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LIST OF VARIABLES AND INDICES

α	Regression Coefficient
AGE	Firm age measured as the number of months since a firm was first covered by Datastream.
B	Bad news
$\beta_{i,k}$	Stock i's sensitivity to factor k
B/M	Book-to market ratio: The book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year
CFVOLA	Cash-flow volatility; the standard deviation of the net cash flow from operating activities standardized by average total assets in the past three years
$e_{i,t}$	Stock i's firm specific component
ε	Error term
$f_{k,t}$	Return on a zero-cost portfolio k mimicking the most important factors at time t
G	Good news
$H_{i,t-1}^{52}$	Stock i's highest price during the one year period ending at the first day of month $t-1$
$H_{i,t-1}^{x}$	The highest price of stock i over a period of x month length that ends at the beginning of month $t-1$
hl	Dummy Variable that takes one if a stock is included in the 52-week high loser portfolio at a specific time and zero otherwise
HML	High minus low. Value premium. Return difference between a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks
hw	Dummy Variable that takes one if a stock is included in the 52-week high winner portfolio at a specific time and zero otherwise
Hx	52-week High Portfolio x
I_PHR	The price-52-week high ratio for industry I
J	Length of the ranking period in months
K	Length of the holding period in months

$L^{52}_{i,t-1}$	The lowest price of stock i over a period of x month length that ends at the beginning of month $t-1$
LHR	Quotient of the lowest price of a stock within the past 52 weeks and the highest price of the stock within the last 52 weeks
$\mu_{i,t}$	Expected return on stock i conditional on information available at time t
ml	Dummy Variable that takes one if a stock is included in the momentum loser portfolio at a specific time and zero otherwise
MV	Market capitalization of a stock at the beginning of month t
mw	Dummy Variable that takes one if a stock is included in the momentum winner portfolio at a specific time and zero otherwise
Mx	Momentum Portfolio x
v_t	Information about a stock that can be good (G) or bad (B)
v	Information about a fundamental value of a firm
π	Profits
P	Adjusted price of a stock
PHR^{52}	Price-52-week high ratio
$P(k)$	The "predictability-profitability index"
R^{Wi}	Return of the winner portfolio
R^{Lo}	Return of the loser portfolio
R_i	Return of stock i
$R^{sb}_{i,t}$	Size and BE/ME adjusted return of stock i
$R^{sb,I}_{i,t}$	Size, BE/ME and industry adjusted return of stock i
R_f	Risk-free return
R_m	Market portfolio return
s	Observed signal (news) about a company
S	Length of the skip period in months
$size$	Market value of a stock at a specific time

SMB	Small minus big; size premium; return difference between a portfolio of small stocks and a portfolio of large stocks
t	Time in months
T	Share of loser return on the 52-week high profits
$\sigma^2_{\beta_k}$	Cross-sectional variance of the portfolio loadings
$\sigma^2_{\theta_m}$	Cross-sectional variance of the industry sensitivities
θ_i	Stock i's sensitivity to an industry component
Ux	Information Uncertainty Portfolio x
VOLA	Stock volatility; the standard deviation of weekly market excess returns over the year ending at the beginning of month t
ω	Portfolio weight
WML	Winner minus loser; momentum return
WRSS	Weighted relative strength strategy
$X_t^p(a,b,c)$	The share of stocks in portfolio p that is included in country momentum portfolio a, in industry portfolio b and in momentum portfolio c
z_t	Industry portfolio returns at date t

INTRODUCTION

So far, after literally thousands of studies, no consensus has been reached whether financial markets are efficient (Lo, 1997, p.6). In the eyes of many researchers, the Efficient Markets Hypothesis (EMH) is *"one of the most controversial and well-studied propositions in all the social sciences"* (Lo, 1997, p.11). A market can be considered "efficient" if stock prices always "fully reflect" all available information. This definition goes back to Fama (1970) who differentiates between three important sets of information. A market can be "weak form efficient" if the information set just consists of historical prices and volume information, it can be "semi-strong form efficient" if stock prices fully include all information that are publicly available or a market can be considered "strong form efficient" if prices adjust to *any* information that can either be public or private (see Fama and French, 1970, p.383). A challenge to the Efficient Market Hypothesis is called an "anomaly", which is defined as "*a regular pattern in an asset's return which is reliable, widely known and inexplicable*" (Lo, 1997, p.13). Researchers have discovered many pricing anomalies such as the size effect (Banz, 1981), the January effect (Keim, 1983, Roll, 1983), the relation between price/earnings ratios and expected returns (Basu, 1977), the Value Line enigma (Copeland and Meyers, 1982) or calendar effects (Lakonishok and Smidt, 1988). However, many market anomalies related to profit opportunities have disappeared after their discovery (see e.g. Schwert, 2003) or are shown to be captured by rational risk models such as the Fama and French (1993) three-factor model (Fama and French, 1996).

A pattern that is still consistent with the definition of an anomaly is the intermediate-term continuation of stock prices. Jegadeesh and Titman (1993) are the first to examine the stock price momentum effect, which implies that stocks with high returns over the past 3 to 12 months continue to outperform stocks with a poor past performance within the next 3 to 12 months. This implies that strategies long in past winners and short in past losers generate significant abnormal returns. Its profits are not captured by the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) or by the three-factor model of Fama and French (Fama and French, 1996). Unless researchers do not find a richer asset-pricing model or other risk factors that explain momentum profits, or if researchers document that they are not a compensation for risk, the effect would be in conflict with the weak form market efficiency hypothesis according to which excess returns cannot be earned by simple strategies building on historical stock prices. Given the potential of stock price momentum to question the efficiency of markets, this field of research is especially interesting, important and controversial.

Therefore, the research topic of my thesis is the stock price momentum effect. My work is structured into three main parts. The first one gives an overview about the present stand of the literature. It becomes clear that the profitability of momentum strategies is documented in many studies, for different samples and for different periods. However, it is worth to mention that most of the studies employ a similar methodology. While this indicates on a broad agreement of the literature how to measure momentum returns, it might also be the cause for systematic measurement errors. Therefore, a substantial fraction of Part I presents, discusses and evaluates the common methodology.

In the search for an explanation for the profitability of momentum strategies, the literature has not come to a consensus: One the one hand, according to the rational-based approach, momentum profits represent a compensation for risk and is consistent with the EMH. On the other hand, the behavioral finance theories attempts to explain the existence of the momentum effect with a non-rational behavior of at least some investors. In the remainder of Part I, I discuss and structure the different proposals and show that so far, none of the two groups has brought forward a convincing theory that cannot be challenged by other studies.

The second and the third part of my thesis are closely linked[1] and examine the behavioral explanation approach that stock price momentum can be explained by the anchoring bias – a specific form of non-rational behavior. It states that investors orientate too much on a reference point when forming estimates. This idea goes back to George and Hwang (2004) documenting that the momentum effect can be explained by profits to the 52-week high strategy, which itself is assumed to be driven by the anchoring bias. Based on this theory, the null hypothesis of both parts of my thesis states: Stock price momentum cannot be explained by anchoring. In Part II, I propose three tests to examine the relation between momentum and the 52-week high strategy and between the 52-week high strategy and anchoring. These are conducted for a sample composed of all stocks traded in Germany between 1980 and 2008. My results present evidence to reject the null and point on anchoring as the driving force behind the momentum effect.

[1] Although the same null hypothesis is examined in Part II and Part III, I have nevertheless decided not to integrate them into one major part because of the differing approach to test the null hypothesis and because of the different sample.

In Part III, a different approach is chosen to test the null hypothesis. An insight of the psychological literature states that behavioral biases have more room when uncertainty is large. Motivated by this, I examine whether the ranking criterion of the 52-week high strategy and of the momentum strategy have more predictive power when information uncertainty is larger. This should be the case if anchoring is behind the 52-week high and behind the momentum strategy. This examination is conducted for a sample that includes all UK stocks between 1989 and 2008. As in Part II, this investigation supports anchoring as the explanation of the momentum effect.

Finally, Part III is succeeded by a summary and a conclusion of my work.

Part I

An Overview about the Existing Explanation Attempts for the Stock Price Momentum Effect

1. Introduction

The first part of my thesis presents the current stand of the literature about the stock price momentum effect and about the causes for its existence. Chapter 2 focuses on the methods to document the existence of the effect (Section 2.1). In Section 2.2 and 2.3, the stand of the literature about the profitability of momentum strategies is presented for the U.S. market and for other countries. Section 2.4 relates to the profitability of momentum strategies after consideration of transaction costs, while Section 2.5 concludes the chapter with a brief discussion whether short-sale constraints can hint investors from implementing the strategy.

In opposite to Chapter 2, in which the focus is more on the measurement and on the existence of the momentum effect, Chapter 3 introduces, compares and evaluates the different explanation attempts for the existence of the price momentum effect. They can be mainly subdivided into three groups: data mining, which is already discussed in Chapter 2, the rational approach (Section 3.1) and the behavioral proposals (Section 3.2). The rational theory views momentum profits as a compensation of investors for bearing risk and attempts to explain its profitability with a risk-based theory. With a theoretical decomposition of momentum returns, I classify the various rational-based theories in one of four potential risk categories. The behavioral finance literature, however, argues that momentum strategies are profitable since at least some investors show a non-rational behavior. It is shown that the multiple proposals can be arranged under four main hypotheses, an approach that is new to my knowledge to structure the behavioral momentum literature. While others (e.g. Ding, 2007) sort the behavioral studies based on the assumed non-rational behavior and therefore according to their employed assumptions, my four hypotheses offer the advantage that it arranges the theories according to their explanations. It becomes clear that some studies assume a different non-rational behavior but are quite similar as they find support for the same hypothesis for the existence of the momentum effect. This shows one of the biggest disadvantages of the behavioral finance literature: the variability of judgment biases that can be employed to come to a similar conclusion.

In Chapter 4, both, the rational and the behavioral approaches, are compared. It becomes obvious that, so far, no consensus has been reached about the driver of momentum. Neither the rational-based proposals nor the behavioral approaches have yet succeeded in identifying the driver(s) of the momentum effect. Section 5 summarizes the insights and concludes the first part of my thesis.

2. The Profitability of Momentum Strategies

2.1 Momentum Portfolio Characteristics

While some methods might seem straightforward, it is nevertheless inevitable to examine the methodology in detail, to analyze its strengths and weaknesses and to compare different approaches. Otherwise, a model can be employed that delivers biased results. An extreme example how results are influenced by using an inappropriate method can be observed in the Journal of Finance paper of Chordia and Shivakumar (2002). Their core finding is strongly doubted by Cooper et al. (2004) (also JoF) showing that the results of Chordia and Shivakumar (2002) are biased by missing methodological adjustments of their portfolios to mitigate microstructure concerns.[2] While the latter believe to have found a model explaining the momentum effect, Cooper et al. (2004) documents that it almost has no explanatory power at all under consideration of the adjustments.

To examine stock price momentum returns, the literature typically differentiates between three periods: the formation period, the investment period and the skip period. These three periods will be discussed now in more detail.

Formation Period

Momentum strategies invest in stocks with a high return in the past and sell stocks with low past return. The formation period determines the length of "the past". Stocks are ranked based on their buy-and hold return during the formation period and assigned to different portfolios. According to the literature, the profitability of momentum strategies is largest for a formation period between six and 12 months (see Table 1 and Table 2).

[2] Cooper et al. (2004) argue that Chordia and Shivakumar's (2002) results are biased for several reasons: First, stocks with a price below $1 are not excluded in order to eliminate illiquid stocks or stocks with high trading costs. Secondly, they do not include a skip period between the formation period and the investment period. Such a skip is necessary to reduce spurious reversals due to bid-ask bounce. These problems will be discussed on the next pages.

Investment Period

At the beginning of the investment period, a momentum portfolio is constructed that is long in stocks with a good performance during the formation period and short in stocks with a bad performance. Such a strategy is self-financing since the acquisition of winner stocks is financed by the sale of loser stocks. The portfolio is then held over the investment period. There are two methods commonly employed in the literature to form momentum portfolios: the "Quantile Method" and the "Weighted Relative Strength Strategy" (WRSS).

<u>"Quantile Method"</u>

The "Quantile Method" ranks stocks in ascending order based on their buy-and hold return during the formation period. The top quantile of stocks is assigned to the winner portfolio and the bottom quantile of stocks forms the loser portfolio. The momentum strategy is long in the winner portfolio and short in the loser portfolio. Hence, this strategy only considers stocks with an extreme past performance, while stocks that are not in the top or in bottom quantile are not taken into consideration by the strategy. Studies about price momentum use different quantiles to form winner and loser portfolios. In Jegadeesh and Titman (1993) for example, the winner portfolio consists of the 10% of stocks with the highest past returns over the formation period and the loser portfolio includes the 10% of stocks with the lowest past returns. Many studies employ these breakpoints (Rouwenhorst, 1998, Jegadeesh and Titman, 2001, Chordia and Shivakumar, 2002, Korajczyk and Sadka, 2004, among others). Other empirical work examines the top (winner) and bottom (loser) 20 percent of stock returns (i.e. Nagel, 2001, Griffin et al., 2003) or even document momentum profits for a portfolio that is long in the top 30 percent of stocks and short in the bottom 30 percent of stocks (i.e. Moskowitz and Grinblatt, 1999 and Hong and Stein, 2000).

The main reason to include more than 10 percent of the stocks in the winner and loser portfolio (as proposed by Jegadeesh and Titman, 1993) is lack of data. Griffin et al. (2003), for example, consider momentum profits for different countries across the world. For some markets, not more than 50 stocks are available which implies that a portfolio, which includes the top decile would only contain five stocks in total. A portfolio with such a small number of stocks is not well diversified and its performance might be influenced by a single stock. Furthermore, a small number of stocks lead to large standard error in the test statistics. This lack of data problem does not only exist if the total data sample is small but it is also present if the momentum strategy is examined across subsamples. Hong and Stein (2000) for example examine momentum returns within size groups. Therefore, the sample is divided into ten classes by size and then into three portfolios based on the momentum criterion.[3] Such a sorting procedure increases the number of subsamples and reduces the number of stocks within each subportfolio even if the total sample is large. To reduce this problem, less subsamples can be created either by sorting stocks into fewer groups based on the momentum or by the second criterion. Hence, including more stocks in the winner and loser portfolios than the top and bottom decile increases the number of stocks within each portfolio.

Momentum profits measured by the "Quantile Method" depend on the weighting scheme. Stocks within the winner and loser portfolios can be either equally weighted or value weighted.[4] Most studies concentrate on equally weighted strategies (e.g. Jegadeesh and Titman, 1993, 2001, Fama and French, 1996, Grundy and Martin, 2001). However, the weighting method has influences on the obtained returns (Lewellen, 2004 and Korajczyk and Sadka, 2004). Korajczyk and Sadka (2004) show that momentum returns (before trading costs) are in general larger when stocks are equal-weighted than when stocks are value-weighted. This is because momentum is stronger in stocks with a small market capitalization (e.g. Hong and Stein, 1999, Hong et al., 2000). The portion of stocks with a small market value is larger in equal-weighted portfolios than in value-weighted portfolios. Moreover, equal-weighted and value weighted portfolios do also differ with respect to potential biases: Lo and Mac Kinlay (1988, p. 56-57) argue that, compared to equally weighted portfolios, value weighting is more robust to lead-lag effects[5] associated with firm size or volume (as a proxy for liquidity).

To increase the power of the tests, Jegadeesh and Titman (1993) examine portfolios with overlapping holding periods, a strategy subsequently followed by other papers as well (e.g. Rouwenhorst (1998, p.269), Chordia and Shivakumar (2002, p.990), Griffin (2003, p.2518) among others). Let J be the length of the formation period, S the length of the skip interval and K the investment period. At the end of each month t, a portfolio is formed that is long in winners

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[3] In Hong and Stein (2000), the lack of data problem becomes even more severe in a further test, where the sample is first subdivided into four size categories and then each size category is further subdivided into three residual coverage classes. Momentum returns of each of the 16 different portfolios are then compared. The larger the number of portfolios gets, the smaller becomes the number of assets within each portfolio (see Subsection 3.2.1 for further information about the work of Hong and Stein, 2000).

[4] Korajczyk and Sadka (2004) weight stocks based on a liquidity measure. Since this weighting method is only used in this paper, it is not discussed here in further detail. Yet, the work of Korajczyk and Sadka (2004) is presented in Section 2.4.

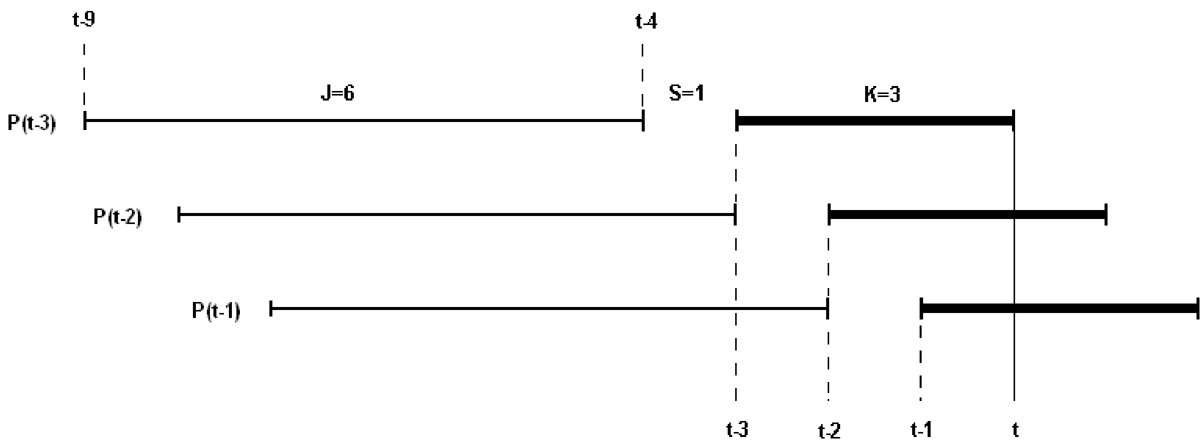
[5] Among others, Lo and MacKinlay (1990, p.178) show that stock price reactions of smaller stocks are correlated with former stock price reactions of larger stocks. This dependence is called "lead-lag" structure in the literature. See the next subsection for further details.

and short in losers according to their performance during the formation interval J. If the holding period is longer than one month, the total momentum portfolio in month t consists of a series of K portfolios of equal size each starting one month apart between $t-k$ and $t-s$. In order to illustrate the composition of a momentum portfolio with overlapping holding periods, consider an example with a formation interval of six months ($J=6$), a skip of one month ($S=1$) and an investment period of three months ($K=3$). Figure 1 presents the formation, skip and investment periods for the three components of an overlapping portfolio with an investment period $K=3$. The first component, portfolio $P(t-1)$ is formed in $t-1$, the second portfolio $P(t-2)$ in $t-2$ and the third portfolio $P(t-3)$ is implemented in $t-3$. Each portfolio buys winner stocks and sells loser stocks based on their performance over the previous six months. Hence, the formation period for $P(t-3)$ is between $t-9$ and $t-4$, that for $P(t-2)$ between $t-8$ and $t-3$ and that for $P(t-1)$ between $t-7$ and $t-2$ (thin lines in Figure 1). These portfolios are held over the 3-month investment period (thick lines). The gap between the thin line (formation period) and thick line (investment period) represents the skip or waiting period of one month. Consequently, at time t, the momentum portfolio consists of the three portfolios $P(t-1)$, $P(t-2)$ and $P(t-3)$. At the end of month t, the portfolio $P(t-3)$ is liquidated and replaced by a portfolio formed in t. Hence, in $t+1$, the overlapping momentum portfolio is composed of portfolios formed in $t-2$, $t-1$ and t. Therefore, from one month to the next, only one third of the assets in the momentum portfolio is revised whereas the rest is carried over from the previous month. To be more general, given an investment period of K months, only $1/K$ of the assets in the momentum portfolio is altered per month.

Figure 1

Portfolios with Overlapping Holding Periods

The formation period is six months *(J=6)*, the skip between the formation and investment period is one month *(S=1)* and the investment period is of length 3 months *(K=3)*.



A portfolio with overlapping holding periods increases the power of momentum tests and allows using simple t-statistics for monthly returns (Lee and Swaminathan, 2000, p.2022). Moreover, even without a skip interval between the ranking and investment period, the risk of getting spurious results due to the lead-lag effect is reduced since only a fraction of $1/K$ of stocks was recently picked by the ranking criterion.

Weighted Relative Strength Strategy (WRRS)

Beside the "Quantile Method", returns to momentum strategies are also measured with the "Weighted Relative Strength Strategy" (WRRS) (see Conrad and Kaul, 1998, Chan et al., 2000, Jegadeesh and Titman, 2002 and Lewellen, 2004), where momentum portfolios are formed that hold assets in proportion to their market-adjusted returns. This method allows a formal decomposition of momentum profits into different components that could be responsible for the significant momentum returns (see Section 3.1). To get an idea how momentum portfolios are formed according to the WRRS, suppose that stocks are ranked based on their performance during the k-month lasting formation period ending in $t-1$. Then at time t, a momentum portfolio is formed that invests the fraction $\omega_{i,t}$ in stock i. It depends on the market excess return of stock i during the formation period. Specifically, a stock's portfolio weight in month t is:

$$\omega_{i,t} = R_{i,t-1}^{k} - \bar{R}_{t-1}^{k} \qquad (1)$$

where $R_{i,t-1}^{k}$ is the return on stock i during the formation period that lasts k months and ends in $t-1$ and $\bar{R}_{t-1}^{k}$ denotes the cross-sectional average return during that period. A portfolio implemented following Equation (1) buys all stocks with a positive market excess return during the formation period $(R_{i,t-1}^{k} - \bar{R}_{t-1}^{k} > 0)$. Yet, in opposite to the "Quantile Method", the weighting of stocks within the portfolios is based on the excess returns: The larger the difference between $R_{i,t-1}^{k}$ and $\bar{R}_{t-1}^{k}$, the larger is the fraction $\omega_{i,t}$. In other words, the WRRS invests more in stocks that heavily outperformed the market during the formation period while stocks with a return that only weakly exceeded the average during the same period receive only a minor weight. The same is true for the short side of the portfolio: all assets with a negative market excess return are sold $(R_{i,t-1}^{k} - \bar{R}_{t-1}^{k} < 0)$. The strategy holds the largest short position in stocks that heavily underperformed the market. It is easy to show that the weights of the WRRS sum to zero: $\sum_{i=1}^{N} \omega_{i,t} = 0$ which implies that – as the "Quantile Method" – the WRRS is a self-financing (zero-cost) strategy.

The main difference between the WRRS and the "Quantile Method" is the weighting scheme. The WRRS weights stocks based on their past performance: The strategy denotes a greater portfolio fraction to stocks with a more extreme performance during the formation period while stocks with a return similar to the cross-sectional average get only a minor weight. For the "Quantile-Method", however, the performance of a stock during the formation period serves only as a criterion whether the stock is included in the portfolio or not. The weighting of stocks that are assigned to the momentum portfolio is independent from past returns since assets are either equal- or value-weighted. The two methods do also differ in the fraction of assets considered. A momentum portfolio formed according to the "Quantile Method" only comprises stocks in the top and bottom quantile while the majority of stocks are excluded. A WRSS portfolio in contrast invests in all stocks (except for those with an excess return of exactly zero) and not just in assets with extreme past returns. The WRSS portfolio is mainly employed in theoretical studies as in contrast to the "Quantile" method, the WRRS can be used for a theoretical decomposition of momentum profits in different potential drivers (Jegadeesh and Titman, 1993, Moskowitz and Grinblatt, 1999 and Chordia and Shivakumar, 2002, among others). This allows structuring the search for potential sources of this phenomenon. Such a theoretical decomposition with the WRRS is carried out in Section 3.1.

Skip Period

To obtain unbiased results, it has become a common practice to skip a short time period between the formation and the investment period in order to avoid some of the microstructure concerns documented in Jegadeesh (1990, p.895-896), Lehmann (1990, p. 9-11) and Lo and MacKinlay (1990, p.191-192). Since stock returns are normally measured close-to-close and trade at the bid or at the ask price, a momentum strategy may spuriously appear to earn abnormal returns because of the bid-ask bounce which can be illustrated with a small example: Suppose that the price of a stock remains constant between $t-1$ and $t+1$. The stock closes at time t at the bid price while the probability that the stock closes at the ask price at the end of $t-1$ and $t+1$ is roughly 50%. If a constant bid-ask spread is assumed, it is obvious that the measured return for t is either zero or negative and for $t+1$ either zero or positive. Consequently, if returns are measured over closing prices, they can appear to be negatively correlated. This might lead to the wrong conclusion that past prices predict future prices although they are completely uncorrelated (see Roll (1984) for a formal analysis of the bid-ask spread). In light of the momentum effect, the bid-ask bounce should bias momentum returns towards zero.

Estimates of momentum abnormal returns can also be biased by the lead-lag effect. According to the common intuition, small capitalization stocks trade less frequently than larger stocks. Therefore, new information first influences the prices of larger stocks. Then afterwards, it is finally impounded into small capitalization stocks. This lag can lead to a positive correlation in an equally weighted portfolio (Lo and MacKinlay, 1990, p.178).

A skip period between the formation and investment period helps to avoid some of these microstructure distortions and lead to a better estimation of momentum profits. Most studies on stock price momentum chose a length of one month for this gap.[6] How important it is to consider a skip period in the tests can be seen in the work of Chordia and Shivakumar (2002). While Chordia and Shivakumar (2002) present a model and show that some macroeconomic variables can explain the momentum effect, Cooper et al. (2004, p.1355-1357) argue that the results are biased as no skip period is included in the tests and since stocks with a price below \$1 are not excluded from the sample[7]. Taking these aspects into consideration, Cooper et al. (2004) show that the variables do not have any explanatory power of momentum returns (p.1356). This does also indirectly challenge the results of Nelles et al. (2007) examining the momentum effect for the German market, but also do not consider a skip period between the ranking and holding period. It might be the case that their results are also heavily influenced and biased by microstructure effects.

2.2 Momentum Returns and the US Market

Table 1 presents the most important studies related to momentum returns in the U.S. Column 1 gives information about the paper in which the respective results are published. Column 2 reports the length of the formation period, J, the investment period, K, and the skip period, S, expressed in months. For example, $J = 12/\, S = 0.25/\, K = 3$ means that stocks are sorted based on their past 12 months return ($J = 12$). The portfolios are formed one week (0.25 months) after the ranking period ended ($S = 0.25$) and are then held for 3 months ($K = 3$). Column 3 documents which of the two methods (the "Quantile Method" and the WRRS) are employed to calculate

[6] Famous exceptions are Jegadeesh and Titman (1993) and Lee and Swaminathan (2000) with a shorter skip of one week.
[7] Stocks priced below \$1 are excluded since these stocks are highly illiquid and have high trading costs.

momentum returns. If the "Quantile Method" is chosen, column 3 additionally informs about whether the stocks are equally weighted or value weighted and which quantiles are chosen to form winner and loser portfolios. Column 5 gives information about the sample period and the last column documents the (average) momentum return per month net of trading costs. If a study examines the performance of several momentums strategies, the one with the highest significant returns is presented in Table 1.[8]

Table 1

Overview of Momentum Returns Documented for the U.S. Market

Paper	Interval	Data	Portfolio formation	Sample Period	Momentum return per month
Jegadeesh and Titman (1993)	J=12 / S=0.25 / K=3	NYSE/AMEX stocks	10% winners / 10% losers Equal-weighting	1965-1989	1,96%
Conrad and Kaul (1998)	J=9 / S=0 / K=9	NYSE/AMEX stocks	WRRS	1962-1989	0,71%
Moskowitz and Grinblatt (1999)	J=6 / S=0 / K=6	NYSE/AMEX/Nasdaq stocks	30% winners / 30% losers Equal-weighting	1963-1995	0,78%
Hong et al. (2000)	J=6 / S=0 / K=6	NYSE/AMEX/Nasdaq stocks	30% winners / 30% losers Equal-weighting	1980-1996	0,53%
Lee and Swaminathan (2000)	J=9 / S=0 / K=9	NYSE/AMEX stocks	10% winners / 10% losers Equal-weighting	1965-1995	1,15%
Jegadeesh and Titman (2001)	J=6 / S=0 / K=6	NYSE/AMEX/Nasdaq stocks	10% winners / 10% losers Equal-weighting	1965-1998	1,23%
Chordia and Shivakumar (2002)	J=6 / S=0 / K=6	NYSE/AMEX stocks	10% winners / 10% losers Equal-weighting Only non-January months	1951-1963 1963-1994	0,83% 0,73%
Jegadeesh and Titman (2002)	J=6 / S=0 / K=6	NYSE/AMEX stocks	WRRS	1965-1997	0,37%
Griffin et al. (2003)	J=6 / S=1 / K=6	NYSE/AMEX stocks	20% winners / 20% losers Equal-weighting	1926-2000	0,59%
Avramov et al. (2007)	J=6 / S=1 / K=6	NYSE/AMEX/Nasdaq stocks	10% winners / 10% losers Equal-weighting	1985-2003	1,49%

Table 1 shows that momentum returns are positive during different sample periods between 1926 and 2003. Each study in Table 1 reports momentum returns that are statistically significant on conventional levels. It is especially remarkable that momentum strategies remain profitable after their discovery in 1993 (see among others Jegadeesh and Titman, 2001). Other anomalies in contrast have disappeared after they became public (see Schwert, 2003)[9]. Moreover, Table 1

[8] Note that not all papers try to find the momentum strategy with the highest abnormal returns.

[9] In the sample period precedent of the publication of Banz (1981) between 1965 and 1981, the average Fama-French size factor was 0.53% per month (t-statistic: 2.34) while the average size factor was only -0.18% (t-statistic: -1.01) in the 1982 to 1998 sample period. A similar effect is documented for the book-to-market factor return.

shows that there is not any study reporting statistically insignificant momentum returns for a similar methodology and similar $J/S/K$ intervals over a longer period. Only for some subperiods, it is shown that momentum strategies are not profitable: Between 1926 and 1951, momentum returns are measured that are not significant (Chordia and Shivakumar, 2002, p.990). Henker et al. (2006) and Hwang and Rubesam (2007) measure non-significant momentum returns after 2001. Yet, the literature does not consider this as evidence that the momentum effect has disappeared as its profitability is documented for other samples after 2001 (e.g. Dimson, 2008 and this work for the German and U.K. stocks).

While there seems to be strong evidence for the existence of momentum in the U.S., one needs to be aware that all studies are quite similar with respect to the methodology employed. It has become a common practice to form zero-cost portfolios, which are long in past winner stocks and short in past loser stocks. Furthermore, most studies employ the "Quantile Method" and calculate returns on an overlapping investment period basis. All papers in Table 1 estimate profits to momentum strategies before trading costs, use a similar data set and make related adjustments: All studies presented in Table 1 employ monthly data[10]. Moreover, it has become a common practice to exclude stocks with a price and/or a market value below a specific value. It is argued that these adjustments are necessary in order to ensure that results are not driven by low priced and extremely illiquid stocks. All these adjustments seem straightforward and useful. The fact that all studies employ a similar methodology indicates that there is a broad consensus in the literature how to measure momentum returns. Yet, one needs to be aware that evidence for the momentum effect crucially depends on the correctness of this methodology.

Table 1 also shows that the profitability of momentum strategies substantially differs across the studies. Four empirical studies report average monthly momentum returns well above one percent whereas others obtain much lower momentum returns. These differences can at least partly be explained by the construction of momentum portfolios. It is a common view that momentum strategies are more profitable when limited to stocks with an extreme past performance (see e.g. Hong et al., 2000, p.274), while strategies with larger quantiles generate lower returns. Studies, reporting monthly momentum returns above one percent, only assign the top and bottom 10% of stocks to their winner and loser portfolios. Papers with lower momentum returns however do also consider stocks with a less extreme performance in the portfolios; either

[10] It is argued that using daily data, momentum returns could be overstated due to the bid-ask spread and thin trading. This potential bias is likely to be reduced substantially with monthly returns (Jegadeesh, 1990, p.896).

by including the top and bottom 20% or 30% of assets or by employing the WRRS, where all stocks are considered. The weighting scheme of stocks in the momentum portfolio can also influence its performance. Compared to equally weighted portfolios, value-weighting seems to reduce the average return and volatility of the strategy (see Moskowitz and Grinblatt, 1999, p.1259, Korajczyk and Sadka, 2004).

2.3 Momentum Returns and non-US Markets

An overview of studies examining momentum profits outside the U.S. is given in Table 2. It can be seen that the momentum effect is examined for European countries, emerging markets, African markets, American countries and Asian stock markets.

Rouwenhorst (1998), Griffin et al. (2003) and Doukas and McKnight (2005) present evidence for the existence of the momentum effect in Europe. Rouwenhorst (1998) uses a sample that consists of stocks from 12 European countries between 1978 and 1995.[11] Irrespective of the origin, the top 10% of stocks is bought while the bottom 10% of stocks is sold. Rouwenhorst (1998, p.271) find that for each formation and investment interval between 3 and 12 months, past winners outperform past losers by about one percent per month. Furthermore, it is shown that momentum strategies work in all 12 countries except Sweden. Other studies focus on a specific European country when examining momentum returns: Among other markets, significant profits to momentum strategies are reported for UK stocks (Liu et al., 1999, Hon and Tonks, 2003, Agyei-Ampomah, 2007, Dimson, 2008) for the Spanish market (Forner and Marhuenda, 2003), for Greek stocks (Tsouknidis, 2006) and for the German market between 1973 and 1997 (August et al., 2000) and between 1999 and 2006 (Nelles 2007).

[11] The 12 countries are Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom.

Table 2

Overview of Momentum Returns Documented for Non-U.S. Markets

Paper	Strategy	Portfolio Formation	Country/Region	Sample Period	Momentum Return per month
Rouwenhorst (1998)	J=9 / S=1 / K=6	10% Winners / 10% losers Equal-weighting	Europe (12 countries)	1978-1995	1.45%
Rouwenhorst (1999)	J=6 / S=1 / K=6	30% winners / 30% losers Equal-weighting	Emerging Markets (20 countries)	1982-1997	0.39% (0.58%)[12]
Chui et al. (2000)	J=6 / S=1 / K=6	30% winners / 30% losers Equal-weighting	Asian market (8 countries)	1975-2000	0.38% (not significant)
August et al. (2000)	J=6 / S=0 / K=12	10% winners /10% losers Equal-weighting	German market	1973-1997	1,03%
Griffin et al. (2003)	J=6 / S=1 / K=6	20% winners / 20% losers Equal-weighting	International (39 countries)	1975-2000	0.49%
Forner and Marhuenda (2003)	J=12 / S=0 / K=12	WRRS	Spanish market	1967-1997	0.133%
Doukas and McKnight (2005)	J=12 / S=0 / K=12	30% winners / 30% losers Equal-weighting	Europe (13 countries)	1998-2001	0.73%
Agyei-Ampomah (2007)	J=12 / S=1 / K=1	10% winners / 10% losers Equal-weighting	UK market	1998-2003	0.446%
Dimson (2008)	J=12 / S=1 / K=12	20% winners / 20% losers Value-weighting	UK market	1900-2007	0,90%

The continuation phenomenon is not limited to the U.S. and the European market. Griffin et al. (2003, p.2518-2520) examine the existence of momentum returns for individual African and south American markets. Data is available for two African countries and six American countries. Past winners outperform past losers in both African countries and five of six American markets (However, not for all examined markets, the momentum returns are significant.). Moreover, Rouwenhorst (1999) shows that momentum returns are also positive in 17 out of 20 emerging markets between 1982[13] and 1997[14].

[12] The average monthly return of a momentum portfolio in which stocks of all 20 countries are equally weighted is 0.39%. If however, the 20 countries are equal-weighted in the portfolio, it yields 0.58% per month.

[13] To be specific, the starting dates vary for the individual countries: While data is available for Argentina, Brazil and Chile by 1982, for Turkey the sample does not start until 1990.

However, in Asian markets, past winner stocks do not significantly outperform past loser stocks. Using data of eight different Asian countries between 1976 and 2000, Chui et al. (2000, p.14) find significant positive momentum returns only for Hong Kong. They explain the lack of significance with a high volatility of momentum returns during the financial crises in 1997. Yet, even after excluding the period of the crisis, momentum portfolios generate significant positive returns only in about half of the examined Asian countries. Insignificant momentum returns are also reported in Griffin et al. (2003, pp.2518) where the continuation effect is examined for 14 Asian countries during 1975 and 2000[15]. Even for all Asian countries, momentum returns have a t-statistic of 1.64 and are not significant on conventional levels. Further evidence for momentum strategies not being significant in Asia is given by Haugen and Baker (1996, p.433) documented weak and insignificant momentum in Japan.

Griffin et al. (2003, p.2322-2524) extends the research on momentum profits and examines whether momentum returns are correlated across regions (Africa, America (ex. U.S.), Asia (ex. Japan), Europe, Japan, U.S.). They find only low intraregional and interregional correlations for their data sample. The highest correlation is documented for the United States and the countries of Europe. This finding is in line with Rouwenhorst (1998, p.282) documenting that the continuation effects in Europe and the U.S. are not uncorrelated (correlation of 0.43).

The biggest difference between empirical momentum studies for the U.S. market and for non-U.S. markets lies in the sample size. Researchers of the U.S. market dispose of a much larger data sample when examining stock price momentum – both in the cross-sectional and the time-series dimension. While about 3000 to 4600 stocks are available for the U.S. market (e.g. Moskowitz and Grinblatt, 1999, p.1252, Grundy and Martin, 2001, p.32, Avramov et al., 2007, p.2505), the number is much smaller for other markets: Research on momentum in European countries is based on data sets with often less than 500 firms for an individual country (e.g. Rouwenhorst, 1998, Forner and Marhuenda, 2003 and Doukas and McKnight, 2005). However, lack of data in the cross-sectional dimension is not only limited to European markets. Examining the momentum effect in Africa, Griffin et al. (2003) disposes of data of only two countries and to

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[14] In Rouwenhorst (1999), positive momentum returns during the sample period are observed for the following countries: Brazil, Chile, Colombia, Greece, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Thailand, Turkey, Venezuela and Zimbabwe. Returns are significantly different from zero in Chile, Colombia, Greece, India, Jordan, Nigeria and Portugal. Rouwenhorst (1999, p.1450) cannot find positive momentum returns for Argentina, Indonesia and Taiwan.

[15] The starting dates for the sample of each country vary: By 1975, data are available for Australia and Japan. Coverage for the other 12 Asian countries begins between 1983 and 1993.

a total number of only 280 stocks. Rouwenhorst (1998, p.1444) is confronted with the same problem for emerging markets. For each country, not more than 100 stocks are available. In the time dimension, U.S. data cover a much longer period than the datasets for non-U.S. markets. While recorded returns for U.S. stocks date back until 1926 (e.g. Chordia and Shivakumar, 2002, p.990, Cooper et al., 2004, p.1348), most studies for non-U.S. markets cover a much shorter period (see Table 2).[16]

Empirical results critically depend on the quality and on the size of the available data set. Therefore, one should take into consideration the time history and the number of stocks available when drawing conclusions about the existence of momentum. For example, the evidence for a rejection of the hypothesis "price momentum does not exist for the U.S. market" is based on 3000 to 4600 stocks, on different time periods and on a couple of different studies. This cannot be compared to the evidence for a rejection of the hypothesis "price momentum exists for African countries" based on only one study (Griffin et al., 2003) and a total sample size of 280 stocks. Yet, this does not mean that the existence of price momentum for non-U.S. markets should be questioned in general. As Table 2 states, a large number of studies report significant momentum returns for various data samples outside the U.S and hereby confirm that the momentum effect is not a U.S. specific phenomenon. Nevertheless, I rather recommend taking into consideration the size of the data set when interpreting the results; one should at least be aware that these findings are based on a much smaller data sample than those for the U.S. market.

2.4. Momentum Profits net Transaction Costs

The Efficient Markets Hypothesis requires that *"prices fully reflect all available information"* (Fama 1970, p.383) and is based on the assumption that trading costs are zero. Yet, according to the literature, trading frictions in stock markets are non-zero. Therefore, Fama (1991) defines that markets are efficient if *"... prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs"* (p.1575)[17] This definition allows delays or friction in the price adjustment process in a fully rational market even if there are no zero cost arbitrage opportunities. Hence, according to this definition, one cannot conclude from the existence of momentum profits that are net of trading

[16] The study of Dimson (2008) represents an exception with a sample dating back until 1900. However, the number of stocks available for the ranking procedure is so small in the first decades that it seems questionable to consider such a long period.

[17] See also Goldsmith (1976) and Jensen (1978) among others.

costs on the invalidity of the market efficiency. Trading costs need to be taken into consideration. While there has been much research on the profitability of momentum strategies before trading costs, much controversy exists about the magnitude of trading costs. Jegadeesh and Titman (1993, p.77) refer to Berkowitz et al. (1998) and assume a one-way cost of 0.50%. Yet, this estimate does not take into account the *type* of stock that goes into momentum portfolios. While the transaction cost estimate of Jegadeesh and Titman (1993) is based on the trading costs for large liquid stocks, Lesmond et al. (2004, p.354-356) document that momentum portfolios (and especially the loser portfolios) are composed of small, low price and high beta stocks. Hence, momentum profits are generated by assets that seem to be relatively less liquid. Furthermore, Jegadeesh and Titman's transaction cost estimate does not consider the frequency of trades from rebalancing the momentum portfolio (Agyei-Ampomah, 2007, p.777).

Therefore, a couple of studies examine the costs of trading momentum portfolios (Lesmond et al., 2004, Korajczyk and Sadka, 2004, Hanna and Ready, 2003, Keim, 2003) and show that they are much higher than previously assumed. However, mixed evidence is found whether momentum strategies generate profits after consideration of transaction costs. While Korajcyk and Sadka (2004) argue that transaction costs are substantial but not large enough to explain the existence of the momentum anomaly, Lesmond et al. (2004) suggest that momentum profits are subsumed by the costs of trading. Agyei-Ampomah (2005) examines momentums strategies for the U.K. and find profitable momentum returns net of transaction costs for longer horizons (formation and investment period longer than six months), whereas for shorter periods (formation and investment periods that do not exceed three to six months), the costs of transaction costs dominate momentum profits. In summary, although trading costs are substantial for momentum strategies, there is no clear evidence that momentum profits are subsumed by trading costs.

2.5 Momentum Profits and Short-sale Constraints

Beside trading costs, short-sale constraints can also make it difficult to realize profit opportunities of momentum strategies. Momentum portfolios are long in past winner stocks and short in past loser stocks. Therefore, momentum returns can be driven by the positive returns of the winner portfolio or by the negative returns of the loser portfolio. The findings of Hong et al. (2000) indicate that momentum profits are largely generated by loser stocks. For their NYSE/AMEX sample from 1965 to 1989, they examine the returns of winners and loser portfolios separately and show that loser stocks contribute to approximately three quarters of total momentum returns (see Hong et al., 2000, Table III, p.275). They obtain this percentage by calculating the fraction of the return difference between the loser portfolio (bottom 30 percent of past returns) and the middle return portfolio (middle 40 percent of past returns) to the total momentum returns. Similar findings are reported for other markets (Doukas and McKnight, 2005, p.323, Lesmond et al., 2004, p.352, Korajczyk and Sadka, 2004, p.1043 and Agyei-Ampomah, 2007, p.784). These observations indicate that any short-selling constraints may affect the viability of momentum strategies. Moskowitz and Grinblatt (1999) argue that not all stocks can be borrowed that easily for short sales. Further, margins from short sales are often less than the market rate of return (p.1272). Consequently, given that momentum profits largely arise from loser stocks, short-selling constraints can make momentum profits difficult to be realized. Yet, the literature has not yet found a possibility to model the effect of short-selling constraints on the realization of momentum profits.

3. Potential Explanations for the Momentum Phenomenon

3.1 Momentum and the Fama French Three Factor Model

Fama and French (1993) identify three stock market factors that seem to explain much of cross-sectional variation in average stock returns: the market excess return, $R_m - R_f$, the return difference between a portfolio composed of small stocks and a portfolio of large stocks, SMB (small minus big), which represents the size premium, and the return difference between a portfolio composed of high book-to-market stocks and a portfolio of low book-to-market stocks, HML (high minus low), that represents the value premium. To estimate the factor sensitivities, the excess market return, the size factor and the book-to-market factor are regressed on the return of a portfolio i in excess of the risk-free-rate, $R_i - R_f$:

$$R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + s_i \text{ SMB} + h_i \text{ HML} + \varepsilon_i \qquad (2)$$

If the three factor model is able to explain the cross-sectional variation in stock returns, α_i should be close to zero. The intercept can be interpreted as the risk-adjusted return of the portfolio relative to the three factors. Fama and French (1996) document that their model can explain most Capital Asset Pricing Model (CAPM) anomalies[18], but have to admit that the three factors fail to capture the momentum effect (Fama and French, 1996, p.68). Beside the three-factor model, other traditional pricing measures as the capital asset pricing model (CAPM) are also not able to explain this phenomenon (Jegadeesh and Titman, 1993, pp.73).

Since standard asset-pricing models do not explain the profitability of momentum strategies, two different types of theories are discussed in the literature beside data mining. First, asset-pricing is irrational and the profits to momentum strategies cannot be explained in the framework of the traditional assumptions that investors are strictly rational and that they dispose of an unlimited computational capacity (Hong and Stein, 1999, p.2144). This relatively young field of research argues that some of the financial phenomena can only be understood by using models in which at least some investors are not completely rational and exhibit various psychological biases. Second, asset pricing is rational and the standard asset-pricing theories are not complete. Therefore, it is necessary to find further risk factors and/or to look for a better model within the traditional framework. This theory is called the "rational approach" in this work since the assumption of complete rationality is not dismissed. Both attempts to explain the intermediate-term stock price momentum – the rational proposals and the behavioral based theories – are presented in the next two sections.

3.2. Rational Explanation Attempts

3.2.1 Overview

A momentum portfolio is constructed according to the Weighted Relative Strength Strategy (WRRS)[19]. This method implements self-financing portfolios (with $\sum_{i=1}^{N} \omega_{i,t} = 0$) and invests the fraction $\omega_{i,t}$ in stock i, which depends on the market excess return of stock i during the formation period. For simplicity, the formation and the investment period are assumed to be of length one month (According to Lewellen (2004, p.542), results can be easily adapted to longer formation and investment periods). Therefore, in Equation (1), k is equal to one and the WRRS invests the fraction $\omega_{i,t}$ in stock i:

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[18] Researchers have identified many patterns in stock returns. For example, it is shown that stock returns depend on firm characteristics such as long-term past return, size, earnings/price ratio (E/P), cash flow/price ratio, the ratio of the book value of common stocks to their market value and past sales growth (see: Banz, 1981, Basu, 1983, Rosenberg et al., 1985, DeBondt and Thaler, 1985, Lakonishok et al., 1994). Fama and French (1996, p.57) argue that their model can explain many of these so-called CAPM anomalies.

[19] See for further details Section 2.1 and Equation (1).

$$\omega_{i,t} = R_{i,t-1} - \bar{R}_{t-1} \qquad (3)$$

where $\bar{R}_{t-1}$ denotes the cross-sectional average return in period $t-1$. As mentioned in Section 2.1, a portfolio constructed in line with the WRRS is long in stocks that outperformed the market during the formation period $\left(\omega_{i,t} = R_{i,t-1} - \bar{R}_{t-1} > 0\right)$ and short in stocks with a negative market excess return during the formation period $\left(\omega_{i,t} = R_{i,t-1} - \bar{R}_{t-1} < 0\right)$. The momentum strategy is profitable when past winner stocks continue to outperform and when past loser continue to underperform the markets. In other words:

$$E\left[\omega_{i,t}\left(R_{i,t} - \bar{R}_{t}\right)\right] = E\left[\left(R_{i,t-1} - \bar{R}_{t-1}\right)\left(R_{i,t} - \bar{R}_{t}\right)\right] > 0 \qquad (4)$$

In order to identify potential sources of momentum returns, it has become common practice to decompose expected profits with a simple model (see e.g. Moskowitz and Grinblatt, 1999, pp.1253, Chordia and Shivakumar, 2002, pp.1009). Therefore, the following multifactor linear process is considered:

$$R_{i,t} = \mu_{i,t} + \sum_{k=1}^{L} \beta_{i,k} f_{k,t} + \sum_{m=1}^{M} \theta_{i,m} z_{m,t} + e_{i,t}\,, \qquad (5)$$

with

$R_{i,t}$:	Return on stock i at time t
$\mu_{i,t}$:	Expected return on stock i conditional on information available at time t
$f_{k,t}$:	Return on a zero-cost portfolio k mimicking the most important factors (e.g. the three Fama-French factors) at time t
$\beta_{i,k}$:	Stock i's sensitivity to factor k
$z_{m,t}$:	Industry portfolio returns orthogonal to the L factors at date t
$\theta_{i,m}$:	Stock i's sensitivity to component m
$e_{i,t}$:	Stock i's firm specific component

Further, it is assumed that the firm-specific components, the industry terms and the factor portfolios are contemporaneously uncorrelated, as well as:

$E(f_{k,t}f_{l,t-1}) = 0$, for all $l \neq k$; $\quad E(z_{m,t}f_{l,t-h}) = 0$, for all m, l and $h = \pm 1$;

$E(e_{i,t}e_{j,t-1}) = 0$, for all $i \neq j$; $\quad E(e_{i,t}f_{k,t-h}) = 0$, for all i, k and $h = \pm 1$;

$E(z_{m,t}z_{n,t-1}) = 0$, for all $m \neq n$; $\quad E(e_{i,t}z_{m,t-h}) = 0$, for all i, m and $h = \pm 1$;

with $E(z_{m,t}) = 0$ for all m and $E(e_{i,t}) = 0$ for all i. According to these assumptions, the variables are allowed to be autocorrelated but not cross-autocorrelated. Moreover, it is assumed that sensitivities to the factor portfolios (the book-to-market, the size, the excess market portfolios etc.) do not change over time. Therefore, time subscripts are lacked in the factor sensitivities of Equation (5). Given the assumed return-generating process from Equation (5), the expected return in Equation (4) can be decomposed as follows:

$$\begin{aligned} E\left[(R_{i,t-1} - \bar{R}_{t-1})(R_{i,t} - \bar{R}_t)\right] = \; & (\mu_{i,t-1} - \bar{\mu}_{t-1})(\mu_{i,t} - \bar{\mu}_t) \\ & + \sum_{k=1}^{L} (\beta_{i,k} - \bar{\beta}_k) Cov(f_{k,t-1}, f_{k,t}) \\ & + \sum_{k=1}^{L} (\theta_{i,m} - \bar{\theta}_m) Cov(z_{m,t-1}, z_{m,t}) + Cov(e_{i,t-1}, e_{i,t}). \qquad (6) \end{aligned}$$

The average momentum profits across all N stocks are equal

$$\begin{aligned} & \frac{1}{N}\sum_{i=1}^{N} (\mu_{i,t-1} - \bar{\mu}_{t-1})(\mu_{i,t} - \bar{\mu}_t) + \sum_{k=1}^{L} \sigma_{\beta_k}^2 Cov(f_{k,t-1}, f_{k,t}) \\ & + \sum_{m=1}^{M} \sigma_{\theta_m}^2 Cov(z_{m,t-1}, z_{m,t}) + \frac{1}{N}\sum_{i=1}^{N} Cov(e_{i,t-1}, e_{i,t}), \qquad (7) \end{aligned}$$

where the cross-sectional variances of the portfolio loadings and the industry sensitivities are denoted with $\sigma^2_{\beta_k}$ and $\sigma^2_{\theta_m}$. The above decomposition in Equation (7) suggests four potential sources of momentum profits:

1. **The variation in expected returns:** $1/N \sum_{i=1}^{N} (\mu_{i,t-1} - \bar{\mu}_{t-1})(\mu_{i,t} - \bar{\mu}_t)$

   This component leads to positive momentum returns if the conditionally expected return of stock i is larger than the expected return across all stocks during the formation $(t - 1)$ and the holding period (t).

2. **The serial correlation in the factors:** $\sum_{k=1}^{L} \sigma^2_{\beta_k} Cov(f_{k,t-1}, f_{k,t})$

   If the factor portfolio returns are positively serially correlated, the second term is positive. It is useful to think that the $f's$ are well proxied by the three Fama-French factor portfolios. So, if the correlation of the profits from a market-beta, size or book-to market portfolio is positive, momentum portfolios are generated by this term.

3. **The serial correlation in industry return components:** $\sum_{m=1}^{M} \sigma^2_{\theta_m} Cov(z_{m,t-1}, z_{m,t})$

   This term contributes to momentum profits when industry components are positively serially correlated.

4. **The serial correlation in the idiosyncratic components:** $1/N \sum_{i=1}^{N} Cov(e_{i,t-1}, e_{i,t})$

I will now focus in further detail on the four potential components and classify the existing rational explanations into one of the four groups.

3.2.2. Momentum Profits due to Variation in Expected Returns

Studies finding evidence for the first component in Equation (7) can be subdivided into two groups. The first one assumes stationary mean returns while the second body does not rely on this assumption and claims that dispersion in *time-varying* expected returns is responsible for the profitability of momentum strategy.

Cross-sectional dispersion in time-invariant mean returns

Conrad and Kaul (1998) find support for the first term in Equation (7) to be the main determinant of momentum profits. While in Equation (7), expected returns are considered time variant, Conrad and Kaul rely on the assumption that mean returns of individual stocks are stationary over the period momentum strategies are implemented.[20] Their work presents theoretical and empirical evidence that cross-sectional dispersion in mean returns is an important component of the profitability of momentum strategies. Instead of using the decomposition of momentum profits in Equation (7), they follow the framework of Lehmann (1990, pp.3) and Lo and MacKinlay (1990, p.182-184) and decompose the expected profits of the momentum strategy with a holding period of length k, denoted with $E[\pi_t(k)]$, into two components: The first one is time-series predictability in stock returns, which is denoted with $P(k)$. It consists of the negative of the first-order autocovariance of the market portfolio and the average of the first-order autocovariances of all N individual stocks that are included in the momentum portfolio. Conrad and Kaul (1998, p.498) name $P(k)$ the "predictability-profitability index"[21] since it is completely determined by return predictability. The second source of the total expected momentum profits is $\sigma^2[\mu(k)]$ and represents the cross-sectional dispersion in mean returns of stocks.

In order to prove theoretically that momentum strategies remain profitable even if stock returns are completely unpredictable, Conrad and Kaul (1998, p.499) introduce a benchmark model where stock prices are assumed to follow a random walk. In the random walk framework, strategies that rely on time-series predictability are not profitable by construction first since stock returns are assumed to be not autocorrelated and secondly, since returns are not predictable across different assets. This framework demonstrates that momentum strategies can generate profits even if stock prices are entirely unpredictable as it is assumed by the random walk model. The momentum strategy is profitable simply by being long in high-mean stocks and short in low-mean assets[22], but not by exploiting time series patterns. Given the theoretical background, Conrad and Kaul (1998, pp.502) use a sample of all NYSE/AMEX stocks between 1926 and 1989 and estimate the total average profits, $\hat{E}[\pi_t(k)]$, and the two components of the decomposition, $\hat{P}(k)$ and $\sigma^2[\hat{\mu}(k)]$, for five different time periods (1962-1989, 1926-1989, and three subperiods) and eight different holding periods k (between 1 week and 3 years). If stock prices follow random walks, $\sigma^2[\hat{\mu}(k)]$ should be constant and represent 100 percent of total profits. This hypothesis cannot be rejected: The cross-sectional variance of mean returns has a

[20] Conrad and Kaul's (1998) study also critically depends on the assumption that the cross-sectional distribution of the in-sample mean returns is an accurate measure of the true cross-sectional variation in the mean returns.
[21] Lo and MacKinlay (1990), as well, name this term the "predictability-profitability index".
[22] Winner stocks can have high returns either because they are high-mean stocks or because they have experienced a high current shock. On average however, winner stocks will be high-mean stocks and loser stocks will be low-mean stocks (Conrad and Kaul, 1998, pp.501).

significant effect on $\hat{E}[\pi_t(k)]$ and contributes more than 100 percent to the expected momentum profits in 16 out of 20 cases where positive momentum returns were observed. The time-series component $\hat{P}(k)$ in contrast is either negative or, if positive, not significantly different from zero. Therefore, Conrad and Kaul (1998) cannot reject the hypothesis that the main determinant of momentum profits is the cross-sectional variation in mean returns. Their study implies that the momentum effect and the random walk hypothesis might not be conflicting theories; momentum strategies can be profitable even if stock prices *do* follow random walks (with drifts). According to these findings, momentum may not be a price continuation effect generated by market inefficiencies but a strategy that exploits the cross-sectional differences in mean returns by being long in high-mean stocks and short in low-mean assets.

However, some papers do not agree with Conrad and Kaul (1998). With Moskowitz and Grinblatt (1999), Jegadeesh and Titman (2001), Jegadeesh and Titman (2002), Grundy and Martin (2001) and Lewellen (2002)[23], several researches do not support the hypothesis of Conrad and Kaul (1998).

Moskowitz and Grinblatt (1999, pp.1257) use a similar decomposition of momentum returns as in Equation (7), but assume like Conrad and Kaul (1998, p.489) time invariant mean returns. For a CRSP and COMPUSTAT data file for between 1963 and 1995, Moskowitz and Grinblatt (1999) find that the profitability of momentum strategies largely arises from the third term, the serial correlation in industry components, $\sum_{m=1}^{M} \sigma_{\theta_m}^2 Cov(z_{m,t-1}, z_{m,t})$. The dispersion in unconditional mean returns in contrast does not seem to determine trading profits of individual momentum strategies (Moskowitz and Grinblatt 1999, p.1262). They argue that if the first term is the main determinant of momentum, individual momentum profits should be significantly larger than industry momentum profits since the cross-sectional variation in mean returns for individual stocks is much larger than the cross-sectional variation in mean industry returns. Yet, comparing equal-weighted momentum returns for individual stocks to equal-weighted industry momentum returns, Moskowitz and Grinblatt (1999, p.1262) find industry momentum profits being 90 basis points larger than momentum returns for the individual stocks.

Jegadeesh and Titman (2001) use a different approach to reject Conrad and Kaul's (1998) hypothesis. They argue that according to the theory of Conrad and Kaul (1998), returns of a

[23] The study of Lewellen (2002, p.556) is not discussed here in further detail since its method to find evidence against the Conrad and Kaul (1998) conjecture is similar to that of other papers presented here (e.g. Moskowitz and Grinblatt, 1999).

momentum portfolio must remain positive in the long run since the success of winner stocks is determined by high unconditional expected rates of return that is assumed to remain unchanged over time. In other words, stocks that were initially bought by the momentum strategy should continue to outperform stocks that were initially sold in any postranking period. Jegadeesh and Titman (2001) examine the postholding period returns of momentum portfolios for NYSE and AMEX stock data over the 1990 to 1998 sample period and find substantial return reversals in the years two to five after portfolio formation. At the end of month 12 after the formation date, cumulative momentum profits peak at 12.17% while they decline to -0.44% by the end of month 60. Hence, the findings of Jegadeesh and Titman (2001, p.711) are clearly inconsistent with the Conrad and Kaul (1998) hypothesis.

Grundy and Martin (2001) also do not find evidence for the Conrad and Kaul (1998) hypothesis. Using data of all NYSE and AMEX-listed stocks between 1926 and 1995, they measure momentum returns that are adjusted for the estimated Fama and French three factors and learn that, compared to raw returns, the average momentum payoff increases. If the three-factor model adequately documents differences in mean returns, this finding is clearly at odds with the Conrad and Kaul (1998) theory predicting that the cross-sectional variance in mean returns is the main determinant of momentum profits. As an additional test for the Conrad and Kaul (1998) conjecture, Grundy and Martin (2001, pp.57) use each stock as its own risk control and adjust each stock's investment month return by its time-series mean. However, even after this adjustment, momentum returns remain significantly and economically large what is clearly against the hypothesis of Conrad and Kaul (1998).

Opposition against Conrad and Kaul's (1998) theory is also presented in Jegadeesh and Titman (2002). They argue that the Conrad and Kaul bootstrap results are biased. After controlling for the small sample bias, unconditional expected returns seems to explain only very little, if any, of the momentum returns (pp.152).

Cross-sectional dispersion in time-varying mean returns

Chordia and Shivakumar (2002) test the hypothesis that momentum payoffs are derived from cross-sectional differences in *time-varying* expected returns.[24] The theoretical models of Berk et al. (1999) and Johnson (2002) offer the intuition for the study of Chordia and Shivakumar

[24] It is necessary to note that there is concern in the literature over how to adequately modeling time variation in risk. Ghysels (1998), for example, shows that methods of modeling variations in risk do not improve static risk models.

(2002). Both models show that momentum can be explained by economic risk factors. In the study of Johnson (2002), a positive relationship between firm growth rates and expected returns generate momentum profits. Momentum profits in the model of Berk et al. (1999) arise from changes in the firm's asset portfolio over its life cycle and from the interaction between these changes and interest rates. Although the theory of Chordia and Shivakumar (2002) differs from the hypothesis of Conrad and Kaul (1998) which states that it is dispersion in *time-invariant* expected returns what generates momentum profits, both theories have in common to view systematic variation in expected returns as the main driver of momentum profits.

The analysis of Chordia and Shivakumar (2002) shows time-variation in momentum returns: It is documented that a large portion of the six-month momentum profits can be explained by commonly used macroeconomic variables that are linked to the business cycle. These are default spread, dividend yield, yield on three-month T-bills and term structure spread. Their lag is used to predict one-month-ahead stock returns. After controlling [25] for these predicted returns, momentum portfolios do not generate significant profits anymore. In other words, according to these results standard macroeconomic variables related to the business cycle seem to explain the profitability of momentum strategies. In the eyes of Chordia and Shivakumar (2002), this finding indicates time-varying expected returns to be the driver of momentum profits. They argue that if these macroeconomic variables are able to capture time-varying risk, differences in conditionally expected returns across stocks determine the momentum phenomenon. This interpretation is consistent with recent theoretical and empirical work creating a link between cross-sectional variation in expected returns and macroeconomic variables (e.g. Bernanke and Gertler, 1989, Kiyotaki and Moore, 1997, Berk et al., 1999)[26].

Yet, the work of Chordia and Shivakumar (2002) is heavily criticized by Cooper et al. (2004, pp.1354). They replicate the analysis of Chordia and Shivakumar (2002), but cannot find any explanatory power of their proposed macroeconomic model of returns. Cooper et al. (2004, pp.1356) argue that the findings of Chordia and Shivakumar (2002) are biased due to missing methodological adjustments: First, illiquid and high-trading cost stocks are not excluded from

[25] Chordia and Shivakumar (2002, pp.1003) control for the predicted returns by employing a two-way dependent sort: First, they sort all stocks into quintiles according to the past six month buy and hold raw returns and then they sort each quintile further into quintiles according to the predicted returns (They also report results when stocks first are sorted by predicted returns and then by raw returns).

[26] Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) document that changing credit market conditions can differently influence the risks of small and large firms and their expected returns. Berk et al. (1999) present a theoretical model predicting that expected stock returns of firms are differently affected by changing interest rates. In this theoretical work, interest rates can be viewed as a macroeconomic proxy.

their sample and secondly no skip period between formation and investment period is implemented to reduce spurious reversals driven by bid-ask bounce.[27] Considering these common screens to reduce microstructure-induced biases, the macroeconomic model shows little or no ability to explain momentum returns (Cooper et al., 2004, pp.1364). Beside Cooper et al. (2004), the macroeconomic variables as driver of the momentum effect are also questioned by the study of Griffin et al. (2003, pp.2530) showing that the model[28] fails to explain momentum in markets outside the U.S.[29].

Griffin et al. (2003, p.2536) state that if macroeconomic risk is the driver of relative strength returns, momentum strategies should underperform in at least some states of the world (when the marginal utility of returns is higher). Therefore, their work examines and compares the profitability of momentum portfolios during strong and poor economic states. Griffin et al. (2003, p.2536) argue that negative (positive) returns of relative strength strategies during bad economic states (good economic states) support the hypothesis that the momentum phenomenon is driven by macroeconomic risk.[30] Griffin et al. (2003) use stock price data from 22 markets around the world[31]. Choosing seasonally adjusted real GDP, aggregate stock market movements and states of industrial production growth as indicator for the business cycle state, Griffin et al. (2003) find significant positive momentum payoffs during both expansionary and recessionary periods and conclude that momentum profits cannot at all be explained by compensation for bearing macroeconomic risk. This is at odds with the findings of Chordia and Shivakumar (2002, pp.992) for U.S. stocks between 1926 and 1994 that document significantly positive returns on momentum portfolios only during expansionary periods, whereas payoffs are negative but not significant during recessions. The dependence of momentum returns on the state of the economy is also documented in Cooper et al. (2004), Avramov (2006) and Avramov (2007). As Cooper et al. (2004), Griffin et al. (2003) attribute the results in Chordia and Shivakumar (2002) to the missing skip period between the formation and the investment period.

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[27] For further details, see Section 2.1.
[28] Griffin et al. (2003) omit the credit quality spread (DEF) variable from the regression model since the bond markets outside the U.S. are not well developed for low quality credits. The exclusion of DEF however is not expected to affect the results (Griffin et al., 2003, p.2530).
[29] To be more precise, Griffin et al. (2003) examine momentum profits for stocks from two African countries, 6 American countries (except the U.S.), 14 Asian markets and 17 European markets.
[30] Supporters of the behavioral finance literature view interpret high momentum returns during expansionary periods and low or insignificant momentum returns during deflationary periods as evidence for their theory and do not link this to risk. See Chapter 4 for a more detailed comparison between rational and behavioral explanation attempts for the momentum effect.
[31] In their study, Griffin et al. (2003) examine more than 22 markets around the world. Yet, for this test, only markets are excluded for which the OECD provides GDP data.

As shown, literature does not agree whether momentum returns depend on the state of the economy or not. Hence, researchers are far from a conclusion about whether momentum represents a compensation for macroeconomic risk. Even worse, if it *was* conclusively shown that momentum strategies are only profitable during expansionary periods for different markets and time periods, not all researchers would then interpret this finding as evidence for momentum profits being a compensation for bearing macroeconomic risk. Supporters of the behavioral finance literature view a relationship between momentum profits and the state of the economy as confirmation for their overreaction hypothesis: Traders overreact to news and this is more likely during periods with high stock returns. This hypothesis is discussed in detail in the next section.

This relationship between the business cycle and momentum profits found by Chordia and Shivakumar (2002) and Cooper et al. (2004) is the starting point for another important study about intermediate-term stock price momentum. Avramov et al. (2007) argue that credit risk varies with the business cycle and focus on the relationship between credit risk and the profitability of momentum strategies. The study documents a close connection between momentum payoffs and the credit-risk of firms. Based on a sample of NYSE, AMEX and Nasdaq firms over the 1985 to 2003 period, they examine momentum strategies with different formation periods and analyze momentum winner and loser stocks. Avramov et al. (2007) show that the momentum portfolios mainly consist of high credit-risk firms: While the average S&P credit risk rating is BBB for the entire sample, it is on average substantially lower for the loser (BB-) and for the winner portfolio (BB+). Sorting all ranked stocks on three credit rating groups and on 10 past six-month returns, they show that the profitability of momentum increases with credit risk. While momentum strategies generate large and significant profits for high credit risk firms, they appear to be not profitable for firms with low credit risk: For the best credit quality tercile, momentum portfolios yield an insignificant 0.27% per month, but for the worst quality group, the strategy generates a high and significant monthly return of 2.35%. This significant positive return for low-grade firms is largely due to loser stocks. Avramov et al. (2007) also show that the low-graded firms that generate the momentum profits represent less than four percent of the overall market capitalization of all rated firms. This is documented by measuring momentum payoffs for subsamples when sequentially worst rated firms are dropped. After the exclusion of firms with a rating of BB- and worse, momentum returns of the remaining stocks (representing 96.6% of the overall market capitalization and 78.8% of the total number of rated firms) are not significantly different from zero anymore. The finding that momentum is mainly derived from a small fraction of firms with the poorest quality of outstanding debt leads to the assumption that momentum payoffs should be larger during recessionary periods. However, inconsistent with this idea, some papers (e.g. Chordia and Shivakumar, 2002, Cooper et al., 2004) show that momentum profits are economically and statistically significant only during expansions. Avramov et al. (2007) cannot explain this discrepancy and leaves it open for future research.

3.2.3. Momentum due to Serial Factor Correlation

According to the analytical decomposition of momentum profits in Equation (7), the intermediate-term stock price momentum effect might also be due to the second term, the serial correlation in the factors, $\sum_{k=1}^{L} \sigma_{\beta_k}^2 Cov(f_{k,t-1}, f_{k,t})$. Moskowitz and Grinblatt (1999, p.1259) use a portfolio of all CRSP-listed stocks to analyze the contribution of the second source to the profitability of momentum strategies. The portfolio is equally weighted and monthly rebalanced. It is employed for two reasons: First, the firm-specific risk component is close to zero (e becomes arbitrarily small as the number of stocks becomes arbitrarily large) and secondly, the sensitivity of the return of this equal-weighted portfolio to the returns of any single industry is close to zero ($\bar{\theta}_m$ is negligible for all m industries). Hence, the serial covariance of the portfolio returns is approximately[32]:

$$Cov(\bar{R}_t, \bar{R}_{t-1}) = \sum_{k=1}^{L} \bar{\beta}_k^2 \, Cov(f_{k,t}, f_{k,t-1}), \qquad (8)$$

where $\bar{r}_{t-1}$represents the cross-sectional average return of all stocks in period $t-1$, as before. Thus, Equation (8) allows examining the influence of the serial factor portfolio correlation on momentum returns. Moskowitz and Grinblatt (1999, p.1259) measure the covariance of consecutive and nonoverlapping six-month returns (where t denotes a six-month period) and find that $Cov(\bar{R}_t, \bar{R}_{t-1})$ is -0.001 and does not significantly differ from zero. This result is similar to that of Jegadeesh and Titman (1993, p.73) who document a weakly negative (-0.0028) serial portfolio covariance. According to Moskowitz and Grinblatt (1999, p.1262), this portfolio has historically a high risk premium. Hence, some of the $\bar{\beta}_k$'s should be large.

[32] Since all CRSP-listed stocks are included, it is intuitive that the first term in Equation (7) is also zero: the expected return of this all-stocks portfolio μ_i is equal to $\bar{\mu}$.

Consequently, in terms of Equation (8), an insignificant $Cov(\bar{R}_t, \bar{R}_{t-1})$ combined with at least some large $\bar{\beta}_k$'s means that the serial covariance in at least some of the factor portfolios does not contribute to the profitability of relative strength strategies. Moreover, Moskowitz and Grinblatt (1999, p.1262) document that the serial covariance for each of the three Fama-French (1993) factor-mimicking portfolios is not significantly different from zero.[33] Grundy and Martin (2001, p.49) come to a similar conclusion for a two factor model (with the excess return on an equal-weighted market portfolio as the first factor and the difference in returns in the first and tenth deciles of equity values as the second factor) by regressing the realization of factor j in month t on the cumulative factor realization during the formation period and a constant.

In summary, Moskowitz and Grinblatt (1999), Jegadeesh and Titman (1993) and Grundy and Martin (2001) find almost zero serial covariation in returns[34] on the Fama-French factor mimicking portfolios and on the equal-weighted market index. Hence, according to the findings, the second component in Equation (7) does not seem to be a driver of the profitability of momentum strategies. However, some (e.g. Grundy and Martin, 2001, p.72) argue it might be possible that the right cross-sectional risk factors have not yet been detected and that the serial covariance in these factors is the main driver of momentum returns.

3.2.4. Momentum due to Serial Correlation in Industry Return Components

According to the decomposition of momentum profits in Equation (7), the third component is $\sum_{m=1}^{M} \sigma_{\theta_m}^2 Cov(z_{m,t-1}, z_{m,t})$ and represents serial covariance in industry return components. The work of Moskowitz and Grinblatt (1999) is the most important paper claiming that this component is the main driver of the individual momentum phenomenon. They show that for NYSE, AMEX and Nasdaq stocks between 1963 and 1995, an industry momentum strategy yields profits that are identical in magnitude compared to the profits of an individual momentum strategy[35]. Industry momentum returns are obtained by sorting 20 industry portfolios (in which stocks of the same industry are value weighted) according to their past six-month returns. The

[33] $Cov\left([R_m - R_f]_t, [R_m - R_f]_{t-1}\right) = -0.00008$, $Cov(SMB_t, SMB_{t-1}) = 0.00007$ and $Cov(HML_t, HML_{t-1}) = 0.00004$ and the serial correlation is -0.038 for the excess market portfolio, 0.102 for the SMB portfolio and 0.061 for the HML portfolio (Moskowitz and Grinblatt, 1999, p.1262).

[34] To be specific, the mentioned returns are consecutive nonoverlapping six-month returns.

[35] This individual momentum strategy ranks stocks based on their past six-month performance, buys the top 30 percent of stocks, and sells the bottom 30 percent of stocks. Assets are value-weighted and held for an investment period of six months. Moskowitz and Grinblatt (1999) follow Jegadeesh and Titman (1993) and use the "overlapping holding period" technique presented in Chapter 2.

strategy is long in the top three industries and short in the bottom three industries. Within the portfolio, industries are equally weighted.

The finding that industry momentum strategies are as profitable as individual momentum strategies does not necessarily mean that (industry and/or individual) momentum profits are driven by the third term in Equation (7) and might also be caused by the variation in expected returns across industries[36]. With a decomposition similar to that in Equation (5), Moskowitz and Grinblatt (1999) document that the cross-sectional variation in industry mean returns and the factor serial correlation is small which implies that the serial correlation in industry components does mainly contribute to industry momentum profits.

To exclude the possibility that the industry momentum effect is generated by individual stock momentum returns, Moskowitz and Grinblatt (1999) use the Daniel, Grinblatt, Titman, and Wermers (1997), henceforth DGTW, adjustments in order to show that industry momentum profits do exist after accounting for individual stock momentum profits: Individual stock returns are adjusted for size, book-to-market equity and for individual momentum profits. Whereas DGTW-adjusted profits are not significantly different from zero for individual stock returns, DGTW-industry momentum profits (measured using the DGTW-adjusted individual stock returns) are still significantly positive.[37]

To show that the third term of Equation 7 does also explain the profitability of individual momentum strategies, Moskowitz and Grinblatt (1999) analyze the contribution of the four potential sources to momentum profits according to the decomposition profits in Equation (7). Whereas Moskowitz and Grinblatt (1999) document that serial covariance in factor portfolios is almost zero and the dispersion in average mean returns[38] is negligible, the firm-specific component might also drive momentum profits. To show that the fourth component in Equation (8) is not the main determinant, Moskowitz and Grinblatt (1999) report industry-adjusted

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[36] Industry momentum returns cannot be caused by the firm-specific component (the last term of Equation 7) since well-diversified portfolios do not exhibit substantial firm-specific risk.

[37] DGTW-adjusted profits are only used for the investment period, but not for the formation period. To form portfolios, past *raw* returns are taken. Hence, the “winner” and “loser” stock selection remains the same.

[38] As mentioned earlier, in contrast to Equation (7), in the study of Moskowitz and Grinblatt (1999), mean returns are assumed constant over time.

individual stock momentum profits (that are also adjusted for size and BE/ME[39]), $R_{i,t}^{sb,I}$, that are defined as follows (Moskowitz and Grinblatt; 1999, Equation 15):

$$R_{i,t}^{sb,I} \equiv R_{i,t}^{sb} - R_{I,t}^{sb} \quad \text{for } i \in I \qquad (9)$$

where $R_{i,t}^{sb}$ is size and BE/ME characteristic-adjusted return of stock i (following Daniel and Titman, 1997) and $R_{I,t}^{sb}$ is the size- and book-to-market adjusted return on industry I. The size-, BE/ME-, and industry-adjusted profits generated by the individual momentum strategy can be written as (analogue to Moskowitz and Grinblatt 1999, Equation 16):[40]

$$\frac{1}{N}\sum_{i=1}^{N} E\left[\left(R_{i,t}^{sb} - R_{I,t}^{sb}\right)\left(R_{i,t-1} - \bar{R}_{t-1}\right)\right]$$
$$= \sum_{k=1}^{L} \sigma_{\beta_k}^2 Cov\left(f_{k,t-1}, f_{k,t}\right) + \frac{1}{N}\sum_{i=1}^{N} Cov\left(e_{i,t-1}, e_{i,t}\right) \qquad (10)$$

Moskowitz and Grinblatt (1999) find only negligible profits for the individual stock momentum strategy when returns are adjusted for size, BE/ME and industry effects.[41] Since the first term on the right hand side in Equation (10) is shown to be zero (see Moskowitz and Grinblatt, 1999, pp.1259 and Section 3.2.3), this finding indicates that $Cov\left(e_{i,t-1}, e_{i,t}\right)$ must also be zero. Hence, individual momentum seems to be primarily driven by the serial covariance in industry components.[42]

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[39] This is done to control for potential dispersion of mean returns across industries. Moskowitz and Grinblatt (1999) show that this adjustment does not significantly reduce individual momentum profits (pp.1263).

[40] Since the returns are size-, BE/ME-, and industry adjusted, the decomposition in Equation (10) does not include the first term of Equation (7) (the cross-sectional dispersion in mean returns) as well as the third term of Equation (7) (the serial covariance in industry components).

[41] Moskowitz and Grinblatt (1999) further examine this finding with Fama and MacBeth (1973) cross-sectional regressions and document that industry momentum strategies do capture the profits for individual stock momentum except for the 12-month-individual relative-strength strategies (see Moskowitz and Grinblatt 1999, pp.1278).

[42] This point is further examined by Moskowitz and Grinblatt (1999): They form “random” industry portfolios where each stock in industry I is replaced by another stock that had a similar past six-month performance. Momentum profits are nonexistent for these “random” industry portfolios. This is further evidence that individual stock momentum is mainly driven by industry

The theory of Moskowitz and Grinblatt (1999) is confronted with substantial opposition (Grundy and Martin, 2001, Chordia and Shivakumar, 2002 and Nijman et al., 2004). Grundy and Martin (2001, p.31) argue that the profits to industry momentum portfolios is due to an intra-industry lead-lag effect and that it is too early to conclude that *"the true industry [is] the important component behind momentum profits"* (Moskowitz and Grinblatt 1999, p.1268). They find that much of the observed industry momentum profit arises in the first month immediately following the formation period. In their study, industry momentum profits are compared to a value-weighted "random" industry strategy, which replaces each asset in industry *I* with another asset that has a similar past six-month performance. This method ensures that each "random" industry portfolio includes stocks from various industries, but has the same momentum attributes than the real industry momentum portfolio. Therefore, if momentum is only driven by industry components, the "random" industry portfolio should not exhibit any profits. Grundy and Martin (2001) use NYSE and AMEX stocks between 1963 and 1995 and focus on strategies with a six-month formation and a one-month investment period. Once included a one-month skip between the formation and investment period to control for short-term reversals, neither the industry momentum strategies nor the "random" industry strategies are profitable and the difference in the profits of the two strategies is insignificant. Yet, repeating these tests without a skip month, Grundy and Martin (2001) show that industry momentum portfolios yield significant returns whereas "random" industry ones do not and that the return difference between both a significantly different from zero. Thus, this implies that the returns in the month immediately following the formation period are crucial to determine whether the (value-weighted) industry momentum portfolio outperforms the "random" industry momentum portfolio.[43] Therefore, Grundy and Martin (2001) suppose that industry momentum profits are driven by lead-lag effects.

Moskowitz and Grinblatt (1999, p.1279) show that industry momentum profits are nearly unaffected by lead-lag effects measured by size, liquidity or microstructure effects[44]. Although Moskowitz and Grinblatt (1999) have to admit that momentum may be generated by other lead-

components. The importance of industry components for the profitability is also shown by forming industry-neutral portfolios (see Moskowitz and Grinblatt 1999, pp.1267).

[43] Grundy and Martin (2001) however have to admit that the real industry momentum portfolio significantly outperforms the "random" industry portfolio when equal-weighted strategies are compared. Yet, when equal-weighted, the "random industry" portfolio does exhibit significant returns in non-January month what is at odds with the theory that momentum is exclusively due to serial covariation in industry components.

[44] Moskowitz and Grinblatt (1999) refer to the working paper of Grundy and Martin from 1999, which was however not published before 2001 in the Review of Financial Studies.

lag relations than size, liquidity or microstructure effects, they do not view industry momentum to be a spurious finding (Moskowitz and Grinblatt, 1999, p.1279).

Chordia and Shivakumar (2002) also doubt the findings of Moskowitz and Grinblatt (1999) and claim that data mining is the reason for the profitability of industry momentum strategies. To examine whether individual momentum is subsumed by industry momentum returns, Chordia and Shivakumar (2002, pp.1007) follow Moskowitz and Grinblatt (1999) and calculate the difference between raw returns of individual stocks and their industry returns; these industry-adjusted stock returns are used to form momentum portfolios. Yet, in contrast to Moskowitz and Grinblatt (1999), Chordia and Shivakumar (2002) employ a different data sample and limit their tests to stocks that experienced more extreme returns during the formation period: While Moskowitz and Grinblatt (1999) include Nasdaq stocks in their sample and construct momentum portfolios that are long in the top 30 percent and short in the bottom 30 percent, Chordia and Shivakumar (2002) use only NYSE and AMEX stocks for their research and form portfolios that are long in the top decile and short in the bottom decile. The findings of Chordia and Shivakumar (2002) conflict the observations of Moskowitz and Grinblatt (1999): Between 1951 and 1994, momentum profits remain significantly positive even after adjusting for industry returns. This leads them to the conclusion that industry momentum and individual stock momentum are two distinct and independent phenomena.

Nijman et al. (2004) also do not support the hypothesis that intermediate-term stock price continuation is subsumed by industry momentum. For a data sample of European stocks between 1990 and 2000, they determine the influence of country, industry and individual momentum on the intermediate-term stock price continuation effect with the help of a portfolio-based regression technique.[45]

3.2.5. Momentum due to Serial Correlation in Firm-specific Components

With Grundy and Martin (2001) and Nijman et al. (2004), two papers view serial covariation in firm-specific components as the main determinant of the momentum effect since both studies fail to identify other (risk-related) sources. Grundy and Martin (2001) compare profits of a total return momentum strategy to two momentum strategies with different ranking criteria. Each strategy sorts stocks according to its specific ranking criterion and attributes the top decile of

[45] The study and the portfolio-based regression technique of Nijman et al. (2004) is presented in Subsection 3.2.5.

stocks to the winner portfolio and the bottom decile to the loser portfolio. The ranking period is between $t-7$ and $t-2$. The first alternate strategy is called the "factor related return momentum strategy". It sorts stocks based on an estimate of the factor components of the ranking period returns. The second alternate strategy is named the "stock-specific return momentum strategy" and sorts stocks according to an estimate, which is a component of the ranking period returns in excess of the three Fama-French (1993) factors.

To implement the two strategies, the parameters of the following variation of the Fama and French (1993) three-factor model have to be estimated. The following regression is undertaken for each investment month t and for each NYSE and AMEX stock i. It is conducted over a period between $\tau = \max(t-61, t - \text{first observation})$ and $\tau = t-2$ or over a time window of at least 36 months between $t-37$ and $t-2$ (Grundy and Martin 2001, p.64):

$$R_{i,\tau} = \alpha_{0,i} D_\tau + \alpha_{1,i}(1-D_\tau) + \beta_i R_{m,t} + s_i SMB_\tau + h_i HML_\tau + e_{i,\tau} \ , \qquad (12)$$

where

$$D_\tau = \begin{cases} 1, & \text{if } \tau \in \{t-7, \dots, t-2;\} \\ 0, & \text{otherwise,} \end{cases}$$

$r_{i,\tau}$ is the return on stock i in excess of the risk free rate, $r_{m,t}$ represents the excess return on the Fama-French market index in month τ, SMB_τ (Small minus Big) is the return on the size factor, and HML_τ (High minus Low) is the return on a distress factor. The "stock specific return momentum strategy" ranks stocks according to the estimate of $\alpha_{0,i}$ whereas the "factor-related return momentum strategy" chooses winner and loser stocks based on $\sum_{\tau=t-7}^{t-2}\left(\hat{\beta}_i R_{m,\tau} + \hat{s}_i SMB_\tau + \hat{h}_i HML_\tau\right)$. For their data sample between 1965 and 1995, Grundy and Martin (2001) find that the "stock-specific return strategy" generates marginally higher profits than the total return strategy and notably larger returns than the "factor related return strategy".

This finding leads Grundy and Martin (2001) to the conclusion that the profitability of the momentum effect is (at least in part) driven by momentum in the stock-specific component of returns.[46] Grundy and Martin (2001) define the "stock-specific component" as the component of returns that is not related to the Fama-French factor realization. However, this part might also include exposure to common factors not captured by the Fama-French model. To be more precise, this term should be called the "non-Fama-French-factor-related component of returns".

Like Grundy and Martin (2001), Nijman et al. (2004) also find empirical evidence that momentum is driven by idiosyncratic stock effects. Analyzing 1581 large European stocks between 1990 and 2000, they employ a portfolio-based regression technique in order to evaluate the influence of country, industry and individual momentum on the intermediate-term stock price continuation effect. Compared to the traditional methods, this technique has two major advantages: First, traditional sorting approaches might produce imprecise estimates when stocks are sorted based on numerous characteristics since they deliver many cells (portfolios) with only few observations. Therefore, results might be distorted by idiosyncratic firm effects. The portfolio-based regression technique, however, produces more precise results as it requires ranking on at most two dimensions even if a larger number of characteristics are investigated. This will become obvious in the light of the portfolio-based regression equation below. Secondly, more powerful and reliable tools are available for the regressions technique than for the traditional methods to compare the influence of different effects on the momentum effect. Using the double sort or the two-way sort, the relative importance of effects can only be measured by comparing the average returns of sorted portfolios. In contrast, for the regression technique, several widely used statistical methods are available and can be employed to compare the influence of effects on the momentum phenomenon.

Following this regression method, Nijman et al. (2004, p.475) distinguish country (COU), industry (IND) and individual stock (STOCK) momentum and use the following regression equation:

$$R_{t+1}^{p} = \alpha + \sum_{a=2}^{3} \beta_a^{COU} X_t^p(a,\cdot,\cdot) + \sum_{a=2}^{3} \beta_b^{IND} X_t^p(\cdot,b,\cdot) + \sum_{c=2}^{10} \beta_c^{STOCK} X_t^p(\cdot,\cdot,c) + \varepsilon_{t+1}^{p} \quad , \quad (13)$$

[46] Empirically, patterns in stock price reactions to firm-specific information are also documented in the work of Bernard (1992), Chan et al. (1996) and La Porta (1996).

where R_{t+1}^{p} is the expected return on portfolio p in period $t+1$. X_t^p denotes the holdings of portfolio p in a specific momentum portfolio. For example, $X_t^p(a,\cdot,\cdot)$ represents the share of stocks in portfolio p that is included in the country momentum portfolio a. There are three country-momentum portfolios (second term on the right-hand side), three industry momentum portfolios (third term) and ten individual momentum portfolios (forth term). The last term ε_{t+1}^{p} is assumed to be uncorrelated with the regressors by construction. α is the expected return on a reference portfolio in which stocks are included that are in the bottom country ($a = 1$), bottom industry ($b = 1$) and bottom individual stock ($c = 1$) momentum portfolio. The additional expected return of portfolio p for being in another momentum portfolio than the reference portfolio is captured in the parameters β^{COU}, β^{IND} and β^{STOCK}. With the estimated betas, one can determine the expected return of an *individual* stock being in specific momentum portfolios. For example, the expected return of a stock that is in the bottom country, bottom industry and bottom individual stock momentum portfolio yields a return of α. The expected return of a stock however, that is in the top country *and* the top industry *and* the top individual momentum portfolio consists of α plus the country winner return β_3^{COU} plus the industry winner return β_3^{IND} plus the individual winner return β_3^{STOCK}.

Using this portfolio-based regression technique, Nijman et al. (2004) find for their available dataset that the momentum phenomenon is primarily driven by individual momentum which accounts for about 55 percent ($\beta_{10}^{STOCK} = 0{,}55$), while industry momentum with about 30 percent ($\beta_3^{IND} = 0{,}31$) and country momentum with 10 percent ($\beta_3^{COU} = 0{,}12$) have only a weak effect. In order to ensure that these results are not driven by size and value effects, these are also included in the model, but the conclusion of Nijman et al.(2004) that industry and country effects do not explain momentum remains unchanged (Nijman et al., 2004, p.477). In summary, Nijman et al. (2004) view these results as evidence for idiosyncratic stock effects to be the driving force behind the momentum effect.

Chordia and Shivakumar (2002, pp.1016) however present evidence against the thesis that the momentum phenomenon is generated by serial covariation in the firm-specific returns. Using a simple return-generating process, they measure the serial correlation (ρ) in the firm-specific components of returns, but cannot find plausible estimates for ρ in their sample. Therefore, Chordia and Shivakumar (2002) consider it unlikely that the forth term in Equation (7) is the main driver of momentum profits. Lewellen (2004) also do not attribute momentum to firm-specific returns. They form size and B/M portfolios and document that these portfolios do exhibit momentum as strong as (and in some cases even stronger than) individual stock momentum or industry momentum. Since the size and B/M portfolios contain on average 350 stocks for the sample period 1941-1999, they can be considered as well diversified. Therefore, they conclude that these portfolios should not contain much idiosyncratic risk. As the returns of size and B/M portfolios reflect systematic risk, momentum seems not to be driven by firm-specific news (Lewellen, 2002, p.538).

3.2.6 Summary

In this section, attempts to explain the momentum phenomenon with the classical rational approach are presented. Based on a simple return-generating model, momentum profits are decomposed in four potential components (Equation 7) and the studies are classified into one of the four categories. It becomes clear that researchers have not yet come to an agreement about the main driver of relative-strength profits. Table 3 gives an overview about the main studies examining the relevance of the four components proposed by Equation (7) on the profitability of momentum strategies.

So far, attempts to explain the momentum phenomenon with risk factors have been made. However, this seems to be a “tremendously difficult task” (Nagel, 2001, p.1). Since this effort seems so unpromising “that asset pricing theories have mostly seen the task as simply one of deciding which sort of investor irrationality is at work” (Johnson, 2002, p.585). This field of explanation will be discussed in further detail in the next section.

Table 3

Overview of the Main Rational-based Studies

This table gives an overview about the papers finding support for or against one of the four potential components of momentum profits from Equation (7).

	First component $1/N\sum_{i=1}^{N}(\mu_{i,t-1}-\bar{\mu}_{t-1})(\mu_{i,t}-\bar{\mu}_t)$	**Second component** $\sum_{k=1}^{L}\sigma_{\beta_k}^2 Cov(f_{k,t-1}, f_{k,t})$.	**Third component** $\sum_{m=1}^{M}\sigma_{\theta_m}^2 Cov(z_{m,t-1}, z_{m,t})$	**Forth component** $1/N\sum_{i=1}^{N}Cov(e_{i,t-1}, e_{i,t})$
Support	Conrad/Kaul (1998) Berk et al. (1999) Chordia/Shivakumar (2002) Johnson et al. (2002) Avramov et al. (2007)		Moskowitz/Grinblatt (1999) O'Neal (2000) Swinkels (2002) Scowcroft/Sefton (2005): *(for large stocks)*	Conrad/Kaul (2001) Nijman et al. (2004) Scowcroft/Sefton (2005): *(for small stocks)*
Contradiction	Moskowitz/Grinblatt (1999) Jegdeesh/Titman (2001) Grundy/Martin (2001) Lewellen (2002) Griffin et al. (2003) Cooper et al. (2004)	Jegadeesh/Titman (1993) Moskowitz/Grinblatt (1999) Grundy/Martin (2001)	Chordia/Shivakumar (2002) Grundy/Martin (2001) Lewellen (2002) Nijman et al. (2004)	Chordia/Shivakumar (2002) Lewellen (2002)

3.3. Behavioral Explanation Attempts

3.3.1 Overview

In the traditional finance literature, there are no frictions and subjects are assumed Rationality first implies that agents update their beliefs in a correct manner according to the Bayes' law after the arrival of new information. Secondly, rationality means that, given their beliefs, agents make choices that are consistent with Savage's idea of Subjective Expected Utility (Barberis and Thaler, 2002, p.2). Within this framework, a stock's price is the discounted sum of expected cash flows, investors process all available information correctly when forming expectations and the discount rate is a preference specification that is normatively acceptable (Barberis and Thaler, 2002, p.3). This hypothesis that actual prices reflect fundamental values is called the Efficient Market Hypothesis (EMH). Under this theory, an investment strategy cannot yield an average return that exceeds the required compensation for risk.

The behavioral finance theory states that asset prices partially deviate from fundamental value and that these deviations are due to investors acting not fully rational. Supporters of this field argue that models in which not all agents are assumed rational might help to understand at least some financial phenomena. Hence, since agents are included in behavioral models that display human limitations and complications, the behavioral finance theory can be considered as a combination of psychology and economics (Mullainathan and Thaler, 2000, p.1). In other words, behavioral finance examines what happens when one or both assumptions of rationality are relaxed: whereas in some models, agents make choices that are not consistent with Subjective Expected Utility, other models include agents that do not adequately update their beliefs.[47]

The existing behavioral theories on stock price momentum only question the first implication of rationality and include (at least some) traders that do not correctly update their beliefs. It can be divided into two groups. The first one claims that the continuation effect is due to traders' initial underreaction to news whereas the second group of models posits that momentum is caused by traders' initial overreaction to news. However, the basic idea of all models is that investors do not correctly interpret and react to new information. The link between theses behavioral models and the observed price momentum effect is that extreme past returns indicate on the arrival of new information.

In the following subsections, it is shown that the behavioral literature has produced four different and contrasting main hypotheses why the momentum phenomenon exists. The first and the second hypothesis fall into the first group and view momentum as an initial underreaction phenomenon. The third hypothesis is related to the second group and predicts that momentum is generated by overreaction. The last behavioral hypothesis reconciles the underreaction and the overreaction idea of the two groups and states that momentum might *be either* an underreaction *or* an overreaction phenomenon. Whether it is the first or the last effect depends on the trading level. To the best of my knowledge, this sorting approach is new and first classifies the different behavioral approaches into different groups. These are presented in the following four subsections.

[47] For a general review about the stand of behavioral finance literature, see Fuller (2000), Hirschleifer (2001), Barberis and Thaler (2002) and Subrahmanyam (2008).

3.3.2. Momentum – An Initial Underreaction Phenomenon

The first behavioral hypothesis why stock price momentum strategies are profitable can be formulated as follows:

H1: Momentum is generated by an initial underreaction followed by a correction

Underreaction is defined by Barberis et al. (1998, pp.310) as follows: Suppose that in period t, an investor gets information about a stock, which is denoted with v_t. The news can be either good ($v_t = G$) or bad ($v_t = B$). Underreaction means that in time t, good (bad) news are not correctly incorporated into the stock price: Initially after the announcement of good (bad) news, the stock price increases (decreases) less than it should. This is corrected in $t + 1$ with a higher return (lower return) of the stock. In other words, in terms of stock performance in the period following the announcement ($t + 1$), underreaction is present if the average return of a stock in $t + 1$ is larger after the announcement of good news than the average return in $t + 1$ after the announcement of bad news:

$$E(R_{t+1}|v_t = G) > E(R_{t+1}|v_t = B) \qquad (14)$$

Barberis et al. (1998, p.1313) define overreaction in a similar but not analogue way. Overreaction means that the average return of a stock in $t + 1$ is smaller after the announcement of *a series* of good news than after the announcement of a *series* of bad news about the stock:

$$E\big(R_{t+1}\big|v_t = G, v_{t-1} = G, \dots, v_{t-j} = G\big) < E\big(R_{t+1}\big|v_t = B, v_{t-1} = B, \dots, v_{t-j} = B\big)\ , \qquad (15)$$

where j is at least one.

Barberis et al. (1998) contribute to the examination of the above hypothesis and present a model in which investors make systematic errors when they forecast future cash flows using public information. With conservatism and representativeness, two psychological phenomena are incorporated in the framework. Conservatism implies that individuals change their beliefs only very slowly after the arrival of new evidence (Edwards, 1968). For example in the light of good earnings announcements by a firm, conservatism means that the price of the firm rises too little since investors do not react sufficiently to the news. As Barberis' (1998) definition of underreaction in Equation (12) implies, the asset's price is then below its fundamental value which leads to higher subsequent returns and hence to price momentum.

The second psychological phenomenon included in the model is representativeness: "*A person who follows this heuristic evaluates the probability of an uncertain event, or a sample, by the degree to which it is (i) similar in its essential properties to the parent population, (ii) reflects the salient features of the process by which it is generated"* (Tversky and Kahneman, 1974, p.33). Although representativeness is often very helpful, it might generate two severe biases: base rate neglect and sample size neglect.[48] An important aspect of representativeness heuristic for the following model is that people observe patterns in sequences that are in fact purely random, a finding discussed in detail by Kahneman and Tversky (1974). This leads to overreaction as defined in Equation (15): When a firm has published good earnings for many periods, people might believe that the series of good earnings in the past is representative of an earnings growth potential in the future. While such a sequence of good earning news might be nothing more than a random draw that is unlikely to repeat itself again, people believe to see a pattern that will persist. Hence, they overestimate the growth potential and push the price of the firm too high. In the future, they will be disappointed when earnings do not grow as much as they have assumed what results in long-term reversals. According to Barberis et al. (1998, p.316), this is what overreaction is all about.

Barberis et al. (1998) include these psychological phenomena – conservatism and representativeness – in a model with a single representative investor that is risk neutral. Earnings are assumed to follow a random walk. This is not know by the investors who believes that, at any time, one of two regimes can predict future earnings: a "mean-reverting" state in which earnings revert to their mean and a "trending" state in which earnings trend, i.e., have a high probability to

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[48] To understand the bias base rate neglect, consider an experiment of Kahneman and Tversky (1974, p.1125): People get a detailed description of the personality of an individual, which is quite similar to the description of an individual belonging to a particular profession. When asked to estimate the probability that the person belongs to that profession, people significantly overestimated its probability in the experiment. Hence, while they overweight the representative description, they put too little weight on the base rate evidence that only a small number of people belong to that profession (see also Barberis and Thaler, 2002, p.13). The second bias induced by representativeness is sample size neglect. For instance, people might judge a financial analyst to be successful after he had recommended three stocks that generated high returns afterwards. Yet, it is obvious that a sample of three is not representative of a good or a bad analyst. A famous example for representativeness is the "hot hand" phenomenon: After a basketball player made three shots in a row, some sports fans believe that he will score again although data give no evidence for a hot hand (Gilovich et al., 1985).

rise further after an increase. The phenomenon of representativeness is included in the model through the "trending-regime" as it is assumed that the investor sees a trend in the earnings announcement sequence that in fact is random. The "mean-reverting" regime captures conservatism as the investor puts too little weight on the latest earnings announcement piece relative to its prior believe. Hence, after the arrival of good news, the investor believes that part of the shock will be reversed in the subsequent period. Having this in mind, she underreacts to new information as it is implied by conservatism. Given these two regimes, the investor thinks that the two regimes change exogenously and sees her task in learning whether earnings are generated by the first or the second regime.

In summary, Barberis et al. (1998) show that conservatism and the representativeness heuristic can generate momentum returns and long-term reversals.[49] Since in the model, momentum is due to traders' underreaction to news induced by conservatism, the work of Barberis et al. (1998) can be linked to behavioral hypothesis H1, which states that momentum is driven by initial underreaction and subsequent correction.

One might argue that it is not necessary to discuss representativeness heuristic and its influence on stock returns in this work as it leads to long-term reversals, which is not directly linked to momentum – the topic of this study. However, the model implies that intermediate-term momentum and long-term reversal are closely linked. Barberis et al. (1998) show that for a wide range of parameter values, both underreaction and overreaction is commonly present in the model. Whether momentum and long-term reversals are parts of the same phenomenon is heavily discussed in the literature (see Section 4 for further details).

Doukas and McKnight (2005)[50] find empirical support for the theory of Barberis et al. (1998) that investors exhibit conservatism and fail to update their beliefs adequately. In order to examine this psychological phenomenon empirically, Doukas and McKnight (2005) refer to another description of conservatism. According to Griffin and Tversky (1992), investors do not adequately take the "weight" of news into consideration: In an experiment, they show that people evaluate new information based on its strength (upward or downward changes that is implied by the new information) and on its weight (the credibility of the new information). In these terms,

[49] Barberis et al. (1998) also show that the two psychological phenomena can also generate post-earnings announcements and cross-sectional forecasting power for scaled-price ratios. However, this does only play a minor role for the topic of this work.
[50] The relevance of the Barberis et al. (1998) model is also examined for option markets: Poteshman (2001) finds evidence for such an expectation formation process presented by Barberis et al. (1998) in these markets.

conservatism means that people underreact to news with high weights (Barberis and Thaler, 2002, p.13-14). Based on this definition, Doukas and McKnight (2005) test whether investors underestimate high-weight news. As a proxy for weight of information, dispersion in analysts' earnings forecast is employed which reflects uncertainty about the future economic performance of a firm (Barron et al., 1998, p.422). Based on Griffin and Tversky's (1992) description of conservatism momentum profits should be larger for stocks with low analyst dispersion (and hence higher weight of information) as lower dispersion strengthens the credibility of analyst's earnings forecasts. Doukas and McKnight (2005) find evidence for the conjecture that momentum is the result of investors' psychological conservatism using a sample of 3,084 stocks for 13 European countries.

In the studies of Barberis et al. (1998) and Doukas and MacKnight (2005), a weakness of the behavioral finance approach becomes obvious: presenting empirical evidence for the theories and assumptions. It is difficult to provide empirical support for the behavioral patterns conservatism and representativeness heuristic on which the model of Barberis et al. (1998) builds on. First, a proxy such as dispersion in analysts' earnings forecast might not necessarily have a connection to the respective behavioral pattern and could stand for other effects than these phenomena as well (e.g. it might represent compensation for uncertainty or risk). Secondly, it is often the case that a variable employed to proxy a behavioral heuristic does not have the power to completely explain the existence of the momentum effect and capture at most only a part of its profits. For example, Doukas and MacKnight (2005) can only show that momentum strategies "work better" (p.337) for stocks with low analyst coverage than for all stocks.

Beside Barberis et al. (1998), with Hong and Stein (1999), a second important model exists that supports behavioral hypothesis H1. While Barberis et al. (1998) use a representative agent model in order to construct an asset-price continuation and reversal framework, Hong and Stein (1999) take a different approach and focus on heterogeneous traders that interact with one another. In this model, two types of agents are present: "news watchers" and "momentum traders". Each type is assumed boundedly rational and able to process only a part of the available public information: News watchers depend exclusively on private information whereas momentum traders solely consider past price changes for their trading activity. A second key assumption in the model is that news watchers learn about private information only gradually. It leads to a setting where news watchers underreact to private information. This attracts the second group of investors, momentum traders trying to exploit this underreaction effect with a simple arbitrage strategy. Their trading activity leads to an eventual overreaction to news. In the long run, prices revert to their fundamental levels. Consequently, in the model of Hong and Stein (1999), gradual diffusion of private information in combination with the inability of news watchers to get this information from prices leads to return continuation. As Barberis et al. (1998), Hong and Stein (1999) propose a model that considers intermediate-term momentum and long-term reversals to be part of the same phenomenon. This is especially doubted by studies supporting the behavioral hypothesis H3 (see below).

Three key implications can be extracted from this theoretical work. First, according to the model, intermediate-term momentum and long-term reversals should be stronger in stocks for which information diffusion takes place more slowly. Secondly, initially private news should cause a more long-run overreaction than public news announcements. Third, return autocorrelations and momentum traders' horizon should be related. The model proposes that the longer the trading horizon of momentum traders the longer autocorrelations need to switch from positive to negative.

The first implication of Hong and Stein's (1999) model is tested empirically by the work of Hong et al. (2000). They examine whether intermediate-term stock price momentum is in fact stronger in stocks for which information diffuses only slowly. Hong et al. (2000) chose two measures for information diffusion: Firm size and analyst coverage. They argue that firm size is a plausible variable for the speed of information diffusion as information get out more slowly for small stocks. This can be explained by investors having fixed costs of information acquisition. Therefore, they prefer to focus on larger stocks in which they can invest more. However, firm size also captures other things than the speed of information (see e.g. Merton, 1987, Grossmann and Miller, 1988). For example, market making might be thinner for stocks with lower market capitalization. Hence, supply shocks for smaller stocks could lead to a greater reversal tendency, which masks the slow information diffusion effect. Further, if arbitrage capacity is less in small-capitalization stocks, the importance of gradual information diffusion might be overstated since less arbitrage means that *any* behavioral driver of momentum has a stronger effect on smaller stocks. As a second measure for the rate of information diffusion, Hong et al. (2000) employ "analyst coverage". It is argued that it takes more time until firm specific information diffuse across the public if no or only few analysts report on a stock. To be precise, in order to have a purer proxy, their "analyst coverage" measure is controlled for size[51].

Their findings support the hypothesis. Hong et al. (2000) use a NYSE/AMEX sample between 1980 and 1996 and sort stocks independently by their past six month returns and by firm size. They show that apart from the very smallest stocks, a negative relationship exists between momentum returns and market capitalization. In a second set of tests, they check whether momentum strategies yield higher returns in low-analyst-coverage stocks. Therefore, stocks are sorted independently according to their six month past performance and based on their residual analyst coverage (measured six month before the start of the ranking period), where the residual is obtained from a regression of analyst coverage on firm size. Hong et al. (2000) find support for the hypothesis that analyst coverage has explanatory power on momentum profits as they observe roughly 60% higher momentum returns for the one-third of stocks with the lowest analyst coverage. Moreover, the large momentum effect for small stocks and for stocks with low analyst-coverage is mainly driven by loser stocks. This finding represents a further evidence for their hypothesis that the momentum effect is larger in stocks with slow information diffusion: When firms can publish good news, they have the incentive to report them as quickly as possible. In contrast, firm managers are not willing to diffuse bad news at once, so outside analysts play a more important role in publishing negative information.

Beside Hong et al. (2000), other studies support the hypothesis implemented by Hong and Stein (1999): Doukas and McKnight (2005) chose a similar approach as Hong et al. (2000) and test Hong and Stein's (1999) theory for 13 European markets between 1988 and 2001. Like Hong and Stein (2000), they document that gradual diffusion of private information explains momentum returns. The work of Chan et al. (1996) gives some evidence that momentum strategies yield abnormal returns even after controlling for post earnings announcement drifts. This suggests that momentum is at least in part driven by information that is – unlike earnings news – not made publicly available to all at once.

In summary, Barberis et al. (1998) show in a model that momentum and long-term reversals are driven by two updating biases - conservatism and representativeness – whereas Hong and Stein (1999) argue that gradual diffusion of private information generates momentum and reversals.

[51] This proxy also might be endogenously related to other stock-specific factors apart from size. The correlation between analyst coverage and share turnover, industry factors, beta and market-to-book is controlled for in various sensitivity tests.

Both theoretical studies consider initial underreaction to be the driver of the momentum effect and see a link between intermediate-term price momentum and long-term reversals.

3.3.3. Momentum – A Conditional Underreaction Phenomenon

The second behavioral hypothesis can be defined as follows:

H2: Momentum is due to underreaction, which depends on a specific level

H2 considerably differs from hypothesis H1 stating that momentum is generated by an initial underreaction followed by a correction. While the behavioral hypothesis H1 states that momentum is caused by underreaction and by a subsequent overreaction that amplifies the continuation effect, hypothesis H2 posits that momentum and reversals are distinct phenomena. Further, while hypothesis H1 assumes that momentum arises due to initial underreaction to news, hypothesis H2 refines this point and states that the degree of underreaction varies with a specific level. Either this level can be a price level such as in Grinblatt and Han (2002) and George and Hwang (2004) or it can be a non-price level such as in Zhang (2006). While Grinblatt and Han (2002) relate the degree of underreaction to the acquisition price and while George and Hwang (2004) present a connection between the degree of underreaction to the 52-week high price of a stock, Zhang et al. (2006) document a relationship between the degree of underreaction and the level of uncertainty about the impact of news on the stock price.

In the study of George and Hwang (2004), the behavioral explanation behind the hypothesis that the degree of underreaction (and hence momentum) is linked to a price level is the "adjustment and anchoring bias" (Kahneman and Tversky, 1974, p.1128-1130)[52] and relates to the way subjects form estimates. When people estimate a value, they often begin with an initial value that might be derived arbitrarily and then correct it. Kahneman and Tversky show that this correction is insufficient. The study of George and Hwang (2004) builds on this finding and hypothesizes that subjects use the 52-week high price of a stock (the highest price of a stock within the past 52 weeks) as an "anchor" when estimating the potential impact of news about a firm on the stock price. This piece of information can be assumed to be an anchor as it is publicly available since it is regularly published in many newspapers reporting on stocks. When a stock is at or near its 52-week high price and additional good news arrives, investors strongly underreact to this

[52] Evidence for the existence of the anchoring bias is also found by Ginsburg and van Ours (2003).

information and are unwilling to push the price higher. As the news eventually prevails, the price slowly rises towards the stock's fundamental value and momentum arises. Similarly, when the stock price is far from its 52-week high, and additional bad news arrive, investors are not prepared to sell the stock at a price as low as the news suggest and underreact as well. Since the bad news remains present, the price slowly declines and induces momentum. If however the stock trades at a price neither near nor far from the 52-week high price, investors adapt their beliefs quickly, which does not lead to an underreaction and hence to a momentum effect for those stocks. In other words, the unwillingness of traders to revise their beliefs depends on a price level: near and far from the 52-week high the unwillingness is greatest.

George and Hwang (2004) implement a strategy that takes a long position in the 30 percent of stocks whose current price is closest to the 52-week high and is short in the 30 percent of stocks whose current market price is furthest from the 52-week high. The nearness of the current stock price to its 52-week high is measured based on $P_{i,t-1}/high_{i,t-1}$ where $high_{i,t-1}$ is the highest price of stock i over the last 12 months between $t-13$ and $t-1$ and $P_{i,t-1}$ is the stock's price at the end of month $t-1$. George and Hwang (2004) compare the returns of this strategy to Jegadeesh and Titman's (1993) momentum strategy and to Moskowitz and Grinblatt's (1999) industry momentum strategy.[53] For the CRSP sample between 1963 and 2001, George and Hwang (2004) measure the returns generated by theses three strategies over an investment period of 6 and 12 months. Using a two-way sort, George and Hwang (2004) show that the 52-week high strategy dominates the momentum and the industry momentum strategy.

The theoretical and empirical findings of Grinblatt and Han (2002) are also in line with the behavioral hypothesis H2. In their model, two types of investors trade and determine the market price of a risky stock. The first group of investors is assumed rational with a price elastic demand function while the second group of investors has a greater tendency to sell stocks in which they have a paper gain than to sell stocks in which they have lost money. This behavioral phenomenon is called "the disposition effect" (Shefrin and Statman, 1985) and leads to an (excess) demand function of "disposition" investors that depends negatively on imbedded capital gains, which in turn affects market prices. Disposition investors are less prepared to sell a stock

[53] Momentum and industry momentum strategies have a raking period of six months. Two different approaches are used to compare the three strategies. Both lead to similar results. First, George and Hwang (2004) conduct pairwise nested comparisons (a conditional sort): Stocks are ranked according to one criterion in a winner, middle and loser portfolios. Within each portfolio, stocks are ranked according to another criterion. If the first criterion is good at prediction, the second criterion should not yield significant returns. As a second approach, George and Hwang (2004) use Fama-MacBeth (1973) style cross-sectional regressions that allow comparing all three strategies simultaneously.

with a paper loss leading to a larger excess demand. However, they have a higher tendency to sell stocks with a paper gain, which means a lower excess demand because of the selling pressure. Grinblatt and Han (2002) test their hypothesis empirically for all ordinary common NYSE and AMEX stocks between 1962 and 1996 and find support that the disposition effect is the driving force of momentum returns: It is shown that a variable called “capital gains overhang” largely explains price continuation. This variable measures the difference between the market price and the acquisition price.

Consistent with George and Hwang (2004), Grinblatt and Han (2002) show that there is a greater predictability of future prices for stocks with a price near and far from a long-term high. Both do also agree that this is due to a reference point, which traders take into consideration when making their trading choices. This “anchor” is however different in the two studies. George and Hwang (2004) consider the 52-week high as the reference point against which investors evaluate the impact of news. Grinblatt and Han (2002, p.12) in contrast propose that the acquisition price serves as an “anchor”. In their model, stocks with a price close or far from the long-term high price (e.g. the 52-week high) show a stronger momentum behavior, which is consistent with George and Hwang (2004). The idea behind this proposition is that “disposition” investors have a lower excess demand function for stocks that trades at or close to a long-term high as many investors acquired the stocks for a lower price. If (further) goods news arrives, it is not fully incorporated in the stock price at once as the demand of disposition investors is lower or since the selling pressure of disposition investors is larger than it would be in rational market. As the stock price eventually reverts to its fundamental, it will rise further and generate momentum. A similar effect is observed when stock prices are at their long-term low.[54]

George and Hwang (2004) evaluate both proposed “anchors” and empirically compare their 52-week high strategy with the method of Grinblatt and Han (2002). For their data sample, they show that although Grinblatt and Han’s ranking criterion predicts significant returns, it is clearly dominated by the 52-week high strategy (George and Hwang, 2004, pp.2162).

An important implication of the behavioral hypothesis H2 is that the momentum effect and long-term reversals are distinct phenomena. This is captured in the work of Grinblatt and Han (2002)

[54] If stock prices are below the investors’ acquisition prices, “disposition” investors have a higher excess demand function compared to investors in a fully rational market since their propensity to sell the stock is very low. Therefore, the stock price decline will understate the full impact of bad news. As the stock prices decline further and eventually converge to the fundamental value, momentum is generated.

and George and Hwang (2004). The latter study documents that long-term reversals do not occur when stocks are ranked based on the nearness to their 52-week high and based on the acquisition price as proposed by Grinblatt and Han (2002). In the literature, long-term reversals are often viewed as evidence for intermediate-term overreaction, which is corrected over the longer term. The finding of George and Hwang (2004) indicates that momentum profits are explained solely due to underreaction and not by a combination of underreaction and a subsequent overreaction. This finding puts into question the theoretical approaches of Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999) suggesting that intermediate-term momentum and long-term reversals are components of the same phenomenon. According to the results of George and Hwang (2004) and Grinblatt and Han (2002) momentum and long-term reversals are distinct phenomena for which separate models should be implemented.

The behavioral hypothesis H2 also leaves the door open for an underreaction story that depends on a level that is not related to a price. Zhang (2006) argues that intermediate-term stock price momentum is an underreaction effect that depends on the degree of uncertainty. The main hypothesis builds on the idea that stock investors underreact to new information since they suffer from behavioral biases (e.g. Chan et al., 1996, Barberis et al., 1998, Hong and Stein, 1998)[55]. According to the psychology literature, behavioral biases are larger when uncertainty is high. Based on this insight, Zhang examines whether information uncertainty increases the predictability of future expected stock returns: Following good (bad) news, expected stock returns are higher (lower) when uncertainty about the impact of new information on stock value is greater. To link this idea to the momentum phenomenon, Zhang argues that past losers imply bad news and past winners imply good news. As momentum strategies are long in winner and short in loser stocks, its profits are expected to increase in information uncertainty. Zhang (2006) uses six different measures for information uncertainty. First, firm size is employed since smaller firms are generally less diversified than larger ones and since it is expected that less information is available for smaller firms. A second proxy is firm age since more information is available for companies with a longer firm history. Thirdly, analyst coverage is included as a proxy for information uncertainty as analysts collect and distribute firm information to investors. The fourth proxy is dispersion in analyst earnings forecast, the fifth one is stock volatility and the

[55] Zhang (2006, p.109) classifies momentum as an underreaction story. Therefore, this work represents a further evidence for the underreaction hypothesis. Yet, Zhang et al. (2006) can also be linked to the model of Daniel et al. (1998, 2001) that sees overreaction as the main determinant of the momentum effect. According to Daniel et al. (1998, 2001) and the finding of Hirshleifer (2001, p.1575), greater uncertainty about the impact of news on stock value leaves more room for psychological biases such as investors' overconfidence in private information: Firms with greater uncertainty lead investors to be more overconfident what increases return predictability.

final measure is cash flow volatility. To test the hypothesis for NYSE, AMEX and Nasdaq stocks between 1983 and 2001, Zhang conducts a two-way nonindependent sort by the type of news and by an information uncertainty proxy. For all six measures, evidence for the hypothesis is found in the data: Greater information uncertainty leads to higher expected returns following goods news and lower expected returns after bad news have arrived.

The studies of Grinblatt and Han (2002), Hwang and George (2004) and Zhang (2006) have in common to show that momentum profits are an underreaction phenomenon of which the intensity depends on a specific level. Hwang and George (2004) measure this level as the distance to the 52-week high, an easily available piece of information, Grinblatt and Han (2002) view the acquisition price of the stock as the relevant level while Zhang (2006) argues that it is information uncertainty that influences the intensity of underreaction.

3.3.4. Momentum – An Initial Overreaction Phenomenon

According to the behavioral hypotheses H1 and H2, momentum is due to traders' underreaction to new information. In contrast, behavioral hypothesis H3 states that the momentum phenomenon is an overreaction effect:

H3: Momentum is generated by initial overreaction followed by even more overreaction

It is supported by the theoretical studies of Daniel et al. (1998) and DeLong et al. (1990). While the model of Barberis et al. (1998) relies on conservatism and representativeness, Daniel et al. (1998) propose two other patterns from psychology as explanation for the momentum effect and long-term reversals: overconfidence[56] and self-attribution bias. In general, overconfidence means that people overestimate their judgment – especially when they have to estimate quantities and probabilities (see e.g. Barberis and Thaler, 2002, p.12). DeBondt and Thaler (1995, p.793) state, *"perhaps the most robust finding in the psychology of judgment is that people are overconfident"*. In this context, investors are overconfident about their ability to generate and analyze information. Investors and analysts can get information for trading through various channels such as analyzing financial statements, interpreting rumors and listening to the

[56] Overconfidence is also used as an explanation for other phenomena: It is argued that overconfidence can explain the observed excessive trading volume puzzle (see e.g. the model of Gervais and Odean, 2001, Hirshleifer and Luo, 2001, Scheinkman and Xiong, 2003, Chuang and Lee, 2006). Moreover, overconfidence is employed to show that stock prices are more volatile than they should be according to the efficient market hypothesis (e.g. Shiller, 1981, Campbell and Cochrane, 1999, Gervais and Odean, 2001, Chuang and Lee, 2006).

management. This research can be done with different levels of skill. If investors overestimate their ability in doing that, they will underestimate forecast errors and overestimate the precision of their private information (in contrast to the precision of public information, which are not overestimated). When a positive private signal arrives at the investors, they will overweight this information and push the stock price too high compared to the fundamental value. With the arrival of public information, the deviation of the price from its fundamental value is slowly corrected. Daniel et al. (1998) show that this overreaction-correction framework is consistent with long-run reversals.

To get a post-earnings effect and a momentum effect, a second psychological phenomenon is included in the model: the self-attribution bias. According to the attribution theory (Bem, 1965), people tend to attribute the success of their actions to their ability and the failure of their actions to sabotage or bad luck. In the model, an investor trades based on her private information. Afterwards public information arrives. If it confirms the private signal, the investor's confidence rises, if it does not, she gives les attention to the public information and her confidence falls only modestly, if at all. Hence, biased self-attribution implies that overconfidence is on average succeeded by even more severe overconfidence. This continuing overreaction leads to momentum, but after the gradual arrival of public information, the stock price reverses to its fundamental value. In summary, Daniel et al. (1998) show that overconfidence and biased self-attribution cause momentum profits and long-term reversals.

The idea that momentum and reversals are generated by overconfidence and biased self-attribution is tested in the paper of Cooper et al. (2004), where the theory of Daniel et al. (1998) is extended. It is assumed that following market gains, aggregate overconfidence increases. This is quite intuitive since keeping the self-attribution bias in mind, investors attribute gains in their portfolios more than they should to their own ability. Therefore, during periods in which the overall market has increased, investors are likely to make profits what induces them to become increasingly self-confident. Hence, according to this idea, overconfidence is larger following market increases. Thus, the profits of momentum strategies are expected to depend on market states and should be higher following positive market returns than following negative market returns. In general, the literature does not agree whether momentum depends on the market state (see Section 3.2 or Griffin et al., 2003, Avramov, 2006 and Avramov, 2007). The findings of Cooper et al. (2004, pp.1359) indicate that the relationship between lagged market returns and momentum profits is inverted u-shaped. While the profitability of momentum considerably increases from the lowest level of lagged market returns, it peaks at the median levels and diminishes for larger market return levels. Two explanations are offered for this nonlinear relationship. First, highest lagged market returns might indicate the end of the overreaction phase and the beginning of reversals. Secondly, in extreme levels of the market's performance, investors are not able to get that much private information to which they can overreact (Cooper et al., 2004, pp.1360).

Beside the work of Daniel et al. (1998), with DeLong et al. (1990) another central model exists that presents evidence for the overreaction hypothesis H3. The study proposes a framework in which the presence of positive feedback traders causes momentum and long-term reversals. Positive feedback traders are investors who buy more of a stock that has recently increased in value.[57] If the price of a stock goes up this period due to good news, positive feedback traders buy the asset in the subsequent period. This leads to momentum and post-earnings announcement. Yet, since the stock price has increased more than it shall according to the news, the return will be lower on average in the following periods and therefore generate long-term reversals. Several explanations exist why investors might be positive feedback traders. First, it might be the case since investors extrapolate expectations and use past returns to form expectations about the future value of an asset (Barberis and Thaler 2002, p.40). This behavior is called representativeness, which is presented in more detail in Section 3.3.1.. While Long et al. (1990) uses this behavior to explain why investors extrapolate *past returns* too far into the future, it is employed by Barberis et al. (1998) to show that investors extrapolate *past cash flows* too far into the future. Second, positive feedback trading can also be exhibited by institutional features such as investors being unable to meet margin calls or buyers of portfolio insurance (DeLong et al., 1990, p.379).

In their model, DeLong et al. (1990) consider four periods with only two assets: a stock and cash. Investors trade with each other and determine the price of the stock in each period. The stock is liquidated in the last period and pays a risky dividend that consists of a first part, which is not released before the end of the last period, and a second part, which becomes public in period 2. A signal about the second part of the final dividend, that is either noiseless or imperfectly informative, is released to informed traders in period 1. Beside the informed rational investors, two other types of speculators are included in the model, passive investors and positive

[57]Evidence for the tendency of traders to be trend chasing comes from the experimental study of Andreassen and Kraus (1988) and from empirical work e.g. Case and Shiller (1988) and Frankel and Froot's (1988).

feedback traders: It is assumed that passive investors trade solely based on the price relative to the fundamental value while positive feedback traders buy stocks when the price of the asset has risen (when the price change between the former and the present period was positive) and sell when the price have gone down (when the price change between the former and the present period was negative). In this framework, rational investors destabilize the stock price in the presence of feedback traders. When in period 1, rational investors obtain a positive signal about the stock's fundamental value (that is not published to the uninformed and the feedback trader), they anticipate that the initial price increase subsequently leads to purchases by the feedback traders. In anticipation of this, informed traders acquire more stocks after the release of the signal and drive the stock price higher than its fundamental value. In the subsequent period, these rational investors stabilize the price now by selling the stock with a profit. Yet, the stock price remains higher than the fundamental value since feedback traders buy the stock in response to the former price increase. Hence, according to the theory of DeLong et al. (1990), overreaction arises due to the anticipatory trades by rational investors and the response of positive feedback speculators to such trades. The model predicts that stock price reverses to their fundamental values in the long run.

3.3.5. Momentum – An Underreaction and an Overreaction Phenomenon

The forth behavioral hypothesis states that:

H4: Momentum is an overreaction *and* an underreaction phenomenon. Whether it is the one or the other phenomenon depends on trading volume.

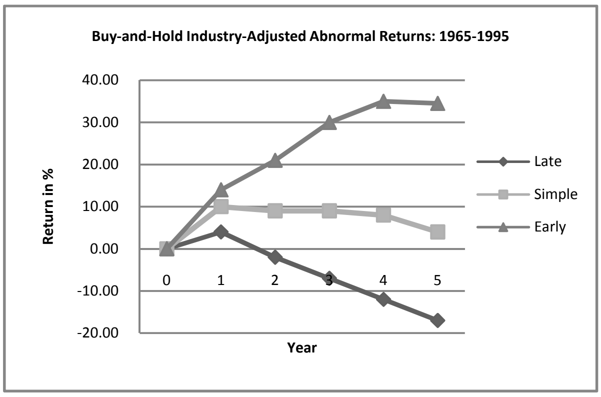
This hypothesis reconciles the overreaction idea (see behavioral hypothesis H3) with the initial underreaction theory (see behavioral hypothesis H1 and H2). According to the finding of Lee and Swaminathan (2002), it depends on trading volume whether momentum can be considered an overreaction or an underreaction effect. For NYSE and AMEX stocks between 1965 and 1995, Lee and Swaminathan (2002) find that low trading volume stocks outperform stocks with a high trading volume. Low trading volume losers experience larger returns than high trading volume losers for a five-year period following the portfolio formation date and low trading volume winners outperform high trading volume winners in the years 2 to 5 after the portfolio formation. In addition, in the five-year period after the portfolio formation data, low volume losers and high volume winners are more likely to experience price reversals whereas price momentum is more pronounced among high volume winners and low volume losers. These findings propose two volume-based momentum strategies. The first one is long low volume winners and short high volume losers. Lee and Swaminathan (2002, p.2039) call this strategy an "early-stage" strategy to indicate that these portfolios experience momentum returns over a longer period. The second volume-based strategy is named the "late-stage" momentum strategy that involves buying high volume winners and selling low volume loser stocks. It is called "late-stage" since price momentum in these stocks exhibits faster reversals.

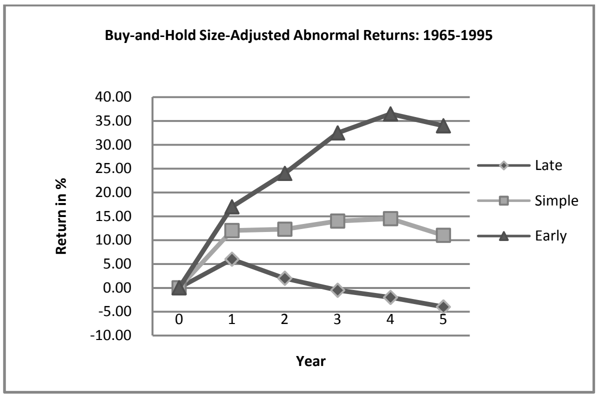
Figure 2 shows the buy-and-hold long-term profits to these two strategies and to the simple strategy that is long in past winners and short in past losers. On the left hand side, returns are industry-adjusted and on the right hand side, returns are size-adjusted.

Figure 2

Buy-and-Hold Abnormal Returns

The figure shows the buy-and-Hold abnormal returns for all NYSE and AMEX listed firms during 1965 and 1995. On the left hand side, returns are industry-adjusted, on the right hand side, abnormal returns are size-adjusted. See Figure 1 and Figure 2 in the work of Lee and Swaminathan (2000, pp.2044).





The "early-stage" strategy generates positive returns for three to five years without any reversal pattern. Based on this strategy, momentum is due to investors' underreaction to new information. However, according to the "late-stage" strategy, momentum seems to be an overreaction phenomenon, as returns turn negative after one year. Hence, the two graphs show that whether momentum returns are linked to underreaction or to overreaction depends on trading volume.

3.2.6. Critical Notes on the Behavioral Finance Approach

The behavioral finance literature is far from a consensus about the drivers of momentum and there are substantially different explanations attempts within this field of research. A similar empirical finding is considered consistent with different theories. The studies of Doukas and McKnight (2005) and Zhang (2006) report higher momentum returns when the strategy is limited to stocks with high dispersion in analyst earnings forecast. Doukas and McKnight (2005) view this as evidence for conservatism being the driver of the momentum effect. This would be in line with the theoretical model of Barberis et al. (1998) and the behavioral hypothesis H1. Zhang (2006) views dispersion in analyst earnings forecast as a proxy for information uncertainty and presents support for the behavioral hypothesis H2.

Moreover, some behavioral models use the same assumptions about the behavior of traders but come to different conclusions why the momentum effect exists. The models of Daniel et al. (1998), Long et al. (1999) (see hypothesis H3) and Barberis et al. (1998) (see hypothesis H1) consider the same psychological phenomenon – representativeness – in their models. While the first two models document that the momentum effect is an overreaction phenomenon, the latter links it to investors' underreaction behavior.

A further problem of the behavioral finance field is the difficulty to find empirical evidence for theoretical proposals since it is hard to document a behavioral pattern in stock prices. Variables that are employed as proxies for a specific behavior can often be used as proxies for other psychological heuristics or they can be linked to risk. While some assumptions of behavioral models might appear intuitive, *"we should be skeptical of theories based on behavior that is undocumented empirically"* (Barberis and Thaler, 2002, p.61).

Furthermore, it needs to be questioned whether the behavioral finance literature has indeed provided evidence against market efficiency so far (Fama, 1998). Currently, the behavioral finance literature searches for anomalies, shows that these are due to an incorrect reaction to information and conclude that this challenges the assumption that the response of prices to a new piece of information is short-lived. This is problematic since the behavioral finance literature explains some of the patterns with overreaction behavior while others are considered an underreaction phenomenon. As underreaction is used as explanation roughly as often as overreaction (Fama, 1998, p.284), Fama views this as strong evidence for the *efficiency* of markets, since in an efficient market, overreaction should be about as present as underreaction. Hence, in the eyes of Fama (1998), the behavioral finance literature can only seriously question the Efficient Market Hypothesis, if only one pattern is mentioned as explanations for the existing anomalies.

The behavioral finance approach is further criticized for not settling an alternative to market efficiency (Fama, 1998, p.284). The alternative hypothesis of most studies is simply “market inefficiency”. Fama (1998) states that market efficiency is like all models only a imperfect description of price formation and can only be replaced by a better theory, which itself can be tested empirically. Such a model has not yet been proposed by the behavioral finance literature and one might get the impression that the goal is to rather destructive by find evidence against the efficiency hypothesis instead of providing support for a new theory.

4 Comparison between the Rational and Behavioral Approach

Neither the rational approach nor the behavioral proposals so far have succeeded in undoubtedly identifying the driver(s) of intermediate-term stock price momentum. The main difference between the two groups is the assumption of the behavior of subjects. While the rational approach relies on the assumption that agents are rational, researchers of the behavioral finance literature depart from it and believe that only theories where at least some traders are assumed to be non-rational have the power to explain the profitability of momentum strategies.

How problematic it is to find support for the one or the other field can be seen in the fact that some empirical findings are considered as evidence by both approaches. For example, it is documented in the literature that small stocks experience greater momentum than larger stocks (see e.g. Jegadeesh and Titman, 1993, p.78). While supporters of the rational-based theory argue that firm size is a risk factor of special hedging concern to investors (see e.g. Fama and French, 1993, p.8), researchers that favor the behavioral idea consider firm size as a proxy for slow information diffusion (see Hong and Stein, 1999, Hong et al., 2000) or as a measure for information uncertainty that increases behavioral biases (Zhang, 2006). Another example for a different interpretation of the same finding is the relationship between momentum returns and the state of the economy: Griffin et al. (2003, p.2536) view positive momentum returns in good states and negative returns in bad market states as evidence for macroeconomic risk being the driver of the momentum phenomenon. In contrast, Cooper et al. (2004) consider such a relationship being consistent with the behavioral proposals of Daniel et al. (1998) and Hong and Stein (1999) (see Section 3.3.2). Furthermore, the finding that momentum strategies are profitable on industry levels and the potential ability of macroeconomic variables to predict stock returns can be linked to both theories (Moskowitz and Grinblatt, 1999, pp.1250, Chordia and Shivakumar, 2002, pp. 1014).

Moreover, in cases where the rational-based and the behavioral theory predict diametrical different patterns, the literature does not agree about the correctness of the empirical findings. While some behavioral models theoretically show that intermediate-term momentum and long-term reversals are components of the same phenomenon, the rational proposal of Konrad and Kaul (1998) predicts that the success of winner stocks is determined by high unconditional expected rates of return that remains unchanged over time. This implies that momentum profits should not reverse in the long run and that stocks in the winner portfolios should outperform momentum loser stocks in any postranking period. Among others[58], Jegadeesh and Titman (2001, pp.707) measure negative postholding period returns of momentum portfolios, but warn the reader to interpret this finding with caution for several reasons. First, whether postholding period returns of the momentum portfolio are negative seems to depend on the sample period. While they find long-term reversals for NYSE, AMEX and Nasdaq stocks in the 1965 to 1981 subperiod, there is less evidence for its existence in the 1982 to 1998 period. Secondly, the composition of the sample has influence on the findings: According to Jegadeesh and Titman (2001, p.718), smaller stocks seem to experience stronger postholding return reversals. Finally, evidence for long-term reversals depends on whether returns are risk-adjusted or not. Since it seems to be controversial whether momentum and long-term reversals are connected, the present stand of research does not allow finding evidence for the one or the other theory.

In summary, neither the behavioral nor the rational-based approach has so far succeeded in solving the momentum puzzle. Moreover, researchers of both theories have also not yet succeeded in rejecting the hypotheses of the other side.

5 Conclusion

The stock price momentum effect states that past winner stocks continue to outperform past loser stocks. This is shown by Jegadeesh and Titman (1993) documenting that a strategy long in stocks with the highest past 3-12month buy-and hold returns and short in stocks with the worst performance during that period yield significant positive returns within the next 3-12 months. Its

[58] See e.g. DeBondt and Thaler (1985, pp.799), Jegadeesh and Titman (1993, pp.83), Lee and Swaminathan (2000, pp.2026), Cooper et al. (2004, pp.1352).

profits cannot be explained by the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) and by the three-factor model of Fama and French (1993). This has induced a large body of empirical and theoretical literature that focuses on the cause of the profitability of momentum strategies. The approaches can mainly be subdivided into three broad groups: data mining, risk-explanations and behavioral explanation attempts. As I show, there is substantial evidence for the existence of the momentum effect: for different markets, different samples, different measurement methods and over varying time periods, past winner stocks seem to outperform past loser stocks. Simple strategies that buy past winners and sell past losers appear to be profitable both statistically and economically. Therefore, data mining and measurement errors seem to be unlikely.

Further, this work presents potential explanations for the momentum effect from the rational perspective and from the behavioral standpoint. The various risk-based explanations are structured by employing a theoretical decomposition of momentum returns. It becomes clear that the literature finds evidence for and against each of the four potential rational components. The behavioral ideas are classified into four broad categories. To the best of my knowledge, this classification does not exist in literature so far. Neither supporters of the rational idea nor behaviorists have yet found a convincing explanation for the existence of intermediate-term stock price momentum. Furthermore, they have not yet managed to refute the proposals of the opponent group. Hence, the evidence on momentum stands out as a major unresolved puzzle and further research is necessary to identify the driver of this phenomenon. This is especially important for the validity of the Efficient Market Hypothesis. If researchers succeed in identifying one or more risk factors that explain momentum profits, this effect is not in conflict with market efficiency as abnormal momentum returns can be viewed as compensation for risk. If however, it is shown that momentum is driven by traders acting non-rationally, this phenomenon presents a serious challenge to the Efficient Market Hypothesis.

Part II

Can Stock Price Momentum be Explained by Anchoring?

1. Introduction

This part of my thesis can be assigned to the behavioral field and tests whether anchoring, a specific form of non-rational behavior, can explain the momentum effect. It builds on the work of George and Hwang (2004). They hypothesize that momentum can be explained by a strategy that uses the nearness of a stock's price to its 52-week high price as a ranking criterion. Stocks that are at or near their 52-week high price are included in the winner portfolio while stocks with a price far from the highest price within the last one year are assigned to the loser portfolio. George and Hwang assume that the profitability of the 52-week high strategy is caused by "anchoring", a type of non-rational [59] behavior that describes the way people make estimations. Tversky and Kahneman (1982, pp.1128) argue that subjects focus too much on a reference point when forming estimates. Applying the anchoring phenomenon to the 52-week high strategy, investors estimate the impact of news on the stock price and therefore use the 52-week high price of a stock as reference point – an easily "accessible piece of information" (George and Hwang, 2004, p.2146) as it is published in nearly all newspapers reporting on stocks. If good news has pushed a stock to or close to its 52-week high price, investors are not prepared to bid the price higher even if the information warrants it. Since the information is not completely incorporated in the stock price at once, the price subsequently increases which results in continuation. Similarly, when bad news has pushed the stock price to a level far from its 52-week high, investors are also unwilling to sell the stock for a price as low as it should be based on the bad news. Subsequently, the news is incorporated in the stock price, which results in a decrease. Hence, investors are unwilling to immediately revise their beliefs. This unwillingness is largest for stocks close to or far from the 52-week high. For stocks that are traded neither close nor far from their 52-week high, news is faster incorporated into the stock price, which does not result in any observable predictability.

This work examines the assumption of George and Hwang (2004) that anchoring is the driver of momentum profits. Therefore, it needs to be tested whether first, the 52-week high strategy dominates the momentum strategy, and secondly, whether anchoring qualifies as explanation for the 52-week high profits. This is illustrated in the very simply graphic of Figure 3. In short, this work tests whether anchoring can explain (indirectly through the 52-week high

[59] Barberis and Thaler (2002, p.11) consider the "anchoring bias" as an irrational behavior. However, in general, literature views a behavioral heuristic as a non-rational behavior.

strategy) the momentum effect. Hence, the null hypothesis states that momentum cannot be explained by anchoring.

Figure 3

Illustration of the Core Research Question

The focus of this part of my thesis lies in the exploration of the second relation – whether anchoring explains the 52-week high profits. Therefore, three different types of tests are proposed. To my knowledge, this study is the first that tests the link between this behavioral pattern and the 52-week high. The first test examines the 52-week high strategy at industry level. According to the anchoring hypothesis, the industry-52-week high strategy should not dominate the 52-week high since the one year high price of an industry is not publicly available and hence does not qualify as a potential reference point. I further test whether a strategy with a ranking criterion that employs the highest price of a stock over a period longer or shorter than one year is more profitable than the 52-week high. The highest price of a stock over most intervals is not published. Therefore, this measure is not easily accessible to investors and cannot be used as reference point. Thirdly, the profitability of the 52-week high strategy is measured during the dot-com bubble. A couple of papers document irrational behavior such as overreaction or herding as the cause for its emergence. When subjects herd or overreact, they do not suffer from the anchoring bias at the same time. This implies that people should not anchor during the dot-com bubble and hence, the 52-week high strategy is expected to be unprofitable during this period if it is caused by anchoring.

2. Data and Method

My sample includes all listed stocks on German exchanges that were traded during the period January 1980 and March 2008, a total of 339 months. For each stock and each month, the price (adjusted for subsequent capital actions), the market value, the 52-week high price and the 52-week low price are obtained from Datastream. The intraday high price of each stock is collected on a daily basis. To mitigate microstructure effects that are associated with low-priced and illiquid stocks, only stocks with a price larger than one Euro and a market value above 50 Mio. Euro are considered for the ranking in month t. On average, the number of stocks available is 750 per month. The sample includes both surviving and non-surviving stocks and does not suffer from a survivorship bias.[60]

Portfolios for all strategies are constructed as in Jegadeesh and Titman (1993). At the end of each month, all traded stocks are ranked in ascending order based on the strategy's respective ranking criterion. The top 30% of stocks are assigned to the winner portfolio, the bottom 30% to the loser portfolio and the rest to a portfolio that is referred to as the middle one. These portfolios are equally weighted and not rebalanced during the holding period. To be precise, this implies that stocks are only perfectly equal-weighted at the date of the portfolio formation. As the portfolios are not rebalanced during the holding period, stocks with a price increase get a larger fraction in the portfolio, while stocks with a negative return during the holding period get a smaller weight. The investment strategy is self-financing: it buys winner stocks and sells loser stocks. Hence, the strategy profits are computed as the arithmetic difference (WML) between the returns of the winner portfolio (R^{Wi}) and the returns of the loser portfolio (R^{Lo}):

$$\text{WML} = R^{Wi} - R^{Lo} \qquad (16)$$

To abstract from potential microstructure effects and the bid/ask bounce, I skip one month between the ranking and holding period which is common in the momentum literature. If a stock is delisted during the holding period, I follow Forner (2003, p.72) and assume that the remaining proceeds are equally invested in the remaining stocks.

Consistent with Jegadeesh and Titman (1993), monthly portfolio returns are calculated on an overlapping holding period basis. Compared to non-overlapping returns, this method increases the power of the statistical tests and provides cleaner results as the bid-ask bounce effects are reduced (Moskowitz and Grinblatt, 1999, p.1258).[61] Hence, measuring returns on an overlapping period basis implies that the monthly average profits to K strategies (with K

[60] Some studies using Datastream suffer from a survivorship bias since delisted stocks are missing if the data is taken unadjusted and in its raw state from the database. Yet, this does not mean that it is impossible to get a survivorship-free sample using Datastream. It provides dead stock files, which can be applied to recreate the complete sample.

[61] Calculating non-overlapping returns leads to similar conclusions and are therefore not report in this work.

equals to the length of the holding period in months) are reported, each beginning one month apart. For example, at the beginning of month t, the winner portfolio with a holding period of 3 months consists of three subportfolios: one formed at the beginning of $t-3$, one built in $t-2$ and one started in $t-1$. At the beginning of month $t+1$, the monthly return is measured for the subportfolios constructed in $t-2$, $t-1$ and t while the portfolio formed in $t-3$ is replaced by the one built in t.

I also conduct an experimental analysis to test whether subjects do in fact suffer from the anchoring bias. Therefore, 105 undergraduate students take part in this test and have to estimate a percentage number. Without their knowledge, students are subdivided into three groups. This is done by giving different information, which they might employ when estimating the percentage, to the participants. In order to ensure that the results are not biased by a group dynamic, I make sure that a participant's estimation is not influenced by her neighbor firstly by leaving enough space between the subjects and secondly by ensuring that the information are not the same for students sitting next to each other. Furthermore, as the test is anonymous and as I do not offer payoffs for accuracy, the risk that decisions are made based on other criteria than the own estimate is quite small.

3. Momentum and the 52-week High Strategy

3.1 Performance of the Strategies

Formally, the main difference between the momentum strategy and the 52-week high strategy is the ranking criterion. According to the momentum strategy, stocks are ranked based on their past buy-and hold performance. The 30% of stocks that performed best during the ranking period is attributed to the winner portfolio while the 30% of stocks with the worst buy-and-hold returns is assigned to the loser portfolio. The notation $(J/S/K)$ applies to the momentum strategies and indicates a ranking period of J months, a skip period of S months and a holding period of K months.

Measuring returns on an overlapping holding period basis allows calculating simple t-statistics (Rouwenhorst, 1998, Lee and Swaminathan, 2000). This is future ensured with a Breutsch-Godfrey test. Therefore, I regress the monthly returns R_t of the strategies on a constant c and an error term u_t: $R_t = c + u_t$. The obtained $\hat{u}_t$ (least squares) are regressed on their p lags in a simple AR(p) model: $\hat{u}_t = c_0 + \gamma_1 \hat{u}_{t-1} + \gamma_2 \hat{u}_{t-1} + \cdots + \gamma_p \hat{u}_{t-p} + \varepsilon_t$. I chose different values for p between 1 and 12. From this auxiliary regression, I obtain R^2 which is necessary to get the test statistics that is denoted with $(t - r)R^2 \sim \chi_r^2$.

In Panel A of Table 4, average monthly momentum returns are reported for different ranking and holding periods. Winner and loser profits are returns in excess of the Datastream Germany Price Index[62]. Table 4 documents that momentum strategies yield substantial and mainly highly significant profits over the sample period 1980 to 2008. Stocks that were winners over the previous 3 to 12 months continue to outperform past loser stocks over the next 3 to 12 months. All examined momentum strategies yield positive returns. For 12 out of 16 strategies, returns are significant on the 10% level, for 10 strategies on the 5% level and for 4 out of 16 strategies, momentum profits are significant on the 1% level. The highest monthly returns are generated by the $(9/1/3)$ and the $(6/1/6)$ portfolios.

At first glance, the momentum profits in Table 4 seem rather low in comparison to the study of Jegadeesh and Titman (1993) reporting an average monthly return of about 1% for U.S. stocks. Yet, this results from the examination of the return differences between the top and bottom tercile while Jegadeesh and Titman (1993) focus on the top and bottom decile. The 30% and 70% breakpoints are chosen for two reasons: Firstly, I use German data. Compared to the number of stocks traded in the U.S., my sample is much smaller which implies that winner and loser portfolios contain fewer stocks. This disadvantage can be reduced by including a larger fraction of stocks in the portfolios. And secondly, in opposite to Jegadeesh and Titman (1993) who are interested in presenting evidence for the existence of the momentum effect, I focus on the *driver* of this phenomenon and therefore, I put less emphasize on the tails of the distribution.

Some papers point out that the momentum effect has disappeared in the post-2000 era (Henker et al., 2006, Hwang and Rubesam, 2007). Yet, my results show that this is not the case for momentum in Germany. Between January 1, 2000 and March 1, 2008, the $(6/1/6)$ momentum portfolios generate an average monthly return of 0.60% (not in the tables). This finding is consistent with Dimson et al. (2008) examining UK stocks and reporting an average

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[62] The Datastream Germany Price Index was chosen as it includes substantially more stocks as the MSCI Germany Price Index with only about 60 stocks.

monthly profit of 0.86% for momentum portfolios after 2000. Hence, the results indicate that it is premature to pronounce the disappearance of momentum.

The ranking criterion of the 52-week high strategy is the distance of a stock's current price to its 52-week high (PHR^{52}: Price-52-week high ratio). Formally, let $P_{i,t-1}$ be the price of stock i at the first day of month $t-1$ and $H_{i,t-1}^{52}$ stock i's highest price during the one year period ending at the first day of month $t-1$.

$$PHR_{i,t-1}^{52} = \frac{P_{i,t-1}}{H_{i,t-1}^{52}} \qquad (17)$$

By construction, PHR^{52} takes positive values but cannot be larger than 1. The 30% of stocks with a price closest to their 52-week high (stocks with the largest PHR^{52}) are attributed to the winner portfolio and the 30 of stocks with a price furthest from their 52-week high (stocks with the smallest PHR^{52} values) are assigned to the loser portfolio.

Panel B of Table 4 shows the average monthly returns of the 52-week high strategy for different holding periods. Stocks with a price close to the 52-week high significantly outperform stocks with a price far from the 52-week high over all four examined investment periods. The profits to the 52-week high strategy are approximately as high as the top momentum strategy for each investment period.

Momentum and 52-week high returns might be influenced by the turn-of-the-year effect: Stocks with a poor performance strongly rebound at the beginning of a new year. According to Roll (1983), Griffiths and White (1993) and Ferris et al. (2001), this anomaly is due to tax loss selling: In order to realize tax loss benefits, investors sell loser stocks at the end of the year. This leads to lower prices at year-end for loser stocks. At the beginning of the following year, the selling pressure vanishes and the prices of the loser stocks recover.

Table 4

Profits to Momentum and 52-week High Strategies

This table reports the average monthly portfolio returns in excess of the Datastream Germany Price Index average return from February 1981 through March 2008, for momentum strategies (Panel A) and 52-week high strategies (Panel B). For the momentum portfolios, stocks are picked based on their buy-and-hold return over the ranking period. The 52-week high portfolios chose stocks based on the ratio of the current price to the highest price within the past 12 months. All portfolios are held over the investment period. Between the ranking and holding period, a skip period of 1 month is included to abstract from bid/ask bounce. The winner (loser) portfolios on the momentum strategy are the equally weighted portfolios of the 30% of stocks with the highest (lowest) return over the ranking period. The winner (loser) portfolios of the 52-week high strategy are the equally weighted portfolios of the 30% of stocks with the highest (lowest) quotient of the current price to the 52-week high. For the ranking, all German stocks on Datastream with a price larger than 1 Euro and a market value above 50 Million Euro are considered; t-statistics (two-tailed) are reported in parentheses. *;**;*** are the significance levels on the 10%, 5% and 1% level.

Ranking Period (in months)		Holding Period (in months)			
		3	6	9	12
	Panel A: Average Monthly Returns				
3	Winner	0.0016	0.0019	0.0021	0.0023
	Loser	-0.0006	-0.0013	-0.0016	-0.0010
	Winner-Loser	0.0022	0.0032*	0.0038**	0.0032**
		(1.05)	(1.83)	(2.52)	(2.33)
6	Winner	0.0032	0.0034	0.0031	0.0023
	Loser	-0.0018	-0.0022	-0.0019	-0.0011
	Winner-Loser	0.0049**	0.0056***	0.0050***	0.0034**
		(2.02)	(2.75)	(2.86)	(2.20)
9	Winner	0.0038	0.0034	0.0023	0.0016
	Loser	-0.0024	-0.0019	-0.0014	-0.0005
	Winner-Loser	0.0062***	0.0053***	0.0037**	0.0021
		(2.72)	(2.68)	(2.05)	(1.25)
12	Winner	0.0030	0.0025	0.0019	0.0014
	Loser	-0.0012	-0.0011	0.0002	0.0008
	Winner-Loser	0.0042*	0.0036**	0.0018	0.0006
		(1.95)	(2.07)	(0.92)	(0.32)
	Panel B: Average Monthly 52-week-High Returns				
	Winner	0.0036	0.0033	0.0029	0.0024
	Loser	-0.0022	-0.0025	-0.0021	-0.0015
	Winner-Loser	0.0059**	0.0058**	0.0050**	0.0039*
		(2.12)	(2.24)	(2.08)	(1.74)

In order to examine momentum and 52-week high profits when the turn-of-the-year effect is excluded, I report the returns for both strategies in non-January months in Table 5. Compared to the results in Table 4, loser portfolio returns are substantially lower for both, the momentum and the 52-week high strategy. This is consistent with the turn-of-the-year effect, which states that loser stocks perform well at the beginning of the year. The exclusion of January returns does also lead to lower profits in the winner portfolios. This is not unusual when the turn-of-the-year effect is excluded (see George and Hwang, 2004, p.2150). Yet, the decrease of loser returns is larger compared to the decrease of the winner profits which leads to slightly higher average monthly returns for momentum and 52-week high strategies.

The sample period includes the dot-com bubble around the year 2000. In order to ensure that my findings are not driven by this short period, I exclude all months between October 1, 1998 and March 1, 2000 during which the speculative bubble has grown. March 1 was chosen as the ending date since the German equivalent to the Nasdaq Composite, the NEMAX50, peaked at the beginning of March 2000. The choice of a beginning date is less clear for the dot-com bubble. I decide for October 1, 1998 since the NEMAX50 increased by only 1.3% within 6 months before that date and rose by 17% from October 1, 1998 to November 1, 1998, by 43% until January 1, 1999 and by 359% to March 1, 2000. Table 6 reports the average monthly momentum and 52-week high returns for all months except for those during the dot-com bubble period. Most momentum returns and all 52-week high profits are higher when the dot-com bubble period is excluded. As in Table 4, the most profitable momentum strategy and the 52-week high yield returns that are approximately similar for each holding period. During the dot-com bubble, neither the momentum nor the 52-week high strategies performed well. Between October 1998 and March 2000, 13 out of 16 momentum strategies yield negative returns and only two have a slightly positive average monthly return. The four 52-week high strategies perform even worse and generate with -0.8% to -1.3% (not reported in the tables) substantially negative average monthly profits. Hence, momentum and 52-week high strategies seem to be profitable between 1981 and 2008. The profits are not due to the turn-of-the year effect or due to the dot-com bubble period.

Table 5

Non-January Profits to Momentum and to 52-week High Strategies

This table reports the average monthly portfolio returns in excess of the Datastream Germany Price Index average return from February 1981 through March 2008, for momentum strategies (Panel A) and 52-week high strategies (Panel B) excluding returns in Januaries. For the momentum portfolios, stocks are picked based on their buy-and-hold return over the ranking period. The 52-week high portfolios chose stocks based on the ratio of the current price to the highest price within the past 12 months. All portfolios are held over the investment period. Between the ranking and holding period, a skip period of 1 month is included to abstract from bid/ask bounce. The winner (loser) portfolios on the momentum strategy are the equally weighted portfolios of the 30% of stocks with the highest (lowest) return over the ranking period. The winner (loser) portfolios of the 52-week high strategy are the equally weighted portfolios of the 30% of stocks with the highest (lowest) quotient of the current price to the 52-week high. For the ranking, all German stocks on Datastream with a price larger than 1 Euro and a market-value above 50 Million Euro are considered; t-statistics (two-tailed) are reported in parentheses. *;**;*** are the significance levels on the 10%, 5% and 1% level.

Ranking Period (in months)		Holding Period (in months) 3	6	9	12
		Panel A: Average Monthly Returns			
3	Winner	0.0006	0.0008	0.0010	0.0006
	Loser	-0.0026	-0.0032	-0.0033	-0.0026
	Winner-Loser	0.0032	0.0040**	0.0043***	0.0032***
		(1.58)	(2.37)	(3.08)	(2.70)
6	Winner	0.0022	0.0023	0.0018	0.0011
	Loser	-0.0036	-0.0039	-0.0034	-0.0025
	Winner-Loser	0.0058**	0.0062***	0.0053***	0.0036**
		(2.45)	(3.13)	(3.10)	(2.34)
9	Winner	0.0026	0.0021	0.0010	0.0004
	Loser	-0.0040	-0.0034	-0.0028	-0.0018
	Winner-Loser	0.0066***	0.0054***	0.0038**	0.0022
		(3.01)	(2.76)	(2.06)	(1.23)
12	Winner	0.0017	0.0012	0.0006	0.0002
	Loser	-0.0026	-0.0021	-0.0012	-0.0006
	Winner-Loser	0.0043**	0.0033*	0.0018	0.0007
		(1.98)	(1.85)	(0.90)	(0.38)
		Panel B: Average Monthly 52-week High Returns			
	Winner	0.0029	0.0025	0.0022	0.0017
	Loser	-0.0044	-0.0046	-0.0041	-0.0034
	Winner-Loser	0.0073***	0.0071***	0.0062***	0.0051**
		(2.80)	(2.91)	(2.75)	(2.34)

Table 6

Dot-com Bubble-free Profits to Momentum and 52-week High Strategies

This table reports the average monthly portfolio returns in excess of the Datastream Germany Price Index average return from February 1981 through March 2008, for momentum strategies (Panel A) and 52-week high strategies (Panel B) excluding the period of the dot-com bubble from October 1st 1998 to March 1st 2000. For the momentum portfolios, stocks are picked based on their buy-and-hold return over the ranking period. The 52-week high portfolios chose stocks based on the ratio of the current price to the highest price within the past 12 months. All portfolios are held over the investment period. Between the ranking and holding period, a skip period of 1 month is included to abstract from bid/ask bounce. The winner (loser) portfolios on the momentum strategy are the equally weighted portfolios of the 30% of stocks with the highest (lowest) return over the ranking period. The winner (loser) portfolios of the 52-week high strategy are the equally weighted portfolios of the 30% of stocks with the highest (lowest) quotient of the current price to the 52-week high. For the ranking, all German stocks on Datastream with a price larger than 1 Euro and a market-value above 50 Million Euro are considered; t-statistics (two-tailed) are reported in parentheses. *;**;*** are the significance levels on the 10%, 5% and 1% level.

Ranking Period (in months)		Holding Period (in months)			
		3	6	9	12
		Panel A: Average Monthly Returns			
3	Winner	0.0015	0.0016	0.0020	0.0017
	Loser	-0.0008	-0.0017	-0.0019	-0.0013
	Winner-Loser	0.0023	0.0033**	0.0039**	0.0031**
		(1.05)	(1.79)	(2.48)	(2.51)
6	Winner	0.0027	0.0032	0.0030	0.0026
	Loser	-0.0020	-0.0024	-0.0020	-0.0012
	Winner-Loser	0.0048**	0.0057***	0.0051***	0.0038**
		(1.87)	(2.63)	(2.86)	(2.40)
9	Winner	0.0037	0.0033	0.0029	0.0022
	Loser	-0.0024	-0.0020	-0.0012	-0.0003
	Winner-Loser	0.0062***	0.0054***	0.0041**	0.0025
		(2.60)	(2.69)	(2.20)	(1.49)
12	Winner	0.0035	0.0031	0.0027	0.0022
	Loser	-0.0008	-0.0008	0.0004	-0.0010
	Winner-Loser	0.0043**	0.0040**	0.0023	0.0012
		(2.06)	(2.44)	(1.27)	(0.74)
		Panel B: Average Monthly 52-week High Returns			
	Winner	0.0040	0.0040	0.0036	0.0031
	Loser	-0.0018	-0.0028	-0.0031	-0.0016
	Winner-Loser	0.0066**	0.0067**	0.0058**	0.0047**
		(2.36)	(2.50)	(2.45)	(2.16)

3.2 Comparison of the Strategies with the Same Ranking Period

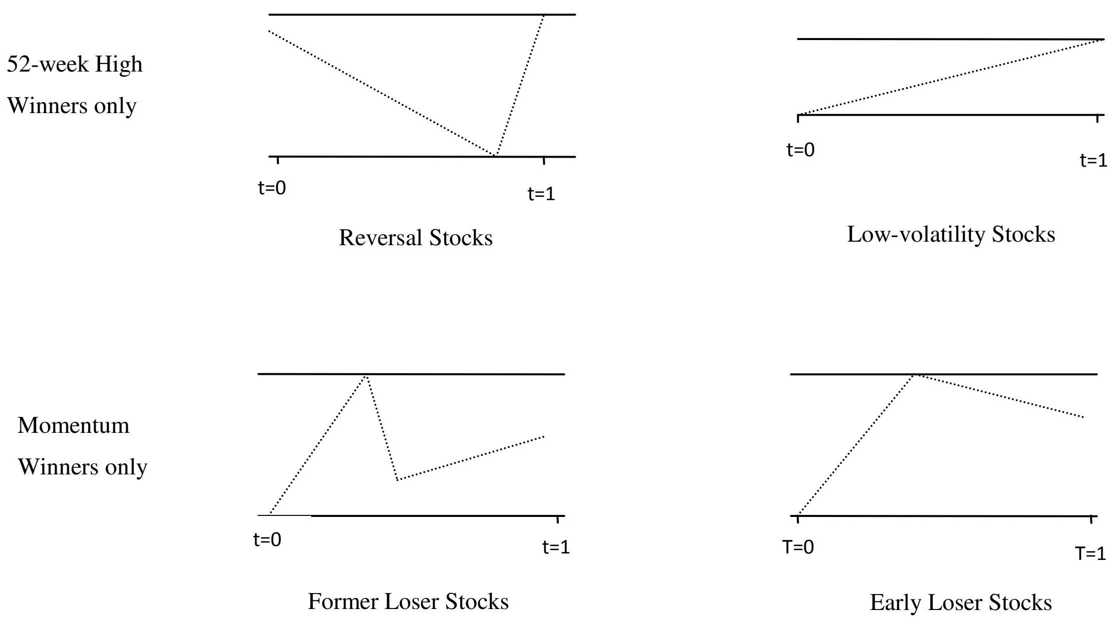
Momentum strategies with a ranking period of 12 months cover a ranking period which is as long as that of the 52-week high strategies (momentum focuses on the past 12 months performance while the 52-week high uses the highest price over the past one year in its ranking measure). Despite of the identical length of the ranking period, momentum strategies are substantially less profitable for all examined holding periods (see Table 4-Table 6). This leads to the question, which stocks are included in the winner (loser) portfolio according to the 52-week high criterion but are not in the winner (loser) portfolio based on the 12 months momentum measure and the other way round.

The first line in Figure 4 illustrates two types of stocks that are in the winner portfolio of the 52-week high strategy but not in that of the momentum strategy. In the second line of Figure 4, two types of stocks are illustrated which are in the momentum winner portfolio but not in the 52-week high winner portfolio. Each graphic shows the stock price from $T = 0$ to $T = 1$. This time horizon is defined as 12 months. The top horizontal line represents the 52-week high between $T = 0$ and $T = 1$, while the bottom horizontal line shows the lowest price within this interval. The first graphic illustrates "Reversal Stocks" which lose value at the beginning but recover and are near or close to the 52-week high in $T = 1$. As the buy-and-hold return between $T = 0$ and $T = 1$ is small, these stocks are not winner stocks according to the momentum criterion. "Low-volatility Stocks" are also stocks that are only 52-week high winners. For this type of stocks, the distance between their 52-week high and low is small. In the second line of Figure 4, the price pattern of stocks that are only momentum winners is illustrated. "Former Loser Stocks" suffer from great loses at the beginning and stabilize on a certain level (or slightly recover). They are only momentum winner stocks as the return between $T = 0$ and $T = 1$ is large but do not belong to the 52-week high winners as the stocks trade far from their 52-week high. In the bottom left graphic, the price pattern of "Early Loser Stocks" which yield high returns at the beginning of the period but have a poor performance at the end. As the 52-week high strategy is substantially more profitable than the $(12/1/x)$ momentum strategy, either stocks that are only considered winner stocks by the 52-week high strategy perform well or stocks that are only momentum winners underperform. Hence, either "Reversal Stocks" or "Low-volatility Stocks" have a good performance in the holding periods or "Former Loser Stocks" or "Early Loser Stocks" must perform poorly. Symmetric conclusions can be drawn for loser stocks.

Figure 4

Types of Stocks Responsible for the Difference between the $(12/1/x)$ Momentum and the 52-week High Strategy Performance

The figure shows types of stocks that are 52-week high winners but not momentum winners (H1 and H2) and types of stocks that are included in the winner portfolio by the momentum criterion but not by the 52-week high measure (M1 and M2). Each graphic illustrates the stock's price pattern from $t = 0$ to $t = 1$. This time span between $t = 0$ to $t = 1$ is defined as 12 months. The top horizontal line represents the 52-week high between $t = 0$ and $t = 1$ while the bottom horizontal line shows the lowest price within this interval.



This brief illustration has two interesting implications. First, it theoretically shows that there are types of stocks that are only considered as winners by one criterion. These types could make the difference in the performance between the 52-week high and the $(12/1/\mathrm{x})$ momentum strategy. Secondly, these four graphics show that the $(12/1/\mathrm{x})$ momentum is slower in identifying future winner stocks: Since it is less profitable than the 52-week high, stocks that are only momentum winners are expected to have a bad or at least modest performance while stocks that are only 52-week high winners are assumed to perform well. "Reversal Stocks" and "Low-volatility Stocks" are assigned to the 52-week high winner portfolio in $\mathrm{t} = 1$. Due to their excepted performance, they will also be included in the momentum winner portfolios to a later date. Hence, the 52-week high strategy seems to earlier invest in a future winner stock than momentum. A similar pattern can be observed for the "Former Loser stocks" and "Early Loser Stocks". While the 52-week high does not include those stocks in the winner portfolio in $\mathrm{t} = 1$, the momentum criterion does. Finally, after $\mathrm{t} = 1$, after a bad or modest performance of those stocks, the momentum measure does also refuse to call these stocks winners. Hence again, while the poor performance of these stocks is identified by 52-week high in $t = 1$, the $(12/1/x)$ momentum measure is much slower. In summary, these four types of stocks indicate that the 52-week high is faster in identifying winner stocks than the momentum strategy with a ranking period of 12 months.

4. Dominance of the 52-week High Strategy

In Table 4-6, the profitability of momentum strategies with different ranking and holding periods are compared to the returns of 52-week high strategies with different holding periods. Measuring the performance of both strategies over a variety of ranking and holding periods is important in order to completely examine their relationship. For example, it is not sufficient to compare only the (6/1/6) momentum strategy with the 52-week high strategy, since it is not necessarily the most profitable momentum strategy (Rouwenhorst, 1998, Forner and Marhuenda, 2003, Doukas and McKnight, 2005, Agyei-Ampomah, 2007). This chapter examines whether stock price momentum and the 52-week high are independent or whether one ranking criterion dominates the other. Therefore, with the sorting and the regression approach, two different methods are employed. The sorting approach attributes stocks to different portfolios based on both the 52-week high and the momentum criterion. This method can further be subdivided in a conditional sort and a two-way sort. Based on the conditional sort, stocks are first sorted and collected in different portfolios according to one strategy. Then within the portfolios, stocks are further ranked on the criterion of the second strategy. The two-way method ranks stocks *independently* based on the first and on the second ranking criterion and forms portfolios based on the independent rank of both strategies. For example, winners according to one ranking criterion are subdivided into different portfolios based on the second independent sort. A big advantage of the sorting approach is that this methodology offers a simple and intuitive insight in the relationship between two strategies, as stocks are included in different portfolios of which the returns can be easily compared and interpreted. A potential problem, however, is the unevenly balanced number of stocks within the portfolios. For example, there are more stocks ranked as winners by both criteria than stocks that are momentum winners and at the same time losers based on the 52-week high. A further disadvantage is the construction of test statistics, which is less clear for the sorting approach compared to other methods (Nijman et al., 2004). Beside sorts, strategies can also be compared by regressions. They allow the incorporation of other effects in addition to the momentum and the 52-week high effects. For example, firm size can be controlled for, as a relationship between firm size and momentum returns is documented in some studies

(Rouwenhorst, 1998, Hong, 2000). Moreover, the construction of regressions and the interpretation of the obtained results seem to be well understood. Yet, a drawback of regressions is the functional form they impose on the relationship between the exogenous and the endogenous variables (Fama and French, 2008). This form might be incorrect and therefore lead to wrong conclusions. In order to ensure that my results are not driven by the drawbacks of the employed method, I use both approaches to test the relationship between the momentum and the 52-week high strategy.

As a first method to examine the relationship between the momentum and the 52-week high strategy, Fama-MacBeth (1973) style cross-sectional regressions similar to those in George and Hwang (2004) are conducted. As above, I compare the $(6/1/6)$ momentum strategy to the 52-week high with a holding period of six month length.[63] Dummy variables that indicate whether a stock is included in the winner or loser portfolios by a strategy are regressed on the month t return of stock i. In order to control for firm size, the market capitalization of firm i is taken as explanatory variable with a lag. With the return of stock i in $t-1$ as explanatory variable, a second control variable is employed to isolate the bid-ask bounce impact on the coefficient estimates. Hence, the coefficients of the dummy variables help us to measure the return of one strategy in isolation from the second one and in control of size and the bid-ask bounce. As mentioned above, overlapping portfolios are employed to examine a strategy's profitability. Consequently, as I examine the 52-week high and the momentum strategy for a holding period of six months, the winner and loser portfolios of both strategies in month t consist of six subportfolios formed in $t-j$ (with $j = 2, \dots 7$) respectively.

I estimate for each j the following regression in order to examine the relationship between the winner and loser portfolios formed in $t-j$ and the return in month t:

$$\begin{aligned} R_{i,t} &= \alpha_{0t}^{j} + \alpha_{1t}^{j}\, size_{i,t-1} + \alpha_{2t}^{j}\, R_{i,t-1} + \alpha_{3t}^{j}\, mw_{i,t-j} + \alpha_{4t}^{j}\, ml_{i,t-j} \\ &= +\alpha_{5t}^{j}\, hw_{i,t-j} + \alpha_{6t}^{j}\, hl_{i,t-j} + \epsilon_{it}, \end{aligned} \tag{18}$$

where $R_{i,t}$ is the return and $size_{i,t}$ the market value of stock i in month t. The momentum strategy is considered in the regression by two dummy variables, $mw_{i,t-j}$ and $lw_{i,t-j}$. If in

[63] The conclusions are similar when the 52-week high with a 3-month holding period is compared to the $(9/1/3)$ momentum.

month $t-j$ stock i is ranked in the top (bottom) 30% based on the momentum ranking criterion, $mw_{i,t-j}$ $(lw_{i,t-j})$ is one and zero otherwise. The ranking criterion of momentum is stock i's buy-and-hold return between $t-j-6$ and $t-j$. The dummy variables $hw_{i,t-j}$ and $hl_{i,t-j}$ represent the 52-week high strategy: if in month $t-j$ stock i is among the top (bottom) 30% according to the 52-week high ranking measure, $hw_{i,t-j}$ ($hl_{i,t-j}$) takes one and zero otherwise. The ranking criterion of the 52-week high is the ratio of stock i's price in $t-1$ and its highest price between $t-j-12$ and $t-j$. The intercept α_{0t}^{j} can be interpreted as the monthly return of a portfolio that has hedged out the size effect, the bid-ask bounce, the momentum and the 52-week high effect (Fama, 1976). The dummy variable coefficients α_{3t}^{j} for example can be viewed as the return in excess of α_{0t}^{j} that can be obtained by taking a long position in the $(6/1/6)$ momentum winner portfolio in isolation of all other effects.

In order to obtain the total monthly return of the pure winner or pure loser portfolios, the averages of the coefficients from the six independent regression for each $j = 2, \ldots, 7$ are calculated: $\frac{1}{6}\sum_{j=2}^{7} \alpha_3^j$, …, $\frac{1}{6}\sum_{j=2}^{7} \alpha_6^j$.

Table 7 reports the time-series averages of the total monthly returns and the associated t-statistics. In the bottom of the table, the difference between the winner and loser dummies for the momentum (the 52-week high strategy) represents the average monthly return from a zero-cost portfolio that is long in the momentum (52-week high) winners and short in the momentum (52-week high) losers. The regression results support the general conclusions of the sorting approach. When the dot-com bubble period is excluded, the dominance of the 52-week high strategy is obvious. A self-financing 52-week high strategy yields 0.48%, which is much larger than the momentum return of 0.34%. A similar pattern can be observed when January returns are excluded. Using raw returns, the dominance is less clear and the difference in the 52-week high dummy variables is with 0.40% only weakly larger than the difference in the momentum dummy variables with 0.37%.

Table 7

Comparison between the $(6/1/6)$ Momentum and the 52-week High Strategy: Regression

The table reports the results of six cross-sectional regressions (j=2, ...,7) which are estimated for each month between February 1981 and March 2008. The regressions for $(6/1/6)$ momentum strategy and the 52-week high with a 6-month holding period have the following form:

$$R_{i,t} = \alpha_{0t}^{j} + \alpha_{1t}^{j} size_{i,t-1} + \alpha_{2t}^{j} R_{i,t-1} + \alpha_{3t}^{j} mw_{i,t-j} + \alpha_{4t}^{j} ml_{i,t-j} + \alpha_{5t}^{j} hw_{i,t-j} + \alpha_{6t}^{j} hl_{i,t-j} + \epsilon_{it},$$

where $R_{i,t}$ is the return and $size_{i,t}$ the market value of stock i in month t. The $(6/1/6)$ momentum strategy is included in the regression through the dummy variables $wm_{i,t-j}$ and $lm_{i,t-j}$. The variable $wm_{i,t-j}$ ($lm_{i,t-j}$) takes one if in month $t-j$ stock i is among the top (bottom) 30% according to the ranking criterion (the past six months buy-and-hold return) and zero otherwise. The dummy variables $hw_{i,t-j}$ and $hl_{i,t-j}$ represent the 52-week high strategy. $hw_{i,t-j}$ ($lw_{i,t-j}$) takes one if in $t-j$ stock i is ranked in the top (bottom) 30% based on the strategy's ranking criterion (The ratio of stock i's price in $t-1$ and its highest price between month $t-j-12$ and $t-j$). The coefficients of the independent variables $wm_{i,t-j}$, $lm_{i,t-j}$, $hw_{i,t-j}$ and $hl_{i,t-j}$ are averaged over j=2, ...,7. The table reports the time-series averages of the averaged coefficients measured in percent. The time-series t-statistics are documented in parentheses. The first column reports the results for all months, the second column shows the findings for all months except for those during the dot-com bubble period from October 1998 to February 2000 and the last column reports the returns for non-January months. *;**;*** are the significance levels on the 10%, 5% and 1% level.

	All months	ex Dot-com Bubble	ex Jan
α_i	0.94	0.81	0.81
	(3.65)***	(3.12)***	(3.05)***
$size_{i.t-1}$	-0.02	-0.05	-0.04
	(-0.80)	(-0.76)	(-0.94)
$R_{i,t-1}$	-1.03	-1.04	-1.03
	(-3.96)***	(-3.34)***	(-3.74)***
$mw_{i,t-j}$	0.24	0.25	0.22
	(2.49)***	(2.59)***	(2.30)**
$ml_{i,t-j}$	-0.13	-0.10	-0.13
	(-1.67)*	(-1.70)*	(-1.69)*
$hw_{i,t-j}$	0.17	0.24	0.20
	(1.82)*	(2.10)**	(2.15)**
$hl_{i,t-j}$	-0.24	-0.23	-0.34
	(-1.70)*	(-1.71)*	(-2.05)**
$mw_{i,t-j} - ml_{i,t-j}$	0.37	0.34	0.35
	(2.34)***	(2.28)**	(2.20)**
$hw_{i,t-j} - hl_{i,t-j}$	0.40	0.48	0.55
	(2.16)**	(2.38)**	(2.30)**

As a further sorting method, a conditional sort is conducted[64]: Stocks are assigned to different portfolios based on one ranking measure. Then within the portfolios, stocks are further sorted according to the criterion of the second strategy. This test identifies whether the 52-week high strategy still has explanatory power conditional on the momentum ranking, and vice versa. For consideration of space, I only report the results of the comparison between the most

[64] A conditional sort is used by Rouwenhorst (1998) examining whether size has an influence on momentum returns.

profitable momentum strategy and the 52-week high over a holding period of 6 months (Table 8) and 3 months (Table 9).[65]

In Panel A of Table 8, stocks are first classified into winner, middle and loser portfolios according to the momentum criterion (the past six month performance), and then each of the three portfolios is further subdivided into winner, middle and loser portfolios based on the 52-week high rankings. Panel B documents the results when stocks are first classified based on the 52-week high performance measure and then sorted according to the momentum criterion within the three portfolios. As above, the top 30% of stocks is assigned to the winner portfolio, the bottom 30% is included in the loser portfolio while the rest (40%) is collected in the middle portfolio. The ranking criterion for the momentum strategy is the past return of a stock during $t-7$ and $t-2$ and PHR_i^{52} for the 52-week high strategy.

Panel B shows that the $(6/1/6)$ momentum strategy loses its profitability within the 52-week high winner and loser groups. The returns to momentum W-L portfolios are small at 0.28% or less and not significant. Excluding the dot-com bubble period (column 2) or the turn-of-the-year effect (column 3) or both (column 4) does not increase momentum profits within the 52-week high winner and loser groups. In opposite, the 52-week high strategy still is profitable after controlling for momentum. This is at least true for non-January returns and outside the dot-com bubble where the 52-week high measure yields large and significant profits (0.38% – 0.56% on average per month). The returns to the 52-week high strategy within the winner and loser momentum portfolio are almost two times higher than the profits to the $(6/1/6)$ momentum strategy within the 52-week high winner and loser groups outside the Dot-com period. The dominance of the 52-week high over momentum becomes even more obvious when both the Dot-com period and January returns are excluded (column 4).

[65] As the difference in returns between the most profitable momentum and the 52-week high strategy is smallest for a holding period of three and six month, I do report the results of these tests.

Table 8

Comparison between the (6/1/6) Momentum and the 52-week High Strategy: Conditional Sort

The table reports the average monthly returns of portfolios that are formed according to the (6/1/6) momentum and to the 52-week high strategy with a 6-month holding period from February 1981 through March 2008. In Panel A, stocks are first sorted on the (6/1/6) momentum ranking criterion. The 30% of stocks with the highest (lowest) past 6 month performance are assigned to the winner (loser) portfolio; the rest of stocks are included in the middle portfolio. Within the three portfolios, stocks are further sorted in winner and loser portfolios based on the 52-week high criterion: The 30% of stocks with a price nearest to (furthest from) their one-year high are included in the winner (loser) portfolio. In Panel B, stocks are first sorted according to the 52-week high measure and then subsequently within the portfolios based on the momentum criterion. All portfolios are held over 6 months. In column 3, the average monthly portfolio returns are reported for the total sample period, in column 4 for the total period except for the dot-com bubble period between October 1998 and February 2000. Column 5 reports the average monthly returns for all months except Januaries and within the last column both January returns and dot-com bubble returns are skipped. The t-statistics are in parentheses. *;**;*** are the significance levels on the 10%, 5% and 1% level.

Panel A

Portfolios Classified by the Momentum	Portfolios Classified by the 52-Week High	Ave. Monthly Return	Ave. Monthly Return Excl. 10/98-2/00	Ave. Monthly Return Excl. January	Ave. Monthly Return Excl. Jan. and 10/98-2/00
Winner	Winner	0.0042	0.0040	0.0032	0.0038
	Loser	0.0016	0.0001	-0.0006	-0.0013
	Winner-Loser	0.0027 (1.47)	0.0040 (2.55)**	0.0038 (2.27)**	0.0051 (3.10)***
Middle	Winner	0.0008	0.0019	0.0003	0.0018
	Loser	-0.0019	-0.0019	-0.0035	-0.0030
	Winner-Loser	0.0028 (1.42)	0.0038 (2.09)**	0.0039 (2.08)**	0.0048 (2.57)**
Loser	Winner	-0.0019	-0.0008	-0.0020	-0.0011
	Loser	-0.0043	-0.0051	-0.0077	-0.0082
	Winner-Loser	0.0025 (0.76)	0.0043 (2.11)**	0.0056 (2.22)**	0.0071 (2.81)**

Panel B

Portfolios Classified by the 52-Week High	Portfolios Classified by the Momentum	Ave.Monthly Return	Ave.Monthly Return Excl. 10/98-2/00	Ave. Monthly Return Excl. January	Ave.Monthly Return Excl. Jan. and 10/98-2/00
Winner	Winner	0.0046	0.0040	0.0032	0.0030
	Loser	0.0020	0.0018	0.0003	-0.0014
	Winner-Loser	0.0026 (1.58)	0.0022 (1.37)	0.0029 (1.74)*	0.0016 (1.07)
Middle	Winner	0.0017	0.0011	0.0004	-0.0003
	Loser	-0.0010	-0.0005	-0.0014	-0.0011
	Winner-Loser	0.0028 (1.54)	0.0016 (1.20)	0.0019 (1.39)	0.0007 (0.56)
Loser	Winner	-0.0008	-0.0022	-0.0039	-0.0051
	Loser	-0.0031	-0.0044	-0.0067	-0.0077
	Winner-Loser	0.0024 (1.30)	0.0022 (1.20)	0.0028 (1.67)*	0.0026 (1.54)

Table 9

Comparison between the (9/1/3) Momentum and the 52-week High Strategy: Conditional Sort

The table reports the average monthly returns of portfolios that are formed according to the (9/1/3) momentum and to the 52-week high strategy with a 3-month holding period from February 1981 through March 2008. In Panel A, stocks are first sorted on the (9/1/3) momentum ranking criterion. The 30% of stocks with the highest (lowest) past 9 month performance are assigned to the winner (loser) portfolio; the rest of stocks is included in the middle portfolio. Within the three portfolios, stocks are further sorted in winner and loser portfolios based on the 52-week high criterion: The 30% of stocks with a price nearest to (furthest from) their one-year high are included in the winner (loser) portfolio. In Panel B, stocks are first sorted according to the 52-week high measure and then subsequently within the portfolio based on the momentum criterion. All portfolios are held over 3 months. In column 3, the average monthly portfolio returns are reported for the total sample period, in column 4 for the total period except for the dot-com bubble period between October 1998 and February 2000. Column 5 reports the average monthly returns for all months except Januaries and within the last column both January returns and Dot-Com bubble returns are skipped. The t-statistics are in parentheses. *;**;*** are the significance levels on the 10%, 5% and 1% level.

Panel A

Portfolios Classified by the Momentum	Portfolios Classified by the 52-Week High	Ave. Monthly Return		Ave. Monthly Return Excl. 10/98-2/00		Ave. Monthly Return Excl. January		Ave. Monthly Return Excl. Jan. and 10/98-2/00	
Winner	Winner	0,0050		0.0046		0.0039		0.0035	
	Loser	0.0024		0.0013		-0.0005		-0.0012	
	Winner-Loser	0.0026	(1.33)	0.0033	(1.68)*	0.0044	(2.22)**	0.0047	(2.35)**
Middle	Winner	0.0001		0.0015		0.0001		0.0014	
	Loser	-0.0020		-0.0017		-0.0037		-0.0037	
	Winner-Loser	0.0021	(1.04)	0.0032	(1.55)	0.0038	(1.76)*	0.0051	(2.34)**
Loser	Winner	-0.0021		-0.0015		-0.0028		-0.0024	
	Loser	-0.0047		-0.0062		-0.0074		-0.0083	
	Winner-Loser	0.0025	(0.90)	0.0046	(1.67)*	0.0046	(1.68)*	0.0059	(2.08)**

Panel B

Portfolios Classified by the 52-Week High	Portfolios Classified by the Momentum	Ave. Monthly Return		Ave. Monthly Return Excl. 10/98-2/00		Ave. Monthly Return Excl. January		Ave. Monthly Return Excl. Jan. and 10/98-2/00	
Winner	Winner	0.0052		0.0045		0.0044		0.0038	
	Loser	0.0022		0.0024		0.0019		0.0022	
	Winner-Loser	0.0029	(1.67)*	0.0021	(1.35)	0.0025	(1.38)	0.0016	(1.01)
Middle	Winner	0.0014		0.0008		0.0002		-0.0004	
	Loser	-0.0012		-0.0007		-0.0020		-0.0016	
	Winner-Loser	0.0026	(1.50)	0.0014	(0.94)	0.0022	(1.30)	0.0013	(0.82)
Loser	Winner	-0.0012		-0.0026		-0.0037		-0.0049	
	Loser	-0.0070		-0.0092		-0.0113		-0.0127	
	Winner-Loser	0.0026	(1.20)	0.0020	0.98	0.0025	(1.18)	0.0015	(0.75)

Importantly, for non-January returns or outside the dot-com bubble, the 52-week high strategy remains also profitable within the middle momentum portfolio (with a monthly return of between 0.38% and 0.48%). According to the momentum strategy, these stocks do not have extremely high or extremely low future returns. Hence, if the momentum measure is a powerful predictor of future returns, forming subgroups within the middle portfolios based on the 52-week high criterion should not lead to profits. In contrary, the (6/1/6) momentum measure does not produce large and significant returns within the middle group of the 52-week high.

Over the total sample period, however, the dominance of the 52-week high over momentum is less obvious. Although the momentum criterion does not generate significant returns within the 52-week high groups, this is also not the case for the 52-week high measure within the momentum portfolios. As the findings in Table 8 indicate, either this might be due to the turn-of-the-year effect, which distorts the results related to the relationship between the 52-week high and the (6/1/6) momentum strategy, or it could be influenced by the dot-com bubble period. During this phase, the 52-week high portfolios underperform the momentum ones although both strategies are not profitable. These findings are confirmed by the conditional sort of the (9/1/3) momentum strategy and the 52-week high with a holding period of 3 months (Table 9).

The relationship between the 52-week high and the momentum strategy is further tested using a two-way sort. Based on the momentum criterion, all stocks are divided into three portfolios (M1, M2, M3). The top 30% of the stocks are included in portfolio M1. Independently from this sort, stocks are arranged in three portfolios (H1, H2, H3) based on the 52-week high criterion, with the 30% of stocks closest to the 52-week high included in portfolio H1. Hence, the portfolio M1H1 consists of stocks that are in the winner portfolio according to both the momentum and the 52-week high ranking criterion. As above, the test is conducted for the relationship between the (6/1/6) momentum and the 52-week high with a holding period of six months (Table 10) and between the (9/1/3) momentum and the 52-week high with a holding period of three months (Table 11).

Table 10

Comparison between the (6/1/6) Momentum and the 52-week High Strategy: Two-way Sort

The table reports the average monthly returns of portfolios that are formed according to the (6/1/6) momentum and the 52-week high strategy with a 6-month holding period from February 1981 through March 2008. Stocks are sorted independently by the 52-week high and the (6/1/6) momentum criterion. In portfolio M1 (M3), the top (bottom) 30% of stocks based on the past six month buy-and-hold return are included, while the rest of stocks that are neither winners nor losers are assigned to portfolio M2. Stocks are included in the portfolio H1 (H3) if they belong to the top (bottom) 30% of stocks based on the 52-week high criterion. Stocks that belong neither to H1 nor to H3 are included in portfolio H2. All portfolios are held over 6 months. Panel A reports the average monthly returns over the total sample period. Panel B documents average monthly returns when the dot-com bubble period is excluded, whereas Panel C reports average returns for non-January months. In Panel D, the average monthly profits are shown when both the turn-of-the-year effect and the dot-com bubble period are excluded. The t-statistics are in parentheses. *;**;*** are the significance levels on the 10%, 5% and 1% level.

		52-week High Strategy				
		H1	H2	H3	H1-H3	t-stat
		Panel A: Raw Returns				
(6/1/6) Momentum Strategy	M1	0.0033	0.0015	0.0001	0.0033	(1.10)
	M2	0.0003	-0.0012	-0.0035	0.0039	(1.50)
	M3	0.0001	-0.0012	-0.0042	0.0043	(1.26)
	M1-M3	0.0032	0.0027	0.0043	-0.0011	
	t-stat	(1.56)	(1.51)	(1.94)*		
		Panel B: ex Dot-com Bubble				
	M1	0.0042	0.0016	-0.0013	0.0055	(1.95)*
	M2	0.0017	0.0000	-0.0032	0.0049	(1.84)*
	M3	0.0012	-0.0001	-0.0041	0.0053	(1.49)
	M1-M3	0.0030	0.0017	0.0028	0.0002	
	t-stat	(1.27)	(0.91)	(1.28)		
		Panel C: ex Jan				
	M1	0.0027	0.0004	-0.0029	0.0055	(1.98)**
	M2	0.0003	-0.0005	-0.0041	0.0045	(1.78)*
	M3	0.0000	-0.0007	-0.0048	0.0048	(1.35)
	M1-M3	0.0027	0.0011	0.0020	0.0007	
	t-stat	(1.02)	(0.70)	(0.85)		
		Panel D: ex Jan and ex Dot-com Bubble				
	M1	0.0035	0.0006	-0.0034	0.0069	(2.45)**
	M2	0.0015	0.0000	-0.0038	0.0053	(2.08)**
	M3	0.0011	0.0000	-0.0055	0.0066	(1.82)*_
	M1-M3	0.0024	0.0006	0.0020	0.0004	
	t-stat	(1.13)	(0.65)	(1.26)		

Table 11

Comparison between (9/1/3) Momentum and the 52-week High Strategy: Two-Way Sort

The table reports the average monthly returns of portfolios that are formed according to the (9/1/3) momentum and the 52-week high strategy with a 3-month holding period from February 1981 through March 2008. Stocks are sorted independently by the 52-week high and the (9/1/3) momentum criterion. In portfolio M1 (M3), the top (bottom) 30% of stocks based on the past nine month buy-and-hold return are included, while the rest of stocks that are neither winners nor losers are assigned to portfolio M2. Stocks are included in the portfolio H1 (H3) if they belong to the top (bottom) 30% of stocks based on the 52-week high criterion. Stocks that belong neither to H1 nor to H3 are assigned to portfolio H2. All portfolios are held over 3 months. Panel A reports the average monthly returns over the total sample period. Panel B documents average monthly returns when the dot-com bubble period is excluded, whereas Panel C reports average returns for non-January months. In Panel D, the average monthly profits are shown when both the turn-of-the-year effect and the dot-com bubble period are excluded. The t-statistics are in parentheses. *;**;*** are the significance levels on the 10%, 5% and 1% level.

(9/1/3) Momentum Strategy	52-week High Strategy				
	H1	H2	H3	H1-H3	t-stat
Panel A: Raw Returns					
M1	0,0040	0.0015	0.0010	0.0029	(1.00)
M2	0.0021	-0.0005	-0.0013	0.0034	(1.12)
M3	0.0016	-0.0018	-0.0027	0.0042	(1.10)
M1-M3	0.0024	0.0033	0.0037	-0.0013	
t-stat	(1.11)	(1.41)	(1.54)		
Panel B: ex Dot-com Bubble					
M1	0.0037	0.0012	-0.0004	0.0041	(1.76)*
M2	0.0028	0.0004	-0.0017	0.0045	(1.81)*
M3	0.0011	-0.0018	-0.0028	0.0039	(1.50)
M1-M3	0.0026	0.0030	0.0024	0.0002	
t-stat	(1.21)	(1.34)	(0.96)		
Panel C: ex Jan					
M1	0.0032	-0.0004	-0.0027	0.0059	(2.08)**
M2	0.0017	-0.0010	-0.0030	0.0047	(1.82)*
M3	0.0012	-0.0025	-0.0047	0.0059	(1.86)*
M1-M3	0.0020	0.0021	0.0020	0.0000	
t-stat	(1.13)	(1.10)	(0.88)		
Panel D: ex Jan and ex Dot-com Bubble					
M1	0.0029	-0.0006	-0.0032	0.0062	(2.16)**
M2	0.0026	-0.0003	-0.0036	0.0062	(2.20)**
M3	0.0009	-0.0024	-0.0052	0.0061	(1.88)*
M1-M3	0.0020	0.0017	0.0020	0.0000	
t-stat	(1.13)	(0.65)	(1.26)		

The two-way sort confirms the findings of the conditional sort. Table 10 indicates that the 52-week high dominates the (6/1/6) momentum strategy when the turn-of-the-year effect or the dot-com bubble effect is excluded (Panel B-D). This can be observed in the positive H1-H3 returns that are large and mostly significant. They indicate whether stocks with a price close to the 52-week high outperform stocks with a price far from their one year high within the same momentum portfolio. In opposite, the M1-M3 portfolio returns are small and not significant. They document whether stocks with a good 6-month performance outperform stocks with a poor 6-month return within the same 52-week high portfolio. Hence, the 52-week high strategy seems to dominate the (6/1/6) momentum strategy at least outside the dot-com bubble period or in non-January returns. The results of the two-way sort that examines the relationship between the (9/1/3) momentum effect and the 52-week high strategy with a holding period of three months lead to similar conclusions (Table 11).

So far, the results indicate that the momentum and the 52-week high strategy generate similar returns, but that the 52-week high dominates momentum – at least when it is controlled for the dot-com bubble effect or the turn-of-the-year effect. Yet, this is not enough to reject the hypothesis that momentum is not driven by the anchoring phenomenon. The cause for the profitability of the 52-week high strategy (and hence of momentum) could also be a risk factor not yet detected or another behavioral heuristic than anchoring.

5. The Anchoring Bias as Explanation for the 52-week High Profits

5.1 The Anchoring Bias

A potential explanation for the profitability of the 52-week high strategy is "anchoring" (George and Hwang, 2004). Anchoring refers to the method how people make estimations. Tversky and Kahneman (1982, pp.1128) argue that people form estimates by starting from an initial value and then adjusting to the final guess. Anchoring states that this adjustment is not sufficient and that subjects focus too much on the initial value (or reference point). Hence, anchoring can be defined as the insufficient adjustment of people's estimate from the starting value to the final guess.

To examine this behavior, I carry out an experimental analysis similar to one of Tversky and Kahneman (1982). I ask 105 undergraduate students to estimate the fraction of the area in Germany that is used for agriculture. This question is chosen based on two criteria: First, its answer should be unknown to the subjects so that they in fact have to guess the correct percentage and secondly it should be easily understandable for the participants in order to avoid misunderstandings. In the test, the participants have to answer two questions. In the first one, they are asked to estimate whether the fraction is smaller or larger than a specific number, which is given to them and which varies across the students. The specific number represents the initial value and is 20% for the first group, 50% for the second and 70% for the third group. In a second question, they have to estimate the percentage. In order to ensure that the results are not biased by a group dynamic, I make sure that a student's estimation is not influenced by her neighbor by first leaving enough space between the subjects and secondly by not giving the same initial value to students sitting next to each other. Furthermore, as the test is anonymous and as I do not offer payoffs for accuracy, the risk that decisions are made based on other criteria than the own estimate is quite small.

The core finding of the test is that the arbitrarily numbers have a substantial effect on the estimates. The median estimate for the group that obtains 20% as percentage number is 31% while it is 47% for the group with an initial value of 50%. Participants that have to evaluate whether the percentage is smaller or larger than 70% have a median estimate of 56%. When the estimates are compared pairwise between the groups, the differences are highly significant with a p-value below 0.01.

5.2 The x-month High Strategy

As a first test for anchoring as explanation for the 52-week high and hence for momentum profits, I examine whether the predictive power of the PHR_i^{52} ranking criterion is improved when I replace the 52-week high price by the x-month high price. I define the x-month high price as the highest price of a stock over the past x months. This test allows to examine two implications of my core hypothesis. First, as in the first test, it is tested whether the 52-week high is indeed driven by the described behavioral phenomenon. While many newspapers publish the 52-week high price, this is not the case for most x-month high prices of a stock. As this information is not easily available to traders, they should not be able to use it as a reference point against which they evaluate the impact of news. Therefore, according to the anchoring hypothesis, strategies should not dominate the 52-week high strategy that rank stocks based on their nearness to an x-month high, which is not widely published. If however an x-month high strategy dominates the 52-week high, anchoring would not be the right explanation for the 52-week high (and momentum) profits. Secondly, this test can also be used to examine whether the 52-week high price is the reference point used by traders that suffer from the anchoring bias. For example, some newspapers do also publish the 1-month high or the 3-month high of a stock. If the 1-month high strategy or the 3-month high strategy dominates the 52-week high, anchoring cannot be rejected although the 52-week high price might not be the correct reference point.

The x-month high strategy is constructed similarly to the 52-week high strategy except for denominator. It is represented by $H_{i,t-1}^{x}$, the highest price of stock i over a period of x month length that ends at the beginning of month $t-1$:

$$PHR_i^x = \frac{P_{i,t-1}}{H_{i,t-1}^{x}} \qquad (19)$$

$PHR_{i,t-1}^{x}$ is constructed by using daily data and measuring the maximum intraday high price for stock i during the x-month period.

Table 12 documents the profitability of x-month high strategies during the total sample (column A), for all months except January (column B) and for all months except during the dot-com bubble. The 52-week high strategy dominates all x-month high strategies. This strongly supports the anchoring story since the biggest difference between most x-month high prices and the 52-week high price is the availability of the information and therefore, the 52-week high qualifies as reference point while most x-month high measures do not. Beside the 52-week high, strategies that employ the highest price of a stock over a period close to one year yield the highest returns. This pattern is illustrated in Figure 5 where the monthly average returns of the x-month high strategies are shown graphically. It documents that profits are inverted u-shaped. The closer (further) the length of the period over which the highest price of a stock is measured with respect to the one year high, the smaller (larger) is the difference between the monthly returns. This is not surprising, as with a high probability, the maximum price of a stock over a period close to one year is identical to the 52-week high price. For example, the 1-month high is only equal to the 52-week high if the highest price over the past year is reached within the previous month. In opposite, the chance that the 52-week high and the 9-month high are identical is larger as they have nine months in common.

Table 12

Profitability of x-month High Strategies

This table reports the average monthly portfolio returns in excess of the Datastream Germany Price Index average return from February 1981 through March 2008 for all x-month high strategies except for the 15-month and 18-month high which start in May 1980 and August 1980 respectively. The reason for this is that this sample starts in January 1980 and these strategies require the highest price of a stock over the previous 15 and 18 months (plus a skip period). The highest price of a stock is obtained by using daily intraday prices and calculating the maximum price for each stock over the previous x months. The x-month high portfolios are built based on the ratio of the current price of a stock to the highest price within the past x months. All portfolios are equal-weighted and held over the investment period of six months. Between the ranking and holding period, a skip period of one month is included to abstract from bid/ask bounce. The winner (loser) portfolio of the x-month high strategy consists of the top (bottom) 30% of stocks based on the strategy's ranking criterion. For the ranking, all German stocks on Datastream with a price larger than 1 Euro and a market value above 50 Million Euro are considered; t-statistics (two-tailed) are reported in parentheses. *;**;*** are the significance levels on the 10%, 5% and 1% level

X-month High	All months			ex Jan.			ex Dot-com Bubble		
Strategy	Wi	Lo	Wi-Lo	Wi	Lo	Wi-Lo	Wi	Lo	Wi-Lo
1-month	0.0016	-0.0011	0.0026	0.0019	-0.0027	0.0047**	0.0015	-0.0022	0.0036**
			(1.48)			(2.45)			(1.94)
3-month	0.0019	-0.0010	0.0029	0.0018	-0.0036	0.0055**	0.0018	-0.0022	0.0040
			(1.14)			(1.91)			(1.55)
6-month	0.0027	-0.0019	0.0045	0.0026	-0.0043	0.0069**	0.0026	-0.0032	0.0058**
			(1.58)			(2.44)			(1.95)
9-month	0.0032	-0.0024	0.0056**	0.0030	-0.0047	0.0077***	0.0029	-0.0038	0.0066**
			(2.07)			(2.91)			(2.43)
12-month	0.0033	-0.0025	0.0058**	0.0024	-0.0055	0.0079***	0.0040	-0.0028	0.0067**
(52-week)			(2.24)			(3.08)			(2.50)
15-month	0.0021	-0.0030	0.0051*	0.0018	-0.0050	0.0069***	0.0028	-0.0032	0.0060**
			(1.94)			(2.70)			(2.24)
18-month	0.0023	-0.0024	0.0048*	0.0021	-0.0043	0.0065***	0.0027	-0.0027	0.0055**
			(1.90)*			(2.64)			(1.82)

Furthermore, given that anchoring explains the 52-week high profits, other x-month high prices do not qualify as potential reference points used by traders. Both the 1-month high and the 3-month high prices are also published in some newspapers. However, strategies that use these figures in their ranking criterion are less profitable than the 52-week high and they are not substantially more profitable than other x-month high strategies[65].

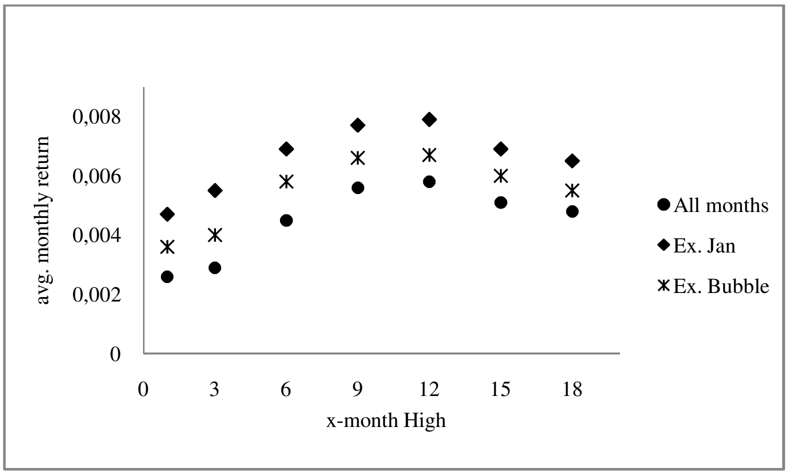
In summary, these findings support anchoring as the explanation for the profits of the 52-week high (and the momentum) strategy and secondly present evidence for the 52-week high as the reference point used by investors.

[65] In Figure 5, the 1-month high performance appears not to nicely fit into the inverted u-shape of the monthly average returns. This might be because the x-month high strategies differ by three months except for the 1-month high which covers a ranking period that is only 2 month shorter than the 3-month high.

Figure 5

Monthly Profits to x-month High Strategies

This graph illustrates the average monthly returns of different x-month high strategies. On the x-axis, the number of months is shown over which the highest price for each stock is measured and on the y-axis, the average monthly return is documented. For each x-month high strategy, the average return for the total period, the average return for all months except January and for the total period except the dot-com bubble period is illustrated.



5.3 The Industry-52-week High Strategy

As documented, momentum strategies are profitable for individual stocks. There is also some evidence that the momentum effect is present at industry level (Moskowitz and Grinblatt, 1999, Nijman et al., 2004). Strategies that buy the top industries and sell the bottom industries based on the past returns over the ranking period generate significant monthly profits. Since momentum and the 52-week high strategies seem to be related, it is worth to examine whether the 52-week high strategy is also profitable at industry level. This test is that powerful as it tests both relationships, that between the momentum and the 52-week high strategy and that between the 52-week high strategy and anchoring (see Figure 4). Evidence for both relationships is obtained by comparing the returns of the momentum and the 52-week high strategy at individual stock level and at industry level. Four potential findings with different interpretations are possible:

First, the industry-52-week high strategy dominates and explains the profitability of the 52-week high strategy at the individual stock level. This finding presents clear evidence against the anchoring hypothesis, which states that traders evaluate the impact on news based on a reference point. It implies that the reference point is a piece of information that is readily available to traders. This is true for the 52-week high of an individual stock as it is reported in nearly all newspapers publishing stock prices. However, this is not the case for the 52-week high of an industry. This figure is not available and needs to be calculated manually. Therefore, the 52-week high price of an industry cannot be considered as an easily obtainable piece of information. Consequently, the industry-52-week high strategy should not be substantially profitable or at least not dominate the 52-week high strategy of individual stocks if anchoring explains its profitability.

Second, the 52-week high strategy is not profitable at industry level. This could imply that the 52-week high is not able to fully explain momentum as it has not the capability to explain its profitability in industry portfolios. Yet, it could also indicate that momentum and industry momentum are independent phenomena with different drivers[66]. Furthermore, this finding does not represent any evidence against anchoring being the driver of the 52-week high as the nearness to the 52-week high price of an industry is (at least) not a better predictor of future returns than the 52-week high price of individual stocks which is an easily available piece of information.

Third, the profits to the industry-52-week high strategy are not larger than those to the 52-week high but different in magnitude compared to the industry momentum returns. As above, since the industry-52-week high does not dominate the 52-week high, this finding does not present evidence against anchoring as the driver of the 52-week high. It also implies that there is a close link between the 52-week high and the momentum strategy, as the profits of the strategies are similar both at individual stock level and in industry portfolios.

Fourth, the profits to the industry-52-week high strategy are not larger than those of the 52-week high but similar to the industry momentum profits. As in the third potential finding, this does not contradict the anchoring idea. Concerning the link between momentum and the 52-week high, this finding points on a close connection between the two strategies as their profits are similar both at individual stock and at industry level.

Only the fourth potential finding presents support for the hypothesis that stock price momentum is driven by anchoring. The other three findings are either at odds with anchoring

[66] Intuitively, due to the similar ranking criterion of momentum and industry momentum, this interpretation appears to be rather unrealistic.

being the driver of the 52-week high or challenge the relation between the 52-week high and momentum.

The construction of the industry-52-week high strategy resembles that of the 52-week high for individual stocks. Yet, since for an industry, neither a price nor a 52-week high exist, I calculate the price-52-week high ratio (I_PHR) for each industry. Therefore, the weighted price of all n_j stocks belonging to industry j at the beginning of month $t-1$ is divided by the weighted 52-week high of all n_j stocks (the highest price of a stock over one year ending at the beginning of month $t-1$). Within industry j, the n_j stocks are weighted based on the factor $\omega_{i,t-1}$. If stocks are value-weighted within the industries, it represents the fraction of stock i's market value in $t-1$ to the total market value of industry j in $t-1$. If however, stocks are equal-weighted within an industry, $\omega_{\ i,t-1}$ is equal to one divided by n_j:

$$I\_PHR_{j,t-1}^{52} = \frac{\sum_{i=1}^{n_j} \omega_{i,t-1} P_{i,t-1}}{\sum_{i=1}^{n_j} \omega_{i,t-1} H_{i,t-1}^{52}} \qquad (20)$$

By construction, the I_PHR measure can take positive values not larger than 1: if all stocks of industry j trade exactly on their 52-week high, I_PHR is one, if industry j's stocks have a price that is extremely far from their one year high, I_PHR takes a value close to zero. The strategy is long in stocks that belong to the 30% of industries with the highest I_PHR value and short in stocks that belong to 30% of industries with the lowest I_PHR measure. The portfolios are held over a holding period of six months. Between the ranking time and the holding period, a skip period of one month is included.

Table 13

Description of Industries, March 1988 – March 2008

Summary statistics of the 20 industry portfolios are reported below. The table represents only 19 industries because "Other" is excluded as it does not contain more than two stocks in most months. The first columns represent the average returns in excess of the Datastream Germany Price Index and the standard deviations of value weighted industry portfolios, while the second ones show the mean and standard deviation of equally weighted industry portfolios. Also reported are the average percentages of total market capitalization, the average number of stocks assigned to each industry and the average PHR (value-weighted) for each industry over the sample period.

Industry	Value-weighted		Equal-weighted		Avg. % of Market Cap.	Avg. No. of Stocks	Average PHR
	Mean	Standard deviation	Mean	Standard deviation			
Automobiles & Parts	0.15	3.15	0.12	2.66	3.98%	30.76	0.92
Banks	0.50	2.74	0.17	1.70	17.01%	83.16	0.90
Basic Resources	0.61	3.52	0.44	2.86	2.47%	52.47	0.94
Chemicals	0.21	2.41	0.33	1.91	3.37%	29.27	0.95
Construct. & Material	0.24	2.67	0.06	2.47	0.85%	35.25	0.95
Financial Services	0.64	3.44	0.21	2.62	5.87%	48.92	0.93
Food & Beverage	0.66	2.07	0.21	1.50	0.69%	38.74	0.94
Healthcare	0.73	2.63	0.67	2.74	8.80%	72.20	0.93
Ind. Goods & Services	0.50	3.11	0.17	2.43	8.09%	154.26	0.92
Insurance	0.23	2.99	0.06	2.48	5.36%	49.84	0.93
Media	0.18	3.79	0.17	4.01	4.19%	37.86	0.89
Oil & Gas	0.65	2.74	0.43	2.85	3.63%	30.69	0.89
Pers & Household Goods	0.34	2.42	0.03	2.07	4.51%	57.49	0.92
Real Estate	0.58	2.64	0.18	2.09	0.95%	34.12	0.95
Retail	0.27	2.67	0.11	2.64	3.25%	46.58	0.92
Technology	0.72	5.02	0.44	4.36	8.43%	139.70	0.89
Telecommunications	0.50	3.53	0.20	3.54	12.21%	33.75	0.90
Travel & Leisure	0.24	2.89	0.13	2.36	1.71%	28.10	0.91
Utilities	0.52	1.82	0.24	1.79	4.63%	31.57	0.95

In order to examine the industry-52-week high strategy, I classify stocks into one of 20 industries according to the FTSE Economic and Industrial sector criterion of Datastream. I decide for this industry measure for three reasons. First, Moskowitz and Grinblatt (1999) also classify stocks into 20 industry categories when examining industry momentum. Secondly, dividing stocks into more than 20 industry groups would imply a smaller number of stocks per industry which increases the risk that results are driven by idiosyncratic effects due to lack of diversification. A broader measure in opposite would reduce the number of industries that is included in the winner and loser portfolios

To ensure that the industry portfolios are well diversified and have only negligible firm-specific risk, I reduce my sample period to the interval between March 1988 and March 2008. This is necessary since the industry-52-week high strategy has stricter requirements on data availability than the momentum and the 52-week high strategies as a sufficient number of stocks is necessary for *each* industry to ensure diversification. Since the number of stocks is small for some industries between 1980 and 1988, this period is ignored in the subsequent research. Additionally, each month, only industry that contain 15 stocks or more are considered.

Table 13 gives a description of the industry portfolios and a summary on them. There are some differences in the average monthly returns of industry portfolios when stocks are value- and equal-weighted within an industry. Therefore, the following tests are computed for both value-weighted and equal-weighted industry portfolios.

Table 14 reports the profits to the industry-52-week high and to the industry momentum strategy. Panel A documents the profits to the strategies when stocks are value-weighted within an industry and Panel B when stocks are equal-weighted within an industry. The industry-52-week high strategy generates significant positive returns both when stocks are value-weighted and equal-weighted within an industry. The strategy remains profitable after the exclusion of the turn-of-the-year effect (line 4 in Panel A and B) and/or of the dot-com bubble (line 6 in Panel A and B). However, compared to the 52-week high strategy for individual stocks, the industry-52-week high is substantially less profitable. The 52-week high with a holding period of six months yields a monthly profit of 0.59% for the total sample, 0.75% for the period except the dot-com bubble and 0.80% for non-January returns between March 1, 1988 and March 1, 2008 (not reported in the tables). The industry-52-week high portfolios generate substantially lower returns with an average profit of 0.32% for the total sample, 0.44% for the non-dot-com bubble period and 0.44% for non-January months (when stocks are value-weighting within industries). To be very precise, I also compare the 52-week high strategy to the industry-52-week high strategy when stocks are not only equal-weighted within the industries but within the total winner and loser portfolios (line 8). This ensures that only the ranking criteria of the 52-week high and of the industry-52-week high strategy are compared, but not also the weighting method. But even with the same weighting within the winner and loser portfolios, the industry-52-week high strategy is still not as profitable as the 52-week high strategy.

Table 14

Profitability of Industry Strategies

This table reports the average monthly portfolio returns from 1st March 1988 to 1st March 2008, for industry momentum and industry-52-week high strategies. In Panel A, stocks are value-weighted within an industry while stocks are equal-weighted within an industry in Panel B. Industry momentum portfolios are built based on the past buy-and-hold returns over the ranking period. The industry-52-week high portfolios are formed based on the ratio of current average price of all stocks belonging to industry j to the highest average price within the past 12 months. All portfolios are held over an investment period of 6 months. Between the ranking and the holding period, a skip period of 1 month is included to abstract from bid/ask bounce. The winner (loser) portfolios of the momentum strategy consist of stocks that belong to the 30% of industries with the highest (lowest) return over the ranking period. The winner (loser) portfolios of the 52-week high strategy include stocks that belong to the 30% of industries with the highest (lowest) quotient of the current average price to the average 52-week high. For the ranking, all German stocks on Datastream with a price larger than 1 Euro and a market value above 50 Million Euro are considered; t-statistics (two-tailed) are reported in parentheses. *;**;*** are the significance levels on the 10%, 5% and 1% level.

	Wi	Lo	Wi-Lo	t-stat
	Panel A: Value-Weighting			
Industry Momentum (6/1/6)	0.0058	0.0024	0.0034	(1.73)*
Industry-52-week High	0.0051	0.0019	0.0032	(1.67)*
Industry Momentum (6/1/6) ex. Jan	0.0053	0.0016	0.0038	(1.83)*
Industry-52-week High ex. Jan	0.0048	0.0004	0.0044	(2.17)**
Industry Momentum (6/1/6) ex. 10/98-2/00	0.0062	0.0028	0.0036	(1.81)*
Industry-52-week High ex. 10/98-2/00	0.0058	0.0013	0.0044	(2.10)**
	Panel B: Equal-weighting			
Industry Momentum (6/1/6)	0.0039	-0.0004	0.0043	(2.27)**
Industry-52week High	0.0033	-0.0007	0.0040	(1.72)*
Industry Momentum (6/1/6) ex. Jan	0.003	-0.0024	0.0053	(2.51)**
Industry-52-week High ex. Jan	0.0029	-0.0025	0.0054	(2.52)**
Industry Momentum (6/1/6) ex. 10/98-2/00	0.0032	-0.0011	0.0044	(2.17)**
Industry-52-week High ex. 10/98-2/00	0.0030	-0.0025	0.0054	(2.57)***
Ind. Mom. (6/1/6) (Equal-weighted portfolios)	0.0038	0.0007	0.0033	(1.75)*
Ind. 52-week High (Equal-weighted portfolios)	0.0038	0.0005	0.0034	(1.72)*

Furthermore, industry momentum does not outperfom the industry-52-week high strategy. Both yield similar profits during the total sample period. For equal-weighted industry portfolios, the difference is 0.03%, for value-weighted portfolios it is only 0.02%. The difference in the profitability is larger when the dot-com bubble period or the turn-of-the-year effect is excluded, but even still below 0.10%.

In summary, the momentum and the 52-week high strategy seem to be linked closely together. Both at individual stock level and across industry portfolios, the returns to the strategies are of similar magnitude. Furthermore, since the industry-52-week high does not dominate the 52-week high strategy for individual stocks, I cannot reject the hypothesis that the 52-week high (and hence momentum) can be explained by anchoring. Moreover, I do not find any evidence that industry momentum can explain the profitability of individual momentum which is documented in Moskowitz and Grinblatt (1999) for the U.S. market.[67] In Table 14, the industry momentum portfolios yield substantially lower returns than individual momentum portfolios. This finding is consistent with Nijman et al. (2004) documenting that industry momentum plays only a minor role in explaining the individual momentum effect for European stocks.

5.4 The 52-week High Strategy during the Dot-com Bubble

As a third test for anchoring being the driver of the 52-week high, I measure the profitability of the 52-week high strategy during the emergence of the dot-com bubble. There is a vast of literature, which documents that bubbles are caused by irrational behavior of subjects. Herding - the tendency of subjects of being influenced by others (see, e.g. Hirshleifer and Hong Teoh (2003) for an overview) and overreaction (e.g. Scheinkman and Xiong, 2003, Hong et al., 2006). This argumentation implies that subjects change their behavior during a bubble. When herding or overreacting to private news, people form their estimates about future stock price based on other criteria than a reference point. This implies that the 52-week high strategy should not be profitable during the Dot-com phase if anchoring is in fact its driver.

As mentioned above, I define October 1, 1998 as beginning and March 1, 2000 as ending date of the dot-com bubble.[68] During that period, the 52-week high portfolios generate substantially negative returns for all examined holding periods (between -0.80% and -1.30% per month on average). Hence, while the 52-week high ranking criterion seems to work well in predicting future stock returns outside the dot-com bubble. This is not the case within this period. The difference in the profitability of the 52-week high in and outside the dot-com

[67] The role of industry momentum in explaining the existence of individual stock momentum is heavily discussed. Conrad and Kaul (1998) Grundy and Martin (2001), Chordia and Shivakumar (2002) among others provide theoretical as well as empirical evidence against Moskowitz and Grinblatt's (1999) hypothesis.

[68] Another possibility to examine the influence of the Dot-com Bubble on the strategies' profitability is to identify candidate firms by the ratio of price-to sales (P/S) and use the highest P/S quantile as Brunnemeier and Nagel (2004). Yet, information about sales is not available for all stocks. Furthermore, in this study, the profitability of the strategies for the total sample is of interest. Therefore, a classification of stocks by industries is preferred.

bubble indicates that the driver of this strategy disappeared during the time. One explanation could be the behavior of investors: while they normally use the 52-week high as orientation in evaluating news and suffer from anchoring, they form their estimations about future stock prices based on other criteria during the bubble (e.g. herding). This might be viewed as evidence that the 52-week high is driven by people's non-rational behavior.

5.5 The 52-week Low Price– An Alternative Anchor?

Beside the 52-week high price, investors could also use the 52-week low price of a stock as a reference point as this information is also easily available. The 52-week low reports the lowest price of a stock within the past 52 weeks. Therefore, I also examine a strategy based on the 52-week low and examine a strategy that buys 30% of stocks of which the price is furthest away from their 52-week low and sells 30% of stocks with a price closest to the 52-week low. This strategy is substantially less profitable than the 52-week high. For a holding period of six months, the 52-week low portfolios generate an average monthly return of 0.39% (t-statistic: 2.46). The profitability of the strategy is not surprising as it partly replicates the 52-week high strategy: The 52-week low portfolios are long in stocks with a price far from the 52-week low and short in stocks with a price close to the 52-week low. Stocks that are far from the 52-week low are often those that are close to their 52-week high and stocks that are close to their 52-week low are often those with a price far from the 52-week high. This can also be seen in the data. Over the total sample period, 46.7% (47.0%) of stocks in the winner (loser) portfolio based on the 52-week high criterion are also in the winner (loser) portfolio based on the 52-week low criterion. Hence, the 52-week low strategy is partially long in stocks that are close to the 52-week high and partially short in stocks with a price far from the 52-week high. Nevertheless, this replication is incomplete as the 52-week high strategy generates a monthly return that is about 49% higher than the 52-week low strategy. If each strategy is only allowed to include stocks that are not considered in the same portfolio by the other strategy, the 52-week high strategy yields higher returns than the 52-week low. I come to this conclusion as the 52-week low strategy yields lower returns than the 52-week high although the number of stocks that are considered winners or losers commonly by both strategies is large. If the 52-week high winners and losers are not allowed to be included into the winner and loser portfolios of the 52-week low strategy, the latter strategy loses its profitability and generates an insignificant average monthly return of 0.14% (t-stat 0.56). Hence, the 52-week low profits seem to be driven by the 52-week high criterion.

6. Robustness Tests

To ensure that the findings are not driven by illiquid stocks, I recalculate momentum and 52-week high returns and only considers stocks for the ranking that are traded continuously in all six months before the ranking date. This approach goes back to Forner and Marhuenda (2003). Table 15 reports the results for the (6/1/6) momentum and the 52-week high strategy with a holding period of six months. It shows that the profits to the strategies are only slightly different under this assumption. Hence, my requirements for stocks to be included in the sample (stocks with a market value larger than 50 million Euro and a price above one Euro) seem to be sufficient.

Table 15

Profits to the Strategies when Limited to Highly Liquid Stocks

This table reports the average monthly portfolio returns in excess of the Datastream Germany Price Index average return from February 1981 through March 2008, for the (6/1/6) momentum strategy and the 52-week high strategy. The momentum strategy ranks stocks based on their past buy-and-hold returns over the ranking period. The top (bottom) 30% of stocks are included in the winner (loser) portfolio. The 52-week high strategy sorts stocks on the ratio of their current price to their highest price within the past 12 months. The 30% of stocks with the highest (lowest) ratio are included in the winner (loser) portfolio. All portfolios are held over the investment period of six months. Between the ranking and the holding period, a skip period of 1 month is included to abstract from bid/ask bounce. In the left column, monthly returns for strategies are reported when only stocks are considered for ranking with a price larger than 1 Euro, a market value above 50 million Euro and which are traded continuously in all six months before the ranking date. In the right columns, stocks are considered with a price larger than 1 Euro and a market value above 50 Million Euro for the ranking. The data contains all German stocks on Datastream; t-statistics (two-tailed) are reported in parentheses. *;**;*** are the significance levels on the 10%, 5% and 1% level.

		Stocks traded continuously			All stocks		
		Wi	Lo	Wi-Lo	Wi	Lo	Wi-Lo
Raw Returns	Mom (6/1/6)	0.0030	-0.0024	0.0053***	0.0034	-0.0022	0.0056***
				(2.89)			(2.75)
	52-week High	0.0029	-0.0023	0.0052***	0.0033	-0.0025	0.0058**
				(3.63)			(2.24)
Ex Jan.	Mom (6/1/6)	0.0019	-0.0039	0.0058***	0.0023	-0.0039	0.0062***
				(3.28)			(3.13)
	52-week High	0.0026	-0.0047	0.0073***	0.0025	-0.0046	0.0071***
				(3.95)			(2.91)
Ex Dot-com Bubble	Mom (6/1/6)	0.0040	-0.0015	0.0054***	0.0032	-0.0024	0.0057***
				(3.68)			(2.63)
	52-week High	0.0037	-0.0019	0.0056***	0.0040	-0.0028	0.0067**
				(3.87)			(2.50)

To further limit the risk of obtaining biased results due to data mining, I follow August et al. (2000) and Göppl and Schütz (1992) and only include those stocks that are traded in at least 50% of all months of the sample. This limitation also does not alter my results and conclusions (not reported in the tables).

In order to ensure that dot-com bubble period does not heavily influence my results, I report monthly returns for all months except those during October 1998 and February 2000. Another way to control for this short episode in finance history is to measure profits of momentum and 52-week high strategies when technology and telecommunication stocks are excluded from the sample. These stocks are most heavily influenced by the emergence and the collapse of the dot-com bubble. Yet, the exclusion does not alter my findings: the $(6/1/6)$ momentum strategy generates an average monthly return of 0.53%, which is only slightly smaller than 0.56% for all stocks; the profitability of the 52-week high strategy is with 0.57% almost identical compared to 0.58% for all stocks.

The last robustness check relates to stocks delisted during the holding period. As in Forner (2003, p.72), this study assumes that the proceeds of the delisted stocks are at once equally invested in the remaining stocks. To ensure that this does not influence the results I use the procedure of Agyei-Ampomah (2003, p.780) and assume a return of zero when a stock is delisted. Yet, as the percentage of stocks that are delisted during each ranking period is small, this assumption does not change my results.

7. Summary

This work relates to the behavioral finance literature and tests the hypothesis whether momentum can be explained by anchoring – a behavioral heuristic documented by Kahneman et al. (1982, p.14-20) which states that subjects focus too much on a reference point when forming estimates. With three different tests, I find support for the 52-week high price of a stock being used as a reference point by investors against which they evaluate the impact of news on the stock price. Based on the results, anchoring cannot be rejected as driver of the 52-week high strategy. This is the main finding of this part of my thesis. Up to my knowledge, this study is the first to test empirically whether anchoring qualifies as the driver of the 52-week high strategy.

Testing whether anchoring qualifies as explanation for the profits to the 52-week high strategy is important as it indicates whether evidence against the EMH is found. Without clear indication for investors' non-rationality driving the 52-week high, the relation between momentum and the 52-week high documented in George and Hwang (2004) only states that one strategy is explained by another although the drivers of both are unknown and could also be linked to risk factors.

I also go further than George and Hwang (2004) in testing the relationship between momentum and the 52-week high strategy. On the one hand, the relation between the two strategies is explored more broadly. Firstly, the profitability of both strategies is compared for different ranking and holding periods. This is important as it is not sufficient to compare the 52-week high to only one or two momentum strategies (e.g. the $(6/1/6)$ strategy) in order to document the dominance of the 52-week high. Secondly, I look at the profitability of both strategies at industry level and find that they generate returns of similar magnitude. The similar profitability of them for industry portfolios further indicates a close relation between momentum and the 52-week high. On the other hand, the link between the two strategies is tested with two sorting and one regression approaches as all methods have strengths but also face substantial drawbacks.

The third contribution of this work is to present some insights into the momentum literature for non-U.S. data. As most studies examine U.S. stocks, it is important to use a different sample in order to exclude data mining as explanation for the momentum effect. This work shows that the momentum effect still exists after 2001, which is doubted by Henker et al (2006) and Hwang and Rubesam (2007). I therefore support the view of Dimson et al. (2008) that the non-profitability of the momentum strategy after 2001 is only limited to the U.S. sample. The data sample also allows a closer look at the momentum effect in Germany. Stock price momentum is profitable for the German market. This is shown by using the common methodology of Jegadeesh and Titman (1993). To my knowledge, this has not yet been verified. With August et al. (2000) and Nelles et al. (2007), two studies of the recent past examine momentum profits for the German market but do not exactly employ the Jegadeesh and Titman (1993) method.[69] Furthermore, this study documents that the industry momentum strategy is profitable. Yet, its returns are in opposite to the U.S. not as large as those of momentum strategies on individual stock level. Finally, this work presents evidence that the 52-week high strategy of George and Hwang (2004) is also profitable outside the U.S for the total sample, but that it does not work during the dot-com bubble between October 1998 and February 2000.

[69] Nelles et al. (2007) do not control for potential microstructure distortions by skipping a month between the ranking and holding period. Furthermore, with CDAX stocks, their work only uses a quite small data sample. August et al. (2000) do not measure momentum returns with overlapping holding periods, but wait to the end of the investment period before they form another one.

Part III

The 52-week High Strategy and Information Uncertainty

1. Introduction

This work resembles the second part of my thesis as it tests the same null hypothesis, which states that the 52-week high strategy cannot be explained by anchoring. Yet, since a different approach to test the null hypothesis is chosen and since another sample is considered, the previous and this work differ substantially and cannot be included in one part of the thesis. To examine the null, I build in this work on an insight of the psychological literature that psychological biases is more present when uncertainty is greater[70]. It implies that a behavioral heuristic such as anchoring should have more room in cases of larger uncertainty. Consequently, given that anchoring explains the 52-week high profits, the 52-week high measure should have more predictive power in cases of larger information uncertainty. Information uncertainty is defined as the doubt about the implication of news on a firm's value (Zhang, 2006); it arises either due to a firm's underlying fundamental volatility or due to poor information. I expect the level of information uncertainty to be positively related to 52-week high winner stocks and negatively related to 52-week high loser stocks if anchoring is the driver of the strategy.

As a measure for information uncertainty, I use six proxies: firm size (market value), firm's book-to-market ratio, the distance between the 52-week high price of a stock and its 52-week low price, stock price volatility, firm age and cash flow volatility. Four out of the six proxies have already been employed by the literature as measures for uncertainty (see e.g. Zhan, 2006). The other two variables (the firm's book-to-market ratio and the distance of a stock's 52-week high price to the 52-week low price) are to my knowledge new in the information uncertainty literature. Although each of the six measures might also contain other effects than information uncertainty, their common element should be the ability to quantify uncertainty about the impact of news on a firm's fundamentals.

2. Information Uncertainty

According to Zhang (2006), information uncertainty is defined as the uncertainty about the impact of new information on the firm's value. Either the ambiguity can arise due to the volatility of the fundamentals of a firm or it could be due to the quality of the information.

[70] See also the work of Daniel et al. (1998, 2001) and Hirshleifer (2001).

Formally, an observed signal s consists of information about the fundamental value v of a firm (e.g. dividend or future cash flow) and a noise term e:

$$s = v + e \qquad (21)$$

Information uncertainty is measured as the variance of the signal:

$$var(s) = var(v) + var(e) + 2 \cdot cov(v, e) \qquad (22)$$

Given that $cov(v, e) = 0$, information uncertainty is equal to the variance of the volatility of the firm's fundamentals and the variance of the noise term. While the first part of the right-hand side can be interpreted as the firm's underlying fundamental volatility, the latter refers to the quality of the information. In the subsequent empirical tests, I do not differentiate between the two sources as it is difficult to distinguish between them empirically. Stocks, for which $var(s)$ is large are called high-uncertainty stocks (H), whereas stocks with a small variance of the signal are named low-uncertainty stocks (L).

Given that a behavioral bias explains the profitability of the 52-week high strategy, I predict that high-uncertainty 52-week high winners have a higher future return than low-uncertainty 52-week high winners and that high-uncertainty 52-week high losers have a lower future return than low-uncertainty losers:

$$R_H^{Wi} - R_L^{Wi} > 0 \qquad \text{and} \qquad R_H^{Lo} - R_L^{Lo} < 0, \qquad (23)$$

where R_H^{Wi} and R_L^{Wi} (R_H^{Lo} and R_L^{Lo}) are returns for high- and low-uncertainty 52-week high winner (loser) stocks. It implies that the 52-week high strategy is more profitable for high-uncertainty stocks than when it is limited to low-uncertainty stocks:

$$R_H^{Wi} - R_H^{Lo} > R_L^{Wi} - R_L^{Lo}. \qquad (24)$$

To proxy information uncertainty, I employ six different variables. Firm size qualifies quite intuitively as a measure since small firms are often less diversified than big ones, which implies a higher volatility in fundamentals. Moreover, small companies do not provide as much information to the market as large ones. They have fewer shareholders, customers and suppliers and may have lower disclosure preparation costs. Additionally, if investors have fixed costs in the acquisition of information, they put in sum more effort in stocks in which they can take larger positions (Hong et al., 2000). Firm size is measured as the market value of each company at the ranking date.[71]

A second proxy is the book-to-market value of a firm. Daniel and Titman (1999) argue that ambiguity is larger for growth stocks than for value stocks. They state that the value of a growth stock heavily depends on future growth possibilities and intangible assets (Daniel and Titman, 1999, p.30), which are especially difficult to measure. Therefore, in the attempt to estimate the value of an investment, investors more heavily depend on subjective information and are confronted with more ambiguity when estimating the value of a growth stock compared to a value stock. Similar to Fama and French (1993), I calculate the book value of a firm as the shareholders' equity plus deferred taxes (balance sheet deferred taxes plus balance sheet investment tax credit). Different to Fama and French (1993), I do not subtract the value of preferred stock, as this type of data is not available from Datastream (see also Nagel, 2001 and Daniel and Titman, 1999). If a book value is negative, I exclude it from the analysis.

Another measure for information uncertainty is the distance of the 52-week high price to the 52-week low price of a stock. The 52-week high (low) is the highest (lowest) price of a stock in the past 52 weeks. The proxy LHR (Low-High Ratio) is calculated as follows:

$$LHR_{i,t-1} = \frac{\mathrm{L}^{52}_{\mathrm{i,t\text{-}1}}}{\mathrm{H}^{52}_{\mathrm{i,t\text{-}1}}} \qquad (25)$$

where $\mathrm{H}^{52}_{\mathrm{i,t\text{-}1}}$ is the highest price of stock i during the one year period ending at the first day of month $t-1$ and $\mathrm{L}^{52}_{\mathrm{i,t\text{-}1}}$ is the lowest price of stock i during this interval. The lower the value of the variable, the higher is the distance between the 52-week high and low of a stock and hence the larger the level of information uncertainty. As I will show, this proxy resembles but is not identical to the volatility of the stock price. Theoretically, if there is few information about a firm, but for which uncertainty is large, price volatility is low as the stock price does

[71] To be very precise, this is formally different from Zhang (2006), where the market value is considered at the portfolio formation date. The differentiation between the ranking date and the beginning of the holding period is important in my study as I include a skip period between the ranking and the holding period in opposite to Zhang (2006).

not heavily move up or down in most days of the year. However, LHR captures these strong implications of the rarely appearing information as it only considers the highest and lowest price of the stock over the past 12 months.

Stock price volatility is another proxy for information uncertainty. It is calculated as the standard deviation of weekly market excess returns over the 12 months before the portfolio formation date. As in Lim (2001) and Zhang (2006), weekly excess returns are calculated from daily prices between Thursday and Wednesday in order to mitigate bid-ask bounce effects or non-synchronous trading. As a market reference, the UK-DS index from Datastream with 550 stocks is chosen.

Further, the age of a firm might also give evidence on the degree of information uncertainty. Compared to recently founded companies, older firms have a longer history of data and more information available to the market (Barry and Brown, 1985). Additionally, Zhang (2006) argues that the age of a firm is also linked to the maturity of the industry. Therefore, the variable implicitly measures the underlying volatility of an industry. Ideally, the variable should capture the time since the firm was founded. As this information is not available for the total sample, AGE is calculated as the number of months since Datastream first covers the firm. This procedure is also employed in Zhang (2006).

The cash flow volatility is another measure for information uncertainty (CFVOLA). It is calculated as the standard deviation of net cash flow from operating activities divided by average total assets of the past 3 years.[72] While the sample period starts in January 1988, this variable is not available before January 1996. Similarly, to Zhang (2006), CVOL is assumed to be missing if there is only 1 or 2 years' data available. For about 70% of stocks in my sample, information about the cash-flow volatility is available.[73]

It is very likely that each variable on its own does also capture other effects than information uncertainty. This might be especially true for firm size. While it is employed as a proxy for information uncertainty in this work, Hong et al. (2000) interpret firm size as a measure for the rate of information diffusion. Merton (1987) and Grossman and Miller (1988) argue that

[72] Zhang (2006) calculates CVOL as the standard deviation of the cash flow of the past 5 years. However, due to the limited period between January 1996 and August 2008, I decide for a shorter period of 3 years.

[73] This might lead to biased results as about 30% of stocks are ignored in the tests if cash-flow volatility is considered. I do not assume a cash-flow volatility of zero when data is missing as otherwise, stocks with missing information would be automatically considered in the lowest-uncertainty stock.

the difference in returns across firm size is explained by the arbitrage capacity and by market making. Therefore, drawing any inferences based on a single proxy about information uncertainty might seem questionable, but taken all together their common element should be information uncertainty.[74]

3. Data and Methodology

This work examines the returns of different strategies between January 1989 and August 2008, a total of 236 months. The data consists of all stocks traded in the UK and is obtained from Datastream on a monthly basis except for stock prices (adjusted for subsequent capital actions), which are also used on a weekly interval to calculate the VOLA proxy. To mitigate microstructure effects that are associated with low-priced and illiquid stocks, only stocks with a market value above 20 Mio. Pounds are considered for the ranking in month t. On average, 965 stocks are available per month. The sample includes both surviving and delisted stocks and should therefore not suffer from a survivorship bias.[75]

With UK stocks, I employ a different sample than in Part II of my thesis, where German stocks are examined. The reason lies in the fact that additional information about a stock is necessary for the tests in this part (e.g. to proxy information uncertainty). For the German sample, this information is not available or only for a fraction of stocks. Moreover, employing a different sample in Part III than in Part II offers the advantage that the same theory (anchoring as driver of the momentum and of the 52-week high strategy) and some patterns documented in the literature can be examined for different samples. For example, this thesis presents support for the profitability of the momentum effect and of the 52-week high strategy for German and UK stocks. Since most important studies investigate US stocks, employing a different sample contributes to the robustness of some already documented patterns.

Portfolios for all strategies are constructed as follows. At the beginning of each month, all traded stocks are ranked in ascending order based on the strategy's respective ranking

[74] I also examine whether information uncertainty varies over time. I therefore test, whether the 52-week high strategy is more profitable in periods when the index volatility is above the median compared to intervals when volatility is below the interval. Yet, I do not obtain consistent and robust findings. Therefore, I only report tests about cross-sectional differences in information uncertainty.

[75] Some studies using Datastream suffer from a survivorship bias since delisted stocks are missing if the data is employed unadjusted and in its raw state from the database. Yet, this does not mean that it is impossible to get a survivorship-free sample using Datastream. It provides dead stock files, which can be applied to recreate the complete sample.

criterion. For most tests in the study, stocks are sorted into quantiles. The top stocks according to the criterion are assigned to the winner portfolio, the bottom to the loser portfolio. For most tests in the paper, a holding period of six months is examined. This is consistent with the literature. The portfolios are equally weighted and not rebalanced during the holding period. To be precise, as for the tests in Part II, this implies that a portfolio is only perfectly equal-weighted at the formation date. Subsequently, stocks experiencing a price increase have implicitly a higher weight than stocks with a price drop. Momentum and 52-week high strategies are self-financing and are long in winner stocks and short in loser stocks. Hence, the profits to the strategies are computed as the arithmetic difference (WML) between the returns to the winner portfolio (R^{Wi}) and the returns to the loser portfolio (R^{Lo}):

$$\text{WML} = R^{Wi} - R^{Lo} \tag{26}$$

To abstract from potential microstructure effects and the bid-ask bounce, a skip of one month is included between the ranking and holding period. If a stock is delisted during the holding period, a return of zero is assumed for the stock (Agyei-Ampomah, 2003, p.780). As the percentage of stocks that are delisted during the holding period is quite small, this assumption does not influence the inferences. (The robustness of the results to the assumed returns for delisted stocks is already shown in Part II for the German sample, where the percentage of delisted stocks is larger compared to the UK sample; this robustness test for the UK sample is available on request).

To increase the statistical power and to reduce the effects of the bid-ask bounce (Moskowitz and Grinblatt, 1999, p.1258), monthly portfolio returns are calculated on an overlapping holding period basis. It implies that the total portfolio return per month is the average return of K strategies (with K equal to the length of the holding period, in months), each beginning one month apart. In each of the K portfolios, a fraction of $1/K$ of the total amount is invested. For example, at the beginning of month t, the winner portfolio with a holding period of 3 months consists of three sub-portfolios: one formed at the beginning of $t-3$, one built in $t-2$ and one started in $t-1$. The return to the winner portfolio in t is the average return of the three subportfolios. At the beginning of month $t+1$, the monthly return is measured for the subportfolios constructed in $t-2$, $t-1$ and t, where the portfolio formed in t replaces the one built in $t-3$. An advantage of this method is that simple t-statistics can be employed (Rouwenhorst, 1998, Lee and Swaminathan, 2000). As in Part II, I test whether returns are autocorrelated by using the Breutsch-Godfrey test. Therefore, I regress the monthly returns R_t of the 52-week high strategy on a constant c and an error term u_t: $R_t = c + u_t$. The obtained $\hat{u}_t$ (least squares) are regressed on their p lags in a simple AR(p) model: $\hat{u}_t = c_0 + \gamma_1 \hat{u}_{t-1} + \gamma_2 \hat{u}_{t-1} + \cdots + \gamma_p \hat{u}_{t-p} + \varepsilon_t$. I chose different values for p between 1 and 12. From this auxiliary regression, I obtain R^2 which is necessary to get the test statistics that is denoted with $(t-r)R^2 \sim \chi_r^2$. The tests show that simple t-statistics can be employed.

As in Part II, the ranking criterion for the 52-week high strategy can formally be described as (see also Equation 17):

$$PHR_{i,t-1}^{52} = \frac{P_{i,t-1}}{H_{i,t-1}^{52}}\ , \qquad (27)$$

where $P_{i,t-1}$ is the price of stock i at the first day of month $t-1$ and $H_{i,t-1}^{52}$ is stock i's highest price during the one-year period ending at the first day of month $t-1$. According to Equation (27), all stocks in month $t-1$ are sorted into five portfolios. The top 20% of stocks – those with the highest PHR value and hence with a price close to their 52-week high – are assigned to portfolio P5, the bottom 20% to portfolio P1. Table 16 reports for each of the five 52-week high portfolios the average monthly raw returns (column 1), the non-January returns[76] to control for the turn-of-the-year effect (column 2) and the Fama-French alphas to control for risk factors[77] (column 3). The difference between P5 and P1, which implies the profits to the 52-week high strategy, is 1.21% for the total sample, 1.44% when January returns are excluded and 1.87% when returns are adjusted for the three Fama-French factors.[78] This verifies that the 52-week high strategy is profitable for my sample. The turn-of-the year effect can also be observed in the data, as the loser stocks (P1) yield lower returns outside Januaries. This is also true for stocks in portfolio P5, yet the difference is more than twice for loser stocks than for winners.

[76] The exclusion of January returns allows obtaining results, which are not biased by the turn-of-the-year effect. It implies that stocks with a poor performance experience a recovery at the beginning of a new year. According to Roll (1983), Griffiths and White (1993) and Ferris et al. (2001), investors sell loser stocks at the end of the year in order to realize tax loss benefits. This leads to lower prices at year-end for loser stocks. At the beginning of the following year, the selling pressure vanishes and the prices of the loser stocks recover.

[77] A detailed description of how the Fama-French alphas are calculated can be found in Section 4.2.

[78] The 52-week high strategy is not profitable during the Dot-com Bubble period between October 1998 and March 2000 with an average monthly return of -1.11%.

Table 16

Profits to the 52-week High and the (6/1/6) Momentum Strategy

This table reports the average monthly portfolio returns from January 1989 to August 2008 for the 52-week high strategy and for the (6/1/6) momentum strategy. The 52-week high portfolios rank stocks based on the ratio of the current price of a stock to its highest price within the past 12 months. For the momentum portfolios, stocks are sorted based on their past six-month buy-and-hold return. All portfolios are held over the investment period of six months. Between the ranking and holding period, a skip period of one month is included to abstract from bid-ask bounce. The highest 20% of stocks based on the ranking criterion is assigned to the portfolio P5 and is equal-weighted, while the bottom 20% is included in portfolio P1. The 52-week high strategy and the momentum strategy are long in P5 and short in P1. For the two strategies, the average monthly return is reported for raw returns, for non-January months and for returns that are adjusted for the three Fama-French factors. The sample covers all UK stocks available from Datastream with a market value above 20 million Pounds; t-statistics (two-tailed) are reported in parentheses.

		P1	P2	P3	P4	P5	P5-P1	t-stat
52-week High	Raw returns	-0.0016	-0.0007	0.0053	0.0071	0.0106	0.0122	(4.49)
	Ex Jan.	-0.0056	-0.0031	0.0033	0.0053	0.0089	0.0144	(5.25)
	Adjusted returns	-0.0021	0.0022	0.0046	0.0124	0.0166	0.0187	(7.96)
(6/1/6) Momentum	Raw returns	-0.0024	0.0016	0.0046	0.0073	0.0095	0.0119	(4.41)
	Ex Jan.	-0.0055	-0.0003	0.0031	0.0058	0.0087	0.0142	(4.77)
	Adjusted returns	-0.0006	0.0016	0.0047	0.0091	0.0167	0.0173	(6.16)

Table 16 also documents the average monthly (6/1/6) momentum returns. The strategy ranks stocks into five portfolios based on their past 6-month buy-and-hold returns. As for the 52-week high strategy, all portfolios are held over a six-month period after a skip of one month. The strategy yields very similar returns as the 52-week high strategy for the total sample, when January is excluded and when returns are "Fama and French"-risk-adjusted. The t-statistics indicate that the momentum returns are highly significant. The similar magnitude of (6/1/6) momentum profits and of 52-week high returns confirms the finding of George and Hwang (2004) for the UK stock market. They show a close connection between the two strategies. The reason why the strategies seem more profitable if controlled for the three Fama-French factors (compared to raw returns) lies in the fact that loser stocks load more on the SMB factor than winners do. This observation is consistent with the findings of Rouwenhorst (1998, p.277) and of Jegadeesh (2001, p.707).

Table 17

Descriptive Statistics of the Information Uncertainty Variables

MV is the market capitalization (in millions of Pounds) at the beginning of month t. Book-to-market value (B/M) is the book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year. LHR is the quotient of the lowest price of a stock within the past 52 weeks and the highest price of the stock within the last 52 weeks. Stock volatility (VOLA) is the standard deviation of weekly market excess returns over the year ending at the beginning of month t, whereas weekly returns are measured from Thursday to Wednesday. Firm age (AGE) measures the number of months since a firm was first covered by Datastream. Cash-flow volatility (CFVOLA) represents the standard deviation of the net cash flow from operating activities standardized by average total assets in the past three years. The sample covers all UK stocks available from Datastream with a market value above 20 million Pounds. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996.

	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
MV	1,381	15,510	20	45	116	431	1319
B/M	0.6382	0.7892	0.0000	0.2746	0.4889	0.8320	83,0900
LHR	0.5998	0.1692	0.0028	0.5035	0.6288	0.7232	0.9811
VOLA	4.71	5.12	0.87	2.72	3.78	5.46	350.85
AGE	113	78	0	49	98	163	347
CFVOLA	0.0497	0.0605	0.0233	0.0193	0.0343	0.0590	1.8489

Table 17 presents descriptive statistics for the six information uncertainty variables employed in the tests. It shows that firm size heavily varies across the sample. Moreover, it documents that the distribution of firm size is skewed. While the smallest market value is slightly above 20 Million Pounds, the largest value is 1.319 Mio. Pounds. The mean firm size is 1.381 Mio. Pounds while the median is 116 Mio. Pounds. Considering the mean volatility (VOLA), a value of 4.71% shows that stock prices are quite volatile during the sample period. Firm age ranges between 0 months and 347 months. The relative low maximum value of AGE leads to the assumption that there is a discrepancy between the beginning of the coverage in Datastream and the actual formation date of the firms, especially for old companies. Yet, the potential measurement error of the age of older firms should not have large influence on the obtained findings: Firm age is used as a proxy for uncertainty since, among other things, the age of a company is related to length of data history available. However, the difference in data history should have a greater impact on the uncertainty level in the first years of a firm's existence. A slightly longer data history should increase the insights of investors into a firm to a larger extend for younger than for older companies. Such a low maximum for the age of a company is not only limited to our study.[79]

[79] Zhang (2006) also employs firm age as a variable for the U.S. sample. The difference in the descriptive statistics for the two samples is not too large: While the median age lies at 13 years for U.S. stocks, it is 8 years in my sample.

4. The 52-week High Strategy and Information Uncertainty

4.1 The Predictive Power of the 52-week High Measure

Before testing the relation between information uncertainty and the 52-week high profits, I first examine the cross-sectional variation of stock returns in the six information uncertainty proxies (mean effect). Each month, stocks are sorted into five portfolios according to the information uncertainty measure. Portfolios are equal-weighted and held over a six-month period. Between the ranking date and the beginning of the holding period, a skip period of one month is included. For the proxies MV, B/M, LHR and AGE, the reciprocals are employed in order to avoid confusion: By doing this, it is assured that for all proxies, a high (low) value implies a high (low) degree of information uncertainty. Table 18 reports the average monthly portfolio returns on an overlapping holding period basis. Except for cash-flow volatility, high information uncertainty stocks generate lower returns than low information uncertainty stocks. However, for five out of six variables, the return difference is not significant on the 5% level. Only a strategy that is long in high book-to-market values and short in low B/M values produces negative returns that are highly significant. Hence, except for B/M, the cross-section variation in stock returns is, if at all, only weak in the uncertainty proxies.[80]

The reason to construct the uncertainty portfolios as described is to make the results comparable to subsequent tests, where the relation between the six variables and the 52-week high profits is documented for portfolios that are constructed in the same manner. I also examine the average monthly portfolio returns without a skip period and with a one-month holding period, which does also not lead to significant return differences between high- and low-uncertainty stocks.[81]

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[80] The mean effect is also examined in a similar setting by Jiang et al. (2004) and Zhang (2006). While Jiang (2004) presents evidence for a significant variation in mean returns, Zhang (2006) does not find a significant negative mean effect. Yet, for data and methodology reasons, Zhang (2006) cannot completely exclude its existence. My results do also not allow to convincingly rejecting the existence of a significant mean effect for my six uncertainty variables.

[81] Results are not reported for consideration of space, but are available on request.

Table 18

Six-month Returns to Information Uncertainty Portfolios

This table reports the average monthly returns of portfolios sorted by each information uncertainty variable. Each month, stocks are ranked according to the information uncertainty proxy into five portfolios, whereas stocks with the highest (lowest) value of the variable are assigned to portfolio U5 (U1). MV is the market capitalization (in millions of Pounds) at the end of month t. Book-to-market value (B/M) is the book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year. LHR is the quotient of the lowest price of a stock within the last one year and the highest price of the stock within the last 52 weeks. Stock volatility (VOLA) is the standard deviation of weekly market excess returns over the year ending at the beginning of month t. Firm age (AGE) measures the number of months since a firm was first covered by Datastream. Cash-flow volatility (CFVOLA) represents the standard deviation of the net cash flow from operating activities standardized by average total assets in the past 3 years. Stocks are equal-weighted and held in the portfolio over six months. Between the ranking date and the formation period, a skip period of one month is included. The table reports the overlapping holding period returns. 1/MV, 1/(B/M), 1/LHR and 1/AGE are the reciprocals of MV, B/M, LHR and AGE. Each month, all actively traded UK stocks on Datastream with a market value above 20 million Pounds are considered. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996.

	U1	U2	U3	U4	U5	U5-U1	t-stat
1/MV	0.0057	0.0043	0.0034	0.0024	0.0018	-0.0039	-(1.21)
1/(B/M)	0.0078	0.0051	0.0034	0.0014	-0.0005	-0.0082	-(3.04)
1/LHR	0.0036	0.0048	0.0043	0.0035	0.0014	-0.0023	-(0.66)
VOLA	0.0061	0.0050	0.0044	0.0022	0.0021	-0.0039	-(1.65)
1/AGE	0.0059	0.0055	0.0048	0.0024	0.0026	-0.0034	-(1.19)
CFVOLA	0.0007	0.0054	0.0060	0.0062	0.0064	0.0056	(1.77)

In order to test whether the 52-week high strategy yields higher returns in cases of higher uncertainty, the following method is conducted: Stocks are first classified into quantiles according to the uncertainty proxy. Stocks with the lowest information uncertainty level are assigned to portfolio U1, whereas stocks with the highest uncertainty level are included into portfolio U5. Within each portfolio, stocks are further sorted into three portfolios according to the 52-week high measure of Equation (27). The top 20% of stocks is assigned to the 52-week high winner portfolio (H1) and the bottom 20% to the 52-week high loser portfolio (H5). The portfolios are formed after a skip period of one month and are held over six months. Returns are calculated on an overlapping holding period basis. Table 19 reports the average monthly profits to the 52-week high strategy that is long in 52-week high winner stocks and short in 52-week high loser stocks within an information uncertainty portfolio. The results present evidence that the predictive ability of the 52-week high criterion is increasing in information uncertainty. A positive relationship between the level of ambiguity and the 52-week high profits can be observed for each information uncertainty measure. The 52-week high portfolios generate an average monthly return that is by 1.36% to 2.36% higher when the strategy is limited to high-uncertainty stocks compared to low-uncertainty stocks. For VOLA, for example, the 52-week high strategy yields an average monthly return of 0.74% across low-uncertainty stocks, but generates a monthly profit of 1.99% for stocks in the high-uncertainty group, which is more than twice as large.

The increase of the 52-week high profits in the level of information uncertainty is driven by both, winner and loser portfolios. The relation between the degree of information uncertainty and the 52-week high winner stock returns is positive and the difference between high-uncertainty winners and low-uncertainty winners is significant on at least the 10% level for most proxies. For the 52-week high loser stocks in opposite, the relation between information uncertainty and monthly returns is negative; the difference between high-uncertainty losers and low-uncertainty losers is with -1.12%, on average, large and highly significant across the proxies. The reason why the winner difference is not as large and significant as the loser difference (in absolute terms) between high- and low-uncertainty stocks might be due to the fact that the uncertainty effect disappears more quickly for winners and good news than for losers and bad news (see Section 5.3). An increase in the 52-week high winner portfolio returns and a decrease in the 52-week high loser portfolio profits in information uncertainty is consistent with my hypothesis that anchoring is the driver of the 52-week high strategy. Higher information uncertainty tends to increase subjects' anchoring bias[82] and leads them to underweight the impact of information. The subsequent correction of the bias generates positive returns to 52-week high winner stocks and negative returns to 52-week high losers.

The increase of the predictive power of the 52-week high criterion in information uncertainty is largest in the tails of the PHR distribution. At least for LHR, VOLA and AGE, the difference between the largest and the lowest information uncertainty group is in absolute terms largest for stocks with a price furthest from the 52-week high price (H4, H5) and for the price closest to the 52-week high price (H1) (see column U5-U1 in Table 19). It is smallest in the H2 and H3 groups for all proxies. These are the portfolios with stocks that are neither close to nor far from the 52-week high price. This is consistent with the anchoring hypothesis, which states that investors' underreaction behavior is mostly observable for stocks close to and far from their respective 52-week high price.

[82] The anchoring bias might be larger as either individuals underestimate the impact of news and focus more on the reference point or as the number of investors employing the 52-week high price of a stock as an anchor increases.

Table 19

The 52-week High Profits for different Information Uncertainty Groups

This table reports average monthly portfolio returns sorted by an information uncertainty proxy and by the 52-week high criterion. Each month, stocks are sorted into quantiles based on the value of the uncertainty variable. The 20% of stocks with the highest variable value (and with the greatest information uncertainty) is included into U5 while the 20% of stocks with the lowest value (and hence with least information uncertainty) are assigned to group U1. Within each information uncertainty quantile, I further sort stocks based on the 52-week high ranking criterion. The top (bottom) 20% is included in the winner (loser) portfolio H1 (H5). MV is the market capitalization (in millions of Pounds) at the beginning of month t. Book-to-market value (B/M) is the book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year. LHR is the quotient of the lowest price of a stock within the last one year and the highest price of the stock within the last 52 weeks. Stock volatility (VOLA) is the standard deviation of weekly market excess returns over the year ending at the beginning of month t. Firm age (AGE) measures the number of months since the firm was first covered by Datastream. Cash-flow volatility (CFVOLA) represents the standard deviation of the net cash flow from operating activities standardized by average total assets in the past 3 years. Stocks are equal-weighted and held in the portfolio over six months. Between the ranking date and the formation period, a skip period of one month is included. The table reports the overlapping holding period returns. 1/MV, 1/(B/M) 1/LHR and 1/AGE are the reciprocals of MV, B/M, LHR and AGE. Each month, all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996; t-statistics (two-tailed) are reported in parentheses.

	U1-Low	U2	U3	U4	U5-Large	U5-U1	t-stat
	INFORMATION UNCERTAINTY PROXY: MV						
H1	0.0084	0.0089	0.0105	0.0124	0.0120	0.0036	(1.60)
H2	0.0075	0.0079	0.0079	0.0076	0.0093	0.0023	(1.23)
H3	0.0071	0.0051	0.0037	0.0021	0.0005	-0.0066	(-2.60)
H4	0.0047	0.0027	-0.0026	-0.0037	-0.0031	-0.0078	(-2.85)
H5	-0.0004	-0.0049	-0.0061	-0.0058	-0.0077	-0.0073	(-2.34)
H1-H5	0.0088	0.0138	0.0166	0.0181	0.0197	0.0109	
t-stat	(2.52)	(4.19)	(5.06)	(5.45)	(6.12)		
	INFORMATION UNCERTAINTY PROXY: 1/(B/M)						
H1	0.0094	0.0105	0.0101	0.0095	0.0130	0.0026	(1.56)
H2	0.0089	0.0089	0.0080	0.0067	0.0110	0.0021	(1.32)
H3	0.0080	0.0062	0.0042	0.0030	0.0014	-0.0066	(-3.29)
H4	0.0074	0.0033	0.0011	-0.0021	-0.0056	-0.0130	(-4.35)
H5	0.0069	-0.0024	-0.0054	-0.0093	-0.0100	-0.0169	(-6.58)
H1-H5	0.0025	0.0128	0.0154	0.0188	0.0230	0.0236	
t-stat	(0.68)	(4.47)	(5.69)	(6.52)	(7.58)		
	INFORMATION UNCERTAINTY PROXY: 1/LHR						
H1	0.0068	0.0087	0.0103	0.0115	0.0135	0.0067	(2.20)
H2	0.0062	0.0074	0.0090	0.0079	0.0086	0.0023	(1.10)
H3	0.0042	0.0059	0.0054	0.0048	0.0012	-0.0030	(-0.80)
H4	0.0024	0.0031	0.0013	-0.0007	-0.0059	-0.0083	(-2.20)
H5	-0.0014	-0.0012	-0.0048	-0.0062	-0.0083	-0.0068	(-1.54)
H1-H5	0.0082	0.0099	0.0151	0.0177	0.0218	0.0136	
t-stat	(6.36)	(6.59)	(8.30)	(8.17)	(6.18)		

continued

	U1-Low	U2	U3	U4	U5-Large	U5-U1	t-stat
	INFORMATION UNCERTAINTY PROXY: VOLA						
H1	0.0067	0.0099	0.0115	0.0101	0.0120	0.0052	(1.92)
H2	0.0060	0.0077	0.0085	0.0080	0.0077	0.0017	(0.40)
H3	0.0063	0.0050	0.0039	0.0031	0.0013	-0.0050	(-2.16)
H4	0.0043	0.0025	-0.0017	-0.0027	-0.0050	-0.0093	(-3.53)
H5	-0.0006	-0.0014	-0.0031	-0.0047	-0.0079	-0.0073	(-2.60)
H1-H5	0.0074	0.0112	0.0146	0.0148	0.0199	0.0125	
t-stat	(4.31)	(5.40)	(6.05)	(5.38)	(5.34)		
	INFORMATION UNCERTAINTY PROXY: AGE						
H1	0.0080	0.0104	0.0113	0.0114	0.0120	0.0041	(1.99)
H2	0.0075	0.0081	0.0093	0.0079	0.0095	0.0020	(1.27)
H3	0.0070	0.0062	0.0057	0.0040	0.0042	-0.0028	(-2.16)
H4	0.0051	0.0026	0.0014	-0.0038	-0.0051	-0.0103	(-3.36)
H5	0.0023	-0.0027	-0.0058	-0.0083	-0.0073	-0.0097	(-2.92)
H1-H5	0.0057	0.0131	0.0171	0.0197	0.0194	0.0137	
t-stat	(1.92)	(4.20)	(5.61)	(5.75)	(5.46)		
	INFORMATION UNCERTAINTY PROXY: CFVOLA						
H1	0.0056	0.0085	0.0097	0.0116	0.0133	0.0077	(2.21)
H2	0.0060	0.0078	0.0076	0.0079	0.0084	0.0024	(1.04)
H3	0.0081	0.0067	0.0039	0.0069	-0.0009	-0.0090	(-2.48)
H4	0.0055	0.0044	0.0031	-0.0031	-0.0062	-0.0117	(-2.74)
H5	0.0030	0.0018	0.0009	-0.0058	-0.0090	-0.0119	(-2.04)
H1-H5	0.0026	0.0067	0.0088	0.0175	0.0222	0.0196	
t-stat	(0.58)	(1.50)	(2.14)	(3.77)	(3.71)		

For three out of six variables, the strategy generates highly significant profits in the U1 group, where strategy returns are assumed low based on the main hypothesis. Yet, this is not against the main hypothesis. This study does not predict that subjects are free from an anchoring bias when information uncertainty is low. The underlying idea behind the tests is that this behavioral heuristic is increasing in information uncertainty. Hence, it is not necessary to document a non-profitability of the 52-week high strategy when information uncertainty is low to reject the main hypothesis that anchoring drives the 52-week high returns. Evidence against the null is found if a positive relationship between information uncertainty and the predictive power of the 52-week high criterion is documented.

4.2 Robustness of the Information Uncertainty Effect

In order to ensure the obtained results are not driven by other effects, I conduct the same test as above but control for potential influences. Industry effects might have an impact on the relation between the information uncertainty proxies and the 52-week high returns. The employed variables might just capture differences across industries instead of being a proxy for ambiguity about information. Firm size, for example, might implicitly sort stocks based on their industries instead of their level of uncertainty, as the average firm size is not identical across industries: The mean (median) market value is 410 (74) Mio. Pounds for technology stocks, 916 (120) Mio. Pounds for media stocks and 1889 (330) Mio. Pounds for insurance firms. Hence, the fraction of insurance companies should be larger in the lowest uncertainty portfolios formed by MV, while the share of technology firms is expected to be higher in high-uncertainty portfolios based on MV. For other characteristics, similar differences across industries can be found as well. To control for industry effects, I calculate industry-adjusted holding period returns. Specifically, the adjusted returns are defined as

$$R_{jt}^{I} = R_{jt} - R_{t}^{I} \qquad (28)$$

where R_{jt} is the monthly return of security j in month t and R_t^I is the value-weighted monthly return of industry I in month t. To calculate R_t^I, stocks are sorted according to the INDM3 criterion of Datastream into 20 industries. Such a classification seems sensible as it represents a compromise between a precise arrangement of stocks into industries and a sufficient diversification within an industry. Stocks within an industry portfolio are value-weighted. Therefore, the one month lagged market value is employed.

Table 20 presents the results of the conditional sort, where stocks are classified into quantiles according to the respective uncertainty proxy. Then within each group, stocks are further sorted into five portfolios based on the 52-week high measure. The holding period is still six months, portfolio returns are measured on an overlapping basis and are calculated as described in Equation (28). It is shown that the effect of information uncertainty on the 52-week high profits is still present after controlling for industry effects. As for raw returns, the strategy is more profitable when limited to high-uncertainty stocks. However, the return differences of the 52-week high strategy between high and low uncertainty stocks are slightly smaller. For the LHR proxy, it is 1.36% using raw returns, but it is 1.15% when returns are controlled for industry effects. The reduction in the 52-week high return difference is due to a smaller return difference in the winner and in the loser portfolio between the highest and lowest information uncertainty level. Nevertheless, controlling for industry effect does not lead to the disappearance of the effect of information uncertainty on the profitability of the 52-week high strategy.

Table 20

The 52-week High Profits for Different Information Uncertainty Groups- Industry-Adjusted Returns

This table reports average monthly portfolio returns sorted by an information uncertainty proxy and by the 52-week high criterion adjusted for industry returns. Each month, stocks are assigned to one of five portfolios based on the value of the uncertainty variable. The 20% of stocks with the highest variable value (and most information uncertainty) is included into U5 while the 20% of stocks with the lowest value (and hence with least information uncertainty) is assigned to group U1. Within each information uncertainty quantile, I further sort stocks based on the 52-week high ranking criterion. The top (bottom) 20% is included in the winner (loser) portfolio H1 (H5). MV is the firm's market capitalization (in millions of Pounds) at the end of month t. Book-to-market value (B/M) is the book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year. LHR is the quotient of the lowest price of a stock within the last one year and the highest price of the stock within the last 52 weeks. Stock volatility (VOLA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Firm age (AGE) measures the number of months since the firm was first covered by Datastream. Cash-flow volatility (CFVOLA) represents the standard deviation of the net cash flow from operating activities standardized by average total assets in the past 3 years. Stocks are equal-weighted and held in the portfolio over six months. Between the ranking date and the formation period, a skip period of one month is included. The table reports the overlapping holding period returns. For each stock, the monthly return in excess of the monthly return of its industry is measured. The industry return is obtained by classifying stocks into 20 industries according to the INDM3 criterion of Datastream. Within each industry, stocks are value-weighted. 1/MV, 1/(B/M), 1/LHR and 1/AGE are the reciprocals of MV, B/M, LHR and AGE. Each month, all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996; t-statistics (two-tailed) are reported in parentheses.

		U1	U2	U3	U4	U5	U5-U1	
1/MV	Winner	0.0017	0.0034	0.0046	0.0065	0.0050	0.0033	(1.65)
	Loser	-0.0035	-0.0071	-0.0084	-0.0085	-0.0118	-0.0083	(-2.50)
	Wi-Lo	0.0052	0.0105	0.0130	0.0150	0.0168	0.0116	(4.24)
	t-stat	(2.48)	(4.55)	(5.07)	(5.14)	(-5.91)		
1/(B/M)	Winner	0.0048	0.0044	0.0047	0.0038	0.0039	-0.0010	(-0.70)
	Loser	0.0049	-0.0060	-0.0083	-0.0112	-0.0184	-0.0234	(-7.66)
	Wi-Lo	-0.0001	0.0104	0.0130	0.0150	0.0223	0.0224	(7.04)
	t-stat	(-0.03)	(4.41)	(6.18)	(7.24)	(8.38)		
1/LHR	Winner	0.0013	0.0025	0.0044	0.0057	0.0082	0.0069	(3.21)
	Loser	-0.0063	-0.0056	-0.0098	-0.0098	-0.0109	-0.0047	(-1.30)
	Wi-Lo	0.0076	0.0081	0.0142	0.0154	0.0192	0.0115	(3.83)
	t-stat	(6.82)	(6.63)	(9.04)	(8.28)	(5.95)		
VOLA	Winner	0.0015	0.0039	0.0056	0.0045	0.0061	0.0046	(2.35)
	Loser	-0.0045	-0.0059	-0.0076	-0.0072	-0.0115	-0.0070	(-2.61)
	Wi-Lo	0.0061	0.0098	0.0132	0.0117	0.0176	0.0116	(3.93)
	t-stat	(4.49)	(6.30)	(6.74)	(4.98)	(5.53)		
1/AGE	Winner	0.0021	0.0041	0.0056	0.0055	0.0065	0.0044	(2.46)
	Loser	-0.0017	-0.0059	-0.0078	-0.0111	-0.0107	-0.0091	(-3.93)
	Wi-Lo	0.0038	0.0100	0.0134	0.0166	0.0172	0.0134	(5.50)
	t-stat	(1.65)	(3.80)	(5.31)	(5.58)	(6.28)		
CFVOLA	Winner	0.0023	0.0033	0.0054	0.0053	0.0077	0.0054	(2.53)
	Loser	0.0005	-0.0013	-0.0002	-0.0048	-0.0086	-0.0091	(-1.83)
	Wi-Lo	0.0018	0.0046	0.0056	0.0101	0.0163	0.0145	(2.93)
	t-stat	(0.66)	(1.14)	(1.71)	(2.98)	(3.26)		

The results in Table 20 also provide support that the profitability of the 52-week high strategy cannot be explained by industry components. For almost each uncertainty subsample, irrespective of the uncertainty measure, the strategy generates positive and significant returns after controlling for industry effects. This finding is important as Moskowitz and Grinblatt

(1999) document that stock price momentum loses its profitability when controlled for industry effects. This finding is heavily discussed in the literature. It is important for the robustness of the 52-week high strategy to document that the strategy remains profitable after consideration of potential industry influences as this has not been done yet.

The effect of information uncertainty on the profitability of the 52-week high strategy is also examined when returns are controlled for risk. In order to examine the idiosyncratic component of a stock return, monthly excess returns on the three Fama-French factors are examined. For different information uncertainty levels, the monthly excess returns of the 52-week high winner and loser portfolios on the risk-free rate $(R_{i,t} - R_{f,t})$ are regressed on an intercept, the excess return of the FTSE All Share $(R_{m,t} - r_{f,t})$ and on the SMB and the HML factors:

$$R_{i,t} - R_{f,t} = \alpha + \beta_i(R_{m,t} - r_{f,t}) + s_i\mathrm{SMB}_t + h_i\mathrm{HML}_t + \varepsilon_{i,t} \qquad (29)$$

SMB and HML are constructed exactly as described in Fama and French (1993): In June of each year between 1989 and 2008, all stocks are sorted into two groups based on their market value. Stocks with a market value above (below) the median are attributed to portfolio B (S). Independently from this sort, stocks are assigned to three book-to-market portfolios (H, M, L) according to the 30% and 70% breakpoints. Stocks with the highest (lowest) B/M-ratio are included in portfolio H (L). From the intersections of the two market value portfolios and the three book-to-market ratio groups, six value-weighted portfolios are constructed (S/L, S/M, S/H, B/L, B/M, B/H). SMB represents the difference between the average return of small stocks (S/L, S/M, S/H) and of big stocks (B/L, B/M, B/H) per month. HML is constructed by calculating the difference between the average return of the two high book-to-market ratio portfolios (S/H, S/L) and the average return of the two low book-to-market ratio portfolios (S/L, B/L) per month:

$$SMB = \frac{R_{S/L} + R_{S/M} + R_{S/H}}{3} - \frac{R_{B/L} + R_{B/M} + R_{B/H}}{3} \qquad (30a)$$

$$HML = \frac{R_{S/H} + R_{B/H}}{2} - \frac{R_{S/L} + R_{B/L}}{2}, \qquad (30b)$$

where R is the monthly return of the respective portfolio. Table 21 reports the intercepts of the 52-week high winner and loser portfolios for different levels of information uncertainty. Stocks with the lowest (highest) level according to the different proxies, and hence with the lowest (highest) degree of information uncertainty, are attained to portfolio U1 (U5). Even after controlling for the three Fama-French factors, the profitability of the 52-week high strategy is still monotonically increasing in the level of information uncertainty. The 52-week high profits for high-uncertainty stocks are significantly larger than the returns for low-uncertainty stocks and the return difference of between 1.30% and 2.04% per month for the variables is comparable to the findings in Table 19 where raw returns are examined. As for raw returns, the positive relation between 52-week high profits and information uncertainty can be attributed to both winner stocks and loser stocks. Compared to the 52-week high winner portfolios, loser portfolios show a larger return difference between high- and low-uncertainty stocks. However, the differences in the profits for winners is positive, substantial and for most proxies highly significant.

The coefficients on the three variables are as expected and consistent with the findings and conclusions of Fama and French (1993, 1996) (not reported in the table). The betas of all 60 portfolios are highly significant with a t-statistic almost always above 20. The betas are smaller for low-uncertainty stocks compared to high-uncertainty stocks. The risk loadings on SMB are higher for high-uncertainty stocks suggesting that these stocks are or behave like small stocks. The loadings on HML are generally lower for high-uncertainty stocks with the only exception when information uncertainty is measured by past stock price volatility. This implies that stocks with a high information uncertainty degree are more likely growth stocks. The adjusted R^2 are for almost all portfolios at least 0.80 (and for some above 0.90), indicating that the three-factor model has reasonable explanatory power.

Table 21

Three-Factor Risk-Adjusted Excess Returns

The table shows the intercepts obtained from regressions conducted as follows:

$$R_{i,t} - R_{f,t} = \alpha + \beta_i(R_{m,t} - R_{f,t}) + s_i\mathrm{SMB}_t + h_i\mathrm{HML}_t + \varepsilon_{i,t},$$

where $R_{i,t} - R_{f,t}$ is the monthly excess return of 52-week high winner and loser portfolios over the risk-free rate (the UK Stearling one-month rate) and $R_{m,t}$ is the monthly return of the FTSE ALL SHARE. The variable SMB is the monthly excess return on a portfolio of small stocks over a portfolio of large stocks and HML is the monthly excess return on a portfolio of stocks with a high book-to-market ratio over a portfolio of stocks with a low book-to-market ratio. The regressions are conducted for 52-week high strategies within different portfolios of information uncertainty. SMB and HML are constructed exactly as described in Fama and French (1993): In June of each year between 1989 and 2008, all stocks are sorted into two groups based on their market value Stocks with a market value above (below) the median are attributed to portfolio B (S). Independently from this sort, stocks are sorted into three groups (H,M,L) with the 30% and 70% breakpoints based on their book-to-market ratio. Stocks with the highest (lowest) ratio are included in portfolio H (L). Six value-weighted portfolios are constructed from the intersections of the two market value and the three book-to-market ratio groups (S/L, S/M, S/H, B/L, B/M, B/H). SMB represents the difference, each month, between the average return of the small stocks portfolios (S/L, S/M, S/H) and the average return of the big stocks portfolios (B/L, B/M, B/H). HML is constructed by calculating the difference, each month, between the average return of the two high book-to-market ratio portfolios (S/H, S/L) and the average return of the two low book-to-market ratio portfolios (S/L, B/L). The table reports the intercepts of the winner and loser portfolios (the top and bottom 30% of stocks according to the 52-week high ratio) for different information uncertainty levels, where U1 (U5) represents the stocks with the lowest (highest) uncertainty level according to the respective proxy. For the regressions, all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996. t(α) is the intercept divided by its standard error.

		U1	U2	U3	U4	U5	U5-U1	U1	U2	U3	U4	U5	U5-
		α						t(α)					
1/MV	Winner	0.1090	0.1167	0.1689	0.3411	0.3718	0.2628	2.65	0.85	1.32	2.66	1.83	2.04
	Loser	-0.6204	-1.2798	-1.5855	-1.6592	-1.9739	-1.3535	-2.32	-4.29	-5.36	-5.38	-7.02	-4.87
	W-L	0.9294	1.3964	1.7544	2.0003	2.3458	1.6164	2.85	4.69	6.23	6.81	8.89	4.92
1/(B/M)	Winner	0.0016	0.1186	0.2166	0.3865	0.4861	0.4845	0.01	0.94	1.04	2.65	3.08	2.87
	Loser	-0.0739	-1.6799	-0.8860	-1.2564	-1.6253	-1.5514	-0.22	-4.24	-5.69	-7.91	-8.71	-7.35
	W-L	0.0755	0.7985	1.1026	1.6429	2.1114	2.0359	1.73	6.11	6.88	7.96	8.23	5.81
1/LHR	Winner	0.0608	0.2004	0.3042	0.3192	0.4023	0.3415	0.55	1.72	2.69	2.60	1.20	2.80
	Loser	-0.7980	-0.8291	-1.2942	-1.5532	-1.8789	-1.0809	-5.03	-4.60	-6.47	-6.93	-5.44	-3.63
	W-L	0.8589	1.0294	1.5984	1.8724	2.2811	1.4223	7.23	7.19	9.27	8.88	6.54	4.33
VOLA	Winner	0.2490	0.2883	0.3576	0.3461	0.5652	0.3162	2.30	2.48	3.33	1.09	2.32	2.26
	Loser	-0.4479	-0.8203	-1.1260	-1.3847	-1.9215	-1.4736	-2.57	-3.90	-4.76	-5.14	-5.87	-5.08
	W-L	0.6968	1.1086	1.4836	1.7308	2.4867	1.7898	4.48	5.71	6.65	6.07	6.21	4.48
1/AGE	Winner	0.1847	0.3158	0.3328	0.2491	0.4534	0.2313	2.46	2.29	2.56	1.97	0.67	1.78
	Loser	-0.5039	-1.2113	-1.5293	-1.9667	-1.6407	-1.3670	-1.78	-4.03	-5.41	-6.43	-6.14	-4.79
	W-L	0.6886	1.5271	1.8621	2.2158	2.1941	1.3055	2.86	5.48	6.79	7.34	6.31	4.62
CFVOLA	Winner	0.1517	0.2584	0.2363	0.2326	0.2944	0.1427	1.15	1.46	1.19	1.21	1.49	1.17
	Loser	-0.3012	-0.5247	-0.6633	-1.4077	-2.0639	-1.7627	-0.87	-1.11	-1.56	-2.93	-3.76	-3.32
	W-L	0.4573	0.7831	0.8996	1.6404	2.3583	1.9054	1.40	1.78	2.19	3.53	4.09	2.89

Given a specific information uncertainty level, the 52-week high profits are larger when the three Fama-French factors are controlled for. The 52-week high monthly raw return is 1.31% for AGE when limited to the U2 group (see Table 19) while it is 1.52% when controlled for the three factors. This is because loser stocks load more on the SMB factor and have a larger market premium than winners.[83] It suggests that losers behave more like small stocks (Rouwenhorst, 1998, p.276).

I also control for the turn-of-the year effect, which states that stocks with a poor performance strongly recover in the first weeks of a year. According to the tax-loss selling hypothesis, this pattern arises as investors heavily sell loser stocks at year-end in order to realize tax loss benefits. This behavior leads to lower prices for loser stocks at the end of a year. At the beginning of the new year, the selling pressure vanishes and the prices of former loser stocks recover. To abstract the relation between the 52-week high strategy and information uncertainty from the turn-of-the year effect, I examine the monthly portfolio returns for all months except Januaries. Yet, the uncertainty effect is even more visible when controlled for this effect.[84]

5. Are the Variables Proxies for Information Uncertainty?

5.1 One-Variable-Effect

In Section 4.1, a test is conducted where stocks are assigned to quantiles based on an information uncertainty proxy. Based on this test, Table 22 shows the characteristics of the five uncertainty portfolios for each proxy. For each, the mean and median values of the other five variables are reported. Table 22 shows that irrespective of the chosen variable, high-uncertainty portfolios contain stocks with the lowest market value, the lowest book-to-market value, the lowest ratio between the 52-week high and low, the highest stock price volatility, the highest cash-flow volatility and stocks of the youngest firms. Low uncertainty portfolios in opposite contain large and old firms with the highest book-to-market values and with the lowest stock price and cash flow volatility as well as the lowest distance between the 52-week high and low. Hence, when stocks are sorted on one information uncertainty variable, they are at least partly ranked according to other proxies as well.

Moreover, Table 22 reports the fraction of loser returns on the 52-week high profits within a given information uncertainty groups. This allows examining whether winners or losers

[83] Examining stock price momentum, Jegdeesh (2001, p.707) and Rouwenhorst (1998, p.278) also document higher returns when controlled for the Fama-French factors. They also show that this increase is due to loser stocks that load more on beta and the SMB factor than winners do.

[84] Results are not reported for consideration of space. They are available on request.

mainly contribute to the profitability of the strategy. In the test of in Section 4.1, within an uncertainty group, stocks are sorted into five portfolios based on the 52-week high measure. The top (bottom) 20% are assigned to portfolio H1 (H5). The fraction

$$T = \frac{(H3 - H5)}{(H1 - H5)} \tag{31}$$

gives information about the share of the losers on the 52-week high profits. Consider for example column 1 for the MV proxy in Table 19. The 52-week high profits (H5-H1) are 0.88% per month. Of that, about 0.74% per month (or 86% of the total profits) comes from the difference between the average performers and the losers (H3-H5). For all proxies except for the B/M ratio, the performance of the 52-week high is mainly due to the short side when limited to low-uncertainty stocks. This might indicate that the profitability of the 52-week high for low-uncertainty stocks is due to short-sale constraints as not all stocks can be easily borrowed (Moskowitz and Grinblatt, 1999, p.1272). The large 52-week high profits for high-uncertainty stocks, however, are both due to the winner and to the loser stocks and are not a loser stock phenomenon. For all proxies except for B/M, the fraction of Equation (31) does not exceed 0.55% for high information uncertainty groups which indicates that roughly half of the 52-week high returns is due to the winner part.

Table 22

Characteristics of Information Uncertainty Portfolios

This table gives information about the characteristics of the portfolios constructed based on an uncertainty proxy. MV is the firm's market capitalization (in millions of Pounds) at the beginning of month t. Book-to-market value (B/M) is the book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year. LHR is the quotient of the lowest price of a stock within the last one year and the highest price of the stock within the last 52 weeks. Stock volatility (VOLA) is the standard deviation of weekly market excess returns over the year ending at the beginning of month t. Firm age (AGE) measures the number of months since the firm was first covered by Datastream. Cash-flow volatility (CFVOLA) represents the standard deviation of the net cash flow from operating activities standardized by average total assets in the past 3 years. As the stocks are equal-weighted in the portfolio, the simple cross-sectional averages over time for the respective values are reported below. On the left hand side, the table shows the means, on the right hand side, the median values are reported. Within the uncertainty portfolios, stocks are sorted based on the 52-week high ranking criterion. The top (bottom) 20% are included in the winner (loser) portfolio H1 (H5). Hence, the fraction (H3-H5)/(H1-H5) gives the differences of the returns between the middle (H3) and the loser (H5) portfolio in relation to the total 52-week high returns and shows the loser proportion of the 52-week high profits.

	U1	U2	U3	U4	U5	U1	U2	U3	U4	U5
	MEAN					MEDIAN				
	1/MV									
MV	6,418	352	124	57	44	1,960	315	118	55	38
(B/M)	0.54	0.58	0.62	0.74	0.79	0.44	0.44	0.47	0.57	0.58
LHR	0.65	0.61	0.60	0.57	0.57	0.67	0.64	0.62	0.60	0.59
VOLA	3.31	4.01	4.47	5.33	6.01	2.86	3.41	3.71	4.27	4.92
AGE	167	135	116	107	99	168	130	107	95	84
CFVOLA	0.03	0.05	0.06	0.06	0.07	0.02	0.03	0.04	0.04	0.05
(H3-H5)/(H1-H5)	0.86	0.73	0.59	0.43	0.47					
	1/(B/M)									
MV	2,738	713	886	679	3079	804	193	83	41	89
B/M	1.48	0.78	0.52	0.33	0.15	1.26	0.74	0.48	0.32	0.14
LHR	0.64	0.62	0.60	0.58	0.53	0.67	0.64	0.63	0.61	0.56
VOLA	3.37	4.04	4.42	5.07	6.17	3.06	3.39	3.65	4.15	4.86
AGE	140	119	106	97	103	142	113	91	80	78
CFVOLA	0.04	0.04	0.05	0.06	0.08	0.02	0.03	0.03	0.04	0.05
(H3-H5)/(H1-H5)	0.22	0.66	0.62	0.65	0.63					
	1/LHR									
MV	2,716	1,870	1356	941	399	146	196	160	116	72
B/M	0.77	0.69	0.64	0.59	0.54	0.60	0.54	0.51	0.44	0.37
LHR	0.78	0.69	0.62	0.54	0.37	0.78	0.70	0.63	0.55	0.38
VOLA	2.91	3.43	3.95	4.82	7.87	2.67	3.17	3.61	4.35	6.55
AGE	127	132	125	110	88	120	124	115	97	73
CFVOLA	0.04	0.04	0.05	0.06	0.09	0.03	0.03	0.03	0.04	0.06
(H3-H5)/(H1-H5)	0.68	0.72	0.68	0.62	0.44					
	VOLA									
MV	4,231	1,452	933	403	292	304	230	143	84	65
B/M	0.75	0.66	0.64	0.60	0.58	0.55	0.53	0.51	0.46	0.39
LHR	0.72	0.67	0.62	0.55	0.42	0.73	0.68	0.63	0.57	0.43
VOLA	2.43	3.14	3.85	4.95	8.79	2.24	2.89	3.61	4.69	7.55
AGE	143	133	120	102	81	136	125	110	89	67
CFVOLA	0.03	0.04	0.05	0.06	0.09	0.02	0.03	0.04	0.05	0.07
(H3-H5)/(H1-H5)	0.67	0.56	0.48	0.53	0.56					

continued

	1/AGE									
MV	2,858	849	2,200	654	536	699	134	96	78	73
B/M	0.73	0.75	0.66	0.56	0.54	0.54	0.59	0.49	0.41	0.40
LHR	0.64	0.62	0.60	0.56	0.56	0.66	0.64	0.62	0.59	0.59
VOLA	3.53	4.20	4.54	5.16	5.70	3.06	3.59	3.83	4.23	4.31
AGE	212	158	107	63	26	211	153	108	62	25
CFVOLA	0.03	0.05	0.06	0.08	0.07	0.03	0.03	0.04	0.05	0.05
(H3-H5)/(H1-H5)	0.82	0.68	0.67	0.62	0.55					
	CFVOLA									
MV	7,537	1,773	1,564	822	1,025	571	267	205	153	122
B/M	0.93	0.70	0.65	0.61	0.48	0.71	0.56	0.51	0.48	0.35
LHR	0.64	0.60	0.58	0.55	0.50	0.66	0.63	0.61	0.58	0.53
VOLA	3.83	4.37	4.74	5.22	6.21	3.36	3.87	4.07	4.44	5.14
AGE	179	177	163	147	112	193	185	167	149	102
CFVOLA	0.01	0.02	0.04	0.06	0.13	0.01	0.02	0.04	0.05	0.10
(H3-H5)/(H1-H5)	1.95	0.73	0.73	0.34	0.36					

The ratio of Equation (31) also allows a closer look at the LHR measure. Instead of being a proxy for information uncertainty, the LHR ratio could also just mechanically hint the 52-week high criterion from picking the right stocks, especially for the low information uncertainty groups. In those portfolios, only stocks with a large LHR are considered. Since:

$$PHR_{i,t-1}^{52} = \frac{P_{i,t-1}}{H_{i,t-1}^{52}} \qquad \geq \qquad \frac{L_{i,t-1}}{H_{i,t-1}^{52}} = LHR_{i,t-1}, \qquad\qquad (32)$$

it is possible that the 52-week high strategy cannot choose stocks with a low $\mathrm{PHR}_{\mathrm{i,t-1}}^{52}$ for loser portfolios within the U1 group as $P_{i,t-1} \geq L_{i,t-1}$. If this is the case, the low 52-week high profits in the U1 portfolio compared to the U5 portfolio can be explained by a limited access of the 52-week high criterion to loser stocks and might not be due to low information uncertainty. Then, within the U1 group, winner stocks should largely generate the 52-week high profits. Table 22, however, shows that, with a value of 32%, loser stocks contribute to a substantial part to the 52-week high returns in the U1 portfolio. Compared to other proxies, this percentage is not particularly low. Furthermore, the return of winner portfolios is larger within the LHR U5 group with 1.35% than within the U1 portfolio with 0.68%. As this potential problem of the LHR variable only applies to loser stocks, the higher predictive power of the 52-week high ranking criterion for winners in U5 compared to U1 cannot be explained by a limited access of the 52-week high ranking criterion to stocks in U1. Consequently, the T measure of Equation (31) and the higher monthly returns for winner stocks from U1 to U5 indicate that the positive relationship between the profitability of the 52-week high strategy and 1/LHR is explained by something different (e.g. information uncertainty) than the limited access of the 52-week high criterion to loser stocks.

Table 22 documents a weakness of the two-way sorts conducted in Section 4.1. The ultimate goal of the tests is to examine the effect of one variable on the 52-week high profits given that all other variables are constant. However, Table 22 shows that a sort on one specific uncertainty measure leads to an implicit ranking based on all other uncertainty proxies as well, which brings along two potential problems:

First, the similar relation of the six variables on the 52-week high profits might be only due to one characteristic as each variable does implicitly sort stocks based on other proxies. For example, all proxies group stocks implicitly based on firm size into five portfolios (as well as based on other variables; see Table 22). Stocks with the smallest market value are assigned to portfolio U5, where the 52-week high profits are largest. If only a single variable is behind the relation of the six measures on the 52-week high profits, it seems rather arbitrary to explain the relation with information uncertainty. If for example firm size is the single variable behind the documented relation, other explanations exist. A large body of research documents a negative relationship between firm size and momentum returns for which various theories are proposed: Lo and MacKinlay (1990, p.178) and Grundy and Martin (2001, p.31) argue that lead-lag effects are larger for small stocks. Hong (1999) and Hong et al. (2000) claim that firm size is a proxy for the speed of the diffusion of information and that for small firms information comes out more slowly, which leads to higher future momentum returns. Fama and French (1993) view a risk factor in firm size. Lesmond (2004) and Roll (1983) find a relationship between firm size and the bid-ask-spread which itself is employed as a proxy for trading costs. With high trading costs, investors are unable to realize the theoretical momentum profits. In summary, if firm size is behind the relation between the variables and the 52-week high, other explanation attempts than information uncertainty exist and the findings are not necessarily in line with my hypothesis.

As one specific proxy does not exist for information uncertainty, I employ a bundle of variables and argue that the common element of them is information uncertainty although each also captures other effects. Therefore, it is necessary to ensure that the third variable behind the six proxies is information uncertainty and not one of the variables itself.

Secondly, the two-way sorts do not ensure that each employed variable is worth to be used as proxy for information uncertainty and not subsumed by another variable. Especially for LHR, it is important to justify its consideration, as it has not yet been employed as proxy for information uncertainty. Specifically, it is necessary to show that LHR is not subsumed by stock price volatility. Table 22 does not exclude this possibility as the portfolios sorted on LHR also differ in VOLA.

To address both potential problems, I conduct conditional sorts by two information uncertainty variables. First, stocks are sorted into five portfolios based on one uncertainty measure. Then within each of the five portfolios, stocks are further subdivided into three portfolios according to the second uncertainty measure. Subsequently, stocks of each portfolio are sorted into three portfolios on the 52-week high measure ($PHR^{52}_{i,t-1}$). Stocks within these 45 portfolios are equal-weighted and held over six months. Between the ranking and the holding period, a skip period of one month is included. The 52-week high profits are calculated by subtracting the average monthly loser portfolio return from the average winner portfolio return within each of the 15 double-sorted uncertainty portfolios. This test examines the effect of one uncertainty proxy on the 52-week high profits by keeping another uncertainty variable fixed. Hence, this method allows to pairwise test whether the effect of one proxy on the strategy's profitability is subsumed by another variable. Ideally, it would be wishful to examine this relationship when all other variables are kept fixed. Yet, the problem is that each further sorting level substantially reduces the number of stocks in the portfolios. Therefore, a further subdivision or a more precise one is not possible without the loss of diversification in the portfolios.

Table 23 reports the average monthly 52-week high profits for all potential uncertainty measure combinations. In order to ensure that the results are not influenced by the ranking order of the uncertainty level, they are reported for both sorting ways of the uncertainty proxy. For example, the 52-week high returns are calculated when stocks are first sorted on MV and then subsequently based on LHR, but the profits are also reported when stocks are first ranked based on LHR and then on MV.

As it can be seen from the table, the effect of one information uncertainty proxy on the 52-week high profits is not diminished when controlled for another information variable. When stocks are first sorted on MV and then subsequently on LHR, the table reports that, within a size class, the LHR sort leads to significantly differences in the 52-week high profits. For four out of five size classes, the 52-week high generates significantly higher profits when limited to stocks with a low 1/LHR ratio than for stocks with a high ratio. The size matching is almost flawless. Within a given MV group, the stocks in the highest LHR ratio portfolio have a similar average market value compared to the stocks in the lowest LHR ratio group. For example, within the smallest size group, with 29 Mio. Pounds, the average market value of the stocks in the LHR low-uncertainty portfolio is almost identical to the average market value for stocks in the LHR high-uncertainty group. Only for the quantile of stocks with the largest market value, the size matching is not that good but the difference in firm size is much smaller between the LHR portfolios. The lowest 1/LHR ratio stocks have a median size of 2.118 Mio. Pounds, while the 20% of stock with the highest ratio have a median of 1.783 Mio. Pounds.

Most importantly, the results in Table 23 exclude the possibility that firm size or the book-to-market ratio is behind the relationship of the six variables on 52-week high profits. In the first column of Table 23, it is documented that each variable still has explanatory power on the profitability of the 52-week high strategy when stocks are first subdivided into five MV classes: For each variable, the return difference between high and low uncertainty groups is highly significant within most firm size groups.

Table 23

Sorts on Two Information Uncertainty Variables – 5x3x3 Portfolios

This table reports average monthly portfolio returns sorted by two information uncertainty proxies and by the 52-week high criterion. First, stocks are assigned into five portfolios based on one uncertainty measure. Then within each of the five portfolios, stocks are further subdivided into three portfolios according to the second uncertainty measure. Subsequently, stocks of each portfolio are sorted into three portfolios on the 52-week high measure. Stocks within these 45 portfolios are equal-weighted and held over six months. Between the ranking and the holding period, a skip period of one month is included. The 52-week high profits are calculated by subtracting the average monthly loser portfolio return from the average winner portfolio return within each of the 15 double-sorted uncertainty portfolios. MV is the firm's market capitalization (in millions of Pounds) at the beginning of month t. Book-to-market value (B/M) is the book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year. LHR is the quotient of the lowest price of a stock within the last one year and the highest price of the stock within the last 52 weeks. Stock volatility (VOLA) is the standard deviation of weekly market excess returns over the year ending at the beginning of month t. Firm age (AGE) measures the number of months since the firm was first covered by Datastream. Cash-flow volatility (CFVOLA) represents the standard deviation of the net cash flow from operating activities standardized by average total assets in the past 3 years. Stocks are equal-weighted and held in the portfolio over six months. Between the ranking date and the formation period, a skip period of one month is included. The table reports the overlapping holding period returns. 1/MV, 1/LHR and 1/AGE are the reciprocals of MV, LHR and AGE. Each month, all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996; t-statistics (two-tailed) are reported in parentheses.

		First sort														
		1/MV					1/(B/M)					1/LHR				
		S1	S2	S3	S4	S5	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
1/MV	U1						-0.0019	0.0063**	0.0077***	0.0086***	0.0139***	0.0032**	0.0032*	0.0060**	0.0102***	0.0165***
	U2						0.0037	0.0102***	0.0114***	0.0143***	0.0230***	0.0074***	0.0076***	0.0126***	0.0162***	0.0176***
	U3						0.0047	0.0163***	0.0172***	0.0228***	0.0259***	0.0100***	0.0124***	0.0190***	0.0187***	0.0238***
	U3-U1						0.0066*	0.0100***	0.0094***	0.0142***	0.0120***	0.0068***	0.0091***	0.0130***	0.0085***	0.0073*
1/(B/M)	U1	0.0016	0.0038	0.0072**	0.0025	0.0071**						0.0050***	0.0061***	0.0093***	0,0092***	0,0107***
	U2	0.0064**	0.0086**	0.0125***	0.0143***	0.0193***						0.0075***	0.0081***	0.0144***	0.0178***	0,0202***
	U3	0.0125	0.0161	0.0227***	0.0275***	0.0220***						0.0090***	0.0134***	0.0200***	0,0217***	0,0262***
	U3-U1	0.0109***	0.0123***	0.0155***	0.0250***	0.0149***						0.0040**	0.0072***	0.0107***	0,0126***	0,0155***
1/LHR	U1	0.0030**	0.0040***	0.0077***	0.0130***	0.0112***	0.0038**	0.0078***	0.0079***	0.0084***	0.0140***					
	U2	0.0042*	0.0064***	0.0150***	0.0178***	0.0197***	0.0063***	0.0108***	0.0122***	0.0145***	0.0230***					
	U3	0.0126***	0.0190***	0.0160***	0.0168***	0.0241***	0.0067*	0.0181***	0.0214***	0.0218***	0.0263***					
	U3-U1	0.0096***	0.0149***	0.0083**	0.0037	0.0129***	0.0030	0.0104***	0.0136***	0.0134***	0.0123***					
VOLA	U1	0.0019	0.0054***	0.0082***	0.0146***	0.0130***	0.0029	0.0059***	0.0066***	0.0079***	0.0111***	0.0053***	0.0058***	0.0073***	0,0134***	0,0156***
	U2	0.0053**	0.0074***	0.0146***	0.0183***	0.0173***	0.0041	0.0112***	0.0138***	0.0145***	0.0191***	0.0054***	0.0082***	0.0133***	0,0125***	0,0212***
	U3	0.0113***	0.0164***	0.0129***	0.0140***	0.0209***	0.0058	0.0141***	0.0186***	0.0187***	0.0242***	0.0097***	0.0085***	0.0137***	0,0166***	0,0201***
	U3-U1	0.0094***	0.0111***	0.0047	-0.0005	0.0080**	0.0030	0.0082**	0.0120***	0.0108***	0.0131***	0.0044***	0.0026	0.0064***	0,0032	0,0045
1/AGE	U1	0.0054*	0.0049*	0.0106***	0.0111***	0.0144***	0.0004	0.0050*	0.0076***	0.0073***	0.0154***	0.0024*	0.0037***	0.0078***	0,0108***	0,0119***
	U2	0.0062*	0.0120***	0.0130***	0.0186***	0.0193***	0.0018	0.0115***	0.0130***	0.0187***	0.0208***	0.0076***	0.0069***	0.0128***	0,0174***	0,0212***
	U3	0.0123***	0.0150***	0.0206***	0.0194***	0.0180***	0.0054	0.0162***	0.0160***	0.0191***	0.0281***	0.0104***	0.0130***	0.0187***	0,0184***	0,0222***
	U3-U1	0.0070***	0.0102***	0.0100***	0.0083**	0.0036	0.0049	0.0112***	0.0084***	0.0118***	0.0128***	0.0081***	0.0093***	0.0109***	0,0076***	0,0103***
CFVOLA	U1	0.0036	0.0024	0.0012	0.0109***	0.0056	0.0014	0.0043	0.0068*	0.0035	0.0074	0.0053***	0.0035	0.0106***	0,0084**	0,0079
	U2	0.0063	0.0100**	0.0136***	0.0095**	0.0113**	0.0019	0.0092***	0.0092***	0.0115***	0.0178***	0.0058***	0.0059***	0.0102***	0.0174***	0,0104**
	U3	0.0161***	0.0193***	0.0216***	0.0135**	0.0026	0.0064	0.0090**	0.0140***	0.0206***	0.0281***	0.0080***	0.0101***	0.0189***	0,0147***	0,0096
	U3-U1	0.0125**	0.0169***	0.0204***	0.0025	-0.0030	0.0050**	0.0047	0.0071	0.0171***	0.0207**	0.0027	0.0066**	0.0083***	0.0063	0.0017

continued

		VOLA					1/AGE					CFVOLA				
		S1	S2	S3	S4	S5	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
1/MV	U1	0.0033*	0.0046*	0.0093***	0.0103***	0.0156***	0.0035	0.0072**	0.0124***	0.0152***	0.0138***	0.0233***	0.0144***	0.0092*	0.0040	0.0032
	U2	0.0059***	0.0080***	0.0136***	0.0137***	0.0168***	0.0060**	0.0133***	0.0150***	0.0186***	0.0188***	0.0238***	0.0143***	0.0109**	0.0051	0.0038
	U3	0.0101***	0.0174***	0.0155***	0.0166***	0.0194***	0.0067**	0.0100***	0.0174***	0.0207***	0.0192***	0.0065	0.0132***	0.0055	0.0057	0.0074*
	U3-U1	0.0068***	0.0128***	0.0062***	0.0063*	0.0039	0.0032	0.0028	0.0050*	0.0055*	0.0054*	-0.0168**	-0.0012	-0.0037	0.0016	0.0042*
1(B/M)	U1	0.0030	0.0065***	0.0071***	0.0069**	0.0099**	0.0013	0.0005	0.0053	0.0122***	0.0093**	0.0074	0.0092*	0.0002	0.0025	-0.0020
	U2	0.0062***	0.0097***	0.0140***	0.0131***	0.0196***	0.0064***	0.0118***	0.0134***	0.0178***	0.0164***	0.0183***	0.0154***	0.0105***	0.0045	0.0048
	U3	0.0077***	0.0125***	0.0192***	0.0196***	0.0237***	0.0070***	0.0171***	0.0196***	0.0226***	0.0291***	0.0270***	0.0225***	0.0111**	0.0041	0.0070
	U3-U1	0.0047*	0.0060***	0.0121***	0.0127***	0.0138***	0.0057*	0.0166***	0.0143***	0.0104**	0.0197***	0.0196***	0.0133***	0.0110**	0.0016	0.0090**
1/LHR	U1	0.0057***	0.0071***	0.0091***	0.0080***	0.0082***	0.0020	0.0068***	0.0073***	0.0108***	0.0122***	0.0147***	0.0063***	0.0076***	0.0043**	0.0061***
	U2	0.0054***	0.0070***	0.0141***	0.0131***	0.0108***	0.0045**	0.0095***	0.0108***	0.0174***	0.0180***	0.0169***	0.0126***	0.0069**	0.0066***	0.0032
	U3	0.0076***	0.0120***	0.0147***	0.0130***	0.0217***	0.0073**	0.0140***	0.0226***	0.0207***	0.0210***	0.0109	0.0172***	0.0090*	0.0063	0.0088*
	U3-U1	0.0019	0.0049***	0.0056**	0.0049*	0.0135*	0.0053*	0.0072*	0.0153***	0.0098***	0.0088**	-0.0038	0.0109*	0.0015	0.0019	0.0027
VOLA	U1						0.0023*	0.0051***	0.0072***	0.0137***	0.0124***	0.0102***	0.0082***	0.0094***	0.0046*	0.0017
	U2						0.0060***	0.0093***	0.0136***	0.0167***	0.0172***	0.0205***	0.0176***	0.0098***	0.0072*	0.0053*
	U3						0.0056	0.0126***	0.0192***	0.0195***	0.0209***	0.0091	0.0117*	0.0060	0.0041	0.0084*
	U3-U1						0.0033*	0.0074**	0.0120***	0.0059	0.0086***	-0.0011	0.0036	-0.0034	-0.0005	0.0067*
1/AGE	U1	0.0017	0.0054**	0.0069***	0.0098***	0.0097***						0.0197***	0.0117**	0.0065*	0.0022	0.0031
	U2	0.0058***	0.0083***	0.0156***	0.0139***	0.0206***						0.0188***	0.0175***	0.0110**	0.0043	0.0044
	U3	0.0103***	0.0161***	0.0168***	0.0182***	0.0205***						0.0168**	0.0147***	0.0085*	0.0080	0.0054
	U3-U1	0.0086***	0.0107***	0.0099***	0.0084***	0.0108**						-0.0029	0.0030	0.0020	0.0058	0.0023
CFVOLA	U1	0.0029	0.0036	0.0093***	0.0007	0.0137*	0.0022	0.0082**	0.0017	0.0063	0.0087					
	U2	0.0060**	0.0083***	0.0103***	0.0128***	0.0027	0.0025	0.0102**	0.0151***	0.0127***	0.0185**					
	U3	0.0078***	0.0120***	0.0243***	0.0173***	0.0131	0.0128***	0.0187***	0.0156***	0.0152**	0.0074					
	U3-U1	0.0049*	0.0085***	0.0150***	0.0166**	-0.0006	0.0107***	0.01054**	0.0140**	0.0089	-0.0014					

This is crucial since, as mentioned above, the literature proposes several explanations for a relation between a strategy's performance and the stock's market value. Similarly, the book-to market ratio, which is employed by Fama and French (1993) to form a risk factor, does also not explain the effects of the variables on the 52-week high profits. Keeping the B/M ratio variation fixed does not lead to insignificant differences between high- and low uncertainty groups formed by other variables.

Table 23 also justifies the choice of the LHR variable as information uncertainty. In four out of five stock price volatility portfolios, the 52-week high strategy is significantly more profitable within the highest 1/LHR ratio than in the lowest 1/LHR ratio. When stocks are first sorted on the LHR proxy, stock price volatility has a weaker but still substantial effect on the strategy's performance. In all five LHR portfolios, the 52-week high strategy generates higher monthly returns for stocks with a high volatility; and in two out of five portfolios, the difference is highly significant.

When stocks are first sorted into five groups based on cash-flow volatility, the difference in the 52-week high returns is not significant between high-uncertainty and low-uncertainty stocks based on most proxies. The weak significance could be explained by the shorter sample period. While the other information uncertainty proxies are calculated from January 1988, cash-flow volatility is not available before January 1996.

It could be argued that the two-way sort conducted above leads to portfolios that are not well diversified as the number of stocks within a portfolio is small.[84] In order to present evidence that the results are not biased by a lack of diversification in the portfolios, I repeat the two-way sort, but reduce the number of portfolios: In this test, stocks are first sorted into three instead of five portfolios according to an uncertainty proxy. Then, as in the test above, the stocks are further subdivided into three groups based on a second uncertainty variable. Subsequently, within each portfolio, three 52-week high groups are formed. To assign stocks to three instead of five portfolios in the first sorting level heavily reduces the number of portfolios from 45 to 27 and increases the number of stocks within each portfolio. However, such a weaker sorting criterion limits the ability of the method to test whether one information uncertainty proxy has an effect on the 52-week high profits given that another variable is kept

[84] The minimum number of stocks within a portfolio is at about 20 within the test. The number seems to be quite large. However, I measure equal-weighted portfolios and hence, it is safe to check the results of the test with a less strict subdivision procedure.

fixed. Forming three portfolios according to one proxy does not reduce the variation in the proxy as effectively as when five portfolios are built which implies that a rank based on the second proxy also is a partial sort based on the first measure. The test in Table 24 shows that the main findings remain unchanged and do not depend on the number of subportfolios. For this test, the relation between a variable and the 52-week high returns is not diminished when controlled for another uncertainty proxy. Yet, compared to the 5x3x3 test, the difference in the 52-week high returns between high- and low uncertainty stocks is statistically different from zero within more subportfolios. For this 3x3x3 test, the five variables do have a significant effect on the 52-week high profitability within cash-flow variation groups which was not the case in Table 23, where for LHR, AGE and VOLA, the return differences are not or only weakly significantly different from zero.

In summary, all six examined information uncertainty measures seem to have influence on the 52-week high profits. The difference in the 52-week high returns for high- and low-uncertainty stocks is positive and significantly different from zero. Moreover, none of the six variables explains the documented effect of the other measures on the 52-week high profits. Hence, each variable appears to possess incremental information and is worth to be included in the tests. It is especially important for LHR to show that it is not subsumed by other proxies, as it has not yet been employed as information uncertainty variable. The relation between the six uncertainty proxies and the strategy is present if I control for industry effects, for risk-components and for the turn-of-the-year effect. These findings support the idea that the 52-week high profits are explained by a non-rational behavior called anchoring and present evidence to reject the null that the 52-week high is not explained by anchoring.

Table 24

Sorts on Two Information Uncertainty Variables – 3x3x3 Portfolios

This table reports average monthly portfolio returns sorted by two information uncertainty proxies and by the 52-week high criterion. First, stocks are sorted into five portfolios based on one uncertainty measure. Then within each of the three portfolios, stocks are further subdivided into three portfolios according to the second uncertainty measure. Subsequently, stocks of each portfolio are sorted into three portfolios on the 52-week high measure. Stocks within these 27 portfolios are equal-weighted and held over six months. Between the ranking and the holding period, a skip period of one month is included. The 52-week high profits are calculated by subtracting the average monthly loser portfolio return from the average winner portfolio return within each of the 15 double-sorted uncertainty portfolios. MV is the firm's market capitalization (in millions of Pounds) at the end of month t. Book-to-market value (B/M) is the book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year. LHR is the quotient of the lowest price of a stock within the last one year and the highest price of the stock within the last 52 weeks. Stock volatility (VOLA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Firm age (AGE) measures the number of months since the firm was first covered by Datastream. Cash-flow volatility (CFVOLA) represents the standard deviation of the net cash flow from operating activities standardized by average total assets in the past 3 years. Stocks are equal-weighted and held in the portfolio over six months. Between the ranking date and the formation period, a skip period of one month is included. The table reports the overlapping holding period returns. 1/MV, 1/(B/M), 1/LHR and 1/AGE are the reciprocals of MV, LHR and AGE. Each month, all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996; t-statistics (two-tailed) are reported in parentheses.

		1/MV			1/(B/M)			1/LHR			VOLA		
		S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
1/MV	U1				0.0002	0.0074***	0.0127***	0.0032**	0.0059**	0.0172***	0.0032	0.0082	0.0134
	U2				0.0068**	0.0123***	0.0210***	0.0075***	0.0124***	0.0177***	0.0060***	0.0090**	0.0157***
	U3				0.0075**	0.0179***	0.0243***	0.0118***	0.0169***	0.0208***	0.0116***	0.0157***	0.0194***
	U3-U1				0.0074**	0.0105***	0.0116***	0.0086***	0.0110***	0.0036	0.0084***	0.0075***	0.0060*
1/(B/M)	U1	0.0026	0.0064**	0.0062*				0.0048***	0.0083***	0.0107***	0.0039**	0.0075***	0.0065
	U2	0.0088***	0.0147***	0.0182***				0.0071***	0.0130***	0.0216***	0.0068***	0.0132***	0.0190***
	U3	0.0132***	0.0241***	0.0227***				0.0106***	0.0186***	0.0254***	0.0096***	0.0181***	0.0223***
	U3-U1	0.0106***	0.0178***	0.0166***				0.0059***	0.0103***	0.0147***	0.0057***	0.0106***	0.0158***
1/LHR	U1	0.0032*	0.0099***	0.0053***	0.0050***	0.0060***	0.0118***				0.0056***	0.0081***	0.0126***
	U2	0.0057***	0.0158***	0.0128***	0.0086***	0.0125***	0.0211***				0.0059***	0.0122***	0.0168***
	U3	0.0176***	0.0183***	0.0192***	0.0096***	0.0214***	0.0242***				0.0084***	0.0159***	0.0210***
	U3-U1	0.0144***	0.0084***	0.0139***	0.0046	0.0154***	0.0124***				0.0028*	0.0078***	0.0085**
VOLA	U1	0.0029*	0.0105***	0.0138***	0.0041**	0.0065***	0.0103***	0.0057***	0.0072***	0.0145***			
	U2	0.0063***	0.0156***	0.0170***	0.0070***	0.0125***	0.0180***	0.0063***	0.0119***	0.0169***			
	U3	0.0142***	0.0145***	0.0219***	0.0082**	0.0185***	0.0228***	0.0089***	0.0132***	0.0193***			
	U3-U1	0.0112***	0.0040	0.0081**	0.0041	0.0119***	0.0124***	0.0032**	0.0060***	0.0047			
1/AGE	U1	0.0045*	0.0099***	0.0148***	0.0014	0.0072***	0.0119***	0.0027**	0.0071***	0.0126***	0.0023	0.0076***	0.0109***
	U2	0.0074***	0.0163***	0.0184***	0.0053*	0.0131***	0.0209***	0.0075***	0.0115***	0.0200***	0.0059***	0.0143***	0.0181***
	U3	0.0144***	0.0204***	0.0180***	0.0094***	0.0173***	0.0268***	0.0121***	0.0178***	0.0217***	0.0119***	0.0169***	0.0197***
	U3-U1	0.0099***	0.0105***	0.0032	0.0080***	0.0101***	0.0149***	0.0094***	0.0107***	0.0091***	0.0096***	0.0093***	0.0088**
CFVOLA	U1	0.0039	0.0063*	0.0088	-0.0639	0.3986	0.4197	0.0036*	0.0074***	0.0086	0.0019***	0.0061***	0.0020***
	U2	0.0075**	0.0123***	0.0049	0.5779	1.0595***	1.8072***	0.0055**	0.0095***	0.0110**	0.0058***	0.0119***	0.0062***
	U3	0.0193***	0.0196***	0.0231**	0.4713	1.8481***	2.7050***	0.0096***	0.0157***	0.0168***	0.0093***	0.0228***	0.0076***
	U3-U1	0.0154***	0.0133**	0.0144	0.5352*	1.4495***	2.2853***	0.0060**	0.0083***	0.0082	0.0074***	0.0167***	0.0057

continued

		1/AGE			CFVOLA		
		S1	S2	S3	S1	S2	S3
1/MV	U1	0.0033*	0.0072***	0.0150***	0.0027	0.0094***	0.0153***
	U2	0.0070***	0.0139***	0.0170***	0.0037	0.0130***	0.0230***
	U3	0.0078***	0.0163***	0.0182***	0.0085**	0.0153***	0.0198***
	U3-U1	0.0045**	0.0091***	0.0032	0.0058*	0.0059*	0.0045
1/(B/M)	U1	0.0029	0.0072***	0.0106***	-0.0016	0.0113***	0.0169***
	U2	0.0077***	0.0137***	0.0171***	0.0048	0.0164***	0.0247***
	U3	0.0090***	0.0195***	0.0248***	0.0100***	0.0174***	0.0237***
	U3-U1	0.0061***	0.0123***	0.0142***	0.0116***	0.0061***	0.0067***
1/LHR	U1	0.0036***	0.0080***	0.0138***	0.0054***	0.0067***	0.0093***
	U2	0.0071***	0.0129***	0.0161***	0.0032*	0.0094***	0.0147***
	U3	0.0087***	0.0193***	0.0218***	0.0086	0.0118***	0.0163**
	U3-U1	0.0051**	0.0113***	0.0080**	0.0032	0.0051*	0.0070**
VOLA	U1	0.0043***	0.0079***	0.0117***	0.0013	0.0084***	0.0089***
	U2	0.0064***	0.0133***	0.0154***	0.0057**	0.0108***	0.0207***
	U3	0.0063***	0.0158***	0.0212***	0.0067	0.0124***	0.0107*
	U3-U1	0.0020	0.0079***	0.0095***	0.0054*	0.0040*	0.0018
1/AGE	U1				0.0019	0.0074*	0.0172***
	U2				0.0043	0.0112***	0.0162***
	U3				0.0060	0.0126***	0.0165***
	U3-U1				0.0041	0.0052*	-0.0007
CFVOLA	U1	0.0048**	0.0050	0.0044			
	U2	0.0065**	0.0100***	0.0119***			
	U3	0.0104***	0.0161***	0.0127**			
	U3-U1	0.0057**	0.0112***	0.0083			

5.2 Risk

It cannot be excluded that the variables represent a risk factor instead of information uncertainty. However, Table 18 shows that, except for B/M, the variables do not have a significant effect on unconditional expected returns (on the 1% and 5% significance level). Combined with the fact that the proxies are associated with both higher returns for winner stocks and with lower average returns for loser stocks makes it more unlikely that the variables reflect missing risk factors.[85] This diametrical effect of the variables on winner and loser stocks makes it difficult to implement a risk-based theory for this pattern. Moreover, Zhang (2006) examines the market reaction to subsequent earnings announcements and shows that the variables still have an effect on the subsequent daily returns. This is clear evidence against risk factors behind the proxies as risk-based models would predict a zero returns for this short period (Fama, 1998).

5.3 The Persistence of the Information Uncertainty Effect

Further, to ensure that the six variables proxy information uncertainty, I examine the long-term effect of the variables on the 52-week high returns. Therefore, the profits to the 52-week high strategy with a holding period of one month are measured for each of the first 36 months after the portfolio formation. If the variables are in fact proxies for the ambiguity about information, I expect the information uncertainty effect to disappear within the first months. As described above, this paper builds on the insights of psychologists that behavioral biases have more room when uncertainty is large (see also Hirshleifer, 2001 and Daniel et al., 2001). Combined with the definition of information uncertainty (the doubt about the implication of news on a firm's value), it implies that greater information uncertainty leads to a reduced speed until news is completely incorporated into the stock price. Yet, after a certain time, the information should be completely incorporated into the stock price. In this line of argumentation, the return differences between high-uncertainty winners (losers) and low-uncertainty winners (loser) should become insignificant in the long run. This implies that the difference in 52-week high returns between high- and low-uncertainty stocks should disappear after a couple of months following the formation of the portfolio.

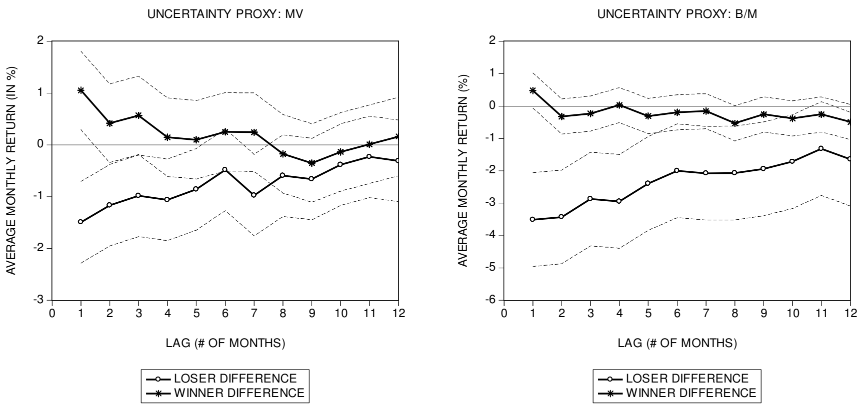
[85] The Information uncertainty effect is also present when stocks are first sorted on the 52-week high criterion and then subsequently based on the uncertainty variable.

Figure 6 shows the average monthly return differences between high and low-uncertainty stocks in the 52-week high winner and loser portfolios. They have a holding period of one month and are implemented with a lag of x months after the ranking date, where x can take values between zero and 12[86]. The figures show that for the winner portfolio, the return difference between high and low-uncertainty stocks becomes insignificant after one or two months for all variables except for LHR. The difference between high and low-uncertainty loser stocks is not significantly different from zero on the 5% level after three to five months for most variables. The differences are largest in the first month after the ranking date for both winners and losers. The pattern that the return difference quickly disappears after the ranking date is consistent with the information uncertainty story.

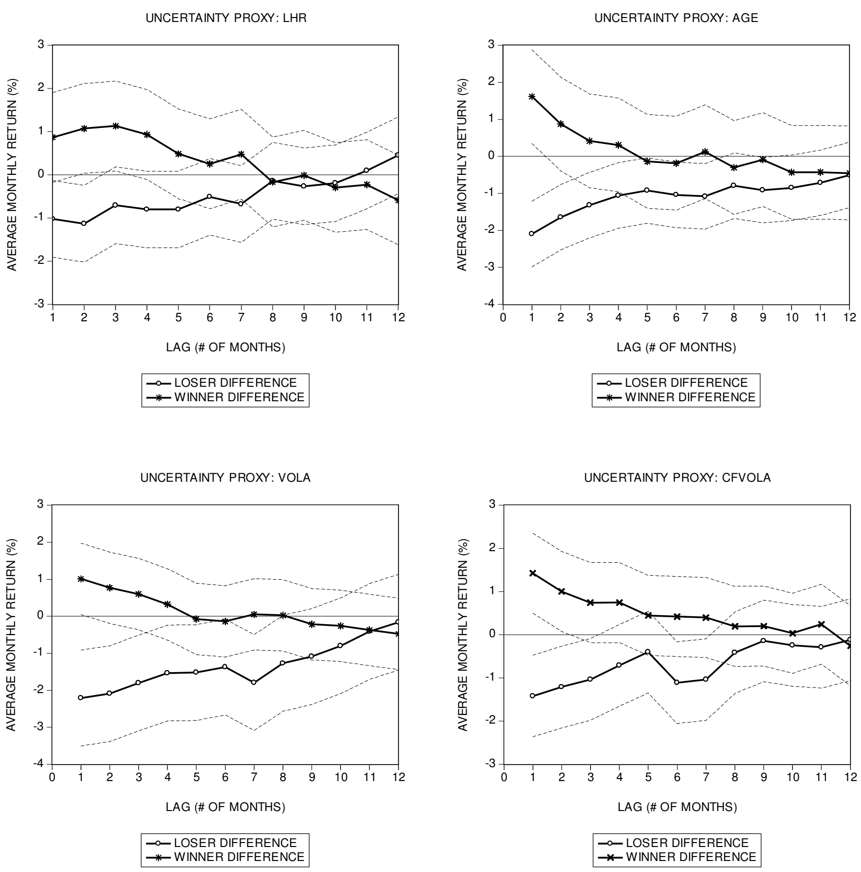
Figure 6

Uncertainty Effect in 52-week High Portfolios across Time

At the beginning of each month, stocks are ranked based on the information uncertainty proxy into five groups with a certain lag. Within each group, stocks are further subdivided according to the 52-week high measure. The ranking is executed with a certain lag measured in the number of months. The top (bottom) 30% are assigned to the winner (loser) portfolio. Stocks are equal weighted and held in the portfolio for one month. In the figures below, the return differential between the highest- and the lowest uncertainty portfolios are documented for winners and losers, respectively. The broken lines indicate the 95% confidence interval. The sample consists all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996.



[86] As mentioned above, the returns are calculated for the first 36 months after the ranking date. For a better illustration, the figures are limited to the first 12 months after the ranking date.

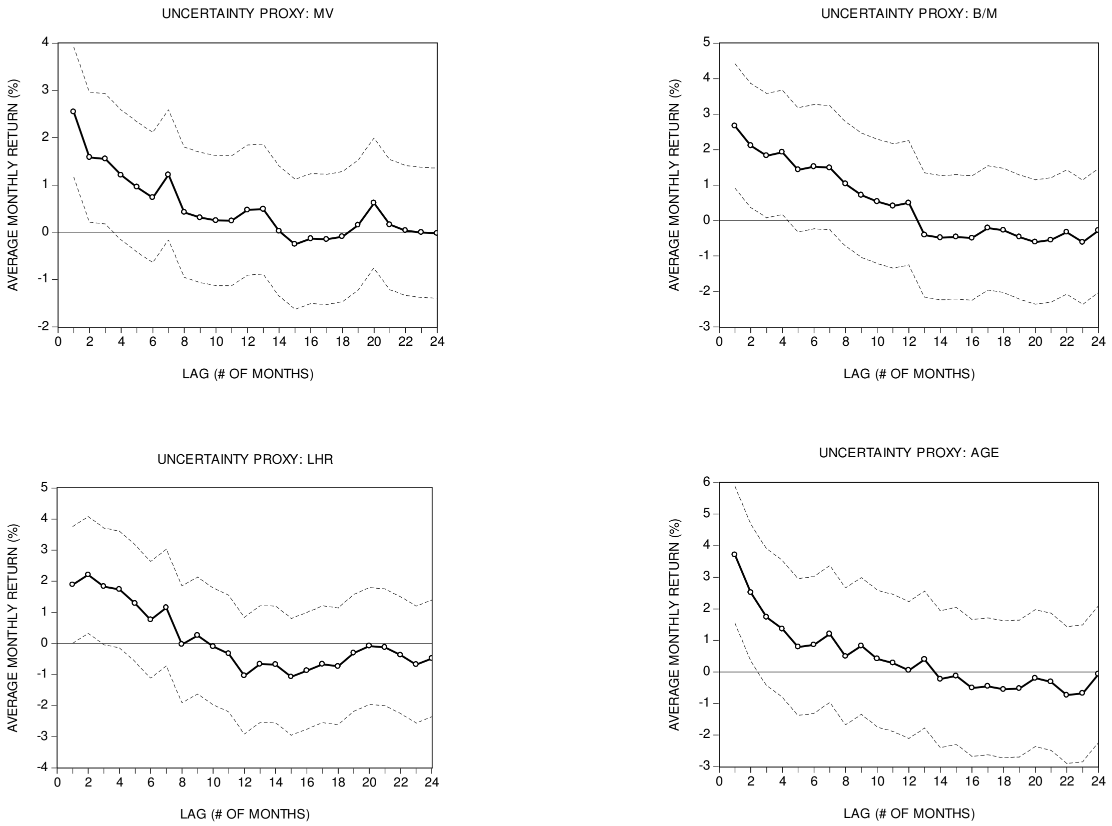


Furthermore, the finding that the uncertainty effect has a longer persistence in the loser portfolio compared to winners stocks might explain a finding of Table 19-21: it is shown that the 52-week high return increase in uncertainty is to a larger part due to the decrease in loser returns than due to the increase in winner returns. In these tables, the returns to 52-week high portfolios are reported on an overlapping holding period basis for a holding period of six months. Consequently, the average monthly winner and loser portfolio return in month t is composed of portfolios that are formed between $t-6$ to $t-1$. Hence, according to Figure 6, the uncertainty effect has already disappeared for the subportfolios implemented furthest in the past. Therefore, such a portfolio construction implicitly considers the length of the uncertainty effect when comparing the return differences between high and low uncertainty stocks for losers with those for winners. In opposite, Figure 6 presents evidence that the positive relation between uncertainty and 52-week high returns is due to winners *and* losers as the absolute difference between high and low-uncertainty stocks is of similar magnitude for the uncertainty measures LHR, AGE and CFVOLA. Only when information uncertainty is measured by B/M, the 52-week high increase in uncertainty seems to be largely a loser phenomenon.[87]

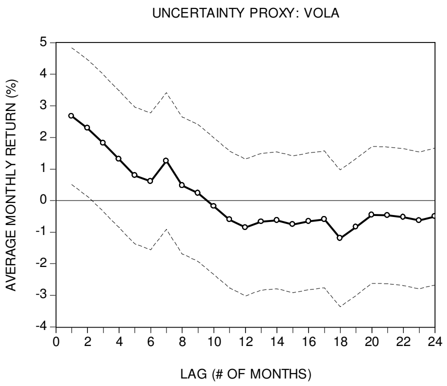
Figure 7

The 52-week High Difference in Uncertainty

At the beginning of each month, stocks are ranked based on the information uncertainty proxy into five groups. Within each group, stocks are further subdivided according to the 52-week high measure. The top (bottom) 30% is assigned to the winner (loser) portfolio. The ranking is executed with a certain lag measured as the number of months Stocks are equal weighted and held in the portfolio for one month. In the figures below, the return differential of the 52-week high strategy between the highest- and the lowest uncertainty portfolio is documented, respectively. The broken lines indicate the 95% confidence interval. The sample consists of all actively traded UK stocks on Datastream with a market value above 20 Million Pounds. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996.



[87] All obtained findings in Figure 6 remain merely unchanged if returns are controlled for the turn-of-the-year effect. Results are not reported for consideration of space. The figures are available on request.



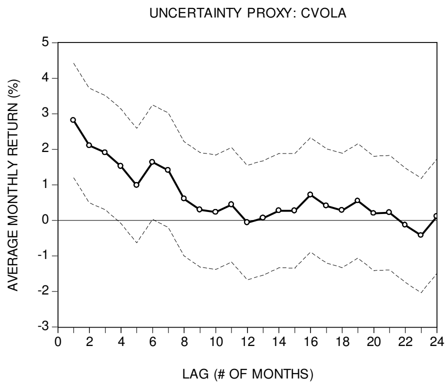


Figure 7 illustrates the difference between the profitability of the 52-week high strategy when limited to high-uncertainty stocks and the strategy's profits when limited to low-uncertainty stocks. It supports the findings from above and shows that only within the first three to four months after the ranking date the uncertainty effect leads to significant differences in the 52-week high returns. For larger portfolio formation lags, the profits to the 52-week high strategy do not depend on the level of information uncertainty. Consequently, the relation between the six variables and the 52-week high profits is not a permanent phenomenon, which is strong support that the variables do indeed measure information uncertainty and do not represent a compensation for risk.

6. The Information Uncertainty Effect and Anchoring

So far, the finding that higher information uncertainty leads to higher 52-week high returns is interpreted as evidence for anchoring. However, in the framework of anchoring, the profitability of the 52-week high strategy does not represent the level of underreaction caused by this behavioral heuristic. The profits rather document the correction that follows to the initial underreaction. Hence, it is concluded from the profitability of the 52-week high strategy that represents the intensity of the correction on the initial underreaction due to anchoring.

This approach implicitly assumes that the strength of underreaction differs across the level of information uncertainty, while the manner how investors correct the bias remains unchanged. However, it cannot be excluded that the subsequent correction is (also) driven by a psychological bias. For example, the model of Barberis et al. (1998) shows that, after an initial underreaction, a behavioral phenomenon called representativeness heuristic leads investors to overreact. Based on the insight that psychological biases increase in uncertainty, it might also be that the representativeness heuristic gets more room in uncertainty. This implies that not only the initial underreaction, but also the correction might be influenced by a behavioral pattern that depends on the level of information uncertainty. Consequently, the positive relation between the 52-week high profits and information uncertainty might also be due to a psychological bias that leads to a more biased correction behavior beside or instead of a higher degree of anchoring.

In order to ensure that that this is not the case, I examine the long-term performance of the 52-week high strategy for different levels of information uncertainty. In Table 25, the long run profitability of the 52-week high strategy is reported for different levels of information uncertainty. U1 (U5) refers to the lowest (highest) uncertainty level. The averages of five lagged portfolio returns are documented. As above, the 52-week high winner and loser portfolios are formed after a lag of x months and are held over one month, where x can take values between one and 48. It is necessary to point out that the number of monthly observations decreases in x: The sample starts in January 1989[88], but if the 52-week high strategy is examined with a lag of 48 months, the first monthly return is not obtained before the end of January 1993.

Irrespective of the level of information uncertainty, the 52-week high strategy does not yield significant negative returns within the examined four-year period. Only for LHR and for VOLA, the 52-week high strategy generates weakly significant negative returns across the highest uncertainty stocks. Yet, this is only the case for one single sub-period respectively. However, in general, for all information uncertainty levels, the profits to the 52-week high strategy are not significantly different from zero after the first 12 months. Furthermore, there is no evidence that high uncertainty stocks experience a stronger reversal in the long-term as the returns of the 52-week high strategy are in general not lower when limited to high uncertainty stocks. For MV, B/M and AGE, for example, the 52-week high strategy generates higher negative returns within the U1 group than in the U5 group for most intervals between month 12 and 48 after the portfolio formation.

[88] The sample starts in January 1989 for all variables except for CFVOLA that starts in 1996.

Table 25

Long-term 52-week High Profits

The table reports average monthly returns for portfolios formed based on information uncertainty and the 52-week high criterion with a certain lag. First, stocks are sorted into five portfolios based on one uncertainty measure. Then within each of the three portfolios, stocks are further subdivided into three portfolios according to the second uncertainty measure. The top (bottom) 30% is assigned to the winner (loser) portfolio. Stocks within a portfolio are equal-weighted and held over one month. The ranking is executed with a certain lag, which is denominated in the number of months. The table shows the average monthly returns of the 52-week high strategy within a certain holding period interval. MV is the firm's market capitalization (in millions of Pounds) at the beginning of month t. Book-to-market value (B/M) is the book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year. LHR is the quotient of the lowest price of a stock within the last one year and the highest price of the stock within the last 52 weeks. Stock volatility (VOLA) is the standard deviation of weekly market excess returns over the year ending at the beginning of month t. Firm age (AGE) measures the number of months since the firm was first covered by Datastream. Cash-flow volatility (CFVOLA) represents the standard deviation of the net cash flow from operating activities standardized by average total assets in the past 3 years. 1/MV, 1/(B/M), 1/LHR and 1/AGE are the reciprocals of MV, B/M, LHR and AGE. Each month, all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996; t-statistics (two-tailed) are reported in parentheses.

		Months 1-6	Months 7-12	Months 13-18	Months 19-24	Months 25-30	Months 31-36	Months 37-42	Months 43-48
1/MV	U1	0.0087	0.0054	-0.0008	-0.0006	-0.0032	-0.0034	-0.0036	-0.0037
		(2.42)	(1.74)	-(0.32)	-(0.29)	-(0.82)	-(1.06)	-(1.92)	-(0.81)
	U2	0.0146	0.0101	-0.0010	-0.0010	-0.0015	-0.0001	-0.0005	0.0009
		(4.19)	(3.58)	-(0.40)	-(0.50)	-(2.15)	-(0.42)	-(0.14)	-(0.13)
	U3	0.0197	0.0081	-0.0018	-0.0043	-0.0028	-0.0016	-0.0014	-0.0006
		(5.85)	(2.70)	-(0.75)	-(1.89)	-(1.55)	-(1.22)	-(1.71)	-(0.77)
	U4	0.0211	0.0099	-0.0021	-0.0026	-0.0014	0.0001	-0.0010	-0.0009
		(6.00)	(3.48)	-(0.79)	-(1.11)	-(0.74)	-(0.72)	-(1.43)	-(0.68)
	U5	0.0230	0.0103	-0.0010	0.0010	-0.0039	0.0004	-0.0006	-0.0016
		(6.77)	(3.50)	-(0.37)	(0.49)	-(0.48)	-(0.85)	-(0.27)	-(0.47)
1/(B/M)	U1	0.0022	0.0015	-0.0024	0.0009	0.0002	0.0010	-0.0011	-0.0028
		(0.59)	(0.48)	-(0.91)	(0.41)	(0.24)	(0.56)	-(0.63)	-(1.41)
	U2	0.0136	0.0067	-0.0019	-0.0011	-0.0015	-0.0013	-0.0051	-0.0022
		(3.94)	(2.59)	-(0.82)	-(0.52)	-(0.79)	-(0.83)	-(3.40)	-(2.01)
	U3	0.0176	0.0073	-0.0031	-0.0029	-0.0050	-0.0026	-0.0031	-0.0006
		(6.36)	(2.58)	-(1.35)	-(1.41)	-(2.32)	-(1.00)	-(1.55)	-(0.99)
	U4	0.0213	0.0112	-0.0002	-0.0029	-0.0036	-0.0046	-0.0038	-0.0022
		(7.12)	(4.52)	-(0.09)	-(1.26)	-(1.66)	-(2.04)	-(2.29)	-(1.45)
	U5	0.0293	0.0156	0.0046	0.0009	-0.0039	-0.0019	-0.0021	-0.0001
		(2.93)	(5.11)	(1.66)	(0.35)	-(1.33)	-(0.56)	-(1.07)	-(0.18)
1/LHR	U1	0.0092	0.0066	0.0006	-0.0009	0.0004	0.0002	-0.0002	-0.0009
		(7.07)	(5.27)	(0.49)	-(0.77)	(0.35)	(0.23)	-(0.31)	-(0.95)
	U2	0.0109	0.0070	-0.0002	-0.0004	-0.0029	0.0002	-0.0038	-0.0005
		(7.06)	(5.13)	-(0.13)	-(0.77)	-(2.25)	-(0.27)	-(3.15)	-(1.02)
	U3	0.0156	0.0102	0.0010	-0.0020	-0.0013	0.0018	-0.0039	-0.0013
		(8.39)	(6.13)	(0.67)	-(1.24)	-(1.08)	(1.05)	-(3.14)	-(1.02)
	U4	0.0197	0.0105	-0.0019	-0.0033	-0.0016	-0.0016	-0.0029	-0.0021
		(8.83)	(4.72)	-(1.10)	-(1.86)	-(1.11)	-(0.85)	-(2.37)	-(1.64)
	U5	0.0254	0.0065	-0.0072	-0.0043	-0.0061	-0.0020	-0.0032	-0.0042
		(6.64)	(2.25)	-(2.71)	-(1.82)	-(2.61)	-(0.40)	-(1.17)	-(2.06)

continued

		Months 1-6	Months 7-12	Months 13-18	Months 19-24	Months 25-30	Months 31-36	Months 37-42	Months 43-48
VOLA	U1	0.0078	0.0055	0.0004	0.0008	0.0000	-0.0013	-0.0010	0.0007
		(4.46)	(3.54)	(0.24)	(0.60)	-(0.10)	-(0.81)	-(0.87)	(0.62)
	U2	0.0116	0.0081	0.0000	-0.0007	-0.0028	0.0008	-0.0016	0.0006
		(5.28)	(4.37)	(0.01)	-(0.50)	-(2.09)	(0.74)	-(1.49)	(0.46)
	U3	0.0157	0.0086	-0.0006	-0.0023	-0.0038	-0.0011	-0.0042	-0.0016
		(6.19)	(4.15)	-(1.23)	-(1.31)	-(2.60)	-(0.60)	-(2.82)	-(1.21)
	U4	0.0173	0.0084	-0.0024	-0.0031	-0.0036	-0.0006	-0.0023	-0.0009
		(5.97)	(3.52)	-(1.23)	-(1.56)	-(2.05)	-(0.02)	-(1.53)	-(0.60)
	U5	0.0237	0.0060	-0.0070	-0.0047	-0.0032	-0.0002	-0.0008	-0.0037
		(5.85)	(2.01)	-(2.68)	-(2.10)	-(1.32)	-(0.02)	-(1.72)	-(1.71)
1/AGE	U1	0.0056	0.0030	-0.0016	-0.0012	-0.0032	-0.0034	-0.0036	-0.0037
		(1.86)	(1.20)	-(0.67)	-(0.67)	-(1.87)	-(1.70)	-(2.10)	-(2.17)
	U2	0.0147	0.0086	-0.0001	0.0029	-0.0015	-0.0001	-0.0005	0.0009
		(4.57)	(3.06)	-(0.05)	(1.22)	-(0.66)	-(0.04)	-(0.47)	(0.30)
	U3	0.0188	0.0082	-0.0027	-0.0031	-0.0028	-0.0016	-0.0014	-0.0006
		(5.87)	(2.99)	-(1.10)	-(1.40)	-(1.36)	-(0.82)	-(0.88)	-(0.33)
	U4	0.0226	0.0098	-0.0025	-0.0020	-0.0014	0.0001	-0.0010	-0.0009
		(6.29)	(3.07)	-(0.84)	-(0.81)	-(0.44)	(0.18)	-(0.54)	-(0.36)
	U5	0.0239	0.0085	-0.0045	-0.0054	-0.0039	0.0004	-0.0006	-0.0016
		(6.39)	(2.99)	-(1.29)	-(1.64)	-(1.59)	(0.52)	-(0.44)	-(0.61)
CFVOLA	U1	0.0039	0.0025	-0.0011	-0.0011	-0.0043	0.00021	0.00014	0.00249
		(1.00)	(0.61)	-(0.23)	-(0.31)	-(0.23)	(0.05)	(0.12)	(0.62)
	U2	0.0061	0.0045	0.0005	0.0014	-0.00358	-0.00189	0.00002	0.00157
		(1.35)	(1.18)	(0.14)	(0.56)	-(0.29)	-(0.46)	(0.65)	(0.71)
	U3	0.0099	0.0032	-0.0057	-0.0030	-0.00417	0.00033	-0.00020	-0.00057
		(2.37)	(0.86)	-(1.41)	-(0.90)	-(1.45)	(0.08)	-(0.13)	-(0.11)
	U4	0.0199	0.0113	0.0067	0.0010	0.00258	-0.00191	-0.00109	0.00235
		(4.31)	(2.88)	(1.66)	(0.28)	(1.02)	-(0.73)	-(1.42)	(1.12)
	U5	0.0231	0.0122	0.0042	0.0002	-0.0021	-0.00120	-0.00400	0.00177
		(3.86)	(2.32)	(0.95)	(0.05)	-(0.49)	-(0.73)	-(1.42)	(0.29)

Moreover, for all levels of uncertainty, the persistence of the profitability of the 52-week high strategy is similar. This is documented in Figure 8, where the 52-week high profits for the first 20 months after the ranking date are illustrated for different information groups sorted based on AGE. The returns to the strategy are only reported for AGE as the results for the other measures are similar and do not contain additional information. Irrespective of the level of information uncertainty, the 52-week high portfolios only generate significant positive returns within the first twelve months and turn negative in month 13 to 14 after the ranking date (Yet, the negative returns are not significantly different from zero). This implies that the relation between the 52-week high returns and information uncertainty can also not be explained by a different speed to correct the initial bias across uncertainty groups.

The results related to the long-term performance of the 52-week high strategy might be biased towards zero due to the assumption[89] that stocks, which are delisted during the holding period

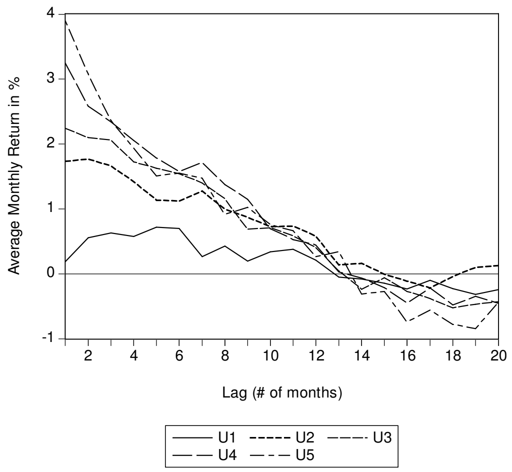
[89] This assumption is also employed in Agyei-Ampomah (2003, p.780).

generate an average return of zero. With an increasing number of months between the ranking date and the portfolio formation, the fraction of delisted stocks is expected to grow. However, it is ensured that the results are not biased by this assumption: the drawn inferences are not different if the portfolios are constructed under Forner's (2003, p.72) assumption that the proceeds of delisted stocks are at once equally invested in the remaining stocks of the winner or loser portfolio. The findings of this section are also not influenced by the turn-of-the year effect. Measuring the long-term performance of the 52-week high strategy in non-January months does also not change the pattern observed for the total sample.[90]

Figure 8

Long-term Performance of the 52-week High Strategy across AGE Groups

The figure shows the average monthly return of the 52-week high strategy within an information uncertainty portfolios based on AGE within the first 20 months after the ranking date. At the beginning of each month, stocks are ranked based on the information uncertainty proxy AGE into five groups with a certain lag. Within each group, stocks are further subdivided according to the 52-week high measure. The top (bottom) 30% are assigned to the winner (loser) portfolio. The ranking is executed with a certain lag, measured as the number of months. Stocks are equal weighted and held in the portfolio for one month. The sample consists of all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. The sample period is between January 1989 and August 2008.



Hence, the variation of the strategy's profits in information uncertainty seems not to be driven by a different manner to correct the initial bias and further confirms the idea that it is anchoring and hence the level of underreaction which varies with information uncertainty. Moreover, the finding that long-term reversals seem not to occur when stocks are ranked based on the 52-week high strategy contributes to a growing controversial literature. It is consistent with the finding of George and Hwang (2004) and provides further evidence that separate theories for the intermediate-term and the long-term predictability in prices are

[90] Results are not reported for consideration of space. They are available on request.

necessary. Yet, it contradicts the behavioral models of Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999) and the empirical findings for momentum strategies on international stock indexes of Du (2007).

Table 26

Momentum Profits for Different Information Uncertainty Groups

This table reports average monthly portfolio returns sorted by an information uncertainty proxy and by the (6/1/6) momentum criterion. Each month, stocks are assigned to one of five portfolios based on the value of the uncertainty variable. The 20% of stocks with the highest variable value (and with the highest degree of information uncertainty) is included into U5 while the 20% of stocks with the lowest value (and hence with the lowest level of ambiguity) is assigned to group U1. Within each information uncertainty quantile, I further sort stocks based on the (6/1/6) momentum criterion. The top (bottom) 20% are included in the winner (loser) portfolio. MV is the market capitalization (in millions of Pounds) at the beginning of month t. Book-to-market value (B/M) is the book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year. LHR is the quotient of the lowest price of a stock within the last one year and the highest price of the stock within the last 52 weeks. Stock volatility (VOLA) is the standard deviation of weekly market excess returns over the year ending at the beginning of month t. Firm age (AGE) measures the number of months since the firm was first covered by Datastream. Cash-flow volatility (CFVOLA) represents the standard deviation of the net cash flow from operating activities standardized by average total assets in the past 3 years. Stocks are equal-weighted and held in the portfolio over six months. Between the ranking date and the formation period, a skip period of one month is included. The table reports the overlapping holding period returns. 1/MV, 1/(B/M), 1/LHR and 1/AGE are the reciprocals of MV, B/M, LHR and AGE. Each month, all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. The sample period is between January 1989 and August 2008 except for CFVOLA, which is not available before January 1996; t-statistics (two-tailed) are reported in parentheses.

		U1	U2	U3	U4	U5	U5-U1	
1/MV	Winner	0.0063	0.0098	0.0104	0.0122	0.0110	0.0047	(2.34)
	Loser	-0.0020	-0.0023	-0.0051	-0.0064	-0.0103	-0.0083	(-2.91)
	Wi-Lo	0.0084	0.0121	0.0155	0.0186	0.0213	0.0129	(3.98)
	t-stat	(2.56)	(3.88)	(5.33)	(6.44)	(7.07)		
1/(B/M)	Winner	0.0093	0.0111	0.0118	0.0105	0.0111	0.0018	(0.94)
	Loser	0.0039	-0.0022	-0.0058	-0.0092	-0.0123	-0.0162	(-7.09)
	Wi-Lo	0.0051	0.0134	0.0176	0.0197	0.0233	0.0183	(5.50)
	t-stat	(1.66)	(5.53)	(7.43)	(7.06)	(6.96)		
1/LHR	Winner	0.0072	0.0085	0.0102	0.0105	0.0104	0.0033	(2.24)
	Loser	0.0000	0.0000	-0.0036	-0.0045	-0.0095	-0.0096	(-2.28)
	Wi-Lo	0.0071	0.0084	0.0138	0.0149	0.0200	0.0128	(3.99)
	t-stat	(6.20)	(5.80)	(8.03)	(7.08)	(5.63)		
VOLA	Winner	0.0058	0.0111	0.0121	0.0095	0.0098	0.0040	(2.44)
	Loser	-0.0020	-0.0014	-0.0024	-0.0050	-0.0091	-0.0071	(-3.15)
	Wi-Lo	0.0079	0.0125	0.0144	0.0146	0.0189	0.0110	(3.44)
	t-stat	(4.49)	(6.24)	(6.27)	(5.53)	(5.32)		
1/AGE	Winner	0.0063	0.0101	0.0116	0.0108	0.0105	0.0041	(2.12)
	Loser	0.0008	-0.0030	-0.0046	-0.0100	-0.0101	-0.0109	(-3.97)
	Wi-Lo	0.0056	0.0130	0.0162	0.0208	0.0206	0.0150	(4.91)
	t-stat	(2.23)	(4.89)	(5.92)	(6.71)	(5.66)		
CFVOLA	Winner	0.0064	0.0087	0.0112	0.0125	0.0093	0.0029	(1.54)
	Loser	0.0012	0.0030	-0.0002	-0.0060	-0.0084	-0.0096	(-2.26)
	Wi-Lo	0.0052	0.0057	0.0114	0.0186	0.0177	0.0125	(2.56)
	t-stat	(1.50)	(1.68)	(2.99)	(4.45)	(3.44)		

7. Information Uncertainty and Stock Price Momentum

George and Hwang (2004) show that the 52-week high profits largely explain the profitability of stock price momentum. In order to examine whether the two strategies are closely linked, I extend my analysis and test whether the information uncertainty proxies are also linked to momentum profits. A positive relation between momentum returns and information uncertainty would further support George and Hwang's (2004) hypothesis that the two strategies are closely connected since it implies that both are related to the same variables. Table 26 reports the average monthly (6/1/6) momentum returns within different uncertainty groups. The (6/1/6) strategy is constructed as described above. It is preferred against other momentum strategies simply as it is the most commonly examined.

In Table 26, stocks are sorted into five portfolios according to the uncertainty proxy each month. U1 represents the group of stocks with the lowest degree of information uncertainty while U5 captures the high information ambiguity stocks. Within each of the five portfolios, stocks are further sorted based on the momentum criterion into a winner portfolio (the top 30%) and a loser portfolio (the bottom 30%). The momentum return is the difference between winners and losers. As the table shows, for each proxy, momentum returns are larger for high-uncertainty stocks than for low-uncertainty assets. While the average monthly momentum return is 0.56% within the U1 group according to AGE, it is with 2.06% per month substantially larger for the highest uncertainty group. The positive relation between information uncertainty and momentum profits is due to winner and loser stocks. The future return of past winner stocks is higher and that of past loser stocks lower in the highest uncertainty stock group than in the U1 portfolio.

The effect of the uncertainty variables on the performance of the (6/1/6) momentum strategy and of the 52-week high strategy is quite similar. A larger degree of information uncertainty implies a similar increase in the predictive power of both ranking measures and leads to a similar increase in the profitability of both strategies. While the difference of the 52-week high strategy is 1.37% between the U1 and the U5 group sorted by AGE (see Table 19), it is with 1.50% only slightly larger for the momentum strategy. For the 52-week high strategy, the difference of 1.37% consists of a return difference of 0.41% for winners and -0.97% for losers while for the momentum strategy, it is composed of 0.41% for the winner and -1.09% for the loser portfolio. For other information uncertainty proxies, the magnitude of the information uncertainty effect on the strategies' returns is also quite comparable. As both, the (6/1/6) momentum and the 52-week high strategy seem to depend similarly on the same variables, further support for the hypothesis of a close relation between the two strategies is presented.

Moreover, as the momentum and the 52-week high strategy seem to depend on information uncertainty further supports the idea that momentum is explained by anchoring. Similar to the 52-week high measure, the momentum ranking criterion improves its forecasting power when information uncertainty is larger. In line with the psychological insight that behavioral biases increase in uncertainty, it provides further evidence that stock price momentum is driven by the anchoring bias. Documenting the relationship between the uncertainty measures and the (6/1/6) momentum strategy alone[91] leaves the door open for other behavioral explanations such as conservatism and representativeness (Barberis et al., 1998), loss aversion (Grinblatt and Han, 2002) or overconfidence and the "self attribution bias" (Daniel et al., 1998).

8. Robustness Tests

The robustness of the finding that the performance of the 52-week high strategy is positively related to information uncertainty is checked across different subperiods. Table 27 shows the average monthly 52-week high returns for different uncertainty groups between January 1989 to December 1998 (Panel A) and between January 1999 and August 2008 (Panel B). The table shows that the documented relation is not time-specific. In both subsamples, a zero-cost portfolio that is long in stocks with a price close to their 52-week high and short in stocks far from their 52-week high generates higher returns for high-uncertainty stocks than it does for low-uncertainty portfolios.

[91] See for example Zhang (2006).

Table 27

Subperiod Analysis

This table reports average monthly portfolio returns sorted by an information uncertainty proxy and by the 52-week high criterion. Each month, stocks are assigned to one of five portfolios based on the value of the uncertainty variable. The 20% of stocks with the highest variable value (and most information uncertainty) is included into U5 while the 20% of stocks with the lowest value (and hence with least information uncertainty) are assigned to group U1. Within each information uncertainty quantile, I further sort stocks based on the 52-week high ranking criterion. The top (bottom) 20% is included in the winner (loser) portfolio H1 (H5).). MV is the market capitalization (in millions of Pounds) at the end of month t. Book-to-market value (B/M) is the book value of shareholders equity plus deferred taxes divided by its market value at the end of the last fiscal year. LHR is the quotient of the lowest price of a stock within the last one year and the highest price of the stock within the last 52 weeks. Stock volatility (VOLA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Firm age (AGE) measures the number of months since the firm was first covered by Datastream. Cash-flow volatility (CFVOLA) represents the standard deviation of the net cash flow from operating activities standardized by average total assets in the past 3 years. Stocks are equal-weighted and held in the portfolio over six months. Between the ranking date and the formation period, a skip period of one month is included. The table reports the overlapping holding period returns. 1/MV, 1/(B/M), 1/LHR and 1/AGE are the reciprocals of MV, B/M, LHR and AGE. Each month, all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. In Panel A, the sample period is between January 1989 and December 1998 except for CFVOLA, which is not available before January 1996. Panel B reports returns for the period between January 1999 and August 2008; t-statistics (two-tailed) are reported in parentheses.

	U1	U2	U3	U4	U5	t-stat
Panel A: Feb 1989-Dec 1998						
1/MV	0.0080	0.0111	0.0149	0.0190	0.0204	0.0124
	(2.79)	(3.67)	(4.02)	(4.63)	(5.35)	(3.93)
1/(B/M)	0.0046	0.0153	0.0149	0.0178	0.0255	0.0209
	(0.74)	(4.11)	(5.75)	(7.77)	(8.78)	(4.66)
1/LHR	0.0081	0.0102	0.0156	0.0189	0.0257	0.0176
	(4.73)	(5.69)	(6.97)	(6.95)	(5.88)	(4.80)
VOLA	0.0078	0.0117	0.0134	0.0157	0.0220	0.0142
	(3.92)	(4.75)	(4.67)	(4.94)	(5.22)	(4.02)
1/AGE	0.0069	0.0103	0.0189	0.0205	0.0205	0.0136
	(1.45)	(2.77)	(5.59)	(5.45)	(5.84)	(4.93)
CFVOLA	0.0002	0.0159	0.0184	0.0259	0.0272	0.0270
	(0.07)	(2.50)	(3.46)	(2.82)	(3.46)	(2.13)
Panel B: Jan 1999-Aug 2008						
1/MV	0.0097	0.0165	0.0184	0.0173	0.0190	0.0094
	(3.59)	(2.78)	(3.31)	(3.19)	(3.59)	(2.79)
1/(B/M)	0.0002	0.0102	0.0160	0.0199	0.0266	0.0264
	(0.08)	(2.26)	(3.33)	(3.64)	(4.16)	(4.76)
1/LHR	0.0083	0.0096	0.0146	0.0165	0.0177	0.0094
	(4.28)	(3.94)	(5.02)	(4.70)	(3.11)	(1.79)
VOLA	0.0069	0.0107	0.0160	0.0138	0.0176	0.0107
	(2.49)	(3.16)	(3.95)	(3.00)	(2.78)	(1.93)
1/AGE	0.0046	0.0164	0.0155	0.0191	0.0184	0.0138
	(0.88)	(3.17)	(2.97)	(3.21)	(2.91)	(2.77)
CFVOLA	0.0034	0.0037	0.0057	0.0148	0.0206	0.0173
	(0.74)	(0.77)	(1.17)	(2.79)	(2.75)	(2.54)

A further proxy for information proxy might be analyst coverage. According to Zhang (2006), with an increasing number of analysts covering a firm, more information about the company is available, which implies less information uncertainty. Like Hong et al. (2000), each month, I measure analyst coverage as the number of I/B/E/S analysts providing fiscal year one earnings estimates that month.[92] If the number of analysts is not available, as Hong et al. (2000), I set the coverage for these stocks to zero. However, as there are many stocks each month with zero analysts, the stocks are divided into only four groups according to the variable.[93] The breakpoints are 0.25%, 0.50% and 0.75%. Stocks with the lowest number of analysts are considered high-uncertainty stocks (U4) while stocks with a high number of analysts are low-uncertainty stocks (U1). Within each uncertainty portfolio, stocks are further sorted into a 52-week high winner and loser portfolio. The average monthly returns are reported in Table 28. Similar to the other six variables, the 52-week high measure has a higher forecasting power of future stock returns when limited to high-uncertainty stocks. While the 52-week high return is 0.91% for stocks in the U1 group, it is 2.22% in the U4 portfolio. The higher profits in the U4 group are due to winners and losers. In opposite to other variables, the increase of the winner returns in analyst coverage is with a t-statistic of 0.99 not statistically significant. Yet, this might also be due to the reduced sample period since analyst coverage is not available before September 1999.

Table 28

52-week High Profits for Groups sorted by Analyst Coverage

This table reports average monthly portfolio returns sorted by the information uncertainty proxy analyst coverage and by the 52-week high criterion. Each month, stocks are assigned to one of five portfolios based on the value of the uncertainty variable. The 20% of stocks with the highest variable value (and with the highest degree of information uncertainty) are included into U5 while the 20% of stocks with the lowest value (and hence with the lowest level of ambiguity about information) is assigned to group U1. Within each information uncertainty quantile, I further sort stocks based on the 52-week high ranking criterion. The top (bottom) 25% is included in the winner (loser) portfolio H1 (H5). Stocks are equal-weighted and held in the portfolio over six months. Between the ranking date and the formation period, a skip period of one month is included. The table reports the overlapping holding period returns. Each month, all actively traded UK stocks on Datastream with a market value above 20 Million Pounds are considered. The sample covers the period between January 2000 and August 2008; t-statistics (two-tailed) are reported in parentheses.

	U1	U2	U3	U4	U5-U1	t-stat
Winner	0.0055	0.0064	0.0076	0.0087	0.0032	(0.99)
Loser	-0.0036	-0.0113	-0.0103	-0.0136	-0.0100	-(2.16)
Wi-Lo	0.0091	0.0177	0.0178	0.0222	0.0132	(2.96)
t-stat	(1.75)	(2.99)	(2.30)	(4.55)		

However, the obtained results for analyst coverage must be considered with caution. First, as mentioned, the sample period for this proxy is much shorter than for other variables. Second, the number of stocks within the four portfolios varies since the distribution of analyst

[92] After an extensive search, I obtained these data from an anonymous source.
[93] For the other variables in the tests above, stocks are assigned to five uncertainty groups.

coverage is heavily skewed to zero. In each month, the 0.25% quantile corresponds to zero analysts. Yet, in some months, more than 30% of all stocks have coverage of zero and are therefore included into the group U4. This explains why the 52-week high return in the U4 group has a higher t-statistic compared to the profits of the strategy in U1, U2 or U3. Due to the high percentage of stocks with zero coverage, it cannot be excluded that the results for this variable are biased. Therefore, I only shortly discuss this proxy for information uncertainty.

Another potential measure for information uncertainty would be the dispersion in analyst forecasts. A large body of literature has employed this variable for the uncertainty about future earnings (e.g. Diether et al., 2002, Imhoff and Lobo, 1992, Lang and Lundholm, 1996). Dispersion in analyst forecast is also considered in Zhang (2006). However, for my UK sample, using I/B/E/S data, information about the standard deviation of analyst forecasts exists for less than 500 stocks each month starting from January 2000. As this type of information is only available for a part of the sample, results might be heavily biased. Therefore, this variable is not considered in the study.

9. Conclusion

As the second part of my thesis, this work examines whether the profitability of the 52-week high strategy is due to anchoring – a behavioral phenomenon documented in Kahneman and Tversky (1982). In order to test the hypothesis, I examine the effect of information uncertainty on the profitability of the 52-week high strategy. An insight of the psychological literature is that psychological biases increase in uncertainty. Hence, if the behavioral phenomenon called anchoring explains the 52-week high returns, the 52-week high ranking criterion should have more predictive power in cases of larger uncertainty. To proxy information uncertainty, I use firm size, a firm's book-to-market value, the distance between the 52-week high and low price, stock price volatility, firm age and cash-flow volatility.

The core finding of this part of my thesis is that the profitability of the 52-week high strategy varies with the level of information uncertainty. Consistently for all six proxies, greater information uncertainty leads to higher future returns for stocks with a price close to their 52-week high price and to lower future returns for stocks with a price far from their 52-week high. Hence, higher information uncertainty seems to have an impact on both the 52-week high winners and losers. The diametrical effect of larger uncertainty on 52-week high winner stocks and on 52-week high loser stocks leads to higher 52-week high profits in information uncertainty. This presents evidence against the null hypothesis that the 52-week high is not explained by anchoring. The positive relationship between uncertainty and the 52-week high profits is also robust when it is controlled for risk (the three Fama-French factors), for industry effects and for the turn-of-the-year effect.

Moreover, this part shows that the employed six variables do also have an impact on momentum returns. As for the 52-week high strategy, a greater level of uncertainty implies higher future returns for winner stocks and lower future returns for loser stocks. Momentum portfolios generate two times larger profits when limited to high-uncertainty stocks than for low-uncertainty stocks. Since both the momentum strategy and the 52-week high strategy react similarly to the same variables, further evidence for a close connection between the two strategies is provided. This makes it more likely that the strategies have the same drivers and supports the view that anchoring is also the explanation of the price momentum effect. Documenting the effect of information uncertainty on momentum profits alone would have left the door open for other psychological biases such as overconfidence, representativeness or conservatism[94] as explanation for the momentum returns.

Some models of the momentum literature argue that short-term momentum co-exists with long-term reversals. Many theoretical papers in the field of behavioral finance propose models in which short-run underreaction and long-term overreaction are components of the same process (Barberis et al., 1998, Daniel et al., 1998, Hong and Stein, 1999). An examination of the 52-week high strategy in the long run reveals that the 52-week high profits do not reverse in the post three years. Irrespective of the information uncertainty level, the 52-week high strategy does not generate significantly negative returns in the 36 months after the portfolio formation date for all six uncertainty proxies. Hence, subjects seem not to overreact when correcting their anchoring bias. This indicates that short-term momentum and long-term reversals are not part of the same phenomenon and that separate theories are necessary.

[94] Overconfidence belongs to one of the most often examined patterns in the behavioral finance theory. It is employed in the model of Daniel et al (1998) which can also be applied to the momentum literature. It shows that these patterns might arise due to investors who are overconfident about their private information and suffer from a biased self-attribution. According to Barberis et al. (1998), the momentum effect can be explained by two other behavioral phenomena found by psychologists about the way people form beliefs: representativeness and conservatism. For an overview of different psychological biases documented in the literature and for a description, see Barberis and Thaler (2002).

This work also provides support for the finding of Zhang (2006) that higher information uncertainty leads to more predictability. Greater information uncertainty leads to higher future stock returns following good news and lower future stock returns following bad news. As a measure of news, Zhang (2006) uses post-analyst forecast revision drift and stock price momentum. This work provides further evidence for this theory in different aspects. First, I show that the information uncertainty effect is also present when another measure for news is employed: the distance of a stock's price to its 52-week high price. Using this proxy in order to differentiate between good and bad news is new to my knowledge and seems quite intuitive. For a stock whose price is at or close to its 52-week high price, good news has pushed the price of the stock to such a high price. For a stock that trades at a price far from its 52-week high price, bad news has recently arrived[95]. Hence, a small distance between a stock's price and its 52-week high is classified as good news and a large distance as bad news. Secondly, this study examines the robustness and the persistence of the uncertainty effect. For two measures of news (the distance of a stock's price to the 52-week high price and for Zhang's (2006) past six-month return), it is shown that the effect is not driven by other phenomena and that it is robust to the turn-of-the-year effect and to industry effects. It also seems less likely that the uncertainty proxies reflect missing risk factors as they do lead to higher future returns for 52-week high winners and lower future returns for 52-week high losers but are except for the book-to-market ratio not related to unconditional expected returns. Furthermore, the uncertainty effect is not permanent and disappears after several months. The return difference between high-uncertainty and low-uncertainty stocks becomes insignificant after, on average, two months for the 52-week high winners and after, on average, five months for the 52-week high losers. Third, employing a UK sample, this paper is the first to document the existence of the uncertainty effect for non-U.S. data. This reduces the likelihood that the effect documented in Zhang (2006) is due to data mining.

[95] George and Hwang (2004, p.2146) use a similar explanation to justify their choice of employing the 52-week high price of a stock in the ranking criterion and show that their 52-week high strategy dominates the momentum strategy. However, they do not explicitly employ this proxy as a measure for good and bad news.

Summary

SUMMARY

This work examines the stock price momentum effect and the cause for its existence. Specifically, my thesis can be linked to the behavioral finance field and tests whether the momentum effect is caused by the non-rational behavior of at least some investors that suffer from the anchoring bias.

In the first part of my thesis, the current stand of the literature about the momentum effect is presented. The different methods to measure momentum returns are evaluated and compared. It is documented that there is broad consensus among researchers about the existence of the momentum effect. However, nearly all studies employ a similar method to obtain momentum returns. Hence, finding a weakness in the methodology could put into question the apparent strong evidence for the existence of the momentum effect. Subsequently, the current stand of the literature about the drivers of the momentum effect is documented. The explanation attempts can be divided into two broad groups. One the one hand, the rational-based approach assumes that momentum profits represent a compensation for risk. Studies that belong to this group aim to identify additional risk factors and/or attempt to implement a richer risk model. Within the rational-based field, four subgroups can be formed by employing a theoretical decomposition of momentum profits. On the other hand, the behavioral explanations assume that momentum strategies are profitable since at least some investors do not behave completely rational. The various approaches are arranged under only four hypotheses, a way that is new to structure the behavioral finance momentum literature. It becomes clear that all behavior studies have in common to explain momentum profits with investors that do not adequately react to new information; they either overreact or underreact to news. In summary, the first part of my thesis presents, evaluates and compares both the rational and the behavioral approach and shows that none of the two groups has yet succeeded in fully explaining the existence of the stock price momentum effect.

In the second and third part, my study examines whether a specific non-rational behavior of investors explains the returns of momentum strategies. The null hypothesis states that momentum cannot be explained by anchoring. This behavioral heuristic is first documented in Tversky and Kahneman (1974) and implies that subjects orientate too much on a reference point when making estimates. The null hypothesis goes back to George and Hwang (2004) supposing that momentum profits are explained by another strategy called the 52-week high

strategy, which itself is assumed to be profitable due to investors' anchoring bias. In order to test the null, these two connections need to be examined. For a sample composed of all traded stocks in Germany between 1980 and 2008 with a price above one Euro and a market value above 20 Million Euro, the second part of my thesis presents evidence for the first assumed relation. With three different tests it is documented that momentum profits can largely be explained by the returns to the 52-week high strategy, which is long in stocks with a price close to their highest price within the past 12 months and short in stocks with a price far from their 52-week high price. Given this finding, searching for an explanation for the momentum effect implies identifying the driver of the 52-week high strategy. George and Hwang (2004) assume that the profitability of the 52-week high strategy can be explained by investors suffering from the anchoring bias: They orientate too much on the 52-week high price – a widely available piece of information as it is published in many newspapers – when estimating the impact of news on the stock price. My study is the first to formally test whether anchoring qualifies as explanation for the 52-week high returns. Therefore, three different tests are introduced. In summary, the main finding of the second part is that anchoring cannot be rejected as driver of the momentum effect: First, the dominance of the 52-week high strategy over the momentum strategy is documented for the sample and secondly, it cannot be rejected that anchoring explains the profits to the 52-week high strategy.

While the third part of the thesis tests the same hypothesis as the second one, the approach is quite different. The procedure is built on an insight of the psychological literature that behavioral biases increase in uncertainty. According to this insight, the anchoring bias should have more room in cases of larger information uncertainty. Hence, if the 52-week high strategy and the momentum strategy are due to anchoring, their profitability should increase in information uncertainty. Based on this, it is tested whether the ranking criteria of the 52-week high strategy and of the momentum strategy have a higher predictive power when information uncertainty is larger. This is conducted for a sample that consists of all traded UK stocks between 1989 and 2008 with a market value above 50 Million Pounds. To measure the relation between the predictive power of the ranking criteria and information uncertainty, six different variables are chosen as proxies for information uncertainty. Although each of the six variables might also capture other things than information uncertainty, their common element should be ambiguity. I find strong evidence for anchoring as explanation of the momentum and of the 52-week high strategy. For all six variables, a positive relation between information uncertainty and the predictive power of the ranking criteria is documented. With larger ambiguity, the winner portfolios yield higher returns while loser portfolios generate lower returns. The difference between high information uncertainty and low information uncertainty stocks is statistically significant at conventional levels. Moreover, as both, the 52-week high profits and the momentum returns, are similarly related to the same variables, a close relation between momentum and the 52-week high strategy is further confirmed.

My thesis contributes to the behavioral finance literature. This field of research departs from the traditional assumption that investors are fully rational and views it more fruitful to assume that at least some investors behave in a non-rational manner in order to explain many patterns in finance. Documenting that the momentum strategy is profitable due to a non-rational behavior of at least some investors would represent a serious challenge to the Efficient Market Hypothesis (EMH) as it suggests that investors can earn superior returns by considering this behavior without bearing additional risk. Yet, one major weakness of the behavioral finance approach is to document empirically that stock prices reflect such a non-rational behavior of traders. Most empirical behavioral studies – as well as this work – find certain evidence for their theories, but fail to exclude other interpretations for their results. Although my study relates to the behavior finance literature, I am extremely careful to interpret my findings as strong evidence against the EMH since it cannot be excluded that one day, a risk model is implemented and/or a risk factor is found that captures the profits to momentum strategies. Furthermore, my study suffers from the same problems as all other behavioral finance theories so far: I cannot offer a specific alternative theory for the efficiency of markets instead of stating that markets are "not efficient", which seems to be a rather weak hypothesis.

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EHRENWÖRTLICHE ERKLÄRUNG

Gemäß §8 Abs. 2 Nr.4 der Promotionsordnung zum Dr. oec. der Universität Hohenheim.

Hiermit versichere ich, dass die vorliegende Arbeit von mir selbstständig angefertigt worden ist und nur die angegebenen Quellen und Hilfsmittel verwendet wurden. Ferner versichere ich, dass ich wörtlich oder inhaltlich übernommene Stellen als solche gekennzeichnet habe.

Stuttgart, den 30.Juni 2009

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Preise

06/2003	**Scheffelpreis** Preis für besondere Leistungen im Fach Deutsch
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Felix Prothmann Stuttgart, 30.06.2009