Universiteit Twente

Kempen & Co

Master of Science Thesis
Industrial Engineering and Management

Momentum Strategies

Playing the Inefficiency of Financial Markets?

by

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“Change the changeable,
accept the unchangeable,
and avoid the unacceptable.”
by Denis Waitley

Gaudeamus igitur
Iuvenes dum sumus
. . .
Vivat membrum quodlibet,
Vivant membra quaelibet,
Semper sint in flore!
. . .
Quivis antiburchius,
Atque irrisores!

Foreword

I'm very proud! Proud that you are reading this report. Proud to present the result of five months of research. And proud that this will be the last dot on the i's and cross through the t's of my Master of Science in Industrial Engineering and Management.

It was a blast to work at Kempen & Co, and be part of the Asset Allocation Team. I enjoyed more or less every part of this research, and certainly with hindsight all the hurdles that were taken. Therefore I hope that some of that joy shines through the lines and words in this report, making it enjoyable to read.

I would like to thank the team and Kempen & Co for giving me the opportunity to tackle a challenging and broad, but practically relevant topic. Especially the practical aspects made this research more fun and challenging. Although it did not result in what we hoped for, it provided many new insights.

I want to thank my grandpa for all the good discussions on the financial industry in general and this research in particular. It helped me to understand the problems and be able to explain the topic better. It also provided much food for thought, and created the basis for the discussion (see chapter 9).

Finally I would like to thank my parents for allowing me to enjoy the student life for seven years. I will certainly miss it and regard it as one, if not the best, time of my life. My board term at AEGEE-Enschede, my fraternity P.C.S.A. Incognito, all my travels, internships and friends made me cherish every day. So, to all the (future) students: no matter how the landscape changes due to regulation or the government, do the unexpected, get involved, and live and learn from every day! Before you know it, it is over . . .

Io Vivat!

Amsterdam, 24th May 2011

Abstract

The goal of this research is to improve and evaluate the Kempen Allocation Overlay Fund's (KAOF) momentum strategy. Momentum is the tendency of stocks to persist in their trends. There were indications that the current strategy did not fit the current market conditions. Therefore a review based on common momentum strategies used in the academic literature was conducted. The main research question is: 'Which momentum strategy is expected to perform best within KAOF's Investment Framework?'.

A thorough study of the academic literature resulted in six common momentum strategies:

- The R/W/H strategy, based on the performance over the past x months
- The 52-Week High strategy, based on the closeness of an asset's price to its 52-week maximum
- The Business Cycle strategy, based on the asset's expected performance by global macro economical variables
- The Industry Momentum strategy, based on the asset's industry performance
- The Capital Gains strategy, based on the asset's reference price
- The Earnings Momentum strategy, based on earnings surprise

The latter three are not applicable to KAOF, since they do not apply to index futures.

The first three are applicable to KAOF, however use a relative reference (e.g. the top 10% of the assets are included in a portfolio). Due to the market timing nature of KAOF, such a reference is not usable and needs to be transformed to an absolute reference (e.g. assets with a momentum indicator of above x are included). In-sample optimisation proved to be the only method that resulted in well performing thresholds. The translation from the relative cut-off point to a threshold did not prove effective, due to the large contribution of the cross-section variation. Also modelling the relationship between threshold and performance did not suffice, due to the necessary simplifying assumptions leading to an underestimation of the benefit of no position.

The performance of the strategies is measured based on risk-adjusted returns, for which the Sharpe, STARR and Calman ratios are the main metrics. Additionally the robustness of the strategies is reviewed, i.e. is the strategy highly dependent on a certain time period, or certain assets?

The strategies were first tested in a simplified framework (i.e. money-weighted and without KAOF's valuation and business cycle strategies). The R/W/H and 52-Week High strategies outperformed the current strategy (respectively with a Calman ratio of 0.91, 0.60 and 0.49). However the robustness analysis showed significant difference between time periods, and a couple of assets mainly driving the exposure. This severely weakens the robustness of the strategies. Combined with counter-intuitively low thresholds (due to the strong bull markets), makes it questionable whether the strategies offer a real improvement for KAOF. However a Monte Carlo simulation of a random strategy with equal market exposure underperformed significantly on both risks and returns for all momentum strategies.

An evaluation of the parameters and design decisions (i.e. the profit takings and CrossOver filter) of the current strategy did not provide strong evidence for a change. The design decisions did result in a slightly lower performance, however significantly reduced risks. Two alternative strategies (setting the thresholds based on the RSI standard deviation, and an early exit/entry via clicking thresholds) performed worse. All results of this comparison were not significant.

The final test of the strategies in KAOF context (i.e. with KAOF's portfolio construction scheme and the valuation and business cycle strategies) gave a similar picture. The 52-Week High strategy performed best and had a slightly better robustness. However the performance difference decreased. A comparison of the strategies with and without the valuation signals showed no significant difference in returns, but the combination with valuation caused a large decrease in risk. So combining momentum and valuation indeed proves useful.

Overall this leads to the conclusion that, due to the weak robustness, none of the strategies provides an obvious improvement. The weak robustness is primarily caused by the weak predictive power of the momentum indicators and results in all sorts of unwanted sensitivities to factors like the weights, assets, time series and time periods. The strong performances reported in the academic literature are partially driven by the cross-section variation instead of purely momentum. In the market timing context, the 52-Week High strategy performed best. Therefore I suggest that KAOF start looking at the 52-Week High indicator and evaluates over time whether it adds value to the current strategy.

An inherent problem of any financial study is the key underlying assumption that the past is a good predictor of the future. The limitations of this assumption are profound in this research, due to the weak predictive power of the indicators. It results in limited generalisability of the results, and caution should be taken when extrapolating the ex-post performance tests to the future. The weak predictive power by itself is not surprising and is in-line with a weak form of the efficient market hypothesis.

Contents

Chapter 1

Introduction

1.1 Research Goal

This research is conducted for one of the investment funds of Kempen & Co, the Kempen Allocation Overlay Fund (KAOF). KAOF invests based on three strategies: Business Cycle, Valuation and Momentum.

The momentum strategy was developed five years ago and is mainly based on expert knowledge augmented with research. The fund's team has the feeling that there is significant room for improvement and questions whether the current strategy does still fit the current market conditions. Therefore they are interested in a broad research to gain insight in the current state of the academic literature on momentum, and how KAOF's momentum strategy can be improved. The goal of this research is:

'To evaluate and improve KAOF's momentum strategy'

Before the research can be structured, a definition of momentum is needed and a detailed understanding of KAOF. This is covered in the following two sections. Based on this; section four describes how this research is setup. Section five describes the structure of this report.

1.2 Momentum

Moskowitz (2010) defines momentum as:

> 'Momentum is the tendency of investments to exhibit persistence in their relative performance. Investments that have performed relatively well continue to perform relatively well; those that have performed relatively poorly continue to perform relatively poorly.'

Per definition momentum invests too late. Therefore the combination with valuation is powerful (Asness, Moskowitz & Pedersen, 2009). It mitigates the valuation-trap[1] and reduces the lag of momentum.

Momentum should not exist in financial markets if the efficient market hypothesis is true. However, there is a vast amount of academic research indicating the possibility to outperform markets with a momentum strategy. Even more striking is that since the first publication of DeBondt and Thaler (1985) new publications keep on appearing, showing significant effects in new and existing markets. Where the Fama-French anomaly disappeared within a couple of years, the momentum effect seems to persist. Therefore it not only puzzles the academic community on its ability to outperform the market, but also on what causes this phenomenon.

1.3 Kempen Allocation Overlay Fund

KAOF is one of the specialised investment funds of Kempen Capital Management. It aims at providing flexible asset allocation for portfolios in the medium term (one to three years). Its main clients are wealthy individuals and institutional investors.

KAOF can be seen as a layer on top of the normal portfolio, and adjusts the exposure to the asset classes by buying or shorting futures on indices. For instance if an investor wants to invest €110, the investment manager forms a portfolio by investing €40 in equities, €50 in bonds and €10 in currencies; the remainder is invested in KAOF. Now if a crisis is on the doorstep, one would like to temporarily increase the share of bonds and decrease the equities. KAOF does this by buying long futures in the main bond indices and shorting futures on the main equity indices. KAOF uses futures for their low transaction costs, the ease of short-selling, low capital requirements, and the ability to create leverage. Futures only require margins to be posted, therefore the majority of KAOF's assets are available and invested in money funds to generate close to Euribor. KAOF aims to generate the three month Euribor +4% with a maximum draw down of 15%, and is managed on a weekly basis.

KAOF bases the over-/underweight of an asset class on the business cycle, valuation and momentum. These three strategies each determine 1/3 of the position. The actual position (i.e. the actual money amount invested) depends on the risk associated with each asset. Risk is defined as the 95% Quarterly Historic Value at Risk (VAR) on three years of weekly data. 40% of the Net Asset Value (NAV) is available for the bruto VaR (i.e. undiversified) and split according to table 1.1. Thus if the NAV is €100 and the Topix has a 100% long signal with a bruto VaR of €4, the position is $\frac{€4}{€100*40\%*6.8\%} = 1.47$. However the netto VaR (diversified) may not exceed 10% of NAV. Thus if the VaR of the portfolio of all the assets multiplied by their signal is €2, then all positions are divided by 2, resulting in 0.74 long Topix futures. Figure 1.1 visualises this process.

[1] The valuation trap occurs when the price of an asset keeps falling, while the fundamental value stays constant. Valuation indicates then that the asset is getting cheaper and cheaper, and suggests investing more and more.

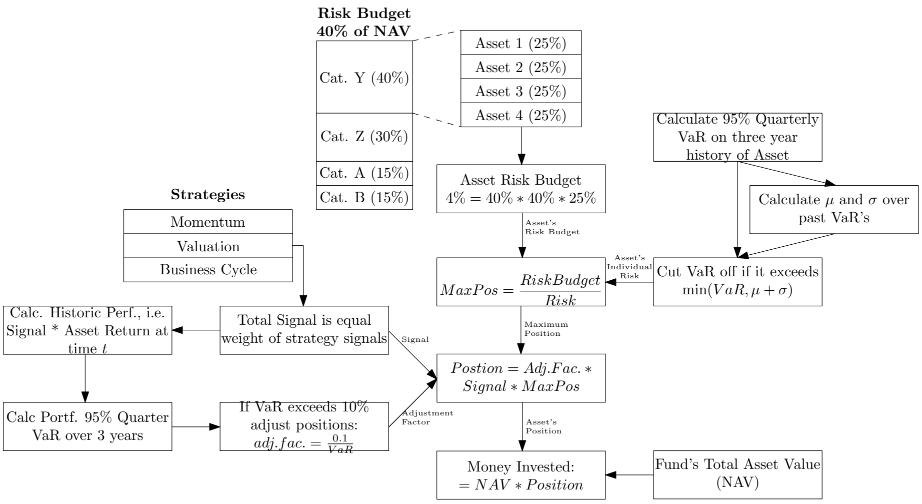

Figure 1.1: KAOF Investment Framework

Table 1.1
Assets associated Risk Budgets for KAOF

Asset Class	Weight	Asset	Weight	Total of NAV
Bonds	34%	German 10y	11.3%	4.52%
		USA 10y	11.3%	4.52%
		Japanese 10y	11.3%	4.52%
Equity	34%	Hang Seng	6.8%	2.72%
		SP 500	6.8%	2.72%
		EuroStoxx 50	6.8%	2.72%
		FTSE 100	6.8%	2.72%
		Topix	6.8%	2.72%
Currencies	16%	EUR/USD	3.2%	1.28%
		EUR/JPY	3.2%	1.28%
		EUR/GBP	3.2%	1.28%
		JPY/USD	3.2%	1.28%
		GBP/USD	3.2%	1.28%
Real-Estate	8%	EPRA Europe	8%	3.2%
Commodities	8%	GSCI	8%	3.2%

1.4 Research Structure

The previous two sections show that there is a vast amount of research on momentum, which provides a good basis for this research and that KAOF uses a complex investment framework, which will challenge the analysis. To provide new and fresh insights, the academic literature is used as foundation. Strategies from the literature are tested in the KAOF context. An evaluation of their performance shows how KAOF's current strategy can be improved. Based on this point of view, the main research question is:

> **'Which momentum strategy is expected to perform best within KAOF's Investment Framework?'**

This entails a 'horse race' between several strategies. However before the race can commence, it must be clear which horses are participating and on what ground is decided which horse wins. In other words the following two subquestions must be answered:

1. Which momentum strategies are applicable to KAOF?
2. How can the performance of the strategies be measured?

However as will be shown, not all strategies do directly fit KAOF's investment framework. To make them fit KAOF, they need to be transformed. This adds a third subquestion:

3. How can the strategies be transformed to fit KAOF?

Finally the race is split into three parts. First the strategies are tested in a simplified investment framework (i.e. without the other strategies, such as Business Cycle and Valuation). This tests them on their pure momentum performance. Secondly the performance of the current strategy is tested in this simplified framework and evaluated to see where improvements are possible. Thirdly, the strategies are tested in conjunction with the other signals and KAOF's portfolio weighting scheme. These tests result in another three subquestions:

4. What is the performance of the academic momentum strategies?
5. How can KAOF's current momentum strategy be improved?
6. How do these strategies perform in conjunction with the other KAOF signals (i.e. Valuation and Business Cycle)?

1.4.1 Scope

The scope of this research is limited to:

- The asset classes of KAOF
- Trading based on a weekly basis
- Taxes[2] and trading costs[3] are not incorporated.

[2] As detailed by Israel and Moskowitz (2010) for a combination of momentum and value the tax effect compared to other strategies is marginal. This is due to the short-term losses from the momentum strategy, which offset against the dividend gain from the value strategy.

[3] The impact of trading costs is very low, since the transaction costs of the highly liquid futures used by the Fund are virtually zero.

1.5 Report Structure

Each of the following chapters is dedicated to one subquestion. The following chapter gives an overview of the different momentum strategies used in the academic literature and practise. The third chapter describes how performance is measured, and how the tests are conducted. The transformation of the academic strategies, to make them fit KAOF's investment framework, is described in chapter four. Chapter five describes the performance of these academic strategies. Chapter six discusses the current strategy of KAOF and several adjustments. The results of the final tests of the strategies with the Business Cycle and Valuation signals are detailed in chapter seven. Chapter eight answers the main research question and discusses how KAOF's strategy can be improved (the research goal). Chapter nine reflects on the conclusions by discussing the implications and limitations.

Chapter 2

Momentum Strategies

This chapter gives an overview of the common momentum strategies. Hereby it answers the first subquestion 'Which momentum strategies are applicable to KAOF?'. These strategies will be tested, to see if improvements are possible to KAOF's current momentum strategy.

The first section outlines the methodology used to find the common strategies. The second section describes the strategies, classified in two groups: the strategies used by the academic community, and strategies based on technical analysis. The third section discusses why momentum appears to outperform the market. Finally, this chapter is concluded by answering the first subquestion.

2.1 Methodology

To give an overview of the common momentum strategies, the academic literature is used as basis. Additionally experts are interviewed to complete the list, by adding strategies used in practise but not covered by the academic literature. This list forms the foundation of this research and defines which strategies are tested.

The vast amount of academic research on momentum is searched through Scopus[1] and Web of Science[2], covering the main and the majority of the journals. To minimise the chance of missing an important strategy, the search has been thoroughly structured. The following paragraphs describe this process.

A long list is obtained by the following combination of keywords:

> "Momentum Strategy" OR "Momentum Strategies" OR "Price Continuation"

This resulted in 134 and 139 publications, respectively via Scopus and Web of Science. The search is restricted to 'momentum strategies' instead of just 'momentum', because the focus is not on the momentum phenomenon in general.

[1] `http://www.scopus.com`
[2] `http://www.isiknowledge.com`

Table 2.1
Literature Article Classification

	New	Application	Explanation	Irrelevant	Total
Long list	4	53	26	29	112
Short list	4	10	8	–	22
Final list	9	14	12	–	35

Price continuation is added as third term, because older publications employ it instead of momentum.

The search is further refined to only include articles related to economics or business & finance. This resulted on both search engines in a similar long list of 112 articles. Further trimming of the list is done by grouping the publications based on the abstracts in four categories:

1. publications introducing new strategies,

2. publications applying existing strategies to (new) markets/assets classes,

3. publications explaining or testing the validity of the results and

4. irrelevant publications.

Table 2.1 page 8 gives a broad overview of this classification, appendix A page 67 shows the full long list. Based on this classification several articles are selected per group for a further review:

- All the publications defining new strategies are selected.

- From the 'application' and 'explanation' groups the most cited articles are selected and publications specifically dedicated to futures or asset allocation.

- Evidently, none of the irrelevant publications are selected.

This selection leads to a short list of 22 publications. The earliest published article in the long list dates from 1995. Therefore a large gap exists between the article of DeBondt and Thaler (1985) and the long list. This gap is closed by including additional articles, based on the citations in the publications of the short list. This resulted in 13 additional articles. The complete list contains 9 articles defining new momentum strategies, 14 articles with important applications and 12 articles explaining momentum.

Two experts are interviewed to complete the list with strategies used in practise. The experts are:

- An ex-fund manager of ABN-AMRO, having developed a momentum based strategy for several funds

- An expert on technical analysis and founder of KAOF's current momentum strategy

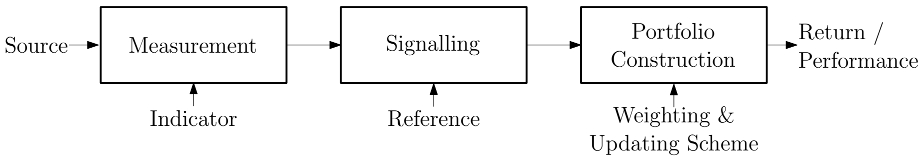

Figure 2.1: General Framework for Investment Strategies

2.2 Common Momentum Strategies

Based on the thorough search of the academic literature and feedback from the expert interviews, several momentum strategies are identified. To describe these strategies in a structured manner, I developed the following framework. It splits a strategy into three distinct and independent phases (see figure 2.1):

1. The *measurement* phase uses an indicator to convert (several) sources to one measure for momentum. E.g. it compresses the asset's history into a single value measuring the trend.
2. The *signalling* phase generates the actual investment signal (e.g. long, neutral, and short) based on comparing the measure from the previous phase to a reference.
3. In the *portfolio construction* phase the actual portfolio is build, i.e. the actual amount of money invested in each asset is defined. This depends on the investment signals and the portfolio weighting and updating scheme, e.g. all assets are equally weighted with a three month buy-hold strategy.

Based on this framework, a strategy is defined by four elements: the sources, the indicator, the reference and the weighting & updating scheme. The strategies are classified according to differences in these elements.

There are two distinct groups of strategies, based on a key difference in the reference phase: (1) strategies used by the academic community and (2) strategies based on technical analysis. The academic strategies use a relative reference (i.e. compare the measure to the other measures in the set), while the technical analysis strategies use an absolute reference (i.e. compare the measure to a fixed threshold). The following two sections describe both groups of strategies.

2.2.1 Academic Strategies

The academic strategies are differentiated based on the indicator. They all employ a similar reference and weighting & updating scheme. All strategies use a relative reference, i.e. sort the measures and associate a long (short) signal to the top (bottom) 10% of the set. Secondly a simple weighting & updating scheme is used; commonly all assets are equally weighted and held for a certain fixed period (commonly six months).

Jegadeesh and Titman (2001) introduce a waiting period between the signalling and portfolio construction phase, postponing the investment. This waiting period is intended to mitigate short-term reversals seen in equity markets due to liquidity and micro-structural effects (Asness et al., 2009). Many authors thereafter confirm the increase in performance with a waiting period of one month[3] in equity markets (Moskowitz & Grinblatt, 1999; Griffin, Ji & Martin, 2005; Blitz & Vliet, 2008). In for instance futures markets this effect is not apparent (Pirrong, 2005; Miffre & Rallis, 2007).

The academic literature search resulted in six distinct momentum strategies (see table 2.2). Three strategies are not applicable to KAOF, because:

- The industry momentum strategy is based on the concept that the assets can be classified to a certain industry. KAOF invests in broad market indices, which are an aggregate of industries.
- The Capital Gains strategy is based on the notion that the investor's reference price for an asset is determined by past prices combined with the volume. The highly liquid futures prices are not set by supply and demand, but primarily by the underlying's value. The underlying index levels do not have trading volumes.
- Earnings Surprise strategies are based on the effect of an earnings announcement on the fundamental values of a stock. Indices do not have earnings announcements, and KAOF also invests in other assets than stocks.

The other three strategies are described in the following subsections, focussing on the source, indicator and their performance.

The R/W/H Strategy

The R/W/H strategy was first introduced by Jegadeesh and Titman (1993). It was the first strategy to introduce the ranking, waiting and holding periods. They use a very basic measure for momentum: the return of an asset over the past period. Commonly the optimal ranking period is around six months in equity markets, with a waiting period of one month and a six month holding period.

The past performance is commonly expressed as the compounded return. Mathematically defined as:

$$I_t^{\mathrm{RWH}} = \prod_{i=0}^{n-1} 1 + r_{t-i} \tag{2.1}$$

where r_t is the return from period $t-1$ to t, n the ranking period and I_t the indicator value at time t. Instead of measuring the raw returns Rachev, Jasic, Stoyanov and Fabozzi (2007) use several risk adjusted measures, such as the Sharpe and STARR ratio.

The majority of the publications are based on this strategy and show outperformance in a very broad set of different markets (see appendix A). Table 2.3 gives a summary overview of the performance reported in several articles. King, Silver and Guo (2002) and Blitz and Vliet (2008) apply this strategy in an asset allocation setting, which significantly outperform their benchmarks.

[3] The academic literature mainly uses monthly data. A one month waiting period is thus the minimum.

Table 2.2
Overview Momentum Strategies

Strategy	Usage[a]	Source	Indicator	Reference	Portfolio
R/W/H	Very High	Returns	Stock Return	Top/bottom decile	Equally weighted
Industry Momentum	Medium	Returns	Industry Return	Top/bottom 3 industries	Equally weighted industries containing value weighted stocks
Business Cycle	Low	Returns	Macro economical variables	Top/bottom decile	Equally weighted
Capital Gains	Low	Price	Unrealised capital gains	Top/bottom quintile	Equally weighted
52-week high	Low		$\frac{\text{price}}{\text{52-week high}}$	Top decile	Equally weighted
Earnings Surprise	Medium	Earnings	SUE	Top/bottom decile	Equally weighted
			ARB	Top/bottom decile	Equally weighted
			REV6	Top/bottom decile	Equally weighted

[a] Based on the number of articles using this method

Table 2.3
Historical Performance of the R/W/H Strategy Across Asset Classes

	Sharpe Ratio	Annualized Return (%)	Time Period
Individual Stocks			
United State	0.7	10.5	1975-2008
United Kingdom	0.6	9.0	1985-2008
Japan	0.2	3.0	1985-2008
Continental Europe	1.1	16.5	1988-2008
Stock Market Equal-Weighted	0.9	13.5	1988-2008
Other Asset Classes			
Bond Market (Developed)	0.3	4.5	1975-2008
Currencies	0.5	7.5	1975-2008
Commodities	0.8	12.0	1975-2008
Equity Indices (Developed)	0.6	9.0	1975-2008
Other Asset Classes Equal-Weight	0.9	13.5	1975-2008
Overall	1.1	16.5	1988-2008

Source: (Asness et al., 2009) in (Moskowitz, 2010)

Business Cycle Strategy

Chordia and Shivakumar (2002) developed an alternative strategy based on the R/W/H idea of measuring momentum based on past returns. Instead of the raw asset returns, they predict the future returns based on macroeconomical variables. Based on the extensively documented correlation between a stock's price and macroeconomical variables, they argue that these variables can predict the direction of the future price trend more steadily.

They use four macroeconomical variables to predict the stock's future return:

- The *value-weighted market dividend yield* (DIV), defined as the total dividend payments accruing to the index over the past 12 month divided by the index level. It has shown high correlation with slow mean reversion in stocks.
- The *default spread* (DEF), defined as the difference in yield between BAA and AAA rated bonds, because it captures the default premiums.
- The *term spread* (TERM), defined as the difference of the average yield between Treasury bonds with 10 years to maturity and three-month T-bills.
- The *three-month T-bill yield* (YLD), since it serves as a proxy for future economic activity.

Their indicator is based on the following factor model:

$$I_t^{\mathrm{Biz}} = \alpha_t DIV_{t-1} + \beta_t TERM_{t-1} + \gamma_t DEF_{t-1} + \delta_t YLD_{t-1} + \epsilon_t \tag{2.2}$$

The model parameters $(\alpha \ldots \delta)$ are estimated based on the previous 60 months of returns. They intentionally omit the intercept in their estimation to prevent controlling for the cross-sectional variation.

Based on a double sort of their indicator and the R/W/H indicator, they show that the portfolios based on the regression better capture the momentum effect. In their article they focus on explaining the momentum effect, and therefore do not report the difference in returns.

52-Week High Strategy

George and Hwang (2004) introduce the 52-week high momentum strategy. The basis for this strategy follows from the 'adjustment and anchoring bias' discovered by Kahneman, Slovic and Tversky (1982, pp 14–20). They view the 52-Week high price of a stock as an important anchor for many investors.

As a simple indicator they employ the ratio between the current price and the highest price over the past 52 weeks:

$$I_t^{52\mathrm{W}} = \frac{\max_{j=t-52,\dots,1}(p_j)}{p_t} \tag{2.3}$$

George and Hwang (2004) only relate the current price to the highest price, because they only take long positions. One of KAOF's key characteristics is the possibility to take short positions. Therefore I extend the idea of George and Hwang (2004) to also include the lowest price over the past year to measure a downward trend. The indicator used in this research is defined as:

$$I_t^{52\mathrm{W}} = \frac{p_t - \min(p_j)}{\max(p_j) - \min(p_j)} \tag{2.4}$$

In their publication they compare the performance of this strategy to the R/W/H and industry momentum strategies, which all result in similar returns (respectively 0.45%, 0.48% and 0.45%). However in the literature there is significant debate about the effectiveness of this strategy. For instance C. Wang, Huang and Lin (2010) and Malin and Bornholt (2010) do respectively not find a significant effect in Taiwan and several emerging markets. Liu, Liu and Ma (2011); Gupta, Locke and Scrimgeour (2010) do not even find a significant effect in the traditional markets.

2.2.2 Technical Analysis Strategies

The strategies commonly used in practise focus on identifying turning points in the asset's time series, and are therefore commonly used for market timing (i.e. timing the market entry and exit of a position). This is in contrast with the academic strategies, which focus on selecting the best/worst performing assets. Therefore the technical analysis strategies employ a different reference and portfolio weighting & updating scheme. For these strategies the reference points are absolute thresholds, defining when a position should be entered/exited independent of the other assets in the set. The portfolio construction phase is skipped and entirely left to the fund/investor.

There are two main building blocks, from which a tremendous amount of variations in strategies are build. Firstly the relative strength indicator (RSI) developed in 1978 by J.W. Wilder. Secondly the crossing of two moving averages.

Both are discussed in the following subsections and are used in the KAOF's momentum strategy (discussed in the third subsection).

Relative Strength Index (RSI)

The RSI was developed to measure the velocity and magnitude of price movements (*Relative Strength Index*, 2010)[4]. Wilder's intention was to develop an indicator that signals over-/underbought situations in stock prices based on rapid price movements.

The RSI generally uses the past fourteen days or fourteen weeks of an asset's returns. It is calculated by splitting the returns in two variables by up and down movement:

$$U_i = \begin{cases} p_i - p_{i-1} & \text{if } p_i > p_{i-1} \\ 0 & \text{otherwise} \end{cases} \tag{2.5}$$

$$D_i = \begin{cases} p_{i-1} - p_i & \text{if } p_i < p_{i-1} \\ 0 & \text{otherwise} \end{cases} \tag{2.6}$$

where p_i is the price of an asset at time t. These are exponentially weighted to express the strength of the past up versus the past down movements. This Relative Strength (RS) measure is converted to the domain [0, 100] to form the RSI:

$$RSI = 100 - \frac{100}{1 + RS} \tag{2.7}$$

$$RS = \frac{EMA(\mathbf{U}, n)}{EMA(\mathbf{D}, n)} \tag{2.8}$$

where n is the time window and $EMA()$ is the exponential moving average.

Cutler proved that the RSI is data length depended due to the exponential moving averages. To overcome this problem he proposed to use a simple moving average. However this can cause the RSI to move incorrectly; if for instance a large up movement leaves the set for a smaller up movement. Therefore Bloomberg and most other systems still use the exponential moving average calculated over the whole available time serie.

The RSI is centred at 50, indicating the neutral zone. Wilder found in his research that an RSI moving through the 30 from below, or through the 70 from above indicates respectively under-/overbought situation (see figure 2.2). Over the past decades several variants have been developed.

[4] Although Wikipedia is vulnerable to providing incorrect information, since changes are not checked on correctness. Based on several checks the reliability of the information in this article is estimated to be adequate. This article has been online since 30$^{\text{th}}$ of March 2004 and more than 209 contributions have been made since. However no major changes have been made since the 1$^{\text{st}}$ of January 2010. In other words, many people have reviewed the article and agreed on the current state.

Figure 2.2: Illustration of Original Workings of the RSI

Source: **Relative Strength Index** ***(2010)***

Crossing Moving Averages

The second building block (crossing moving averages) was developed to mimic the first derivative of an asset's price series. Due to the volatile nature of a price series, taking the first derivative results in even more noise, rendering it impossible to spot turning points. However subtracting a long and short window moving average results in a smoothed series, approximating the first derivative (but delayed).

Different windows are used in practise. The setting depends mainly on the investment horizon. For intra-day trading commonly a 16 vs 26-day window is used, while on longer horizons 50 vs 200 days are common.

Both moving averages are plotted and the indicator is calculated as:

$$Cross_i = SMA(\mathbf{p}, n_s) - SMA(\mathbf{p}, n_l) \tag{2.9}$$

where $\mathbf{p}$ is the price vector, and respectively n_s and n_l are the short and long windows with $SMA()$ denoting the simple moving average.

If the short moving average is above the long, it means an upward price trend and vise versa a downward price trend. When the two moving averages cross each other it signals a change in the trend.

The performance of these and similar measures is highly doubted in the scientific community. Ready (2002) tested a large set of technical trading rules and reported that the often reported performance is caused by data-snooping. He concluded that the profitability of these strategies highly depends on the market situation and thus time period.

KAOF's Momentum Strategy

Confidential

2.3 Rationale

After several decades of research the momentum effect is still unexplained. The debate is currently focussed on three main arguments: data snooping, risk measurement and behavioural finance.

Although the data mining bias is significantly reduced due to the continuation of the effect, there is still a probability that the results are due to luck. If one accounts for all strategies that might ever have been tested, but are probably not reported since they were unsuccessful, the significance of the t-statistics is tremendously reduced (Jegadeesh & Titman, 2001). However as research continues to show outperformance the probability of data snooping reduces.

Secondly the outperformance can also be due to ineffective risk measurement, i.e. momentum strategies have extra exposure to risk that are not yet measured (Chan, Jegadeesh & Lakonishok, 1996; Brush, 2007). The Sharpe Ratio, CAPM, Fama-French model and the Carhart four factor model (Carhart, 1997) fail to fully explain momentum. Karolyi and Kho (2004) succeed in building a time series model that explains 80% of the momentum performance, but still leaves a significant part unexplained.

Therefore the discussion seems to head to the conclusion that there must be a psychological effect at work. Barberis, Shleifer and Vishny (1998) relate the under-/overreaction to the representativeness heuristic and conservatism. I.e. people tend to see trends, where there are no trends and belief trends are more stable than they are. Daniel, Hirshleifer and Subrahmanyam (1998) explain the momentum phenomenon with the overconfidence and attribution bias. This entails that people overestimate the precision of their own investment signals, but not public investment signals. Combined with the effect that they value confirming information, but disregard contradicting information can cause extreme price trends. As final remark, the effect can also be grounded in the culture and difference in risk-attitude. Brush (2007) developed several investor types, which can be very cultural depended. He shows that different mixes of these types can cause momentum effects in markets. This can also explain the difference seen between developed and emerging markets in terms of the momentum effect.

2.4 Conclusion

This chapter described the common momentum strategies. There are six strategies commonly used by the academic literature. Three are useable in KAOF: the R/W/H, Business Cycle and 52-Week High strategy. The other strategies are not applicable due to KAOF's investment vehicles (i.e. futures).

Next to these three strategies there are two main building blocks for the technical analysis strategies: the RSI and moving average crossovers. These also form the basis for KAOF's current strategy.

This answers the first subquestion 'Which momentum strategies are applicable to KAOF?'. However before these strategies can be tested on their performance, the academic strategies need to be transformed. The relative reference used does not fit KAOF. This and the transformation are discussed in chapter four. The performance of the strategies is described in chapters five, six and seven. The following chapter focuses on how the performance is measured and how the tests are conducted.

Chapter 3

Performance Measurement

The previous chapter gave an overview of the common momentum strategies. However before they can be tested on their performance, first must be determined how performance is measured. This is discussed in this chapter as well as how the tests are conducted. It answers subquestion two 'How is the performance of the strategies measured?'.

The first section details how the portfolios are constructed. The second section discusses the performance measurement. The data used in the test is described in section three. This chapter concludes in section four by answering the second subquestion.

3.1 Portfolio Construction

As discussed in the introduction, KAOF uses a rather complicated portfolio construction scheme (see figure 1.1 page 3). This complicates the attribution of several effects in the analysis of the strategies' performance. Therefore the strategies are first tested in a simplified framework.

In this simplified framework, the portfolios are constructed based on money weights, instead of risk weights. This reduces the interference of KAOF's risk framework and the other signals. Only in the final tests the strategies are tested in KAOF's investment framework (i.e. in conjunction with the valuation and business cycle signals).

Not all assets are equally important in KAOF. They are weighted according to their risk exposure. Table 1.1 column four shows the risk budgets per asset (class). To mimic this relative importance, the same weights are employed, but money weighted instead of risks weighted. Figure 3.1 shows how the portfolio is constructed. Mathematically the portfolio returns at time t are given by:

$$r_t^{\text{portf}} = \frac{1}{H} \sum_{h=1}^{H} \sum_{i=1}^{n} s_{i,(t-1-W-h)} \times r_{it} \times w_i \tag{3.1}$$

where H is the holding period, W the waiting period, w_i the weight of asset i, s_{it} the investment signal of asset i based on the indicator calculated at time t, and r_{it} the return of asset i over period $t-1$ to t. If not stated otherwise, a one week holding period and no waiting period is used.

The investment signals are currently based on a threshold that is equal for all assets in KAOF. It is questionable whether this is optimal, and thus whether each asset class or even each asset should have different thresholds. This results in the following hypothesis that will be tested:

Hypothesis 1 *Performance of a momentum strategy can be significantly improved if thresholds are allowed to differ among asset classes or assets.*

Hypothesis 1a (Alt.) *Having fixed thresholds for all assets does not significantly reduce performance.*

However chapter four will show that it is not possible to test this hypothesis. Due the method used to set the thresholds, which bounds the number of independent parameters.

3.2 Performance

To determine which strategies perform well in the tests, three factors are evaluated: return, risk and robustness. Risk and return are common factors and used by many authors in the literature (Jegadeesh, 1990; Rachev et al., 2007; C. Wang et al., 2010). However, robustness is only occasionally added and focusses on the stability and consistence of a strategy's returns (Asness et al., 2009; Griffin et al., 2005; Blitz & Vliet, 2008). The following three sections cover each a factor.

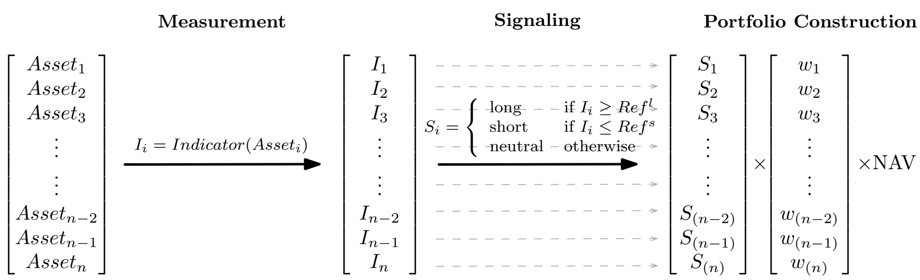

Figure 3.1: Schematic Illustration of Portfolio Construction

3.2.1 Return

Returns are calculated as:

$$r_t = \frac{p_t}{p_{t-1}} - 1 \tag{3.2}$$

where p_t is the price of an asset at time t. Since all analyses are on a weekly basis, the returns are annualised for reporting:

$$r^{\text{annualised}} = (r_t + 1)^{52} - 1 \tag{3.3}$$

Although transaction costs are out of scope, it is still of interest to see how often a strategy changes the investment signals/position. A strategy that changes the investment frequently, is less favourable than a strategy that changes only now and then. As measure the change in position as percentage of the number of time periods is used:

$$\text{SignalChange} = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T} |s_{it} - s_{i,t-1}|}{N(T-1)} \tag{3.4}$$

where s_{it} is the investment signal of asset i at time t, N the number of assets, and T the number of time periods. Analogous to this measure, it is also of interest to see the market exposure:

$$\text{MarketExposure} = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T} |s_{it}|}{N \times T} \tag{3.5}$$

KAOF has the target to generate a return equal to three month Euribor +4%. For this reason it is the prime benchmark. The Euribor returns are calculated as:

$$r_t^{\text{Euribor4}} = \frac{r_{t-1}^{\text{Euribor}} + 0.04}{52} \tag{3.6}$$

Other benchmarks are the MSCI World Index, which mimics the performance of an equity portfolio, and the Dow Jones Credit Suisse Managed Futures Index, which is an index of funds using momentum-like strategies via futures.

3.2.2 Risk

The most commonly applied risk measure in the literature is volatility, and is calculated as:

$$\sigma = \sqrt{Var[r]} \approx \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})}, \quad \bar{r} = \frac{1}{n}\sum_{i=1}^{n} r_i \tag{3.7}$$

where $Var()$ denotes the variance, and r_i is the historic realisation of return r. KAOF uses MaxDrawDown (MDD) and Value at Risk (VaR) as risk measures. The MaxDrawDown is an ex-post risk measure that indicates the maximum loss an investor would have realised independent of the entry moment (Pedersen & Rudholm-Alfvin, 2003). The MDD over period 0 to T is calculated as:

$$\text{MDD}(T) = \max_{t \in (0,T)} \text{DrawDown}(t, T) \tag{3.8}$$

$$\text{DrawDown}(t, T) = p_t - \min(p_t, \ldots, p_T) \tag{3.9}$$

The VaR is the expected worst loss in $x\%$ of the time. KAOF uses a 95% Historic VaR over three years. By assuming an equal probability of occurence of the past 156 observed, the 7.8$^{\text{th}}$ worst observation[1] gives the Value at Risk. The risk measures are annualised by assuming that returns are normally distributed: $\text{RM}^{\text{annualised}} = \text{RM} \times \sqrt{52}$, where RM is the risk measure based on weekly data.

A common measure to express the risk-return trade-off is the Sharpe ratio. Officially defined as: Sharpe $= \frac{E[r - r_f]}{\sigma[r - r_f]}$. However for simplicity it is often calculated as: Sharpe $= \frac{\bar{r}}{\sigma_r}$. This expresses the amount of return per unit risk, in this case volatility. Analogous one can express this ratio with other risk measures. For the VaR and MDD this respectively results in the STARR (Rachev et al., 2007) and Calman Ratio (Pedersen & Rudholm-Alfvin, 2003).

Since the prime risk objective of KAOF is a MDD of maximum 15%, the Calman ratio is the primary risk-return measure.

3.2.3 Robustness

The robustness of a strategy's performance is tested on two fronts: (1) the stability of the returns over time, and (2) whether the performance is due to a specific factor. The stability is tested by subdividing the time period in intervals of five years and then comparing the performance. This allows to assess whether the performance depends on specific time periods.

To test the exposure to a single factor the following calculations are performed:

- The contribution of the different assets to the performance and risks
- The contribution of the long and short positions to the performance

To contribute the risks back to the individual assets, i.e. to incorporate diversification effects, Euler's theorem is used. For the VaR this is called in the literature the Component VaR (Hull, 2010, pp 168–169).

3.3 Data

The primary data are the priceseries of KAOF's futures. Next to this, additional data is needed for the business cycle strategy and the benchmarks. All data is downloaded from Bloomberg. A minimum time series length of 20 years is needed to ensure that enough data points are available, and that the time series

[1] Three years of weekly data gives $3 * 52 = 156$ observations. All with equal probability means that the 5$^{\text{th}}$ percentile is at $156 * 0.05 = 7.8^{\text{th}}$ observation

Table 3.1
KAOF's Futures Data Overview

Asset	Futures	Avail.	Synthetic	Avail.
		Bonds		
German 10y	RX1	30/Nov/1990	–	–
USA 10y	TY1	7/May/1982	–	–
Japanese 10y	JB1	25/Oct/1985	–	–
		Equity		
Hang Seng	HI1	3/Apr/1992	HSI - USGG6M	9/Jan/1970
S&P 500	ES1	27/Mar/1998	SPX - USGG6M	9/Jan/1970
EuroStoxx 50	VG1	26/Jun/1998	SX5E - FD0006M	6/Jul/1990
FTSE 100	Z 1	4/Mar/1988	–	–
Topix	TP1	18/May/1990	TPX - JY0006M	3/Nov/1989
		Currencies		
EUR/USD	EC1	22/May/1998	EURUSDCR	6/Jan/1989
EUR/JPY	RY1	15/Jan/1999	EURJPYCR	6/Jan/1989
EUR/GBP	RP1	15/Jan/1999	EURGBPCR	6/Jan/1989
JPY/USD	JY1	23/May/1986	–	–
GBP/USD	BP1	30/May/1986	–	–
		Real-Estate		
EPRA Europe	RIE1	10/May/2007	EPRA - FD0006M	6/Jul/1990
		Commodities		
GSCI	GI1	31/Jul/1992	SPGSCI[a] - USGG6M	9/Jan/1970

[a] Not the GSCI total return index is used, but the price index, because it has a better fit with the real future.

can be split in an in- and out-of-sample period. All data is downloaded until 25/Mar/2011.

However, several futures do not have a 20 year history (see table 3.1 column 3). To overcome this problem, synthetic futures priceseries are constructed. For equities, real-estate and commodities the synthetic futures are created by subtracting the weekly interest from the asset's weekly return (including dividends and other payments). For currencies the synthetic futures are created by subtracting the difference in the local interest rates from the exchange rate. No synthetic bond futures are created, since the real futures history is long enough.

To construct the synthetic futures, interest rates mimicking the investors cost of capital are needed. For this the local[2] six month rates are used. Only the Hong Kong rate does not have a long history. Therefore, the USA rate is used as an alternative, because it is roughly equal to the Hong Kong rate. Table 3.1 gives an overview of the Bloomberg tickers and the time series' availability. Appendix B shows how the synthetic futures series compare to the real futures series.

Table 3.2 shows the tickers and availability of the benchmarks and business

[2]Local in the sense of the location of the exchange where the real future is traded.

Table 3.2
Other Data Overview

Asset	Timeseries	Ticker	Avail.
	Benchmarks		
3m Euribor +4%	3m FIBOR	FD0003M	6/Jul/1990
MSCI World Index	–	MXWO	9/Jan/1970
DJ/CS Mng. Fut.	–	HEDGFUTR	31/Dec/1993
	Business Cycle		
DIV	MSCI World	MXWO[a]	30/Jan/1970
DEF	Moody's US Corp Bond AAA	MOODCAAA	9/Jan/1970
	Moody's US Corp Bond BAA	MOODCBAA	9/Jan/1970
TERM	US Treasury 10Y Rate	USGG10Y	9/Jan/1970
	US T-Bill 3M Rate	USGG3M	9/Jan/1970
YLD	US T-Bill 3M Rate	USGG3M	9/Jan/1970

Note: All weekly closing prices with Bloomberg field code 'px last', unless noted otherwise.
[a] Bloomberg field code 'MSCI_DVD_YLD'

cycle parameters. The Dow Jone Credit Suisse Managed Futures Index is only available on monthly bases, therefore it is converted to weekly data via linear interpolation. The same business cycle parameters are used as in the article by Chordia and Shivakumar (2002). Only instead of the USA dividend yield, the worldwide dividend yield is used.

3.3.1 Examples and Illustrations

For brevity the chapters discuss the results based on a couple of examples and illustrations or figures. If not stated otherwise these results apply also to the other strategies and assets. Figures that are not included can be made available by the author upon request.

3.4 Conclusion

This chapter detailed how the tests are set-up, and how the performance is measured. A simplified framework is used, in which the other signals (Business Cycle and Valuation) are removed, and the assets are money weighted. Performance is measured based on the return, risk and robustness. Returns and risks are weighted and measured via the Sharpe, STARR and Calman ratios. Robustness is determined by the stability of the returns over time and whether the strategies are driven by a single factor. All data is downloaded from Bloomberg, and several synthetic futures are created to increase the data availability.

This answers the scond subquestion 'How is the performance of the strategies measured?'. Before the strategies from the previous chapter can be tested, the academic strategies must be transformed to fit KAOF. The following chapter discusses several methods for this transformation.

Chapter 4

Making the Academic Strategies fit KAOF

The previous two chapters described the common momentum strategies and how these will be tested. However the context in which the academic strategies are applied differs from KAOF. Therefore the reference used in the reference phase (see figure 2.1 page 9) by the literature is not useable for KAOF. This chapter discusses several methods to estimate the parameters of KAOF's reference. Hereby it answers subquestion three 'How can the strategies be transformed to fit KAOF?'.

The next section details why there is a mismatch and what exactly needs to change. The second section details the three methods. It shows that the first two did not lead to the expected results. However they provided important insights, that are shortly discussed (a broader discussion is given in chapters eight and nine). Finally this chapter concludes by reflecting on the results and by answering the subquestion.

4.1 The Mismatch & Approach

As stated above the context in which the academic community tests the momentum strategies is very different from KAOF. The academic community generally uses what I call an asset selection context. In such a context the primary goal is to select the best performing assets among a large group. Contrasting, KAOF has a fixed set of assets, where the primary question is 'When to invest in these assets?'. This is what I call a market timing context. It is a subtitle difference, but has a big impact as will be shown.

In the asset selection context, it is logical to sort all the assets and invest in the top $x\%$. Such a reference point is relative to the performance of the whole set. Mathematically the reference phase of the strategy framework (see previous chapter) is given by:

$$S_t^{\text{Relative}} = \begin{cases} 1 & \text{if } rank(I_t) \geq 0.9 \\ -1 & \text{if } rank(I_t) \leq 0.1 \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

where I is the indicator value, and $rank(x)$ gives the relative rank of x in the set.

In a market timing context such a reference is not obvious. With a relative reference the performance relative to the other assets is essential. Therefore in a market timing context an absolute reference is used, which expresses the individual attractiveness. Mathematically the investment signals are given by:

$$S_t^{\text{Absolute}} = \begin{cases} 1 & \text{if } I_t \geq l^{\text{long}} \\ -1 & \text{if } I_t \leq l^{\text{short}} \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

where I is again the indicator, and l is the threshold. Additionally there are two reasons why the relative reference is not applicable in KAOF: (1) in a very small set the results are very sensitive to the $x\%$ boundary, and (2) the assets are very different making it questionable whether comparing the performances makes sense[1]. Therefore a method is needed that indicates what thresholds would perform well for each strategy.

Another key difference between both contexts is the difference in systematic risk taking, as will be shown is crucial. In an asset selection context all the money available is invested in the market, thus every period has the same exposure to systematic risk. Contrary, in a market timing context every asset has a fixed budget. If this budget is not invested in the asset, it is placed in a risk-free asset not bearing any systematic risk. This introduces a trade-off between participating in the market (and thus having a probability on a positive return), and not taking systematic risk. This trade-off is crucial as will be shown by method two.

4.2 The Methods

There are two general approaches to develop a method to find the thresholds. The most simple is historic optimisation, i.e. testing ex-post what thresholds would have performed best. However, this method is very prone to datamining and does not provide a rationale.

Another approach is to develop a model based on some rationale that indicates what the optimal thresholds should be. This has as benefit that it provides a reason, which is important for Kempen & Co, because it makes the strategy explainable to investors. Secondly it is far less prone to datamining, and is expected to be more robust. Therefore it is preferred.

[1] In the literature commonly a large set of assets from a similar type (e.g. equity) in the same market is used.

The next two subsections describe two methods by this last approach. However both did not lead to the expected results. The first uses the cut-off points of the relative reference, and translates them into a threshold. It showed that the cross-section variation is a very important factor in an asset allocation context, causing high variability in the cut-off points. The second method describes what the impact is of the threshold on the strategies return. To model this relationship simplifying assumptions were needed, leaving risk out of the equation. However as the results show: risk is very important in the trade-off and must be incorporated.

Therefore the historical optimisation is used as third approach, which has rather good results. This method is discussed in subsection three.

4.2.1 From Relative to Absolute

The relative reference is an obvious starting point to find an optimal threshold, since the literature reports good performances with a relative reference. So the goal is to find a threshold that mimics this relative reference. For this an asset selection context similar to the academic literature is used. Appendix C shows the analysis and construction of this context based on the Dutch equity market. As can be seen the strategies all outperformed the market, with several strategies showing very high performances.

To mimic this performance with a threshold, the relative cut-off points must be rather stable over time. In other words, if every period the top 10% assets have an indicator value above x, than x would be the threshold. Thus, a threshold capturing as much of the top decile assets, while limiting the inclusion of other assets would be very similar to a relative reference. Mathematically this is expressed as:

$$\text{CorrectObs}(l) = |\{I | I \geq l \cup ranking(I) \geq 0.9\}| \tag{4.3}$$

$$\text{IncorrectObs}(l) = |\{I | I \geq l \cup ranking(I) < 0.9\}| \tag{4.4}$$

$$l^{\text{opt}} = \max_{l} \left[\frac{\text{CorrectObs}}{|\{I | ranking(I) \geq 0.9\}|} - \frac{\text{IncorrectObs}}{|\{I | ranking(I) < 0.9\}|} \right] \tag{4.5}$$

where I is the set of all indicator values, l the threshold, $ranking()$ a function giving the ranking of an indicator value for its time period, and $|\dots|$ denotes the number of elements in the set (e.g. cardinality).

This requires that the cut-off point must be stable over time, or put differently there must be a strong relationship between the momentum indicator and the ranking. To test if this is the case, the cut-off points are plotted over time, as well as the relationship (see figures 4.1 to 4.3). It shows that this condition does not hold for all strategies.

The R/W/H and Business Cycle strategies show very variable cut-off points, while the 52-Week High strategy is far more stable. The key difference between the strategies is the domain of the indicator. The R/W/H and Business Cycle strategies compare the asset's 'returns'. The natural range of returns differs very much between assets, e.g. very volatile assets can be expected to have far more extreme returns, than more stable assets. Additionally returns can range

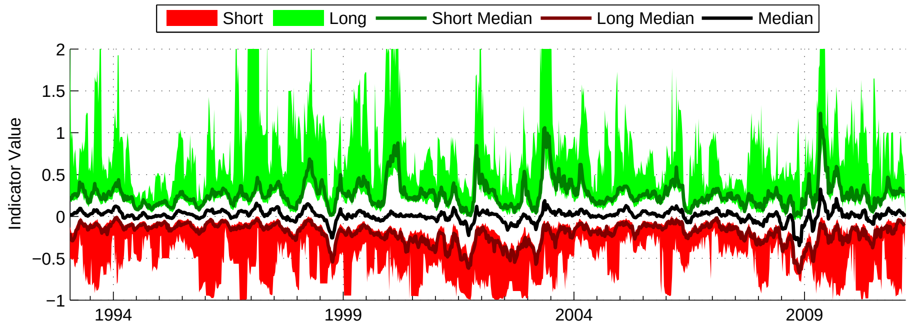

Figure 4.1: Range of R/W/H Indicator forming the Portfolio over Time

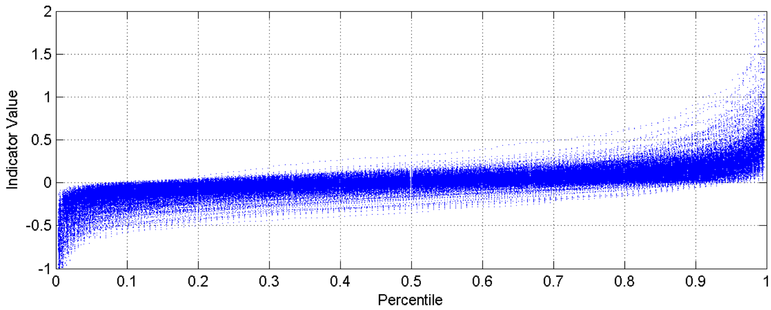

Figure 4.2: Relation between R/W/H Indicator and Ranking

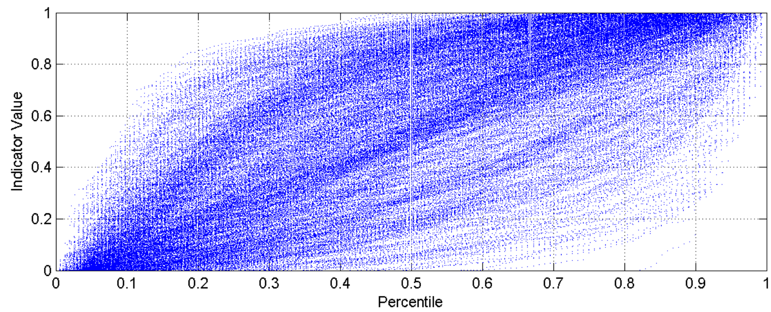

Figure 4.3: Relation between the 52-Week High Indicator and Ranking

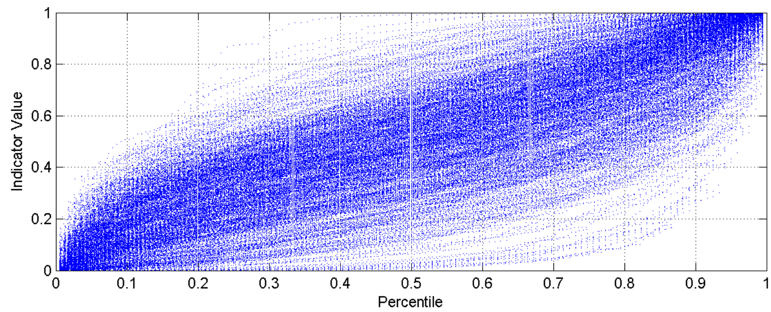

Figure 4.4: Relation between the Transformed R/W/H Strategy and Ranking

from -100% to infinity. While the 52-Week High indicator has values ranging from 0 to 1, with both bounds meaning the same for all assets (i.e. the price is at their last years top/bottom). This has two benefits: (1) it provides upper/lower limits, and (2) makes all the measures comparable.

The R/W/H and Business Cycle indicators can also be transformed to such a domain. Instead of comparing the 'raw' returns, one could compare the probability of such a return for the asset. This makes the measures comparable and provides upper/lower bounds. By assuming returns normally distributed[2], the returns can be transformed to a probability via the inverse normal CDF (Φ^{-1}). The parameters μ and σ are estimated based on the asset's past three years of returns. This transformation indeed improved the stability of the cut-off point (see figure 4.4).

Applying equation 4.3 to the strategies, shows that the cut-off point is still not stable enough to mimic the relative reference performance (see figures 4.5 and 4.6). Especially the short positions show a great mismatch, but also on the long side the equation does not select a threshold close to the ex-post optimum. However the transformation by the normal distribution did improve the stability of the model (compare panel A with C). This leaves to conclude that apparently not only the indicator itself is relevant but also the value in relation to the set.

Jegadeesh and Titman (2001) and Conrad and Kaul (1998) started a big discussion on whether the momentum phenomenon is caused by a real effect or cross-sectional variation in the set. The academic community has more or less concluded that the cross-sectional effect must be minimal. While this analysis shows that the indicator value relative to the set provides crucial information, which leads to higher performance. Ex-post none of the long thresholds performed as well as the relative reference (see figure 4.6). This questions what the effect/contribution is of the momentum indicator.

4.2.2 Optimisation of the Strategies Total Return

The previous section showed that using the cut-off point of the relative reference does not produce optimal thresholds. This section discusses whether modelling the relationship between indicator and future returns proofs effective. Since if the effect of the threshold is known on the performance, then finding the maximum performance leads to the optimal thresholds.

However a model for the performance in KAOF is too complex. Hypothesis 1 (should the thresholds vary over assets/asset classes) would lead to too many input variables (two per varying element), and defining performance as risk-weighted returns requires modelling the correlation between assets. However, modelling the performance of a strategy on a single asset greatly reduces the complexity.

In measuring the performance of a single asset, risk can be left aside. Diversification can not be incorporated, which makes return the only performance

[2]A common assumption, but generally accepted as being false. However the impact of skewness and kurtosis for this exercise is limited. It will slightly over estimate the very high/low probabilities.

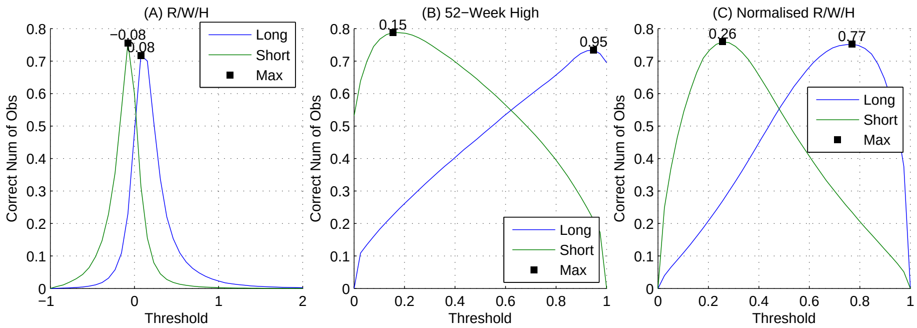

Figure 4.5: Optimal Thresholds based on Mimicking the Relative Reference

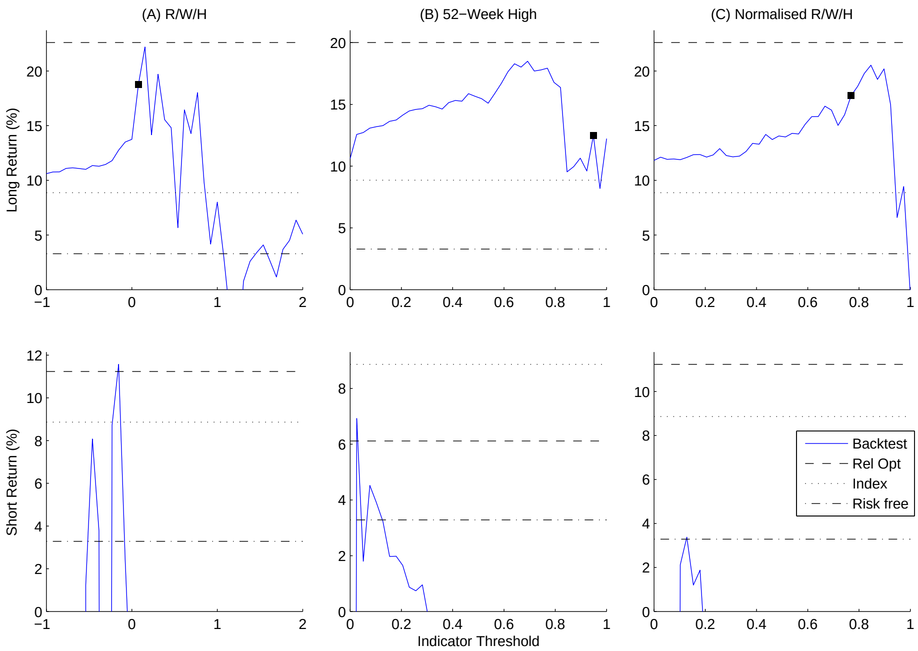

Figure 4.6: Ex-Post Return by Threshold for the Dutch Equity Market

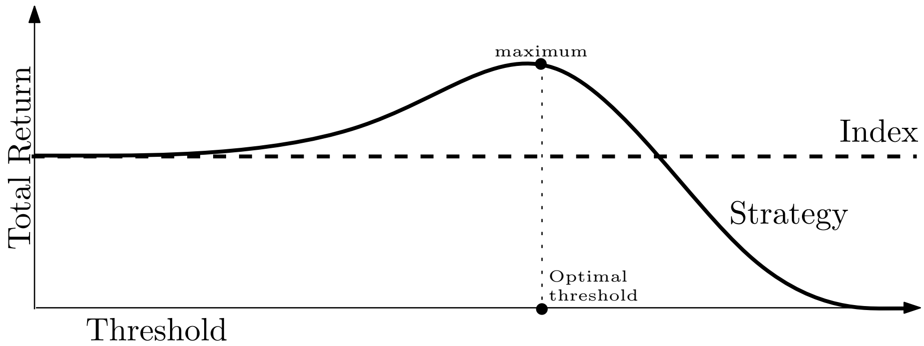

Figure 4.7: Theoretical Relationship between Threshold and a Strategy's Total Return

measure. This simplification also leads to a reduction in independent variables. Each asset has only two thresholds. These are independent, and only restricted long threshold > short threshold. Together this simplifies the relationship to the effect of the long (short) threshold on the returns.

Due to the market timing context, the performance of a strategy does not only depend on the ability to select high performing periods, but also on the number of periods selected. So the return of a strategy is a combination of the returns of the asset and the number of positions. Mathematically the total return of a strategy on an individual asset over n periods is given by (long position only):

$$TR(l) = \prod_{t=1}^{n} [s(I_{t-1}, l) \times r_t + 1] \tag{4.6}$$

$$s(I, l) = \begin{cases} 1 & \text{if } I \geq l \\ 0 & \text{otherwise} \end{cases} \tag{4.7}$$

Assuming the strategies indeed generate outperformance, the following behaviour would be expected:

- For very low thresholds the strategy is always invested, and thus has a return similar as the index.
- By increasing the threshold, the strategy will not anymore invest every period, but based on the assumption, selects periods which generate a much higher return. This results in an increase of the total return.
- However when the threshold becomes very high, the number of positions drops towards zero and so does the return of the strategy.

Figure 4.7 illustrates this behaviour. If the strategies do not have a high correlation in predicting future returns, one would expect a monotonically decreasing function.

Thus the strategies' performance depends on the predictive power of the indicator, times the average number of positions taken over a time period. Mathematically this can be expressed as (see appendix E for the derivation):

$$E[TR(l)] = \mathbb{P}[I \geq l] E[R | I \geq l] \tag{4.8}$$

where I is a random variable with a distribution defined by the historic realisations of the indicator, and R is a random variable of the asset's returns. This model assumes no auto-correlation.

The predictive power of the indicators is weak (see figures 4.8 and 4.9). Especially the correlation structure does not show a strong relationship, however the conditional expectation is indeed increasing with the threshold. This indicates that there is, however marginal, an effect that the indicator captures. Notable are the wide confidence bounds for the R/W/H. While for 52-Week High strategy they stay parallel, meaning more certainty, and thus a stronger predictive power.

In total the model seems to have a good fit with reality (see figures 4.10 and 4.11). Both figures show the ex-post return, and the empirical and smoothed (see appendix E for a description) expected model return. Although the model's returns are higher, the shape is very similar meaning that maximisation would lead to near optimal thresholds. The model results are also very similar to the expected behaviour. The 52-Week High strategy does not show the expected peak, because the increase in returns is exactly compensated by the reduction in positions. This all indicates that the model captures reality quite well, and that there is some momentum effect.

The independently calculated long and short thresholds are often very close together, or do not satisfy the constraint, meaning that both should be equal (see Panel A vs B). This is not what one would expect, because this means the strategies are always invested, either long or short. One would expect a neutral zone, in which the indicators do not have a strong predictive power and thus no position is taken. However panels A and B show that a change in the threshold has the same effect on both positions. Therefore both positions have the same optimum.

This similarity in shape is due to a very weak predictive power of the indicator. Figure 4.12 shows this effect. Panel A shows a strong relationship between the indicator and future returns. The green (red) dot denotes the expected long (short) return for the threshold. When the threshold is moved to the right, the expectations change, due to the removal (addition) of observations. For the long position, there are more observations below the expectation, thus removing them increases the expectation. The same holds for the short position, there are more observations above the expectation, so adding them increases the expectation. Panel B shows what is really happening. The majority of the observations are not correlated with the indicator, and thus have no effect on the average return given a threshold. By increasing the threshold, several very low observations are removed (added). These observations are below both expectations; the long expectation increases and the short decreases. This produces the similarity in shape seen in the figures.

This suggests that the indicator does not affect the average return of a strategy, but reduces the risk by eliminating tail exposure. This raises the following hypothesis:

Hypothesis 2 *The academic momentum strategies do not significantly effect the average return, but reduce risks.*

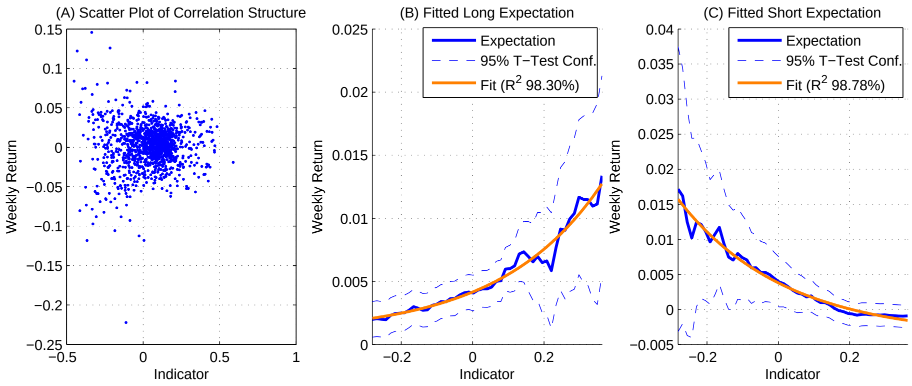

Figure 4.8: Correlation of R/W/H Indicator On EuroStoxx

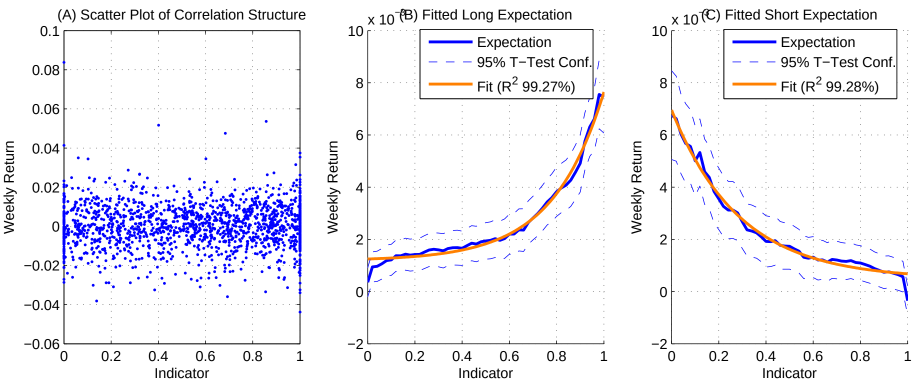

Figure 4.9: Correlation of 52-Week High Indicator On USA 10y Bond

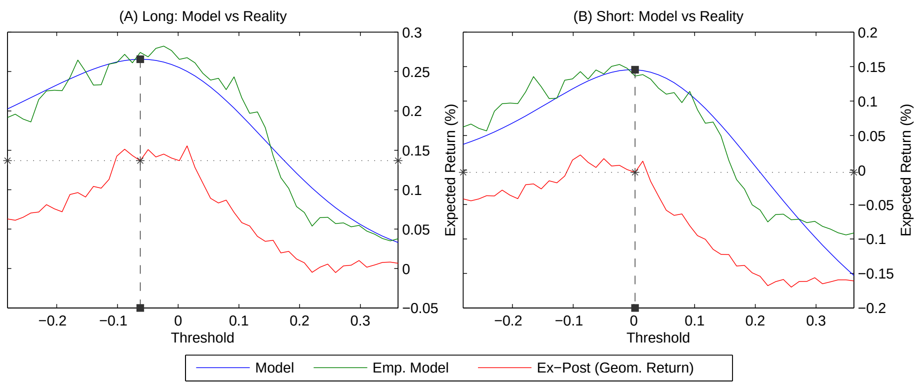

Figure 4.10: Model and Backtest of R/W/H Strategy on EuroStoxx

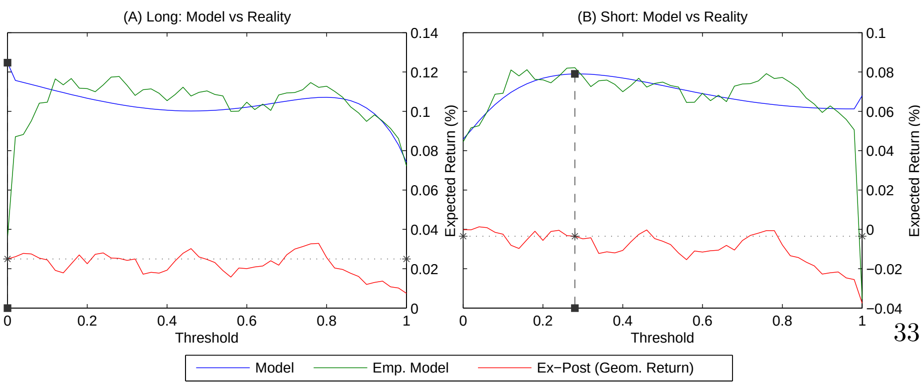

Figure 4.11: Model and Backtest of 52-Week High Strategy on USA 10y Bond

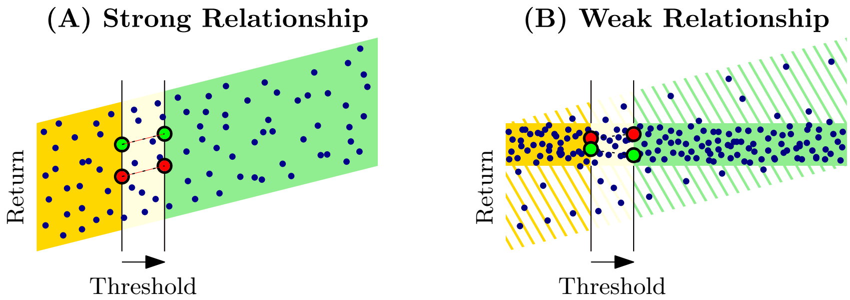

Figure 4.12: Effect or Relationship Strength on Expected Long and Short Return

Hypothesis 2a (Alt.) *The academic momentum strategies are able to differentiate returns, leading to an above average return.*

This hypothesis is tested in the following chapter.

Nonetheless, risks are thus an important part in setting the thresholds. This was not an important factor in the academic publications (i.e. asset selection context, since money was always invested and thus had a similar systematic risk exposure). Due to the all-or-nothing decision of the market timing context, strategies play with the amount of systematic risk exposure. Omitting this factor, overestimates the benefit of a position as illustrated in this analysis.

4.2.3 Historical Optimisation on Portfolio Level

The previous section shows that risk is an important factor in determining a strategy's optimal thresholds. An easy method to incorporate all the interaction effects between assets is historic optimisation. It allows for the calculation of the diversified portfolio risk, but assumes that the past is a reasonable predictor of the future. Therefore this approach has two drawbacks: (1) it is prone to datamining, and (2) significantly constraints the number of parameters.

The first drawback can be minimised by using an in- and out-of-sample period. The in-sample period is used to calculate the optimal thresholds. The out-of-sample period is used to calculate the performance of these thresholds. If the thresholds perform well in both periods, they can be expected to also perform well in the future. The sample for 1991 to 2011 is split at 2001 with the 1st of January 2001 as boundary. This boundary includes two business cycles[3] in the out-of-sample period (*US Business Cycle Expansions and Contractions*, 2010).

The constraint on the number of parameters is caused by and exponential increase of combinations. If there are x elements with independent thresholds, and only n values are tested for each threshold, then there are $\left(\frac{n}{\sqrt{2}}\right)^{2x}$ combinations. For instance testing the hypothesis 1 page 20 that each asset class has its own thresholds with only 10 possible values per threshold ($x = 5$ and

[3] Several publications show that momentum strategies tend to be rather dependent on the market state. The out-of-sample period is selected such that both market states are equally prevalent.

$n = 10$), results 6.25 million possibilities. Therefore it is only possible to have one set of thresholds for all assets, making it impossible to test the hypothesis.

Figure 4.13 shows the performance of the R/W/H strategy over the in-sample period. Panel A confirms the conclusion from the previous section, that purely on a return basis both thresholds should be equal. However panels B to D show that by incorporating risk the thresholds are no longer equal.

Figure 4.14 shows the out-of-sample performance. Although the optimal region moved, mainly due to the severe credit crisis, the optimal thresholds from the in-sample period are still near this period's maximum. Additionally in both periods the tops are rather robust (i.e. not spiky), indicating that small deviations do not have a severe impact.

4.3 Conclusion

This chapter discussed three methods to find 'optimal' thresholds for the academic strategies: (1) by using the relative reference cut-off point, (2) by modelling the relationship between a strategy's return and the threshold, and (3) via historic optimisation.

Method one did not lead to satisfactory results, since the relationship between indicator and ranking was not strong enough. It indicated that in an asset selection context a significant part of the performance is not only due to the momentum indicator, but also due to the cross-section variation (which is captured by the relative reference).

Method two did not lead to correct thresholds, because risk reduction is an important performance factor. In an asset selection context, all the money is generally invested. Therefore every period has a similar systematic risk exposure. However due to the all-or-nothing decision in the market timing context, the systematic risk exposure depends on the threshold, and is thus an important factor.

The only method allowing to determine thresholds based on risk-adjusted returns is historical optimisation. The optimal thresholds in the in-sample period, performed also well in the out-of-sample period. Thus via in-sample optimisation effective thresholds are found for the academic strategies.

This answers subquestion three 'How can the strategies be transformed to fit KAOF?', since with these thresholds the academic strategies also employ an absolute reference. This method is used in the following chapter to determine the thresholds for all academic strategies, necessary to test the strategies on their performance.

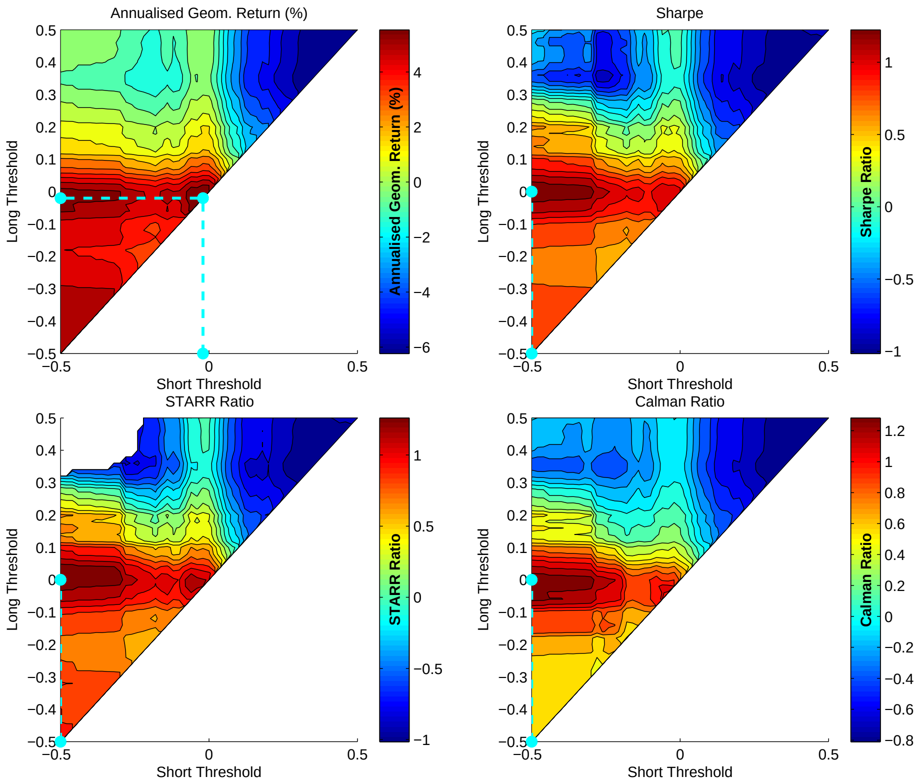

Figure 4.13: In-Sample Backtest Results R/W/H Strategy

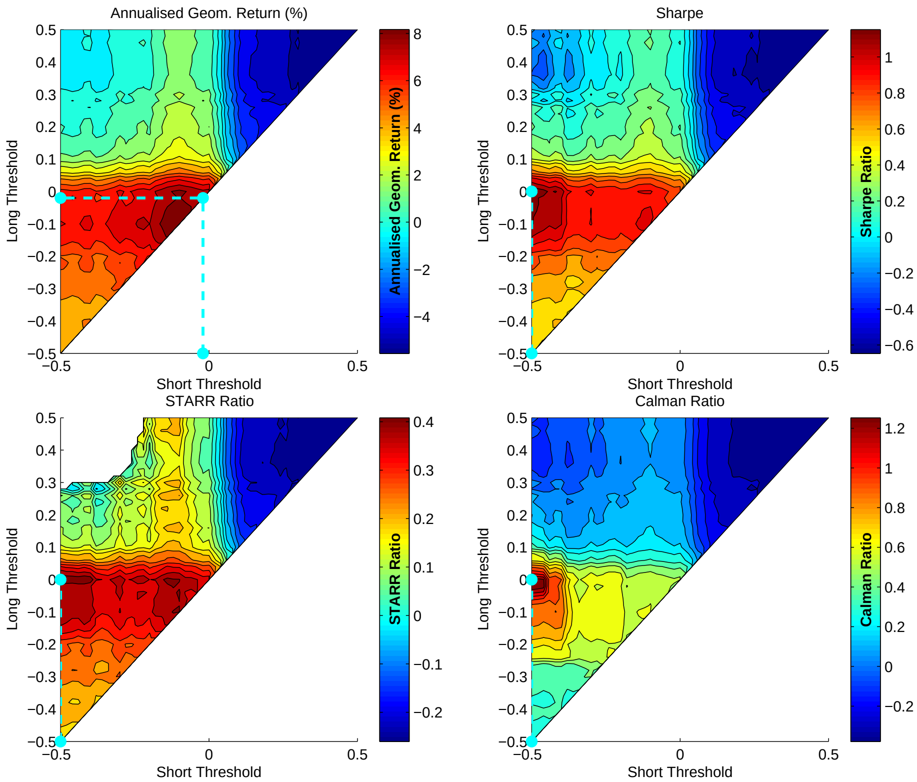

Figure 4.14: Out-of-Sample Backtest Results R/W/H Strategy

Chapter 5

Performance of the Academic Strategies

The previous chapters showed which momentum strategies are commonly used, how the performance is measured, and how the thresholds can be found to employ an absolute reference. This chapter discusses the performance of the academic strategies, as the first part of the 'horse race' to answer the main research question 'Which momentum strategy is expected to perform best within KAOF's Investment Framework?'.

This chapter tests the three academic strategies (the R/W/H, Business Cycle and 52-Week High) in a simplified investment framework (see chapter three). Therefore it tests the strategies purely on their momentum performance. Chapter seven covers their performance in conjunction with the other KAOF strategies (Business Cycle and Valuation).

The first section details how the parameters of the different strategies are set. The second section discusses the first two performance factors (i.e. risk and return). Section three covers the third factor: robustness. In the previous chapter the hypothesis was raised that the strategies do not generate extra return, compared to a random strategy, however they reduce the risks. Section four discusses whether this hypothesis should be rejected or not. Finally, this chapter concludes by answering subquestion four 'What is the performance of the academic momentum strategies?'.

5.1 Parameters & Thresholds

Before the strategies can be tested on their performance, all the parameters of the strategies must be determined. All strategies have four general parameters: the waiting and holding period and the long and short thresholds. The R/W/H strategy additionally has the ranking period. The following paragraphs discuss how the parameters are set.

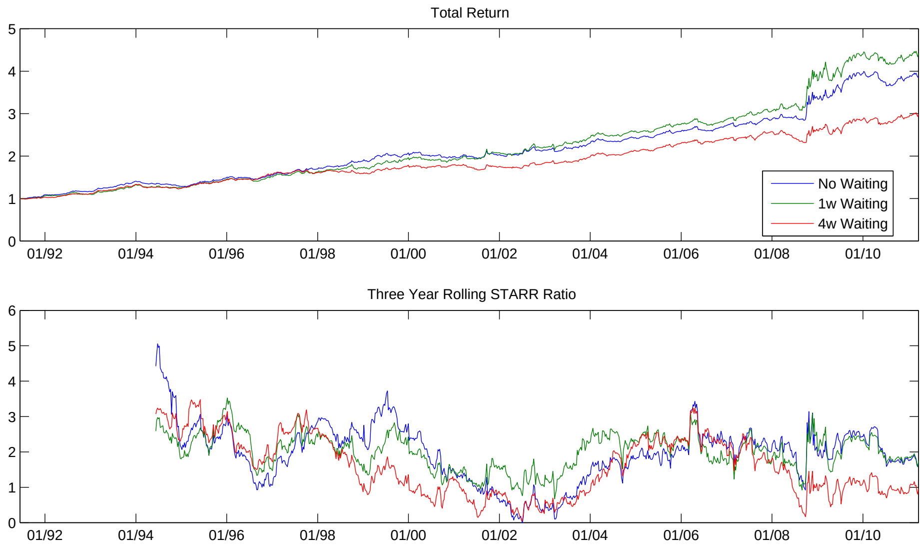

Figure 5.1: Effect of Waiting Periods on 52-Week High Strategy

The holding period is set to one week. This setting has maximum flexibility, and is optimal by selecting the correct waiting period as shown in Appendix C.

A waiting period of zero weeks is chosen, because no setting clearly performed better for any strategy in all different time periods. Figure 5.1 shows this for the 52-Week High strategy. Panel A shows that none of the settings (zero, one or four weeks waiting) outperforms the others over the whole time period on returns. Panel B shows the risk-adjusted returns over time, calculated as the arithmetic average return divided by the three year 95% VaR. This shows even more clearly that the optimal setting heavenly depends on the time period. The setting with no waiting period is the most intuitive and is therefore chosen (e.g. when you have an investment signal you act on it).

The R/W/H strategy has an additional parameter: the ranking period. For several ranking periods (4, 8 12, 26 and 52 weeks) the optimal thresholds are determined via historical optimisation. Figure 5.2 shows how the strategy with these thresholds performs for several ranking periods. Evidently there is no obvious optimum, however, in-line with the literature there seems to be a maximum around the six month period (24 weeks is chosen).

Based on the results from the previous chapter, the only viable option to determine the optimal thresholds for the strategies, is based on in-sample optimisation. With this method hypothesis 1 cannot be tested, due to the tremendous amount of possibilities. The same in- and out-of-sample periods are used as in the previous chapter (i.e. split at January 1^{st} 2001). Table 5.1 shows the thresholds for each strategy based on the maximum Calman Ratio (see appendix F). Only for the 52-Week High Strategy are also the STARR thresholds included in the analysis, since these significantly differ from Calman thresholds.

Interesting is that the thresholds tend to have a bias to the lower end of the

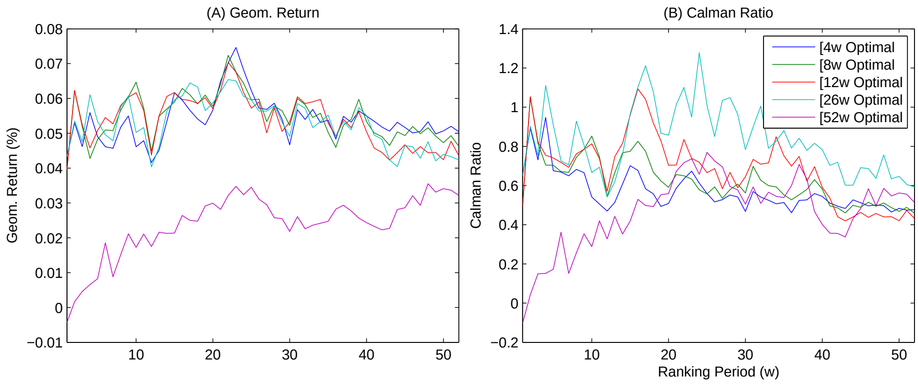

Figure 5.2: Effect of a varying Ranking Period on the R/W/H Strategy's Performance

Table 5.1
Optimal Strategy Thresholds based on Historic Backtesting

	R/W/H	R/W/H (Norm.)	Business Cycle	Business Cycle (Norm.)	52-Week High (Calman)	52-Week High (STARR)
Long	0.0	0.34	-0.002	0.42	0.44	0.58
Short	-0.3	0.24	-0.006	0.10	0.12	0.12

spectrum. This is due to the strong and long persisting bull markets that were seen in the past two decades. However this results in counter-intuitive thresholds which are not in-line with the momentum ideology. For instance if the R/W/H indicator shows a very weak trend (barely a positive past return) it is enough to enter a long position. Also for the normalised version a probability of at least 34% is enough, while one would expect at least a threshold of above 50%. This challenges the explainability of the strategies to investors. Nonetheless these thresholds are used in the remainder of this report.

5.2 Returns & Risks

The three academic strategies (the R/W/H, Business Cycle and 52-Week High) with the parameter settings from the previous section are tested on their performance. The total return of the strategies differs greatly over the period 2001 to 2011 (see figure 5.3). However all strategies outperform KAOF's current strategy in the end, besides the Business Cycle strategy. Also all these strategies have returns significantly different from zero, based on Student t-tests (see table 5.2). The higher performance is explained by the higher exposure (see last column of the table): if a strategy has more exposure, it is more frequently invested, and thus has less money on the bank and more money generating a return (in strong bull markets). Additionally the strategies also tend to switch the signals more often, causing more transaction costs. Although nearly all out-

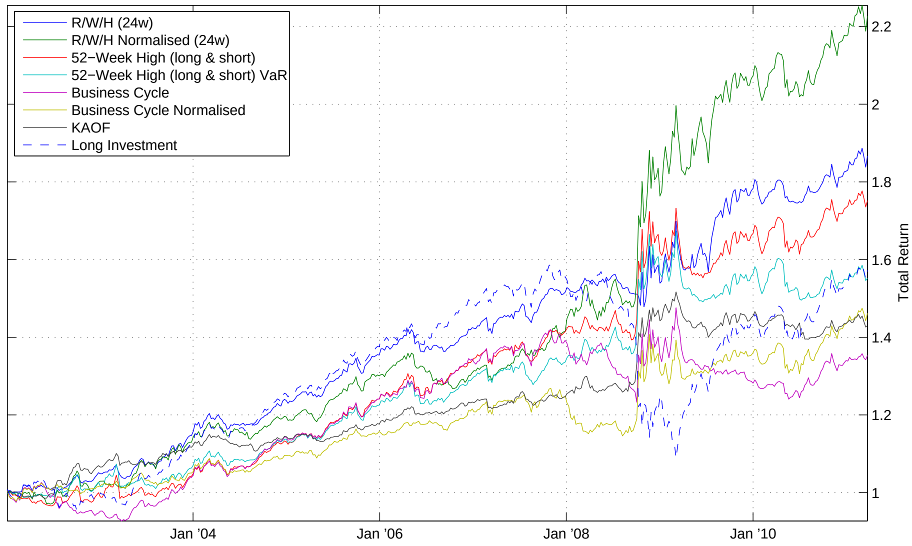

Figure 5.3: Comparison of Strategy's Total Return

perform the current strategy, only the two R/W/H strategies beat the target of Euribor +4%.

From a risk perspective all strategies perform below the requirement of a MDD of 15% (except the Business Cycle strategy), whereas all passive benchmarks have rather high risk levels. So the momentum strategies seem to reduce the risks effectively by choosing the right moments to invest.

Weighting risks and returns, the outperformance of the academic strategies diminishes. Only the R/W/H strategies outperform KAOF on all risk measures. The 52-Week High strategy outperforms only on the Calman Ratio, so the higher performance due to a larger exposure is generally offset by the increase in risk by this larger exposure.

5.3 Robustness

The previous section showed that only the R/W/H strategies and the 52-Week High (Calman) strategy outperformed KAOF on risk-adjusted returns. This section covers whether the strategies also provide robust returns, i.e. are the returns stable through time and not dependent on a single factor.

Figure 5.4 shows how the returns, STARR and Calman ratios vary in subperiods of five years from 1995 to 2011. If a strategy is stable through time, one would expect the relative performance against a long position to be the same in all three periods. The opposite is especially seen for the Normalised R/W/H and Business Cycle strategies. The Normalised R/W/H strategy performs very well during the credit crisis, however lacks performance in the other periods. The business cycle strategies (especially the normalised version) seem to perform

Table 5.2
Performance of the Academic Strategies

	Return (%)	Vol. (%)	p-value	t-stat	VaR	MDD	Sharpe	STARR	Calman	% Positive Returns	% Signals Chg.	% Invested
R/W/H (24w)	6.97	6.99	0.00	3.04	17.30	7.64	1.00	0.40	0.91	60.79	8.14	60.84
R/W/H Norm. (24w)	9.02	9.14	0.00	3.02	20.32	8.96	0.99	0.44	1.01	61.41	13.90	91.25
52W (Calman)	6.24	8.18	0.02	2.38	20.26	10.35	0.76	0.31	0.60	60.79	10.20	79.55
52W (STARR)	4.86	7.96	0.05	1.93	20.21	10.89	0.61	0.24	0.45	60.37	10.71	70.74
Biz	3.32	7.89	0.17	1.38	19.27	15.93	0.42	0.17	0.21	57.47	7.06	84.29
Biz Norm	4.18	7.61	0.08	1.75	17.38	9.64	0.55	0.24	0.43	58.51	11.90	46.99
KAOF	3.93	5.10	0.02	2.38	12.73	8.03	0.77	0.31	0.49	58.51	6.14	46.99
Long Investment	5.00	8.81	0.07	1.82	22.03	31.40	0.57	0.23	0.16	58.92	0.00	100
MSCI World	3.00	18.80	0.44	0.77	50.93	58.37	0.16	0.06	0.05	56.22	–	–
DJ/CS Mng. Fut.	7.90	5.45	0.00	4.33	13.83	13.68	1.45	0.57	0.58	54.15	–	–

The average annualised return of the Euribor +4% was 6.61%.
All numbers are annualised averages over the time period 4/Jan/2002 to 25/Mar/2011

Table 5.3
Performance vs Monte Carlo Simulation

	Return (%)			Volatility (%)			VaR (%)			MaxDrawDown (%)		
	Strategy	Simulation		Strategy	Simulation		Strategy	Simulation		Strategy	Simulation	
		Mean	Stdev		Mean	Stdev		Mean	Stdev		Mean	Stdev
R/W/H (24w)	6.97	3.31±0.01	0.90	1.94	5.84±0.00	0.30	4.80	14.62±0.01	0.96	7.64	20.40±0.05	3.65
R/W/H Norm. (24w)	9.02	2.37±0.02	1.33	2.53	5.64±0.01	0.37	5.63	14.34±0.02	1.10	8.96	18.20±0.07	5.09
52W (Calman)	6.24	3.31±0.02	1.11	2.27	5.83±0.00	0.34	5.62	14.49±0.01	1.04	10.35	19.42±0.06	4.35
52W (STARR)	4.86	2.78±0.02	1.12	2.21	5.24±0.00	0.34	5.60	13.03±0.01	1.01	10.89	17.26±0.06	4.41
Biz	3.32	4.11±0.01	0.92	2.19	6.63±0.00	0.31	5.34	16.45±0.01	0.99	15.93	22.44±0.05	3.59
Biz Norm.	4.18	2.53±0.02	1.10	2.11	5.50±0.00	0.33	4.82	13.92±0.01	1.03	9.64	18.93±0.06	4.40

The confidence of the simulation means are based on 95% Student-t test.
In the simulation 20.000 random portfolios are generated, with the same number of long and short signals as the corresponding strategy.
All numbers are annualised averages over the time period 4/Jan/2002 to 25/Mar/2011

well pre-2000 in the strong bull market, but not in turbulent times. All other strategies have a more stable performance in all three periods.

Next to the stability through time, the dependence on a single factor is tested. Figure 5.5 shows three important factors (long vs short, return and risk) for the best performing strategies (R/W/H, Normalised R/W/H, and 52-Week High). The returns of all strategies are mainly due to the long positions. Only during the credit crises there was a real benefit from the short positions. Several strategies even have a short threshold such that nearly never a short position is taken (see for instance the R/W/H strategy).

All the strategies are mainly driven by a couple of assets. Especially equities, real-estate and commodities drive the returns. Despite the rather large weight of bonds, their performance is far behind. From a risk perspective, the assets generating the returns also contribute the most risk. The currencies are rather low, or even reduce the risk of the portfolio, in case of the Normalised R/W/H Strategy.

To conclude, the R/W/H, 52-Week High and KAOF's strategy are relatively stable through time. However, all are mainly driven by the long positions and several assets.

5.4 Generate Return or Reduce Risk

To test the hypothesis whether the strategies generate primarily returns or reduce risks (see hypothesis 2 page 36), a Monte Carlo simulation is performed. For each strategy over the out-of-sample period 20.000 random 'strategies' are generated with the same number of long and short investment signals. This makes sure that these random strategies have the same market exposure as the momentum strategies.

If the hypothesis is true, one would expect to see a roughly equal return between the momentum strategy and the average of the random strategies, with the academic strategy having a significant lower risk. Table 5.3 shows the results of the Monte Carlo simulation. As is clearly visible all momentum strategies outperform by far the random strategies on returns and risks. Only the Business Cycle strategy has a return below average. Based on this the hypothesis is rejected. The results lead to the conclusion that the strategies perform on both aspects, i.e. generate significant returns at much lower risk than a random strategy with the same exposure.

5.5 Conclusion

This chapter discussed the performance of the academic strategies purely on momentum in a simplified framework. The R/W/H and 52-Week High (Calman) strategy, outperformed the current KAOF strategy on returns as well as risk adjusted returns. However only the R/W/H strategies outperformed the

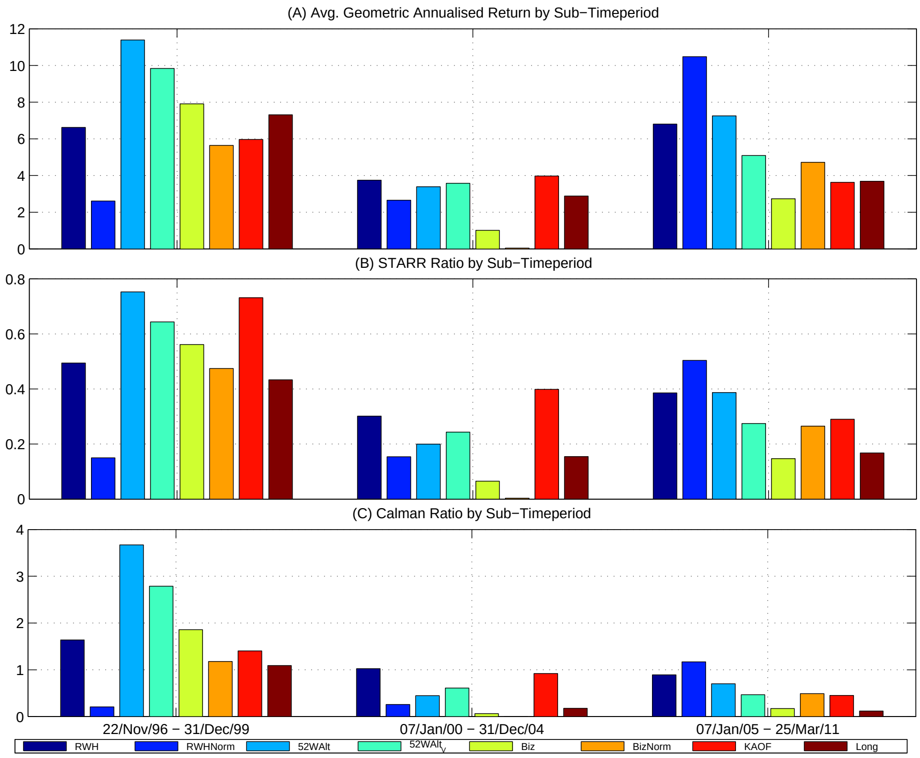

Figure 5.4: Robustness of Performance over Subperiods

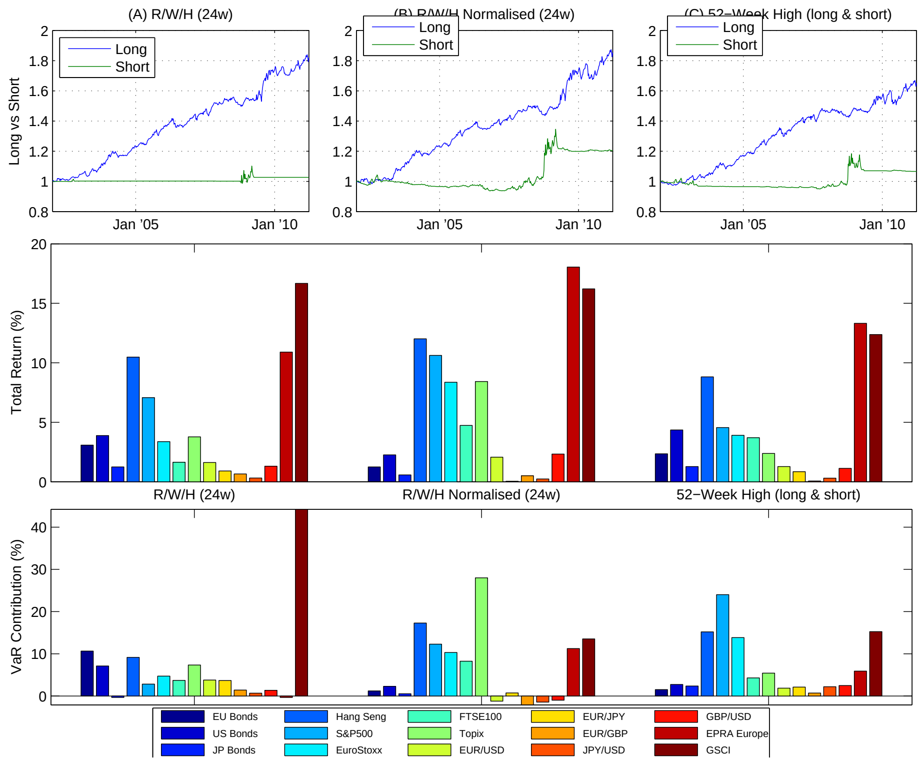

Figure 5.5: Overview of Factors driving the Performance

benchmark of Euribor +4%, but the normalised R/W/H strategy is rather dependent on the time period. All strategies' performance is mainly driven by the long positions and several assets. Therefore all strategies have a rather weak robustness. So purely on the performance measures the R/W/H and 52-Week High (Calman) strategy could bring an improvement.

This answers subquestion four 'What is the performance of the academic momentum strategies?'. However none of the strategies provide a significant improvement on all fields: the strategies have much more exposure and slightly more transaction costs. More important is their weak robustness, making it questionable whether the outperformance continues in the future, and their counter intuitive thresholds which contrast the momentum ideology. The later two topics are more extensively discussed in chapter nine. The following chapter tests whether significant improvements are possible based on an evaluation of the current strategy.

Chapter 6

Improving and Evaluating KAOF's Strategy

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Chapter 7

Momentum in Combination with valuation and the business cycle

The previous chapters tested the performance of the momentum strategies in a simplified framework. This was done to remove the interaction effects with the other strategies of KAOF (i.e. valuation and business cycle), and also allowed for a deeper analysis of the results. However none of the strategies posed a significant improvement versus the current strategy without consequences.

Nonetheless it is important to test the strategies in KAOF's context, which can be seen as the grand finale in this horse race. The previous chapters allowed to develop an understanding of how the strategies work. This forms an important basis to explain the results reported here. This final test aims at answering subquestion six 'How do these strategies perform in conjunction with the other KAOF signals?'. This shows which strategies can be used to improve KAOF's momentum strategy (i.e. the research goal).

In this respect, the first section of this chapter provides some insight in the model used. The second section discusses the performance of the strategies in KAOF. The third section concludes by answering subquestion six.

7.1 The Model

KAOF's team has developed a complex model to historically test changes in the strategies. The model exactly replicates the process visualised by figure 1.1 page 3, and is therefore used to test the momentum strategies in KAOF.

The assets are weighted by the same weights as before (see table 1.1), however not on their money value, but on their risk exposure as percentage of the NAV. The investment signals are constructed by equally weighting all three strategies, i.e. business cycle, valuation and Momentum. However the business cycle signals are not available until August 2010. Also not all asset classes (i.e. currencies and commodities) have a valuation signal, these classes are purely invested based on momentum.

This changes the impact of the assets and momentum on the total return. The weight of bonds is increased for instance, due to the low risk profile. However the impact of momentum is reduced, due to the valuation and business cycle signals. As the previous chapters showed, all strategies are rather dependent on the assets, this is expected to have a significant impact on the results.

Where in the previous chapters several costs were out of scope, this model accounts for transaction and management costs (respectively 0.05% and 1.25%). Also the money on the bank account generates a return of Euribor -0.25%, instead of zero as previously assumed. This will all affect the performance measures.

However a larger effect is expected from the ambiguity in which time series are used. The total return series are used for the risk calculation, and it is expected that synthetic future series are used for the signals. However there is a big difference between these series and the series used previously. The impact of this difference is further discussed in chapter nine. For now nothing is changed, to keep the model as it is.

The model reports the performance of the strategies from 1991 to 2011. Only the out-of-sample period (2001 until 2011) is used, since the in-sample period contains the datasnooping bias. The out-of-sample period is, as before, split in two five year periods, to test for robustness. Previous chapters showed that several strategies (such as the Normalised R/W/H strategy) are very time period dependent.

7.2 Results

Two sets of strategies were tested: (1) the academic strategies, and (2) the improvements on the current strategy. In the simplified context the R/W/H and 52-Week High strategies outperformed KAOF, however all strategies were weak on robustness. None of the improvements significantly outperformed the current strategy; the returns were higher, but with much more risk. The tests in KAOF context show a similar conclusion (see table 7.1).

Based on the returns and risk-ratios, indeed many of the academic strategies outperformed KAOF. Contrary to previous findings the business cycle strategy is the best performer from 2001 to 2006. The strategies performance is driven by the Real-Estate and Commodities indices, and negatively affected by equities. Due to the changes in weights for the assets and strategies, the business cycle strategy thrives in the actual KAOF context.

The alterations perform well on returns solely, however as before risk-weighted the performance diminishes. In the period of 2001 to 2006 none outperform KAOF, however in the second five years the removal of the crossovers and the Click Bounds With Profit Takings have a higher Calman ratio. Still the academic strategies perform much better.

Again the robustness of the strategies is weak. Now not only the Normalised R/W/H strategy, but also the plain R/W/H strategies risk-ratios greatly differ between the two five year periods. Overall the 52-Week high strategies are most stable over time, especially the Calman based version outperforms KAOF in both periods.

To test whether the combination of momentum and valuation indeed improves the performance, the same tests without the other signals are ran. The performance is about equal or a bit lower for all strategies (see table 7.2), but all strategies have significantly more risk reducing the risk-adjusted returns. Especially the business cycle strategies have significantly more risk on their own. Based on these ratios none of the strategies perform better without valuation and business cycle.

7.3 Conclusion

This chapter discussed the results of all the strategies (the academic and alterations on the current strategy) in KAOF's framework, i.e. with valuation, business cycle and risk-weighted portfolios. As concluded before (see respectively chapter five and six), the R/W/H and 52-Week High strategies perform rather well, while none of the alterations significantly improves the performance. However still the robustness of all strategies is weak. Especially both R/W/H strategies are very time dependent. Most stable are the 52-Week High strategies, with the 52-Week Calman version being the best improvement.

The removal of the valuation and business cycle signals did not affect the returns greatly. However it increased the risk of all strategies significantly. Leaving the conclusion, inline with Asness et al. (2009), that combining valuation and momentum improves the strategies' performance.

This answers subquestion six 'How do these strategies perform in conjunction with the other KAOF signals?'. Based on this analysis and the results of the previous chapters, the main research question is answered in the next chapter. Chapter nine discusses the implications and limitations of the conclusion, and focusses especially on the sensitivity of the results to many factors (e.g. the time period or asset dependency).

Table 7.1
Performance in KAOF's Investment Context

	Return (%)	Vol. (%)	MDD (%)	Sharpe	Calman
Period: 2001 to 2006					
KAOF	18.70	10.12	8.28	1.85	2.26
R/W/H (24w)	22.15*	11.07	9.17	2.00*	2.41*
R/W/H Norm. (24w)	21.17*	12.55	10.61	1.69	2.00
52W (Calman)	26.88*	12.61	11.42	2.13*	2.35*
52W (STARR)	24.00*	12.42	11.42	1.93*	2.10
Biz	23.41*	10.63	8.42	2.20*	2.78*
Biz Norm.	17.60	9.81	10.16	1.79	1.73
No Profit	19.59*	13.27	11.61	1.48	1.69
No Cross	18.14	10.19	8.70	1.78	2.09
Stdev Fixed (3y)	18.95*	13.34	12.06	1.42	1.57
Stdev Fixed (7y)	16.76	13.01	12.94	1.29	1.30
Stdev Moving (3y)	12.88	12.68	11.30	1.02	1.14
Stdev Moving (7y)	13.85	13.31	13.36	1.04	1.04
Click No Profit	18.73*	11.40	8.96	1.64	2.09
Click With Profit	19.59*	13.27	11.61	1.48	1.69
Period: 2006 to 2011					
KAOF	9.54	9.40	12.90	1.01	0.74
R/W/H (24w)	12.27*	10.49	24.91	1.17*	0.49
R/W/H Norm (24w)	18.80*	14.23	16.03	1.32*	1.17*
52W (Calman)	16.22*	12.22	15.33	1.33*	1.06*
52W (STARR)	16.77*	11.85	9.90	1.41*	1.69*
Biz	8.85	13.35	35.00	0.66	0.25
Biz Norm	10.29*	11.51	28.30	0.89	0.36
No Profit	11.07*	12.47	16.47	0.89	0.67
No Cross	9.41	9.91	11.80	0.95	0.80*
Stdev Fixed (3y)	10.93*	12.29	16.64	0.89	0.66
Stdev Fixed (7y)	9.98*	12.19	15.89	0.82	0.63
Stdev Moving (3y)	10.75*	12.65	15.98	0.85	0.67
Stdev Moving (7y)	7.02	11.89	14.74	0.59	0.48
Click No Profit	10.07*	10.17	11.85	0.99	0.85*
Click WithProfit	10.78*	12.43	16.47	0.87	0.65

* Denote measures outperforming the current strategy in the respective time period
The benchmark of Euribor +4% had a return of the respective periods of respectively 6.81% and 6.92%.
All numbers are annualised averages over the respective time period.

Table 7.2
Performance in KAOF without the Other Strategies

	Return (%)	Vol. (%)	MDD (%)	Sharpe	Calman
		Period: 2001 to 2006			
KAOF	16.14	11.74	12.55	1.37	1.29
R/W/H (24w)	21.69	12.98	12.90	1.67	1.68
R/W/H Norm. (24w)	17.70	13.34	15.22	1.33	1.16
52W (Calman)	24.91	14.37	15.48	1.73	1.61
52W (STARR)	22.27	13.95	15.43	1.60	1.44
Biz	21.18	14.01	22.79	1.51	0.93
Biz Norm.	15.37	14.41	26.29	1.07	0.58
No Profit	15.23	14.58	15.64	1.04	0.97
No Cross	15.54	11.48	11.69	1.35	1.33
Stdev Fixed (3y)	14.99	14.62	16.57	1.02	0.90
Stdev Fixed (7y)	12.77	14.57	17.76	0.88	0.72
Stdev Moving (3y)	7.36	14.06	19.09	0.52	0.39
Stdev Moving (7y)	8.10	14.15	22.43	0.57	0.36
Click No Profit	15.22	14.58	15.64	1.04	0.97
Click With Profit	15.59	12.86	11.95	1.21	1.31
		Period: 2006 to 2011			
KAOF	10.84	16.20	21.30	0.67	0.51
R/W/H (24w)	16.80	17.12	14.69	0.98	1.14
R/W/H Norm. (24w)	21.14	18.21	20.43	1.16	1.03
52W (Calman)	18.59	18.28	18.24	1.02	1.02
52W (STARR)	19.11	18.13	18.59	1.05	1.03
Biz	7.73	19.15	37.53	0.40	0.21
Biz Norm.	13.30	17.19	34.11	0.77	0.39
No Profit	11.62	18.43	22.41	0.63	0.52
No Cross	10.50	16.46	19.61	0.64	0.54
Stdev Fixed (3y)	11.53	18.48	25.02	0.62	0.46
Stdev Fixed (7y)	10.13	18.44	23.28	0.55	0.44
Stdev Moving (3y)	9.32	17.22	23.23	0.54	0.40
Stdev Moving (7y)	5.50	18.52	29.73	0.30	0.18
Click No Profit	11.66	18.45	22.41	0.63	0.52
Click With Profit	10.50	16.88	23.76	0.62	0.44

* Denote measures outperforming the current strategy in the respective time period
The benchmark of Euribor +4% had a return of the respective periods of respectively 6.81% and 6.92%.
All numbers are annualised averages over the respective time period.

Chapter 8

Conclusion

The goal of this research is: 'To evaluate and improve KAOF's momentum strategy'. To achieve this goal, the research is focused on the main research question (Which momentum strategy is expected to perform best within KAOF's Investment Framework?). This chapter concludes by answering this question based on the results from the previous chapters.

The first part of this report laid the foundation for testing the strategies on their performance. An extensive literature research showed that momentum is a deeply covered subject. To describe and distinguish the strategies a general framework was developed. This framework distinguished six strategies that are frequently used, however only three are usable by KAOF, due to the use of futures; the R/W/H[1], 52-Week High[2] and Business cycle[3]. This framework did not only prove to be effective in describing the strategies, but also in modelling the strategies and revealed an important mismatch between the academic strategies and KAOF.

The academic literature applies the momentum strategies to an asset selection context, and uses a relative reference (e.g. the top/bottom 10% of the assets) to determine the investments. While KAOF is purely focused on market timing, because the money is divided over all the assets and per asset is decided to invest or not. In such a context an absolute reference is used (i.e. a threshold which determines when to invest and when not). Therefore the academic strategies had to be transformed from this relative to an absolute reference. This implied using a method to determine the thresholds. Three methods were tried: (1) mimicking this relative reference by a threshold, (2) optimising the relationship between threshold and returns, and (3) in-sample optimisation.

The first method did not work, because the cut-off point of this relative reference is volatile over time. This combined with the rather weak relationship between momentum indicator and ranking, led to the conclusion that not only the indicator, but also the cross-sectional variation has a big impact on the performance of the strategies in an asset selection context. The source of the

[1]Based on the average return over the past x months
[2]Based on the closeness of the price to its 52-Week High
[3]Based on the predicted return by several global economical variables

momentum profits is an important debate in the literature, which was started by Conrad and Kaul (1998) and Jegadeesh and Titman (2001). This analysis showed that it is neither of the two effects in solitude that drives the outperformance. Especially the contribution of the cross-sectional variation should not be under-estimated, implying that the differentiating effect of the momentum indicator is limited.

The second method (modelling the relationship between threshold and return) did not work either. It showed that not only the returns, but also risk is of essence. In the literature's asset selection context the systematic risk is more or less constant. While in the market timing context with an all-or-nothing decision, the systematic risk varies with the number of positions. Therefore not only the probability of a positive future return determines the thresholds, but also the number of positions (i.e. the balance between reducing risks and the probability of positive returns).

The third method (in-sample optimisation) allowed for the incorporation of risk in the optimisation. The optimal zones did not change much between the in- and out-of-sample periods, and were (depending on the strategy) rather broad. Therefore this method provided well performing thresholds for the strategies.

The performance of the strategies is measured on risk-adjusted returns. Additionally a third factor (robustness) is added based on several publications in the literature. Robustness is measured as the independence of the selected time period, assets, and if the long/short positions contribute equally. Later on in the tests, it was this third factor (robustness) that proved to be crucial, because it challenges the predictability/usability of the results (see the next chapter for a discussion on this topic).

The second part of the report tests the strategies on their performance. The tests are split in three phases: (1) the performance of the academic strategies in a simplified context, (2) an evaluation of the current settings of KAOF's momentum strategy and the performance of two new strategies all in a simplified context, and (3) the performance of all the strategies with the other signals of KAOF to mimic reality. This split proved to be useful, since the first two phases provided insight in the strategies, while the third phase is more practically relevant, however a black-box.

The first test leads to the following conclusions. In concordance with the literature, there is no need for a waiting period with futures. The R/W/H and 52-Week High strategies outperformed the current strategy significantly on risk-adjusted returns. However, the robustness tests showed that this outperformance is not that strong over all subperiods. This combined with the sensitivity towards specific assets and the long positions challenges the robustness of these strategies. Also, accepting this outperformance is not without consequence: the strategies have more exposure, switch signal more frequently and have counter-intuitive thresholds. Especially this last point is interesting, since it shows a strong dependence on the market conditions[4]. Based on this the academic strategies do not provide an obvious improvement.

[4]Due to the long and strong bull markets, the thresholds are very low, to benefit maximally from these markets.

However comparing the strategies in a Monte Carlo simulation to a random strategy with the same exposure, showed a significant outperformance (on both returns and risk-reduction). This is an important result, and suggests that there is some anomaly in the markets, which the strategies apparently capture.

The second test, evaluating the current strategy, did not bring substantial improvements at all. Due to the very low predictive power of the momentum indicators, none of the tests provided strong evidence for change. The parameters values (such as a RSI window of 14w) do not seem to be a bad choice. Removing the profit takings and crossovers increased risk significantly, while marginally effecting returns. Setting the thresholds based on the volatility of an asset improved performance a bit, but not significantly. Partly because the thresholds did not differ much from the current settings. So the current strategy seems to be well designed.

The third test, analysing the performance of the strategies in KAOF's context with the other signals (valuation and business cycle), did not radically change the previous conclusions. However the combination with valuation (compared to momentum alone) proofs very fruitful. Several academic publications already confirm a benefit from combining both strategies (Blitz & Vliet, 2008; Asness et al., 2009; P. Wang, 2011). This research shows that the benefit stems from a reduction in the risks (returns did not change).

To conclude: the 52-Week High strategy showed the highest performance, and outperformed the current strategy in several occasions. However, it is not an obvious improvement, due to the weak robustness of all strategies (i.e. high sensitivity to certain assets, and time period dependence). This also limits the reliability that the results will be similar in the future. Additionally the strategy has several effects that need to be accepted, such as the counter-intuitive thresholds, and more exposure.

This research also showed that there is a momentum effect, although weak. The momentum indicators do not have strong predictive power over future returns. Therefore the strategies exhibit a high sensitivity to specific factors, such as the assets and time periods. The market timing context of KAOF raises the bar to profit from the momentum effect compared to asset selection. The analyses showed that not only returns, but especially risk is an important factor in such a context. Additionally the comparison showed, that outperformance in an asset selection context (commonly used by the academic literature) is for a major part driven by the cross-sectional variation[5]. Indicating that neither Jegadeesh and Titman (2001) nor Conrad and Kaul (1998) are fully right.

The following chapter discusses the limitations and implications of these results. It gives several specific topics for further research, and states several suggestions and considerations for Kempen & Co, in particular KAOF.

[5] I.e. sorting the assets in a set each time period provides crucial differentiating information, which the momentum indicators solely do not provide.

Chapter 9

Discussion, Further Research & Advise

The previous chapter concluded this research by answering the main research question. This chapter reflects on the limitations and implications of these conclusions. The first section discusses the limitations, while the second section provides some tangible implications for Kempen & Co and KAOF, and provides several specific areas for further research.

9.1 Limitations

The previous chapter's conclusion is not strong. There are indications that the 52-Week High strategy can be an improvement, however there are many of unwanted sensitivities and variations softening this conclusion. The following paragraphs discuss these factors, which are all rooted in the unavoidable, but key assumption that the past is highly informative for the future.

The analyses have shown that the outcomes of the strategies are greatly affected by the choice of assets. This also means that the strategies are rather sensitive to the portfolio construction scheme and to the weights. In this research the weights and portfolio scheme of KAOF are used, in order to mimic the actual behaviour. A different scheme, weights and assets can lead to very different conclusions. This limits the generalisability of this research.

Even more problematic is the sensitivity to the actual time series[1], and the time periods. This first point shows that it is very important to use data that is as close to the actual realised returns as possible. So for this research, since the synthetic future prices do not exactly match the actual future prices, and due to small differences in the roll-overs, the results probably deviate from reality. It also shows that small variation (e.g. in the data) can have a large impact, i.e.

[1] I.e. several data sources providing time series data for the same asset have very small difference in the provided data

details matter. This further broadens the gap between the analysis and reality, and makes it questionable if the results hold for the future.

This sensitivity to details, such as the exact time series, also makes the results dependent on several design decisions. Some where set due to the scope of this research (such as the portfolio construction scheme), others where chosen such as the cut-off point between the in- and out-of-sample periods. Nonetheless this is unwanted and further limits the generalisability and the robustness of the results. Exposure to these factors is inevitable, however important to be realised.

All these limitations are rooted in the assumption that the past is highly informative for the future, a doubtful but usable assumption. A thorough robustness analysis is very important to strengthen the conclusions. But as the previous paragraphs have shown, the robustness of the results in this paper is rather weak and limited by many factors. This significantly reduces the strength of the conclusions, and effects measured. By itself, this is not strange; if this research would have led to profound effects, this would be in contradiction to the (weak) efficient market hypothesis. Nonetheless the weak robustness makes the results open for discussion on several grounds.

As final point: viewing the past as a realisation of a stochastic process (which will continue in the future), gives raise to error-terms/noise in the analysis capturing this process. Due to the weak predictive power of the momentum indicators, these error-terms were especially dominant. This challenged the measurability of effects and makes it questionable whether an effect is really due to the process or caused by a specific random sequence of these error-terms. Therefore many analyses in this research did not lead to strong evidence for change, or set different parameters.

To summarise: it is important to realise that the robustness of the conclusions is weak. This makes the believe in the key assumption (i.e. the past is highly informative for the future) very important. All together it weakens the generalisability of the results and any application should be done with care.

9.2 Implications

The conclusions, and especially the limitations, lead to several implications of this research for the academic community but also for practise (e.g. Kempen & Co). The following section discusses the implications for the academic community and ends with a couple of suggestions for further research. The second subsection states the implications for Kempen & Co and ends with several suggestions on how the results can be implemented/used.

9.2.1 Implications & Further Research for the Academic Community

This research augmented the already reported conclusion that there is a momentum effect in financial markets. However this research has contributed by showing that:

- A thorough robustness analysis is essential. Due to the weak momentum effect, many other factors can distort the results. In my opinion the academic literature generally lacks a thorough robustness analysis, making it possible that the momentum effect is overestimated (for instance due to cross-section variation).
- It is important to control for the factors: assets, time periods and portfolio construction scheme.
- It is important to replicate reality is much as possible, especially when selecting the data and portfolio construction scheme. Small variation can have a big impact, increasing the mismatch. This also introduces more complexity limiting the analysis.

Based on these conclusions, I suggest the following areas/topics for further research:

- Due to the weak robustness, more insight is needed in what the effect is of different assets, portfolio schemes et cetera is to increase the generalisability of the results.
- This research showed that in an asset selection context a large part of the results are due to the cross-section variation, instead of the momentum indicator. Since the majority of the academic research focusses on this context, more research to the magnitude of the cross-section effect is essential.
- The translation from relative reference to threshold showed that the performance is not solely due to the indicator, but also for a large part driven by the sorting of the asset (i.e. in the momentum literature discussed as the cross-section variation at a given time point in the set). It would be interesting to see if this effect is also visible in other markets and with other indicators, since it indicates another riddle in the efficient market hypothesis.

9.2.2 Implications & Implementation in Practise

The most important implication in practise is to realise that there are many unwanted factors that significantly impact the results of a momentum strategy. The following points indicate such factors, that are to my opinion worthwhile to review for Kempen & Co:

- The time series used in all the analysis. This research showed that the time series can have large impact on the results. Currently there is no clear overview and policy on what to use. To limit variations and make the analysis comparable a clear decision is needed. The important trade-off is between staying close to reality as much as possible and the length of the data history available.
- The threshold analysis on the current strategy showed that the current thresholds are in a local optimum, but also indicated that a higher more ro-

bust optimum has lower thresholds. However these thresholds are counter-intuitive and primarily driven by the strong bull markets of the past. This poses a trade-off between intuition, the future market outlook and an increase in performance.

- The analysis showed that several assets primarily contribute to the performance. Therefore Kempen & Co should be careful in adding new assets. A thorough analysis of the diversification and performance benefits is essential. Also setting the weights should not be taken lightly, since the effects can be large.

Overall, it is important to realise the effect of the market timing context. The predictive power over momentum indicators is low, therefore it is hard to predict whether the next period will be positive. However not taking a position means no risk. Analogous this can be seen as the decision to participate in a game with a very weak indication that you might win, or do not play and certainly do not loose. Compared to a player which always participates, it might be hard to keep up. Since you only have a weak indication in winning, it will happen frequently that you decided not to participate while you would have won. Therefore the other player might easily outperform you, while probably showing more volatility in his wealth. Instead of such a market benchmark, KAOF has an absolute target, further challenging the strategy. Not playing means, that next period one must make-up for the lost performance against the absolute benchmark (which opposite to the market will always have a positive return). This all indicates that the risk framework and the ability to effectively use leverage is very important, and probably has a greater effect on the profitability than the actual strategy (due to the weak predictive power).

The goal of this research was to improve KAOF's current momentum strategy. Although the results are not strong, the 52-Week High strategy appears to offer an improvement. Due to the weak robustness and the practical consequences (such as counter-intuitive thresholds) I do not suggest that Kempen & Co replaces the current strategy. However this research suggests that there is value in looking at the closeness of an asset's price to its 52-Week High/Low. Running this strategy parallel might offer new and valuable insights for Kempen & Co. It also allows Kempen & Co and clients to develop a feeling with the strategy, change and tweak it before implementing or combining it with the current strategy.

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Appendices

Appendix A

Literature Overview

The tables below show the results of the literature search. Table A.2 shows the publications added after reviewing the articles shown in table A.1. The article indicates by an $*$ are the articles selected for the short list. The *Gr.* column indicates the classification of the publication:
N DesFcribes new momentum strategies
A Applies strategies to different markets or assets classes
E Explains momentum profits or tests the validity
I Irrelevant

Table A.1
Overview of Literature on Momentum Strategies

Authors	Year	Short title	Gr.	Info	R/W/H	Ind.	52w	Earn.	Proof
Chang, Ghon Rhee, et al.	1995	Price volatility of ...	I						
Shastri, Shastri, et al.	1995	Trading mechanisms and ...	I						
∗Chan, Jegadeesh, et al.	1996	Momentum strategies	N	R/W/H	x				+
∗Asness	1997	The interaction of ...	A	Value	x				+
∗Carhart	1997	On persistence in ...	A	Fund	x				+
∗Conrad, Kaul	1998	An anatomy of ...	E						+
∗Rouwenhorst	1998	International momentum strategies	A	International	x				+
Avery, Chevalier	1999	Identifying investor sentiment ...	I						
Chan, Jegadeesh, et al.	1999	The Profitability of ...	A	International	x			x	+
Schiereck, De Bondt, et al.	1999	Contrarian and Momentum ...	A	Germany	x				+
Chan, Hameed, et al.	2000	Profitability of momentum ...	A	International	x				+
Hong, Lim, et al.	2000	Bad news travels ...	E	Information Diffusion					+
∗Grundy, Martin	2001	Understanding the nature ...	E	Risk					–
Huang, Fu, et al.	2001	Daily price limits ...	I						
∗Jegadeesh, Titman	2001	Profitability of momentum ...	E	Various	x				+
Liu, Lee	2001	Does the momentum ...	A	Japan	x				–
Wang	2001	Investor sentiment and ...	A	Futures	x				+
∗Chordia, Shivakumar	2002	Momentum, business cycle, ...	E	Macroeconomic					+
Kang, Liu, et al.	2002	Contrarian and momentum ...	A	China	x				+
Xiang, He, et al.	2002	Continuous overreaction, insiders ...	E	Insiders trading					–
Ahn, Conrad, et al.	2003	Risk Adjustment and ...	E	Stochastic Discounting	x				+
Borensztein, Gelos	2003	A panic-prone pack? ...	I						
Chan	2003	Stock price reaction ...	A	News impact					+
Dewally	2003	Internet investment advice: ...	I						

Table A.1
(Continued)

Authors	Year	Short title	Gr.	Info	R/W/H	Ind.	52w	Earn.	Proof
Garcia, Covarsie, et al.	2003	Over-reaction and under-reaction ...	A	Spain	x				+
Gorman	2003	Conditional performance, portfolio ...	I						
Lin, Wang	2003	Systematic skewness in ...	I						
Moskowitz	2003	An Analysis of ...	I						
Okunev, White	2003	Do momentum-based strategies ...	A	Currencies	x				+
Pastor, Stambaugh	2003	Liquidity risk and ...	I						
Scott, Stumpp, et al.	2003	Overconfidence bias in ...	A	International	x				+
Dare, Holland	2004	Efficiency in the ...	I						
Demir, Muthuswamy, et al.	2004	Momentum returns in ...	A	Australia	x				+
Karolyi, Kho	2004	Momentum strategies: Some ...	E	Bootstrap	x				–
Korajczyk, Sadka	2004	Are momentum profits ...	E	Trading costs					–
Mengoli	2004	On the source ...	E	Italy	x				+
Nijman, Swinkels, et al.	2004	Do countries or ...	A	Country indices	x				+
Pan, Liano, et al.	2004	Industry momentum strategies ...	E	Autocorrelation		x			+
Patro, Wu	2004	Predictability of short-horizon ...	I						
*Aarts, Lehnert	2005	On style momentum ...	N	Style momentum					+
Fong, Wong, et al.	2005	International momentum strategies: ...	E	Stochastic Dominance					+
Frino, Jarnecic, et al.	2005	Bid-ask bounce and ...	I						
Gebhardt, Hvidkjaer, et al.	2005	Stock and bond ...	A	Stock & Bond	x				+
*Griffin, Ji, et al.	2005	Global momentum strategies	A	International	x			x	+
*Grinblatt, Han	2005	Prospect theory, mental ...	E	Mental accounting					+
Lei, Wu	2005	Time-varying informed and ...	I						
Marcato, Key	2005	Direct investment in ...	A	Real-Estate	x				+
Shen, Szakmary, et al.	2005	Momentum and contrarian ...	A	International	x				+
Swanson, Lin	2005	Trading behavior and ...	I						

Table A.1
(Continued)

Authors	Year	Short title	Gr.	Info	R/W/H	Ind.	52w	Earn.	Proof
van der Hart, de Zwart, et al.	2005	The success of …	I						
Chakrabarty, Trzcinka	2006	Momentum: Does the …	E	Database					+
Corredor, Muga, et al.	2006	The profitability of …	E	Seasonality					+
Hong, Yi	2006	On the herding …	A	Korea, Fund	x				+
Huang	2006	Market states and …	E	Market state	x				+
Kho	2006	Interaction of momentum …	A	Korea, Stock & Bond	x				+
Rodriguez, Fructuoso	2006	An analysis of …	A	Spain	x				+
Shieh	2006	Evolution of momentum …	I						
Zhang	2006	Information uncertainty and …	A	Futures	x				+
Agyei-Ampomah	2007	The post-cost profitability …	A	UK	x				+
Antoniou, Lam, et al.	2007	Profitability of momentum …	E	Cycle, Biases					+
Benson, Gallagher, et al.	2007	Momentum investing and …	I						
Caperos, Aquilue	2007	Asymmetric risk and …	E	Skewness					–
Chou, Wei, et al.	2007	Sources of contrarian …	A	Japan, Contrarian	x				+
Lam, Chong, et al.	2007	Profitability of intraday …	A	Short-Term					+
*Miffre, Rallis	2007	Momentum strategies in …	A	Commodity Futures	x				+
Muga, Santamaria	2007	The momentum effect …	A	Latin-America	x				+
Parmler, Gonzlez	2007	Is momentum due …	E	Data-snooping					–
*Rachev, Jasic, et al.	2007	Momentum strategies based …	N	Risk-Reward					+
Rey, Schmid	2007	Feasible momentum strategies: …	A	Switzerland	x				+
Safieddine, Sonti	2007	Momentum and industry …	A	US		x			+
Sagi, Seasholes	2007	Firm-specific attributes and …	E	Firm-specific					+
Sias	2007	Causes and seasonality …	E	Cycle					+/–
Abbes, Boujelbene, et al.	2008	Momentum profits and …	E	Trading costs	x				+

Table A.1
(Continued)

Authors	Year	Short title	Gr.	Info	R/W/H	Ind.	52w	Earn.	Proof
Brown, Yan Du, et al.	2008	The returns to …	A	Asia & Value	x				–
Foster, Kharazi	2008	Contrarian and momentum …	A	Iran	x				+
Goldbaum	2008	Coordinated investing with …	I						
*Kos, Todorovic	2008	S&P Global Sector …	N	Short-Term Survival					+
Luo, Li	2008	Futures market sentiment …	I						
McInish, Ding, et al.	2008	Short-horizon contrarian and …	A	Short-Term, Asia					+
Mulvey, Kim	2008	Active equity managers …	A	Funds		x			+
Naughton, Truong, et al.	2008	Momentum strategies and …	A	China	x				+
Parhizgari, Nguyen	2008	ADRs under momentum …	A	ADRs	x				+
Ranaldo, Haberle	2008	Wolf in sheep's …	I						
Bettman, Maher, et al.	2009	Momentum profits in …	A	Australia	x				+
Chan, Cheng	2009	Price reversals versus …	A	Hong Kong			x		+
Chen, Lin, et al.	2009	Investment preference and …	I						
*Du, Huang, et al.	2009	Why is there …	E	Taiwan					+
Frino, Jarnecic, et al.	2009	An event time …	I						
Fu, Kang	2009	Industry momentum effect …	A	Taiwan	x				+
Muga, Santamara	2009	El efecto momentum …	A	Mexico	x				+
Tziogkidis, Zachouris	2009	Momentum equity strategies: …	A	Firm-specific	x				+
Biais, Bossaerts, et al.	2010	Equilibrium asset pricing …	I						
*Cheng, Wu	2010	The profitability of …	A	Honk Kong	x				+
Chng	2010	Comparing Different Economic …	I						
*Chui, Titman, et al.	2010	Individualism and momentum …	E	Culture					+
Du, Zhao	2010	Momentum and autocorrelation …	E	Cross-serial correlation	x				+
Galariotis	2010	What should we …	A	Australia	x				+
Griffin, Kelly, et al.	2010	Do market efficiency …	I						

Table A.1
(Continued)

Authors	Year	Short title	Gr.	Info	R/W/H	Ind.	52w	Earn.	Proof
*Gupta, Locke, et al.	2010	International comparison of ...	A	International	x	x	x		+/−/−
Hung, Lu, et al.	2010	Mutual fund herding ...	A	Fund, Taiwan	x				+
*Hur, Pritamani, et al.	2010	Momentum and the ...	E	Disposition effect					+
Lee, Kuo	2010	Momentum effect and ...	A	Chinese Real-Estate	x				−
Lin, Swanson	2010	Contrarian strategies and ...	I						
*Malin, Bornholt	2010	Predictability of future ...	A	Emerging markets	x		x		+/−
Peltomaki, Peni	2010	Style rotation and ...	A	Funds	x				+
Phua, Chan, et al.	2010	The influence of ...	A	Australia	x				+
Pota, Wang	2010	The coskewness puzzle	I						
Sigl-Grab, Schiereck	2010	Returns to speculators ...	I						
*Wang, Huang, et al.	2010	Momentum strategy and ...	A	Taiwan	x		x		+/+
Wu	2010	Momentum trading, mean ...	A	China	x				−
Zhou, Geppert, et al.	2010	An anatomy of ...	A	China	x				−
*Liu, Liu, et al.	2011	The 52-week high ...	A	International			x		+

Table A.2
Publications added based on References in Short list

Authors	Year	Short title	Gr.	Info	R/W/H	Ind.	52w	Earn.	Proof
Jegadeesh, Titman	1993	Returns to buying ...	N	R/W/H	x			+	
Barberis, Schleifer, et al.	1998	A model of ...	E	Behavioural					+
Daniel,Hirshleifer, et al.	1998	Investor psychology and ...	E	Behavioural					+
Moskowitz, Grinblatt	1999	Does industry explain ...	N	Industry		x			+
King, Silver, et al.	2002	Passive momentum asset ...	A	Asset allocation	x				+
Ready	2002	Profits from technical ...	E	Moving average					–
George, Hwang	2004	The 52-week high ...	N	52-week high			x		+
Pirrong	2005	Momentum in futures ...	A	Futures	x				+
Galakis, et al.	2006	How a moving ...	N	Moving average					+
Brush	2007	A flexible theory	E	Behavioural					+
Blitz, Vliet	2008	Global tactical cross-asset ...	A	Asset allocation	x				+
Fuertes, Miffre, et al.	2010	Tactical allocation in ...	A	Asset allocation	x				+

Appendix B

Comparison Synthetic Futures

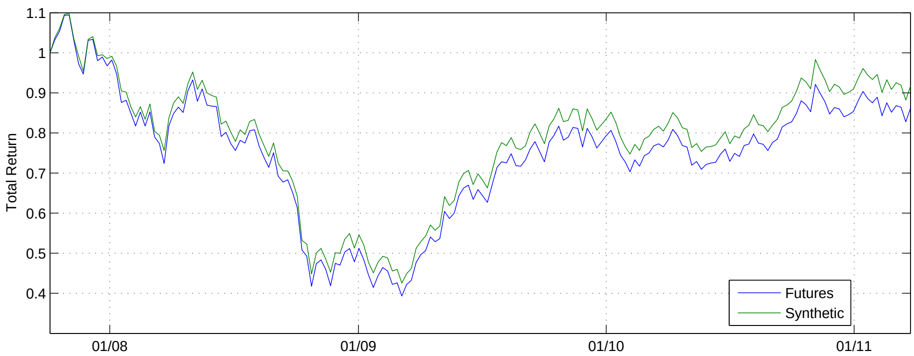

Figure B.1: Hang Seng Synthetic vs Real Futures

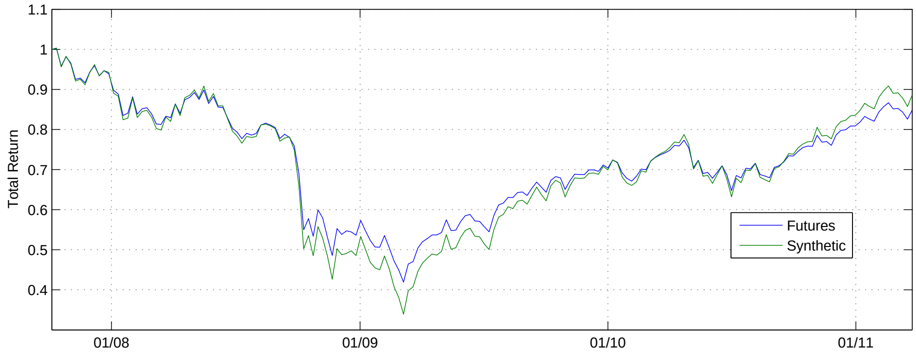

Figure B.2: S&P 500 Synthetic vs Real Futures

Figure B.3: EuroStoxx 50 Synthetic vs Real Futures

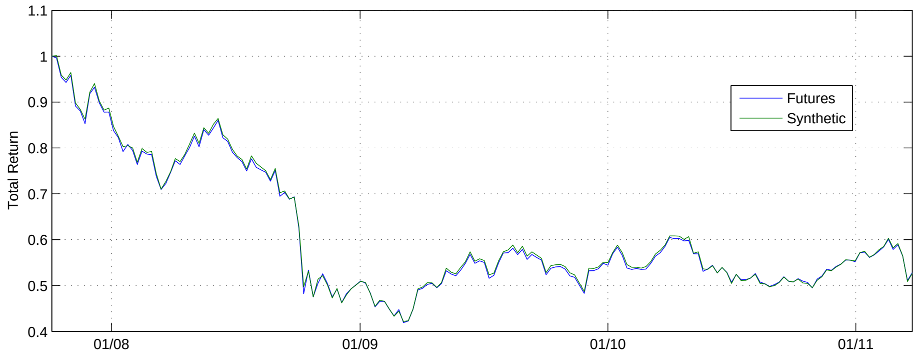

Figure B.4: Topix Synthetic vs Real Futures

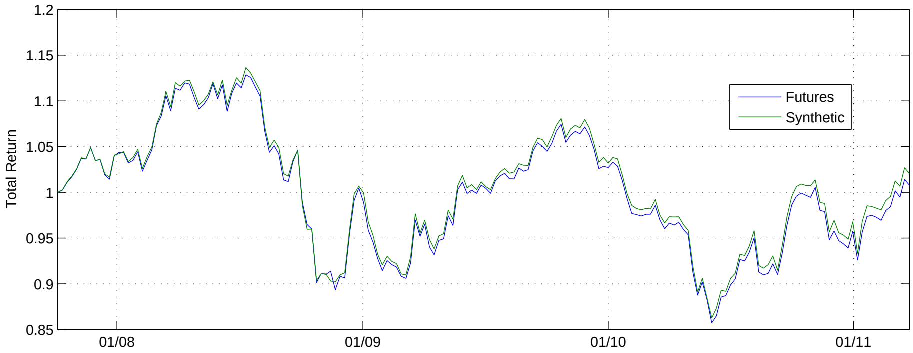

Figure B.5: EUR/USD Synthetic vs Real Futures

Figure B.6: EUR/JPY Synthetic vs Real Futures

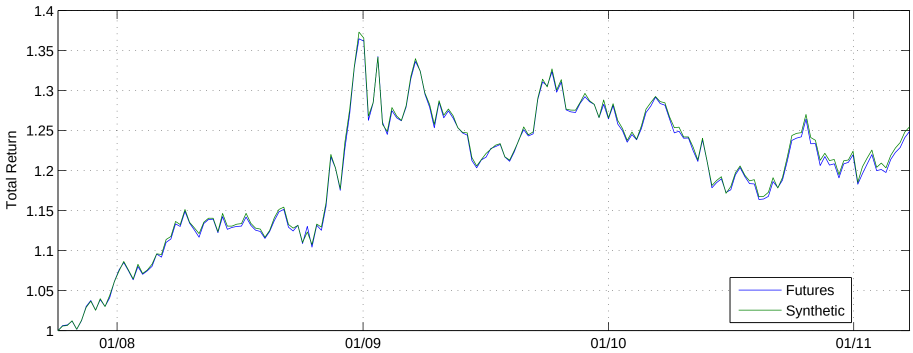

Figure B.7: EUR/GBP Synthetic vs Real Futures

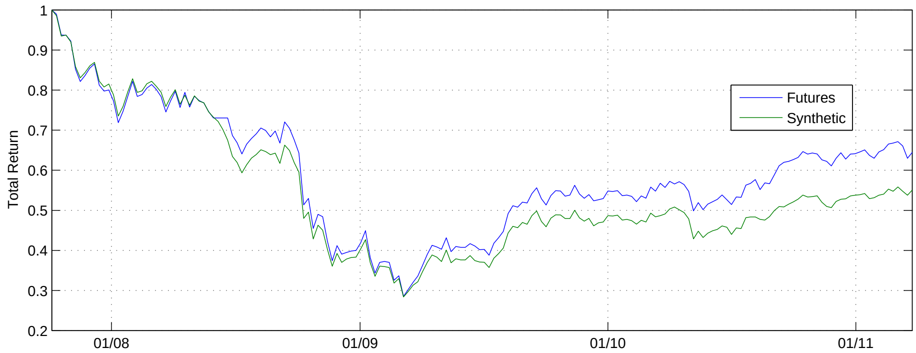

Figure B.8: EPRA Europe Synthetic vs Real Futures

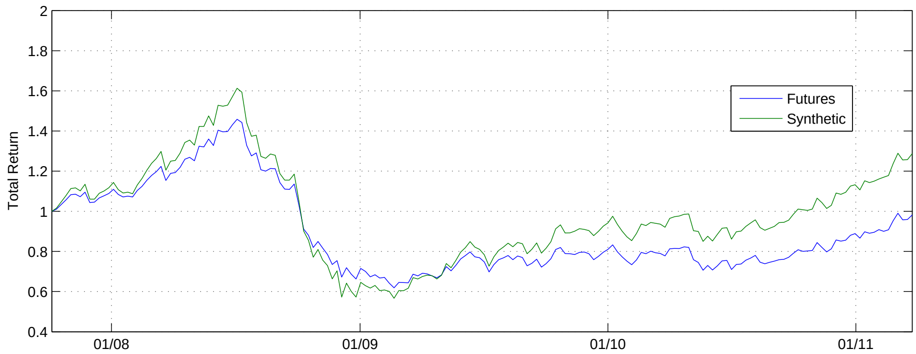

Figure B.9: GSCI Synthetic vs Real Futures

Appendix C

Momentum in the Dutch Equity Market

This appendix gives an overview of the analysis of momentum in the Dutch equity market. The analysis served as first starting point and testing framework for developing absolute reference points for the strategies.

The first section details the data that is used. The second section states the results of each momentum strategy and concludes with a comparison. The final section describes the tests for converting the relative references to absolute references for the strategies. The appendix ends with an overall conclusion, reflecting upon the results.

C.1 Data

All data is obtained from the Thomson Reuter's Datastream. Weekly data of Friday's closing prices are used. Table C.1 gives an overview of the data requirements for the different strategies, which data sources are selected and the availability. The Dutch ten year government bond benchmark has the least availability, therefore all analysis will start from 1/Jan/1988.

The main selection criterion for the sources is the availability. This is why the Dutch interest rates from the British Bankers Association (LIBOR) are not selected, but the Thomson Reuters alternative. The sources for the business cycle data are chosen to fit the Dutch equity market as much as possible, whereas Chordia and Shivakumar (2002) use USA proxies. Only for the default spread no Dutch proxy is available with a long history. For the term spread the benchmark with the shortest duration available is the two year government bond benchmark, while Chordia and Shivakumar (2002) use three month T-bills. The impact of these alternatives is estimated to be minimal, because not the actual spread is relevant but the correlation of the stock returns with these variables.

Table C.1
Data Overview

Requirement	Source	Mnemonic	Data Type	Available
		Equity Market		
Dutch Stocks	Datastream selection	FHOL & DEADNL	Return Index	5/Jan/1973
			Closing Prices	5/Jan/1973
			Turnover Volume	7/Feb/1986
			Number of Shares Outstanding	5/Jan/1973
		Business Cycle Data		
Dividend Yield (DIV)	AEX	AMSTEOE	Dividend Yield	5/Jan/1973
Default Spread (DEF)	Moody's US Corp AAA Bond	FRMCAAA	Interest Rate	5/Jan/1973
	Moody's US Corp BAA Bond	FRMCBAA	Interest Rate	5/Jan/1973
Term Spread (TERM)	NL Benchmark 2Y Gov Bond	BMNL02Y	Interest Yield	1/Jan/1988
	NL Benchmark 10Y Gov Bond	BMNL10Y	Interest Yield	6/Jan/1984
3-M Interest Yield (YLD)	Thomson Reuter 3M Dutch Interest	ECNLG3M	Interest Rate	3/Jan/1975
		General Data		
Benchmark	AEX	AMSTEOE	Return Index	7/Jan/1983
Risk Free Rate	Thomson Reuter 1W Dutch Interest	ECNLG1W	Interest Rate	3/Jan/1975

Table C.2
Stocks Removed from Set

Not enough obs.	Penny Stocks
HAGEMEYER AGM	EUROCOM PROPERTIES
UNI INVEST CERTS	IMEKO HOLDING
VOLKER WESSEL STEVIN	LAURUS SETS
VOLKER WESSEL STEVIN AGM	MAWENZI RESOURCES (AMS)
	MAWENZI RESOURCES (AMS)
	MONTEDISON (AMS)
	NEW VALLEY CORP (AMS)
	QURIUS
	SCHRODER INTERNATIONAL
	UNILEVER PREF DEAD

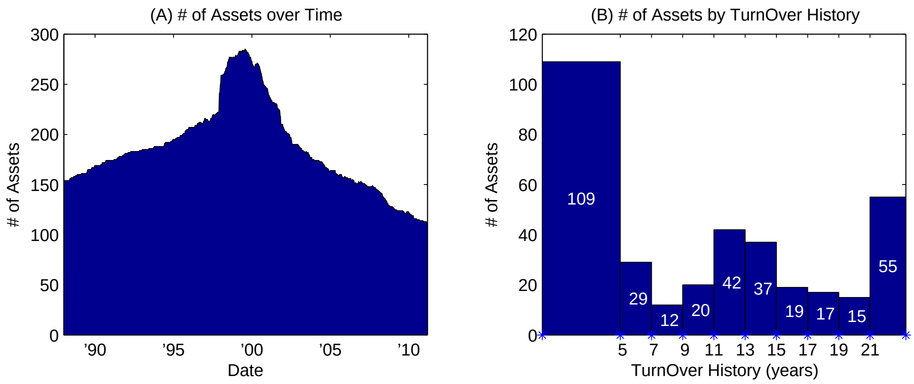

Figure C.1: Availability of Assets and TurnOver History

Ince and Porter (2006) show that some caution should be taken when handling Datastream data of whole equity markets. Inline with their analysis non-pure Dutch equity assets are removed from the set, such as REITs, foreign stocks and trusts[1], and trailing datapoints of delisted stocks are removed. This resulted in four stocks being removed from the set with less than two valid observations (see table C.2). In concordance with Jegadeesh and Titman (1993); Rijken (2007) 'penny' stocks (stocks with a price less than €2) are removed, because they significantly drive profits in the short positions, are illiquid and exhibit non-normal return patterns. This resulted in the deletion of ten stocks (see table C.2). Stocks which price is not in the whole period below the €2 threshold, are not deleted, or these observations are not filtered out, since this can introduce a significant bias (Rijken, 2007). In total a set of 106 currently listed and 249 delisted Dutch stocks is obtained, see panel A of figure C.1 for the availability over time.

For all stocks the total return series are downloaded, because they included capital gains from dividends, and thus give a better representation of the return on investment compared to the price series. The returns over period $t-1$ to t

[1]Only assets with an International Securities Identification Number (ISIN) starting with 'NL', a currency notation in euro's or Dutch guilders (€1 = FL. 2.20371) and with a type set to 'EQ' are included.

are calculated as:

$$r_t = \frac{p_t}{p_{t-1}} - 1 \tag{C.1}$$

when p_t is the total return index value at time t. Absolute weekly returns larger than 100% are filtered out, because they significantly impact the results and are probably due to stock splits/mergers. Table C.3 lists all outlying returns. Some strategies, like the 52-Week High, use prices instead of returns, due to the removal of outliers a new price series is recalculated by:

$$p_t = p_{t-1} \times r_t \tag{C.2}$$

with $p_1 = 1$. The turnover ratio is calculated as the $\frac{\text{traded volume}}{\text{number of shares outstanding}}$. The Capital Gains strategy requires at least five years of history for calculating the indicator value, panel B in figure C.1 shows that 109 out of the 355 assets will not be included in the analysis of the Capital Gains strategy.

Table C.3
Data Overview

Stock	Observation	Weekly Return
AND INTLPUBLISHERS	14-Sep-2001	102.70%
AND INTLPUBLISHERS	07-Dec-2001	102.70%
AND INTLPUBLISHERS	04-Jan-2002	102.70%
AND INTLPUBLISHERS	01-Feb-2002	202.70%
AND INTLPUBLISHERS	29-Mar-2002	102.70%
DICO INTL	07-Jan-2011	126.25%
EGO LIFESTYLE HOLDING	23-Oct-2009	351.37%
EGO LIFESTYLE HOLDING	26-Feb-2010	649.70%
EGO LIFESTYLE HOLDING	16-Apr-2010	674.60%
EGO LIFESTYLE HOLDING	21-May-2010	309.76%
FORNIX BIOSCIENCES	03-Mar-2000	108.69%
HES - BEHEER	12-Jan-2001	108.33%
INNOCONCEPTS NM	01-May-1998	189.85%
MANAGEMENT SHARE	08-Oct-2010	112.02%
ORANJEWOUD 'A'	02-May-1997	133.55%
ORANJEWOUD 'A'	01-Aug-1997	328.45%
PHARMING GROUP	14-Sep-2001	200.00%
PHARMING GROUP	26-Oct-2001	102.78%
QURIUS	06-Jun-2003	121.20%
SIMAC TECHNIEK	09-May-2003	107.99%
VIVENDA MEDIA GROEP	05-Oct-2001	113.33%
VIVENDA MEDIA GROEP	04-Mar-2005	123.68%
AINO	02-May-2003	145.00%
AINO	06-Jun-2003	163.77%
ALLIED DOMECQ CERT(AMS)	08-Jan-1999	129.56%
ARMCO INCCERT (AMS)	08-Jan-1999	125.88%
ASHLAND CERT (AMS)	04-Feb-2000	209.09%
BEGEMANN KONGROEP 'B'	19-Jan-2001	106.63%
BESOUW(VAN CERTS)	29-Mar-1996	188.42%
BESOUW(VAN CERTS)	14-Mar-1997	334.78%
BREDERO VERNBEDR	16-Jun-1989	150.15%
BREDERO VERNBEDR	23-Jun-1989	131.93%
BREDERO VERNCERT	16-Jun-1989	127.03%

Table C.3
(Continued)

Stock	Observation	Weekly Return
CSS NM	02-May-2003	409.09%
DE VRIES ROBBE GROEP	04-Jan-2002	112.50%
DE VRIES ROBBE GROEP	08-May-2009	255.56%
DNC DE NED	02-Jul-1999	124.58%
DNC DE NED	14-Jan-2000	110.00%
DNC DE NED	13-Jun-2003	111.55%
EMBA	22-Jun-1990	136.64%
EMIS EUROMARKETING INFO	29-Mar-2002	172.61%
EVC INTERNATIONAL	16-Nov-2001	119.66%
GETRONICS	21-Mar-2003	164.72%
ING PREF	25-Jul-2008	233.06%
KENNEMERL VISSCHER	24-Dec-1999	899.96%
KPN QWEST 'C'	14-Jun-2002	116.67%
KROGER CERT (AMS)	25-Nov-1988	167.53%
KROGER CERT (AMS)	25-Apr-1997	105.46%
KROGER CERT (AMS)	02-Jul-1999	104.95%
LANDIS GROUP	26-Jul-2002	110.00%
LANDIS GROUP	30-Aug-2002	110.00%
LANDIS GROUP	13-Sep-2002	110.00%
LANDIS GROUP	27-Sep-2002	110.00%
LANDIS GROUP	22-Nov-2002	110.00%
LANDIS GROUP	21-Mar-2003	110.00%
LANDIS GROUP	02-May-2003	210.00%
LCI TECHNOLOGY GROUP	02-May-2003	300.00%
OMNIUM EUROPE	28-Nov-1997	150.31%
OMNIUM EUROPE	27-Mar-1998	366.11%
OMNIUM EUROPE	03-Apr-1998	257.23%
OMNIUM EUROPE	15-Feb-2002	160.06%
ORTHOCENTER	07-Jul-2000	1898.75%
SEAGULL HOLDING	12-Oct-2001	144.00%
TEXTIELGRP TWENTE	05-Apr-2002	131.49%
TOOLEX INTERNATIONAL	14-Sep-2001	230.00%
UTDPAN-EURO COMMS 'A'	12-Oct-2001	106.69%
UTDPAN-EURO COMMS 'A'	16-May-2003	148.48%
VAN DER MOOLEN	23-Jul-2010	102.33%
VAN DER MOOLEN	27-Aug-2010	102.33%
VD HOOP BANKIERS	12-May-2006	100.74%
VERTO CERTS	15-Oct-1993	800.00%
VERTO CERTS	14-Jan-1994	358.21%
VERTO CERTS	14-Oct-1994	114.37%
VERTO CERTS	21-Jul-1995	108.29%
VHS ONROEREND	19-Jun-1992	131.43%
WYERS CERTS	11-Oct-1996	833.43%
WYERS CERTS	01-Nov-1996	114.08%

The risk free rate (Dutch one-week interest) is converted to a weekly return based on the simple interest:

$$r_t^w = \frac{r_{t-1}}{52} \tag{C.3}$$

The return is shifted forward to match the stock returns, which denote the return realised at the end of period t on an investment from $t-1$ to t. The business cycle interest yield is not converted to a weekly return, for the same reason as before that not the actual value is of interest but the correlation with stock returns. The term spread is calculated as the ten year interest yield minus the two year interest yield, and the default spread as the interest on the corporate BAA rated bonds minus the interest on the corporate AAA rated bonds.

C.2 Results of Momentum Strategies

C.2.1 R/W/H Strategy

The indicator of asset i value over a ranking period of R at time t is calculated as:

$$I_{it}^{r} = \begin{cases} \prod_{j=0}^{R-1} r_{i,t-j} & \text{if } r_{i,t-R+1}, \cdots, r_{i,t} \neq \text{n/a} \\ \text{n/a} & \text{otherwise} \end{cases} \tag{C.4}$$

Thus only assets with returns over the past $R-1$ periods are included. The most common strategies are the 6/0/6m and the 6/1/6m (or in weeks 28/0/28w and 28/4/28w). Figure C.2 shows the annualised return of the R/W/H strategy with different settings. Apparent is that independent of the waiting period the surface shows a maximum around a 40 week ranking period. More important is the effect that for no or a one week waiting period the surface slopes downward after the top to the shorter holding periods, whereas for a waiting period of four weeks or longer the maximum is at a holding period of one week. This means that the short-term reversals are effectively mitigated with a waiting period of a month.

Based on these surfaces, the most optimal setting is 32/4/1 achieving an average annual return of 40%. Figure C.3 shows whether all assets attribute equally to the performance. It is clear that there are differences between the assets. For the long positions some assets are selected nearly 40% of their availability, whereas other assets are never selected. In the short positions the difference is even bigger. However there does not seem to be a relation between the frequency an asset is selected for the long portfolio and short portfolio and vise versa. This difference could be driven by volatility, because more extreme price movements results in a higher indicator value. The black line indicates the average volatility of 30 assets. It is clear that indeed the assets which are selected more often have a higher volatility. This effect is seen also seen by Blitz and Vliet (2008).

The outperformance of this strategy compared to the AEX index is apparent from figure C.4. There is also a large difference between the most optimal setting (ex-post) and the default setting. Striking is however that the most optimal setting as well as the default setting underperformed the index for nearly the whole period until 2000, but the R/W/H strategies performed very well during the internet-bull burst in 2000 and the credit-crisis in 2008. The second panel in the figure shows what the contribution of the long and short positions has been in the most optimal setting. The long positions were the main contributors to the outperformance. The underperformance compared to the index before 2000 clearly is caused by the short positions, but during the crises it were the short positions who were the main contributors.

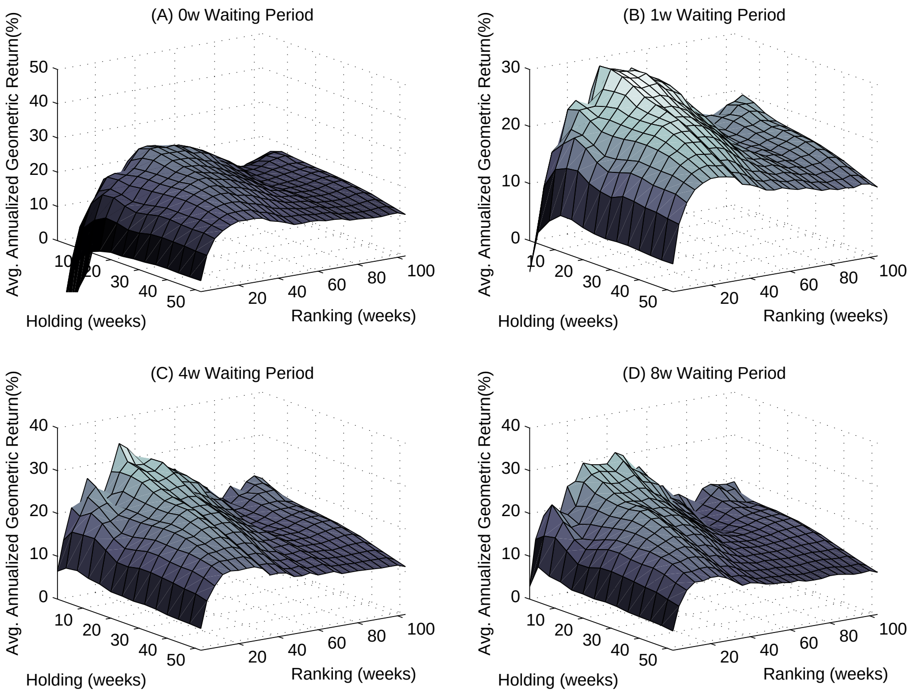

Figure C.2: Optimal R/W/H Strategy Settings

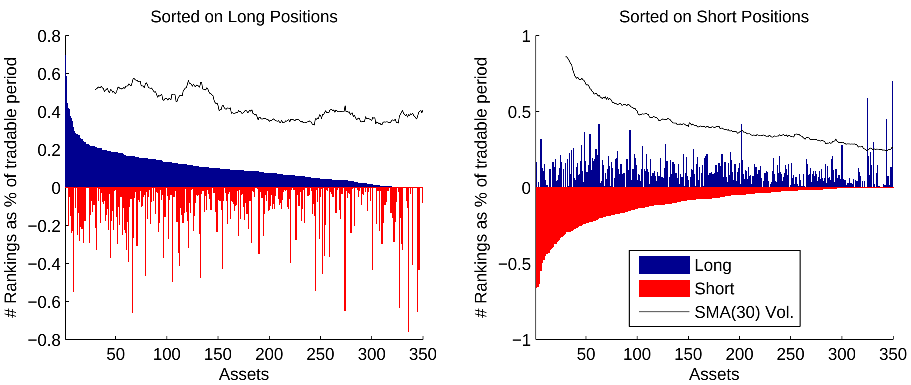

Figure C.3: Asset Selection in R/W/H Strategy with 32w Ranking Period

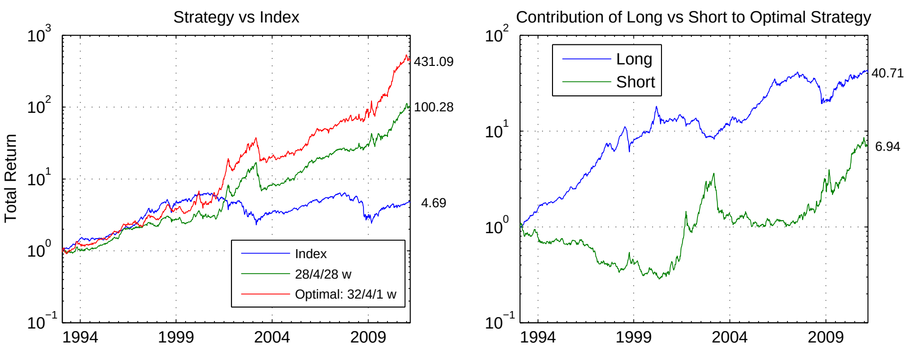

Figure C.4: Performance of R/W/H Strategies

C.2.2 52-Week High Strategies

The indicator for the 52-week high strategy is calculated as:

$$I_{it} = \frac{p_{it}}{max_{j=t-51,\cdots,t}\left(p_{ij}\right)} \tag{C.5}$$

where p_{it} is the price of the asset at time t. The asset prices have been recalculated based on the returns, because large price jumps were removed from the returns. Based on the indicator only long positions are taken, an alternative version is created (see the next section) which allows for short positions.

Figure C.5 shows the effect of the waiting and holding period on the returns. The returns are highest for short holding periods. However with a short holding period the returns are very sensitive to the waiting period. The short-term reversal effect seems to be mitigated with a relative short waiting period of one week. The most optimal setting is a waiting and holding period of four weeks.

The difference in performance between the default and optimal (ex-post) settings is marginal compared to the R/W/H strategies (see figure C.6 vs C.4). Again the out-performance of the index stems from the period after 2000, but pre-2000 the strategy follows the benchmark much better than the R/W/H strategy. This is due to the lack of short positions in the 52-Week High strategy. More remarkable is the negative correlation between volatility and the selection of assets as can be seen from the second panel in figure C.6.

52-Week High Strategies with Short Positions

This strategy is an alternative version of the 52-Week high strategy to allow for short positions. Therefore the price is not only compared the highest prices in the past year but also to the lowest price. The indicator is calculated as:

$$I_{it} = \frac{p_{it} - p_{it}^{\min}}{p_{it}^{\max} - p_{it}^{\min}} \tag{C.6}$$

where $p_{it}^{\max} = max_{j=t-51,\cdots,t}\left(p_{ij}\right)$ and $p_{it}^{\min} = max_{j=t-51,\cdots,t}\left(p_{ij}\right)$.

None of the tested waiting periods seems to mitigate the short-term reversals (see figure C.7), because in all instances a longer holding period performs better. However there is a large difference between the returns with or without a waiting period. Short holding periods of one week or one month seem to be optimal. Again a negative correlation between the volatility and the selection is seen in figure C.8, however only for the long position. Additionally the figure shows us that the stocks in the long portfolio seem to be less likely to also be included in the short positions and vise versa, i.e. there seem to be long and short stocks.

Figure C.9 shows the performance compared to the AEX and the contribution of the long and short positions to the performance. The results are not much different from the R/W/H strategy, which strengths the conclusion that the underperformance pre-2000 is due to the short positions. From figure C.7

C.2.3 Business Cycle Strategies

The indicator for the business cycle is calculates as:

$$I_{it} = \alpha_{it} DIV_t + \beta_{it} TERM_i + \gamma_{it} DEF_t + \delta_{it} YLD_t \tag{C.7}$$

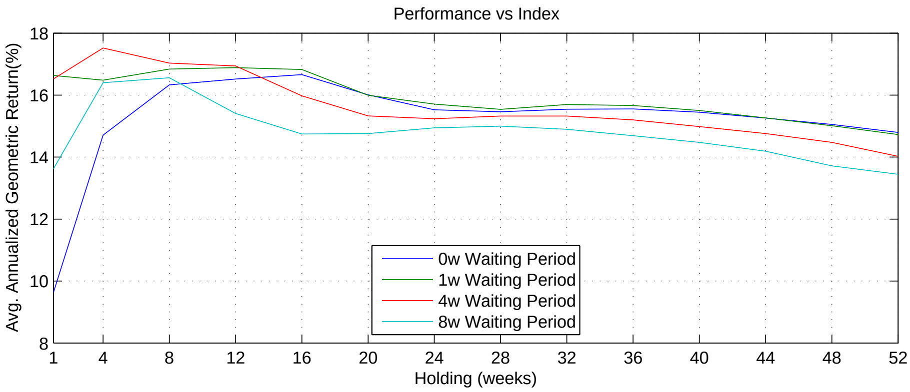

Figure C.5: Optimal 52-Week High Strategy Settings

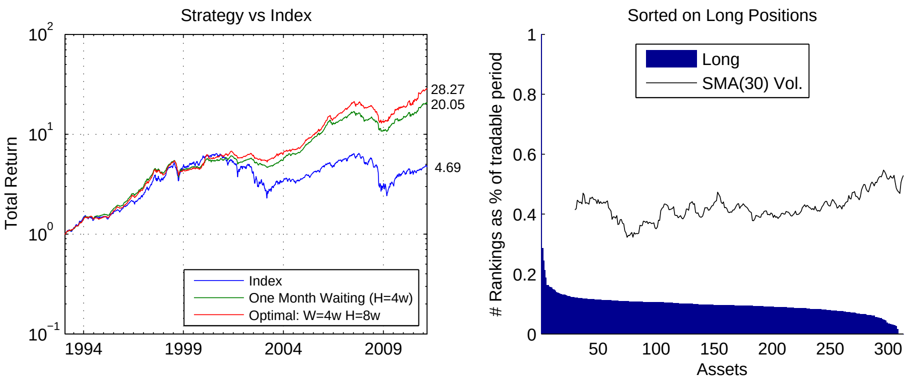

Figure C.6: Performance and Asset Selection of 52-Week High Strategy

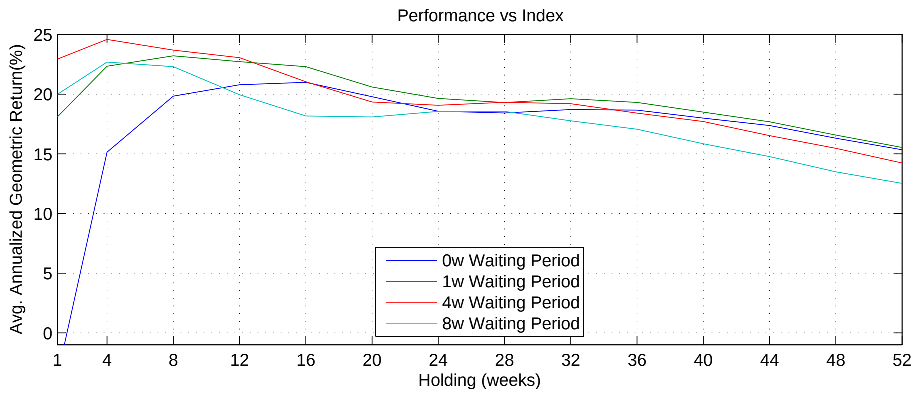

Figure C.7: Optimal 52-Week High (alt) Strategy Settings

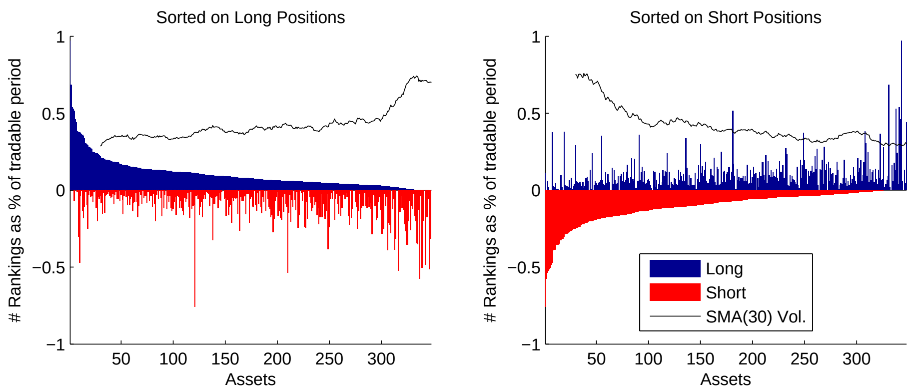

Figure C.8: Asset Selection in 52-Week High Strategy with Long & Short Positions

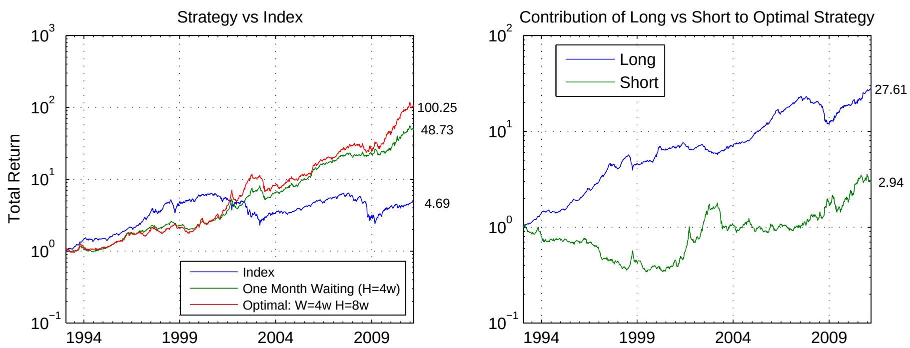

Figure C.9: Performance of 52-Week High Strategies with Short Positions where the parameters α_{it},β_{it}, γ_{it}, and δ_{it} are estimated based on the following equation:

$$\mathbf{r}_{it} = \begin{bmatrix} \mathbf{DIV}_{t-1} & \mathbf{TERM}_{t-1} & \mathbf{DEF}_{t-1} & \mathbf{YLD}_{t-1} \end{bmatrix} \begin{bmatrix} \alpha_{it} \\ \beta_{it} \\ \gamma_{it} \\ \delta_{it} \end{bmatrix} + \boldsymbol{\epsilon}_{it} \tag{C.8}$$

where the **bold** symbols denote vectors of the past 260[2] data points. The world economic factors are lagged one period. The regression is only calculated if at least 24 valid returns are available for stock i and all data points of the economic variables are valid.

The effect of the short term reversals is very prominent in figure C.10, since there is a large difference between the returns with and without a waiting period. Similar to the 52-Week High strategies, there is not much difference between the waiting periods. However a four week waiting period mitigates the short-term reversals, because the returns do not increase for longer holding periods than one week. The most optimal setting (ex-post) is a four week waiting and one week holding period. Figure C.11 shows a larger difference between how often assets are included in the portfolio compared to the R/W/H strategy, however the correlation with volatility is less prominent.

Overall the performance compared to the benchmark of the business cycle strategy is marginal, especially compared to the R/W/H strategy. The short positions only contributed to the returns during a very small window over the whole holding period. Thus this strategy would have performed much better if no short positions were taken, but also the contribution of the long positions is much weaker compared to other strategies.

C.2.4 Capital Gains Strategies

The capital gains indicator is calculated as:

$$I_{it} = \frac{p_{t-W} - R_t}{p_{t-W}} \tag{C.9}$$

$$R_t = \frac{1}{k} \sum_{n=1}^{260} \left(V_{t_n} \prod_{\tau=1}^{n} \left[1 - V_{t-n+\tau}\right] P_{t-n} \right) + V_t P_t \tag{C.10}$$

where p_t is the price of the asset (recalculated as for the 52-Week High strategy), W the waiting period and V_t is the turnover ratio over period $t-1$ to t. This indicator is slightly modified, due to incorrect indexation in the Grinblatt and Han (2005) indicator (see appendix D for the explanation).

Figure C.13 shows as before the effect of the waiting and holding periods on the returns. Compared to the other strategies the returns decline more rapidly with longer holding periods and the maxima are not at the shortest but slightly longer holding periods (i.e. twelve weeks). Figure C.14 shows a very large bias towards certain stocks for the inclusion in the portfolio, which is not caused by volatility what was the case in the other strategies.

Striking is that the performance of this strategy is even worse. The default setting performed roughly equal to the benchmark (see figure C.15), whereas the optimal setting performed slightly better. Overall the effect of the short positions was neutral, however it was substantially negative.

[2]The original strategy is based on a lookback of 60 months, i.e. 5 years. To maintain stability, the lookback period is kept constant and converted to weeks.

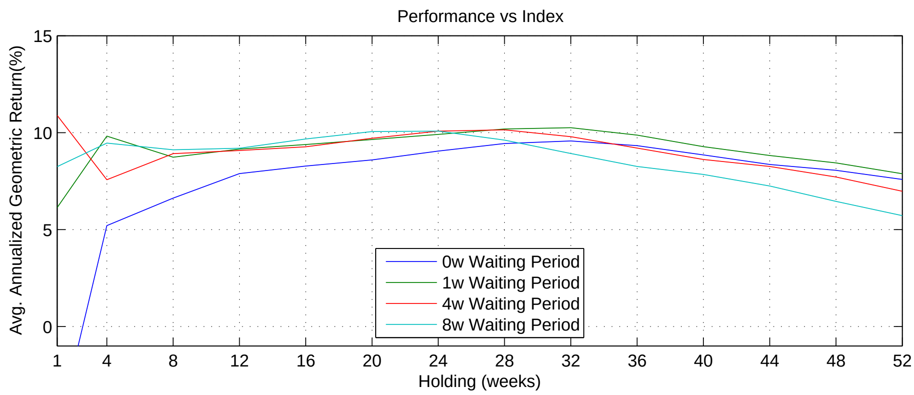

Figure C.10: Optimal Business Cycle Strategy Settings

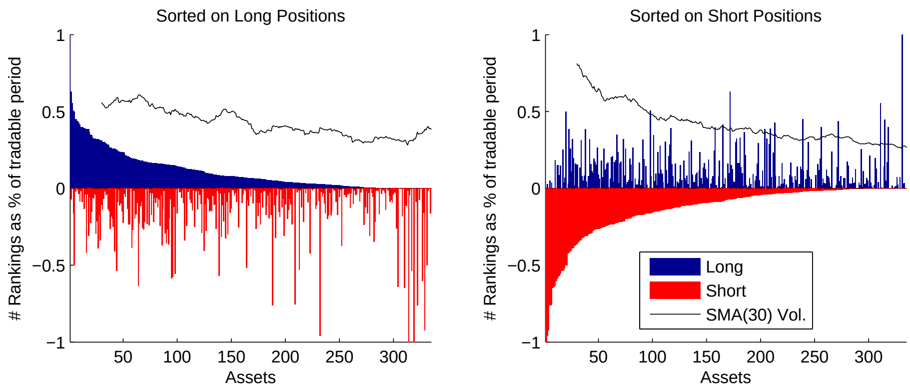

Figure C.11: Asset Selection in Business Cycle Strategy

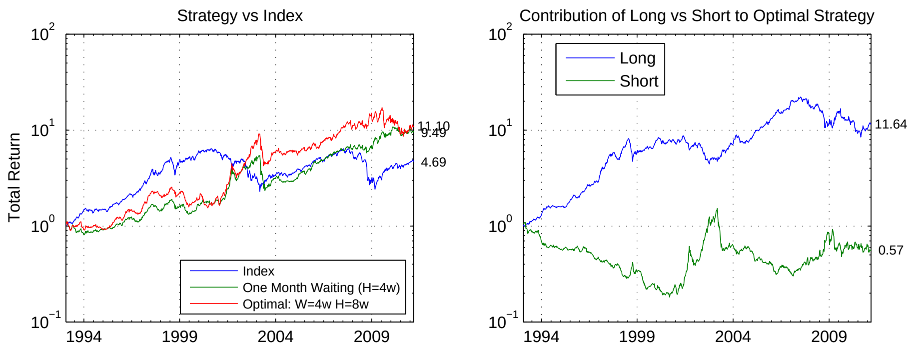

Figure C.12: Performance of Business Cycle Strategies

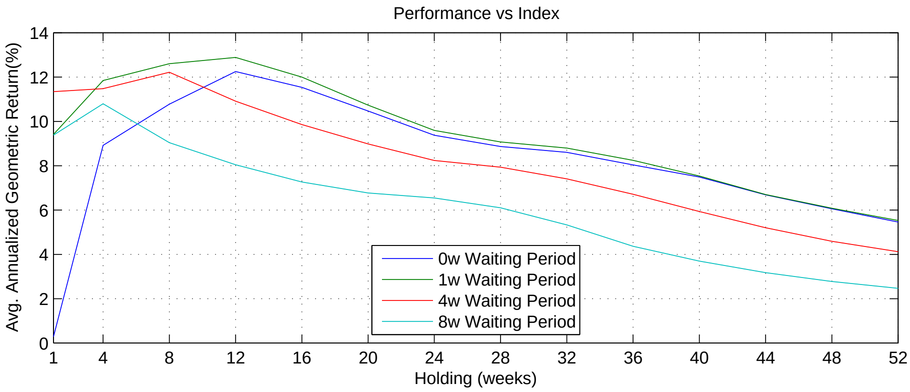

Figure C.13: Optimal Capital Gains Strategy Settings

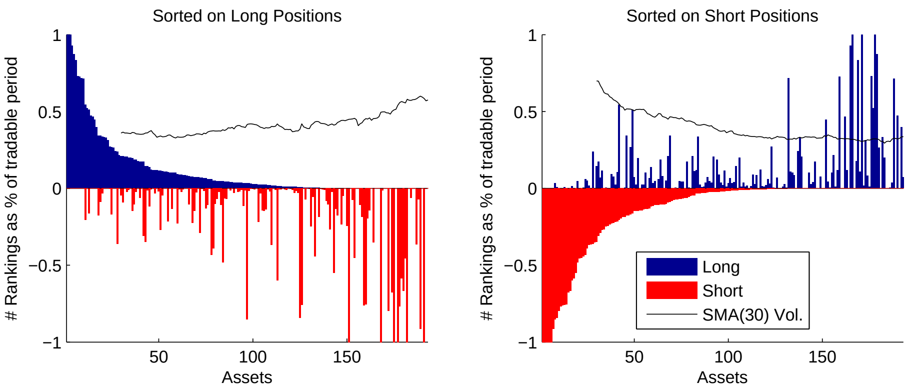

Figure C.14: Asset Selection in Capital Gains Strategy with One Week Lag

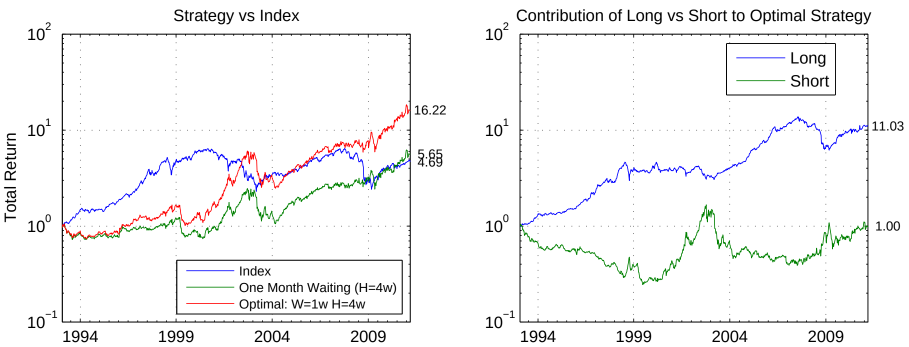

Figure C.15: Performance of Capital Gains Strategies

Capital Gains * Volume Strategies

Grinblatt and Han (2005) described a significant higher forecasting power when the initial indicator (see equation C.9) is multiplied with the current turnover ratio. The alternative indicator is thus:

$$I_{it}^{\text{alt}} = V_{i,t-1} \times I_{it} = V_{i,t-1} \frac{p_{t-1} - R_t}{p_{t-1}} \tag{C.11}$$

Compared to the previous version, this alternative mitigates the short-term reversals better (see figure C.16). Also figure C.17 shows that the bias towards assets for the long positions is significantly decreased, but for the short position not much has changed. Most striking is however the further reduction in performance which can be seen in figure C.18. The contribution of the long and short positions shows that this is mainly due to the very negative performance of the short positions. Without the short positions the strategy would have performed similar to the 52-Week High strategy (long only).

C.2.5 Comparison

Table C.4 summarises the performance of the different strategies discussed above and shows several key statistics. All strategies are assessed on equal timeperiods. The optimal business cycle strategy the longest start-up time, five years of data are needed for a valid indicator level and four weeks of waiting results in the first return begin generated at 29/Jan/1993. Thus all results are based on 29/Jan/1993 tot 11/Mar/2011.

All strategies have a performance significantly different from zero based on a confidence level of 95%. The R/W/H has the highest performance of 45.79% on average annually. While the alternative version of the capital gains strategy has the lowest performance of 13.52%, just higher than the average return of the AEX (12.70%). When accounted for volatility and the risk-free rate, the Sharpe ratios give a similar picture. The 52-Week High and R/W/H strategies perform well, i.e. the 52-Week High strategies have a significant lower volatility for also a lower return. Worst performing are the capital gains and business cycle strategies.

Contrasting, on the R-Ratio the capital gains strategies are doing very well. This due to the high volatility, which apparently results in more upside potential than downside. On the R-Ratio the 52-Week High strategies are performing poorly due to their stability in returns. This can also be seen in the low MaxDrawDown, VaR and Expected Shortfall measures.

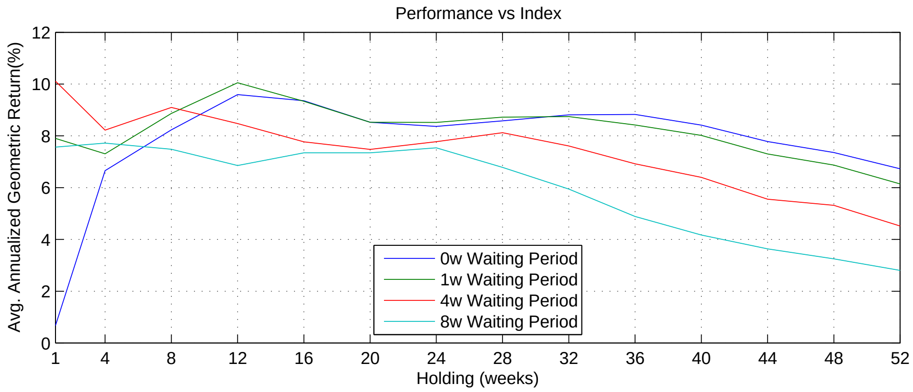

Figure C.16: Optimal Capital Gains * Volume Strategy Settings

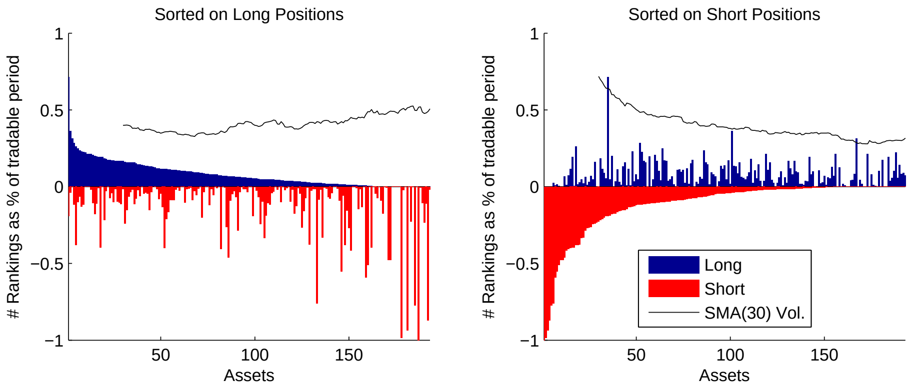

Figure C.17: Asset Selection in Capital Gains * Volume Strategy with Four Week Lag

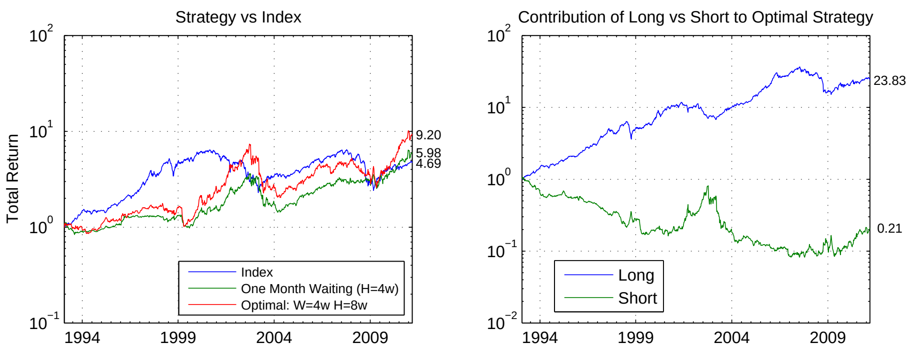

Figure C.18: Performance of Capital Gains * Volume Strategies

Table C.4
Comparison of Momentum Strategies in Dutch Equity Market

Strategy[a]	Geom.	Arim.	Vol.	p-value	t-stat	% Positive	Max	Min	Sharpe	MMD	VaR	ETL	R-Ratio
Benchmark: AEX	10.32%	12.70%	20.52%	0.0050	2.81	57.85%	14.54%	-24.94%	0.3931	64.20%	-32.98%	-49.54%	1.1405
R/W/H Strategies													
Default	28.83%	32.64%	24.13%	0.0000	5.01	60.57%	13.56%	-17.86%	1.1779	59.75%	-36.29%	-56.11%	1.1712
Optimal: 32/4/1w	39.58%	45.79%	29.61%	0.0000	5.45	60.36%	15.61%	-18.66%	1.3902	55.18%	-43.92%	-64.76%	1.2100
52-Week High Strategies													
Default	17.92%	18.70%	11.50%	0.0000	6.37	64.06%	9.60%	-10.99%	1.2971	36.92%	-16.78%	-27.33%	1.0754
Optimal: 4/4w	20.16%	21.12%	12.67%	0.0000	6.46	64.06%	12.88%	-10.06%	1.3621	39.26%	-17.57%	-27.91%	1.0850
52-Week High Long+Short Strategies													
Default	23.82%	25.88%	18.20%	0.0000	5.40	60.78%	13.42%	-12.12%	1.2018	36.28%	-25.97%	-40.50%	1.1241
Optimal: 4/4w	28.82%	32.01%	22.17%	0.0000	5.36	58.99%	15.11%	-16.31%	1.2544	43.09%	-34.38%	-48.31%	1.1529
Business Cycle Strategies													
Default	13.17%	15.73%	21.03%	0.0031	2.97	56.77%	12.76%	-17.91%	0.5730	56.98%	-30.45%	-52.38%	1.1480
Optimal: 4/1w	14.14%	18.22%	26.34%	0.0068	2.71	56.45%	12.58%	-19.33%	0.5494	53.48%	-44.30%	-65.47%	1.1880
Capital Gains Strategies													
Default	9.98%	14.33%	27.67%	0.0390	2.07	55.50%	17.66%	-23.47%	0.3866	57.10%	-44.97%	-68.21%	1.2007
Optimal: 1/12w	16.55%	21.82%	29.55%	0.0044	2.85	56.77%	18.47%	-24.17%	0.6077	59.09%	-45.50%	-71.96%	1.2151
Capital Gains * Turnover Strategies													
Default	10.34%	13.53%	23.58%	0.0217	2.30	56.03%	14.80%	-26.47%	0.4209	60.65%	-32.14%	-61.58%	1.1755
Optimal: 4/1w	12.97%	18.55%	30.51%	0.0174	2.38	57.19%	17.61%	-29.82%	0.4845	72.40%	-48.12%	-79.12%	1.2235

a The default strategies have a 4w waiting period and 26w holding period, in case of the R/W/H strategy a 28w ranking period is used. The parameters of the optimal strategies denote the waiting and holding periods in weeks, e.g. 4/1 means a four week waiting and one week holding period.

C.3 From Relative to Absolute

The previous section details the performance of the strategies in an asset selection setting. This section analyses the performance of the strategies with an absolute reference (threshold) instead of a relative reference (top/bottom decile). For these analysis the same timeperiod is used as in the previous section: from 29/Jan/1993 to 11/Mar/2011.

C.3.1 Thresholds based on Relative Reference

An obvious route taken for the transition is to see whether there is a certain threshold that would mimic the relative reference. Figures C.19 page 96 to C.24 page 97 show for each strategy the value of the indicator of all stocks according to their ranking (percentile). For instance, the bottom decile of the R/W/H contains assets with an indicator value from as low as -1 to as high as 0. But on the other hand the figure also shows that if we would have set the threshold for the short positions at 0, assets ranking at the 90% percentile would also be included. The wide bandwidth and the low correlation, indicate that setting the threshold is not obvious and is a delicate process.

The 52-Week High strategies have a higher correlation, therefore setting the threshold is easier. E.g. a threshold of 0.99 would only include assets ranking at least higher than 50% while still capturing a large portion of the top decile assets. The Business Cycle, and both Capital Gains strategies have an even smaller correlation and larger bandwidth than the R/W/H strategy.

Plotting how the indicator value moves over time; further confirms that the threshold associated with the bottom/top deciles is very volatile (see figures C.25 page 98 to C.30 page 99). In other words, there is not a clear relationship between the deciles and the indicator value, especially for the R/W/H, Business Cycle and Capital Gains strategies. The 52-Week High strategies have upper and lower limits, which provide for obvious bounds. Therefore a possible solution of the other strategies could be to transform them to a scale with an upper and lower limit.

A frequently made assumption is that the returns of an asset are normally distributed. Although it common knowledge that returns are not exactly normally distributed, i.e. the distribution are often skewed and has fat tails. Therefore transforming the R/W/H, Business Cycle and Capital Gains strategies by a normal distribution, bounds the domain of the indicator to $[0, 1]$.

The misfit of the normal distribution to the returns is not necessarily problematic. The stocks in the bottom/top deciles would be located in the tails of the distribution. The normal distribution with slimmer tails would thus scale the indicator closer to the bounds, and the skewness would introduce a slight tilt towards one of the tails. This moves the threshold closer to the bounds. Figure C.31 page 100 shows the empirical pdf and the Q-Q plot vs the Normal Distribution of the R/W/H strategy. Indeed the indicator has more kurtosis than the normal distribution, thus underestimating the probability of an indicator value in the tail.

To test whether the variability in the thresholds of the deciles is reduced, the normal transformation is applied to the R/W/H strategy. The parameters μ and σ of the normal distribution are estimated based on the past three years (156 observations) of the R/W/H indicator. Figures C.32 and C.33 page 101 show indeed that the volatility

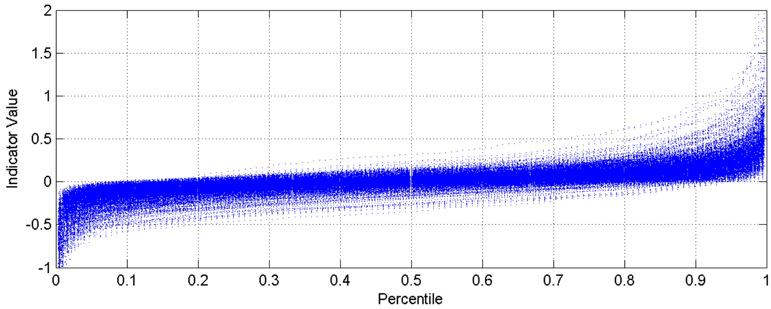

Figure C.19: Range of R/W/H Indicator values by Percentile

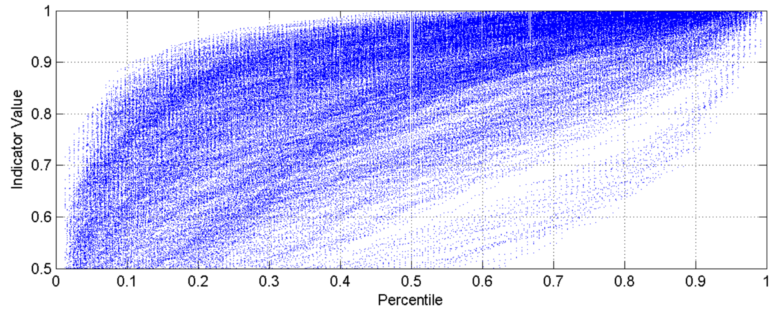

Figure C.20: Range of 52-Week High Indicator values by Percentile

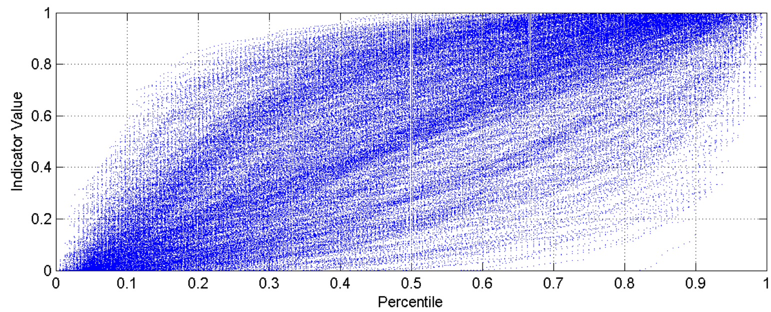

Figure C.21: Range of 52-Week High (long & short) Indicator values by Percentile

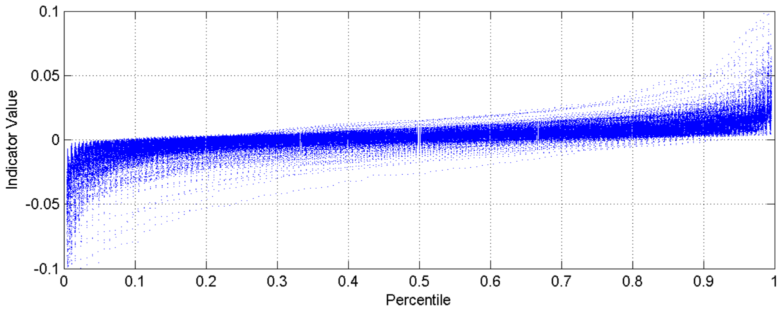

Figure C.22: Range of Business Cycle Indicator values by Percentile

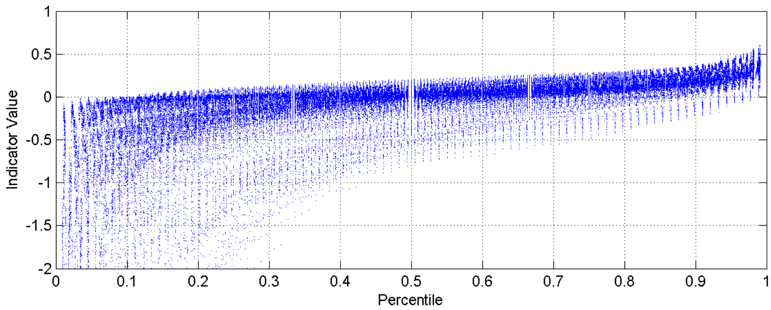

Figure C.23: Range of Capital Gains Indicator values by Percentile

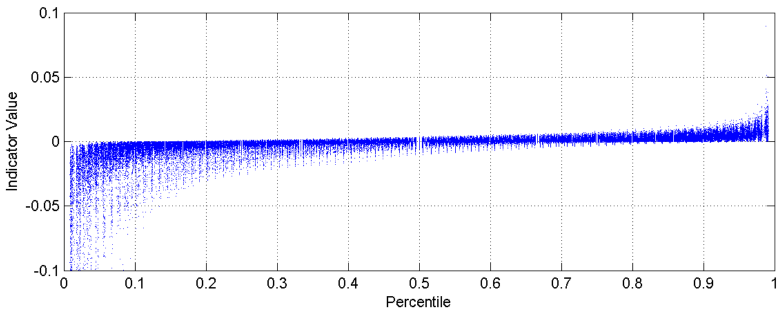

Figure C.24: Range of Capital Gains * Volume Indicator values by Percentile

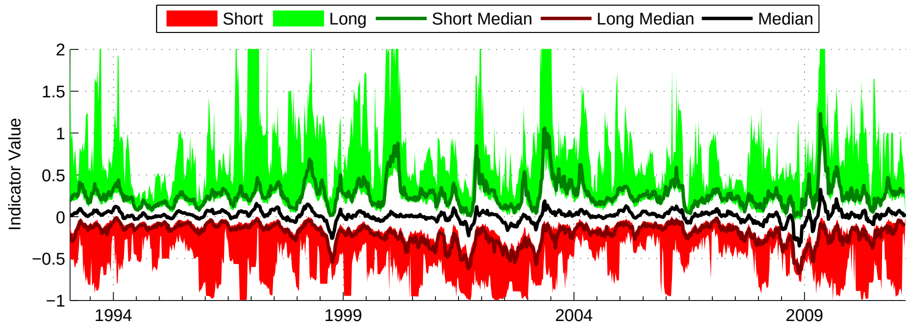

Figure C.25: Range of R/W/H Indicator over Time

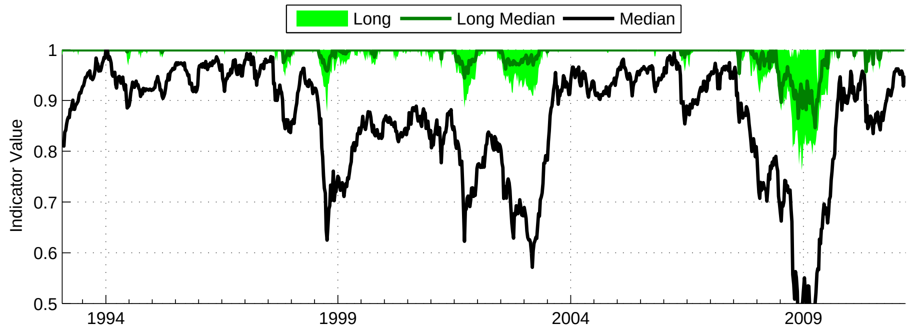

Figure C.26: Range of 52-Week High Indicator over Time

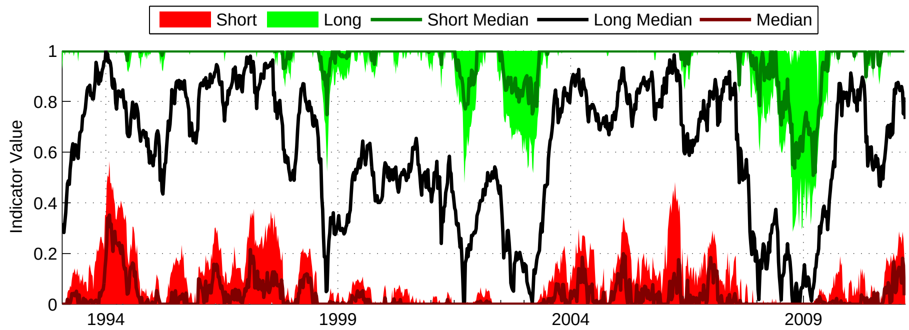

Figure C.27: Range of 52-Week High (long & short) Indicator over Time

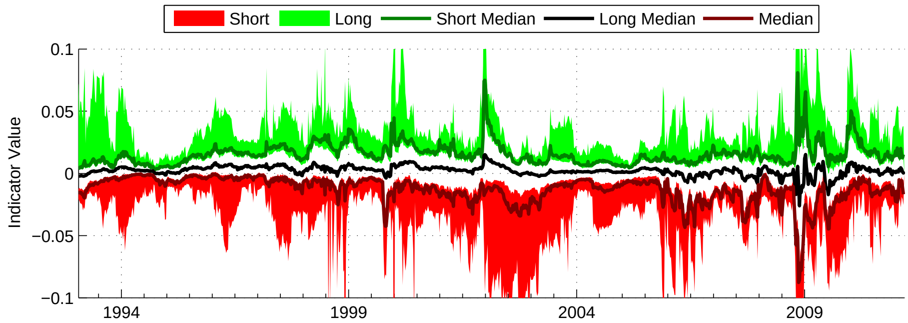

Figure C.28: Range of Business Cycle Indicator over Time

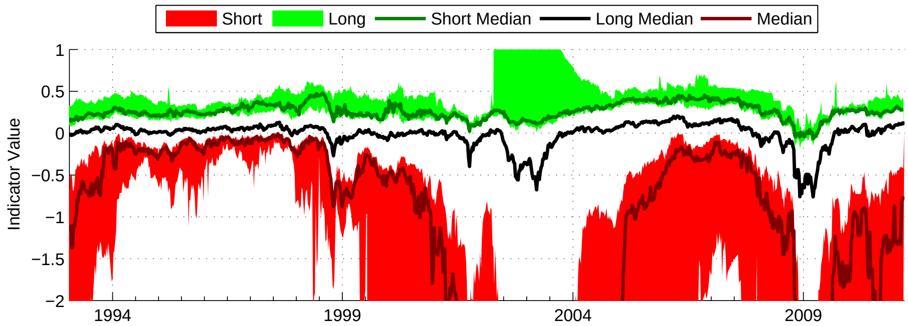

Figure C.29: Range of Capital Gains Indicator over Time

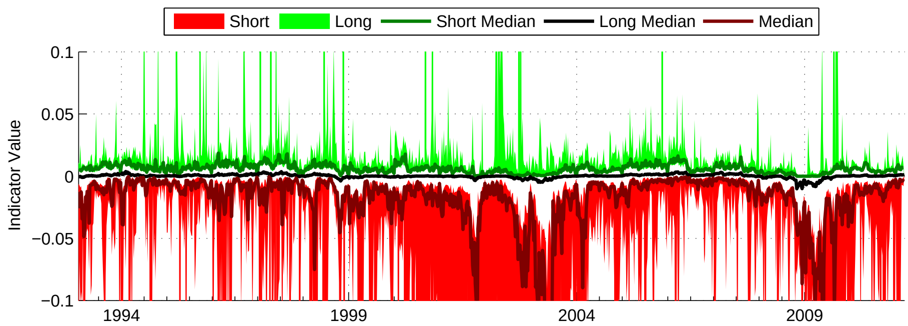

Figure C.30: Range of Capital Gains * Volume Indicator over Time

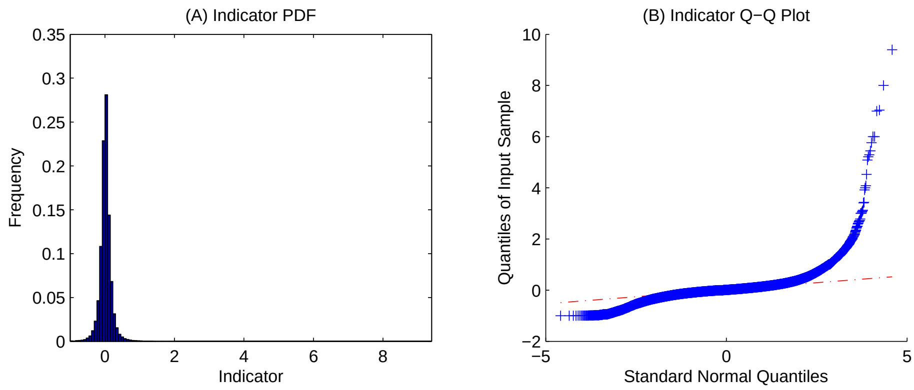

Figure C.31: Frequency & Q-Q Plot versus Normal Distribution of the R/W/H Indicator

is decreased. Setting the threshold between 0.8 and 0.9 would capture most of the top decile assets.

C.3.2 Optimising the Threshold

The previous section shows that setting the thresholds based on the deciles is not straightforward, due to high variability. This would suggest that the return of the strategy is highly sensitive to the threshold. To test this, the return of the strategies is calculated for a wide range of thresholds. Figures C.34 page 103 to C.40 page 105 show what the average annualised geometric return would have been with a certain threshold and waiting period (holding period is one week).

The figures show indeed that especially for the R/W/H Strategy and the Business Cycle strategy the thresholds are very volatile and thus greatly impact the returns. Large jumps and falls are seen, indicating that the threshold should be determined with precision, because being of by a bit causes a significant reduction in return.

Especially the thresholds in the short positions are very sensitive and often do not produce positive results. This effect was also seen with the relative references, since the long positions contributed the most to the outperformance.

Secondly, in all figures the setting with no waiting period produces significantly lower returns than the other settings. Indeed, confirming the evidence of a rather strong short-term reversal. Generally the one week, or one month waiting period produces the best results. Uprising is that generally with the relative reference a one month waiting period was optimal, while with the absolute reference one week seems to perform best.

Thirdly, the transformation by the normal distribution did indeed reduce the volatility in the indicator. Where in figure C.34 the threshold is far from robust, figure C.35 shows a much robuster picture. The same holds for the 52-Week High strategies compared to the others. This suggests that bounding the domain indeed eases setting a threshold.

As final remark, the figures show that the performance of the absolute reference compared to the index or the relative reference varies. The R/W/H strategy does outperform the index for several thresholds, but never outperforms the relative reference portfolio.

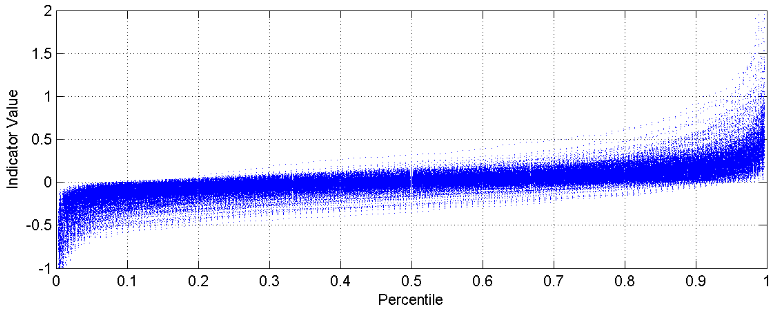

Figure C.32: Range of Transformed R/W/H Indicator by Normal Distribution per Percentile

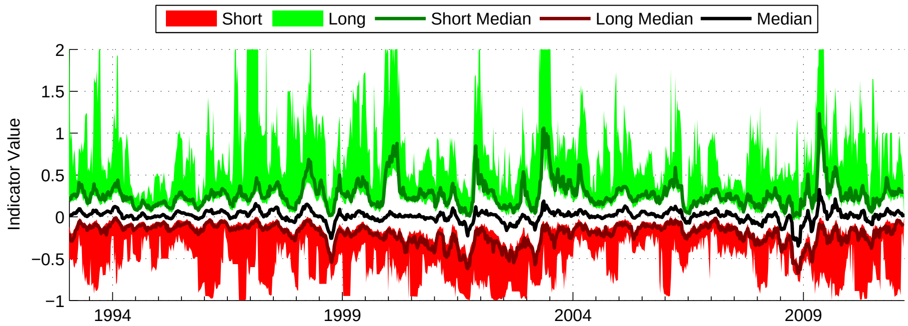

Figure C.33: Range of Transformed R/W/H Indicator by Normal Distribution over Time

The same holds for the 52-Week High strategies. However the Business Cycle and Capital Gains strategies show some peaks performing better than the relative reference portfolio. The performance on the short side is much better, if the optimal threshold is set. Overall the absolute reference portfolio does not perform poorly.

C.4 Conclusions

There are several key conclusions that stem from this analysis of the momentum strategies in the Dutch equity market. The main finding is that the outperformance in the literature is also seen in the Dutch equity market. The R/W/H strategy generated an average return of 40%, the 52-Week High strategies 20% (long only) and 29% (long & short), the business cycle 14%, Capital Gains 17% and 13%, compared to the AEX with 10%. Surprising in this sense is that the most simplistic strategies performed much better, than the more complicated (Business Cycle and Capital Gains).

The 52-Week High strategy also reduced volatility severely producing very stable results. Most strategies had an average volatility around the 30%, the AEX 20%, but the 52-Week High only 13% and 22% (long & short). This is also seen in the Max-DrawDown, VaR and Expected Shortfall.

The analysis on the absolute references based on the decile rankings showed, that the threshold at which the stocks are selected for the deciles varies greatly over time. This resulted in very volatile relationship between the threshold and the returns. Especially the R/W/H and Business Cycle strategy showed this high sensitivity. The 52-Week high strategy, due to the bounds of the indicator domain, shows more robust results.

Although the indicator of the R/W/H Strategy is not normally distributed (showing fatter tails), transforming the indicator with the normal distribution increased the robustness significantly. This suggests that indicators with a bounded domain are better candidates for an absolute reference.

The performance of the absolute reference portfolios was on average below that of the decile portfolios but for many thresholds larger than the index. Especially in the short position are improvements possible.

The analysis showed three interesting effects that need further research. First of all several filters are applied to the initial set. It is currently unknown what the effect is of these filters on the performances. It could very well be that these filters introduced important biases. Especially the filter on penny stocks and the threshold of €2 could have a large impact on the performance of the strategies.

Second, several strategies (especially the R/W/H strategy) showed a bias towards more volatile stocks. Surprisingly the 52-Week High strategy had a bias towards less volatile stocks. It would be interesting to see how the performances change if the volatility is normalised. These biases could explain a large part of the outperformance reported.

As final point, all strategies showed weak performance in the short positions and before 2000. Analysing the lack of performance might lead to interesting results and important improvements on the strategies.

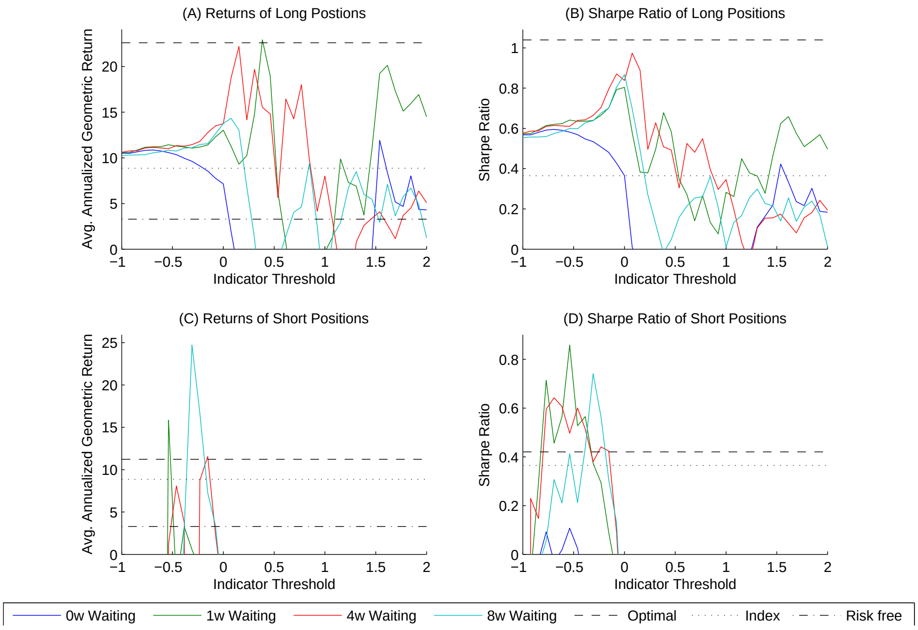

Figure C.34: Optimal Threshold for R/W/H Strategy

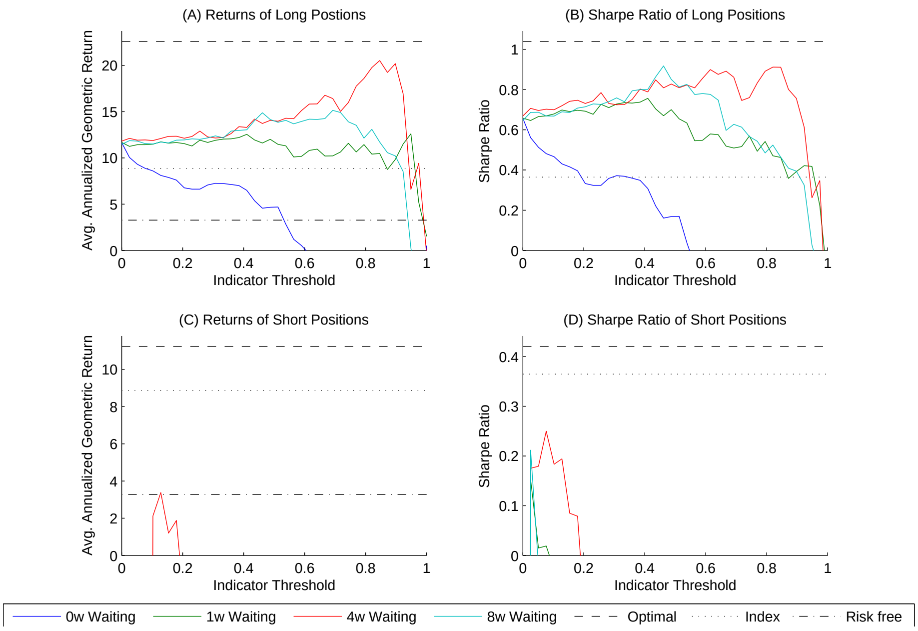

Figure C.35: Optimal Threshold for Transformed R/W/H Strategy by Normal Distribution

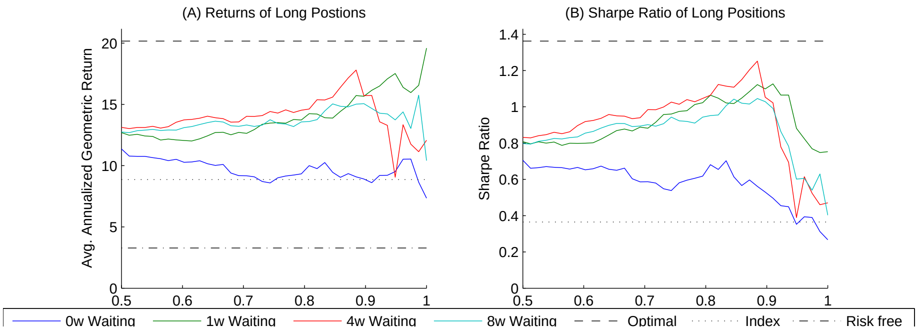

Figure C.36: Optimal Threshold for 52-Week High Strategy

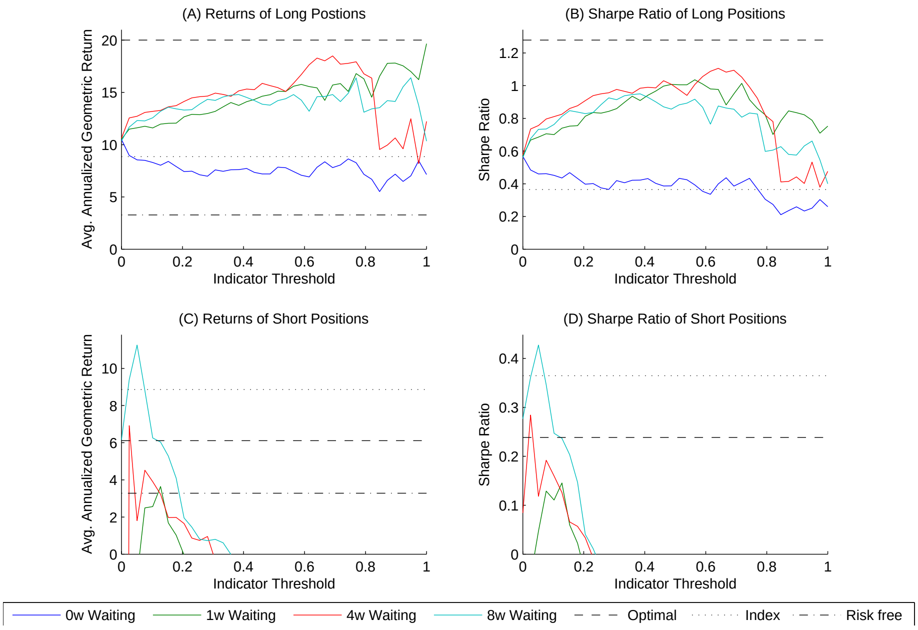

Figure C.37: Optimal Threshold for 52-Week High (long & short) Strategy

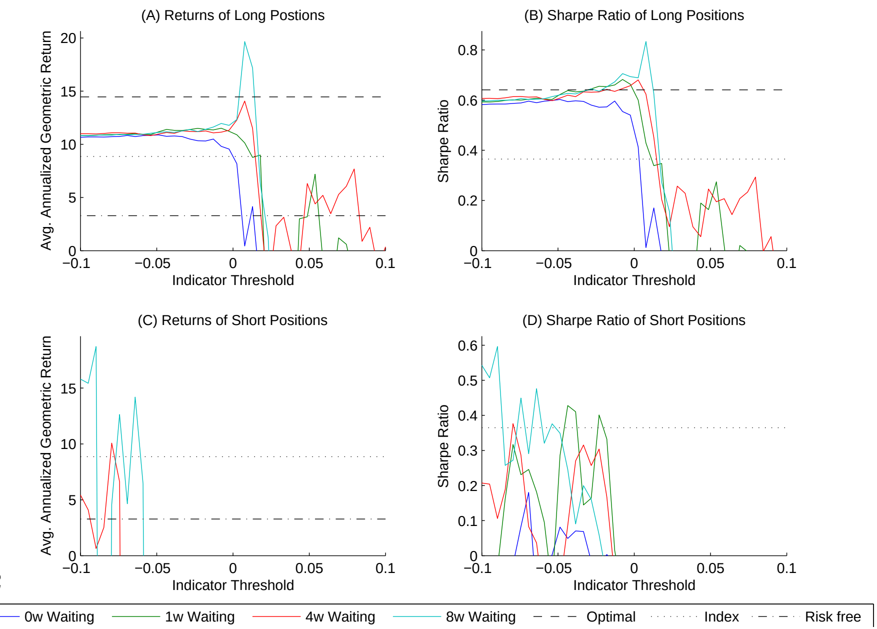

Figure C.38: Optimal Threshold for Business Cycle Strategy

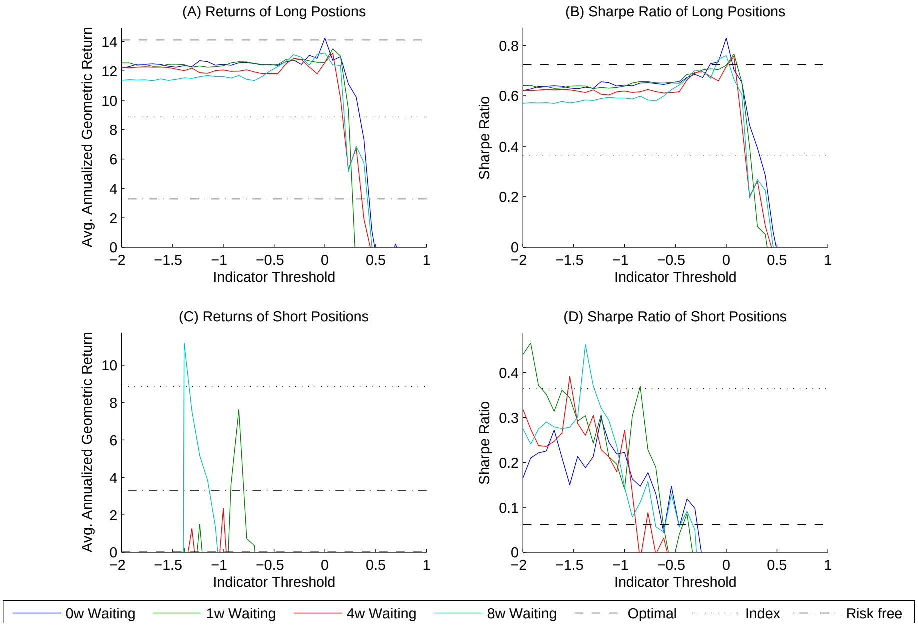

Figure C.39: Optimal Threshold for Capital Gains Strategy

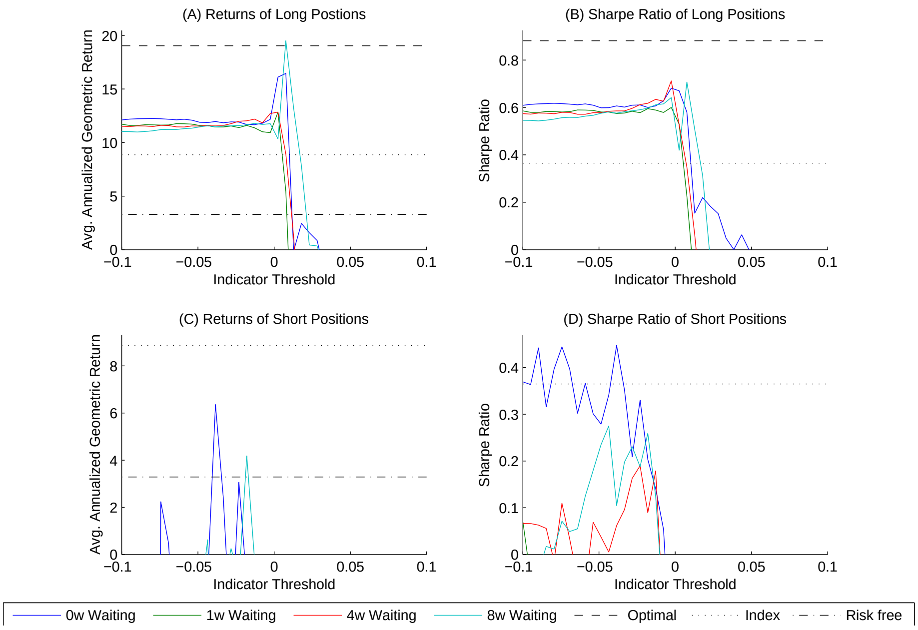

Figure C.40: Optimal Threshold for Capital Gains * Volume Strategy

Appendix D

Recalculation of Capital Gains Estimator

Grinblatt and Han (2005) state the following estimator for the relevant reference price of the mental account of an investor:

$$R_t = \sum_{n=1}^{\infty} \left(V_{t-n} \prod_{\tau=1}^{n-1} [1 - V_{t-n+\tau}] \right) P_{t-n} \tag{D.1}$$

where V_{t-n} is date t's turnover ration in the stock and P_t is the price. The problem with this estimator is that the indexation produces undefined results for $n = 1$, see table D.1. Grinblatt and Han (2005) base their estimator on the recursive formula for defining the updating process of the reference price of an investor:

$$R_{t+1} = V_t P_t + (1 - V_t) R_t \tag{D.2}$$

Table D.1
Indexation of Product in Equation D.1

	τ		t	
n	start	end	start	end
1	1	0	t	$t-1$
2	1	1	$t-1$	$t-1$
3	1	2	$t-2$	$t-1$
4	1	3	$t-3$	$t-1$
		and so on		

By iteration we get:

$$
\begin{aligned}
R_0 &= V_0 P_0 \\
R_1 &= V_1 P_1 + (1 - V_1) R_0 \\
&= V_1 P_1 + (1 - V_1) V_0 P_0 \\
R_2 &= V_2 P_2 + (1 - V_2) R_1 \\
&= V_2 P_2 + (1 - V_2)(V_1 P_1 + (1 - V_1) V_0 P_0) \\
&= V_2 P_2 + (1 - V_2) V_1 P_1 + (1 - V_2)(1 - V_1) V_0 P_0 \\
R_3 &= V_3 P_3 + (1 - V_3) R_2 \\
&= V_3 P_3 + (1 - V_3) V_2 P_2 + (1 - V_3)(1 - V_2) V_1 P_1 + (1 - V_3)(1 - V_2)(1 - V_1) V_0 P_0
\end{aligned}
$$

From this the following recursive structure appears:

$$
R_3 = \underbrace{\begin{array}{cc} 1 & V_3\,P_3 \\ (1 - V_3) & V_2\,P_2 \\ (1 - V_3)(1 - V_2) & V_1\,P_1 \\ (1 - V_3)(1 - V_2)(1 - V_1) & V_0\,P_0 \end{array}}_{\text{Weights}} \begin{array}{c} + \\ + \\ + \\ + \end{array}
$$

This can be written similar to equation D.1:

$$
R_t = \sum_{n=1}^{\infty} \left(V_{t_n} \prod_{i=t-n+1}^{t} [1 - V_i]\, P_{t-n} \right) + V_t P_t \tag{D.3}
$$

$$
= \sum_{n=1}^{\infty} \left(V_{t_n} \prod_{\tau=1}^{n} [1 - V_{t-n+\tau}]\, P_{t-n} \right) + V_t P_t \tag{D.4}
$$

The difference between equation D.3 and D.4 is that i has be rewritten to τ as $\tau = i - t + n$ increasing the similarity with the original estimator of Grinblatt and Han (2005). The key differences are that the product is from $\tau = 1$ to $\tau = n$ instead of $\tau = n - 1$, and the additional term $V_t P_t$.

Appendix E

Total Return Model

E.1 Derivation of Mathematical Model

The total return of a strategy on a single asset over the timeperiod 1 to n is given by:

$$TR(l) = \prod_{t=1}^{n} (S(I_{t-1}, l) \times r_t + 1) \tag{E.1}$$

$$S(I, l) = \begin{cases} 1 & \text{if } I \geq l \\ 0 & \text{otherwise} \end{cases} \tag{E.2}$$

where I_t is a deterministic function of the past returns. The past returns r_t can be seen as realisations of the random variable R_t. In that case, the expected total return over n periods is:

$$E[TR(l)] = E\left[\prod_{t=1}^{n} (S(I(R_{t-1} \ldots R_{t-\infty}), l) \times R_t + 1)\right] \tag{E.3}$$

This function can be simplified by assuming that the return variables (R_t) are not autocorrelated, and thus are independent realisations of the random variable R. In that case the indicator value I can also be seen as a random variable, since it depends on the realisation of the past R's. This gives:

$$E[TR(l)] = E\left[\prod_{t=1}^{n} (S(I, l) \times R + 1)\right] \tag{E.4}$$

$$= (E[S(I, l) \times R] + 1)^n \tag{E.5}$$

To find the optimal threshold l this function must be maximised. This further simplifies the solution, since equation E.5 is the expectation transformed by the function $f(x, n) := (x+1)^n$. This function is monotonically increasing in x, and therefore does not impact the maximisation. This simplifies the problem further to:

$$\max_l E[TR(l)] = \max_l (E[S(I, l) \times R] + 1)^n \tag{E.6}$$

$$= \max_l E[S(I, l) \times R] \rightarrow \tag{E.7}$$

$$E[S(I, l) \times R] = E[S \times E[R|S]] \tag{E.8}$$

$$= E[S \times E[R|I \geq l]] \tag{E.9}$$

$$= \mathbb{P}[I \geq l] \times E[R|I \geq l] \tag{E.10}$$

E.2 Parameter Estimation

The model consists of two elements: (1) the probability on a position/signal, and (2) the expected return made on a position. These two elements can be empirically estimated, or a model can be fitted to smooth the results.

For this last option, two models are needed: (1) that describes the probability distribution (PD) of the momentum indicator (I), and a model for the conditional distribution of the returns ($R|I$).

For the PD of the indicator several theoretical distributions are fitted. The fits are tested via a Chi-square Goodness of Fit test. This resulted reasonable good fits, based on QQ-plots, however the formal test generally rejected the fit (see next subsection).

To model the conditional expectation there are two options. Either a correlation model is needed between the two PDs, or a function is directly fitted to the empirical estimated conditional expectation. This last option is used for its simplicity, and as the second subsection will show provides a very good fit.

E.2.1 Theoretical PDs for the Momentum Indicators

The strategy's indicators have two types of distributions: (1) a bell-shaped distribution of returns and (2) a bounded distribution on the interval $[0,1]$. A logical choice of the first type would be a normal distribution, however to include skewness and kurtosis also the Student t-distribution, Extreme Value and Generalised Extreme Value distributions are fitted. Based on the p-values of a Chi-Squared Goodness of Fit test with 40 bins, the Student t-Distribution describes the R/W/H and Business Cycle indicators best.

The second set of strategy indicators are modelled by a beta distribution, due to its large variety of shapes on a bounded domain. However for the 52-Week High strategy the domain includes the 0 and 1, therefore is modelled by a mixed distribution: $I^{\text{52-Week}} \sim D + \frac{C}{1-d_0-d_1}$ where D is the discrete part with $\mathbb{P}[D=0] = d_0$, $\mathbb{P}[D=1] = d_1$ and otherwise $\mathbb{P}[D] = 0$, and C the continuous part modelled by a beta-distribution. d_0 and d_1 are estimated by dividing the number of observations equal to zero (one) by the total number of observations. And the parameters of the continuous distribution are estimated based on the maximum likely hood estimators of the distributions.

Figures E.1 and E.2 illustrate the fits. The Q-Q plots (panel B) and the CDF plots (panel C) shows a rather good fit. However the formal Chi-Square Goodness of Fit test generally rejects the fit (see table E.1). Nonetheless the Student t-Distribution approximates the CDF very well for the R/W/H and Business Cycle strategies. The Beta Distributions approximate the other indicators reasonably. No better fits were obtainable by other distributions.

E.2.2 Fitting a Function to the Conditional Expectation

To fit a function to the conditional expectation, it must be estimated from the empirical data. The estimator used is given by:

$$\hat{E}[r|I \geq l] = \frac{1}{n} \sum \{r | I(r) \geq l\} \tag{E.11}$$

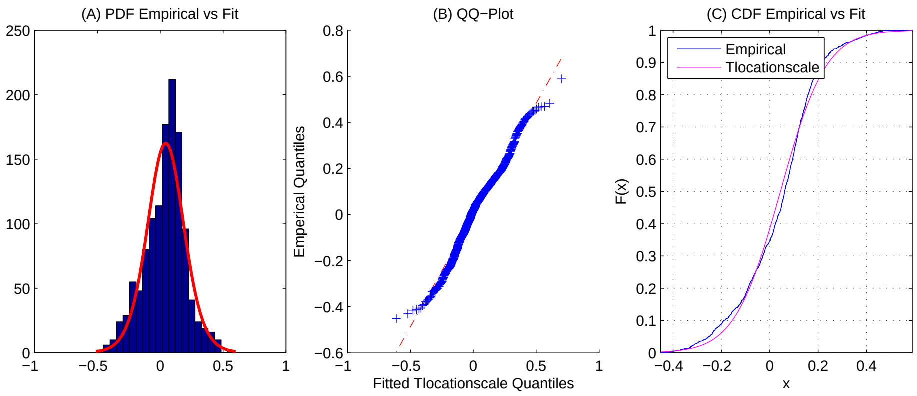

Figure E.1: Probability distribution of R/W/H Strategy on EuroStoxx

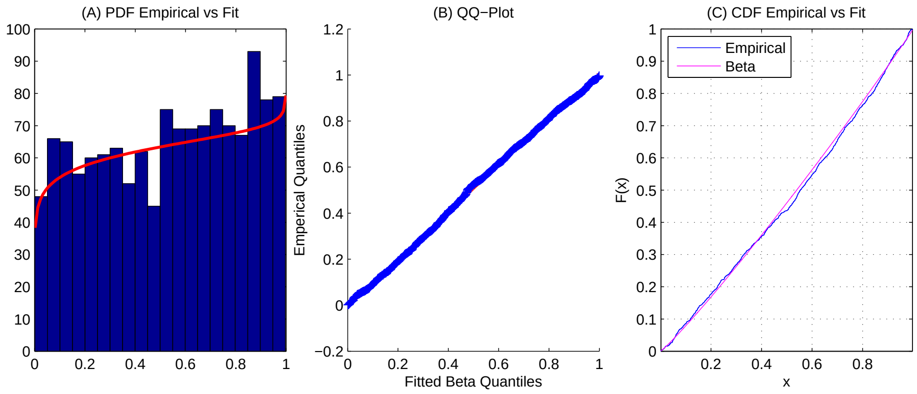

Figure E.2: Probability distribution of 52-Week High Strategy on US 10y Bonds

Table E.1
Fit results of Momentum Indicator PDs

	R/W/H 24w (Student t-Dist)				
	p-value	t-stat	loc. (μ)	scale (σ)	shape (ν)
EU Bonds	0.00%	135.53	7.59e-3	4.47e-2	3.71e1
US Bonds	56.62%	33.96	8.26e-3	5.98e-2	3.65e1
JP Bonds	0.15%	66.37	1.17e-2	3.62e-2	5.61
Hang Seng	0.07%	69.16	8.73e-2	2.04e-1	4.28
S&P500	0.28%	63.92	4.65e-2	1.06e-1	7.56
EuroStoxx	0.00%	122.58	4.41e-2	1.47e-1	1.18e1
FTSE100	0.84%	59.36	4.79e-2	1.01e-1	6.38
Topix	0.00%	86.42	3.16e-2	1.45e-1	1.10e1
EUR/USD	0.00%	90.42	1.29e-3	8.19e-2	3.66e6
EUR/JPY	7.56%	48.79	-1.65e-2	8.49e-2	2.41e1
EUR/GBP	0.01%	78.41	5.54e-3	5.74e-2	2.80e1
JPY/USD	0.00%	81.52	2.03e-2	8.56e-2	2.01e6
GBP/USD	6.06%	49.99	9.89e-3	5.71e-2	4.11
EPRA Europe	4.01%	52.13	6.82e-2	1.28e-1	4.85
GSCI	0.00%	125.55	4.36e-2	1.62e-1	1.61e1
	Normalized R/W/H 24w (Beta Dist.)				
	p-value	t-stat	shape (α)	shape (β)	
EU Bonds	0.00%	123.73	7.99e-1	8.26e-1	
US Bonds	0.00%	86.68	8.59e-1	8.59e-1	
JP Bonds	0.00%	90.81	8.91e-1	9.22e-1	
Hang Seng	0.00%	99.11	7.96e-1	7.80e-1	
S&P500	3.09%	54.64	6.99e-1	7.21e-1	
EuroStoxx	0.18%	67.06	7.05e-1	7.28e-1	
FTSE100	3.47%	54.06	6.83e-1	7.52e-1	
Topix	0.00%	132.81	8.12e-1	7.99e-1	
EUR/USD	0.00%	95.00	7.04e-1	7.29e-1	
EUR/JPY	0.00%	86.42	7.36e-1	7.59e-1	
EUR/GBP	0.00%	99.25	8.18e-1	7.85e-1	
JPY/USD	0.00%	96.62	8.52e-1	7.91e-1	
GBP/USD	0.00%	137.39	7.67e-1	8.14e-1	
EPRA Europe	23.84%	42.73	7.02e-1	6.89e-1	
GSCI	0.00%	94.56	6.55e-1	6.64e-1	
	52-Week High (Beta Dist.)				
	p-value	t-stat	shape (α)	shape (β)	
EU Bonds	34.35%	39.87	9.50e-1	8.36e-1	
US Bonds	3.79%	53.61	1.09	9.74e-1	
JP Bonds	1.62%	57.71	1.14	8.43e-1	
Hang Seng	0.66%	61.70	1.08	7.80e-1	
S&P500	0.00%	153.71	1.15	6.95e-1	
EuroStoxx	2.44%	55.78	1.02	6.68e-1	
FTSE100	0.00%	94.40	1.23	7.47e-1	
Topix	0.14%	67.94	9.94e-1	7.52e-1	
EUR/USD	0.08%	70.19	7.59e-1	8.22e-1	
EUR/JPY	0.00%	111.91	6.87e-1	8.27e-1	
EUR/GBP	13.77%	46.43	9.58e-1	9.36e-1	
JPY/USD	0.00%	80.53	1.03	9.02e-1	
GBP/USD	12.05%	47.25	1.07	9.99e-1	
EPRA Europe	0.04%	72.62	1.06	7.71e-1	
GSCI	0.00%	121.60	7.14e-1	5.44e-1	

Table E.1
Fit results of Momentum Indicator PDs (Cont.)

	Business Cycle (Student t-Dist)				
	p-value	t-stat	loc. (μ)	scale (σ)	shape (ν)
EU Bonds	0.00%	119.29	4.14e-4	1.21e-3	5.92
US Bonds	0.01%	76.71	2.49e-4	1.47e-3	5.83
JP Bonds	0.00%	101.07	4.31e-4	1.05e-3	2.79
Hang Seng	0.00%	135.66	1.67e-3	4.87e-3	4.64
S&P500	0.00%	141.07	2.23e-3	2.90e-3	4.31
EuroStoxx	3.54%	52.75	2.02e-3	4.02e-3	6.37
FTSE100	0.00%	105.76	1.30e-3	2.90e-3	8.58
Topix	0.40%	62.46	-7.21e-5	4.52e-3	1.05e1
EUR/USD	0.00%	80.01	2.97e-5	2.29e-3	9.04
EUR/JPY	0.00%	375.26	-4.54e-4	2.49e-3	8.76
EUR/GBP	0.00%	98.10	3.66e-4	1.36e-3	3.80
JPY/USD	0.00%	95.26	1.00e-3	2.74e-3	7.69
GBP/USD	0.08%	68.73	-3.84e-5	1.78e-3	3.48
EPRA Europe	0.00%	97.37	1.22e-3	2.80e-3	2.27
GSCI	0.00%	222.10	1.22e-3	3.26e-3	2.58
	Normalized Business Cycle (Beta Dist.)				
	p-value	t-stat	shape (α)	shape (β)	
EU Bonds	0.00%	195.03	6.32e-1	6.84e-1	
US Bonds	0.00%	120.41	6.65e-1	7.20e-1	
JP Bonds	0.00%	387.28	6.65e-1	7.15e-1	
Hang Seng	0.00%	95.58	6.22e-1	7.44e-1	
S&P500	0.00%	99.44	5.85e-1	7.39e-1	
EuroStoxx	0.00%	122.99	7.08e-1	7.34e-1	
FTSE100	0.00%	103.83	7.38e-1	8.17e-1	
Topix	0.00%	143.57	7.21e-1	7.51e-1	
EUR/USD	0.00%	84.68	7.11e-1	7.78e-1	
EUR/JPY	0.00%	146.07	6.11e-1	7.14e-1	
EUR/GBP	0.00%	143.42	7.87e-1	7.54e-1	
JPY/USD	0.00%	100.12	7.19e-1	6.68e-1	
GBP/USD	0.02%	74.69	6.70e-1	8.01e-1	
EPRA Europe	0.00%	124.34	5.66e-1	6.76e-1	
GSCI	0.00%	185.58	6.97e-1	6.30e-1	

Note: Parameters are estimated based on maximum likelihood, and tested via a Chi-square Goodness of Fit test with 40 bins.

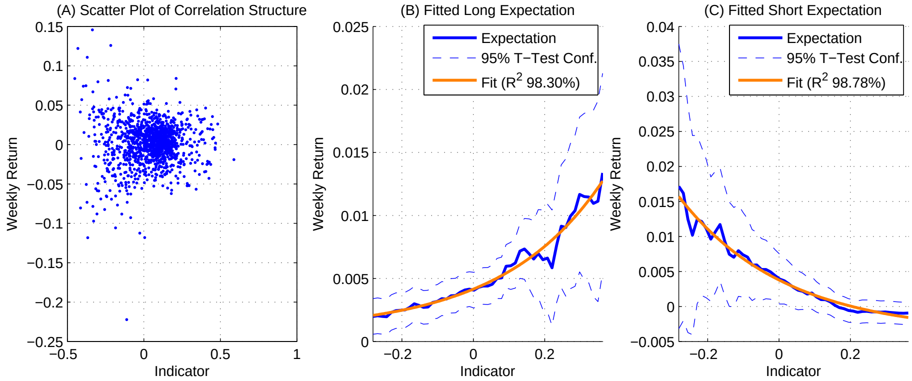

Figure E.3: Conditional Expectation of R/W/H Strategy on EuroStoxx

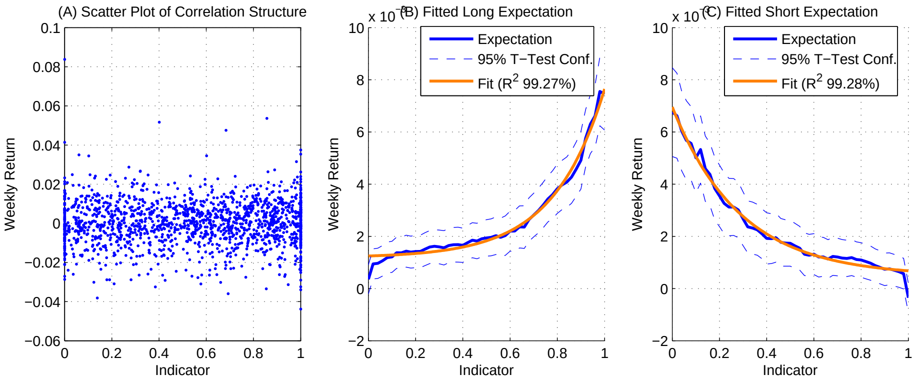

Figure E.4: Conditional Expectation of 52-Week High Strategy on US 10y Bonds

where r is the return, $I(r)$ give the indicator value preceding the return and $n = |\{r|I(r) \geq l\}|$. One would expect for the long (short) positions monotonically increasing (decreasing) function of the threshold. For unbounded domains an exponential function ($y = ae^{bx} + c$) fits this behaviour, and for bounded domains a power function ($y = ax^b + c$) would also be possible.

Figures E.3 and E.4 shows the empirical correlation structure (panel A) and the estimated conditional expectation (panels B and C). Panel A shows no strong correlation, what would indicate a weak predictive power of the indicator for future returns. However the estimated conditional expectations show indeed a small monotonically increasing (decreasing) relationship.

Based on the R^2 of the regression on the estimated conditional expectation the exponential function best fits the conditional expectation of all strategies. Table E.2 shows the estimated parameters and R^2, which generally ranges in the high 90s indicating a very good fit.

Table E.2
Fit Results of $y = ae^{bx} + c$ on Conditional Expectation

	Long Position				Short Position			
	R^2	a	b	c	R^2	a	b	c
R/W/H 24w								
EU Bonds	77.20%	0.0147	9.63e-1	-1.35e-2	99.33%	2.34e-3	-8.82	-1.27e-3
US Bonds	97.92%	0.0020	8.22	-4.61e-4	97.87%	1.89e-3	-1.07e1	-5.93e-4
JP Bonds	99.10%	0.0011	1.23e1	0.00	94.73%	-2.39e2	6.43e-5	2.39e2
Hang Seng	98.52%	0.0092	1.70	-1.54e-3	96.38%	8.51e-3	-2.67	-4.33e-3
S&P500	97.18%	0.0451	2.92e-1	-4.10e-2	98.07%	1.03e-2	-2.46	-7.28e-3
EuroStoxx	98.30%	0.0033	3.53	8.50e-4	98.78%	7.60e-3	-3.36	-3.82e-3
FTSE100	98.32%	0.0049	2.94	-9.82e-4	95.77%	1.63e-2	-1.55	-1.28e-2
Topix	99.62%	0.0066	2.29	-2.37e-3	98.12%	6.58e-3	-3.46	-3.13e-3
EUR/USD	98.74%	0.0012	1.33e1	4.96e-4	99.17%	2.88e-3	-7.82	-7.60e-4
EUR/JPY	97.34%	0.0104	1.75	-8.25e-3	98.98%	4.59e-3	-4.11	-1.87e-3
EUR/GBP	98.00%	0.0035	5.72	-1.79e-3	95.93%	1.10e-3	-1.46e1	-3.62e-5
JPY/USD	95.94%	0.0020	6.14	0.00	97.74%	3.90e-3	-4.91	-2.32e-3
GBP/USD	94.93%	0.0537	2.53e-1	-5.17e-2	97.81%	1.06e-2	-2.12	-8.24e-3
EPRA Europe	98.55%	0.0086	2.18	-3.14e-3	99.55%	6.23e-3	-4.36	-2.91e-3
GSCI	97.63%	0.0045	3.12	-1.45e-4	99.21%	6.55e-3	-3.72	-2.73e-3
Normalized R/W/H 24w								
EU Bonds	98.80%	0.0000	5.33	7.34e-4	98.09%	3.66e-3	-2.46	-3.05e-4
US Bonds	92.98%	0.0005	2.30	0.00	96.65%	3.99e-3	-2.39	-3.12e-4
JP Bonds	95.56%	0.0004	2.06	0.00	92.39%	-1.62e-3	7.89e-1	3.24e-3
Hang Seng	98.13%	0.0014	2.44	2.89e-3	99.04%	1.76e-2	-2.10	-3.69e-3
S&P500	98.79%	-0.0074	-1.05	9.48e-3	98.31%	1.14e-2	-2.84	-1.33e-3
EuroStoxx	96.73%	0.0001	4.93	3.35e-3	96.99%	1.56e-2	-5.39	4.20e-4
FTSE100	96.60%	0.0013	1.73	1.37e-3	97.58%	1.19e-2	-3.07	-9.47e-4
Topix	98.60%	0.0011	2.20	7.62e-4	97.15%	1.70e-2	-7.27	1.15e-3
EUR/USD	98.25%	0.0001	4.69	9.37e-4	98.19%	6.43e-3	-2.41	9.95e-5
EUR/JPY	98.60%	0.0080	5.02e-1	-8.24e-3	99.01%	8.27e-3	-1.20	-1.41e-3
EUR/GBP	98.02%	0.0001	3.66	5.08e-4	97.14%	4.73e-3	-4.60	4.92e-4
JPY/USD	96.74%	0.0004	2.57	7.66e-4	98.25%	6.02e-3	-2.12	-8.93e-4
GBP/USD	98.06%	0.0027	9.65e-1	-2.14e-3	95.35%	7.75e-3	-1.33	-1.88e-3
EPRA Europe	98.26%	0.0032	1.33	-1.70e-4	97.91%	1.15e-2	-2.73	-1.16e-3
GSCI	95.15%	0.0002	3.67	3.37e-3	98.65%	1.36e-2	-2.81	-1.48e-3
52-Week High								
EU Bonds	99.20%	0.0002	2.70	4.43e-4	98.53%	4.95e-3	-4.91	7.60e-4
US Bonds	99.27%	0.0001	4.61	1.18e-3	99.28%	6.48e-3	-3.48	4.79e-4
JP Bonds	99.33%	0.0001	3.13	5.95e-4	98.61%	5.97e-3	-4.79	7.03e-4
Hang Seng	99.42%	0.0004	3.78	5.49e-3	99.14%	3.83e-2	-4.58	2.80e-3
S&P500	98.47%	0.0001	4.76	3.01e-3	98.08%	1.73e-2	-2.83	0.00
EuroStoxx	98.73%	0.0000	5.44	3.45e-3	98.73%	2.66e-2	-5.04	1.57e-3
FTSE100	98.46%	0.0002	3.82	2.64e-3	98.00%	2.12e-2	-3.39	6.37e-4
Topix	98.50%	0.0002	4.01	2.97e-3	98.68%	1.64e-2	-3.41	1.13e-3
EUR/USD	98.88%	0.0002	3.34	1.23e-3	98.27%	7.18e-3	-5.07	1.58e-3
EUR/JPY	97.36%	0.0002	3.20	1.21e-3	98.69%	7.07e-3	-4.10	1.80e-3
EUR/GBP	99.39%	0.0002	3.44	7.04e-4	98.50%	5.45e-3	-4.76	9.40e-4
JPY/USD	99.44%	0.0004	3.22	1.14e-3	96.24%	6.63e-3	-2.96	8.12e-4
GBP/USD	99.33%	0.0003	3.35	9.75e-4	99.03%	1.18e-2	-4.60	9.51e-4
EPRA Europe	99.50%	0.0003	3.77	3.36e-3	97.64%	1.53e-2	-4.72	2.24e-3
GSCI	96.02%	0.0000	7.04	3.96e-3	98.45%	1.42e-2	-4.88	2.26e-3
Business Cycle								
EU Bonds	96.90%	0.0010	4.37e2	0.00	96.60%	-2.72e-1	2.03	2.74e-1
US Bonds	98.93%	0.0005	6.13e2	2.94e-4	75.20%	2.57e-3	-1.52e2	-1.84e-3
JP Bonds	97.48%	0.0010	2.74e2	0.00	95.45%	-2.49e-1	2.03	2.50e-1
Hang Seng	86.25%	0.0010	1.57e2	2.81e-3	79.68%	-1.20e-1	1.77	1.20e-1
S&P500	95.74%	0.0000	2.98e3	1.99e-3	67.31%	-1.65e-1	1.68	1.65e-1
EuroStoxx	95.13%	0.0005	2.89e2	1.91e-3	78.91%	-7.54e-2	1.94	7.58e-2
FTSE100	72.01%	0.0020	1.66e2	0.00	84.89%	-1.44e3	1.95e-4	1.44e3
Topix	41.81%	918.8634	9.87e-5	-9.19e2	99.20%	1.63e-3	-2.42e2	0.00
EUR/USD	97.23%	0.0019	2.41e2	-9.54e-5	98.91%	2.11e-3	-3.84e2	-4.29e-4
EUR/JPY	94.22%	0.0001	1.32e3	1.10e-3	97.67%	3.89e-4	-5.77e2	1.00e-3
EUR/GBP	94.49%	0.0012	2.90e2	0.00	84.21%	-1.65e-1	2.06	1.66e-1
JPY/USD	98.63%	0.0008	3.48e2	4.95e-4	92.85%	1.19e-3	-3.01e2	0.00
GBP/USD	92.15%	0.0000	1.41e3	1.13e-3	96.92%	3.83e-3	-1.94e2	-1.91e-3
EPRA Europe	94.35%	0.0022	1.68e2	2.31e-3	98.03%	1.23e-2	-8.78e1	-7.73e-3
GSCI	64.88%	-0.0000	2.49e3	2.83e-3	71.50%	-1.21e-1	2.01	1.22e-1

Table E.2
Fit Results of $y = ae^{bx} + c$ on Conditional Expectation (Cont.)

	Long Position				Short Position			
	R^2	a	b	c	R^2	a	b	c
	Normalized Business Cycle							
EU Bonds	96.86%	0.0000	6.90	1.04e-3	96.92%	3.95e-3	-1.90	-7.73e-4
US Bonds	97.61%	0.0000	5.95	6.27e-4	97.30%	2.85e-3	-3.58	-1.86e-4
JP Bonds	87.42%	0.0005	1.60	0.00	99.25%	3.73e-3	-3.65	-5.13e-4
Hang Seng	87.70%	0.0008	1.73	2.50e-3	98.36%	1.37e-2	-6.37	-1.73e-3
S&P500	72.19%	-0.0222	-7.92e-2	2.38e-2	92.93%	6.77e-3	-2.11e1	-9.84e-4
EuroStoxx	98.15%	0.0000	1.19e1	2.83e-3	98.10%	9.53e-3	-4.09	-1.02e-3
FTSE100	87.70%	0.0008	1.82	0.00	94.17%	3.34e-3	-5.13	-8.31e-4
Topix	91.08%	0.0003	2.64	0.00	98.81%	1.38e-2	-6.07	8.69e-4
EUR/USD	92.65%	0.0001	4.36	1.31e-3	98.78%	8.83e-3	-4.21	5.15e-4
EUR/JPY	91.67%	0.0210	1.32e-1	-2.07e-2	93.41%	8.87e-3	-4.52	1.22e-3
EUR/GBP	97.99%	0.0004	2.42	0.00	96.16%	3.96e-3	-3.07	0.00
JPY/USD	96.47%	0.0000	8.84	1.37e-3	62.24%	-1.64e-4	2.27	1.19e-3
GBP/USD	95.34%	0.0004	2.58	3.69e-4	95.76%	1.14e-2	-1.04e1	1.24e-3
EPRA Europe	83.86%	-0.0068	-1.31	9.10e-3	96.97%	2.37e-2	-7.40	6.51e-4
GSCI	85.40%	0.0006	1.73	1.94e-3	98.37%	1.42e-2	-2.82	-2.50e-3

Appendix F

Historical Optimisation of Academic Strategies

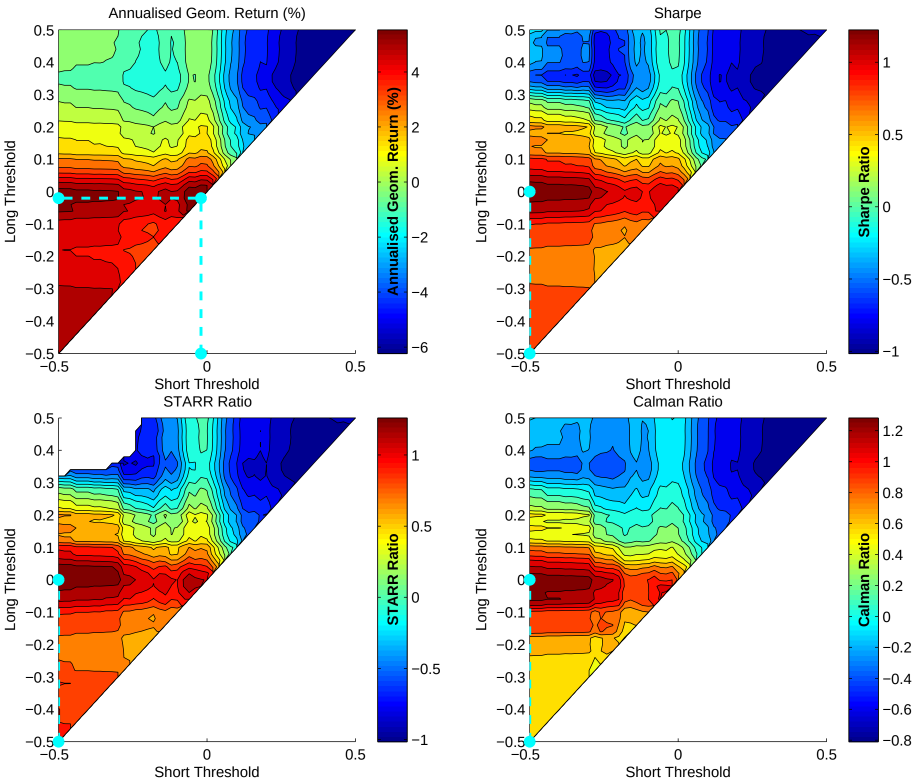

Figure F.1: In-Sample Backtest Results R/W/H Strategy

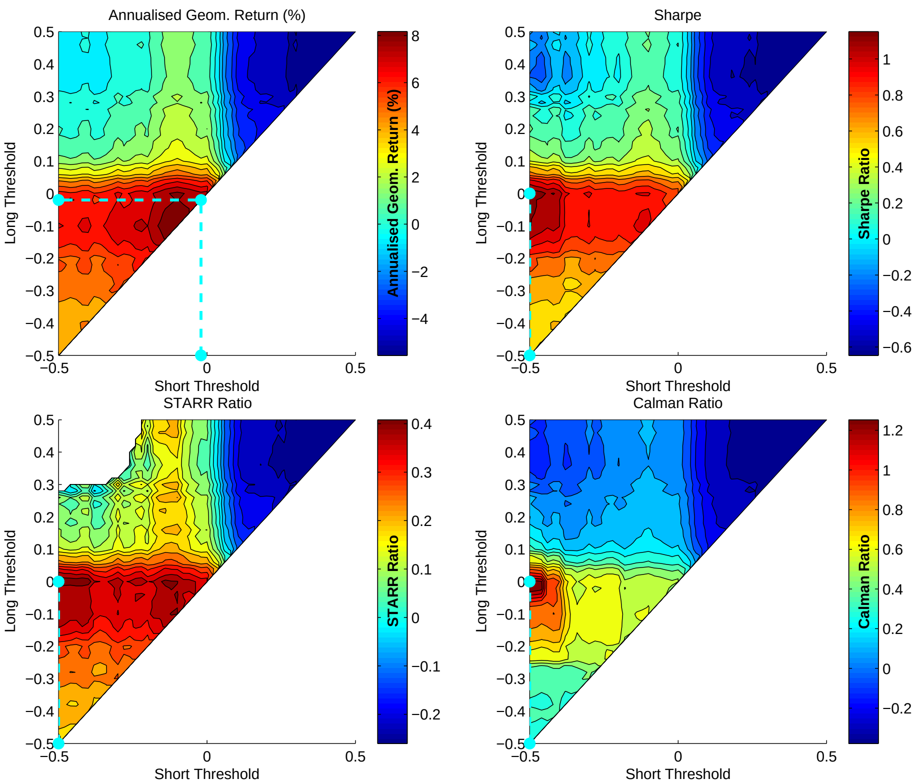

Figure F.2: Out-of-Sample Backtest Results R/W/H Strategy

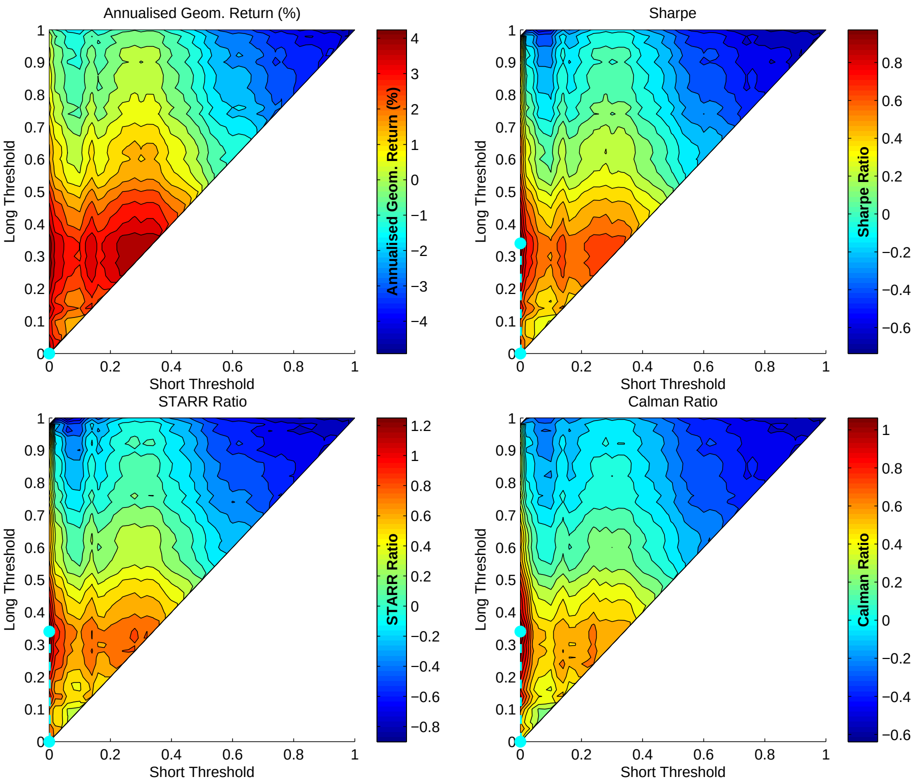

Figure F.3: In-Sample Backtest Results Normalised R/W/H Strategy

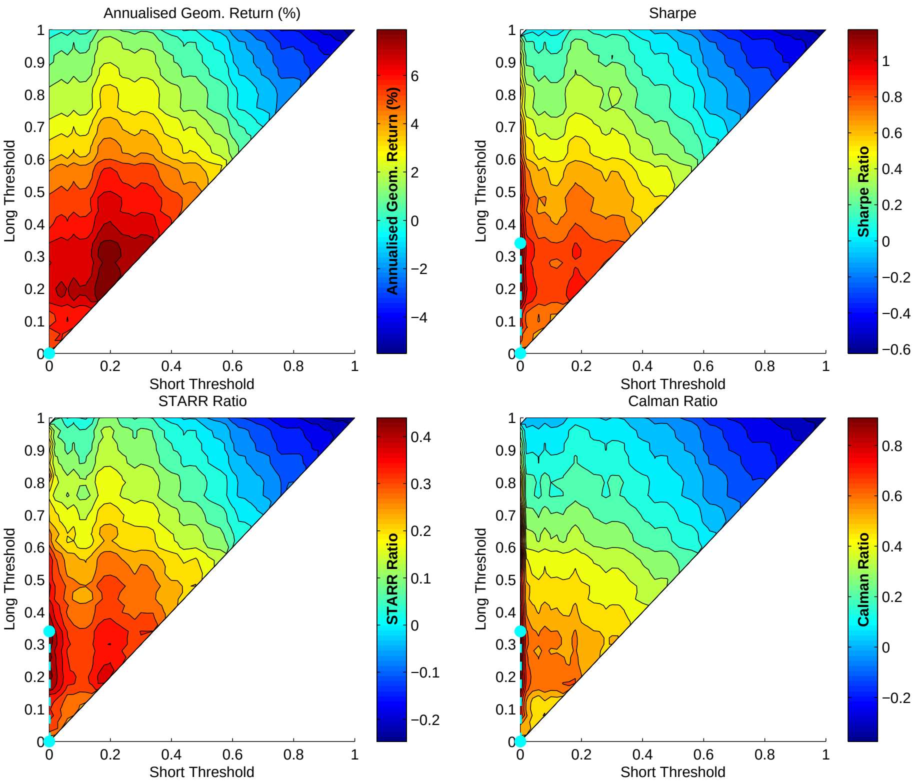

Figure F.4: Out-of-Sample Backtest Results Normalised R/W/H Strategy

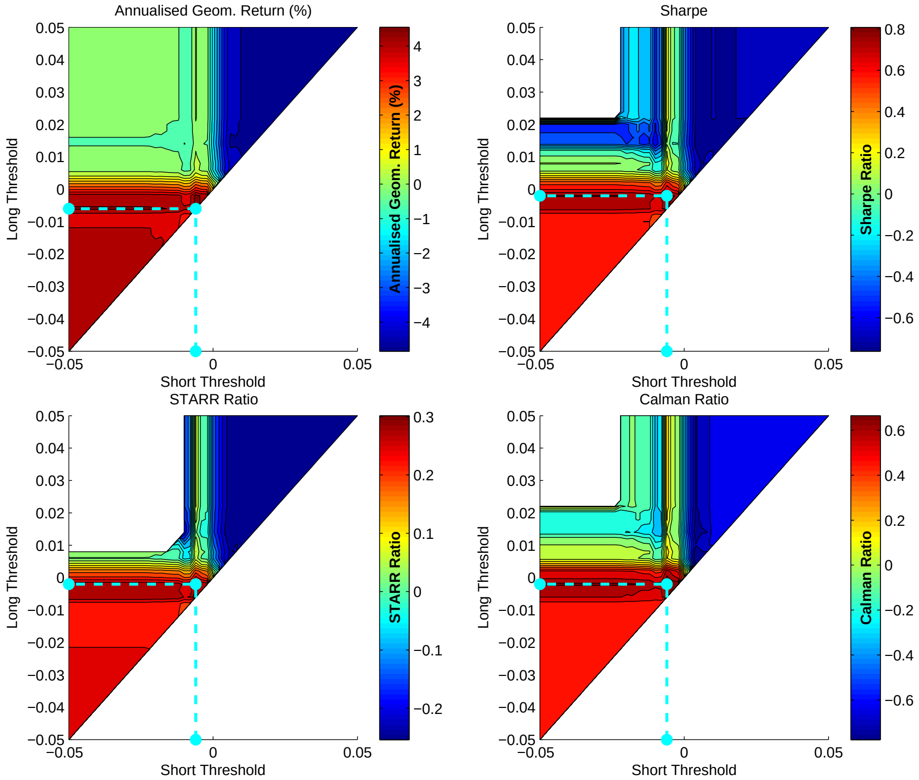

Figure F.5: In-Sample Backtest Results R/W/H Strategy

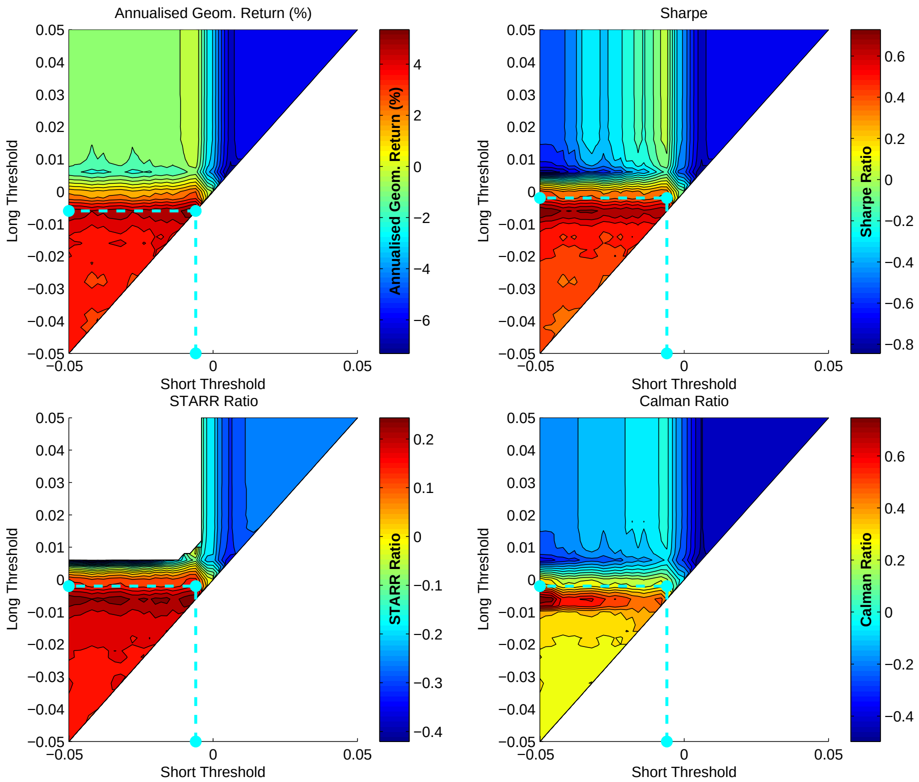

Figure F.6: Out-of-Sample Backtest Results R/W/H Strategy

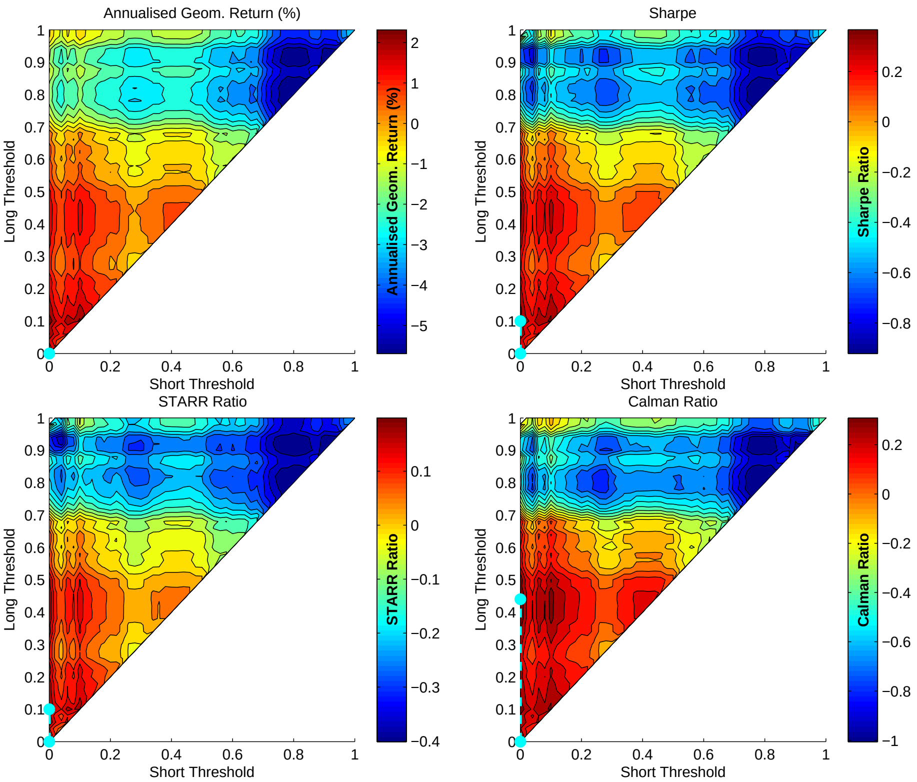

Figure F.7: In-Sample Backtest Results Normalised Business Cycle Strategy

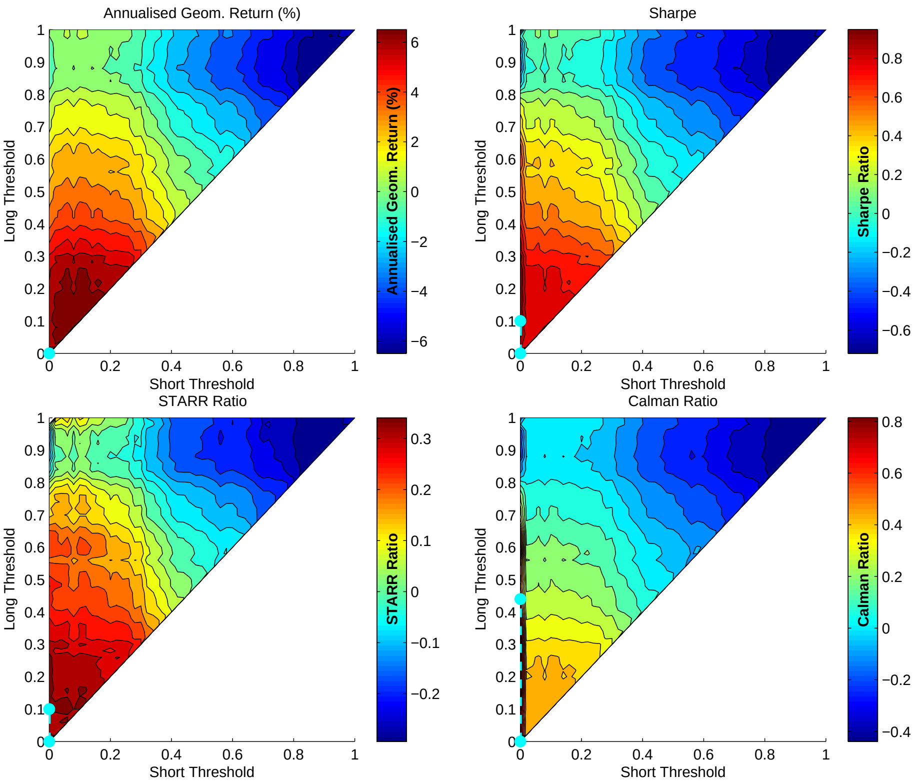

Figure F.8: Out-of-Sample Backtest Results Normalised Business Cycle Strategy

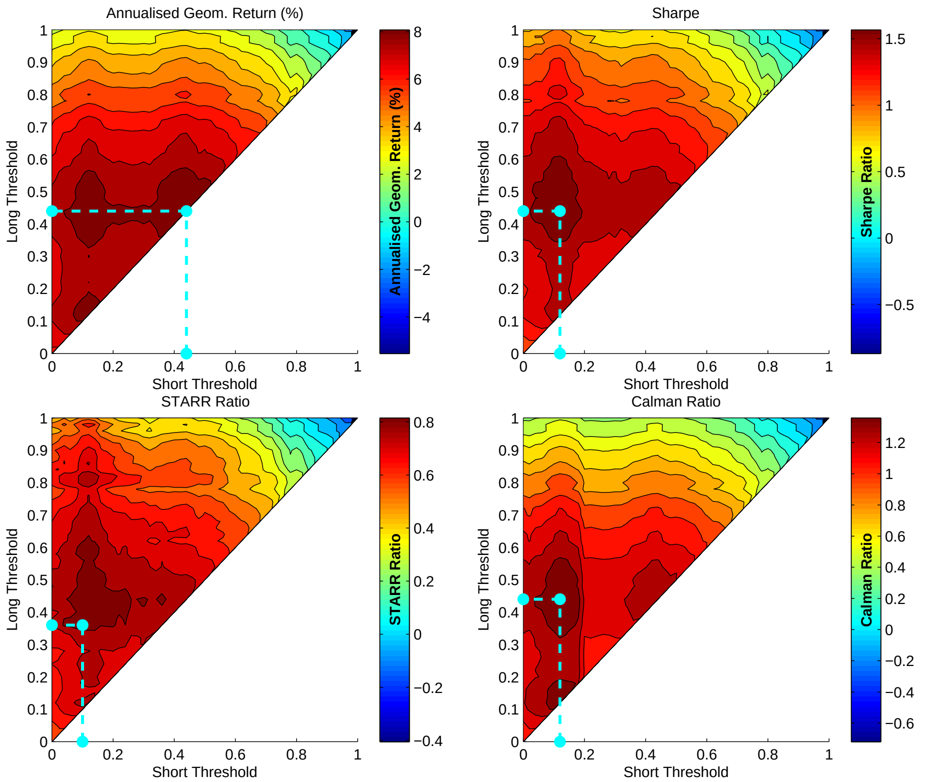

Figure F.9: In-Sample Backtest Results 52-Week High Strategy

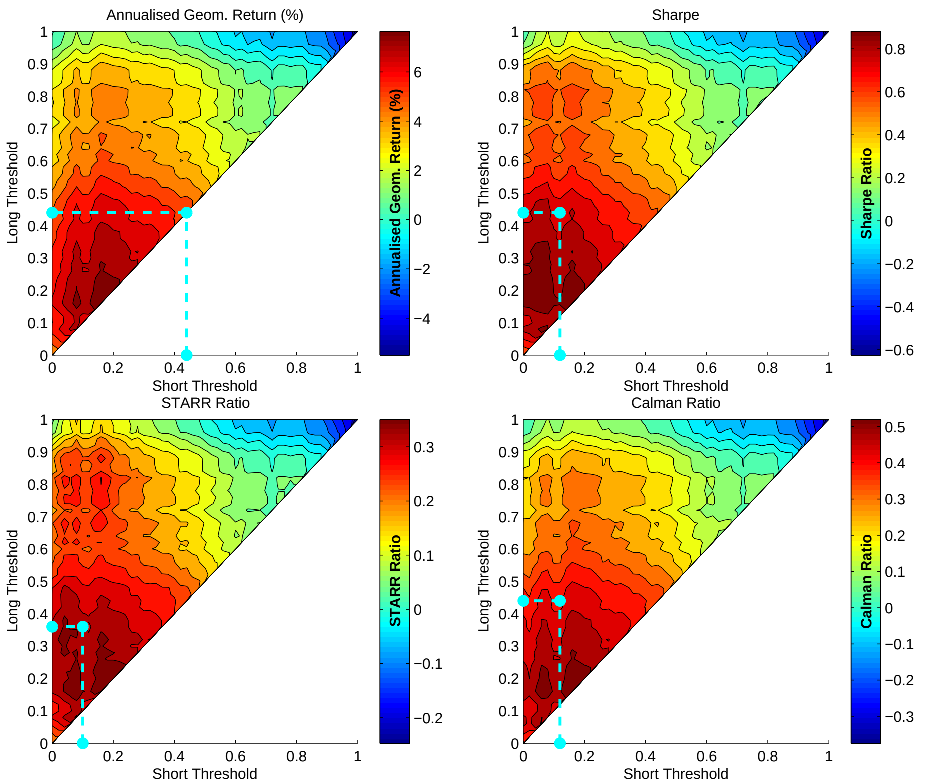

 Figure F.10: Out-of-Sample Backtest Results 52-Week High Strategy