-neutral portfolio is built by taking 10 percent of best and worst firms of each country. This generates a monthly return of 0.0093. The diversified results for the different countries indicate that there is no country effect explaining price persistence.[15]

For the size effect several studies separate the analyzed companies by market capitalization in groups of small size, medium size and large size firms to check for mo-

[12] Griffin et al. (2004)
[13] Rouwenhorst (1998)
[14] Hong and Stein (1999)
[15] Rouwenhorst (1998)

mentum returns.[16] Using the 6-month/6-month approach of Jegadeesh and Titman (1993) for those groups of companies, Rouwenhorst (1998) finds that past 'winners' outperform past 'losers' significantly for all relative strength portfolios. Nevertheless, one can see distinct differences in the monthly returns. Smallest size firms generate a monthly return of 0.0145, while large size firms only bring 0.0073. These results confirm the hypothesis of Hong and Stein (1999), who showed that momentum profits decline with market capitalization. Jegadeesh and Titman (1993) also find similar results supporting the negative correlation of market capitalization and return of momentum strategy. In their study, relative strength portfolio of large size firms only generate monthly returns of 0.0075 whereas the small size firm portfolio returns 0.0099 a month. Although results of medium size relative strength portfolio show a return of 0.0126, which outperforms the other two portfolios, Jegadeesh and Titman (1993) conclude a dependency of size and abnormal returns of momentum. Jegadeesh and Titman (1993) attribute this phenomenon to serial correlation in the firm-specific component of returns, which is a finding that is derived in chapter 4.

Besides comparison between different markets and company size, literature finds dependencies between industries and return of momentum strategy. Although there is only little impact of industries on asset prices, there seems to be a strong influence when stock price returns are conditioned on the information of past prices.[17] In their study Grinblatt and Moskowitz (1999) suggest that a big part of momentum returns comes from cross-sectional variations within industries. By sorting industry portfolios based on their past returns and investing in the best industries, Grinblatt and Moskowitz (1999) find monthly profits which are approximately as high as momentum returns from individual equities. Hence, it seems that a large share of monthly momentum returns comes from correlation of assets within an industry and this is why they accredit a large portion of momentum returns to industry momentum. To give evidence Grinblatt and Moskowitz (1999) investigate momentum returns by distracting the industry return of each stock's individual mo-

[16] Jegadeesh and Titman (1993), Rouwenhorst (1998)

[17] Grinblatt and Moskowitz (1999)

mentum return. Results show that profits decline to a marginally significant 0.0013 (t-statistic: 2.04) per month.[18] Furthermore, Grinblatt and Moskowitz (1999) compare industry-neutralized portfolios. By using the same approach like Jegadeesh and Titman (1993) or Rouwenhorst (1998) when comparing size- and beta-neutral portfolios, equities of each industry are ranked in ascending order and a relative-strength portfolio of being long in 30 percent of best performing stocks and being short in 30 percent of worst performing stocks is generated. Analyzing the returns of individual industries does not return profits significantly different from zero, supporting the finding of Grinblatt and Moskowitz (1999) that momentum in individual equities does not exist. However, when comparing results of a cross-industry strategy by buying 'loser'-stocks of winning industries and selling 'winner'-stocks from losing portfolios significant profits of 0.003 per month can be observed. Nevertheless, it generates negative returns in case of individual stocks being responsible for momentum returns, which is why phenomenon of industry momentum seems to be important for profits of momentum strategy.[19]

Finally, the focus lies on the phenomenon of seasonality. Momentum literature refers to Roll (1983) who reported first about the 'patently absurd' finding of January Effect. He reports that stocks with negative returns over the previous year have higher returns in January.[20] Hence, findings of Roll (1983) imply that relative strength portfolios of momentum strategy should generate negative returns in January. Indeed results of the study of Jegadeesh and Titman (1993) return average loses of 0.07 in January for the considered time horizon from 1965 to 1989. Excluding January from the relative strength strategy generates a profit of 0.0166 per month for 6-month/6-month approach, which is distinctly different from the 0.0095 per month considering all months.[21] A further repetitive occurrence are business cycles. Studies of Chordia and Shivakumar (2002) and Avramov et al. (2007) report of differences of momentum profitability in different phases of business cycles. Chordia

[18] Grinblatt and Moskowitz (1999)
[19] Grinblatt and Moskowitz (1999)
[20] De Bondt and Thaler (1984)
[21] Jegadeesh and Titman (1993)

and Shivakumar (2002) claim that profits of momentum strategy strongly depend on the economic situation. Hence, profits of momentum strategies can be explained by a set of macroeconomic variables and momentum profitability disappears once stock returns are adjusted for their predictability based on these macroeconomic variables.[22] Avramov et al. (2007) further claim that there exists a coherence between momentum and credit ratings. Since credit risk varies over the business cycle, this finding supports the hypothesis of a dependence of momentum profits and business cycles.

In the last subsection various factors are named which are discussed as possible explanation for profitability of momentum strategy. Although there is no consent about these momentum drivers most of the studies of momentum strategy refer to markets, company size, industry or seasonality. In the empirical study in chapter 6 out of the named factors the focus will be on the industry factor but also seasonality and business cycles can be investigated.

3 Market Efficiency and Traditional Asset Pricing

In the last chapter evidence of momentum profitability is proven by referring to different studies investigating momentum strategy during the last decades. Results show that there is indeed a significant abnormal return by making use of stock price persistence. Nevertheless, there are inconsistent explanations for profitability. Hence, although approach and results including significant positive returns from momentum strategy are widely accepted, source of profits and explanation for the evidence is controversially debated.[23] Especially well known assumptions of financial literature like market efficiency and famous asset pricing models struggle with the occurrence of momentum profits. Since most of popular financial market models are based on the efficient market hypothesis (EMH), validity of EMH and asset pricing

[22] Chordia and Shivakumar (2002)

[23] Jegadeesh and Titman (1993)

models are investigated in the next sub-chapter.

3.1 Random Walks and Efficient Market Hypothesis

Results of momentum literature report that the source of abnormal return from momentum strategy might be either due to the fact of serial correlation in assets or cross-sectional variation between equities of a specific industry. The former was one of the findings of Jegadeesh and Titman (1993) who report that profitable trading strategies exist if stock prices overreact or underreact to information. Overreactions of stock prices, called ’fads’, predict autocorrelation over all time intervals, which reject the martingale behavior of asset prices.[24] This martingale behavior is in strong connection to random walks of stock prices and hence it is sufficient for the efficient market hypothesis. Findings of momentum literature indicate strong contradictions to the efficient market hypothesis and the assumption that prices of securities ’fully reflect’ available information.[25]

Since subsequent models claim that efficient market hypothesis has to hold, theory of random walks has to be introduced. In order to define the framework of random walk hypothesis the patterns of stock prices have to be defined. Thus, the stock price at time t is denoted by p_t and $x_t = \ln p_t$ defines the log-price process. Accordingly,

$$x_{t+1} = x_t + \epsilon_t, \quad \epsilon_t \sim \quad IID\ \mathcal{N}(0, \sigma)$$

and the stock return is defined by the increment:

$$r_t = x_{t+1} - x_t = \epsilon_t,$$

where ϵ_t is normally distributed with mean 0 and variance σ^2 and r_t is the increment sequence.[26] Random walk theory assumes that all increments are independent and hence stock prices are subject to the following restriction:

[24] Lehmann (1990)

[25] Fama and French (1969)

[26] Campbell, Lo and MacKinlay (1997)

$$\mathbb{E}[p_{i,t+1}|\phi_t] = p_{i,t} \quad \text{or} \quad \mathbb{E}[r_{t+1}|\phi_t] = 0,$$

where ϕ_t is a general symbol for all information until time t. Therfore, the expected value of next period's stock price p_{t+1} constrained to currently available information ϕ_t is equal to the current stock price p_t. From perspective of forecasting, martingale hypothesis suggests that the best prediction of tomorrow's stock price is its price today. Since all non-overlapping price changes, increments, are uncorrelated at all leads and lags it is not efficient to forecast future price changes from historical prices. Thus, the martingale hypothesis has been considered as a necessary condition for EMH for a long time.[27]

Weak-form Efficiency:
The information set includes only the history of prices or returns themselves.

Semi-strong-form Efficiency:
The information set includes all information known to all market participants (publicly available information).

Strong-form Efficiency:
The information set includes all information known to any market participant (private information).

The requirement of stock prices following random walks has been outlined. However, in the work of Fama (1969) there are 3 more generalized conditions which are necessary for market efficiency. According to his study, a market in which (i) no transaction costs exist for trading securities, (ii) all available information is costless for all market participants and (iii) all participants agree on the implications of current information for prices and distributions of future prices of assets is considered

[27] Campbell, Lo and MacKinlay (1997)

to be efficient.[28] Hence, the third condition is most strongly connected to the martingale theory and its assumption about stock price patterns. On that basis Fama (1969) investigated 3 forms of efficiency: While in the test of weak-form the incorporation of past price histories in the information subset is investigated, semi-strong form is tested by speed of price-adjustments to other publically available information. Furthermore, strong-form can be analyzed by testing for monopolistic access to information by any market participant.

Empirical work of Fama (1969) apparently supports his thesis about efficiency of markets. Weak-form can easily be confirmed by statistically significant results for successive price changes and its patterns' behaving according to martingale theory. Although, there is evidence for stock price persistence as well as stock price reversals, Fama (1969) finds that information is not completely evaluated immediately. Therefore, first day's adjustment of prices is unbiased, which supports random walk hypothesis. For semi-strong form of market efficiency, Fama (1969) examines if stock splits concerning future dividend payments are reflected in the price of the share at the time of the split. Findings of Fama (1969) and further researchers confirm that this information is contained, for which reason semi-strong form can not be rejected. Eventually, strong-form of market efficiency is tested through investigations on the appearance of deviations from market efficiency.[29] In fact, there are findings like monopolistic access to information used to generate trading profits, which are used by Fama (1969) to illustrate scepsis about strongest form of market efficiency. Nevertheless, Fama (1969) concludes that corporate insiders and specialists are the only two groups with monopolistic access to information, such that efficient market models seem to be close to reality.

Evidently, results of Fama (1969) suggest that efficient market hypothesis actually holds. Nevertheless, there is no consensus among economists about the verifiability of EMH. Thus, momentum literature and further studies about the patterns of dynamic asset pricing suggest the absence of market efficiency as defined Fama

[28] Fama (1969)

[29] Niederhoffer and Osborne (1966)

(1969). Attaching the condition of frictionless markets indeed evokes doubts about EMH. E.g. Grossmann and Stiglitz (1980) investigate the impossibility of informationally efficient markets. Particularly, they claim that in presence of market efficiency and costly information, markets will break down. Further studies, which challenge EMH, tie the market efficiency strongly to the mentioned random walk hypothesis. Although findings in several studies about stock price patterns suggest the rejection of EMH, it is difficult to interpret the behavior of portfolios that reflects time-varying returns in the framework of market efficiency.[30] Thus, security price patterns contradicting the random walk hypothesis do not necessarily imply the inefficiency of stock price formation, even if empirical results impose restriction to plausible economic models for asset pricing.[31] In particular, established tests of EMH may not be most informative methods of gauging efficiency of markets.[32] Hence, even economic researchers who find evidence of contradictions to random walk hypothesis do not ultimately reject efficient market hypothesis and claim that markets are at least semi-strong efficient.

3.2 Capital Asset Pricing Model

Findings of the previous sub-chapter point out the importance of efficient market hypothesis but also challenge whether EMH holds. Nevertheless, economists emphasize that in the theoretical framework of financial markets no better assumption exists. However, results of momentum literature prove evidence of abnormal returns from momentum strategy, which either contradict the EMH, or alternatively support the hypothesis that returns from this strategy compensate for risk from investing in recent winners.[33] Common understanding of capital markets suggests that risky investments such as stock market investments yield a higher return.[34] Hence, the most famous asset pricing model in financial literature is introduced, which is built on the hypothesis of efficient markets and risk compensation.

[30] Lehmann (1990)
[31] Lo and MacKinlay (1988)
[32] Lo and MacKinlay (2002)
[33] Jegadeesh and Titman (2001)
[34] Campbell, Lo and MacKinlay (1997)

Capital asset pricing model (CAPM) was established by William Sharpe (1964) and John Lintner (1965) and is until today a common model to price assets in the financial markets. As with in the efficient market hypothesis, certain assumptions have to hold so that the model is consistent. According to the capital asset pricing model of Sharpe and Lintner all investors are averse to risk and are single period expected utility of terminal wealth maximizers. Furthermore, all investors have identical decision horizons and homogeneous expectations regarding investment opportunities, all investors are able to choose among portfolios solely on the basis of expected returns and variance returns, all transaction costs and taxes are zero and all assets are infinitely divisible.[35] CAPM is also based on the portfolio selection theory of Markowitz (1952) and implies that expected returns must be linearly related to the covariance of its return with the return of the market portfolio.[36] In fact, market includes two prices, allowing for a higher return by incurring additional risk: the price of time, or the pure interest rate, and the price of risk.[37]

Modern portfolio theory reports of two sorts of risk. On the one hand, there is systematic risk, which is the part of asset's risk that can not be diversified away due to securities' correlation with the return of market portfolio. However, investors deal also with unsystematic risk, which can be eliminated through right portfolio selection, i.e. minimization of portfolio variance. Predicted standard deviation of return of a portfolio, consisting of two assets i and j, has the following structure:

$$\sigma_P \;=\; \sqrt{(x^2\,\sigma_{r_i}^2 + (1-x)^2\sigma_{r_j}^2 + 2\,\rho_{i,j}\,x\,(1-x)\,\sigma_{r_i}\,\sigma_{r_j})}\,, \qquad x \,\in\, (0,1)$$

where $\rho_{i,j}$ illustrates the correlation coefficient of returns of asset i and asset j. The latter allows to measure the risk, i.e. systematic risk, which is implied by the asset pricing model. According to CAPM the variance of a single asset i is the covariance of its return with the market return, divided by the variance of the market return:[38]

[35] Jensen (1967)

[36] Campbell, Lo and MacKinlay (1997)

[37] Sharpe (1964)

[38] Fama and French (2004)

$$\beta_{i,M} \; = \; \frac{\mathrm{Cov}(r_i, r_M)}{\sigma^2(r_M)}$$

where

$$\mathrm{Cov}(r_i, r_M) \; = \; 2\,\rho_{iM}\,x\,(1-x)\,\sigma_{r_i}\,\sigma_{r_M}\,.$$

Apparently, systematic risk represents the share of the total risk which is due to covariance with market returns. Hence, common assumption of risk aversion among investors suggests a diversified portfolio considering minimization of systematic risk. Finally, one can infer the Sharpe and Lintner version of the capital asset pricing model picturing the expected return of security i as

$$\mathbb{E}[r_i] = r_f + \beta_{i,M}\,(\mathbb{E}[r_M] - r_f) \qquad \forall i\,.$$

Until today Sharpe-Lintner Version of CAPM is the most known model to price securities. Nevertheless, empirical literature challenges consistency as well as applicability of CAPM. Jensen (1967) remarks that relation between expected return and market beta can be tested with a time-series regression. Thus, CAPM implies that the expected value of security's excess return can be explained by CAPM risk premium, which is also known as 'Jensen's alpha' (α_i):[39]

$$r_i - r_f = \alpha_i + \beta_{i,M}\,[r_M - r_f]\, + \epsilon.$$

The latter model is a famous tool to measure the performance of a portfolio manager. The ability of investors to predict future security prices is described by performance. Indeed performance measure α_i will be zero applying a naive random buy and hold strategy, and will be even negative, if a portfolio manager is not doing well.[40] Nevertheless, even if the portfolio managers outperform the market one can not necessarily

[39] Fama and French (2004)

[40] Jensen (1967)

conclude that this is due to his ability of stock price forecasting. Instead, it is unlikely that an investor will be able to use past history of stock prices to increase his profits.[41]

Empirical findings of regression tests apparently show that capital asset pricing model is an important tool to model asset prices, but fails when it comes to performance measures of portfolio managers. Results exhibit too high values for alpha, i.e. manager performance, while beta values describe market movements. Since researchers empirically do not find satisfactory results, describing performance measures, further models are developed including factors like value, size and momentum. Since the latter is in the focus of this study capital asset pricing model is extended in the following subsection.

3.3 Multifactor Models

Over the last decades CAPM has been investigated in detail and the model of Sharpe and Lintner sustainably established itself in the context of financial literature. However, different research studies find evidence that CAPM can not capture all components, which are responsible for performance of investors. Two of the most studied capital market phenomena are the relation between an asset's return and it's book value relative to it's current market value (book-to-equity divided by market value, BE/ME), as well as the asset's return and it's relative historic performance, i.e. momentum.[42] Despite value and momentum also the influence of size and beta (which is already captured by CAPM) on asset returns is referred to. Since these patterns in average stock returns are not explained by the CAPM of Sharpe (1964) and Lintner (1965), they are typically called anomalies.[43] Hence, a multifactor model, commonly known as Fama-French three-factor model, is introduced:

$$\mathbb{E}[r_i] - r_f = \beta_{i,M}\,[\mathbb{E}[r_M] - r_f] \,+\, \beta_{SMB_i}\,\mathbb{E}[\text{SMB}] \,+\, \beta_{HML_i}\,\mathbb{E}[\text{HML}].$$

[41] Jensen (1969)

[42] Asness, Moskowitz and Pedersen (2012)

[43] Fama and French (1996)

The model of Fama and French (1993) describes the expected return of a portfolio in excess of risk-free rate in dependence to sensivity of its return to the following factors: (i) excess return on a broad market portfolio like in CAPM ($r_M - r_f$), (ii) difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (size effect, SMB, small-minus-big), and (iii) difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks (value effect, HML, high-minus-low). Hence, $\mathbb{E}[r_M]$, $\mathbb{E}[\text{SMB}]$ and $\mathbb{E}[\text{HML}]$ are expected premiums and factor sensitivities β_{M_i}, β_{SMB_i}, β_{HML_i} are the slope of the time series regression,[44]

$$r_i - r_f = \alpha_i + \beta_{i,M}\,[r_M - r_f] \,+\, \beta_{SMB_i}\,\text{SMB} \,+\, \beta_{HML_i}\,\text{HML} + \epsilon.$$

Findings of Fama and French (1993) provide evidence that their three-factor model captures much of cross-sectional variance and that the model is a good description of portfolios based on size and value. In addition, the three-factor model also seems to include price reversals occurring after a holding period of 12 months as described by the study of De Bondt and Thaler (1984). In their empirical work, Fama and French (1996) investigate the Jensen alpha by linearly regressing on the momentum returns. Their model seems to capture well the returns of momentum strategy with a formation period of $t - 60$ to $t - 13$, i.e. formation period of approximately 4 years, where price reversals have been confirmed in various studies. However, the three-factor model does not explain well the returns of momentum approach with short-term formation period of about 10 months ($t - 12$ to $t - 2$). Results of the latter show alpha values that are significantly different from zero, implying that short-term price continuation can not be captured by the three-factor model of Fama and French (1993).

Hence, Fama and French (2011) add a momentum factor to their model based on the four-factor model of Carhart (1997). Since there is a negative correlation between value and momentum strategies which both have high positive expected returns,

[44] Fama and French (1996)

a simple combination of the two strategies should be much closer to the efficient frontier than either strategy alone.[45] Accordingly, adding the momentum factor to the model should imply a more efficient model.

In the study of Carhart (1997) an additional factor capturing Jegadeesh and Titman's (1993) one-year momentum anomaly is added to the Fama and French (1993) three-factor model for the sake of its inability to explain cross-sectional variation in returns of momentum strategy:

$$r_i - r_f = \alpha_i + \beta_{i,M}\left[r_M - r_f\right] + \beta_{SMB_i}\,\mathrm{SMB} + \beta_{HML_i}\,\mathrm{HML} + \beta_{MOM_i}\,\mathrm{MOM} + \epsilon.$$

By MOM the returns are characterized on a value-weighted portfolio for one-year momentum in stock returns. Further factors are similar to the one derived by Fama and French (1993). In his empirical work, Carhart (1997) finds that his four-factor model substantially improves average pricing errors of CAPM and three-factor model of Fama and French (1993). Mean absolute errors from CAPM, three-factor, and four-factor model are 0.35 percent, 0.31 percent, and 0.14 percent, respectively. Nevertheless, although the four-factor model seems to explain returns better, results of Fama and French (2011) are still not significantly different from zero. However, they come to a similar conclusion, being comfortable using the four-factor model to explain the returns of global portfolios, e.g. to evaluate the performance of a mutual fund, since the local four-factor model performs as well or better than the three-factor model or CAPM.

Apparently, several linear multifactor models based on the CAPM fail to completely explain the contribution of momentum to the performance of portfolios. For that reason the sources of momentum profits are decomposed in the following chapter.

[45] Asness, Moskowitz and Pedersen (2012)

4 Analytical Decomposition of Momentum Strategy

In the previous chapters various models which are used in financial literature to price securities were discussed. However, empirical studies suggest that these models do not fully capture momentum factor. Furthermore, the previous chapter outlines the influence of size, beta and industry to the profitability of momentum strategies. In this section, sources of momentum are decomposed in detail to provide evidence about the importance of common factors as well as firm-specific information in explaining profitability of momentum-based trading strategies.[46]

4.1 Decomposition of Momentum Profits

First, the approach of Lo and MacKinlay (1990) and Lehmann (1990) is reviewed, where abnormal momentum returns are credited to the occurrence of (auto-) correlations and the lead-lag relations among stocks.[47] Therefore, the 'Weighted Relative Strength Strategy' is recalled where weights of stocks in the relative strength portfolio depend on the past performance during the observation period and hence each security is considered for the portfolio. Specifically, the weight of asset i in month t can be expressed as

$$w_{i,t} = (r_{i,t-1} - r_{m,t-1}),$$

where $r_{i,t}$ represents return of asset i at time t and $r_{m,t}$ describes the return of an equally-weighted market index in month t or as considered from now on, as the cross-sectional average. Furthermore, the following multifactor model is considered for stock returns:

$$r_{i,t} = \mu_{i,t} + \sum_{k=1}^{K} \beta_{i,k} \, f_{k,t} + \sum_{m=1}^{M} \theta_{i,m} \, z_{m,t} + e_{i,t}, \tag{4.1}$$

[46] Chordia and Shivakumar (2002)

[47] Lewellen (2002)

where $\mu_{i,t}$ represents the expected return on security i conditional on the information set ϕ at time t. By $f_{k,t}$ the return on the factor mimicking portfolio k is illustrated, which can be compared to the Fama-French factors. Furthermore, $\beta_{i,k}$ is the factor loading of security i on factor k and $e_{i,t}$ is the firm-specific component of return. $z_{m,t}$ represents industry portfolio returns orthogonal to returns on factor-mimicking portfolios and $\theta_{i,m}$ is stock i's sensitivity to the return on industry m.[48] In addition, the K factor portfolios, the industry components and the idiosyncratic terms are uncorrelated by construction which is ensured by the following equations:

$$
\begin{aligned}
\mathbb{E}[f_{l,t}, f_{k,t-1}] &= 0, \quad \forall l \neq k; \\
\mathbb{E}[e_{i,t}, e_{j,t-1}] &= 0, \quad \forall i \neq j; \\
\mathbb{E}[z_{m,t}, z_{n,t-1}] &= 0, \quad \forall m \neq n; \\
\mathbb{E}[z_{m,t}, f_{k,t-h}] &= 0, \quad \forall m, k \text{ and } h = \pm 1; \\
\mathbb{E}[e_{i,t}, f_{k,t-h}] &= 0, \quad \forall i, k \text{ and } h = \pm 1; \\
\mathbb{E}[e_{i,t}, z_{m,t-h}] &= 0, \quad \forall i, m \text{ and } h = \pm 1;
\end{aligned}
$$

and $\mathbb{E}(e_{i,t}) = 0$ for all i and $\mathbb{E}(z_{m,t}) = 0$ for all m. Hence, profits of relative strength portfolio can be tied to the autocorrelation and cross-serial correlation of returns that have unconditional mean $\mu = \mathbb{E}[r_i]$ and autocovariance $\Omega = \mathbb{E}[(r_t - \mu)(r_{t-1} - \mu)']$.[49]

Findings of momentum literature exhibit returns significantly different from zero of relative strength strategies, which imply that stocks which generate higher than average returns in one period perform equally well in the following period:[50]

$$
\begin{aligned}
&\mathbb{E}[r_{i,t} - \bar{r}_t | r_{i,t-1} - \bar{r}_{t-1} > 0] > 0 \\
&\text{and} \\
&\mathbb{E}[r_{i,t} - \bar{r}_t | r_{i,t-1} - \bar{r}_{t-1} < 0] < 0,
\end{aligned}
$$

[48] Chordia and Shivakumar (2002)
[49] Lewellen (2002)
[50] Jegadeesh and Titman (1993)

where a bar above a variable denotes its cross-sectional average. Hence, momentum strategy is profitable if the following equation holds:

$$\mathbb{E}[w_{i,t}\,(r_{i,t} - \bar{r}_t)] \;=\; \mathbb{E}[(r_{i,t-1} - \bar{r}_{t-1})\,(r_{i,t} - \bar{r}_t)] \;>\; 0.$$

This equation illustrates that expected profits from zero-cost trading strategy, which weights stocks by their past returns less past equally weighted index returns, equal the cross-sectional covariance.[51]. Hence, by integrating the multifactor linear process, momentum profits can be decomposed in the following way:

$$\begin{aligned}
\mathbb{E}[(r_{i,t-1} - \bar{r}_{t-1})\,(r_{i,t} - \bar{r}_t)] = {} & (\mu_{i,t} \,-\, \bar{\mu}_t)\,(\mu_{i,t-1} \,-\, \bar{\mu}_{t-1}) \\
& + \sum_{k=1}^{K} (\beta_{i,k} \,-\, \bar{\beta}_k)^2\,\mathrm{Cov}(f_{k,t}, f_{k,t-1}) \\
& + \sum_{m=1}^{M} (\theta_{i,m} \,-\, \bar{\theta}_m)^2\,\mathrm{Cov}(z_{m,t}, z_{m,t-1}) \\
& + \mathrm{Cov}(e_{i,t}, e_{i,t-1}).
\end{aligned}$$

Furthermore, the average over all N stocks is taken, which implies that the momentum profit equals

$$\begin{aligned}
\frac{1}{N}\sum_{i=1}^{N}(\mu_{i,t} \,-\, \bar{\mu}_t)\,(\mu_{i,t-1} \,-\, \bar{\mu}_{t-1}) \,+\, \sum_{k=1}^{K}\sigma^2_{\beta_k}\,\mathrm{Cov}(f_{k,t}, f_{k,t-1}) \\
+ \sum_{m=1}^{M}\sigma^2_{\theta_m}\,\mathrm{Cov}(z_{m,t}, z_{m,t-1}) \,+\, \frac{1}{N}\sum_{i=1}^{N}\mathrm{Cov}(e_{i,t}, e_{i,t-1}),
\end{aligned} \tag{4.2}$$

where $\sigma^2_{\beta_k}$ and $\sigma^2_{\theta_m}$ are the cross-sectional variances of the portfolio loadings and the industry sensitivities respectively.[52]

Consequently, four different sources of momentum profits can be identified as possible momentum drivers. First term, $(\mu_{i,t} - \bar{\mu}_t)\,(\mu_{i,t-1} - \bar{\mu}_{t-1})$, of the derived equation

[51] Chordia and Shivakumar (2002)

[52] Chordia and Shivakumar (2002)

(4.2) characterizes the expected return of securities. Thus, stocks might be positively autocorrelated in a way that momentum strategy yields profits if firms with a high (low) return today are expected to have high (low) returns in the future.[53] Second term of equation (4.2), $\sum_{k=1}^{K} \sigma^2_{\beta_k} \operatorname{Cov}(f_{k,t}, f_{k,t-1})$, describes the contribution of serial correlation in the factors. Equation (4.2) highlights that serial correlation of the factor portfolio return is a function of cross-sectional variance of the betas. Hence, if the factor portfolio exhibits positive serial correlation, momentum strategy tends to pick stocks with high β's, implying extreme past returns.[54] Third term, $\sum_{m=1}^{M} \sigma^2_{\theta_m} \operatorname{Cov}(z_{m,t}, z_{m,t-1})$, represents serial correlation in the industry return components, which is a finding of Grinblatt and Moskowitz (1999) and is already emphasized in chapter 2.3 where momentum drivers are presented. Last term, $\operatorname{Cov}(e_{i,t}, e_{i,t-1})$, describes the serial correlation in firm-specific components.

In the following subsections, the previously mentioned components of momentum profits are analyzed in more detail.

4.2 Variation in Expected Returns

$$\frac{1}{N} \sum_{i=1}^{N} (\mu_{i,t} - \bar{\mu}_t)(\mu_{i,t-1} - \bar{\mu}_{t-1})$$

First, the influence of the first term of equation (4.2) is tested, which illustrates the cross-sectional dispersion of mean returns. Momentum literature provides two different approaches, which are responsible for the occurrence of a positive contribution in terms of momentum profits. Specifically, in the studies of Conrad and Kaul (1998) the influence of time-invariant mean returns and their cross-sectional variation is discussed, which is accompanied by the assumption of stationary mean returns in financial literature. Nevertheless, there is also evidence for profitability of momentum strategy due to dispersion in time-varying mean return, e.g. Chordia and Shivakumar (2002).

[53] Lewellen (2002)

[54] Jegadeesh and Titman (1993)

Momentum literature provides findings which indicate that profitability of momentum strategy is related to cross-sectional dispersion in time-invariant mean returns. As mentioned before, these findings are based on the assumption that mean returns of securities are stationary. Referring to random walk hypothesis, contribution of expected mean returns is fully due to its variance:[55]

$$\mathbb{E}[r_t^k] = \sigma^2(\mu^k)$$

However, Conrad and Kaul (1998) find in their empirical study that more than 100 percent is responsible for momentum returns, i.e. out of 18 cases with positive momentum returns they find 16 cases where variation in expected returns has contributed more than 100 percent to momentum returns while other factors have had a negative impact on momentum. Hence, Conrad and Kaul (1998) find that cross-sectional dispersion in mean returns is an important component of momentum profitability. This finding implies that momentum strategy does not necessarily contradict random walk hypothesis. Moreover, it supports their assumption that momentum profitability is due to cross-sectional dispersion in mean returns from buying high-mean stocks and selling short low-mean securities.

Nevertheless, momentum literature also provides evidence that variance of mean returns does not contribute to profitability of momentum strategies. Grinblatt and Moskowitz (1999) report that there is a strong dependence between momentum profitability and industry momentum. Thus, one can find a strong and persistent momentum effect which does not appear to be explained by microstructure effects, individual momentum, or cross-sectional dispersion in mean returns.[56] They investigate industry-based strategies by testing for stock price performance of all industries, while buying the best three industries and selling worst three industries over an observation period. Results of their empirical studies exhibit larger returns (about 90 basis points) than individual momentum returns of Jegadeesh and Titman (1993). Therefore Grinblatt and Moskowitz (1999) argue that the first term of decomposed

[55] Conrad and Kaul (1998)

[56] Grinblatt and Moskowitz (1999)

momentum returns can not be a main determinant, since individual momentum profits are not significantly larger than industry momentum returns.

Moreover, contradictions to the assumption of Conrad and Kaul (1998) can be found, which claim that momentum profitability is not due to buying high-mean stocks and selling low-mean stocks. In the study of Jegadeesh and Titman (2001) the time horizon of profitable momentum strategies is determined. Findings of their empirical research confirm evidence for time reversals after a holding period of 12 months and exhibit that profits are on average negative from month 13 to month 60 of holding period. Hence, they find contradiction and argue that one would expect average return of about 1 percent from month 6 until end of observation period in month 60, if momentum profits were entirely due to differences in unconditional risk between winner and loser portfolios.[57] Nevertheless, Jegadeesh and Titman (2001) qualify their statement, with regard to the derivation of the momentum decomposition used in their work, and conclude that Conrad and Kaul (1998) only overestimate the magnitude of cross-sectional dispersions in mean returns. Similar results can be found in empirical studies of Lewellen (2002), Du and Watkins (2007) where the returns of momentum strategies are decomposed into the following three components: variation in expected returns, serial correlations in returns and cross-sectional covariances. Results of their empirical work support the hypothesis that cross-sectional dispersion of mean returns is not the main determinant of momentum profits.

Additionally, cross-sectional dispersion can be examined from time-varying mean returns as suggested by Chordia and Shivakumar (2002). In their study, momentum returns are explained by economic risk factors. More specific, time-variation in momentum profits seems to depend on commonly known macroeconomic variables like value-weighted market dividend yield, default spread, term spread and yield on three-month Treasury bills. Hence, Chordia and Shivakumar (2002) claim that after controlling for these predicted returns, momentum strategy does not generate abnormal returns anymore, which implies that business cycles have a strong contribution

[57] Jegadeesh and Titman (1993)

to momentum profits. Consequently, empirical results from the study of Chordia and Shivakumar (2002) suggest that significantly positive returns from momentum strategy only occur during expansionary periods. Empirical work of Avramov et al. (2007) aims towards a similar hypothesis by linking momentum profitability to firm's credit rating. They claim that after extracting firms with credit ratings below investment grade, momentum strategy payoffs from remaining firms are insignificant. It can be argued that credit risk varies with the business cycle, findings of this empirical work seem to support the hypothesis of Chordia and Shivakumar (2002).

Literature shows that there is no broad consent about momentum profitability being linked to cross-sectional dispersion of mean return - neither time-invaryring nor time-varying. Thus, findings of this chapter suggest to consider further factors of the decomposed momentum returns than cross-sectional variance of mean returns.

4.3 Serial Factor Correlation

$$\sum_{k=1}^{K} \sigma^2_{\beta_k} \operatorname{Cov}\left(f_{k,t-1}, f_{k,t}\right)$$

In chapter 3.2 the Capital Asset Pricing Model is introduced and the anomalies which are not captured by the CAPM but by multifactor model of Fama and French (1993) are presented. Second term of decomposition (4.2) actually includes the factors of the three-factor model. If the factor-mimicking portfolio returns exhibit positive serial correlation, momentum profits are implied due to cross-sectional variances of the betas β_k.[58]

Given the multifactor model (4.1), the following two properties can be assumed: (i) a large number of stocks implies negligible firm-specific risk and (ii) its return is negligibly sensitive to the returns of any single industry (i.e. θ_m is very small for all m). Thus, serial covariance of the portfolio of all stocks is approximately,

[58] Jegadeesh and Titman (1993)

$$\text{Cov}\left(\bar{r}_t, \bar{r}_{t-1}\right) = \sum_{k=1}^{K} \beta_k^2 \, \text{Cov}\left(f_{k,t}, f_{k,t-1}\right),$$

where t is a six month period.[59] More specific, if relative strength profits are due to serial covariance of factor-related returns, serial covariance of equally-weighted index returns is required to be positive.[60]

In the study of Grinblatt and Moskowitz (1999) the approach of Jegadeesh and Titman (1993) is used to investigate the covariance of consecutive non-overlapping six-month returns on the equally-weighted index. Apparently, their findings report that covariance is insignificantly different from zero. Results from Jegadeesh and Titman (1993) even exhibit negative covariance, $\text{Cov}(\bar{r}_t, \bar{r}_{t-1}) = -0.0028$, which reduces the profits of the relative strength portfolio. Furthermore, Grinblatt and Moskowitz (1999) report that the risk premium of this portfolio historically is high, which implies that β_k's must be large. Moreover, large betas imply that serial covariance in at least some of the unconditionally efficient portfolios is not contributing to momentum profits. Hence, literature suggests almost zero serial covaration in Fama and French factor-mimicking portfolios and therefore second component of equation (4.2) does not seem to contribute to the profitability of momentum trading strategies.

4.4 Serial Correlation in Industry Return Components

$$\sum_{m=1}^{M} \sigma_{\theta_m}^2 \, \text{Cov}\left(z_{m,t-1}, z_{m,t}\right)$$

Serial covariance in industry return components is represented by the third term in the decomposition of momentum profits. In chapter 3.3 the finding of Grinblatt and Moskowitz (1999) and the connection of industry momentum and profitability of momentum strategies is presented. In their empirical research, stocks from

[59] Grinblatt and Moskowitz (1999)

[60] Jegadeesh and Titman (1993)

American stock markets are screened for momentum for a time horizon from 1963 to 1995. In extent to the common known approach of individual momentum strategy, industry momentum is obtained by sorting industry portfolios according to their performance of the most recent 6 months. Afterwards, the performance of a long-short strategy is measured by buying top three industries and selling worst three industries. Obtained results indicate that a big share of momentum profits might be due to serial correlation of industry return components.

In fact, findings of Grinblatt and Moskowitz (1999) report that returns of industry momentum strategy are on average 0.43 percent per month, which is in magnitude identical to their results from momentum strategy for individual stocks. Furthermore, they provide tests to refute the assumption that also industry momentum profits are due to individual stock momentum. Decomposing the industry momentum trading profits in the following way,

$$\begin{aligned}\frac{1}{20}\sum_{I=1}^{20}\mathbb{E}\left((R_{I,t}-\bar{r}_t)(R_{I,t-1}-\bar{r}_{t-1})\right) =& \sigma_{\mu_I}+\sum_{k=1}^{K}\sigma_{\beta_{I,k}}\mathrm{Cov}(R_{k,1},R_{k,t-1}) \\ &+\sum_{m=1}^{M}\sigma_{\theta_{I,m}}\mathrm{Cov}(z_{m,t},z_{m,t-1}),\end{aligned}$$

where $R_{I,t}$ is the return of industry portfolio I and $\bar{r}_t$ is the equally-weighted average return across industry portfolio, implies that profits are mostly due to industry, since σ_{μ_I} is small for industry sample and $\mathrm{Cov}(R_{k,1},R_{k,t-1})\approx 0$ at least for Fama-French factor portfolios.[61] Hence, in the absence of factor serial correlation and negative cross-sectional industry mean dispersion, for industry momentum the following holds:

$$\sum_{m=1}^{M}\sigma^2_{\theta_m}\mathrm{Cov}(z_{m,t-1},z_{m,t}) \quad > \quad 0.$$

Additionally, Daniel, Grinblatt, Titman and Wermers (1997) investigate the contri-

[61] Grinblatt and Moskowitz (1999)

bution of size and BE/ME to adjust the returns of momentum strategy. Findings of several studies support the hypothesis that there is low influence towards momentum profitability. Moreover, Grinblatt and Moskowitz (1999) analyze the contribution of industry momentum return after subtracting stock's contemporaneous industry return from its own return. They find negligible profits, where size effect contributes most to the 13 basis points of momentum profits and industry adjusted return can be illustrated in the following way

$$r_{j,t}^{sb,I} = r_{j,t}^{b} - R_{I,t}^{sb} \quad \forall j \in I,$$

where $R_{I,t}^{sb}$ is the size- and BE/ME-adjusted return on industry I, to which stock j belongs at time t and $r_{j,t}^{sb}$ is the size and BE/ME characteristic-adjusted return on security j. Hence, individual stock momentum strategy can be decomposed as

$$\begin{aligned} \mathbb{E}\,(r_{j,t}^{sb} - R_{I,t}^{sb})(r_{j,t-1}^{sb} - \bar{r}_{t-1}) &= \sum_{k=1}^{K} \sigma_{\beta_k}^2 \operatorname{Cov}(R_{k,t}, R_{k,t-1}) \\ &+ \frac{1}{N} \sum_{j=1}^{N} \operatorname{Cov}(e_{j,t}, e_{j,t-1}) \end{aligned}$$

Since the first term on the right hand side is assumed to be zero and results of the empirical work exhibit industry-adjusted return of zero for individual stock momentum strategy, one can claim that

$$\operatorname{Cov}(e_{j,t}, e_{j,t-1}) = 0.$$

Thus, by adjusting individual stock returns for size, book-to-market equity and for individual momentum profits, individual momentum is not significantly different from zero, whereas industry momentum profits are still significantly positive.[62]

Grinblatt and Moskowitz (1999) emphasize the importance of industry momentum for the profitability of momentum strategies. Their empirical work indicates that industry momentum profits are not affected by lead-lag effects measured by size,

[62]Daniel, Grinblatt, Titman and Wermers (1997)

liquidity and microstructure effects. Therefore, after analyzing empirical evidence, the magnitude of serial correlation of industry returns seems to be most distinct for profitability of momentum strategies.

4.5 Serial Correlation in Firm Specific Components

$$\frac{1}{N}\sum_{i=1}^{N}\mathrm{Cov}(e_{i,t}, e_{i,t-1})$$

Last term of decomposed sources of momentum profitability illustrates the contribution of serial correlation in firm specific components. In the study of Grundy and Martin (2001) firm specific components are seen as one of the main determinants of momentum profits. Their research work compares profits of momentum strategy to two ranking criteria. Specifically, this empirical work distinguishes between a factor-related and a stock-specific part of returns of momentum strategy, where factor-related return momentum strategy ranks stocks based on the Fama-French factor component and stock-specific return momentum strategy ranks stocks based on an estimate of the component that is not related to Fama-French factors.

For a ranking period from $t-7$ to $t-2$ (equals a formation period of 6 months), stocks are sorted according to the ranking criterion, which allocates a winner portfolio of top decile companies as well as a loser portfolio with bottom decile companies. Furthermore, the following three-factor model is used to display returns:

$$R_{i,t} = \alpha_{0,i}\, D_t + \alpha_{1,i}\,(1 - D_t) + \beta_i\, r_{m,t} + \beta_{SMB_i}\,\mathrm{SMB}_t + \beta_{HML_i}\,\mathrm{HML}_t + e_{i,t},$$

where

$$D_t = \begin{cases} 1, & \text{if} \quad t \in \{t-7, ...t-2\} \\ 0, & \text{otherwise.} \end{cases}$$

At time $t \in max\{t - 61, t - \text{first observation}\}$ and in the regression model stocks from NYSE and AMEX are covered where monthly returns are available over at least 36-month window.[63] Firm-specific momentum strategy chooses winners and losers according to estimated $\alpha_{0,i}$, while factor-related momentum strategy ranks stocks based on $\sum_{t=t-7}^{t-2} \beta_i \, r_{m,t} + \beta_{SMB_i} \, \mathrm{SMB}_t + \beta_{HML_i} \, \mathrm{HML}_t$ from the three-factor model.

Results of the empirical work of Grundy and Martin (2001) exhibits risk-adjusted profitability of a stock-specific return strategy which is marginally greater than total return strategy and is distinctly larger than the factor-related return strategy's risk-adjusted profitability. Although, findings are not significant for the three-factor model approach, Grundy and Martin (2001) suggest that firm-specific serial correlation is a main driver of profits from momentum effect.

Nevertheless, in the previous chapter the coherence of time-varying expected returns is explained through business cycle components and momentum profits. The study of Chordia and Shivakumar (2002) questions the hypothesis of Grundy and Martin (2001), which relates momentum profitability to serial correlation of firm-specific components. In their study Chordia and Shivakumar (2002) investigate whether momentum payoffs are attributable to the predicted portion of business cycle model or the unexplained portion of return due to firm-specific components. Results of the empirical work exhibiting payoffs of momentum strategies based on stock-specific returns are insignificantly different from zero. Hence, in contrast to Grundy and Martin (2001) they claim, that profitability of momentum effect is rather due to predicted component of returns than due to unpredicted and firm-specific components respectively.

4.6 Summary

Assuming that markets are at least semi-strong efficient, source of momentum profitability seems to be based on compensation for risk.[64] In chapter 4 the source of momentum returns is decomposed in a rational approach. Based on a three-factor asset pricing model various research studies derive possible risks, i.e. (co-)variances,

[63] Grundy and Martin (2001)
[64] Jegadeesh and Titman (2001)

that might lead towards positive momentum returns. Momentum literature provides different approaches, arguing for and against the four components. Obviously there is no consent about one of the four possible drivers of momentum profitability. Nevertheless, empirical evidence and argumentation indicate that positive return of momentum strategy is rather due to serial correlation within industry return components or serial correlation within firm specific components than due to variation in expected returns or factor correlation. Hence, the industry component will be investigated in the empirical study in chapter 6. Furthermore, a new firm specific component will be investigated by analyzing the impact of companies' sustainability on momentum profitability.

Apparently, an empirical derivation of the source of momentum phenomenon seems to be difficult and risk compensation is hard to determine. Hence, Jegadeesh and Titman (1993) among other academics also consider overreaction and underreaction towards information as possible source of momentum profits. Thus, behavioral finance explanations are taken into account in addition to risk-based explanations. However, this thesis will focus on a risk-based approach and hence an additional upcoming factor called liquidity will be considered. During last decade the importance of liquidity grew and its influence on asset pricing is undoubted. Therefore, liquidity of securities is introduced and momentum profitability is discussed in that context in the following chapter.

5 The Role of Liquidity in Asset Pricing

Previous chapters stressed the difficulties of explaining the anomaly of momentum profitability and its drivers. During the last decade the term liquidity became more and more popular in financial theory. Academics claim that liquidity should be incorporated in asset pricing models. Therefore, in this section liquidity of securities is examined and its coherence with momentum is investigated.

5.1 Introduction of Liquidity

So far, the mentioned asset pricing models incorporate various risk measures like market correlation, value and size factors. However, the effect of liquidity risk is not included in any of the traditional asset pricing models. Riskiness of liquidity is due to its variation over time and its uncertainty. Hence, the occurence of illiquidity influences asset prices and can be measured by the cost of immediate execution.[65] Indeed it seems reasonable that investors need to get compensated on assets that have higher sensitivities to aggregate liquidity.[66] Since there is a strong connection between the execution of a trade and the liquidity of a security, it becomes obvious that profits (losses) of a stock buy (sell) might be lower (higher) in magnitude if prices move quickly and trade execution takes a longer time for illiquid assets. Therefore, liquidity of securities is considered an important factor and academics claim that this has to be taken into account in asset pricing models. Thus, one can claim that across stocks and over time, expected returns are an increasing function of expected liquidity.[67]

Liquidity becomes not only an important factor for asset pricing models, but also momentum literature assigns value to liquidity. However, while asset pricing models that incorporate liquidity factors suggest that investors need to be compensated for illiquid securities, it is not intuitive how liquidity correlates with momentum effects. Momentum strategy follows the approach of buying recent 'winners' and selling 'loser'-stocks. Behavioral finance theory supports findings that 'winners' tend to be liquid, since investors are willing to sell and realize gains. However, investors are reluctant to realize loses.[68] Hence, investors are prone to ride 'losers' which is why 'loser'-stocks tend to be illiquid. Thus, these findings support the hypothesis that momentum strategy generates large (weak) profits when market is highly liquid (illiquid).[69] Nevertheless, literature also finds converse evidence. Results of Ibbotson

[65] Amihud and Mendelson (1986)
[66] Pastor and Stambaugh (2003)
[67] Amihud (2002)
[68] Odean (1998)
[69] Avramov, Cheng and Hameed (2014)

et al. (2013) claim that high momentum returns coincide with low liquid securities. Accordingly, this anomaly will be analyzed in more detail later.

In this section measures of liquidity are introduced. Furthermore, the relationship between asset pricing and liquidity risk is outlined through the liquidity asset pricing model (LAPM). Finally, findings of the coherence of momentum profitability and liquidity are presented.

5.2 Measures of Liquidity

According to Amihud and Mendelson (1986) liquidity, marketability and trading costs are among the primary attributes of investment plans and financial instruments. Hence, they are one of the first academics investigating the influence of illiquidity on asset pricing and describing illiquidity measures. Liquidity is often viewed as an important feature of the investment environment and macroeconomy.[70] Furthermore, liquidity illustrates a rudimentary component of market microstructure studies. In this subsection several liquidity measures are introduced.

In general, a liquid security enables buying or selling significant quantities of the asset quickly at a low cost level with little price impact. Hence, market microstructures suggest that liquidity can be classified into the following four categories: (i) transaction cost measures that capture costs of trading financial assets and trading frictions in secondary markets; (ii) volume-based measures that distinguish liquid markets by the volume of transactions compared to the price variability, primarily to measure breadth and depth; (iii) equilibrium price-based measures that try to capture orderly movements towards equilibrium prices to mainly measure resiliency and (iv) market-impact measures that attempt to differentiate between price movements due the degree of liquidity from other factors.[71]

First point of the mentioned categories is the most popular and usually illustrated through bid-ask spreads. In market microstructure liquidity providers often take

[70]Pastor and Stambaugh (2003)

[71]Sarr and Lybek (2002)

the form of market makers or dealers, who need to be compensated for the possibility that some buy or sell orders are originated with traders in possession of asymmetric information.[72] Dealers recover asymmetric costs as well as other cost like order-processing costs, inventory costs or oligopolistic market structure costs by purchasing at a lower bid price and selling at a higher ask price.[73] Therefore, the difference between bid and ask prices, also known as quoted spread, is an established measure of transaction costs. High transaction costs reduce the demand for trades and therefore the number of potentially active participants in a market, which associates transaction costs with illiquidity.[74]

Bid-ask spreads can be illustrated in several ways. Sarr and Lybek (2002) simply measure the bid-ask spread by the absolute difference between bid and ask prices:

$$S_{i,t} = A_{i,t} - B_{i,t}.$$

Bessembinder and Venkatamaran (2009) further define the quoted half-spread, which describes the execution costs for a single trade on a percentage basis:

$$QS_{i,t} = 100 \, \frac{A_{i,t} - B_{i,t}}{2 \, M_{i,t}},$$

whith $A_{i,t}$ and $B_{i,t}$ representing the posted ask and bid price for security i at time t and $M_{i,t}$ the quote midpoint or mean of $A_{i,t}$ and $B_{i,t}$.[75] Furthermore, they state that orders also might be executed outside the quote. Especially, in electronic markets where traders allow for hidden order sizes, quoted prices pertain only quoted depth, but larger orders then exhaust depth of the order book.[76] Consequently, trades can occur either within or outside the quoted spread. Hence, a better measure of trading costs is the percentage effective half spread, which is based on the actual trade price:

[72] Bessembinder and Venkatamaran (2009)

[73] Sarr and Lybek (2002)

[74] Sarr and Lybek (2002)

[75] Both, quoted spread and effective half spread are measured in basis points, which is why they are multiplied by 100.

[76] Bessembinder and Venkatamaran (2009)

$$ES_{i,t} = 100\ D_{i,t}\,\frac{P_{i,t} - V_{i,t}}{V_{i,t}},$$

where $P_{i,t}$ is the transaction price for security i at time t, $D_{i,t}$ is an indicator that equals 1 for buy orders and -1 for sell orders. $V_{i,t}$ is an observable proxy for true underlying value of security i at time t.[77]

Besides the transaction costs illustrated by bid-ask spreads, also volume-based measures are found most useful in measuring breadth and depth. Markets that are deep tend to foster breadth since large order can be divided into several orders to minimize impact on transaction prices.[78] Sarr and Lybek (2002) recognize trading volume as a traditionally used approach measure to determine the existence of numerous market participants and transactions. Hence, they claim that trading volume is more meaningful by relating it to outstanding volume of the asset being considered. Price-based measures and market-impact measures are mentioned as liquidity indicators. Although both are less popular. Price-based measures of liquidity display the market efficiency by arguing that price movements are more continuous in liquid markets. Market-impact measures refer to the relationship between market risk and liquidity and can be compared to asset pricing models.

Mentioned influencing factors of market microstructures describe well the liquidity of security and financial markets. Nevertheless, Amihud (2002) claims that data used for market microstructure measures is very fine and data might not always be available in all stock markets. Hence, he claims that his own developed Amihud measure describes market illiquidity best. Amihud (2002) interprets illiquidity as the daily price response associated with one dollar of trading volume. Thus, roughly spoken, the illiquidity measure can be described as a ratio of absolute stock return to its dollar volume.

Although Amihud (2002) confesses that his illiquidity measure is more coarse and less accurate, it is capable for the study of time series effects of liquidity since it is

[77]Bessembinder and Venkatamaran (2009)

[78] Sarr and Lybek (2002)

available over a long time horizon. Following Kyle's (1985) concept of illiquidity, where response of price to order flow is measured, daily absolute return is observed for a specific security and related to the trading volume on that day. $|R_{iyd}|$ illustrates the return of stock i on day d in year y. Furthermore, VOLD_{iyd} is the respective daily volume in USD. Therefore, illiquidity measure can be calculated as follows

$$\text{ILLIQ}_{iy} = \frac{1}{D_{iy}} \sum_{t=1}^{D_{iy}} \frac{|R_{iyd}|}{\text{VOLD}_{iyd}},$$

where D_{iy} is the number of days at which data is available for stock i in year y.[79]

As mentioned, the provided Amihud measure allows to test the effects of illiquidity on stock excess returns through long time series. Hence, Amihud (2002) claims that expected stock returns also reflect compensation for expected market illiquidity, i.e. excess return is an increasing function of expected market illiquidity. Accordingly, a lot of academics use this measure to study effects on values of stocks. One finding of these studies is the liquidity asset pricing model, which will be presented in the next section.

5.3 Liquidity Asset Pricing Model

Over the last decade various academics constitute that traditional asset price models do not cover all essential parts that influence security price movements. Amihud and Mendelson (1986) state the importance of liquidity in assets in the 1980s and liquidity nowadays becomes even more important. Especially, since the financial crisis in 2008, when financial markets have been tremendously illiquid, central banks of the United States and Europe provide a lot of liquidity through asset purchase programs, which impacts the pricing of securities. Hence, academics have been come up with asset pricing models that take into account liquidity risk. In this subsection the liquidity asset pricing model of Acharya and Pedersen (2004) is presented.

Measures of liquidity were presented in previous subsection. Furthermore, empirical

[79] Amihud (2002)

studies are employed to examine the cross-section effect of illiquidity on expected stock returns.[80] Academics conclude a negative correlation of liquidity and asset price returns. In the model of Acharya and Pedersen (2004) CAPM is adapted and a liquidity-adjusted capital asset price model is derived incorporating liquidity risk. Furthermore, they state that expected return of a security is increasing in its expected illiquidity and its 'net beta', which is proportional to the covariance of its return less the exogenous illiquidity costs with the markets portfolio's net return. Accordingly, the conditional expected net return of security i is

$$\mathbb{E}_t[r_{i,t+1} - c_{i,t+1}] = r_f + \lambda_t \frac{\mathrm{Cov}_t(r_{i,t+1} - c_{i,t+1}, r_{M,t+1} - c_{M,t+1})}{\mathrm{Var}_t(r_{M,t+1} - c_{M,t+1})}. \tag{5.3}$$

where r_i is the return of security i, c_i illustrates its illiquidity costs and market portfolio M's net return is described as $r_M - c_M$. Additionally, $\lambda_t = \mathbb{E}_t[r_{M,t+1} - c_{M,t+1} - r_f]$ is the risk premium. Moreover, Acharya and Pedersen (2004) decompose the net beta into market beta and three betas representing different forms of liquidity risk. These liquidity risks are associated with: (i) commonality in liquidity with the market liquidity, $\mathrm{Cov}(c_i, c_M)$; (ii) return sensitivity to market returns, $\mathrm{Cov}(r_i, c_M)$; and (iii) liquidity sensitivity to market returns, $\mathrm{Cov}(c_i, r_M)$.[81] Equivalently, the conditional expected gross return is

$$\begin{aligned}\mathbb{E}_t[r_{i,t+1}] = {} & r_f + \mathbb{E}_t[c_{i,t+1}] \\ & + \lambda_t \frac{\mathrm{Cov}_t(r_{i,t+1}, r_{M,t+1})}{\mathrm{Var}_t(r_{M,t+1} - c_{M,t+1})} + \lambda_t \frac{\mathrm{Cov}_t(c_{i,t+1}, c_{M,t+1})}{\mathrm{Var}_t(r_{M,t+1} - c_{M,t+1})} \\ & - \lambda_t \frac{\mathrm{Cov}_t(r_{i,t+1}, c_{M,t+1})}{\mathrm{Var}_t(r_{M,t+1} - c_{M,t+1})} - \lambda_t \frac{\mathrm{Cov}_t(c_{i,t+1}, r_{M,t+1})}{\mathrm{Var}_t(r_{M,t+1} - c_{M,t+1})}.\end{aligned} \tag{5.4}$$

Comparable to traditional CAPM, required security return in LAPM of Acharya and Pedersen (2004) increases linearly with market beta plus additional effects from liquidity risks.

80 Amihud (2002)

81 Acharya and Pedersen (2004)

First part of the decomposed liquidity risk, $\mathrm{Cov}_t(c_{i,t+1}, c_{M,t+1})$, implies that return increases with the covariance between asset's illiquidity and market illiquidity. Chordia et al. (2000) find that illiquidity of most stocks is positively related to market illiquidity. Hence, required return needs to be raised by commonality-in-liquidity effect. Particularly, investors want to be compensated for holding a security that becomes illiquid when the market itself becomes illiquid.[82]
Second term of the required return decomposition (5.4), $\mathrm{Cov}_t(r_{i,t+1}, c_{M,t+1})$, illustrates the return premium which is due to covariation between security's return and market illiquidity costs. The decomposition highlights that there is a negative effect of this term. Apparently, investors are willing to accept a lower return on securities with high return when markets become illiquid. Pastor and Stambaugh (2003) find that for a time period from 1966 to 1999 stock returns of securities with high sensitivity to liquidity exceed stocks with low sensitivities by 7.5 percent annually. Hence, they claim that higher liquidity betas exhibit larger returns.
Third part of the derived decomposition of liquidity betas, $\mathrm{Cov}_t(c_{i,t+1}, r_{M,t+1})$, states the negative relationship between covariation security's illiquidity and return of the market portfolio. This effect occurs since investors are willing to pay a premium for securities that are liquid in a down market. Acharya and Pedersen (2004) determine that in declining markets investors' ability to sell easily is especially valuable since additional illiquidity in assets would increase losses even further.

Covariations of decomposed asset pricing model (5.4) characterize well the liquidity risk of a security. Although, the liquidity-adjusted CAPM (5.3) of Acharya and Pedersen (2004) describes required net returns equally well, the decomposition highlights the three additional betas of liquidity risk. Derivations of the decomposition exhibit the importance of liquidity in this asset pricing model and emphasize the growing popularity of liquidity in modern financial theory. Coming back to momentum, the following subsection focuses on the relation between liquidity, asset pricing and momentum profitability.

[82] Acharya and Pedersen (2004)

5.4 Liquidity Effects on Momentum Profitability

Through the derivation of the LAPM it becomes obvious why various academics claim that liquidity of securities plays an important role in asset pricing. In momentum literature several risks are named as potential profitability drivers. Hence, academics not only include liquidity risks into modern asset pricing models, but also the relation between momentum effect and liquidity is investigated. Comparable to other market anomalies, several empirical research studies analyze dependencies between momentum and liquidity by testing profitability of combinations from high to low momentum and liquidity respectively. Furthermore, empirical work determines patterns of liquidity in 'winner'- and 'loser'-portfolios as well as relations between momentum profitability and market liquidity.

So far momentum effect is manifested as an anomaly that exhibits profitability, which can't be explained easily. Most recent papers about momentum in relation to liquidity accredit profitability to arbitrage effects. Arbitrage illustrates a transaction where rational agents try to profit from mispricing.[83] Furthermore, largest mispricing occurs in stocks with highest arbitrage costs. Pontiff (2006) states that arbitrage costs can be decomposed in transaction costs and holding costs. The latter are described as costs that arise in every period over which stocks are held by the investors. E.g. Pontiff (2006) names the opportunity cost of capital, the opportunity cost of not receiving full interest on short-sale proceeds and idiosyncratic risk exposure. In the previous chapter transaction costs were characterized in detail. Most common measure of transaction costs is named as bid-ask spread and captures both implicit and explicit transaction costs. A basic intuition tells one that arbitrage is easier in liquid markets.[84] In other words, if markets are most liquid the anomaly of momentum vanishes with the arbitrage possibility. However, if arbitrage costs are high, arbitrage effects are trimmed and momentum is persistence. Empirical studies show different results on this topic.

This supports the hypothesis that momentum effects are persistent in stocks with

[83] Pontiff (2006)

[84] Avramov, Cheng and Hameed (2014)

higher arbitrage costs, i.e. when stocks are illiquid. Both Lee and Swaminathan (2000) as well as Ibbotson et al. (2013) investigate momentum strategy regarding the liquidity of stocks. In their empirical work portfolios are double-sorted according to their past stock price returns and liquidity. For the latter, Lee and Swaminathan (2000) used past trading volume. Afterwards returns of different momentum portfolio are analyzed, i.e. 'winner'- and 'loser'-portfolios, while it is differentiated by liquidity of the portfolios. Findings imply that past trading volume impacts magnitude and persistence of stock price momentum. Furthermore, it indicates that high (low) volume 'winners' ('losers') experience faster stock price reversals.[85] Hence, results of their empirical work exhibit higher returns for low volume stocks than for high volume stocks. I.e. low volume 'losers' outperform high volume 'losers', and low volume 'winners' outperform high volume 'winners'. For a formation period of 9 months and a holding period of 6 months results of Lee and Swaminathan (2000) exhibit higher monthly returns of low volume stocks for 'winners' and 'losers' of 0.26 percent and 1.02 percent respectively. Similar findings are provided by Ibbotson et al. (2013) where mid-high momentum low-liquidity stocks attain a yearly return of 14.76 percent and high momentum high-liquidity stocks only achieve 4.56 percent per year. Furthermore, low momentum low-liquidity obtain returns of 13.90 percent yearly, while low momentum high-liquidity stocks only return 7.24 percent per year. Obtained outcomes support the assumption of LAPM that illiquid stocks require higher returns with increasing illiquidity.

While previous results only compared returns of low volume and high volume 'winners' and 'losers' respectively, one can further distinguish between cross-sectional liquidity of 'winners' and 'losers'. Momentum strategy follows the approach to buy winners and sell losers. Whereas 'winners' tend to be liquid popular stocks according to recent performance, 'loser'-stocks are less admired and likely to be bought.[86] Furthermore, this is in line with findings from behavioral finance that claim that investors are prone to ride 'losers' while they are likely to sell 'winners'.[87] Investors

[85] Lee and Swaminathan (2000)
[86] Avramov, Cheng and Hameed (2014)
[87] Odean (1998)

tend to sell 'winner'-stocks to early for the sake of realizing gains, while they are reluctant to sell 'losers' and admit wrong buying decisions. Furthermore, Daniel, Hirshleifer and Subramanyam (1998) argue that investors are overconfident and overreact to private information. If market movements confirm private information and buy decisions, investors overestimate their ability to value stocks accurately. However, if market movements contradict investors stock valuation, theory of self-attribution bias argues that investors blame other factors than themselves for failure.[88] According to these behavioral finance findings, investors tend to trade winners rather than losers. Hence, winner stocks seem to be more liquid than loser stocks.

Last but not least Avramov, Cheng and Hameed (2014) relate the aggregate market liquidity to momentum profitability. Apparently, for aggregate market illiquidity a positive relation to momentum profitability can be assumed. Hence, Avramov, Cheng and Hameed (2014) claim that momentum strategy is most profitable in liquid markets. While results of Lee and Swaminathan (2000) exhibit highest returns for high volume relative strength portfolio, returns of 'winner'- and 'loser'-portfolios behaves converse. Asness, Moskowitz and Pedersen (2013) give an intuitive explanation about the positive correlation between momentum and liquidity. According to them, liquidity shocks influence 'winner'-stocks more than 'loser'-stocks. Since 'winner'-stocks are more popular and frequency of trades is high, investor liquidations put more price pressure on 'winner'-stocks. Nevertheless, this finding seems to apply for actual shocks of aggregate liquidity, whereas empirical findings imply the opposite. For 6m formation period and 6m holding period portfolio Lee and Swanimathan (2000) find highest returns for low volume 'winners' and 'losers' of 1.92 percent per month and 0.99 percent per month respectively. However, relative strength portfolio generates highest monthly return of 1.7 percent for the high volume portfolio while the low volume portfolio only returns 0.94 percent per month. Figures indicate that differences in returns according to the liquidity are higher for the 'loser'-stocks. However, since less liquid stocks should earn higher returns according to LAPM, it is difficult to understand why the relative strength

[88] Daniel, Hirshleifer and Subramanyam (1998)

portfolio of high volume, i.e. liquid, stocks should be less liquid and hence more profitable.[89] Avramov, Cheng and Hameed (2014) find similar results and raise the question whether differences in performance depend on the relative illiquidity of 'winners' and 'losers'. According to the hypothesis of additional returns in illiquid stocks ('losers') they claim that momentum strategy is likely to pay off in times when cross-sectional difference in illiquidity between 'loser'- and 'winner'-portfolio is large. Thus, to test this assumption, the notion of an illiquidity gap is introduced as follows:

$$\mathrm{ILLIQGAP}_{t-1} = \mathrm{ILLIQ}_{\mathrm{WINNER},t-1} - \mathrm{ILLIQ}_{\mathrm{LOSER},t-1}$$

where $\mathrm{ILLIQ}_{WINNER,t-1}$ ($\mathrm{ILLIQ}_{LOSER,t-1}$) is the average of stocks' Amihud illiquidity measure in the 'winner'- ('loser'-) decile.[90] Avramov, Cheng and Hameed (2014) find that the illiquidity gap is more negative when aggregate market liquidity is low. Furthermore, they confirm the result of Lee and Swanimathan (2000) and state that when markets become more liquid returns of the 'loser'-portfolio diminish. Additionally, high aggregate liquidity markets seem to lower momentum profitability due to higher returns associated with illiquid 'loser'-stocks. In this scenario the illiquidity gap widens and result as shown with Lee and Swanimathan (2000) can also exhibit negative momentum returns.

LAPM emphasizes a positive relation between illiquidity of securities and its expected return. However, this subsection signalizes three different hypotheses regarding liquidity and momentum. Assumption of additional required returns of illiquid securities implies increasing momentum returns with growing illiquidity. However, with aggregate market liquidity the assumption of LAPM can not be confirmed since momentum returns seem to be more profitable in liquid markets. Furthermore, it was found that 'loser'-stocks are more illiquid than 'winner'-stocks with behavioral finance arguments. These findings will be further investigated in the empirical study of the subsequent chapter.

[89] Lee and Swanimathan (2000)
[90] Avramov, Cheng and Hameed (2014)

6 Empirical Evidence of Momentum Profitability

Previous chapters of this study provide an analysis of momentum profitability and its potential drivers. Moreover, discussions stress that there is no consent about the source of positive momentum returns. In the empirical study the profitability of momentum strategy is tested for the time horizon between 2001 and 2014, whereas the observed horizon is split into a period before financial crisis in 2008 and a period after until summer 2014. In both periods, performance of relative strength portfolios is monitored. Furthermore, potential drivers of momentum profitability are analyzed. Traditional momentum literature finds industry momentum as one of the driving factors of momentum profitability. Additionally, modern literature suggests to take liquidity into account. Thus, industry momentum and liquidity are observed in the empirical study. For the after-crisis time horizon data is available regarding the sustainability of considered companies. Responsible investments have been receiving increasing attention over last years and become a growing branch in the financial industry. Hence, an investigation to determine differences in momentum returns between securities of sustainable and unsustainable companies has been performed.

6.1 Data and Approach

The data set used for the empirical testing consists of the stock universe with approximately 3300 securities, which capture more than 95 percent of MSCI World Index. Besides liquidity and industry momentum, the empirical study is analyzing the influence of sustainability of companies on momentum profits. Hence, the investment universe is chosen by the availability of sustainability ratings. The database of sustainability ratings dates back to beginning of the year 2008. Furthermore, stock prices of companies are obtained from Bloomberg starting from year 2001. Correspondingly, industry of respective companies and liquidity measures were obtained for the considered time horizon.

In the momentum approach, every month, stocks are ranked according to their most recent stock price performance, i.e. during the last 3, 6, 9 and 12 months respectively without the last month (skipping period). To be specific, average prices are calculated during the formation period and compared to the current stock price (last day of previous month). Due to small size effects and very illiquid stocks, low capitalized companies with a stock price less than USD 3 are omitted. Then stocks are sorted ascending into deciles P10 to P1 according to the ratio of current price and average price during formation period. Furthermore, different holding periods are observed and 'winner' ('loser') stocks are kept in portfolio P10 (P1) for four different holding periods: 3, 6, 9 or 12 months.

Once the portfolios are constructed according to momentum strategy, the performance of 'winner'-portfolio and 'loser'-portfolio is calculated for every month of the observed time horizon. Like in the approach of Jegadeesh and Titman (1993), equally weighted portfolios are constructed and extreme portfolios P10 and P1 are monitored only. All stock prices are converted into US Dollar and dividend payments are included into stock prices. Correspondingly, the performance of the equally weighted portfolio is measured according to security i's weekly variation at time t:

$$r_{i,t} = x_{i,t+1} - x_{i,t},$$

where $x_{i,t} = \ln p_{i,t}$ equals the price according to a logarithmic price scale and $p_{i,t}$ represents the company's stock price at time t.

According to that procedure, the performance of 'winner'-, 'loser'- and relative strength portfolios is measured for all 16 combinations of formation (3m, 6m, 9m and 12m) and holding periods (3m, 6m, 9m and 12m). For a better understanding of momentum profitability in different market situations, the research study is split into two sub-samples. Since the horizon of the empirical work includes the financial crisis of 2008/2009, analysis is done for a pre-crisis period from 2001-2008 and for an after-crisis sub-sample starting in March 2008 and ending in June 2014. This approach provides the possibility to see differences of momentum behavior in bull and bear markets as well as variations in markets with different liquidity characteristics.

In the empirical study several results are computed according to the described approach and profitability of momentum strategy is compared. First, the pre-crisis period is analyzed and profitability of momentum strategy before the sub-prime crisis in 2008 is determined. Afterwards, after-crisis period is investigated where momentum profitability can be examined for sustainable securities and unsustainable stocks according to their ESG rating. Hence, the concept of sustainable investing is explained first.

6.2 Sustainable Securities

The empirical study during the after-crisis period includes an investigation of differences in momentum returns between sustainable securities and ordinary securities. By referring to sustainable investing, the full integration of environmental, social and governance (ESG) factors into the investment decision is defined. This is a very modern approach of what is traditionally called Socially Responsible Investment (SRI). Literature about SRI claims that risk is considered in the sustainability rating of companies, which indicates that sustainable securities behave differently. Therefore, momentum strategy in the second time period is applied on three different universes of securities by distinguishing securities according to the sustainability rating of oekom.

Both the importance as well as the volume of total assets under management of investment funds based on sustainable securities gained a big increase during the last two decades. According to studies of Eurosif, the assets under management of sustainable funds are steadily increasing and contributing approximately 22 percent to the total assets under management of global investment funds.[91] All of the big players in financial industry cover funds labeled as sustainable investment. Based on a report of Triodos Bank, around USD 13.6 trillion are influenced by some kind of responsible investment strategy. This perfectly stresses the crux in sustainable

[91] Eurosif is the leading non-for-profit pan-European sustainable and responsible investment (SRI) membership organisation whose mission is to promote sustainability through European financial markets. Source: http://www.eurosif.org/about/mission/

securities and investment approaches of asset managers. Same as names vary from 'Social Responsible Investments' (SRI) over 'Responsible Investments' to 'Sustainable and Responsible Investments' as well as the basis of the approach also varies between different countries, asset managers and organizations.

Not only importance of sustainable investing is increasing - academics also claim that sustainable securities have the potential to outperform unsustainable securities. For that reason this form of investing is presented in more detail.

6.2.1 Evolution of Sustainable Investments

Sustainable investments are nothing new. In 18th century religious organizations already followed the concept of investing in sustainable companies. Applying the exclusion criteria approach, by withdrawing companies involved in alcohol, tobacco or gambling, organizations achieved to combine financial returns with seek of social return.[92] Until today religious constitutions play an important role in sustainable investments. Not only Islamic organizations following the traditional shariah concept by applying a lot of exclusions to their investment approach, but also European churches invest their money according to SRI concepts. Additionally, both religious communities and other institutional investors, like insurance companies and pension funds, are important clients of SRI funds as they believe in the concept of responsible investing.

While the idea of sustainable investments used to be based on ethics, modern view of sustainable investments developed to a broader approach incorporating environmental, social and corporate governance aspects (ESG). Since the inception of sustainable investments, various social developments triggered the increase of sustainability in investments. The mentioned religious and ethical approach emphasizes the importance of religion in the past. Furthermore, Hudson (2006) mentions social movements like anti-racism in the 1960s added a further component to the understanding of responsible investing. During the last decades, the awareness of society

[92] Renneboog, Horst and Zhang (2008)

for natural disasters led to the increasing sense of environmental responsibility.[93] All these factors enhance the desire of society to influence the future in a positive way and to reflect this in financial investments.

Besides the development of the concept of sustainable investments, also the understanding of financial return in sustainable investments has changed. For a very long time sustainable investments were associated with lower returns due to fewer diversification possibilities. In consequence to increasing academic research and growing popularity, this assumption was mitigated. In particular, empirical work also emphasizes outperformance opportunities of sustainable securities. Renneboog, Horst and Zhang (2008) outline two main theories, which might drive performance of sustainable assets. At first, theory states that sustainable securities might underperform since fewer investable securities offer less diversification possibilities. Hence, unsystematic risk can not be fully diversified away. Since asset pricing models claim that there is no compensation for taking unsystematic risk and only perfectly diversified portfolio without unsystematic risk lies on the efficient frontier, SRI funds should only be able to generate inferior risk-adjusted returns.[94] However, Renneboog, Horst and Zhang (2008) also invoke that SRI portfolio managers might have a deeper knowledge about companies. If the hypothesis that market prices incorporate all information including ESG ratings does not hold, asymmetric information gives managers the possibility to outperform. Indeed, managers who observe sustainability ratings might have the ability to find and value risks from the ESG factors and use findings for their stock picking. During the last decade, several academics came up with studies analyzing the performance behavior of sustainable funds in comparison to ordinary funds. Still there is no consent about an advantage or disadvantage of sustainable securities regarding financial performance.

In the context of this empirical work the sustainability feature is claimed as additional information that takes into account risks. Since firm-specific components are expected to drive momentum profitabilities, it will be tested if sustainable compa-

[93] Hudson (2006)

[94] Renneboog, Horst and Zhang (2008)

nies incorporate less risks. Hence, they might obtain larger price persistence and exhibit higher momentum profits.

6.2.2 Measures of Sustainability

The development of sustainable investments already emphasizes the broad and different view of sustainability in investments. Indeed, there is no consensus about what is responsibility in the context of investments. Moreover, there is no common definition of sustainable investing and which criteria are sufficient to measure sustainability of companies. For that reason, it is also difficult to compare different SRI labeled funds. Also research agencies that rate companies according to their sustainability, have different approaches to identify the level of sustainability in the business of a company. Looking at two of the largest sustainability research agencies, MSCI ESG and oekom research, brings up large differences in rating approaches. MSCI ESG focuses on ESG risk factors, companies are exposed to. Hence, criteria are considered, that are an important part for the business of the company and the industry the company belongs to. Oekom research follows the ethical concept of 'Frankfurt-Hohenheimer Leitfaden', but also considers criteria that are important for the business and industry of the company.[95] In terms of complexity differences in the rating approaches of research agencies can be observed. However, both ratings are based on the three pillars of environmental, social and corporate governance criteria.

In addition, there is no consent about a rating benchmark that makes a company sustainable. In the evolution of sustainable investments, exclusion criteria played an important role. However, there are more approaches to measure sustainability. One common approach is the 'best-in-class' approach, where fund managers only invest in companies that are best rated in their class, i.e. industry. Besides 'best-in-class' a popular approach is the 'best-of-class' approach where a specific but subjective rating benchmark must be met such that the company is investable. Since it is the

[95] Frankfurt-Hohenheimer Leitfaden is a in 1997 presented concept to support the rating methodology of research agencies regarding the sustainability of companies. Source: http://www.cric-online.org/ethischinvestieren/f-h-leitfaden

easiest way to distinguish between sustainable and unsustainable companies as soon as an appropriate benchmark is defined, this approach is the one which is used in the following empirical study.

As the basis for this momentum approach, securities covered by research agency oekom are used. Ratings are available from March 2008 to June 2014. The number of companies covered by oekom research increased from about 900 in 2008 to 3500 in 2014. While first ESG studies cover the American market and are based on US research agencies, this study uses data from oekom research, based in Munich, Germany, and focuses on European markets. Nevertheless, in 2014 oekom research covered about 95 percent of the companies of MSCI World Index. Therefore oekom research covers a broad range of securities including all companies from established stock market indices and further companies from all over the world, which suggests a good sample for the empirical work. Ratings are provided from oekom research with updates on a monthly basis over the time horizon of more than 5 years. Thus, ESG ratings are observed for every month and distinguished between sustainable companies, which have a rating of at least C (A+ to C), and unsustainable companies with a rating of C- and worse (C- to D-). Accordingly, the best-of-class approach is applied to differentiate between sustainable and unsustainable securities and exclusion criteria are disregarded. Hence, a universe of sustainable securities and a second of unsustainable securities are obtained. The first includes all companies with a rating of C and better for each month from March 2008 to June 2014, the latter incorporates all companies with a rating of C- and worse. In addition, the momentum approach is considered on a third universe of securities including all companies without consideration of ESG rating.

6.3 Pre-Crisis Analysis

In the pre-crisis analysis, the opportunity to generate excess returns from momentum strategy is determined. From 2001 to 2008 world economy experienced a recovery from dot-com bubble in 2000 and was heading into next crisis in 2008. Hence, the considered period ends with a boom phase before burst of the sub-prime crisis in summer 2008. During this time horizon, the strategy is pursued to buy stocks which performed well over the most recent months and to sell stocks which did otherwise.

6.3.1 Results

In the approach of momentum strategy, results are obtained for the performance of 16 strategies during a time horizon of approximately 7 years before the financial crisis. For each strategy profits of the 'winner'-, 'loser'- and relative strength portfolio are computed. Findings of this approach indicate profitability of momentum strategy during the time between 2001 and 2008 and further confirm statements from momentum literature about the profitability of mid-term momentum in stock prices. Each of the 16 strategies exhibits positive return of the relative strength portfolio. Furthermore, it can be observed that the returns of momentum strategy increases in the length of formation period, i.e. the longer the formation period the higher returns of relative strength portfolio. However, for the holding period it behaves vice versa. Hence, the shorter the holding period for the securities in the portfolio the higher momentum returns can be observed.

Accordingly, highest return of 14.774 percent per year or 1.136 percent per month can be achieved by selling the 'loser'-portfolio and buying the 'winner'-portfolio with 12 month formation period and 3 month holding period. However, also the 3m12m relative strength portfolio yields a positive monthly return of 0.23 percent, which is the lowest return out of the 16 strategies. Figure 2 provides both yearly and monthly returns of all 16 strategies including 'winner'-, 'loser'- and relative strength portfolio and emphasizes the described findings.

Figure 2: Momentum returns of the pre-crisis study

Yearly Returns

			Holding Period			
			3m	6m	9m	12m
Formation Period	3m	Loser	0.15228	0.15279	0.14986	0.15183
		Winner	0.20698	0.19338	0.18674	0.18167
		Rel. Strength	0.05470	0.04059	0.03688	0.02984
	6m	Loser	0.13975	0.14118	0.14261	0.14799
		Winner	0.22392	0.21220	0.20677	0.19669
		Rel. Strength	0.08417	0.07102	0.06416	0.04870
	9m	Loser	0.12107	0.12119	0.12344	0.12809
		Winner	0.24017	0.23424	0.22567	0.21186
		Rel. Strength	0.11910	0.11305	0.10223	0.08377
	12m	Loser	0.09959	0.10755	0.11249	0.11702
		Winner	0.24733	0.25057	0.23692	0.23278
		Rel. Strength	0.14774	0.14302	0.12443	0.11575

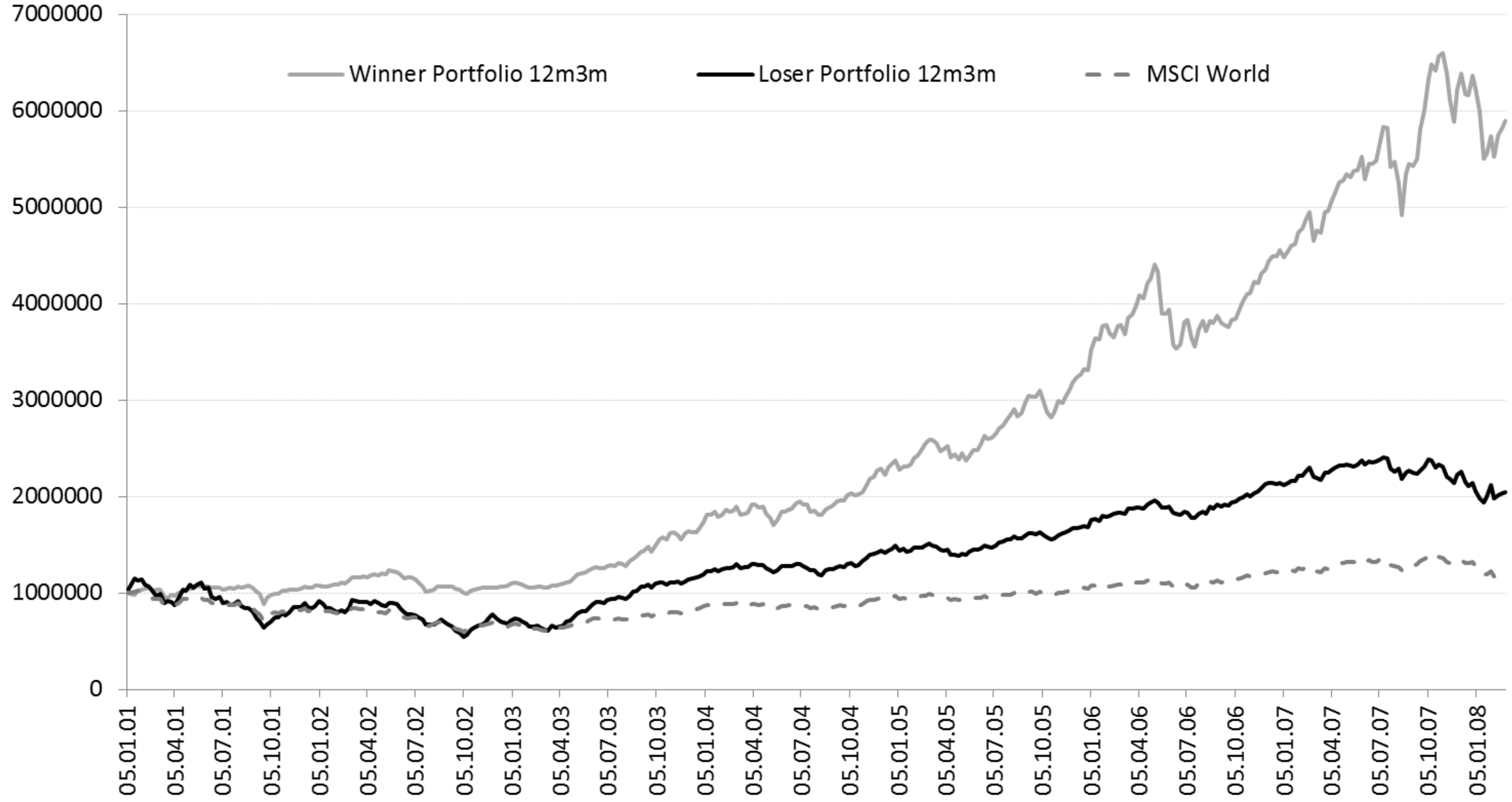
Monthly Returns

			Holding Period			
			3m	6m	9m	12m
Formation Period	3m	Loser	0.01171	0.01175	0.01153	0.01168
		Winner	0.01592	0.01488	0.01436	0.01397
		Rel. Strength	0.00421	0.00312	0.00284	0.00230
	6m	Loser	0.01075	0.01086	0.01097	0.01138
		Winner	0.01722	0.01632	0.01591	0.01513
		Rel. Strength	0.00647	0.00546	0.00494	0.00375
	9m	Loser	0.00931	0.00932	0.00950	0.00985
		Winner	0.01847	0.01802	0.01736	0.01630
		Rel. Strength	0.00916	0.00870	0.00786	0.00644
	12m	Loser	0.00766	0.00827	0.00865	0.00900
		Winner	0.01903	0.01927	0.01822	0.01791
		Rel. Strength	0.01136	0.01100	0.00957	0.00890

This table provides yearly and monthly returns of the 'winner'-, 'loser'- and relative strength portfolio (long 'winners', short 'losers') of the Momentum strategy during the pre-crisis period from 2001 to 2008 for different formation and holding periods.

In addition, the development of the momentum profits can be tracked over the considered time horizon. In contrast to the previous analysis, the focus is not longer on the relative strength portfolio but on the performance of holding the ’winner’-portfolio (P10) as well as the ’loser’-portfolio (P1). Figure 3 illustrates the outperformance of the ’winner’-portfolio during time and highlights that momentum profit is increasing in the considered time period. While return of relative strength portfolio, i.e return of ’winner’- (grey line) minus return of ’loser’-portfolio (black line) seems to be low in the beginning, it becomes larger after 2004 for the second half of the time horizon. Hence, this finding implies that momentum strategy might be more profitable in bull markets, since sub-prime bubble pushed stock markets before burst of the crisis.

Figure 3: Performance of 12m3m 'winner'- and 'loser'-portfolio of the pre-crisis study



The chart provides an overview over development of 'winner'- and 'loser'-portfolio of 12m3m Momentum strategy for the full sample during the pre-crisis period. The chart includes the MSCI World Index for a comparison reason (dashed line). In this sample a distinct outperformance of the winner portfolio is observable for the last 3 years of the considered period.

6.3.2 Head-To-Head Analysis

By comparing the different relative strength portfolios of momentum strategy for several combinations of formation and holding periods, this approach provides a quick overview regarding profitability of momentum strategy. Figure 2 includes the yearly and monthly returns from all combinations of observed momentum strategies. These results indicate a higher profitability of momentum approach with a long observation (formation) period and a shorter holding period. Hence, the head-to-head analysis provides more detailed results from 4 combinations of momentum strategies including 4 different formation periods and holding periods respectively.

For each of the 4 formation periods of the 16 momentum strategies from figure 2, one observes largest profits for the shortest holding period of 3 months. However, for each of the 4 holding periods, profits are largest for the longest formation period of 12 months. Accordingly, the combination 12 months formation period and 3 months holding period returns the most, while momentum strategy of 3 months formation period and 12 months holding period generates lowest profits. Hence, head-to-head analysis compares the following 4 combination to investigate risk-return profiles of momentum strategies: 3m12m, 6m9m, 9m6m and 12m3m.[96] Each of the 4 considered momentum strategies generate positive returns for the relative strength portfolio. However, according to the mentioned finding of increasing returns in length of formation period and decreasing returns in length of holding period, results are distinctly different for the 4 relative strength portfolios. Figure 4 provides both, yearly and monthly returns of each of the 4 strategies. Investigations of profits from 'loser'- and 'winner'-portfolios indicate two drivers for the found profitability patterns. On the one hand profits of the 'loser'-portfolio are highest for the shorter formation period and longer holding period of securities in the portfolio, which implies stock price reversals for those combinations. However, for longer formation periods and shorter holding periods profits of the 'loser'-portfolio decrease. Accordingly, profits of the 'loser'-portfolio decrease from 1.17 percent per month

[96] First part illustrates the formation period and second part the holding period. E.g. 6m9m observes price patterns for 6 months and holds securities for 9 months in the related portfolio.

to 0.77 percent per month with increasing formation period and shrinking holding period. In contrast, 'winner'-portfolios generate highest profits for longest considered formation period of 12 months and shortest holding period of 3 months. Thus, monthly profits increase from 1.4 percent to 1.9 percent with increasing formation and decreasing holding periods. Corresponding to this reverse profitability patterns, relative strength portfolios exhibit highest returns of 1.14 percent per month for the momentum strategy with 12 months formation period and 3 months holding period, while relative strength portfolio for 3 months formation period and 12 months holding period only returns 0.0034 percent per month. Furthermore, figure 4 provides results of the standard deviation of the 4 momentum strategies. Volatility of momentum profitability increases with length of observation period and decreases in length of holding period, i.e. it is positive correlated with the profit findings. Additionally, the Sharpe Ratio is computed, which measures the average excess return over risk-free rate divided by standard deviation:

$$SR_P = \frac{r_{P,t} - r_{f,t}}{\sigma_P},$$

where $r_{P,t}$ represents portfolio return at time t, $r_{f,t}$ is the risk-free rate and σ_P illustrates the standard deviation of the portfolio.[97] Hence, the higher the Sharpe Ratio the better is the performance of the portfolio. Findings of the empirical work exhibit highest SR for the relative strength portfolio of 12m3m strategy. Although both volatility and returns increase with formation period length, portfolio performance seems to be best for longer formation periods and shorter holding periods respectively.

[97] 3m LIBOR is used for the risk-free rate.

Figure 4: Head-To-Head analysis of the pre-crisis study

Portfolio Strategies	Avg. Y-o-Y Return	Avg. monthly Return	St. Dev. Y-o-Y	Sharpe Ratio	Skewness	Kurtosis
<u>3m12m</u>						
Loser	0.1518	0.0117	0.1795	0.6727	-0.3694	2.2048
Winner	0.1817	0.0140	0.1628	0.9250	-0.9127	2.3842
Relative Strength	**0.0298**	**0.0023**	**0.0752**	**-0.0164**	**-3.2086**	**25.8243**
<u>6m9m</u>						
Loser	0.1426	0.0110	0.1963	0.5682	-0.0421	2.5459
Winner	0.2068	0.0159	0.1697	1.0354	-0.9948	2.7778
Relative Strength	**0.0642**	**0.0049**	**0.1210**	**0.2733**	**-2.2898**	**14.4137**
<u>9m6m</u>						
Loser	0.1212	0.0093	0.2013	0.4478	-0.2042	1.6094
Winner	0.2342	0.0180	0.1776	1.1441	-0.8836	2.6849
Relative Strength	**0.1131**	**0.0087**	**0.1435**	**0.5711**	**-0.9016**	**3.7551**
<u>12m3m</u>						
Loser	0.0996	0.0077	0.2134	0.3211	-0.2132	1.4876
Winner	0.2473	0.0190	0.1837	1.1775	-0.9725	3.0011
Relative Strength	**0.1477**	**0.0114**	**0.1720**	**0.6784**	**-0.6496**	**2.0243**

This table provides a comparison of the 4 Momentum strategies with different formation and holding periods. Figures provide yearly and monthly average returns of the Momentum portfolios as well as standard deviation, sharpe ratio, skewness and kurtosis. Numbers emphasize that returns of Momentum strategy the longer the formation period and the shorter the holding period is.

6.3.3 CAPM Analysis

After proving and investigating profits of momentum strategy for different combinations of formation and holding periods, it is of interest to test significance of the profitability. In the capital asset pricing model, portfolio performance usually is determined by the Jensen alpha. Hence, by regressing momentum returns against the market portfolio Jensen's alpha is obtained and within the excess return from momentum strategy. Results in figure 5 exhibit Jensen alphas for the 4 considered momentum strategies. While alpha values indicate momentum profits that are significantly different from zero, values for R^2 imply that the regression model describes well the performance of 'winner'- and 'loser'-portfolios but not for the relative strength portfolio.

For the linear regression the following model is used which was presented in chapter 3.2:

$$r_p - r_f = \alpha_p + \beta_{p,M} \left[r_M - r_f \right] + \epsilon \,,$$

where r_p describes the return of the momentum portfolio, i.e. relative strength portfolio, r_f illustrates the risk-free rate and r_M displays the market portfolio. For the risk-free rate, the 3m LIBOR is used and the market portfolio is represented by the MSCI World Index. Results from the regression model exhibit positive values for alpha for each portfolio from the 4 strategies. However, findings indicate that 'winner'- and 'loser'-portfolios are positively correlated with market performance, while the relative strength portfolio is negatively correlated with the market portfolio.[98] Highest alpha values are found for the 'winner'-portfolios and lowest alpha values are obtained in the 'loser'-portfolios. Both patterns show similar behavior to performance findings, i.e. increasing (decreasing) values for 'winner'- ('loser'-) portfolios in length of formation period and shorter holding periods. Accordingly, highest alpha value of 0.002943 is found for the relative strength with 12 months

[98] MSCI World Index is used for the market portfolio. MSCI World Index captures large and mid cap representation across 23 Developed Markets (DM) countries.

formation period and 3 months holding period. Thus, model findings imply by following the 12m3m momentum strategy - buying the ’winner’-portfolio and selling the ’loser’-portfolio - one can achieve an outperformance of 15.31 percent per year over the market portfolio. Moreover, this alpha value is significantly different from zero under a significance level of 0.05. However, the lowest alpha value is found for 3m12m relative strength portfolio, where an alpha value of 0.000611 indicates that momentum profit is not significantly different from zero. Furthermore, 6m9m relative strength portfolio exhibits an alpha value of 0.001293 which is not significant and 9m6m momentum strategy features profits with an alpha of 0.002253 which are significantly different from zero according to a significance level of 0.05.

Accordingly, figure 5 provides results for significance of the momentum strategy over time between 2001 and 2008. The figures imply that the relative strength portfolios of momentum strategies with formation periods of 9 months and 12 months respectively generate profits which are significantly different from zero. However, performance of relative strength portfolios seems to be not well described by the capital asset pricing model.

Figure 5: CAPM analysis of the pre-crisis study

Portfolio Strategies	alpha	t statistic	market beta	t statistic	R squared
3m12m					
Loser	**0.003034** ***	5.1750	1.0838 ***	37.8368	0.7942
Winner	**0.003600** ***	7.5572	1.0078 ***	43.3045	0.8348
Relative Strength	**0.000566**	1.0571	-0.0760 ***	-2.9057	0.0223
6m9m					
Loser	**0.002862** ***	3.8817	1.1346 ***	31.4957	0.7278
Winner	**0.004083** ***	7.1208	1.0151 ***	36.2352	0.7797
Relative Strength	**0.001221**	1.4164	-0.1194 ***	-2.8356	0.0212
9m6m					
Loser	**0.002455** ***	3.3450	1.1758 ***	32.7970	0.7435
Winner	**0.004612** ***	6.7155	1.0149 ***	30.2497	0.7115
Relative Strength	**0.002157** **	2.1165	-0.1609 ***	-3.2315	0.0274
12m3m					
Loser	**0.002044** **	2.4994	1.2238 ***	30.6274	0.7166
Winner	**0.004863** ***	6.3655	1.0155 ***	27.2073	0.6661
Relative Strength	**0.002819** **	2.3143	-0.2083 ***	-3.4999	0.0320

This table provides results of the CAPM analysis of Momentum strategies. Linear regression determines the Jensen alpha and further it is investigated how well Momentum returns are described by the CAPM. P-values: *p < 0.10; **p < 0.05; ***p < 0.01

6.3.4 Fama-French Analysis

While results of CAPM analysis and the determined Jensen alphas indicate that momentum profits can not be explained through CAPM, further asset pricing models might incorporate momentum returns. Hence, the three-factor model of Fama and French (1996), which was already presented in chapter 3.3, is tested on coverage of momentum. By regressing returns on this model, various additional factors are tested as explaining factors of momentum profitability. Fama-French three-factor model has been introduced in chapter 3.3 and incorporates the following factors:

$$r_p - r_f = \alpha_p + \beta_{p,M}\,[r_M - r_f] \,+\, \beta_{SMB_p}\,\mathrm{SMB} \,+\, \beta_{HML_p}\,\mathrm{HML} + \epsilon.$$

where r_p illustrates the return of the momentum portfolio, i.e. relative strength portfolio, 3m LIBOR is used for the risk-free rate and the market portfolio is represented by the MSCI World Index. In addition, the HML factor is is computed by subtracting returns of MSCI World Growth Index from the returns of MSCI World Value Index. The SMB factor is captured by subtracting profits of MSCI World Small Cap Index from the returns of MSCI World Index.[99]

Applied linear regression models yields positive alpha values for each of the momentum portfolios for the following considered portfolios: 3m12m, 6m9m, 9m6m, 12m9m. In addition, beta values of several Fama-French factors are computed in figure 6. Comparable to the results of the CAPM analysis, a positive correlation of returns from 'winner'- and 'loser'-portfolio and the market portfolio is obtained. However, the results of the relative strength portfolio only exhibit positive alpha values but a negative correlation with the performance of the whole market. Furthermore, the regression provides positive values of the SMB factor, β_{SMB}, and mixed values, i.e. positive and negative, for the HML factor, β_{HML}. While the

[99] MSCI World Small Cap Index captures small cap representation across 23 Developed Markets (DM) countries. MSCI World Value Index captures large and mid cap securities exhibiting overall value style characteristics across 23 Developed Markets countries. MSCI World Growth Index captures large and mid cap securities exhibiting overall growth style characteristics across 23 Developed Markets countries. Source: http://www.msci.com/

factor β_{HML} is not significantly different from 0 for most of the portfolios, results for market beta and β_{SMB} are significant under the 99 percent confidence interval for all of the computed momentum portfolios. Values for alpha are positive and significantly different from 0 under the 99 percent confidence interval for all 'winner'-portfolios and 3 out of 4 'loser'-portfolios. However, alpha values for the relative strength portfolio only is significant under the 95 percent significance level for the 12m3m momentum strategy.

Findings of the Fama-French analysis indicate that momentum profits of the pre-crisis study are partially explained by the Fama-French three-factor model. Specifically, beta values of the market and the SMB factor indicate that a share of momentum profits can be explained through the market portfolio and the outperformance of small cap companies against large cap companies. Also t-statistics imply that contribution of these factors are significantly different from zero under the 99 percent confidence interval. However, only market beta and returns of 'winner'- and 'loser'-portfolios obtain a positive correlation, while the relative strength portfolio behaves vice versa. HML factor features mixed beta values, whereas most of them are not significant. Although values for alpha are positive for all considered momentum portfolios, only relative strength portfolio of 12m3m momentum strategy exhibits an alpha value which is significantly different from 0 under 90 percent confidence interval. According to this alpha value momentum features approximately 11.22 percent per year to the computed profit.

Figure 6: Fama-French analysis of the pre-crisis study

Portfolio Strategies	alpha	t statistic	market beta	t statistic	SMB factor	t statistic	HML factor	t statistic	R squared
3m12m									
Loser	**0.002285 *** **	4.5154	1.1138 ***	45.2254	0.6220 ***	11.5812	-0.1633 ***	-2.6272	0.8503
Winner	**0.002629 *** **	8.5900	1.0417 ***	69.9397	0.7563 ***	23.2848	0.0358	0.9529	0.9334
Relative Strength	**0.000344**	0.6483	-0.0721 ***	-2.7927	0.1343 **	2.3857	0.1992 ***	3.0559	0.0624
6m9m									
Loser	**0.002156 *** **	3.1575	1.1639 ***	35.0277	0.5964 ***	8.2316	-0.2032 **	-2.4230	0.7722
Winner	**0.003004 *** **	7.4244	1.0534 ***	53.5099	0.8467 ***	19.7234	0.0129	0.2602	0.8930
Relative Strength	**0.000848**	0.9873	-0.1105 ***	-2.6447	0.2503 ***	2.7473	0.2162 **	2.0499	0.0529
9m6m									
Loser	**0.001801 *** **	2.6003	1.2017 ***	35.6493	0.5398 ***	7.3433	-0.1283	-1.5080	0.7769
Winner	**0.003422 *** **	6.6147	1.0584 ***	42.0504	0.9465 ***	17.2453	-0.0505	-0.7955	0.8403
Relative Strength	**0.001620**	1.6021	-0.1433 ***	-2.9122	0.4067 ***	3.7905	0.0778	0.6261	0.0655
12m3m									
Loser	**0.001434 * **	1.8152	1.2477 ***	32.4572	0.5008 ***	5.9740	-0.1025	-1.0563	0.7419
Winner	**0.003592 *** **	6.0845	1.0627 ***	36.9921	1.0179 ***	16.2477	-0.0884	-1.2190	0.8054
Relative Strength	**0.002158 * **	1.7888	-0.1850 ***	-3.1506	0.5171 ***	4.0391	0.0141	0.0952	0.0732

This table provides results of the Fama-French analysis of Momentum strategies. A linear regression determines the Jensen alpha and further it is investigated how well Momentum returns are described by the Fama-French 3-factor model. P-values: *p < 0.10; **p < 0.05; ***p < 0.01

6.4 After-Crisis Analysis

In the after-crisis analysis the profitability of momentum strategy of the time horizon from spring 2008 to summer 2014 is determined. Hence, the sub-prime crisis is fully experienced by the analyzed momentum portfolio. Furthermore, European debt crisis is incorporated in the observed period as well as the asset purchase program from the FED to deliver financial markets with liquidity. These factors might impact the profitability of momentum strategy in one way or the other. Furthermore, an additional feature, ESG ratings, for securities is investigated in the after-crisis analysis. Principles of sustainable investing was introduced in subsection 6.2. Hence, the opportunity of rating observation is used to determine differences in stock price persistence between sustainable and unsustainable companies.

6.4.1 Results

During the considered time horizon of 5 years and 3 months, profits of the applied 16 momentum strategies are monitored. Furthermore, it is distinguished between sustainable securities, unsustainable securities and the full sample of observed securities. Accordingly, the performance on yearly and monthly basis is calculated to compare the profitability of different formation and holding periods for all samples. Results for the sustainable securities provide profits which are mostly positive and support the findings of momentum literature. From 16 strategies only 3 strategies exhibit negative returns. Only strategies with a formation period of shortest time horizon, 3 months, generate negative momentum returns for holding periods of 6 months, 9 months and 12 months respectively. However, analyzing momentum profitability for securities of the whole sample of securities (sustainable and unsustainable companies), less profitable momentum strategies are found. Out of 16 strategies 7 strategies remain profitable. Selling short the 'loser'-portfolio and buying the 'winner'-portfolio yields negative momentum returns for 9 strategies, while especially shorter formation periods of 3 months and 6 months seem to be unprofitable. From short-term formation periods only the combination of 6 months formation period and 9 months holding period yields positive momentum returns. Even worse figures are determined by applying the momentum strategy on a sample of unsustainable stocks. None of the 16 strategies exhibit positive returns. Results illustrate that the absence of profitability is related to high returns of 'loser'-portfolios. Compared to the other samples the 'winner'-portfolios of the unsustainable stocks seem to return at least as much as 'winner'-portfolios of the sustainable and the full sample. Moreover, returns of 'loser'-portfolios are higher, which indicates higher stock price reversals in unsustainable securities.

Figure 7 provides the returns for the three samples and all 16 strategies. Monitored strategies feature largest returns for the sustainable sample in longer formation periods. Combinations of 12m formation period and 3m holding period, 6m formation period and 9m holding period and 6m formation period and 9m holding period are most profitable of the 3 formation period classifications with 0.603, 0.437 and 0.177 percent per month respectively. For the full sample the three combinations are most profitable as well, while monthly returns are lower with 0.134, 0.202 and 0.020 percent respectively. The sample of unsustainable securities only provides negative returns of the relative strength portfolio while highest return (-0,001) can be found for 12m formation period and 12m holding period.

Figure 7: Monthly Momentum returns of the after-crisis study

All Securities

			Holding Period			
			3m	6m	9m	12m
Formation Period	3m	Loser	0.00237	0.00342	0.00337	0.00383
		Winner	0.00193	0.00175	0.00233	0.00282
		Rel. Strength	-0.00044	-0.00167	-0.00104	-0.00101
	6m	Loser	0.00242	0.00291	0.00263	0.00323
		Winner	0.00131	0.00265	0.00283	0.00299
		Rel. Strength	-0.00112	-0.00026	0.00020	-0.00024
	9m	Loser	0.00057	0.00153	0.00166	0.00208
		Winner	0.00192	0.00355	0.00399	0.00426
		Rel. Strength	0.00134	0.00202	0.00233	0.00218
	12m	Loser	-0.00077	0.00030	0.00073	0.00163
		Winner	0.00279	0.00342	0.00425	0.00425
		Rel. Strength	0.00357	0.00312	0.00352	0.00262

Sustainable Securities

			Holding Period			
			3m	6m	9m	12m
Formation Period	3m	Loser	0.00126	0.00227	0.00200	0.00240
		Winner	0.00169	0.00143	0.00199	0.00220
		Rel. Strength	0.00044	-0.00084	-0.00001	-0.00025
	6m	Loser	0.00091	0.00135	0.00094	0.00140
		Winner	0.00148	0.00244	0.00271	0.00258
		Rel. Strength	0.00057	0.00109	0.00177	0.00177
	9m	Loser	-0.00146	-0.00082	-0.00043	0.00007
		Winner	0.00146	0.00356	0.00393	0.00395
		Rel. Strength	0.00292	0.00437	0.00436	0.00388
	12m	Loser	-0.00319	-0.00164	-0.00120	0.00008
		Winner	0.00284	0.00409	0.00444	0.00410
		Rel. Strength	0.00603	0.00573	0.00564	0.00402

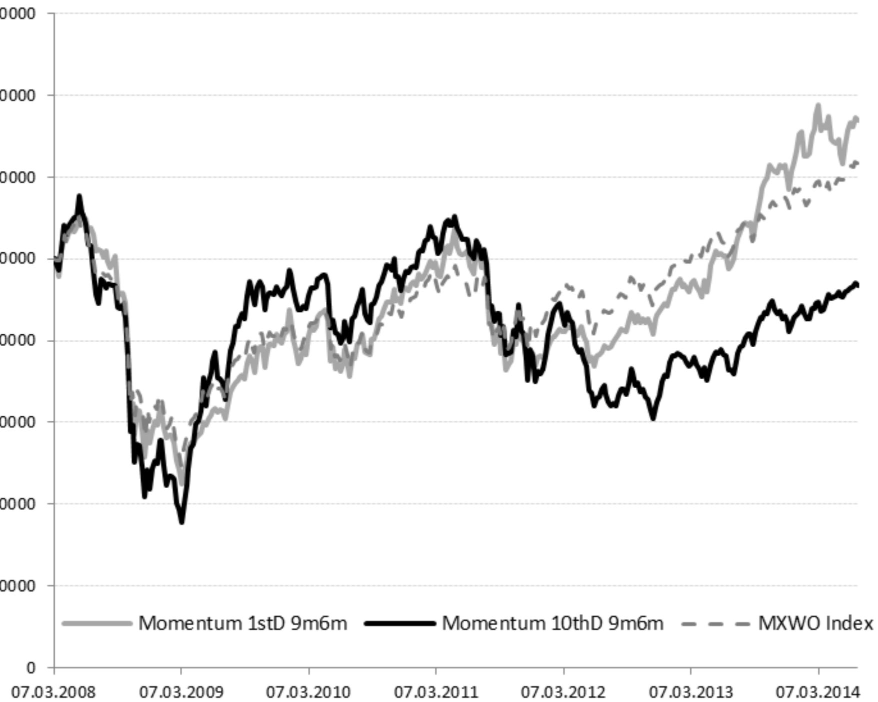
Unsustainable Securities

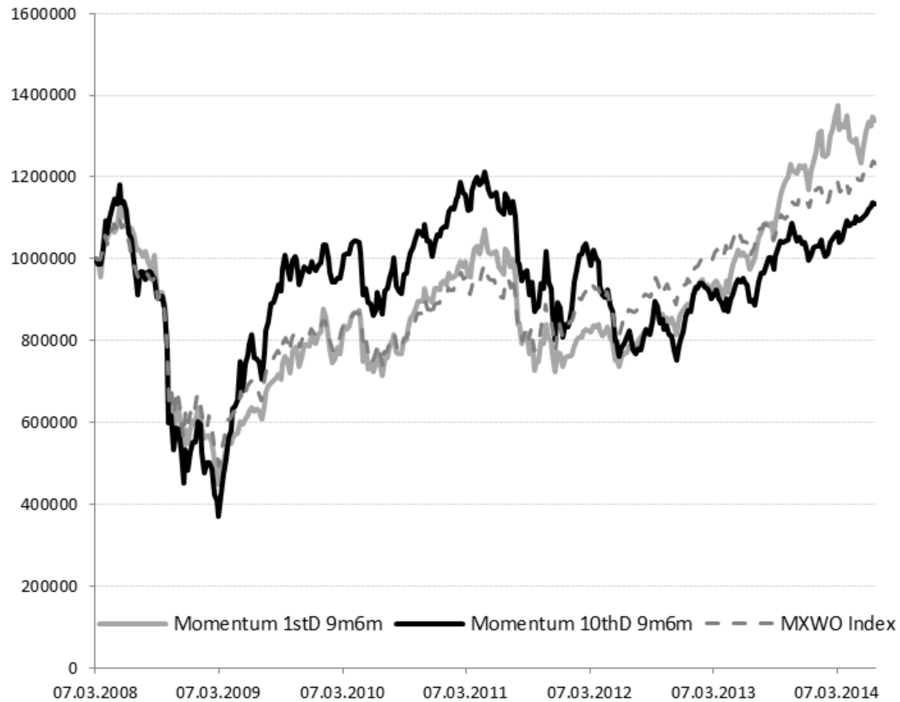
			Holding Period			
			3m	6m	9m	12m
Formation Period	3m	Loser	0.00569	0.00603	0.00634	0.00657
		Winner	0.00376	0.00359	0.00424	0.00511
		Rel. Strength	-0.00193	-0.00244	-0.00210	-0.00146
	6m	Loser	0.00762	0.00721	0.00584	0.00653
		Winner	0.00271	0.00374	0.00449	0.00501
		Rel. Strength	-0.00492	-0.00347	-0.00136	-0.00152
	9m	Loser	0.00715	0.00740	0.00641	0.00683
		Winner	0.00375	0.00457	0.00529	0.00564
		Rel. Strength	-0.00340	-0.00283	-0.00113	-0.00119
	12m	Loser	0.00726	0.00654	0.00610	0.00641
		Winner	0.00351	0.00433	0.00477	0.00541
		Rel. Strength	-0.00374	-0.00221	-0.00133	-0.00100

Furthermore, the development of momentum portfolios is observed during the time horizon between 2008 and 2014. By comparing the performance of 'winner'- and 'loser'-portfolio one can observe when momentum strategy works best. Following figure 8 represents an example for one of the profitable momentum strategies with mid-term formation period of 9 months and holding period of 6 months for the two samples, sustainable securities (lhs) and the full sample (rhs).[100] Several charts of the other combinations of formation and holding periods exhibit similar patterns and can be found in appendix II. It seems that for the whole sample 'loser'-stocks behave different than 'losers' from the sustainable stock universe, while the 'winner'-portfolios of both samples feature similar portfolio developments with comparable absolute returns. It becomes salient that 'loser'-stocks develop differently during the period after financial crisis in 2008. Apparently, 'loser'-stocks with a lower ESG rating, which must be included in the full sample 'loser'-portfolio, seem to obtain extreme price reversals and become 'winner'-stocks. This observation supports the findings for the returns of the unsustainable sample. A similar but less extreme behavior can be observed for the sustainable 'loser'-securities. The 'loser'-portfolio outperforms the 'winner'-portfolio from the sustainable sample from beginning of 2009 to the end of 2010. However, this is weaker in magnitude and offsets earlier than in the whole sample of securities. Furthermore, analogous findings for short-term formation periods can be identified. The shorter the formation period the more extreme are price reversals of 'loser'-stocks between 2009 and 2011. Hence, momentum strategy for observed securities in the chosen time horizon is less profitable or exhibits even negative returns for 3 month formation period (and 6 month formation period for full sample) while momentum strategy becomes more profitable the longer the formation period is.

[100] Since results for the sample of unsustainable securities exhibits negative returns for all combinations of relative strength portfolios, the observation of these portfolios is skipped.

Figure 8: Performance of 'winner'- and 'loser'-portfolios of the after-crisis study





The charts provide an overview over development of 'winner'- and 'loser'-portfolio of 9m6m Momentum strategy for the sustainable sample (left chart) and the full sample (right chart). For charts the MSCI World Index is included for comparison reasons (dashed line). In the sustainable sample an outperformance of the 'winner'-portfolio is observable for the last two years of the considered period. 'winner'-portfolio of the full sample only outperforms the 'loser'-portfolio in the last months of the test period.

Results of the empirical work indicate a first impression that there seems to be a difference in profitability of momentum strategy between sustainable securities and stocks of rather unsustainable companies. Figure 7 presents returns of the constructed momentum portfolios and stresses that relative strength portfolios generate larger returns for the sample of sustainable securities. Further, different patterns of 'loser'- and 'winner'-portfolios can be observed over the considered period. Whereas 'loser'-stocks seem to exhibit price reversals during the time after financial crisis, 'winner'-portfolios especially outperform 'loser'-portfolios from beginning of 2012 to the end of the observed period. Therefore, momentum strategies are further investigated in the next subsections. First, results are compared for the two different samples of securities in a head-to-head analysis where positive returns of relative strength portfolios are tracked. Moreover, the significance of momentum profits is analyzed with previously mentioned asset pricing models.

6.4.2 Head-To-Head Analysis

In order to determine possible momentum drivers, the empirical work differentiates between the subsamples of sustainable and unsustainable securities as well as the full sample of assets. While the head-to-head analysis of the pre-crisis analysis focused on different combinations of formation and holding periods, this analysis determines the variations in returns of the three samples of securities. The comparison between relative strength portfolios of several combinations of formation and holding periods and different security samples provides a deeper insight regarding profitability of momentum strategy. Figure 7 includes the monthly returns from all combinations of observed momentum strategies and indicates that momentum strategy generate larger profits for sustainable securities compared to the return of the subsample of unsustainable companies and the whole universe of securities. Since the subsample of unsustainable securities does not generate positive momentum returns, results are not longer taken into account for the head-to-head analysis.

Comparing results from figure 7 one notices that the profits of relative strength portfolio, buying 'winners' and selling 'losers', exhibits larger profits for sustainable security sample. Specifically, in each of the 16 combinations of momentum strategy, larger profits are obtained for the subsample of stocks from sustainable companies. While both samples with positive momentum returns exhibit comparable profitability regarding formation period, magnitude of momentum return seems distinctly larger in case of sustainable assets. Correspondingly, momentum profits are especially positive for formation periods of 6 months to 12 months. For these strategies positive monthly returns from 0.2 percent to 0.6 percent are tracked, while from these 12 strategies only 7 are profitable from full sample of securities. For a formation period of 6 months, momentum strategy exhibits negative returns for holding periods of 3 months, 6 months and 12 months respectively for full sample. Further, all of the profitable strategies return only 0.02 to 0.35 percent a month and negative returns are higher in magnitude also for the 3 unprofitable strategies of sustainable securities with a formation period of 3 months (holding period: 6, 9 and 12 months). Since the universe of sustainable stocks is only about a third of the whole sample, the finding of higher profitability of momentum strategy in sustainable securities challenges the diversification argument. Although, there is a smaller quantity of stocks in the relative strength portfolio of sustainable companies, it seems that momentum returns are larger in the sample of sustainable securities and stock price persistence of sustainable stocks offsets the diversification aspect.

From now on, the focus will be on 3 momentum strategies, which are profitable for the 2 samples and cover 3 different holding periods. Being accurate, analysis of momentum strategies is limited on the following 3 combinations: 6m9m, 9m6m and 12m3m. From 2 out of 3 strategy combinations these are the most profitable ones according to the formation period, while the 9m6m combination is most profitable of this formation period for the sustainable subsample but also second most profitable for the whole sample. Therefore, the following analysis focuses on these momentum strategies. Figure 9 contains descriptive statistics of 'winner'-, 'loser'- and relative strength portfolio of each of the 3 mentioned strategies and both samples. Yearly average returns for the sustainable sample exceeds the whole sample in each of the 3 combinations and exhibits average returns of 2.3 percent, 5.64 percent and

7.84 percent per year for 6m9m, 9m6m and 12m3m strategy respectively. Further, standard deviation of the average yearly return is lower for sustainable sample in the 2 strategies with 6 months and 9 months formation period and similar for the 12 months formation period strategy. Accordingly, results of the Sharpe Ratio indicate best portfolio performance of the relative strength portfolios of 9m6m and 12m3m strategies in the sustainable subsample, while results of the full sample are distinctly lower for each of the 3 strategies.

Figure 9: Head-To-Head Analysis of the after-crisis study

	Portfolio	Avg. Y-o-Y Return	Avg. monthly Return	St. Dev. Y-o-Y	Sharpe Ratio	Skewness	Kurtosis
	Strategies						
	6m9m						
Sustainable Securities	Loser	0.0122	0.0009	0.2935	-0.0028	-1.0375	5.6598
	Winner	0.0352	0.0027	0.2710	0.0819	-1.4149	6.6138
	Relative Strength	**0.0230**	**0.0018**	**0.0549**	**0.1826**	**-0.2579**	**2.2858**
All Securities	Loser	0.0341	0.0002	0.3007	0.0703	-0.8837	5.4259
	Winner	0.0368	0.0000	0.2540	0.0936	-1.2541	5.8779
	Relative Strength	**0.0027**	**0.0017**	**0.0946**	**-0.1094**	**-0.4095**	**2.4208**
	9m6m						
Sustainable Securities	Loser	-0.0106	-0.0008	0.3233	-0.0731	-0.9535	5.4179
	Winner	0.0462	0.0036	0.2618	0.1270	-0.3383	4.1270
	Relative Strength	**0.0569**	**0.0044**	**0.1499**	**0.2926**	**-0.2811**	**2.7882**
All Securities	Loser	0.0199	0.0015	0.3183	0.0215	-0.8044	5.1114
	Winner	0.0461	0.0035	0.2463	0.1345	-1.3117	5.8912
	Relative Strength	**0.0263**	**0.0020**	**0.1519**	**0.0874**	**-0.2455**	**3.4680**
	12m3m						
Sustainable Securities	Loser	-0.0415	-0.0032	0.3541	-0.1539	-0.8445	5.3388
	Winner	0.0369	0.0028	0.2575	0.0928	-1.6499	8.2272
	Relative Strength	**0.0784**	**0.0060**	**0.2124**	**0.3079**	**-0.3129**	**2.0508**
All Securities	Loser	-0.0100	-0.0008	0.3478	-0.0662	-0.7854	5.4221
	Winner	0.0363	0.0028	0.2411	0.0967	-1.4647	6.7162
	Relative Strength	**0.0463**	**0.0036**	**0.2108**	**0.1582**	**-0.3077**	**2.6337**

This table provides a comparison of the 4 Momentum strategies with different formation and holding periods. Figures provide yearly and monthly average returns as well as standard deviation, sharpe ratio,s kewness and kurtosis. Numbers emphasize that returns of Momentum strategy the longer the formation period and the shorter the holding period is.

6.4.3 CAPM Analysis

While the head-to-head analysis provides proof of profitability of most momentum strategies in the subsample of sustainable securities and in half of the strategies of the full sample, significance of the profits is tested in a CAPM analysis. Like in the pre-crisis analysis, significance is investigated through a regression against the market portfolio and the obtained Jensen alpha.

Beta values implying that a large share of momentum profits is explained through market profits. Accordingly, values of t-statistic are very high and prove significance of market beta values. However, alpha values are very low for both, relative strength portfolio as well as 'winner'- and 'loser'-portfolios respectively. Hence, according to asset pricing model the profits can not be accredited to momentum strategy, but to the market performance. While alpha values for the sustainable subsample are positive for each of the three considered relative strength portfolios, 6m3m relative strength portfolio of the full sample exhibits even a negative alpha value. Largest alpha value of 0.0017 can be found for the 12m3m relative strength portfolio of sustainable securities. Although values imply no statistical significance, this indicates a yearly excess return due to momentum effects of 8.68 percent.

Results of the after-crisis study generate positive momentum returns for at least most of the strategies on the sustainable subsample. However, magnitude of profits compared to the pre-crisis analysis is weaker. Hence, CAPM analysis indicates that only a small share of the profits is due to momentum. In contrast to the pre-crisis sample, a bigger fraction is captured by the capital asset pricing model. Since values o R^2 for 'winner'- and 'loser'-portfolio reach from 0.8132 to 0.9366, the model seem to describe the performance development of the two portfolios sufficiently well. Whilst values of R^2 for relative strength portfolio are rather low, market beta values are even negative and indicate a negative correlation with momentum profits.

Figure 10: CAPM analysis of the after-crisis study

	Portfolio Strategies	alpha	t statistic	market beta	t statistic	R squared
	6m9m					
Sustainable Securities	Loser	-0.0003	-0.3731	1.3346 ***	53.0676	0.8962
	Winner	0.0002	0.4167	1.1600 ***	65.1456	0.9287
	Relative Strength	**0.0005**	**0.7333**	**-0.1746 *****	**-7.6191**	**0.1512**
All Securities	Loser	0.0001	0.2097	1.3074 ***	56.4861	0.9073
	Winner	0.0003	0.5509	1.1220 ***	69.3722	0.9366
	Relative Strength	**0.0001**	**0.1880**	**-0.1854 *****	**-8.5865**	**0.1844**
	9m6m					
Sustainable Securities	Loser	-0.0007	-0.7923	1.3681 ***	44.7033	0.8597
	Winner	0.0005	0.6785	1.1280 ***	51.6491	0.8911
	Relative Strength	**0.0012**	**1.1010**	**-0.2401 *****	**-6.7666**	**0.1232**
All Securities	Loser	-0.0001	-0.1694	1.3583 ***	47.6217	0.8743
	Winner	0.0005	0.8038	1.0689 ***	55.4136	0.9040
	Relative Strength	**0.0006**	**0.5829**	**-0.2893 *****	**-8.2913**	**0.1742**
	12m3m					
Sustainable Securities	Loser	-0.0014	-1.2418	1.4764 ***	40.5836	0.8348
	Winner	0.0003	0.3477	1.0599 ***	37.6680	0.8132
	Relative Strength	**0.0017**	**1.1332**	**-0.4165 *****	**-8.5882**	**0.1845**
All Securities	Loser	-0.0008	-0.7482	1.4671 ***	43.6682	0.8540
	Winner	0.0003	0.4084	1.0055 ***	40.6215	0.8350
	Relative Strength	**0.0011**	**0.7540**	**-0.4616 *****	**-9.8753**	**0.2303**

This table provides results of the CAPM analysis of Momentum strategies. Linear regression determines the Jensen alpha and further it is investigated how well Momentum returns are described by the CAPM. P-values: *p < 0.10; **p < 0.05; ***p < 0.01

6.4.4 Fama-French Analysis

Already capital asset pricing model seems to explain the profits of momentum strategy during the after-crisis study well. Equivalently, an analysis of momentum returns in the Fama-French three-factor model supports these findings and indicates that other factors are responsible for excess returns of momentum strategy. Hence, profitability of momentum strategy can not be confirmed according to the considered asset pricing models.

Figure 11 provides the results of regressing momentum profits on the three Fama-French factors. Apparently, alpha values for all 'winner'- and relative strength portfolios are positive but low. Moreover, t-statistics imply that returns of momentum strategy are not significantly different from 0 under significance levels from a two-sample t-test. Like in the CAPM analysis results indicate that a big share of momentum returns can be accredited to market portfolio. According to the t-statistics, β_{MKT} is significantly different from 0 under a 99 percent significance level for all of the considered momentum strategies on both samples. Unlike the Fama-French pre-crisis analysis, the influence of HML companies seems to be higher than SMB companies. Accordingly, most of the values for β_{HML} are significant at least under a 95 percent interval, while β_{SMB} exhibit mixed values, which are not significantly different from 0.

Findings of the Fama-French analysis support the results from CAPM analysis and indicate that returns from momentum strategy in the after-crisis period can be explained by the market beta to a large extent. Furthermore, results suppose that growth companies outperform value companies. This finding also seems to be responsible for excess returns of approached momentum strategy. Although alpha values are positive for all of the profitable momentum strategies, t-statistics exhibit too low values, such that profitability of momentum strategy can not be confirmed after asset pricing analysis.

Figure 11: Fama-French analysis of the after-crisis study

	Portfolio Strategies	**alpha**	t statistic	market beta	t statistic	SMB factor	t statistic	HML factor	t statistic	R squared
	6m9m									
Sustainable Securities	Loser	**-0.0003**	-0.3823	1.3243 ***	49.7321	0.0210	1.1253	0.0116	0.1326	0.8967
	Winner	**0.0002**	0.2933	1.1672 ***	62.6230	-0.0038	-0.2889	-0.1755 ***	-2.8612	0.9306
	Relative Strength	**0.0004**	0.6529	-0.1571 ***	-6.5571	-0.0248	-1.4751	-0.1871 **	-2.3728	0.1757
All Securities	Loser	**0.0001**	0.2119	1.2995 ***	52.9951	0.0149	0.8658	0.0266	0.3296	0.9076
	Winner	**0.0002**	0.4283	1.1323 ***	67.2032	-0.0105	-0.8937	-0.1728 ***	-3.1173	0.9389
	Relative Strength	**0.0001**	0.0899	-0.1672 ***	-7.4345	-0.0254	-1.6137	-0.1994 ***	-2.6951	0.2139
	9m6m									
Sustainable Securities	Loser	**-0.0008**	-0.8092	1.3562 ***	41.8454	0.0255	1.1238	-0.0062	-0.0582	0.8603
	Winner	**0.0004**	0.5523	1.1334 ***	49.5218	0.0023	0.1439	-0.2127 ***	-2.8243	0.8938
	Relative Strength	**0.0011**	1.0392	-0.2228 ***	-5.9564	-0.0232	-0.8858	-0.2065 *	-1.6779	0.1349
All Securities	Loser	**-0.0001**	-0.1612	1.3449 ***	44.5737	0.0248	1.1734	0.0535	0.5387	0.8751
	Winner	**0.0004**	0.6986	1.0809 ***	53.6201	-0.0133	-0.9401	-0.1842 ***	-2.7767	0.9069
	Relative Strength	**0.0005**	0.5177	-0.2640 ***	-7.2130	-0.0381	-1.4851	-0.2376 **	-1.9733	0.1931
	12m3m									
Sustainable Securities	Loser	**-0.0014**	-1.2231	1.4590 ***	37.9276	0.0307	1.1394	0.0934	0.7377	0.8359
	Winner	**0.0002**	0.2167	1.0682 ***	36.2574	0.0008	0.0382	-0.2819 ***	-2.9083	0.8181
	Relative Strength	**0.0015**	1.0491	-0.3908 ***	-7.6730	-0.0299	-0.8385	-0.3753 **	-2.2395	0.2012
All Securities	Loser	**-0.0007**	-0.7134	1.4458 ***	40.8374	0.0356	1.4360	0.1451	1.2455	0.8560
	Winner	**0.0002**	0.2644	1.0170 ***	39.4521	-0.0058	-0.3206	-0.2853 ***	-3.3637	0.8411
	Relative Strength	**0.0009**	0.6569	-0.4288 ***	-8.7823	-0.0414	-1.2105	-0.4304 ***	-2.6790	0.2542

This table provides results of the Fama-French analysis of Momentum strategies. A linear regression determines the Jensen alpha and further it is investigated how well Momentum returns are described by the Fama-French 3-factor model. P-values: *p < 0.10; **p < 0.05; ***p < 0.01

6.5 Determinants of Momentum

Momentum literature provides various indications about potential drivers of momentum profitability. Markets, industry, size or seasonality are investigated in the literature review chapter. Hence, momentum portfolios of the empirical study are tested for several of these factors to analyze their influence on momentum profitability. Grinblatt and Moskowitz (1999) outline the importance of industry momentum which is incorporated in several traditional momentum analyses. Modern momentum literature relates profits of this strategy to liquidity anomalies and finds distinctions between liquidity measures of 'winner'- and 'loser'-portfolios. Furthermore, after-crisis analysis distinguishes security samples of sustainable and unsustainable companies. Therefore, sustainability ratings of companies in the momentum portfolios are analyzed. This determinant enables identification of coherence between sustainability of companies and price persistence of its stocks. Mentioned factors are perceived as important factors for momentum profitability in the applied empirical work and might be main determinants of momentum. Thus, the three factors and their connection to momentum profits are presented in the following subsections.

6.5.1 Liquidity

Increasing importance of securities' liquidity in asset pricing models has been previously outlined in chapter 5. Furthermore, latest momentum literature connects liquidity patterns with 'winner'- and 'loser'-portfolios of momentum approach. Literature emphasizes differences between 'winner'- and 'loser'-stocks with respect to their liquidity. Moreover, Avramov, Cheng and Hameed (2014) find that momentum profits are higher in liquid markets and Ibbotson et al. (2013) claim that relative strength portfolio of less liquid securities generates higher profits than the one of more liquid stocks. Therefore, portfolios of the empirical study are tested for liquidity anomalies to identify and confirm literature findings and check the coherence between stock liquidity and momentum profits.

For the after-crisis time horizon, bid- and ask-prices are observed to measure the liquidity of considered securities. Moreover, liquidity of the 'winner'- and 'loser'-

portfolios is determined for three profitable momentum strategies with different formation and holding periods in the sustainable sample and unsustainable sample of securities. An established vehicle to measure stock price liquidity is the bid-ask spread. Accordingly, each month the liquidity of stocks is measured by the quoted spread, which can be calculated by the following formula:

$$QS_{i,t} = 100 \frac{A_{i,t} - B_{i,t}}{2 M_{i,t}},$$

Since all securities in the portfolios are equally weighted, the liquidity of 'winner'- and 'loser'-portfolios can be calculated by the average of all stocks in the portfolio. Hence, the average quoted spread can be observed for the after-crisis period for 'winner'- and 'loser'-portfolios of several momentum strategies.

For each of the analyzed momentum strategies similar liquidity patterns can be found. The assumption that 'loser'-stocks are less liquid (bid-ask spreads are higher) than 'winner'-stocks can be confirmed by the results. Comparing the development of 'winner'- and 'loser'-portfolios of the 12m3m momentum strategy of the two samples in figure 12, 'loser'-portfolios obtain a higher illiquidity measure over almost the whole period. While the 'loser'-portfolio's quoted spread of the sustainable sample 12m3m momentum strategy is distinctly larger after 03/2012, the 'loser'-portfolio of the same strategy in the unsustainable sample exhibits highest quoted spread during 2011. Appendix III provides bid-ask spreads of the portfolios for the following momentum strategies of the sustainable and unsustainable samples: 12m3m, 9m6m and 6m9m. Each of the 'winner'-portfolios features a lower quoted spread on average than the 'loser'-portfolio. Furthermore, one can observe that the portfolios of the sustainable sample show differences that are more distinct in liquidity of 'winner'- and 'loser'-portfolio than in the unsustainable sample. Since results of the empirical study exhibits higher momentum profits for the sustainable sample, this finding suggests that liquidity of securities correlates with the profitability of momentum.

Figure 12: Quoted spreads of ‘winner’- and ‘loser’-portfolios of 12m3m Momentum strategy

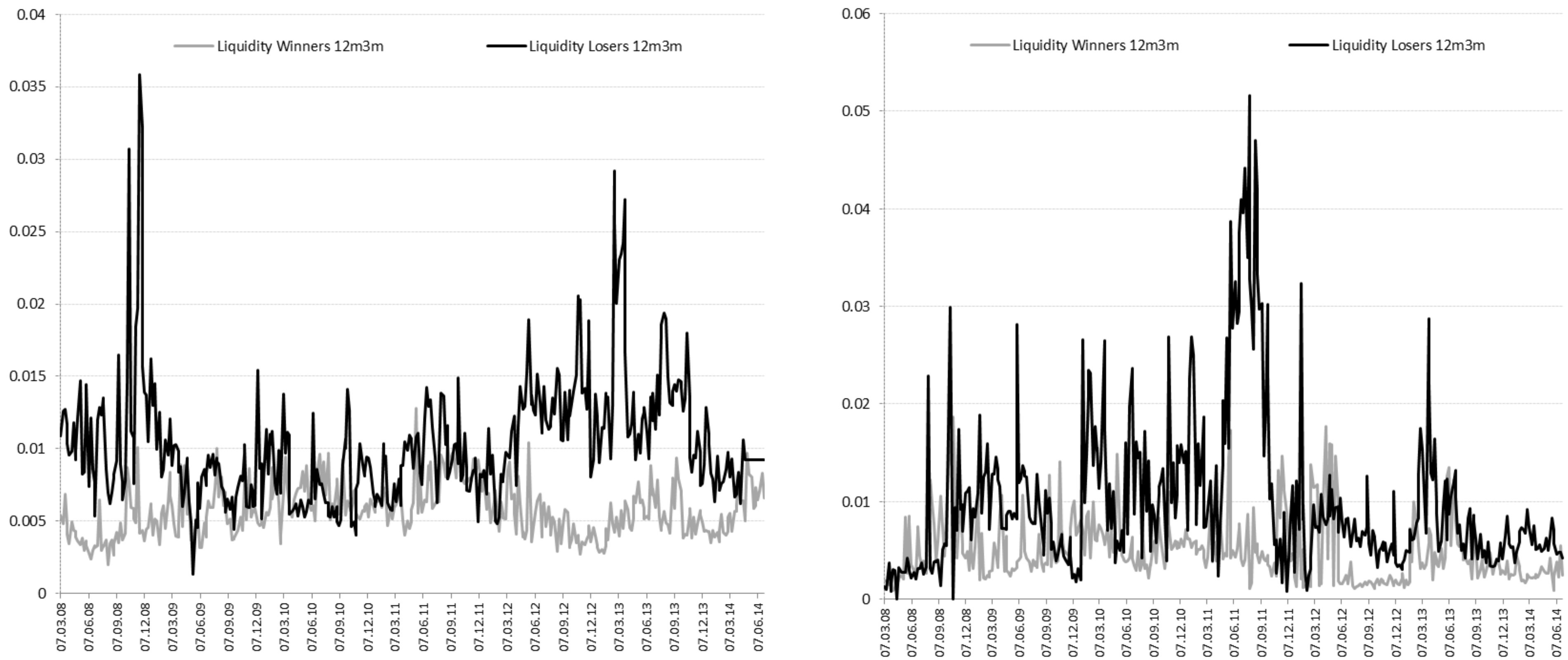


Figure 12 pictures the liquidity of 12m3m ‘winner’- and ‘loser’-portfolios during after-crisis period for the sustainable sample (left chart) and full sample (right chart) respectively. Liquidity of the portfolios is measured through average bid-ask spreads over the incorporated securities. Hence, the lower the average of the bid-ask spread the more liquid are the securities in the respective portfolio. ‘Loser’-portfolio of the sustainable sample appears to be less liquid in nearly over the whole observed time horizon. However, the liquidity differences between ‘winner’- and ‘loser’-portfolio in the full sample is less distinct.

Besides differences in liquidity of 'winner'- and 'loser'-stocks, empirical research also finds a connection between momentum profitability and market liquidity. In the study of Avramov, Cheng and Hameed (2014), it is pointed out that momentum strategy is most profitable in liquid markets. While intuition suggests that anomaly of momentum can be rather arbitraged away in liquid markets, they claim that momentum profits are higher when cross-sectional differences in illiquidity between 'winner'- and 'loser'-portfolio are large. Hence, study returns of the relative strength portfolio are compared with market liquidity for the empirical study.

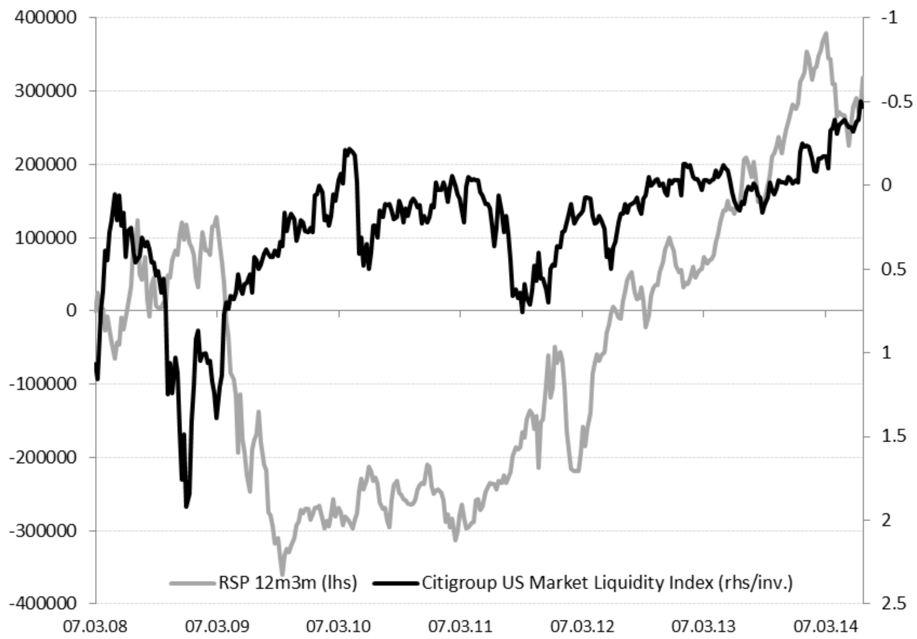
Data providers and financial institutions track several liquidity indices for various markets. For the analysis of the momentum returns in the empirical study, the Citigroup US Market Liquidity Index is compared to the relative strength portfolio. This index is derived from five indicators in the swap and option markets to identify market liquidity of US stock markets.[101] Citigroup's index of market liquidity rises if liquidity dries up and falls if markets become more liquid. Thus, indicators like this index illustrate investor sentiment and reflect the mood of the market as a whole. US market liquidity is compared with momentum returns for both periods, the pre- and after-crisis period. Figure 13 presents market liquidity of US stock markets (values are inverted) with the most profitable momentum strategy, 12m3m, for both time horizons. The chart mirrors a slightly positive correlation of market liquidity and momentum returns. In the left chart the pre-crisis momentum return increases until the subprime bubble bursts. Equivalently, the market liquidity increases until 2007 and declines sharply with first signs of the financial crisis. For the after-crisis analysis the right chart provides US market liquidity index and relative strength portfolio for 12m3m momentum strategy on the sustainable sample. Similar to the pre-crisis chart momentum profits rise with US market liquidity. While market liquidity was dried out after the subprime crisis, it increased since then until the

[101] Bloomberg provides the following information, equation and components for the Citigroup US Market Liquidity Index: CMLXUS = 0.2*[(Swaption Price)/200.7 - (Rate Swaps)/0.68 + (Swap Spreads)/22 + (CDX.NA.IG)/57.71 + (VIX Futures)/11.30 -1.2074] Swap Spreads: The difference between the current 10yr Interest Rate Swap yield (Bloomberg Ticker: USSW10 Curncy) and the yield of the current reference 10yr Treasury Bond Future (Bloomberg Ticker: TY1 Comdty)

end of the observed period in June 2014. Also the value of the relative strength portfolio increased from mid-2009 until end of the considered time horizon.

In this section a coherence between momentum and liquidity patterns was investigated. Literature claims that momentum strategy generates higher profits when aggregate market liquidity is high. Furthermore, it is stated that 'winner'-stocks tend to exhibit higher liquidity than 'loser'-stocks. These findings were confirmed in the analysis of the empirical work. Hence, one can conclude that there exists a relation between liquidity of securities and momentum profitability.

Figure 13: Overview of Momentum returns and market liquidity



The charts provide an overview of US market liquidity and return of the two most profitable relative strength portfolios in pre-crisis and after-crisis study. US Market liquidity is illustrated by the Citigroup US Market Liquidity Index. Market liquidity provides best measure of investor sentiment. For pre-crisis study (left chart) the market liquidity is compared with the relative strength portfolio of the 12m3m Momentum strategy. For after-crisis study (right chart) the market liquidity is compared with the relative strength portfolio of 12m3m Momentum strategy of the sustainable sample. Both strategies illustrate the most profitable strategies of the relevant time period.

6.5.2 Industries

In the traditional momentum literature industry momentum is named as an important factor of momentum profitability. Although asset pricing models like CAPM, Fama-French and Carhart do not incorporate an impact of industries, literature relates momentum profits to cross-sectional variations within industries. Thus, various studies like Grinblatt and Moskowitz (1999) determine the impact of industry momentum when price returns are conditioned on the information of past prices. Accordingly, results of the empirical work are investigated on industries in the 'winner'- and 'loser'-portfolios.

Portfolio returns are often driven by a specific industry, which does explicitly good during a period. Accordingly, if an industry experiences a tough time, companies of the specific industry might be experiencing reducing portfolio returns. Thus, price persistence of a whole industry might be the reason for momentum profitability. Therefore, Grinblatt and Moskowitz (1999) analyze the share of industry impact in momentum returns by sorting for both industry and its financial performance. Results of their study exhibit momentum profits which are approximately as high as individual stock momentum return and indicate that industries do indeed explain momentum.

Hence, portfolios constructed on momentum approach in the empirical study are examined for the relative share of industries. Considered companies are categorized according to their GICS industry. The classification of GICS industries is popular and acknowledged classification developed by the two leading index providers MSCI and Standard and Poor's, which consists of 67 industries.[102] Thus, this industry allocation provides a sufficient broad differentiation of companies' industry. In appendix IV, the distribution of all GICS industries in the MSCI World Index and in the considered investment universe can be found. In this analysis, companies' indus-

[102]The Global Industry Classification Standard (GICS) is an industry taxonomy developed by MSCI and Standard and Poor's for use by the global financial community. The GICS structure consists of 10 sectors, 24 industry groups, 67 industries and 156 sub-industries into which Standard and Poor's has categorized all major public companies.

try of the 'winner'- and 'loser'-portfolios is determined each month and the relative share is calculated. The 5 industries with the largest share are observed and their aggregate share in the portfolio is computed. Figure 14 provides the development of the relative share of the 5 largest industries in the 'winner'- and 'loser'-portfolios of 3 different momentum strategies on the full sample and the sustainable sample respectively. The charts illustrate that the stake of 5 companies with largest share in the portfolios varies between 25 and 70 percent, while it fluctuate around 45 percent for the sustainable sample in the after-crisis period. During the pre-crisis period similar figures can be identified, although average shares for the largest industries in the portfolios are lower.[103] Furthermore, the share of companies from specific GICS industries in the momentum portfolio versus maximal existing companies from the industries is determined. On average, approximately 26 percent of existing companies from the industry represents the industry with largest share of the 'winner'-portfolio of the 12m3m momentum strategy in the full sample of securities. Appendix VI provides a summary of average stake in the momentum portfolios.

The computed numbers give an overview of the relative share of 5 highest represented GICS industries in the created portfolios in the empirical study. Depending on the industry, all companies of the 5 industries illustrate only a small share of the total 67 industries. In the MSCI World Index, the 5 industries with the largest share in this index after weighting them according to market capitalization account for approximately 30 percent of the portfolio. Hence, in the created portfolios average accumulated stake of the 5 largest industries is about 50 percent higher (or 15 percent in absolute) than the share of 5 largest industries in MSCI World Index. Therefore, a coherence between industry momentum and profitability of momentum strategy is conjecturable. Especially in periods when accumulated relative stake of largest industries amounts to more than 50 percent, a strong influence of industry momentum can be observed. By comparing both portfolios from different momentum strategies, one can conclude that there is an impact on both 'winner'- and

[103] Charts and average shares for the pre-crisis period can be found under appendix V and VI

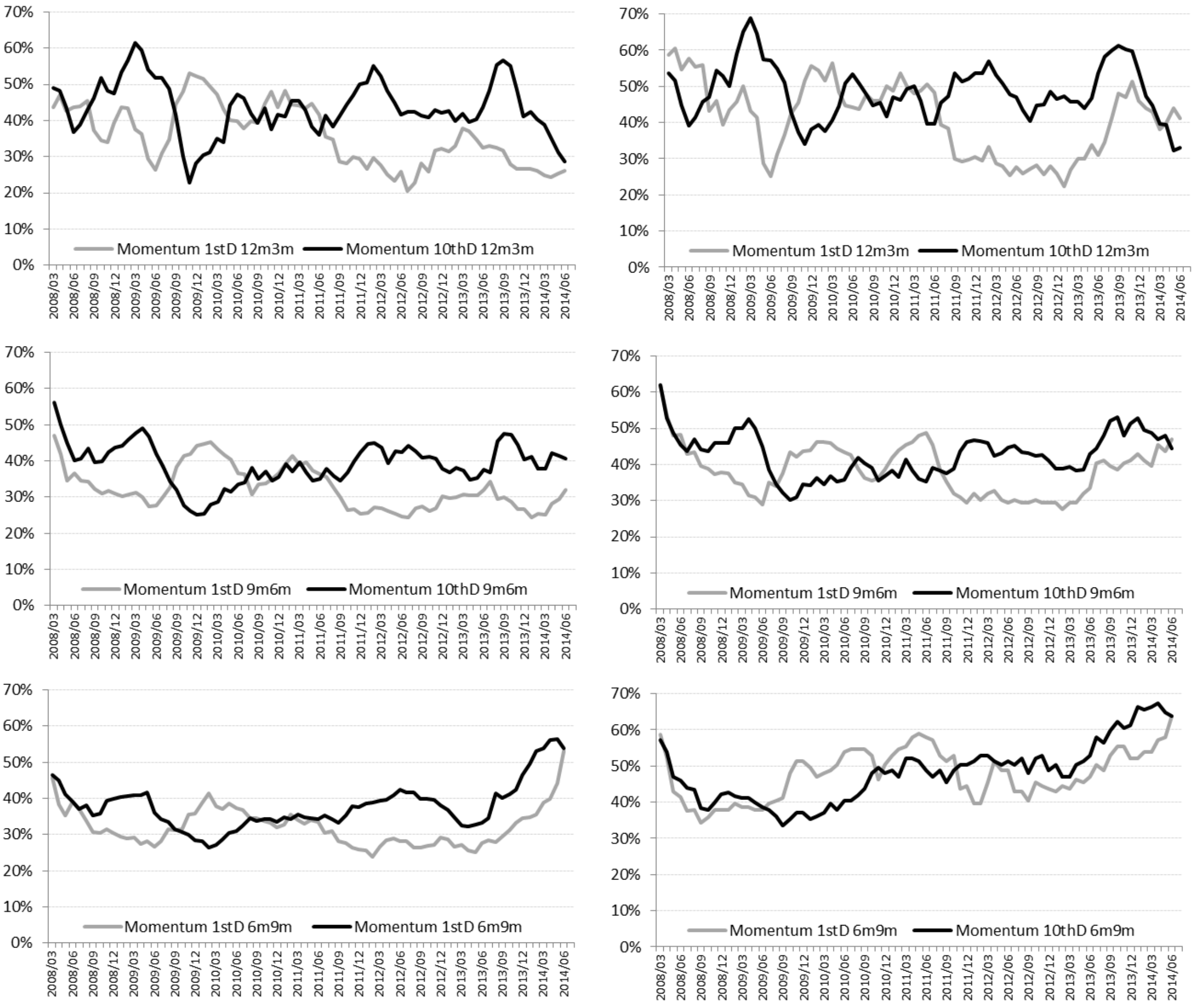
'loser'-side of industry momentum. Accordingly, industry momentum acts in a positive way as well as in a negative way on a portfolio. Correspondingly, it increases the effect of momentum in both portfolios. Momentum strategies are compared with different formation and holding periods and hence different profitabilities. Since the accumulated share of largest industries is not distinctly different, one can state that industry momentum does have an impact and may be a driver of momentum, however one can not determine an influence on the magnitude of profitability of different momentum strategies. Moreover, the average share of driving industries seems to be similar for the three considered momentum strategies.

Findings of this analysis imply that industries indeed play a role in the momentum approach and support the assumption of traditional momentum literature. Accordingly, the accumulated share of best represented industries in momentum portfolios is distinctly larger than in acknowledged indices like MSCI World Index, which implies an overweight of very well and very bad performing industries in the relative strength portfolio. However, since a distinction between the stake of industries within the considered strategies can not be made, the impact of particular industry momentum is not evident. Furthermore, also a differentiation between the full sample of securities and the sample of sustainable securities can not be made.

Figure 14: Share of 5 largest industries in ‘winner’- and ‘loser’-portfolios

Full Sample

Sustainable Sample



The charts provide an overview of the accumulated share of the 5 industries, with the largest individual share in the ‘winner’- and ‘loser’-portfolio. Companies are classified according to the GICS industry, which is an established classification developed by MSCI and Standard and Poor’s. Findings imply an overweight of very well and very bad performing industries in the relative strength portfolio.

6.5.3 Sustainability

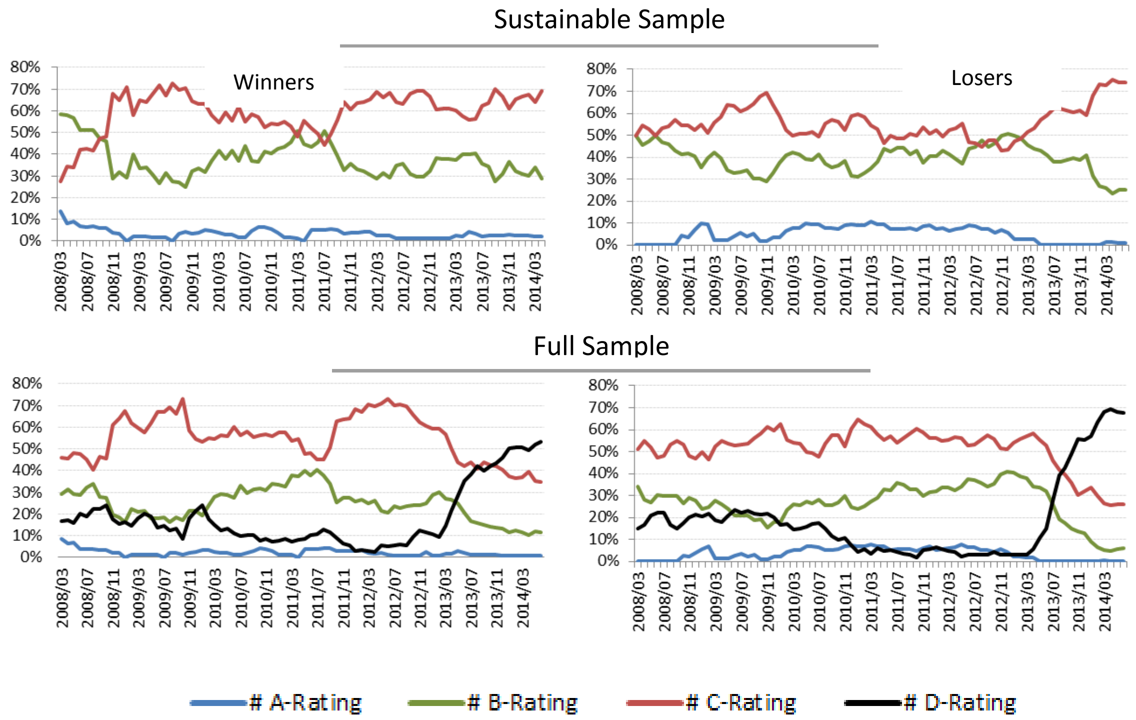
In the after-crisis study, a distinction between the samples of sustainable and unsustainable securities is made. Since the results are distinctively different and momentum strategy only generates positive returns for the sustainable subset, the impact of sustainability factors on price persistence is investigated. Differences in the profitability of the two subsamples suggest that sustainable companies exhibit stock price patterns with higher persistence. Hence, one can claim that momentum strategy is also due to sustainability of the considered companies and the hypothesis is raised that price persistence is larger for sustainable securities.

Portfolios of the after-crisis study are not only sorted by the historic stock price performance but also according to the sustainability rating accredited by oekom research. For the sustainable (unsustainable) subsample, every month only companies are taken into account which have a sustainability rating of C or better (C- or worse). Findings of momentum profitability imply that momentum only occurs in the sample of sustainable companies. Hence, different momentum strategies are compared according to the share of very high rated companies (sustainability rating of A or B) and low rated companies (C rated companies in the sustainable sample, C and D rated companies in the full sample). Figure 15 provides an overview of the relative share of the different ratings in the momentum portfolios for the most profitable strategy 12m3m and the least profitable strategy 3m12m. Accordingly, differences regarding sustainability between the two portfolios with distinct profitability can be investigated. Furthermore, differences between the two samples of sustainable securities and full sample of securities as well as differences between 'winner'- and 'loser'-portfolio can be determined. For the latter apparently no differences can be found, since both 'winner'- and 'loser'-portfolios of both strategies exhibit similar patterns regarding the share of good and bad rated companies. Also for the same strategy and different samples no distinctions can be observed. Besides the fact that full sample of securities includes D rated companies, which increases in magnitude during the last months of the period, the composition of the portfolios is similar. For each of the four portfolios from 12m3m momentum strategy, the stake of C rated companies is the highest. B rated companies follow with second largest share and only a few companies have a very good sustainability rating of A. The stake of D rated companies in the full sample of securities increases tremendously in year 2013 and represents a big share of the portfolios of 'winner'- and 'loser'-stocks in the full sample. Comparing the 12m3m strategy and 3m12m strategy, for which the variation in profitability is highest, one can observe a difference in the pattern of rating shares in the portfolios. However, while the stake of companies from a specific rating seems to be more stable, the order is comparable in both strategies and C rated companies represent the largest share.

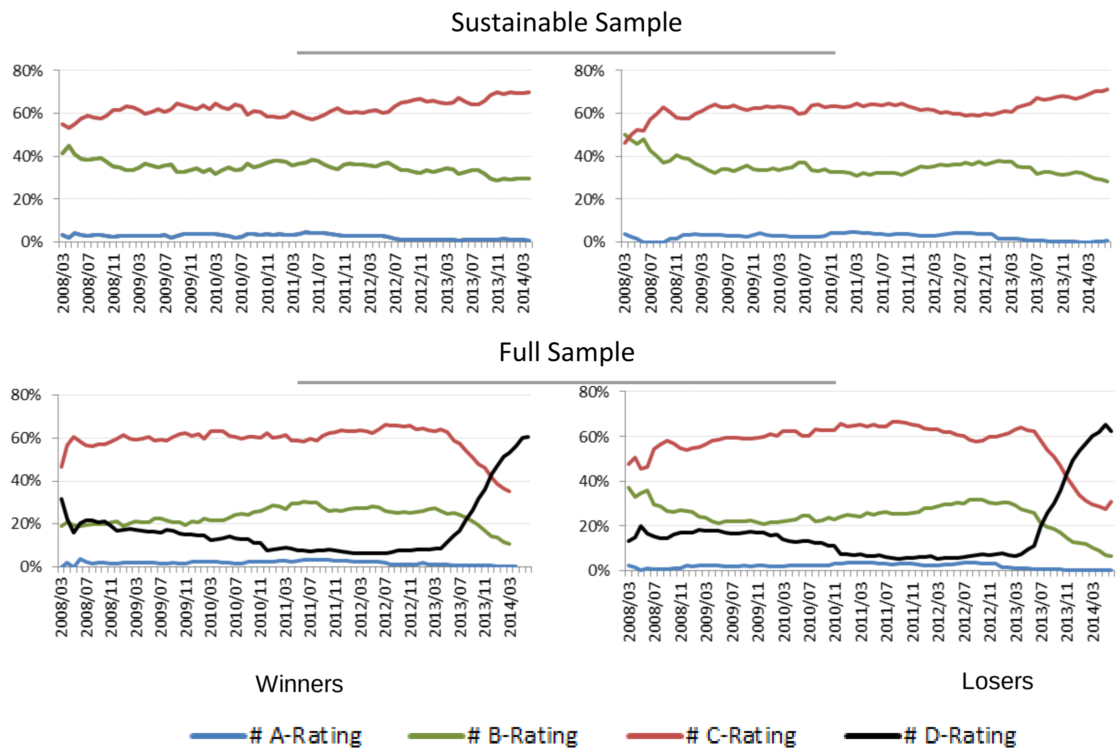
Apparently, the result from the ESG rating analysis does not identify any relations between the sustainability rating and momentum profitability. Moreover, comparing the distribution of ratings in the momentum portfolios suggests similarities with the rating distribution in the universe of observed companies. Appendix X illustrates the distribution of rating through the considered 3300 securities for the ESG rating as well as ratings for the subcategories E, S and G. The charts emphasize that the stake of low rated companies is higher than very sustainably companies. Since the coverage of companies of oekom increased during the last years, especially the amount of low rated companies grew. Therefore, the stake of D rated companies increases in the end of the observed time horizon in the full sample. In addition to the total sustainability rating, subcategories of the rating are investigated, which might give a deeper insight on influencing factors. However, none of the sub-ratings seems to exhibit distinct differences between portfolios, strategies or samples. Variations in the orders can be observed between the three subcategories, although these orders remain the same in each of the four portfolios of the strategy as well as in both strategies. For the Governance rating, it becomes salient that companies are rated better than in the total ESG rating, since B rated companies represent the largest share of each portfolio and also stake of A rated companies is much higher. The analysis of the Social rating features similar results like the ESG rating with high share of C rated companies and also Environmental rating exhibits similar patterns with C rated companies followed by B rated companies in all portfolios.

Although no remarkable difference between portfolios, strategies or samples can be made regarding the rating distribution, variation of return between the sustainable and unsustainable sample is questionable. However, compared to the analysis of liquidity or industry anomalies, no particular characteristic can be found for the sustainability ratings. Accordingly, no conclusion can be made regarding the differences in profitability of momentum strategy between sustainable and unsustainable securities. Nevertheless, as long as observed momentum returns are not obtained due to data mining, a coherence of sustainability in companies' business and firms' industry or its impact on the stocks' liquidity might be a possible momentum driver. Analysis of liquidity and industry in previous subsection exhibits a positive effect on momentum profitability. Hence, if sustainable securities exhibit a salient pattern regarding liquidity or industries, sustainability can be a helpful tool to detect momentum opportunities.

Figure 15: ESG rating distribution in the Momentum portfolios



In the charts above the distribution of total sustainability rating from oekom research is provided for ‘winner’- and ‘loser’-portfolios of 12m3m strategy for sustainable and full sample of securities.



In the charts above the distribution of total sustainability rating from oekom research is provided for ‘winner’- and ‘loser’-portfolios of 3m12m strategy for sustainable and full sample of securities.

7 Conclusion

Momentum strategy is an established investment strategy among investors. At the same time, this phenomenon is controversially discussed and academics struggle explaining momentum profitability. While famous investment strategies are based on fundamental analysis of companies, only the historic stock price is taken into account for momentum strategy. Since financial literature is built on the assumption that stock prices follow random walks, there is no intuitive explanation about the anomaly of excess returns through momentum investing. Hence, the purpose of this thesis was to further examine and provide a deeper insight into the phenomenon of momentum.

In traditional momentum literature, various effects on momentum profits are investigated to identify what drives momentum. Profitability of momentum strategy has been proven for different markets in various studies. Furthermore, academics test factors like size, industry, seasonality and business cycles. In addition, the decomposition of momentum strategy reveals four sources of profits: variation in expected returns, serial factor correlation, serial correlation in industry return components and serial correlation in firm specific components. However, only the industry component as well as firm specific components have emerged as relevant. These findings have been tested and liquidity and sustainability as two additional factors mentioned in the modern literature are introduced in this thesis.

Results of the pre-crisis study confirm findings of the literature and exhibit large profits for the considered universe of securities. Especially in the bull market before the sub-prime crisis, the 'winner'-portfolio generates large excess returns against the 'loser'-portfolio and emphasizes price persistence. In addition, CAPM and Fama-French analysis exhibits alpha values which imply that a large share of the profits is due to momentum. Largest profits can be found for 12m3m strategy, which yields 14.77 percent per year or 1.14 percent per month. Accordingly, the t-statistics confirm this finding and exhibit alpha values which imply that momentum returns are significantly different from zero.

For the after-crisis period, the principle of sustainable investment is introduced and a distinction between sustainable and unsustainable companies is made. Apparently, research agencies identify environmental, social and corporate governance issues and consider those risks to rate the companies according to sustainability. Hence, the hypothesis is set that sustainable securities are more price persistent since those companies bear less risk. Empirical study of the same period distinguishes between the samples of sustainable and unsustainable companies as well as full sample of securities. Profits of the applied momentum strategies interestingly exhibit larger profits in the sustainable sample. This result therefore seems to confirm the hypothesis of price persistence in sustainable securities. Furthermore, none of the 16 momentum strategies applied to the unsustainable sample generates positive profits. Also the full sample features worse results with 7 profitable strategies and 9 negative returns of relative strength portfolios. However, the magnitude of profitable momentum strategy returns is lower than the one of the pre-crisis study. The most profitable strategy of the after-crisis period i.e. 12m3m strategy on the sustainable sample, generates fewer profits, which yields only 0.60 percent per month in the period from 2008 to 2014. Hence, the descriptive statistics imply that momentum returns are not significantly different from zero.

To identify potential momentum drivers, the connection to liquidity, industry and sustainability has been investigated. Academics like Avramov, Cheng and Hameed (2014) claim that momentum profitability is increasing with market liquidity. This assumption can be confirmed after monitoring the results of the empirical study. Comparing the return of 12m3m relative strength portfolio for the pre-crisis and after-crisis with a market liquidity index, one can observe a correlation between profitability and market liquidity. Furthermore, monitoring the performance of 'winner'- and 'loser'-portfolios during the two periods, largest differences in the portfolio returns can be detected at the end of both periods, when markets have been the most liquid. Since several academics attach value to the industry momentum, 'winner'- and 'loser'-portfolios are investigated according to the share of industries in the portfolio. Findings of this analysis indicate that momentum portfolios are driven to a large extent by a small number of industries. However, no difference between the momentum portfolios of different strategies with varying profitability can be observed. Hence, industry momentum seems to impact momentum strategy in general but differences in profitability can hardly be explained by it. Finally, the share of companies with high, middle and low sustainability ratings was observed. However, no particular overweight of a rating class was observed in the portfolios.

In this study, momentum strategy has been analysed and its profitability was confirmed in the empirical study. Furthermore, already established factors impacting momentum have been tested for coherence with momentum profitability. Drivers such as industry and liquidity, previously introduced and examined in momentum literature, are confirmed as influencing factors on momentum returns. Furthermore, the factor sustainability has been tested. The hypothesis of a positive effect of sustainable securities on momentum has been supported by findings of the empirical study. Although no strong and convincing connection between sustainability ratings and momentum profits can be observed, the distinctive results from momentum strategy applied on sustainable vs. unsustainable company samples tend to prove otherwise. There seems to exist a connection between sustainability of company's business and its industry and stocks' liquidity. Accordingly, this provides a supporting argument for the two momentum drivers - industry and liquidity. However, a more detailed analysis of sustainability impact on liquidity and industry is required in order to detect potential momentum profit opportunities in this context. This therefore remains a research question which will be left for further studies and more extensive analyses.

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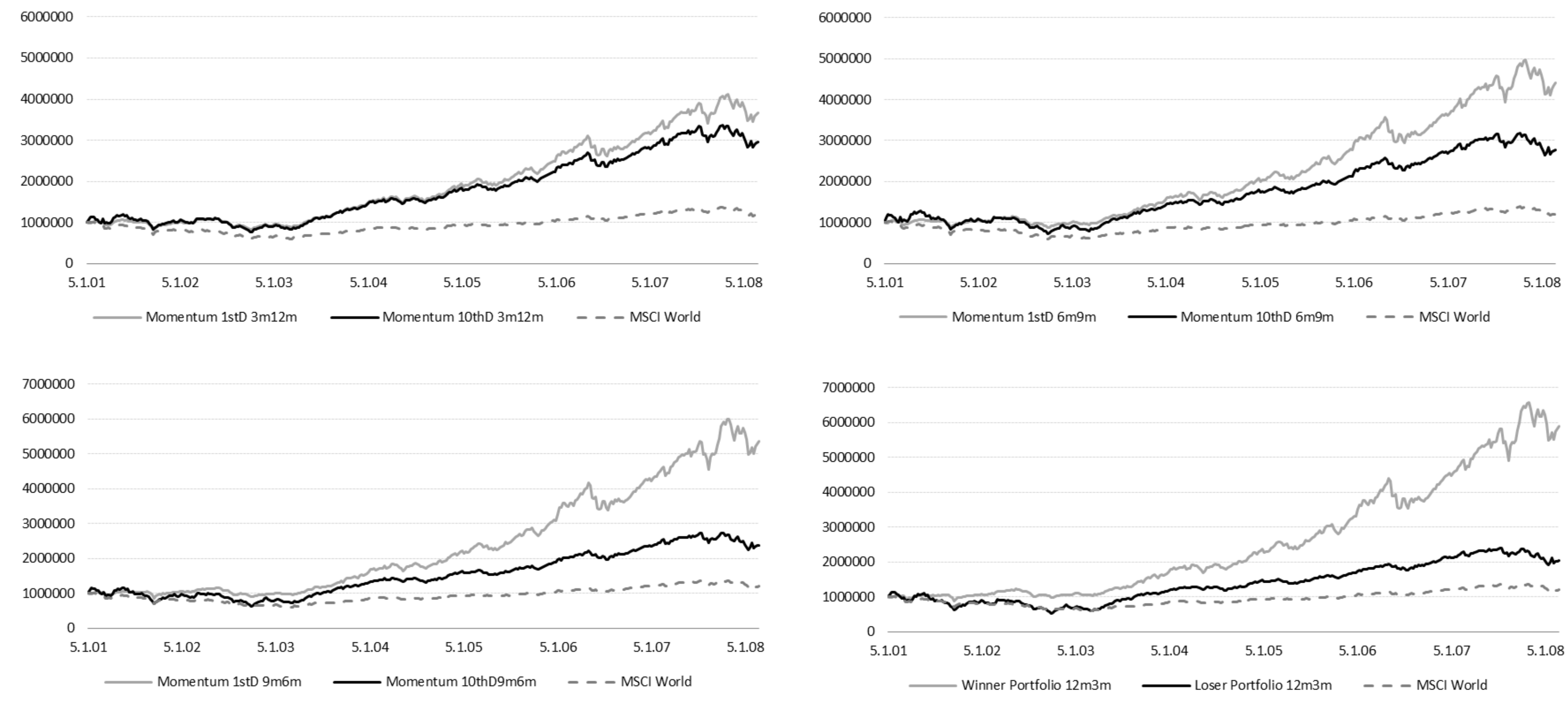
Appendix I: Performance of ‘winner‘- and ‘loser‘-portfolios of the pre-crisis period

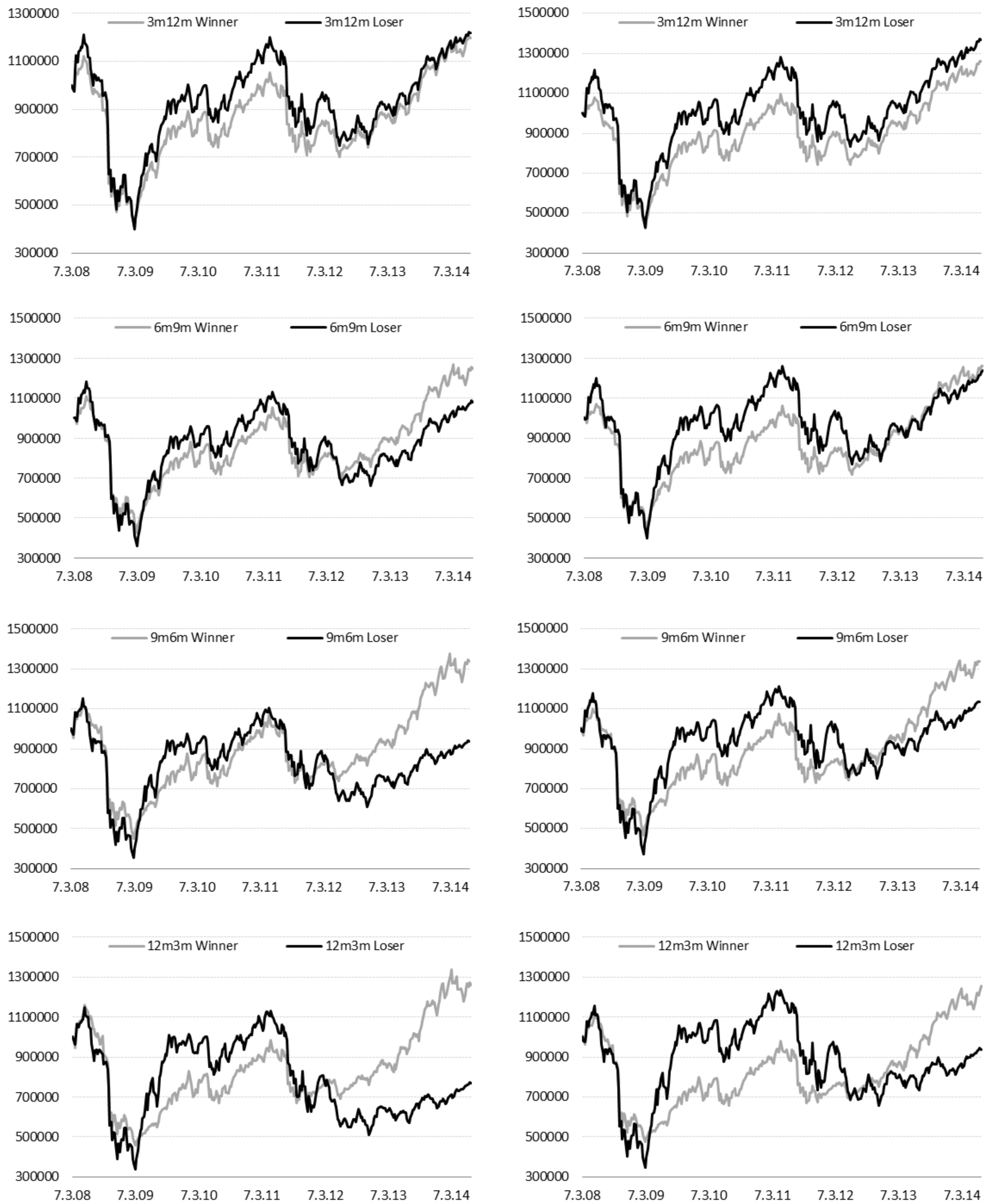


The chart provides an overview over development of ‘winner’- and ‘loser’-portfolios of 4 different Momentum strategies for the full sample during the pre-crisis period. The chart includes the MSCI World Index for a comparison reason (dashed line). In this sample a distinct outperformance of the winner portfolio is observable for the last 3 years of the considered period.

Appendix II: Performance of ‘winner‘- and ‘loser‘-portfolios of the after-crisis period

Sustainable Sample

Full Sample

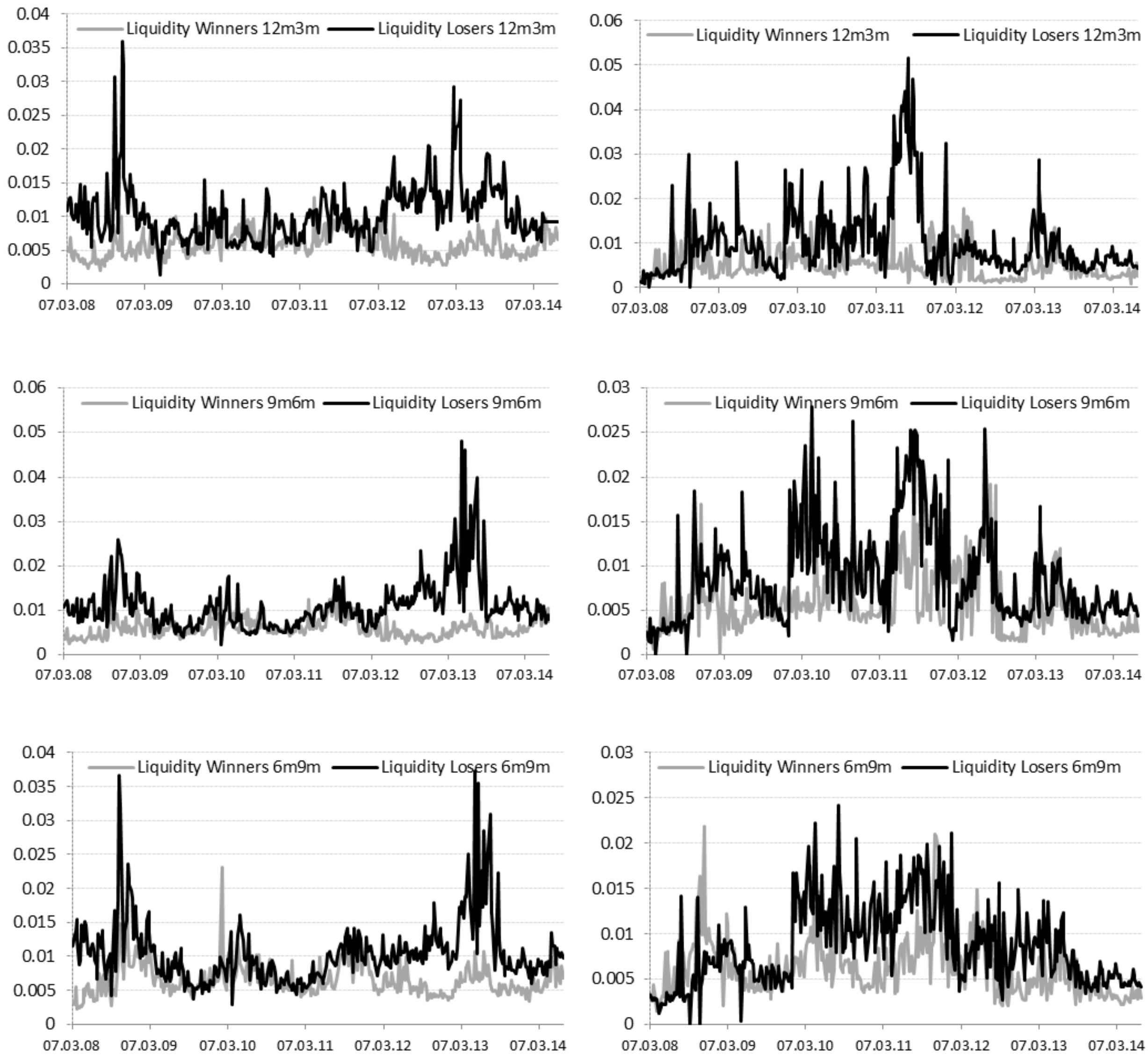


The charts describe the performance of ‘winner’- and ‘loser’-portfolios of the 4 different Momentum strategies for the sustainable smaple and the full sample in the after-crisis period.

Appendix III: Average quoted spreads of ‘winner‘- and ‘loser‘-portfolios

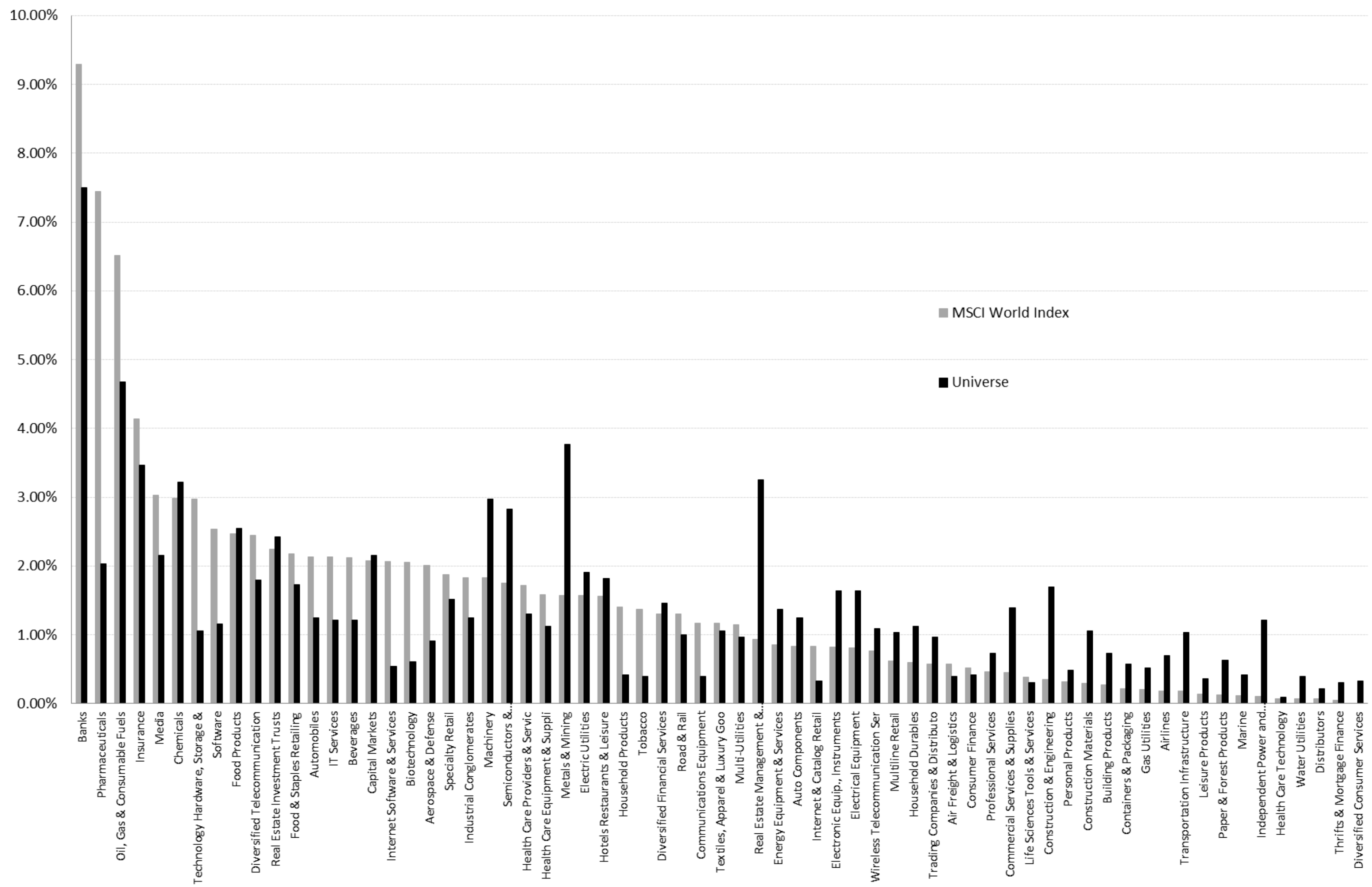
Sustainable Sample

Unsustainable Sample



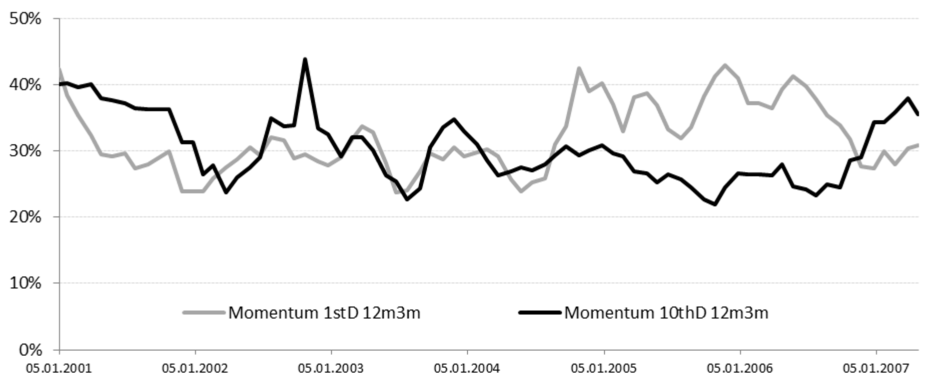
The charts describe the liquity patterns of ‘winner’- and ‘loser’-portfolios of the following Momentum strategies on the the sustainable sample (left) and the unsustainable sample (right): 12m3m Momentum, 9m6m Momentum, 6m9m Momentum. The black curve illustrates the ‘loser’-portfolios and exhibits higher bid-ask spreads than the ‘winner’-portfolios (grey curve) for each strategy.

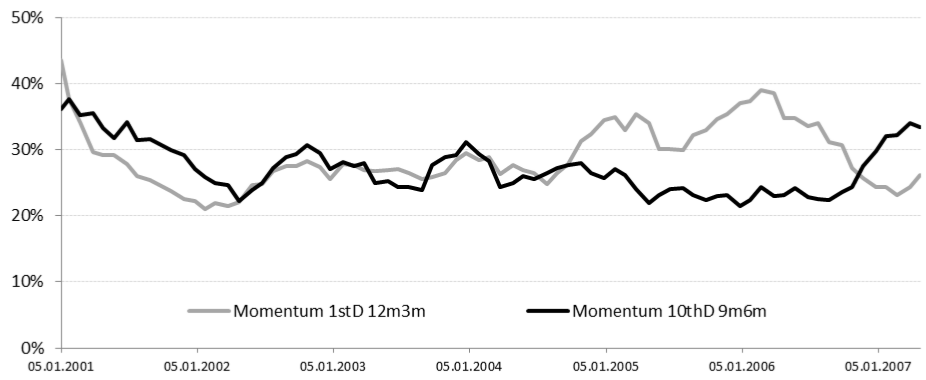
Appendix IV: Share of GICS industries in MSCI World Index and full sample of securities from empirical study

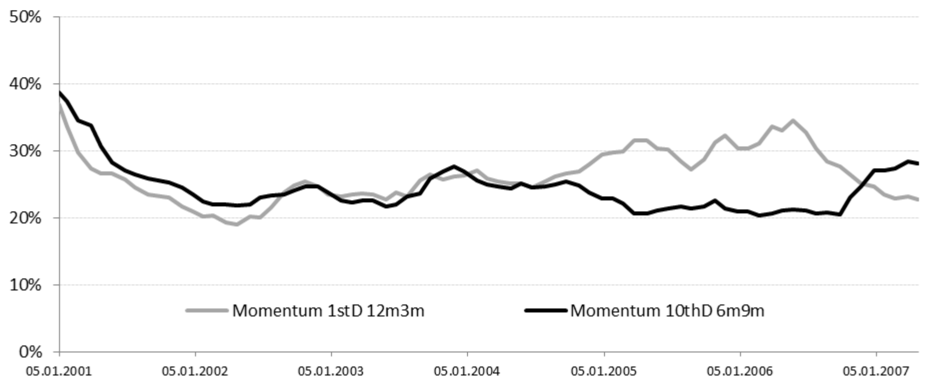


The Chart provides the stake of the 67 GICS industries in the MSCI World Index (weighted by market capitalization) and in the full sample (equally weighted).

Appendix V: Share of 5 largest industries in 'winner'- and 'loser'-portfolios of the pre-crisis period







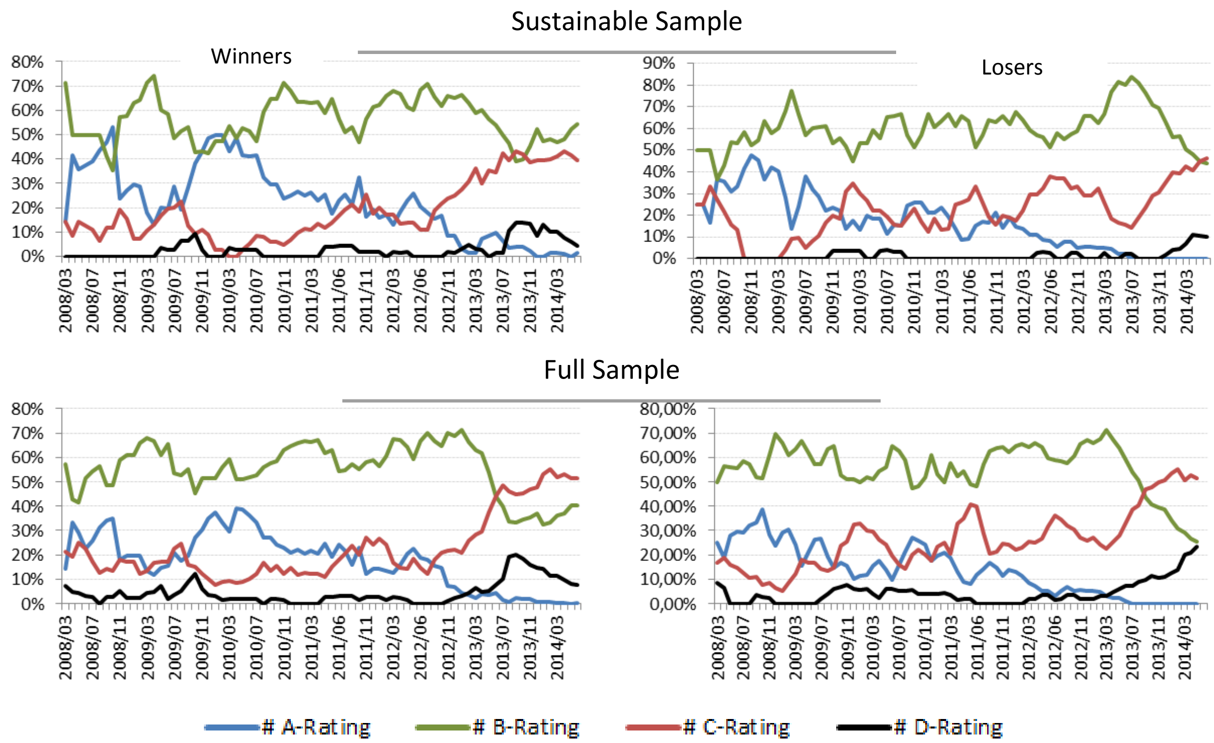
The charts provide an overview of the accumulated share of the 5 industries, with the largest individual share in the 'winner'- and 'loser'-portfolio. Companies are classified according to the GICS industry, which is an established classification developed by MSCI and Standard and Poor's. Findings imply an overweight of very well and very bad performing industries in the relative strength portfolio.

Appendix VI: Share of largest industries and companies in the industries in Momentum portfolios

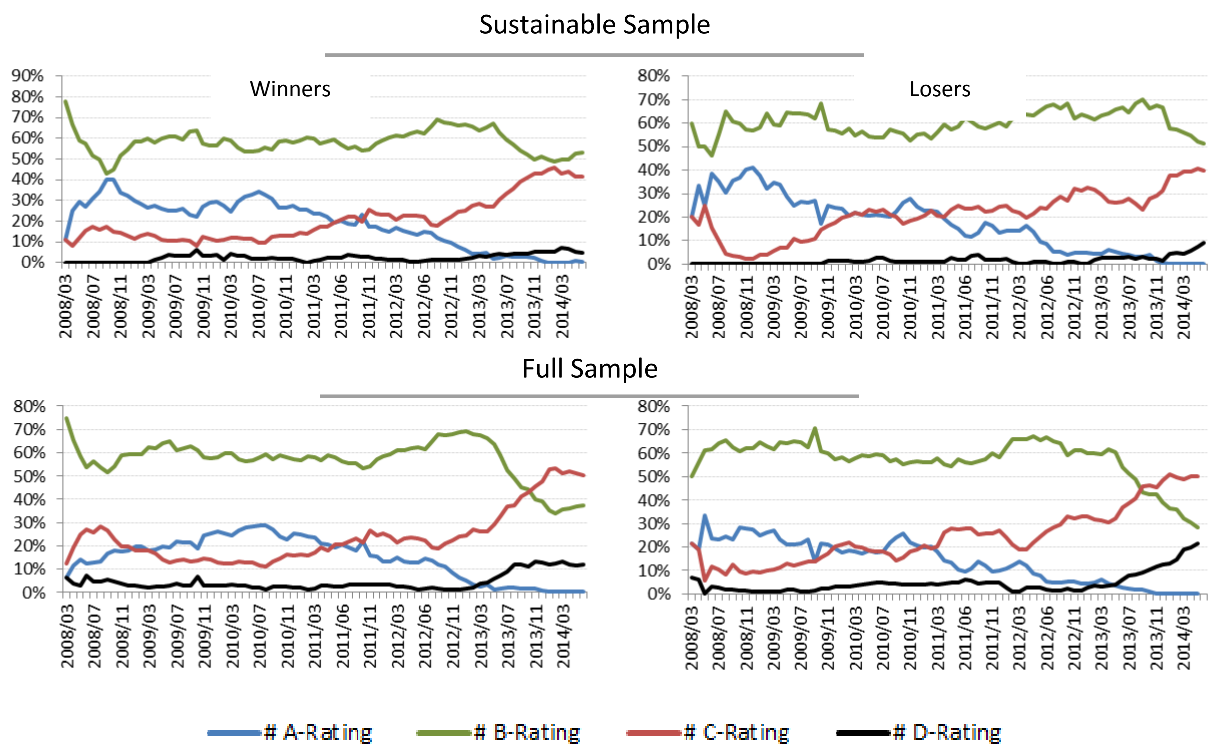
After Crisis Full Sample	Share of largest 5 industries in the portfolio	Share of the best/worst companies in the industry
Momentum 1stD 12m3m	35.91%	26.06%
Momentum 10thD 12m3m	43.60%	22.57%
Momentum 1stD 9m6m	32.47%	32.96%
Momentum 10thD 9m6m	39.09%	29.08%
Momentum 1stD 6m9m	32.14%	39.03%
Momentum 10thD 6m9m	37.82%	37.10%
Sustainable Sample		
Momentum 1stD 12m3m	40.97%	29.00%
Momentum 10thD 12m3m	48.40%	22.10%
Momentum 1stD 9m6m	38.39%	36.25%
Momentum 10thD 9m6m	42.66%	29.32%
Momentum 1stD 6m9m	47.71%	41.81%
Momentum 1stD 6m9m	48.23%	34.37%
PreCrisis Full Sample		
Momentum 1stD 12m3m	32.90%	18.18%
Momentum 10thD 12m3m	30.08%	18.47%
Momentum 1stD 9m6m	29.72%	22.10%
Momentum 10thD 9m6m	27.45%	23.37%
Momentum 1stD 6m9m	27.09%	27.40%
Momentum 1stD 6m9m	24.87%	27.86%

The Chart provides accumulated average values of the 5 best represented industries in the Momentum portfolios (left column). This values states the average accumulated relative share of 5 GICS industries with highest share in the portfolios. Furthermore, the chart illustrates the average stake of companies from best represented industries in the Momentum portfolios. Hence, the number describes the relative share of companies which are represented in the largest industries of the Momentum portfolios.

Appendix VII: Governance rating distribution in the Momentum portfolios

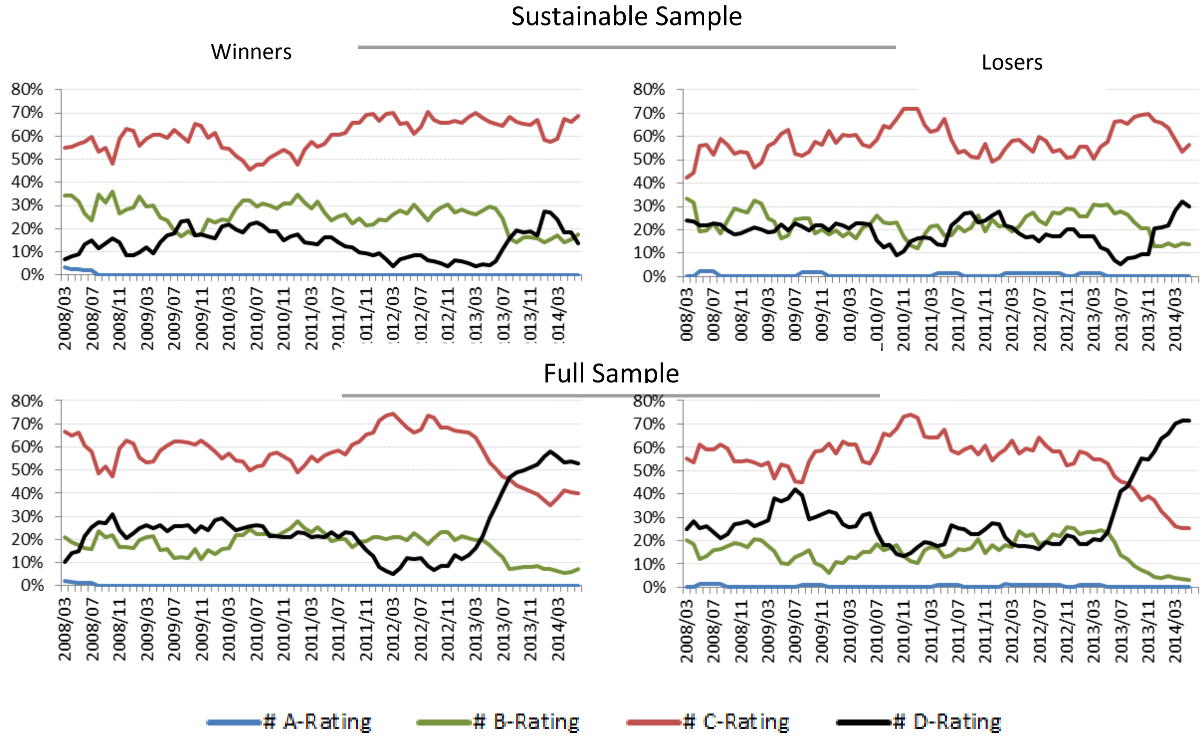


In the charts above the distribution of Governance rating from oekom research is provided for 'winner'- and 'loser'-portfolios of 12m3m strategy for sustainable and full sample of securities.

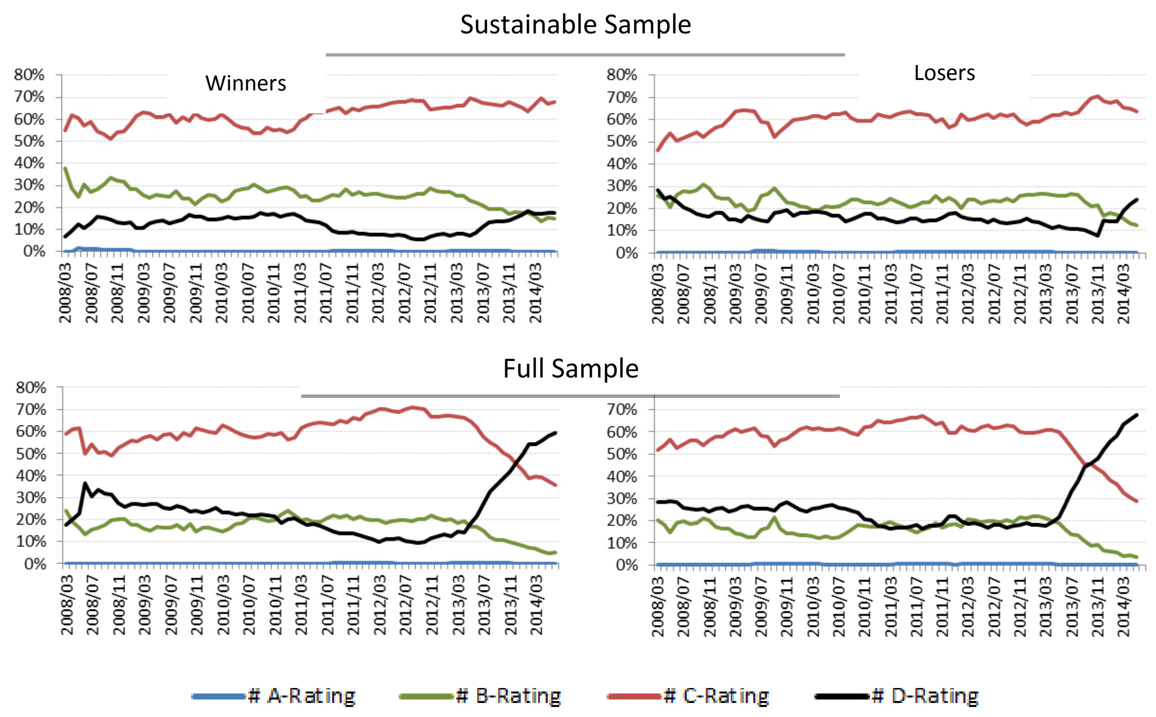


In the charts above the distribution of Governance rating from oekom research is provided for 'winner'- and 'loser'-portfolios of 6m9m strategy for sustainable and full sample of securities.

Appendix VIII: Social rating distribution in the Momentum portfolios

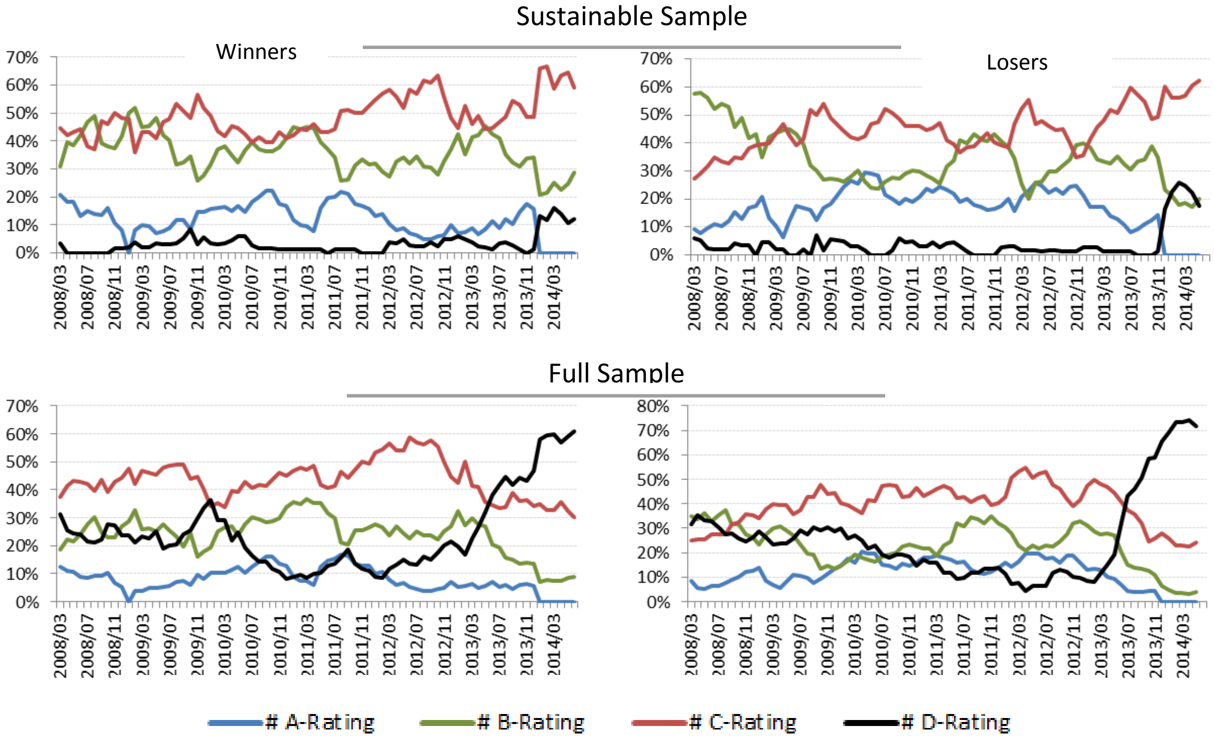


In the charts above the distribution of Social rating from oekom research is provided for 'winner'- and 'loser'-portfolios of 12m3m strategy for sustainable and full sample of securities.

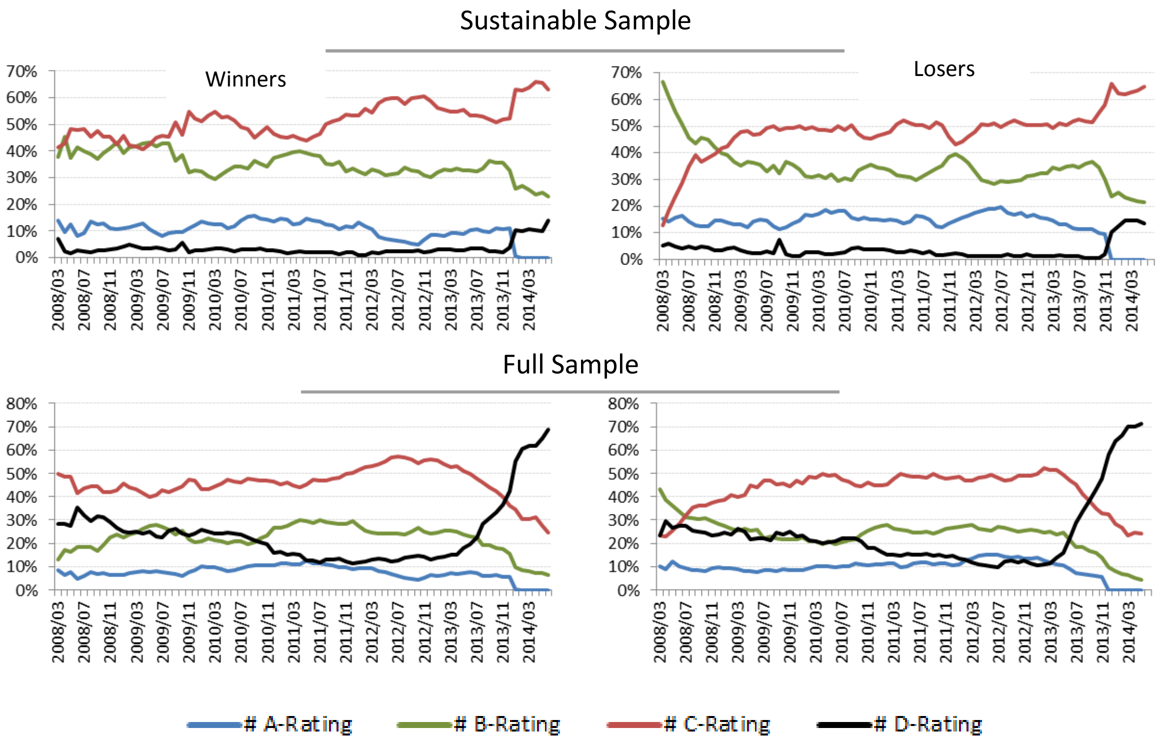


In the charts above the distribution of Social rating from oekom research is provided for 'winner'- and 'loser'-portfolios of 6m9m strategy for sustainable and full sample of securities.

Appendix IV: Environmental rating distribution in the Momentum portfolios

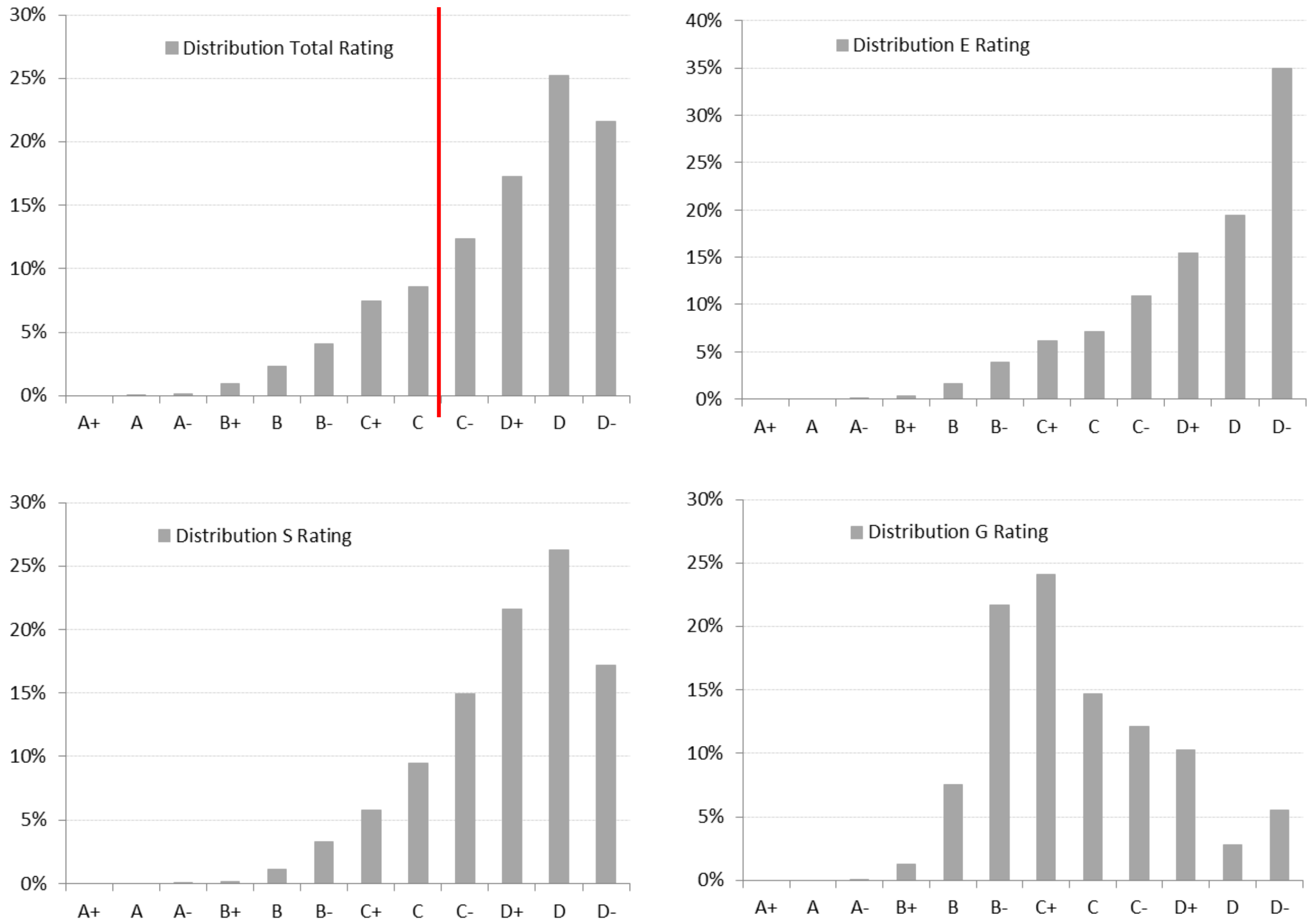


In the charts above the distribution of Environmental rating from oekom research is provided for 'winner'- and 'loser'-portfolios of 12m3m strategy for sustainable and full sample of securities.



In the charts above the distribution of Environmental rating from oekom research is provided for 'winner'- and 'loser'-portfolios of 6m9m strategy for sustainable and full sample of securities.

Appendix X: Distribution of ratings over the full sample of securities at the end of the observed time horizon in June 2014



This chart provides a summary of the rating distribution through all considered ratings from oekom research in June 2014. Besides the Governance rating the stake of companies is highest within ratings of C- or worse, i.e. unsustainable companies. The red line illustrates the threshold between sustainable and unsustainable companies.

Abstract

Kaufe Gewinneraktien und verkaufe Verliereraktien. Was nach einer einfachen Rechnung und logischen Regel klingt, ist tatsächlich eine sehr bekannte Investmentstrategie. Während Investoren bei anderen Strategien hauptsächlich Finanzkennzahlen analysieren, wird bei dieser Strategie lediglich die vergangene Aktienpreisbewegung betrachtet. Da die Finanzmarkttheorie darauf basiert, dass Aktienpreise sämtliche zur Verfügung stehende Informationen beinhalten und keine Profite aus der Chartanalyse generiert werden können, ist eine Erklärung des Momentums nicht intuitiv. Jedoch gibt es Nachweise für die Profitabilität dieser Strategie über einen langen Zeitraum sowie über eine Vielzahl an Märkten, Industrien, Unternehmen verschiedener Größen sowie Anlageklassen. Trotz der nachgewiesenen Profitabilität der Momentumstrategie sind sich Akademiker nicht einig, was der Grund für diese Überrendite ist. In der Literatur zum Momentum werden meist der Industriefaktor sowie firmenspezifische Komponenten genannt. Da das Aufblühen einer Industrie meist eine Vielzahl an Unternehmen beflügelt und die Entwicklung der Aktien antreibt, scheint eine Korrelation innerhalb der Unternehmen eine denkbare Erklärung welche auch in der empirischen Studie der Momentumstrategie zu erkennen ist. In neueren Studien wird oftmals die Liquidität von Aktien in Zusammenhang zum Momentum gebracht. Typischerweise sind Aktien, welche eine gute Performance vorweisen, begehrter als diejenigen, die keine Rendite liefern, weshalb Gewinner meist auch liquider sind. Des Weiteren ergeben Studien, dass die Profitabilität der Momentumstrategie höher ist je liquider Finanzmärkte sind. Die Beobachtungen der empirischen Studie unterstützen diese Hypothesen mit entsprechenden Ergebnissen. Neben klassischen Analysen wird in dieser Studie das Konzept nachhaltigen Investierens vorgestellt. Den Ergebnissen zufolge scheint eine Momentumstrategie bei nachhaltigen Aktien profitabler zu sein. Dieses Ergebnis kann jedoch nicht an Hand von Nachhaltigkeitsratings erklärt werden, da sämtliche Portfolios eine ähnliche Zusammensetzung an nachhaltigen und weniger nachhaltigen Unternehmen vorweisen. Vielmehr kann die Hypothese aufgestellt werden, dass die Nachhaltigkeit von Unternehmen eine Auswirkung auf die Liquidität sowie die Industrie hat.

CURRICULUM VITAE

PERSONAL DETAILS

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EDUCATION AND STUDIES

Oct. 2012 – today	Studies of Quantitative Economics, Management and Finance (M.Sc.) at University of Vienna
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Sept. 1999 - June 2007	Secondary school at the Gymnasium bei St. Michael, Schwäbisch Hall Qualification: Higher Education Entrance
Sept. 1995 - July 1999	Primary school at the Grund- und Hauptschule Untermünkheim

ADDITIONAL SKILLS

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Computer skills	Good working knowledge of several basic software programs including Microsoft Office (Word, Excel, Access, Power Point) Working knowledge in different programming languages including C++, Matlab, R, VBA

PRACTICAL EXPERIENCE

Mar. 2014 – today	Erste Asset Management, Quantitative Analyst, Responsible Investment, Wien, Austria

Jan. 2013 – Feb. 2014	Raiffeisen Bank International, Freelancer, Investment Finance Wien, Austria
July 2013 – Aug. 2013	Erste Group Bank AG, Internship, Major Market Research, Wien, Austria
Apr. 2013 – July 2013	Alu König Stahl, Freelancer, Controlling, Wien, Austria
May 2012 – Aug. 2012	Würth Canada Ltd., Internship, Finance Departement, Mississauga, Canada
Oct. 2011 – Mar. 2012	Commerzbank AG, Internship, Corporates & Markets, Research Interest Rate Strategy, Frankfurt, Germany
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