Master Thesis

# Applied Value and Momentum Trading

An Analysis of Value and Momentum Investing In the US Equity Market


| *Authors:* | *Student IDs:* |
| --- | --- |
| Andreas Malle | 101293 |
| Frederik Kildedal | 101667 |

*Supervisor:*

Martin C. Richter


Number of pages: 103

Number of characters including spaces: 182273

Study Program: Finance and Investments

Date: May 15, 2020

# Acknowledgement

We would like to express our gratitude to all parties involved in the process. We want to thank our supervisor Martin Richter for providing excellent guidance and great academic discussions. A warm thanks to our families for their support and encouragement during this process.

# Abstract

In this paper, the performance of systematic fundamental and momentum driven strategies in the US equity markets is analyzed. We evaluate the performance by backtesting long/short factor portfolios and compare them to an equal-weighted market portfolio. The backtest is implemented from 1997 to 2019 with a trading universe consisting of historical constituents in the Russell 3000 index.

We demonstrate that traditional value and momentum strategies have been a source of positive returns but are exposed to large drawdowns. However, these drawdowns can be mitigated by risk-adjusting the portfolios. It is shown that modern adaptions of the classical factor portfolios have superior performance. Momentum measures that control for factor exposures minimize the risk of momentum crashes. For value, the risk of value traps can also be reduced by controlling for the fundamental quality of the stocks. Moreover, the risk of the factor portfolios can be reduced by beta neutralizing the strategies and thereby further limiting the systematic risk exposure. Volatility managed portfolios are also introduced by leveraging the portfolios to a 10% risk target based on ex-ante volatility estimates. The scaling is shown to have different impacts on the two factors. As the factor strategies have different dynamics and returns distributions, the effect of volatility scaling is positive for momentum and negative for value. However, both of the volatility targeted strategies produce better risk-adjusted returns than the basic strategies and the market portfolio in the backtests. Furthermore, the past performance of combined value and momentum portfolios is analyzed. The negative correlation between the strategies reduces the risk and drawdowns of the combined portfolio while maintaining high returns. Therefore combining value and momentum portfolios provides better risk-adjusted returns than the individual factors and the market portfolio.

The results of the paper verify that individual adaptions of value and momentum strategies have shown strong performance compared to the market in the past decades. Moreover, the performance can be enhanced by combining the strategies. This results in a portfolio with better risk-adjusted returns than the separate factors and is highly superior to market portfolios.

# Contents

# 1. Introduction

Factor investing has become a popular phenomenon in the world of finance in recent decades. There has been a massive increase in research related to factor strategies, and substantial attention is paid to the performance and validity of different factors (Cazalet & Roncalli, 2014). Consistent factors are appealing as it gives investors alternative sources of returns, and enables the construction of portfolios that are not reliant on the market risk premium. Two of the most analyzed and established factors are value and momentum (Asness, Moskowitz, & Pedersen, 2013). These two factors have a long-running history but are still heavily debated on their ability to create excess returns. The value and momentum factors are very different in nature and capture different dynamics in the market. The value factor is created by evaluating stocks on their price relative to fundamental stock data. The goal is to buy "cheap" stocks and sell "expensive" ones by systematically evaluating whether stocks are undervalued (overvalued). The value stocks tend to show a correction in the price, which leads to a positive relationship between the value factor and asset returns. Momentum, on the other hand, focuses on the tendency for the past to repeat itself and tries to capture "momentum" in asset prices. Momentum is based on buying stocks whose price has increased in prior periods and selling stocks which value has decreased. Thereby the momentum factor is betting on the prices to continue in the same direction. Historically both the value and momentum factors have shown periods of high returns, despite the return structures being very different (Asness, 1997). This difference stems from the large contrast in the evaluation of stocks. If a stock has high earnings and the price falls, it will appear cheaper from a value perspective. However, a falling stock price will give the stock a lower momentum score. Therefore the two strategies tend to be negatively correlated and thus perform well (bad) at different times. Both factors are commonly used by practitioners and often mentioned in academic research. However, much of the literature written on the two factors use many simplifications. Often trading costs, market risk exposure, and general volatility are only included in fragments when strategies are analyzed in papers. However, these are essential elements when institutional investors apply these strategies in practice. Hence all of these aspects should be taken into account at once. In this paper, we, therefore, seek to account for such elements and evaluate realistic factor strategies. We analyze the performance of systematic fundamental and momentum driven strategies in more recent years and compare it to simply investing in a market portfolio. Moreover, we look at how the combination of value and momentum strategies can be used to enhance performance.

## 1.1 Problem Statement

In this paper, we asses how the value and momentum factors have performed in the US equity market since 1997. We first describe the theory and rationale behind the factors. This is followed by an empirical analysis of hedge fund-like factor strategies and their performance in comparison with the market. In order to examine the performance, this paper seeks to answer the following questions.

**How have quantitative fundamental and momentum driven trading strategies performed in the US equity market over the past decades?**

- What are the dynamics of classic value and momentum portfolios?
- Which adaptions of these strategies exist, and what impact do the different modifications have on the return premiums?
- How does risk-adjusting the portfolios influence the strategies?
- What effect does combining value and momentum factors have on portfolio performance?

## 1.2 Delimitation

It should be noted that to focus on the most important areas of interest, some delimitations are applied to narrow down the analysis. In the following section, both limitations and delimitations that constrain the research in this thesis are mentioned and explained.

### 1.2.1 Trading Universe

To analyze the US equity market, the market universe needs to be defined. The tradeable universe of the strategies created in this paper, is defined by the Russell 3000 index. This constraint on the tradeable equities is applied such that the most liquid and largest stocks are traded. This makes the trading strategies applicable in practice and the results more relevant.

The time-period analyzed is also constrained to focus on more recent factor performance and because of data limitation. Historical constituent data for the Russell 3000 index prior to February 1995 was not obtainable from the available data sources. Therefore the backtests are limited to the period from the beginning of 1997 to the end of 2019. The reason for starting the backtest in 1997 is that initial data is needed to create signals before trading can commence.

### 1.2.2 Data

The constituent data was gathered using a Bloomberg Terminal, but as a result of the data limitations present, the price and fundamental data were obtained from other sources. Various data sources without limitations were utilized, such as CRSP and Compustat. These were accessed through remote connections. It was not needed to be physically present at the campus to gather data. Therefore, the fundamental and price data used in the analysis are limited to what was obtainable from CRSP and Compustat.

When implementing fundamental trading strategies, sector neutralization is often utilized. In this paper, only the first level of GICS classifications is used. This is done to ensure that there are enough tradeable securities in each of the 11 sectors. Furthermore, it is assumed that the companies in the trading universe do not completely change their primary line of business. Therefore it is assumed that the GICS classifications do not change while they are a part of the Russell 3000. The GICS taxonomy has been revised over the years since its inception. These revisions have mainly been focused around the sub-industry and industry levels. However, in 2016 MSCI and S&P discontinued the Real Estate industry group under Financials. The Real Estate sub-industry was used to create a new sector and given the ID of 60 (MSCI, n.d.). This reclassification introduces a bias in the Financial sector as firms that cease trading prior to the reclassification are not moved.

### 1.2.3 Value and Momentum Measures

For both value and momentum strategies, many different measures and methods to capture the underlying premiums exist. In this paper, we do not investigate all possible variations of the factors but focus on a few conventional methods to construct the factor strategies. For the value strategy, the measures are based on those which are most commonly referenced in different papers. These measures are the book-to-market ratio, the dividend yield, and the price-earnings ratio. Furthermore, three quality measures are selected to constitute the quality part of the "quality at a reasonable price"-factor, gross profit margin, debt-to-assets, and return on assets. We classify and denote the combined value and quality strategy as a value strategy. These can be classified as two individual factors which both utilize fundamental data. However, classical value investors such as Benjamin Graham also uses measures specific to both strategies but are often referred to as the father of value investing (Cazalet & Roncalli, 2014). We denote the strategy as a value strategy but accept that some might prefer to refer to it as a fundamental strategy.

There are also many different versions of momentum strategies. We choose to focus on three versions; price, idiosyncratic, and alpha momentum. The classic price momentum is included as it is the first described momentum factor and the most commonly referenced. However, the traditional price momentum has problems with time-varying systematic risk exposure, and therefore we introduce idiosyncratic and alpha momentum.

### 1.2.4 Investor Type

In this paper, we take the view of an institutional investor without shorting constraints. This perspective introduces a cost structure different from that of an individual investor because of the difference in scale. Furthermore, this view accommodates the creation and implementation of strategies with some degree of operational complexity. However, we do not include performance and management fees since we do not focus on the costs paid by the fund's investors.

### 1.2.5 Theoretical Rationale

Our analysis includes a walkthrough of the theoretical framework and rationale behind the strategies. However, there exist several explanations for the different premiums. We do not test the validity of the individual theories, nor do we prefer one explanation over the other. The focus is on providing an understanding of the background for the different factors. Hence we do not conclude whether these are, in fact, anomalies or risk premiums. Instead, we focus on the performance and profitability of strategies trading these factors.

# 2. Theoretical Framework

In the following section, the theoretical foundation behind the paper is described. The reasoning behind momentum and three different approaches to capturing the factor are described. Additionally, an explanation of the value premium is given alongside the different metrics which can be used to capture the premium. Moreover, the methods and implications of integrating the two factors in a single portfolio are discussed. Along with the theoretical framework for the factors, systematic risk and volatility targeting are described to give an understanding of the theory behind the risk management applied in this paper. Finally, the backtesting framework and its components are explained.

## 2.1 Momentum Investing

The concept of momentum investing was first popularized by Jegadeesh and Titman (1993) in their paper "Returns to Buying Winners and Selling Losers". Momentum investing is the idea that assets that have performed well (poorly) in the past tend to perform well (poorly) in the future. The original momentum framework, as described by Jegadeesh and Titman (1993), is based on ranking stocks on their past returns in a preceding period. Jegadeesh and Titman (1993) documents that a zero-cost strategy shorting a portfolio with the prior period's loser stocks and buying a portfolio with the prior period's winners stocks realizes positive in all but the first of the following 12 months. The strategies used in their original paper evaluates the stocks' on the past returns over 1-4 quarters and across varying holding periods from 1-4 quarters. In each rebalancing period, the stocks are divided into deciles, and the decile containing the top-performing stocks is bought while the decile with the worst-performing stocks is shorted (Jegadeesh & Titman, 1993). The abnormal returns from these strategies verify that the stocks with above (below) average returns in prior periods tend to perform better (worse) than average in the following periods. An abnormal return from a 6/6 strategy would therefore imply:

$$E[r_{it} - \bar{r}_t | r_{it-1} - \bar{r}_{t-1} > 0] > 0 \tag{2.1}$$

and vice versa

$$E[r_{it} - \bar{r}_t | r_{it-1} - \bar{r}_{t-1} < 0] < 0 \tag{2.2}$$

The 6/6 month strategy ranks the stocks on the prior 6 months and holds the portfolio over the following 6 months. In the formulas $r_{it}$ is the return of asset $i$ in a six month period $t$ whereas

$\bar{r}_t$ denotes the cross-sectional average for the period $t$. This relationship between past and future performance is what Jegadeesh and Titman (1993) verifies. Since the publication of their findings, many adaptions of different momentum strategies have been applied and examined in different papers. The most famous and simple momentum measure is based on ranking the stocks on the prior 12 months returns skipping the last month to avoid short term reversals in the stock returns (Asness, Moskowitz, & Pedersen, 2013). This method is used to construct many of the popular factor portfolios. Among others, the Carhart four-factor model, which is an extension of the Fama-French three-factor model. In the Carhart model, twelve months returns where the most recent month is skipped are used when constructing the momentum factor portfolios (Carhart, 1997). This way of measuring momentum has become the most commonly used momentum measure in academia. However, many different ways of measuring momentum exist and are used in practice.

### 2.1.1 Momentum Adaptions

In this paper, we focus on three types of momentum measures, price, idiosyncratic, and alpha momentum. Price momentum is defined as the classical momentum popularised by Jegadeesh and Titman (1993), where momentum is measured by past price returns over a certain period. Accordingly, the common price momentum strategy in this paper is determined as above with a cumulative return across the past twelve months skipping the last month. The stocks are ranked monthly and sorted in decile portfolios, where the best performing portfolio is bought, and the worst is sold short. This portfolio is then held over one month before rebalancing occurs. However, common price momentum is heavily criticized for exhibiting huge crashes and having a significant exposure to systematic risk factors - especially market risk (Blitz, Hanauer, & Vidojevic, 2017). In periods where the general market is increasing, stocks that have performed well over the past 12 months tend to be high beta stocks because of their high market exposure. The worst-performing stocks tend to be low beta stocks. Thus, a long/short momentum portfolio increases its beta in bull-markets and becomes highly vulnerable to sudden market crashes. Moreover, if a bear-market persists, the best (worst) performing stocks have a low (high) beta. Consequently, common price momentum portfolios source negative beta in bear markets and perform poorly at the beginning of a trend reversal. As a way of overcoming these issues with the classical price momentum, new momentum adaptions have emerged. Two accredited extensions are idiosyncratic and alpha momentum measures described by Blitz et al. (2017) and Huhn and Scholz (2013). These two adaptions utilize the three-factor model by Fama and French (1993), where the excess return of stock $i$ is described as:

$$r_{i,t} - r_{rf,t} = \alpha_i + \beta_i RMRF_t + s_i SMB_t + h_i HML_t + e_{i,t} \tag{2.3}$$

RMRF is the market's excess return, and SMB and HML are the size and value factors. Therefore $\alpha$ and $e$ are the non-factor contributions to return while $\beta_i RMRFt + s_i SMBt + h_i HMLt$ is the return part explained by its factor exposure. In the common price momentum strategies, the ranking of returns is highly affected by factor realizations and their contribution to the returns. To minimize the dependency on factor realizations in momentum portfolios Blitz et al. (2017) and Huhn and Scholz (2013) use the part of the returns that cannot be captured by the risk factors to measure momentum.

In their paper, "The Idiosyncratic Momentum Anomaly", Blitz et al. (2017) show how volatility adjusted idiosyncratic returns can be used to improve momentum trading. The idiosyncratic returns are measured by the residuals, $e_{i,t}$ in the Fama-French three-factor regression.

$$e_{i,t} = r_{i,t} - r_{rf,t} - \alpha_i - \beta_i RMRF_t - s_i SMB_t - h_i HML_t \tag{2.4}$$

They apply the regression shown in formula 2.3 on the past 36-months monthly returns and market factor realizations and calculate the residuals as in equation 2.4. Momentum is then defined by the sum of the past 12-month skipping the last idiosyncratic returns adjusted by volatility.

$$Idiosyncratic\ Momentum_{i,t} = \frac{\Sigma_{t-12}^{t-2} e_{i,t}}{\sqrt{\Sigma_{t-12}^{t-2}(e_{i,t} - \bar{e_{i,}})^2}} \tag{2.5}$$

The decile portfolios in the idiosyncratic strategy are formed and ranked the same way as in the price momentum of Jegadeesh and Titman (1993) but with the new momentum measure. Blitz et al. (2017) show that in the past, this strategy has achieved abnormal returns and performed better than price momentum strategies. The volatility of the time-varying factor exposures for the idiosyncratic strategy has historically been lower than for price momentum.

The same principle of calculating momentum in excess of the factor returns are also utilized in alpha momentum. Here, as the name implies, the $\alpha$ coefficient from equation 2.3 is used to capture momentum. In their paper Huhn and Scholz (2013), run the three-factor regressions on daily stock returns and factor realizations instead of monthly returns as in idiosyncratic momentum. Moreover, lead and lagged factors are included in the regression as recommended by Dimson (1979) to deal with infrequent trading. The regressions are estimated over a 12-month period of daily returns, excluding the most recent month, to account for short term reversals. As all observations of the regression are used, the mean of the residuals is zero. Therefore Huhn and Scholz (2013) argue that a better measure of the non-factor contribution to return is the alpha from the Fama-French regression. Decile portfolios are constructed by ranking the stocks on past $\alpha$. As in the price and idiosyncratic momentum strategy, the lowest decile portfolio is shorted while the highest decile portfolio is bought with monthly reranking and rebalancing. Huhn and Scholz (2013) documents that this approach also limits the time-varying risk exposures and reduces the momentum crashes. Even though both alpha and idiosyncratic momentum use non-factor parts of the returns, the two measures still deviate, as shown in the strategy implementation of this paper.

### 2.1.2 Explanations for Momentum

There are several plausible explanations for the momentum premium, both risk and non-risk based. Some argue that behavioral biases drive the momentum premium, and there are two primary behavioral explanations, underreaction, and delayed overreaction (Moskowitz, 2010).

Underreaction is caused by the delay between information becoming publicly available and when the information enters the prices. This delay might be caused by limits in processing and attention capacity and thus cause earning announcements etc. to enter prices slowly. The incremental integration of the information can thereby create a momentum effect. On the other hand, delayed overreaction explains the momentum effect by a bandwagon effect, where feedback mechanisms cause the price to increase above its fundamental value before reversing in the long run (Moskowitz, 2010). Momentum may be driven by both under and overreaction mechanisms, as exemplified by K. Daniel, Hirshleifer, and Subrahmanyam (1998), who argue that traders overreact to private information and underreact to public information.

There are several papers with behavioral models explaining what drives these underreactions and overreactions. For example, much recent work focuses on the disposition effect, a term initially introduced by Shefrin and Statman (1985). The disposition effect builds on the prospect theory described by Kahneman and Tversky (1977), which advances utility theory by showing that there are differences in utility in the gain and loss domain. The disposition effect is the observed tendency for investors to sell rising stocks quickly to lock in profits and being reluctant to sell falling stocks to wait for a reversal in the price movement. This premature selling, causes prices to not immediately jump up to its intrinsic value in case of good news, as many investors sell quickly for profits. On the other hand, when bad news is announced, investors are reluctant to sell the stock, and the price does not instantly decrease as much as it should. This effect has been shown to be present in financial markets by Odean (1998) and (Frazzini, 2006). The underreaction and the slow transition from information into the price results in a momentum effect (Moskowitz, 2010).

There are also risk-based explanations for the momentum factor. In the risk-based explanations, the momentum premium is compensation for taking on risk. H. B. Zhang (2004) argues that the time-varying risk factors are what drives the classical momentum returns, and the premium follows the change in systematic risk. Other risk measures, such as liquidity risk, are used by Sadka (2006) to explain momentum. Sadka (2006) argues that recent winners have higher liquidity risk than recent losers. Therefore a difference in the return premium should be observed. Another possible explanation is that the momentum premium stems from cash-flow risk. Asness (1997) shows that momentum is stronger among growth stocks. Moreover, Johnson (2002) argues that expected returns are based on firms' growth rates, and if stock prices rise, the firm's expectation of the firm's future growth in cash flows has increased. Therefore, momentum stocks have a risk of cash flows not materializing, and this uncertainty could drive the premium. In general, risk-based explanations argue that recent winners have a higher future risk because the price change also induces a change in risk. Hence, in the risk-based framework, the momentum premium is compensation for risk exposure (Moskowitz, 2010).

## 2.2 Value Investing

The idea of buying stocks when they are cheap and sell them when the price is high is arguably the most famous financial proverb. Even though it sounds simple, it is not easily done in practice. Value investing is widely acknowledged and was popularized in the 1930s and 1940s by Benjamin Graham and David Dodd. The focus of value investing is to buy securities that are priced lower than their intrinsic value. These companies are, therefore, classified as being undervalued. The idea behind buying undervalued stocks is that the market corrects itself. Over time, the market value is expected to adjust, such that the price reflects the intrinsic value. The selection of undervalued stocks can be based on various quantitative and qualitative metrics (Kok, Ribando, & Sloan, 2017).

In 1992, Fama and French published the paper, "The Cross-Section of Expected Stock Returns", which was followed by "Common Risk Factors in the Returns on Stocks and Bonds" in 1993. In these papers, they investigated different value risk factors in relation to the CAPM. Fama and French (1992) analyze the relationship between stock returns and the market, value, and size factors. Fama and French (1993) construct the value factor by sorting stocks on their $ln(BE/ME)$. Where $BE$ is the book value of equity, and $ME$ is the market value of equity. They show that both the value, size, and market factors have explanatory power on returns. Hence, stocks with a high book-to-market ratio have higher returns than stocks with a low ratio. This relationship verifies the existence of the value factor and the rationale behind buying "cheap" stocks (Fama & French, 1992).

Based on the results, they formulated the seminal Fama-French 3 factor model as described and referenced in equation 2.3 (Fama & French, 1993). However, the 3-factor model cannot explain all of the monthly returns following the statistical test conducted by Fama and French (1993). They show that including a value factor increases the explanatory power.

### 2.2.1 Explanations for Value

The value premium described by Fama and French (1992) shows that value tends to outperform growth stocks. There are different explanations for why this is the case. Lakonishok, Shleifer, and Vishny (1994) and Piotroski and So (2012) propose a behavioural explanation. They argue that investors overestimate the future performance of growth stocks. The overestimation is present because they overvalue stocks based on the available fundamental data. These investors undervalue current information and instead focus on extrapolating historical fundamentals. Thus, this overestimation for growth stocks eventually leads to a disappointing performance compared to the investors' expectations. Consequently, when ignoring newly arising information, they miss the improved performance of value stocks, indicating a turning-point. Hence, according to Lakonishok et al. (1994), the investors are underestimating value stocks. This simultaneous overvaluation of growth stocks and undervaluation of value stocks leads to the positive value premium, shown by Fama and French (1993).

Another explanation is provided by Fama and French (1997) & Kapadia (2011), who argue that the value premium is compensation for taking on risk. Value firms have high earnings, book value, etc. in relation to their price. Hence the price might be low due to a higher risk associated with the companies. The uncertainty contained in the value premium can be described as distress risk. Thus, the value premium is compensation for taking on exposure to distress risk, which increases sensitivity to business cycle factors (Asness, Frazzini, Israel, & Moskowitz, 2015). According to Fama and French (1997), different value factor portfolios based on ratios such as $BE/ME$, $E/P$, $CF/P$ and $D/P$ are captured by distress risk. Firms in financial distress may be impacted to a greater degree by changes in the market since they are not financially robust. If an economic downturn hits, the distressed companies have a higher probability of going bankrupt. Hence, according to Fama and French (1997), the value premium is not based on behavioral biases, but rather a risk factor.

### 2.2.2 Value Measures

Since the emergence of the value factor, a substantial increase in the number of different financial ratios that try to capture this has emerged. In the paper "Value Everywhere" by Hlavaty (2016), the authors report and analyze the performance of a plethora of different value measures in both developed and emerging markets. These value measures include different variations of book-to-market, price/earnings, dividend/price, and cash-flow ratios. A wide variety of fundamental ratios are according to Hlavaty (2016) capable of capturing value, but the historical performance of these ratios differ.

According to Kok et al. (2017), the reason for the different ratios' ability to capture value can be found in their composition. These ratios contain fundamental information that tries to capture the intrinsic value of the stock. The second component is the price of the security. The ratio measures how much an investor receives of the fundamental value per invested dollar. High intrinsic value and low price indicate that the stock is cheap i.e., a value stock. When stocks have a high value, two things generally happen. Either the price increases or the earnings etc. decreases. Both scenarios result in a reduction of the discrepancy between the underlying value and market value. A third option is an expansion of the divergence as a result of either a price decrease or an increase in the fundamental figure. Kok et al. (2017) show that there is a mean reversion in the fundamental ratios for the constituents of the Russell 3000. Hence stocks that are cheap become more expensive, and expensive stocks become cheaper.

Asness et al. (2015) reports that the value effect is best captured by using a composite of different value measures. According to them, there is no theoretical foundation for favoring a single measure. The value premium cannot necessarily be captured solely by ratios such as book-to-market. The authors' reasoning is that errors are present in each of the value measures, either due to accounting flaws or random errors. Therefore, the utilization of a composite value factor results in a more accurate representation of a firm's value by reducing the noise. If a fundamental ratio is inaccurate, the combination with other ratios decreases the significance of this error. The reduction of noise also results in lower volatility of the strategy's performance (Asness, Frazzini, & Pedersen, 2013).

When using value metrics, it is essential to distinguish between whether the stock is undervalued or cheap for a reason. This phenomenon is described by Pedersen (2019) as the value trap. The value trap describes the scenario where stocks appear to be undervalued, but financial instability justifies the price. The company might be fundamentally flawed, and the low traded price, might not be a discount, but rather a true reflection of the intrinsic value. If the company is flawed, the stock price might drop even further, causing investors to get caught in the value trap (Kok et al., 2017).

### 2.2.3 Quality at a Reasonable Price

The value trap issue can be mitigated by introducing the quality metric described by Asness, Frazzini, and Pedersen (2013) in the paper, "Quality Minus Junk". They formulate the "quality at a reasonable price"-factor (QARP) that reduces the risk of investors falling into the value trap.

The QARP factor is a combination of value and quality, which results in a combined factor. This is useful since value factors are focused on the security price in relation to different metrics. This is evident in the previously described price-to-book or price-earnings ratios, where the price of the security determines the ratio. Quality is only concerned about the quality of the stock and does not include the price. A quote by Warren Buffet encapsulates the main idea behind the QARP factor: "It's far better to buy a wonderful company at a fair price than a fair company at a wonderful price." (Berkshire Hathaway, 1989)

Asness, Moskowitz, and Pedersen (2013) defines the quality measure as a combination of profitability, growth, safety, and payout. Examples of profitability-measures in terms of quality are gross-profit-margin, return on assets, cashflow-over-assets, and accruals. The growth variables consist of the 5-year growth in the profitability measures. The defined safety measures include low beta, low leverage, and low idiosyncratic volatility and lastly, the payout measures are equity net issuance, debt net issuance, and total net payout over profits (Asness, Frazzini, &

Pedersen, 2013).

A z-score for each of the four different quality proxies are created to determine which companies exhibit the most value:

$$z_x = (r - \mu_r)/\sigma_r \tag{2.6}$$

Where $x$ is the measure is to be ranked, $r$ is ranks of the measure $r_i = rank(x_i)$ and $\mu_r$ and $\sigma_r$ is the mean and standard deviation of the ranks. Finally, an overall combined z-score for each of the four proxies is created. Asness, Frazzini, and Pedersen (2013) show that a significant return can be obtained by creating a portfolio consisting of selling stocks with the lowest z-scores and buying stocks with the highest. The significant return thus implies that high-quality stocks are underpriced, and low-quality stocks are overpriced.

To avoid the value trap Asness, Frazzini, and Pedersen (2013) and Piotroski (2000) suggest integrating quality measures into value trading strategies. As these fundamental factors have a low/negative correlation, this can greatly enhance the performance and reduce the risk of getting caught in the value trap.

## 2.3 Value and Momentum

As described in the previous sections, premiums are present in both value and momentum. According to Christensen (2015), excess monthly returns for a value strategy, are observed in 66% of the months from 1990 to 2012. During the same period, excess momentum returns are observed in 60% of the months. Notably, in just 36% of the months, excess returns are observed for value and momentum at the same time. Moreover, only in 10% of the months, neither value nor momentum outperforms the market. Since the performance of the two strategies is not always overlapping, combining the two strategies can enhance the performance (Christensen, 2015). This benefit is further supported by Asness, Moskowitz, and Pedersen (2013). They find a negative correlation of $-0.53$ between value and momentum from 1972 to 2011 in the US equity market. Both Chibane and Ouzan (2019) and Pazaj (2019) validate the negative correlation. They show that positive returns for value portfolios are mirrored by contemporaneous negative returns in momentum. These are especially prevalent during market rebounds, where momentum crashes and value increases.

An intuitive explanation of the negative relationship between the two factors can be found in the price-relation of momentum and value. In value strategies, an increase (decrease) in price results in a lower (higher) value score. The opposite is the case for momentum, where a price increase (decrease) leads to a higher (lower) absolute momentum score. The expectation for a stock exhibiting momentum is that the price continues its trend, i.e., exhibit positive autocorrelation. In contrast, value stocks revert to the intrinsic value over time, hence exhibiting negative autocorrelation (Haghani & Dewey, 2016). Therefore, the nature of the two types of trading strategies are very different and often have opposite dynamics.

### 2.3.1 Combining the Factors

There are several ways of combining value and momentum into one single portfolio. The approach used by Asness, Moskowitz, and Pedersen (2013) consists of simply investing a predetermined weight in both the value and momentum portfolio. The advantage of this model is that the factors are independent, and can as such, be replaced with other factors at will. The disadvantage is that the combined model can consist of conflicting positions since the two portfolios are completely independent (Rabener, 2018a). The return of a combined portfolio is expressed as:

$$r_t^{Combo} = W * r_t^{Value} + (1 - W) * r_t^{Momentum} \tag{2.7}$$

Another approach is to use the intersectional model as described by Rabener (2018a), where the securities are selected at the same time based upon different factors. This can be done by an unconditional sort of two factors at the same time, as shown in table 2.1 below.

| | Momentum Score | | |
|---|---|---|---|
| Value Score | P1 | P2 | P3 |
| | P4 | P5 | P6 |
| | P7 | P8 | P9 |

Table 2.1: Sequential factor combination

By sorting the stocks on several factors simultaneously, quantile portfolios, as in table 2.1, are achieved. Thus the portfolio is constructed by shorting $P1$ and buying $P9$. $P1$ is the quantile containing stocks that have both low value and momentum, whereas the opposite is the case for $P9$. The construction of an intersectional model can also be based upon the z-scores of different factors, thereby sorting on the stocks with the best simultaneous performance of the factors, which could be value and momentum. This can be done by combining the z-scores, shown in equation 2.6, for each security.

$$Intersectional\ Score_i = z_{Value_i} + z_{Momentum_i} \tag{2.8}$$

The outcome of this approach is thus a single value and momentum measure, contrary to the combination of different portfolios. However, the size of the intersectional portfolio is smaller than that of the combined portfolio. It can be an advantage if portfolios become more concentrated with fewer but more preferable positions and lower transaction costs. The smaller size can also be a detriment since fewer stocks result in less diversification. The size of the intersectional model depends on the availability of data and the chosen quantiles. Sorting based on multiple factors at once can lead to a complicated derivation of the portfolio. Moreover, it can be challenging to determine how the factors contribute to returns.

The final approach described by Rabener (2018a) is the sequential approach. This approach constructs a portfolio by sorting on each of the factors in a predetermined sequence. When sorting on multiple factors, the trading universe is quickly reduced based upon the selected quantiles. If the trading universe consists of 3000 stocks, and the top 20% and bottom 20% quantiles are used, 1200 stocks are selected. The next sequence consists of selecting the top 20% and bottom 20% of the remaining universe, resulting in 480 stocks. The trading universe is reduced further if the sorting of factors continues. There is a major difference between the sequential and the unconditional sorting procedure used in intersectional models. In the sequential method, the sub-portfolios are conditional on the first factor. Therefore, the factor which is sorted on first has a much larger influence on the portfolio construction than succeeding factors. Hence, the sequential method assigns higher importance to the initial sorts. The performance of the sequential model will, therefore, differ depending on which factor is chosen in the initial sort.

All of the different methods incorporating multiple factors into a single portfolio are utilized in practice (Rabener, 2018a). As evident, they all have their advantages and disadvantages. In this paper, we focus on the combinational model, such that the performance of the combined portfolio can be directly traced back to the individual strategies.

## 2.4 Systematic Risk

In finance, there are different kinds of risks to account for when investing. An important element is market risk, which is the risk inherent in the overall market. Systematic risk is measured by assets' or portfolios' covariance with the market and shows how their returns are affected by market movements. In general, the risk can be derived from the most famous asset pricing model in finance, namely the Capital Asset Pricing Model, referred to as CAPM. In this one-factor model, the returns of an asset $i$ are described as following:

$$r_i - r_f = \beta_i(r_m - r_f) + \epsilon_i \tag{2.9}$$

According to the CAPM, stock returns are affected by the return of the market $r_m$. This exposure is defined as the systematic risk or market risk and is the risk contribution from market movements i.e. the sensitivity to the market factor. The return variance is measured by two components, the systematic risk and the idiosyncratic risk. Denoting the return of the market, $r_m$, as the market factor $F_m$ using the notation of Munk (2018) the return variance is given by:

$$\begin{aligned} Var[r_i] &= \beta_i^2 Var[F_m] + Var[\epsilon_i] + 2\beta_i Cov[F_m, \epsilon_i] \\ &= \beta_i^2 Var[F_m] + Var[\epsilon_i] \end{aligned} \tag{2.10}$$

It is assumed that $Cov[F_m, \epsilon_i] = 0$. Here the systematic risk component of assets returns is the risk contribution from the market factor. The systematic risk is $\beta_i^2 Var[F_m]$ and the remaining part is the idiosyncratic risk, also called the firm specific risk, is $Var[\epsilon_i]$. Therefore, the exposure to systematic risk can be measured by calculating the sensitivity to the market factor by estimating $\beta$ with formula 2.11:

$$\beta_i = \frac{Cov[r_i, r_m]}{Var[r_m]} \tag{2.11}$$

Under the CAPM assumption, a 1% increase in the market return leads to a $\beta_i$% increase in the asset i's return. The estimations of the assets' betas can thus be used to control the market exposure of trading strategies. By conducting hedges or other types of neutralization, it is possible to reduce a strategy's market exposure if the actual beta of a stock at time t+1 can be estimated. The neutralization enables strategies to be less affected by the overall movements in the markets and returns to be mainly driven by strategy specific factors. However, estimating beta is not always as simple as it seems. Simple historical estimates of betas, using all available history, do not necessarily make reliable forecasts of future betas. A substantial amount of literature has shown that beta can be time-varying (Basu & Stremme, 2007). Investors face a challenging problem when seeking to estimate assets' and portfolios' future sensitivity to the market factor. Several different papers have been written on the subject of beta estimation utilizing a wide variety of different methods.

A time-varying beta can be estimated by running linear regressions, applying formula 2.11 shown above, but across a rolling window. The rolling regressions can be done across varying windows such that the beta is estimated across the past months, years, etc. Moreover, the regressions can use different return frequencies of days, weeks, and months. Daily returns have the advantage of more data to use in the regressions. However, if trading is nonsynchronous lower frequency data can provide better estimates as the returns include several days. To account for the infrequency, one can also use lagged and leaded daily returns. This adjusts for nonsynchronous trading via the relationship with past and future market realizations. Some early adaptions which accounted for this were introduced by Dimson (1979) and Scholes and Williams (1977). In their framework, the estimated systematic risk is based on the sum of the beta coefficient for different times, $t$.

Dimson Beta

$$r_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,t}^{(0)}(r_{m,t} - r_{f,t}) + \beta_{i,t}^{(1)}(r_{m,t-1} - r_{f,t-1}) + \beta_{i,t}^{(2)}(\Sigma_{n=2}^{N} r_{m,t-n} - r_{f,t-n}) + \epsilon_{i,t}$$

If N is set to 1 in the Dimson beta framework, the last term is dropped.

$$\beta_{i,t} = \Sigma_{j=0}^{min(2,N)} \beta_{i,t}^{(j)} \tag{2.12}$$

Scholes-Williams Beta

$$\beta_{i,t} = \frac{\beta_{i,t}^{-} + \beta_{i,t} + \beta_{i,t}^{+}}{1 + 2\rho} \tag{2.13}$$

In the Scholes-Williams estimation, each $\beta$ is estimated from linear regressions as in equation 2.11 but with individual estimations using lagged, current, and leaded market returns. These betas are then added together to estimate the systematic risk. $\rho$ is the first-order autocorrelation in the market returns.

Recent literature has also proposed separating the horizon in correlation and volatility estimation for the beta calculation. Frazzini and Pedersen (2014) propose to use longer horizon estimates for the correlation. They use the sum of three periods log-return to account for infrequent trading in their correlation calculation. When estimating volatility, they use one-day log-returns and a shorter horizon, as volatility changes more dynamically.

Frazzini-Pedersen Beta

$$\beta_{i,t} = \rho_{i,t} \frac{\sigma_{i,t}}{\sigma_{m,t}} \tag{2.14}$$

The volatility is calculated across one year log returns and the correlation $\rho$ is estimated using overlapping log returns for three periods and across five years.

$$r_{i,t}^{3d} = \Sigma_{k=0}^{2} ln(1 + r_{r+k}^{i})$$

Other adaptions of beta estimations also include exponentially weighting the returns such that more recent observations have a larger weight (Fusai & Roncoroni, 2011), shrinkage of betas (Vasicek, 1973), and many more. As shown, there are many ways to obtain an estimate of the systematic risk for assets and portfolios. In this paper, we rely on the results of beta estimation methods applied and tested by Hollstein, Prokopczuk, and Simen (2019) across different anomalies. We use slightly different beta estimates for ex-ante and ex-post calculations and between the two anomalies; value and momentum. The specific estimations methods used for these are shown in the methodology.

## 2.5 Volatility Scaling

When investing in financial markets, it is important to be aware of one's risk tolerance. Financial markets are dynamic, and risk can vary greatly through time. To overcome changing risk profiles of portfolios, hedge funds often apply risk targeting. Funds often seek to maximize the return they can give to investors within a certain level of risk. Hitting a specified volatility target can be done by utilizing leverage, and in the hedge fund industry targeting volatility is more common than using constant leverage (Barroso & Santa-Clara, 2015). By conducting ex-ante estimation of future volatility, investors can lever or delever their portfolios such that the ex-post volatility remains within a specific range. However, prior research has shown that risk targeting not only constrains the risk but also improves the Sharpe ratios of trading strategies.

The use of constant volatility scaling has been shown in many papers to improve factor trading strategies. Moreira and Muir (2017) show that by scaling different factor-based trading strategies by the most recent month's volatility, it is possible to greatly enhance performance. The ex-ante estimated volatility leads to a deleveraging of the portfolios during recessions, therefore minimizing their exposure during bad times. When markets stabilize again, the leverage is increased. Other studies, however, have opposing findings with regards to the success of volatility scaling across different factors. Rabener (2017a) tests the success of volatility scaling across the size, value, and momentum factors and find that the scaled strategies do not improve the performance of the value and size factors. The value factor has a positive skew, and scaling the strategy limits the tail risk, which removes some of the large positive returns for value strategies.

Returns of the momentum factor are negatively skewed, and constant volatility strategies have proven to be especially beneficial for momentum trading. Barroso and Santa-Clara (2015) documents the positive effect of using leverage to control the risk of momentum. In their paper, they validate how the large crash risk inherent in momentum can be reduced by volatility targeting. As also pointed out by K. D. Daniel and Moskowitz (2014), momentum severely under-performs following periods of market declines and high volatility. Forecasting market risk is much harder than forecasting realized variance of momentum. According to Barroso and Santa-Clara (2015) autoregressions of monthly variances has an out-of-sample $R^2$ of 57.62% compared to only 38.61% for an autoregression on the variance of the market portfolio. They also decompose the risk of momentum into a market and momentum specific component and estimate that only 23% of the risk is attributable to systematic risk. Moreover, they find that momentum specific risk is persistent and more predictable than time-varying market betas. The specific risk component has an out of sample $R^2$ of 47.06% compared to 20.87% for the market component. Thus, they argue that this is why hedging only the time-varying systematic risk of momentum portfolios fail. Their scaling of the momentum strategy is done by forecasting volatility from the past half year's (126 trading days) variations in returns and use this to forecast the volatility in the following month.

$$\hat{\sigma}_{p,t}^2 = 21 \frac{\Sigma_{j=0}^{125} r_{t-1-j}^2}{126} \tag{2.15}$$

This volatility forecast is used to increase (decrease) leverage, such that the following returns can be calculated as in formula 2.16 below.

$$r_{p,t,levered} = \frac{\sigma_{target}}{\hat{\sigma}_{p,t}} r_{p,t,unlevered} \tag{2.16}$$

Volatility targeting results in a much-improved momentum strategy. The Sharpe ratio for their sample of the strategies improves from 0.53 for the initial momentum portfolio to 0.97 for the volatility managed portfolio (Barroso & Santa-Clara, 2015). Their test is done without transaction costs - however, the outperformance is of a magnitude, where transaction costs have to be extremely large to counteract this. This type of volatility targeting has also been shown in different papers to have a positive effect on other factor strategies such as low-beta, value, etc. (Moreira & Muir, 2017), (Barroso & Maio, 2016).

In practice, funds often use exponential weights and GARCH models when managing volatility, as it often results in better volatility forecasts. Both the hedge fund MAN AHL and the multinational bank BNP Paribas have written papers on the use of this type of modeling for volatility targeting (Harvey et al., 2018), (Perchet, Carvalho, Heckel, & Moulin, 2015). The standard GARCH model utilizes the clustering in volatility and estimates the process of volatility as in formula 2.17 below, which shows a GARCH (1,1).

$$\begin{aligned} r_t &= \mu + \sigma_t z_t \; with \; z_t \sim i.i.d.N(0,1) \\ \sigma^2_{p,t} &= \omega + \alpha(r_{t-1} - \mu)^2 + \beta\sigma^2_{t-1} \end{aligned} \tag{2.17}$$

The GARCH model can also include more lags - however, the GARCH (1,1) is the most standard approach. When returns follow a GARCH process as in equation 2.17, the volatility will fluctuate around its long-run variance, also called the unconditional variance. The unconditional variance is calculated following equation 2.18.

$$\sigma^2_{p,t} = \frac{\omega}{(1 - \alpha - \beta)} \tag{2.18}$$

Perchet et al. (2015) apply and test different GARCH models for volatility targeting and find that the best method is using the I-GARCH model. The I-GARCH is set to match the GARCH(1,1) in equation 2.17, but with $\omega = 0$ and the constraint: $\alpha + \beta = 1$. As the long-run average variance $\omega$ can be hard to determine in practice and even non-stationary, this model often provides great results when forecasting volatility (Perchet et al., 2015). They forecast volatility with different versions of the GARCH model, such as the standard GARCH, GARCH with student t-noise, GJR-GARCH with white noise, GARCH-in-mean with white noise and I-GARCH. Their results show that the I-GARCH model results in realized ex-post volatility closest to the target level. Moreover, they show that for assets where returns are not normally distributed, exhibit fat tails, and have a negative correlation between return and volatility, the constant volatility strategies yield the largest improvements.

In this paper, we also implement constant volatility targeting for both the value, momentum, and combined strategy. Thus it is ensured that each component in the combined strategy has the same overall risk contribution. Moreover, the positive effect of volatility scaling the momentum factor is exploited. Our approach to constant volatility targeting is elaborated in the methodology section.

## 2.6 Quantitative Investing

In the world of investing, it is common to distinguish between "qualitative" and "quantitative" investment strategies. The qualitative approach is based on metrics that are not easily quantified, such as the quality of a company's business model, the management's competency, or changes in consumer behavior. Whereas quantitative investing uses quantifiable metrics e.g., price, fundamental, sentiment data, etc. in large volumes. (W. Zhang & Skiena, 2010).

However, quantitative and qualitative investing usually regards the utilization of data and information, the terms systematic and discretionary regards the investment decision. The systematic approach utilizes the creation of strategies that output the best, or worst, performing financial instruments based on specified metrics. In the systematic framework, the human biases are excluded, since the decision is not in the hand of individual traders, but rather the previously defined system. In the discretionary funds, the traders have the power to execute orders (AQR Capital Management, 2017). This can be an advantage if the trades are incredibly complex, and individual traders' experience is necessary. A disadvantage of the discretionary systems is the inability to backtest strategies based on this framework. Since the investment decision is more fluid and does not use a rigid set of rules, strategies are impossible to backest. An advantage of the systematic strategies is the ability to measure historical performance. However, the favorite phrase of an institutional investor is: "Past performance is not an indicator of future performance". The phrase relates to the ever-changing nature of the financial markets, and the conditions can easily change, impacting the strategies. The quantitative approach is usually combined with the systematic approach, meaning that copious amounts of information are processed, and an investment decision is based on the data. In this paper, we utilize a quantitative and systematic approach to analyze the prior performance of fundamental and momentum-driven trading strategies.

## 2.7 Backtesting

The backtest methodology can be utilized to analyze the performance and risk associated with different quantitative investment strategies. Pedersen (2019) defines different elements needed to backtest a strategy successfully. A universe of securities needs to be defined, consisting of the stocks that can be bought and sold at a specific time. The trading universe can be determined using a particular metric, for example, a market capitalization above a threshold or membership of a specific index. Signals are created using historical data for the securities in the trading universe, which vary from strategy to strategy. For these signals, trading rules need to be defined. Trading procedures can be defined using entry-exit rules or a portfolio rebalancing approach to determine which stocks are bought and sold. The entry/exit rules are defined as being absolute for each security in the trading universe, and if the security is above the entry signal, the security is bought. Conversely, if the security crosses the exit signal, the security is sold. When using this approach, the position of every entry and the ongoing adjustment needs to be specified. Another approach is to rebalance the portfolio of stocks every set amount of time. The best or worst performing securities at one point in time are selected, and after the specified time has passed, the next period's best or worst performing securities are selected. This approach is relative since the absolute performance of the security is not taken into account. Only the performance relative to the other stocks in the trading universe is important. As a result of the relative nature of rebalancing, the portfolio has a constant amount of securities if a fixed number of stocks are selected, or they can vary if quantiles are used [1]. Rebalancing can lead to a less varying risk exposure as opposed to the entry/exit rules (Pedersen, 2019).

Backtesting is not without its flaws. It is essential to be vigilant of a variety of biases and overfitting/data mining. According to Pedersen (2019), unavoidable biases exist and therefore realized returns are more trustworthy than the returns of a backtest. However, some biases can be avoided, such as the look-ahead and survivorship bias. The look-ahead bias describes situations where information not known at the specific time is used in the backtest. In practice,

[1] Changes in the number of stocks in the trading universe impacts the number of stocks in the portfolio.

data from the 2020 annual report for a company is not available 1st of January 2020 since it is released later in the year. Therefore, it is needed to adjust the data to account for possible time lags, such that the backtest does not utilize data that is not available yet. The S&P500 members have performed well in the past. Otherwise, they would not be a part of the index. If the trading universe of a strategy only comprises the current S&P500 constituents, it excludes bad performing stocks and is therefore biased. To account for the survivorship bias, the trading universe should be adjusted using historical constituents.

Data mining is another concern when backtesting. Data mining can be described as fitting the backtest to maximize historical performance. This fitted historical performance is not necessarily indicative of future results. A possible solution is to divide the historical data into two samples. By doing this, the parameters can be fitted in one sample. Afterward, these parameters can be tested on the unaffected sample(Pedersen, 2019). If the division of samples is not used, it is crucial to select broad signals and parameters, that are robust to slight changes, and have a solid reasoning. Furthermore, by introducing costs into the backtested strategy, it becomes more realistic compared to a backtest without costs (Pedersen, 2019).

In the analysis, we try to account for the biases mentioned above in order to make the results as realistic as possible.

# 3. Methodology

In this chapter, we go through the methodology applied in this paper. To complement this, data and code used to conduct the analysis are attached and described in Appendix B.

## 3.1 Data Sources and Identifiers

The data utilized in this paper was collected from Bloomberg, Compustat, CRSP, and Kenneth French's data library. The Bloomberg, Compustat and CRSP databases are available to CBS students. The Bloomberg database can only be accessed when using a Bloomberg Terminal on campus, whereas Compustat and CRSP can be accessed remotely. Kenneth French's data library is a public source.

This paper's essential data from the primary sources are shown and described in table 3.1.

| Source | Data | Description |
|---|---|---|
| Bloomberg | Russell 3000 Constituents | The Bloomberg ticker for each of the members of the Russell 3000 index from February 1995 to December 2020. |
| | ISIN Codes | The unique standardized identifier given to each tradeable security. |
| CRSP | Adjusted Returns | Historical returns adjusted for dividends, splits and corporate actions from 1993 to December 2019. |
| Compustat | Fundamentals | Quarterly fundamental data for the constituents. The fundamentals include: Earnings per Share, Dividend per Share, Gross Profit Margin, Debt/Assets etc. |
| | GICS Codes | A classifier used to divide companies into sectors, industry groups and industries. |
| | Historical Prices | The historical unadjusted prices used in fundamental ratio calculations. |
| K. French Data | Risk Free Rate | The monthly risk free rate obtained from one-month treasury bills |
| | Fama-French Factor Returns | These are the returns of Small Minus Big, High Minus Low, and Up Minus Down |

Table 3.1: A selection of the most important data with the source and description

First, the data only provided by Bloomberg was collected. Afterward, the Bloomberg identifiers are converted to more general unique identifiers such as International Securities Identification Numbers (ISIN) and "Committee on Uniform Security Identification Procedures" (CUSIP). This is done since the Bloomberg tickers are only usable on a Bloomberg Terminal. More general identifiers are needed to systematically collect data for the same securities from other sources. As a result of this conversion, data from Compustat can be gathered without having to account for detrimental data limitations.

A critical piece of information needed to backtest strategies is which stocks are available to trade. As mentioned, the trading universe is the Russell 3000 index. Thus, the trading universe is defined by its historical constituents. As can be seen from table 3.1, the constituents have been gathered using a Bloomberg terminal. A small section of the output can be viewed in table 3.2.

| Date | Constituent 1 | Constituent 2 | Constituent 3 | Constituent 4 | ··· | Constituent N |
|---|---|---|---|---|---|---|
| 01/02-1995 | 0062761Q UN | 0088043Q UQ | 0111145D UN | 0118113D UQ | ··· | ZZBVL UN |
| 01/03-1995 | 0062761Q UN | 0088043Q UQ | 0111145D UN | 0118113D UQ | ··· | ZRO UN |
| 01/04-1995 | 0062761Q UN | 0088043Q UQ | 0111145D UN | 0118113D UQ | ··· | ZRO UN |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 01/12-2019 | 1767121D US | 8765432D UN | 9912349D UW | A UN | ··· | ZYXI UR |

Table 3.2: A subset of the Bloomberg constituent data output

The output from Bloomberg, exemplified by table 3.2, contains a date column, followed by Bloomberg identifiers for each of the index constituents in a given month. The Russell 3000 index on average consist of 3000 members. A total of 9833 unique constituents are observed across the time period.

For each of the unique constituents, the Bloomberg ticker is converted to ISIN using the Bloomberg terminal. The ISIN codes are 12-digit alphanumeric identifiers. These include a two-character country-code and an end-number, which is based upon a checking algorithm CUSIP (n.d.). An example of an ISIN code is **US0378331005**, which is the ISIN of Apple.

The CUSIP code can be derived from the ISIN. According to CUSIP (n.d.), the ISIN code is an extension of the CUSIP. This can be seen from the CUSIP of Apple, which is **037833100**.

When comparing the two identifiers, it is evident that the ISIN contains two extra letters at the start and an extra digit at the end of the code. This makes the conversion very simple since the only manipulation needed is the exclusion of the first two characters and the last. The extraction and conversion results in the dataset exemplified in table 3.3.

| | Constituent 1 | Constituent 2 | Constituent 3 | ··· | Constituent N |
|---|---|---|---|---|---|
| Bloomberg Ticker | 0062761Q US | 0000630D US | 0047042D US | ··· | ZU US Equity |
| ISIN | US8301371055 | US61980K1016 | US1615681004 | ··· | US9897741040 |
| CUSIP | 830137105 | 61980K101 | 161568100 | ··· | 989774104 |

Table 3.3: A subset of the conversion from Bloomberg to ISIN to CUSIP

The ISIN and CUSIP codes enable data collection from other sources than Bloomberg. Compustat is a financial database provided by S&P. It covers financial and fundamental data for North American and international securities. The CUSIP codes are used to gather the Global Industry Classification Standard (GICS) codes from the Compustat database. The GICS is a taxonomy of what sector/industry group/industry/sub-industry a company belongs to. The GICS classifications were created and are maintained by both MSCI and S&P. The GICS codes have different levels of classification as can be seen from figure 3.1.


Figure 3.1: Taxonomy of GICS classifications

In this paper, only the first of the four possible levels of classification is used. This is done to ensure that there are enough tradeable securities in each of the 11 sectors. Furthermore, it is assumed that the companies in the trading universe do not completely change their primary line of business. Therefore it is assumed that the GICS classifications do not change while they are a part of the Russell 3000, thus included in the trading universe.

Table 3.4 below describes the part of the GICS taxonomy used in this paper. Some of the sectors can, according to GICS, be divided further into industry groups. An example of this would be GICS code 35: Health Care, which can be divided into Health Care Equipment and Services and Pharmaceuticals, Biotechnology and Life Sciences. Whereas sectors such as Energy and Materials are not divided into different industry groups.

| | | | | |
|---|---|---|---|---|
| GICS Sectors | 10: Energy<br>15: Materials<br>20: Industrials | 25: Consumer Discretionary<br>30: Consumer Staples<br>35: Health Care | 40: Financials<br>45: Information Technology<br>50: Communication Services | 55: Utilities<br>60: Real Estate |

Table 3.4: Table of the GICS sectors with the corresponding Sector ID

## 3.2 Price & Return Data Collection & Processing

An essential part of creating a trading strategy is the collection of price data. If no price data is present, the entire premise of backtesting falls apart, and it would not be possible to measure the performance of the formulated strategy.

As is apparent from table 3.1, the return data used in the analysis has been collected from the Center for Research in Security Prices (CRSP). It would not be sufficient to collect the historical quoted and unadjusted prices from 1995 until now. These prices do not take dividends and other corporate actions into account. When companies perform stock splits, the corporate action has a severe impact on the company's stock price. Consequently, the price per share decreases. However, the overall market capitalization of the company remains the same. This exemplifies that it is essential to account for corporate actions. The return data used in this paper takes dividends and corporate actions into account.

Daily returns for each of the 9833 constituents are gathered using the CUSIP code corresponding to each historical constituent of the Russell 3000. This results in an extensive list with 4 variables, a unique CRSP identifier (PERMNO), date, CUSIP, and the daily return. A small sample of the data and the format is provided in table 3.5. The price data is collected in the same way as the returns.

| PERMNO | Date | CUSIP | RET |
|---|---|---|---|
| 10002 | 19941101 | 05978R10 | 0.0000 |
| 10002 | 19941102 | 05978R10 | 0.0000 |
| ⋮ | ⋮ | ⋮ | ⋮ |
| 93436 | 20191231 | 88160R10 | 0.04 |

Table 3.5: A subset of the daily return data gathered from CRSP

The dataset downloaded from the CRSP database has approximately 26.000.000 observations for each column. The CUSIP of the CRSP data is not exactly equal to CUSIP obtained using the conversion. In the CRSP database, the CUSIP codes contain 8 characters, and as previously mentioned, a standard CUSIP contains 9 characters. The missing digit is the unique check-digit. It is possible to exclude the 9th digit while still maintaining a unique CUSIP. The CUSIPs are mapped to the constituent data in table 3.2, which then returns the Bloomberg ticker. The resulting data consists of a large table, where each column represents a single security and the return of the security, as can be seen from table 3.6.

| Date | ACIIQ... | AE... | ⋯ | X3362726Q... | XHR... |
|---|---|---|---|---|---|
| 1993-01-04 | 0.0049 | 0.0000 | ⋯ | NA | NA |
| 1993-01-05 | 0.0441 | 0.0244 | ⋯ | NA | NA |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 2019-12-31 | NA | 0.0226 | ⋯ | NA | -0.0041 |

Table 3.6: Daily return table

Each column of the table above consists of 6804 observations. This is consistent with the daily return observations for all 27 years, 1993-2019. However, only a few of the securities are active over the entirety of the 27 years. If no returns are present for the date, the observations are set to Not Applicable (NA).

## 3.3 Fundamental Data Collection & Processing

The fundamental data, as shown in table 3.1, is collected using Compustat. This data includes the dividends, the book value, number of shares, earnings per share for as many of the 9833 historical constituents as possible. The format of the extracted fundamental data from Compustat is identical to table 3.5. Therefore, the same procedure is used for Compustat fundamental data as for the CRSP data in table 3.6. Using the Compustat database, the earnings, dividends per share, number of shares, and both the book value and market value of equity are collected.

The earnings per share (EPS) is reported without extraordinary items and has a quarterly frequency. Additionally, a 12-month moving average of the EPS is used. This is done to account for cyclicality in the quarterly earnings. The quarterly earnings' reporting date is used instead of the fiscal date to account for the look-ahead bias. The reporting date can be different from the fiscal period. It is crucial to use the actual date the information became public to avoid the look-ahead bias. The dividends per share (DPS) is measured as the dollar amount paid out per stock. We record the DPS at the ex-dividend date. This is the date where the dividend can no longer change owner. Buying the stock after the ex-date does not include the dividend. If two dividend ex-dates occur in one month, these are combined. The book value of equity is defined by Compustat as the sum of common stock, capital surplus, and retained earnings. Furthermore, the equity contained in treasury stocks has been excluded. The number of shares is declared in thousands with a quarterly frequency. This number is net of treasury shares, meaning that the amount of stocks that the company itself is holding is not taken into account. All the collected fundamental variables have been forward filled between the observations. As an example, the earnings remain constant until the next reporting date, and new earnings are observed. This is done to limit the look-ahead bias. The mentioned fundamental data stems from quarterly and annual reports. When using Compustat, it is not possible to differentiate between the original financial statements and restated statements. Therefore, the look-ahead bias can not be eliminated completely. Companies can have restated the fundamental data after the public dates.

### 3.3.1 Creation of Fundamental Ratios

The book-to-market ratio is created by equation 3.1. This ratio is almost identical to the previously referenced equation from Fama and French (1992).

$$Book\ to\ market_t = \frac{Book\ value\ of\ equity_t}{Market\ value\ of\ equity_t} \tag{3.1}$$

As mentioned, the book value of equity has been forward filled until it is certain that new observations have been made public. The market value of equity, also known as the market capitalization, is created as follows:

$$Market\ value\ of\ equity_t = Shares\ Outstanding_t * Price_t$$

The dividend yield describes what fraction of the price is paid out as a dividend. If no dividend has been paid out, the last observation of DPS is used.

$$Dividend\ yield_t = \frac{DPS_t}{Price_t} \tag{3.2}$$

The P/E ratio implies that a lower ratio is more indicative of value since the investor is paying less per dollar of earnings. In the other selected value metrics, a larger ratio is indicative of value. To create congruence between the ratios, the inverse of P/E i.e., the E/P ratio, is created. However, P/E and E/P are going to be used interchangeably to reference the E/P ratio.

$$\frac{E}{P}_t = \frac{EPS_t}{Price_t} \tag{3.3}$$

In the case of negative earnings, using the E/P ratio would produce misleading results. If a company produces negative earnings, the E/P ratio would naturally be negative. If two companies have the same negative earnings, the company with the highest stock price has the least negative E/P ratio. This is problematic for the cross-sectional ranking of stocks. A correction is introduced by multiplying the negative earnings with the price. The correction leads to a decrease in the ratio if the price of a company with negative earnings increases. Equation 3.3 is therefore modified to account for negative earnings, following equation 3.4.

$$\frac{E}{P}_t = \begin{cases} \frac{EPS_t}{Price_t} & \text{if } EPS_t \geq 0 \\ \text{Earnings } \times Price & \text{otherwise} \end{cases} \tag{3.4}$$

### 3.3.2 Quality Ratios

Several quality ratios are introduced and collected to complement the value ratios. These measures also appear in the previously referenced paper by Asness, Frazzini, and Pedersen (2013). These ratios are provided by Wharton Research Data Services (WRDS) and are calculated using both data from Compustat and CRSP. All ratios have been lagged two months, which is done to make sure no information is used before it becomes public. The selected ratios are the two profitability measures gross profit margin (GPM) and return on assets (ROA) followed by the safety ratio debt to assets (Debt/Assets).

Gross profit margin is defined by WRDS as the company's gross profit as a fraction of sales:

$$GPM_t = \frac{Profit_t}{Sales_t} \tag{3.5}$$

The return on assets is estimated as the Operating Income Before Depreciation divided by the average two-period total assets.

$$ROA_t = \frac{Operating\ Income_t}{(Total\ Assets_{t-1} + Total\ Assets_t)/2} \tag{3.6}$$

The last quality measure, debt/assets, is estimated by dividing the total debt at time $t$ with the total assets of the same period.

$$Debt/Assets_t = \frac{Total\ Debt_t}{Total\ Assets_t} \tag{3.7}$$

## 3.4 Trading Universe

As mentioned, the trading universe applied in this paper is based on the Russell 3000 Index. The Russell 3000 index consists of around 3000 publicly traded companies in the US equity market. This is approximately 98% of the tradeable equity in the US markets, with an average market cap of $248.071 billion (Russell, n.d.). Currently, the index is reconstructed in June every year to account for market cap changes in the equities. As the strategy utilizes both long and short investments, the Russell 3000 index is used, such that the trading universe is composed of large and liquid stocks. Thus, it is assumed that the largest 3000 stocks in the US equity market, are available for both buying and shorting. When constructing the trading universe, the historical constituents for the index are used. Each month the trading universe is adjusted, such that only stocks which were part of the index in that given month are in the universe. By adjusting the trading universe in this manner, survivorship bias is avoided.

Due to data availability, it is not possible to trade all of the 3000 stocks in the strategies. From 1995 to 2019, there are 9833 different stocks, which at some point are a member of the Russell

3000 Index. Price and adjusted return data are available for 9178 of these stocks at some point in time. For the different strategies, the mean portfolio size differs depending on the data for the factor measures. For example, when implementing the alpha momentum strategy of Blitz et al. (2017), it has a mean trading universe size of 2773 stocks, where both adjusted return and signal data are available. The size of the trading universe varies over time depending on the data availability and is generally larger as time progresses since data coverage increases. The same trading universe for the combined value measure in this paper is far smaller, with a mean size of 1300 stocks. This is because the fundamental data is far more limited, and thus fewer of the Russell 3000 stocks are available for trading. In appendix 1, this is illustrated with a plot showing the number of tradeable stocks for the value and alpha momentum strategy. The number of tradeable assets for each strategy does not change rapidly but generally increases as time progress, and the more recent years have a slightly larger trading universe. The initial trading universe starting in January 1997 is 2621 for momentum and 1209 for value and grows to 2817 and 1445 by December 2019.

There is also variance in the sector sizes in the trading universe across time. The size of the sector affects which sector that dominates the trading universe. For the value strategy, scoring is done within sectors, and the strategy is weighted by the number of stocks in the sector. Momentum is not evaluated within sectors. Hence the strategy can overweight/underweight each sector in its long and short legs. In figure 3.2 below, the size of the sectors in the overall trading universe is shown across time. The size is evaluated by the number of stocks in the sector and not their market cap as the strategies applied in this paper apply equal weighting.

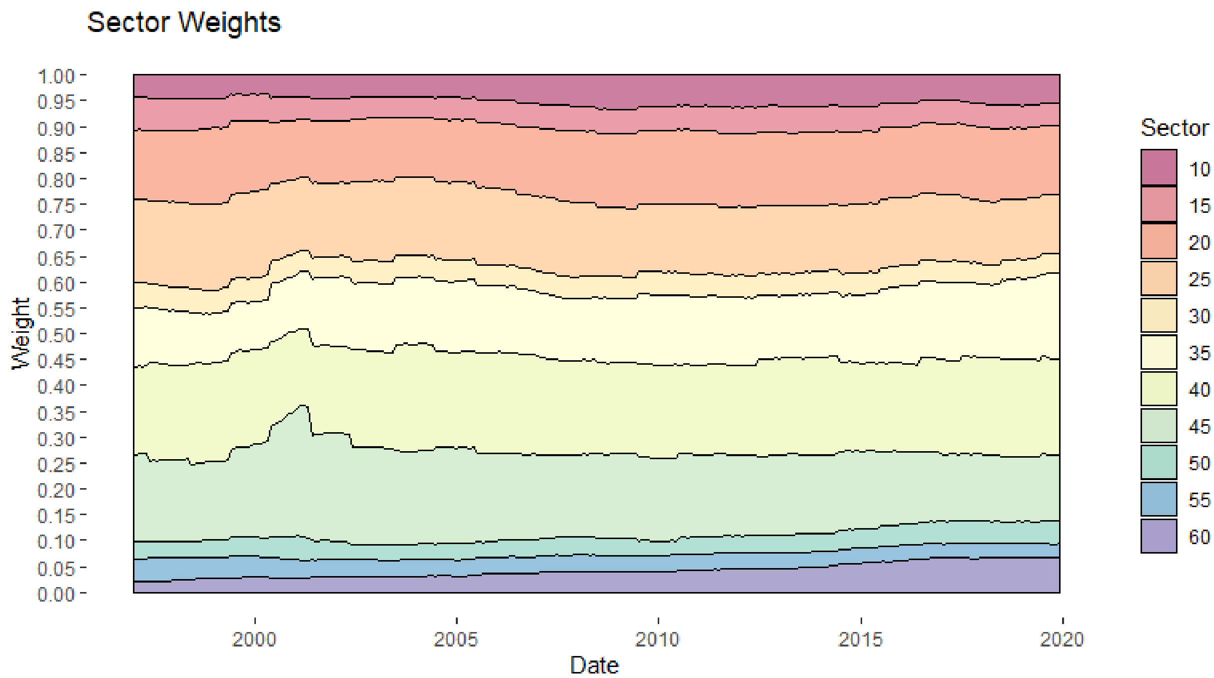



Figure 3.2: Decile Portfolios

In figure 3.2, the sum of the relative sector weights are shown across time. The sectors are represented by colors, and the corresponding color is shown to the right of the figure by the sectors' GICS codes. The figure shows that the sector sizes are rather constant overtime but do show slight variation. As mentioned, revisions have moved some stock classified as Financials (40) into Real Estate (60), which causes the size of this sector to increase over time. Thus, our backtests have a small bias, as some of this variance in sector size is related to reclassifications of GICS code. The GICS codes for the firms still alive have been adjusted, while the code for those no longer traded is equal to the prior classification. The sector weighting graph above is based on the number of stocks in each sector. Therefore the sector weighting corresponds to that of the equal-weighted benchmark, which is based on the Russell 3000.

## 3.5 Equal Weighted Benchmark

A relevant benchmark is needed to evaluate the performance and estimate the market exposure of the portfolios in the paper. The performance of the strategies is evaluated in relation to simply investing in a diversified market portfolio. As the trading universe is defined by the Russell 3000, the benchmark strategy is also based on this. However, the strategies implemented are not value-weighted as the standard Russel 3000 index is (Russell, n.d.). In order to create a relevant index to use for performance comparison, an equal-weighted index of the tradeable stocks is therefore created. The equal-weighted index is based upon the historical constituents of the Russell 3000 index. Each month the equal-weighted index is constructed from the members of the Russell 3000 in that month. The benchmark return is calculated as the mean return of the index constituents in the given month.

$$Benchmark\ Return_t = \Sigma(w_{i,t} * r_{i,t}) \tag{3.8}$$
$$w_{i,t} = \frac{1}{N_t}$$

$N_t$ is the number of constituents in the given month, $w_{i,t}$ is the weight given to the return and $r_{i,t}$ is the return of constituent $i$ in the month $t$. Hence, the index combines the returns of all its members with equal weights, and the movements are not only controlled by the largest companies. The constructed index, however, is subject to small data limitations, as not all adjusted stock returns are available. Therefore the mean stock size of the equal-weighted index is around 2810. In figure 3.3, a plot of the equal-weighted index against the total return of the Russell 3000 index is shown. The annualized standard deviation for the benchmark is 21.5% vs. 18.4% for the value-weighted Russell 3000. As expected, the equal-weighted index has slightly higher volatility as small stocks have a larger impact. However, the annualized returns are also slightly higher for the benchmark (10.9%) compared to the Russell 3000 index's annualized total returns (10.3%).

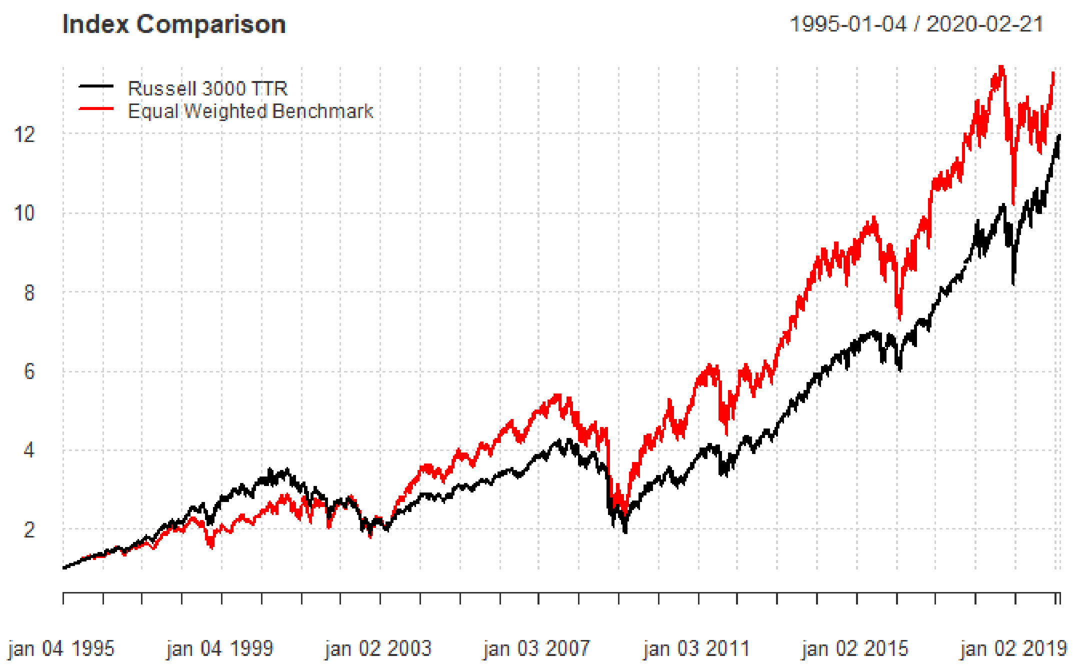



Figure 3.3: The performance of the Value-weighted Russell 3000 index vs the Equal-weighted

In this paper, the equal-weighted version of the Russell 3000 total return index is used instead of the value-weighted. Therefore, calculations of betas, and over (under) performance uses this benchmark. The benchmark does not include trading costs, and therefore the returns of actually trading the index would be slightly lower. However, we want to be pessimistic about the out-performance of the premiums, and not including costs in the benchmark makes it more difficult for the strategies to show better performance. All of the monthly and yearly returns for the benchmark can be found in appendix 2.

## 3.6 Financing & Trading Costs

When implementing a backtest, it is important to note that the returns, Sharpe ratios, and other metrics are not truly indicative of the results an investor could gain. The cost of implementing the specified trading strategy needs to be considered for a more accurate representation of actual returns. The costs of implementation and maintenance are numerous, this paper incorporates different costs, but these are not collectively exhaustive. The covered costs are the trading, financing, borrow, leverage, administration, and dividend costs associated with executing a strategy. In this section, the structure of the cost types and the assumptions needed to provide an estimate of more accurate trading performance is described. When estimating the costs of a long/short strategy, it is necessary to make assumptions. The cost structure varies from broker to broker. Thus the different costs also vary from fund to fund. Hence, no single correct cost framework exists, and general assumptions are needed.

### 3.6.1 Trading Costs

In this paper, trading costs are defined as the combination of transaction and slippage costs. Transaction costs cover the expense paid to brokers to buy and sell different securities. Whereas slippage costs are the difference between the expected price, the security can be traded at and the realized price. It occurs when trying to execute numerous buy or sell orders at a specific price, and the depth of the orderbook is too shallow. If an investor tries to buy a large number of a specific security at a specific price, he/she can buy the stock at the quoted price until the orders at that exact price are filled. Thus, the investor can only execute the remaining orders at a higher price. The opposite is true for sell-orders, i.e., the investor can only sell a given number of shares until the orders at that level are filled, and the next available orders are at a lower price. This cost is prevalent for securities with a smaller traded volume compared to larger stocks with higher liquidity.

Slippage costs are difficult to estimate since it requires orderbook data for all 9833 historical constituents during their membership of the Russell 3000 index. The slippage costs are included as a fee in the transaction costs and are not estimated separately. Transaction costs are explicitly calculated from the turnover since a fee must be paid to the broker every time securities are bought and sold. The trading cost is based upon the actual portfolio turnovers. The trading costs are described by equation 3.9 below.

$$TC = Turnover_{Long} * (Fee + Slippage) + Turnover_{Short} * (Fee + Slippage) \tag{3.9}$$

According to Greenwich Associates (n.d.), the transaction costs for institutional funds are around 5-12 basis points (bps) per traded dollar. In this paper, the transaction costs are assumed to be approximately seven basis points per traded dollar, and the slippage is expected to be five basis points per traded dollar. This leads to a combined cost of 12 basis points i.e. $Fee + Slippage = 12bps$. According to Pedersen (2019), the average trading costs for institutional investors are around 9.5bps. This is lower than the utilized fee of 12bps, but we prefer to use slightly more pessimistic cost estimates.

### 3.6.2 Borrow Fee

When shorting stocks, a borrowing-fee is present. An amount is paid to the securities-lender, which is based upon the dollar amount shorted. The borrowing-fee is highly dependent on the liquidity of the stock. Therefore, the fee for shorting large and popular stocks are lower than less liquid stocks. According to Pedersen (2019), the cost associated with shorting the 90% largest US stocks is 10-20bps. However, if the 10% smallest stocks shorted, the borrowing fee can increase to more than 100bps. As previously referenced, the trading universe consists of 98% of all tradeable equity. Therefore, the cost in the backtests should be higher than the 10-20bps. However, the majority of stocks in the Russell 3000 have large capitalizations, and it is assumed that the strategy shorts a mixture of both high and mid-capitalization stocks at all times. The borrowing fee is in the backtests is assumed to be 40bps per dollar shorted.

### 3.6.3 Administration Fees

Hedge funds usually employ administrators and custodians. These serve to create annual reports, carry out the valuation of the fund's assets, do due diligence, deal with investors, safeguard the assets of the funds, etc., and are essential for daily operations. According to Turner (2017), the yearly administration fee has decreased over the last several years, and the approximate maximum is 12bps. This maximum of 12bps is implemented in the strategy and is paid as a proportion of total fund value.

### 3.6.4 Dividends

In equity investing, it is crucial to take dividends into account. The dividends are an income on the long-leg, but it is an expense on the short-leg of the strategy. When an investor receives a dividend from an owned security, it is required to pay a dividend tax. The dividend tax has an impact on the total return of the long-leg. This paper assumes a dividend tax of 15%. When the security is borrowed from the securities lender and then sold, an agreement is made to pay the received dividends back to the securities lender. Therefore the dividend is an expense when short selling. The dividend costs of this paper are described by equation 3.10.

$$Dividend\ Costs = \$Dividend_{Long} * 15\% + \$Dividend_{Short} \tag{3.10}$$

### 3.6.5 Financing

When launching a long/short fund, it is often assumed that the value of the shorted securities is used to fund the long side of the strategy. If using these funds was a possibility, the fund could be launched without substantial initial equity. However, this cannot be done since the investors cannot use the funds raised by the short sale, which is held by the brokerage that administered the sale (Pedersen, 2019). The brokerage does pay interest on the money stemming from the short sale and is assumed to be the Overnight London Interbank Offered Rate (LIBOR). Not only can the investor not use the money raised from short selling, but the investor also needs to post margin equity, which is assumed to be around 45% of the funds capital. However, the brokerage offers investors to borrow the money needed to fund the long-leg of the strategy. The interest rate paid on the long leg is assumed to be the 1-month LIBOR, including an additional 25 basis points. Therefore there is a spread between the interest rate paid to the fund from the short sale and the interest rate cost the fund pays to borrow. This spread is paid to finance the equity of the strategy and is negative (Pedersen, 2019).

$$Spread = LIBOR_{ON} - (LIBOR_{1M} + 25bps) \tag{3.11}$$

To estimate the broker spread, the average historical Overnight LIBOR and 1M LIBOR is used. These are collected from the Federal Reserve Bank of St. Louis (FRED). The average historical spread between the overnight and 1-month LIBOR is $-0.08328\%$ from 2001-2019. This spread plus the 25 bps leads to a financing fee of $-0.3333\%$, which is equivalent to 33.33 basis points. In cases where leverage is involved, and the dollar amount of the long-leg and short-leg increases, it is assumed that the spread increases linearly. Thus, doubling the dollar amount of the strategy doubles the spread paid to the broker, i.e., from 33.33 basis points to 66.66 basis points. The cost of financing is defined in equation 3.12.

$$Spread = (-0.3333\%) * Leverage \tag{3.12}$$

As mentioned, the brokers require an initial margin when shorting securities. The margin is assumed to be 45% of the fund's capital. If a margin call is triggered, and the fund needs to provide additional funds to the brokerage, liquid funds are required. As a result, the assumption is made that the fund has 15% of its capital in secured and liquid assets. The remaining 40% of equity can either be placed in other safe assets or be used to fund securities in the long-leg, thereby reducing the financing costs. We utilize the latter option for the strategies.

The described placement of equity provides income from received interest rate payments, and indirect interest rate cost reductions. It is assumed that an annual rate of $LIBOR_{ON} - 25bps$

is paid on the 45% margin posted at the brokers, and an interest rate of $LIBOR_{ON} - 10bp$ on the liquidity buffer. When using equity to fund a part of the long-leg, the financing fee of $LIBOR_{1M} + 25bp$ is saved. The average historical $LIBOR_{ON}$ is 1.6%. The interest gained from the margin account is thus: $1.6\% - 0.25\% = 1.35\%$, and the annual interest rate for the liquidity buffer is $1.6\% - 0.1\% = 1.50\%$. This division of capital is assumed to be constant. The initial capital is subject to change over time as a result of the strategy's realized returns. However, this is considered not to impact the described relative fees and income. As such, the defined structure of the capital applies regardless of the changes in fund capital. Using the notation of Pedersen (2019), we summarize the financing cost described above by the following equation:

$$\begin{aligned} Financing = &-r^{Borrowed} * \$Cash^{Borrowed} + r^{Shorted} * \$Cash^{Shorted} \\ &+ r^{Margin} * \$Cash^{Margin} + r^{Buffer} * \$Cash^{Buffer} \end{aligned} \tag{3.13}$$

Where the $r^{Borrowed}$ is the rate paid on borrowed funds from the broker and $r^{Shorted}$ is the rate gained from the short-selling proceeds. The spread between these rates corresponds to equation 3.12. $r^{Margin}$ is the interest paid on the margin account. Finally, $r^{Buffer}$ is the rate paid on the liquidity buffer. As these rates previously have been determined, they can be inserted in equation 3.13, which results in equation 3.14 below.

$$\begin{aligned} Financing = &-(1.9\%) * \$Cash^{Borrowed} + 1.6\% * \$Cash^{Shorted} \\ &+ 1.4\% * \$Cash^{Margin} + 1.5\% * \$Cash^{Buffer} \end{aligned} \tag{3.14}$$

### 3.6.6 Leverage

Changing a strategy's leverage increases portfolio turnover. The monthly turnover when rebalancing increases with leverage. Moreover, the daily adjustment of the leverage leads to a higher turnover. The absolute difference in leverage is multiplied by the cost to capture the increased cost of the adjustments. This is formulated in equation 3.15.

$$Increase\ in\ Costs = |Leverage_t - Leverage_{t-1}| * Trading\ Costs \tag{3.15}$$

Where $Leverage_t$ is the amount of leverage utilized at time t. The difference is absolute since the trading costs associated with levering down and up are the same. If the leverage increases from 1 to 2 and a portfolio consists of 100 shorted stocks and 100 long positions, another 100 stocks need to be sold while 100 more stocks need to be bought. The same is the case if the leverage decreases from 2 to 1.

## 3.7 Momentum Portfolio Construction

In the analysis of the momentum premium, common price momentum, idiosyncratic momentum, and alpha momentum strategies are constructed and compared. The strategies are evaluated in relation to each other and the benchmark index. The benchmark is the equal-weighted portfolio of Russell 3000 stocks and represents the alternative of investing in the market factor. Trading for all momentum portfolios are initiated from 1997 and continues to the end of 2019. The start is selected based on data availability of the Russell 3000 Index constituents, coverage, and initial formation periods.

The common price momentum is based on the work of Jegadeesh and Titman (1993). Decile portfolios are constructed by ranking stocks on their past 12 months returns, skipping the last month to account for short term reversal as described by Jegadeesh (1990). We use continuously compounded returns when calculating the return for momentum. However, using either discrete or continuous returns does not affect the relative ranking. The following formula determines the momentum for each stock in a given month.

$$Mom_{i,t} = ln(P_{i,t-1}/P_{i,t-12}) \tag{3.16}$$

$Mom_{it}$ denotes the momentum factor for stock $i$ at time $t$. $P_{it}$ is the stock's adjusted price. These rankings are made at time $t$. However, the return of the decile portfolios' are based on the equal-weighted momentum returns at $t+1$. Each month the stocks are ranked based on the momentum factor, and the decile portfolios are rebalanced. The long/short strategy for common price momentum is constructed by an equal-weighted long and short position in the monthly top and bottom decile portfolios. A visual representation of how the ranking is done is shown in figure 3.4 below.

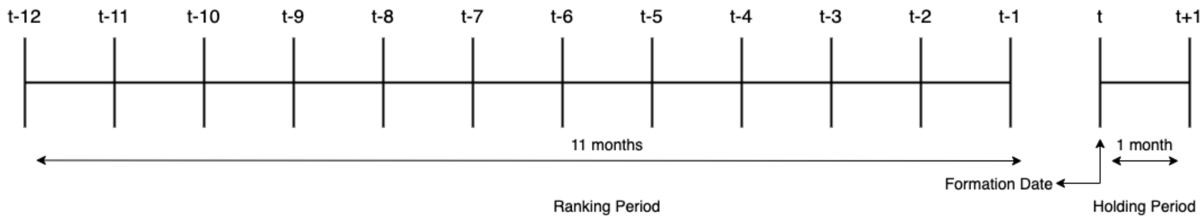



Figure 3.4: Momentum portfolio ranking

The idiosyncratic strategy is constructed in much the same way as price momentum, however, with a different momentum measure. Rolling 36-months Fama-French regressions are applied to the stocks in the trading universe. From the regressions, the idiosyncratic momentum measure is based on the volatility adjusted idiosyncratic returns over the past year, skipping the last month, as shown in equation 2.5. In the same way as the price momentum strategy, these measures are used to rank the stocks, and the long/short portfolio is based on the top and bottom decile portfolios. The monthly factor realizations are obtained from Kenneth French's data library. However, the excess returns from the market factor are replaced with the monthly excess return from our benchmark index. The factor returns from Kenneth French's data library are based on a bigger trading universe of almost all listed stocks in the US. These factors do, therefore, not match the trading universe exactly.

For alpha momentum, the implementation is also based on a 12 month formation period. Daily returns of each of the stocks are regressed on the past 12 months' realized daily factors, skipping the last month. The regression formula is shown in equation 3.17.

$$r_{i,d} - r_{f,d} = \alpha_i^{daily} + \beta_i^{daily} RMRF_d + s_i^{daily} SMB_d + h_i^{daily} HML_d + e_{i,d} \tag{3.17}$$

Based on the estimated alphas, the stocks are sorted into deciles, and the strategy buys the top decile and shorts the bottom decile. The daily factor realizations for the Fama-french regressions are also obtained from Kenneth French's website and the market factor realizations are also replaced with the benchmark. The strategy also has a 1-month holding period. Each period the new alphas are calculated, and the portfolio is rebalanced.

Besides the classical implementation of the momentum strategies, versions with beta neutralization are also conducted to further control the factor exposure. In academia, many beta hedged strategies are created via stratification. Stratification is a method used to control exposure to some factor by initially sorting on this (Hlavaty, 2016). We use a different approach, which is used by many hedge funds in practice. The beta neutralization is based on cross-sectional regressions of stocks' momentum against their beta at time $t$.[1] Please note, the momentum score is converted to z-scores, following equation 2.6, before running these regressions. This ensures that the scores are normalized, and outliers do not cause problems for the regression.

$$Momentum\ Score_{it} = \alpha_{i,t} + \gamma_t \beta'_{i,t} + e_{i,t} \tag{3.18}$$

$\beta'_{i,t}$ is the estimated $\beta$ at that point in time (the beta estimation procedure is shown in the Beta Estimation section). If the relationship between the momentum score and the beta is not linear, then the residual adjustment will be biased and ineffective. In appendix 3 a plot of the betas and the momentum factor is shown for a random month. The plot does not show a strong bias.

$$e_{i,t} = Momentum\ Score_{it} - \alpha_{i,t} - \gamma_t \beta'_{i,t} \tag{3.19}$$

$$Adjusted\ Momentum\ Score = e_{i,t} \tag{3.20}$$

If the residual is largely positive, the momentum is high for a given beta, and if it is largely negative, the momentum is low for a given beta. The different momentum scores for price, idiosyncratic, and alpha momentum are adjusted such that they are equal to the residuals of these cross-sectional regressions. Thus for each momentum strategy, both high and low beta securities are included in the decile portfolios, as they are now ranked on momentum in excess of their beta. This way, the market exposure of the deciles will be reduced, and ideally, the long/short strategy becomes beta-neutral.

## 3.8 Value Portfolio Construction

Portfolios of book-to-market, dividend yield, and price-earnings fundamental ratios are constructed to analyze the value premium. These ratios are formulated in equations 3.1, 3.2, 3.4. The performance of the portfolios is not only compared to each other, but also to the benchmark. As previously referenced, the evidence provided by Asness et al. (2015) indicates superior

[1] The Fama-Macbeth methodology has been described and explained by our supervisor. The approach is used by hedge funds in practice.

performance when using value composite portfolios instead of individual measures. As such, we utilize a combination of different value measures. When combining different value measures, z-scores are calculated in the same way as Asness, Frazzini, and Pedersen (2013) and formulated in equation 2.6. When transforming the value measures into z-scores, the outliers are transformed into standardized values based on the size of the sample. This approach is useful when combining different value measures with different numerical data ranges. In this paper, the composite value strategy is based on a z-score of each individual value z-scores. The value score is calculated from the value composite in equation 3.21.

$$Value = z(z_{P/E} + z_{D/P} + z_{B/M}) \tag{3.21}$$

According to Rabener (2018b), sector neutralization increases operational complexity as a result of the introduction of new long/short portfolios. However, it has a positive effect on the performance of the strategy. When forming the value portfolios based on the value score, the stocks in the trading universe are divided into the 11 GICS sectors shown in table 3.4. This is done to sector-neutralize the value strategies as done by Hlavaty (2016). The neutralization avoids situations where entire sectors are bought (sold) if the value measures are high (low) compared to other sectors.

Value investing seeks to buy stocks that are cheap and sell stocks that are expensive relative to their peers. However, companies operating in other sectors are in this paper not defined as being peers, and as such, the fundamental ratios are only compared inside the same sector. If this was not done, situations could arise where the highest or lowest ratios stemmed from the same sector. After the division, three quantile portfolios, i.e., tertile portfolios, are created in each of the 11 GICS sectors. These portfolios are based upon the selected fundamental ratios, where the highest tertile contains the highest value stocks, and the lowest contains the stocks with the least value. Table 3.7 shows the division based on the GICS sectors and value measures. The rows indicate the three tertiles, from highest to lowest, whereas each of the 11 columns indicates the different GICS Sectors. As an example, $P_{4.1}$ is the tertile of stocks from the 4th GICS sector, Consumer Discretionary, and is a portfolio consisting of the highest tertile. Whereas $P_{4.3}$ is the lowest tertile. Portfolios are constructed within each sector, buying the highest tertile and shorting the lowest.

|  | GICS Sectors | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Value Score | $P_{1.1}$ | $P_{2.1}$ | $P_{3.1}$ | $P_{4.1}$ | $P_{5.1}$ | $P_{6.1}$ | $P_{7.1}$ | $P_{8.1}$ | $P_{9.1}$ | $P_{10.1}$ | $P_{11.1}$ |
| | $P_{1.2}$ | $P_{2.2}$ | $P_{3.2}$ | $P_{4.2}$ | $P_{5.2}$ | $P_{6.2}$ | $P_{7.2}$ | $P_{8.2}$ | $P_{9.2}$ | $P_{10.2}$ | $P_{11.2}$ |
| | $P_{1.3}$ | $P_{2.3}$ | $P_{3.3}$ | $P_{4.3}$ | $P_{5.3}$ | $P_{6.3}$ | $P_{7.3}$ | $P_{8.3}$ | $P_{9.3}$ | $P_{10.3}$ | $P_{11.3}$ |

Table 3.7: Creation of Portfolios Based on GICS Sectors

The size of each sector is used to weight the returns of the sector portfolios. This is done by calculating a sector weight, which is formulated in equation 3.22 below.

$$Sector\ Weight = \frac{Stocks\ in\ Sector}{Stocks\ in\ Trading\ Universe} \tag{3.22}$$

Where Stocks in Sector is the number of securities present in the eleven GICS sectors, and the trading universe is as mentioned, the Russell 3000 index. The sector weights are applied to the return of the highest and lowest tertile portfolios for each portfolio present in table 3.7. This is done to make sure that each stock has the same weight across the sectors. A sector with 30 stocks has a lower weight than a sector with 150 stocks.

The QARP factor is created by a composite including the quality measures described in equations 3.5, 3.6, and 3.7. The quality measures, GPM, ROA and Debt/Assets are combined in the same way as the value z-score composite in equation 3.21.

$$Quality = z(z_{GPM} + z_{ROA} + z_{Debt/Assets}) \tag{3.23}$$

We combine both the value and quality measures to create the QARP-factor as described by Asness, Frazzini, and Pedersen (2013). We do this by combining the z-scores of the value and quality composites, following equation 3.24.

$$QARP = z(z_{Value} + z_{Quality}) \tag{3.24}$$

To create the tertile QARP portfolios, the approach shown in table 3.7 is used once again. Instead of the value score, the combined z-score for QARP described in equation 3.24 is used. The introduction of quality is done to minimize the risk of value traps. However, we define quality at a reasonable price as a value strategy.

Following the same methodology as momentum, a beta neutralization method is used to limit the beta exposure of the value strategy. The cross-sectional regressions are conducted with value scores as the dependent variable, and the beta as the independent variable.

$$Value\ Score_{it} = \alpha_{i,t} + \gamma_t \beta'_{i,t} + e_{i,t} \tag{3.25}$$

Where the $\beta'_{i,t}$ is the beta of the stocks. The beta adjusted value score is captured by the residual, $e_{i,t}$

$$e_{i,t} = Value\ Score_{it} - \alpha_{i,t} - \gamma_t \beta'_{i,t} \tag{3.26}$$

$$Adjusted\ Value\ Score = e_{i,t} \tag{3.27}$$

As with momentum, if the residual is large, it translates into a high value score and vice versa. The beta exposure will be limited since the value scores are controlled for market exposure.

## 3.9 Value & Momentum Combination

As mentioned, it is possible to use different methods for constructing strategies that take advantage of both value and momentum. One approach is to create an intersectional model, where stocks are ranked on a combination of their value and momentum scores. Another method, which we apply in this paper, is combining the individual factor strategies in a portfolio. Thus, the return for each factor part of the portfolio matches those of the individual strategies, and the traded stocks are the same. Both methods can be applied successfully (Rabener, 2018a). However, the top-down approach of combining the two factor-portfolios makes it more obvious what drives the returns. In an intersectional model, different stocks are selected, and it is less transparent what drives the selection of the stocks. Stocks might be included because they rank above average in both value and momentum scores, albeit they do not rank high enough to be in an individual value or momentum portfolio. For this reason, we try to make the return contribution from the factors to the final portfolio as clear as possible by using the top-down approach. Therefore the combined portfolio trades stocks matching the portfolios of the individual factors.

The combined strategy in this paper is a simple equal-weighted portfolio consisting of a 10% volatility scaled alpha momentum strategy and a 10% scaled value strategy. Both of the strategies are beta neutralized, and therefore the combined portfolio also has minimal systematic risk exposure. The return of the combined portfolio is a weighted return of the two strategies.

$$r_{t,combined} = 0.5 * r_{t,momentum} + 0.5 * r_{t,value} \tag{3.28}$$

The portfolio takes advantage of the alpha in both strategies while utilizing the negative correlation to minimize periods of large drawdowns. The diversification in the portfolio also reduces the volatility of the combined portfolio. Therefore leverage and volatility scaling are also applied to the combined strategy to match the 10% risk target. The method used to volatility scale the strategies is explained in section 3.11.

## 3.10 Beta Estimation

The systematic risk can be difficult to estimate ex-ante, and it is, therefore, challenging to beta-neutralize anomaly portfolios. In the code attached to this paper, scripts that estimate the stocks' betas in several of the ways discussed in the systematic risk section can be found. They all provide slightly different estimates of the systematic risk for the stocks and will give small variations when applied to trading. We have chosen to estimate the betas based upon the results of Hollstein et al. (2019). Their paper analyzes beta forecasting in general and beta hedging across different anomalies. The overall best estimate of the future beta, according to Hollstein et al. (2019) are exponentially weighted estimates based on historical data and simple shrinkage adjustments. However, these are not optimal for beta hedging all anomalies. Across all estimation methods, the momentum anomaly is the one in which fewest beta estimation methods succeed in hedging. The systematic risk for momentum strategies is extremely hard to predict, as also shown by Barroso and Santa-Clara (2015). However, Hollstein et al. (2019), succeed in hedging common price momentum by using very short rolling window regressions with daily data. By using very short windows to estimate the systematic risk, the betas become far more responsive (Shaikh, Chaudhry, Hanif, & Khan, 2015). Therefore, we use 3-months linear rolling regressions to forecast the short-term beta for stocks in the momentum strategy. The excess return of the equal-weighted benchmark is used as the market factor, and the risk-free rate is based on the 1-month Treasury bill from Kenneth French's website. The short horizon beta forecasts are estimated via the original beta formula, as in the equation below, but applied across the rolling window.

$$\hat{\beta}_{i_t+1} = \frac{Cov[r_{i,t}, r_{m,t}]}{Var[r_{m,t}]} \tag{3.29}$$

In contrast, the value trading strategy's beta forecast is based on a slightly less responsive beta and is therefore estimated over a longer time-horizon. This follows the results of Hollstein et al. (2019), where it is shown that a slightly longer time-horizon for the simple beta estimate is more effective when hedging the value factor. The same beta forecasting method with rolling linear estimates is applied across the stocks in the value strategy. However, the rolling window is expanded to include 12 months rolling observations of daily returns. Thus, there is a slight deviation in the beta forecasts for the same stocks across the momentum and value strategies. Although, in both cases, the objective is to capture the true forward beta for a given stock. Different beta estimation methods are applied as the main goal is to minimize systematic risk. As the two strategies trade different types of stocks, these stocks have different characteristics. This can lead to variation in how to successfully predict their betas. The results of Hollstein et al. (2019) show that shorter and more dynamic beta estimates provide better hedging for momentum than for other anomalies. This is the reason for the discrepancy between the beta forecasts for the two strategies.

The ex-post beta estimates are calculated with 12 months rolling window regressions using daily returns as in the value strategy. However, the beta estimates use returns realized at the same point in time. These are estimated on the returns of the strategy portfolios and not for the individual stock returns. The ex-post estimates are calculated in the same way for the value, momentum, and combined portfolios. The formula is shown in equation 3.30 below.

$$\hat{\beta}_{i_t} = \frac{Cov[r_{i,t}, r_{m,t}]}{Var[r_{m,t}]} \tag{3.30}$$

The ex-ante beta estimates for the stocks in the momentum and value strategies are applied in the Fama-Macbeth regressions. These are used for beta neutralization, as explained in the strategy methodologies. The effectiveness of the neutralizations is measured by the ex-post estimates of the strategies' beta, which should be close to zero.

## 3.11 Leverage

Leverage is applied to the strategies to hit a targeted risk level of 10% annualized volatility. This is done as it is normal for hedge funds to target a specified level of volatility for their trading strategies (Barroso & Santa-Clara, 2015). Both the value, momentum, and combined strategy apply the 10% volatility target. However, the overall 10% risk is obtained in different ways to account for the intrinsic dynamics of the factors. As mentioned in the volatility scaling section, value and momentum have different return distributions. While they both have fat tails, momentum returns are negatively skewed, while value returns are positively skewed. Volatility scaling of these two factors can, therefore, have a different impact on performance. Constant volatility scaling manages tail-risk and cuts of both the left and right tails (Harvey et al., 2018). This could lead to a great improvement by limiting the risk of momentum strategies, as the left tail, and thus large negative returns are reduced. However, applying the same strategy to value returns can also lead to the removal of large positive returns. Therefore we apply slightly different approaches when volatility scaling our momentum and value strategy, such that the value factor is adjusted slower but remains within the overall risk target. The goal for the factor strategies is not to provide optimal statistical forecasts of the volatility but to maximize the performance of the strategy and thereby Jensen's alpha. As Perchet et al. (2015) conclude the optimal volatility scaling method is the I-GARCH (1,1) model. Therefore, we apply this model to leverage the strategies, and the volatility is forecasted as follows:

$$r_t = \mu + \sigma_t z_t \ with \ z_t \sim i.i.d.N(0,1)$$
$$\hat{\sigma}^2_{p,t+1} = \omega + \alpha(r_t - \mu)^2 + \beta\sigma^2_t \tag{3.31}$$

where

$$\alpha + \beta = 1$$

Moreover, as done by Perchet et al. (2015), we also apply the condition.

$$\omega = 0$$

The forecasts are made using daily data available at time $t$, and the estimate is used to adjust the leverage accordingly, such that the returns at time $t+1$ becomes:

$$r_{p,t+1,scaled\ strategy} = \frac{\sigma_{target}}{\hat{\sigma}_{p,t+1}} r_{p,t+1,unscaled\ strategy} \tag{3.32}$$

where

$$\sigma_{target} = 10\%$$

Instead of estimating the alpha parameter, we apply two fixed and different alpha parameters for the two strategies. This is done to allow for a slower leverage adjustment in the value strategy than for the momentum strategy. The average life of the data, also called the center of mass, is equal to $1/\alpha$, and thus higher alpha values will make the volatility forecasts respond more quickly while lower alpha values will smoothen the volatility forecasts. We set the alpha parameter for the momentum forecasts to 6% such that the center of mass of the weights is equal 16.67 days, and the model thus responds quickly to changes in volatility. This corresponds to the alpha parameter used in RiskMetrics to forecast daily volatilities (J.P. Morgan, 1996). For the value strategy, the alpha parameter is set to 1%, which makes the center of mass of the weights equal to 100 days. The low alpha causes the volatility forecasts to change slower and thereby allow the strategy to have slightly more varying volatility in the short run but still remain close to the 10% volatility target in the long run. In appendix 11 and appendix 22 we have also included strategy results with other fixed alpha parameters, and where maximum likelihood estimates of alphas are produced and reestimated yearly.

The volatility forecasts and leverage adjustments are made daily. However, to minimize trading costs, Perchet et al. (2015) suggest only adjusting the leverage when there are significant changes in volatility. Therefore we only change the strategy's leverage when the target leverage is at least 10% higher or lower than the current leverage.

$$x_t = |\frac{\sigma_{target}}{\hat{\sigma}_{p,t+1}}/leverage_t - 1| \tag{3.33}$$

$$leverage_{t+1} = \begin{cases} \frac{\sigma_{target}}{\hat{\sigma}_{p,t+1}} & \text{if } x_t \geq 10\% \\ leverage_t & \text{otherwise} \end{cases} \tag{3.34}$$

The volatility scaling is also applied to the combined strategy as the negative correlation between value and momentum reduces the volatility in the combined portfolio. Thus further leverage is applied in the value and momentum strategy to preserve a 10% volatility. The volatility forecasts for the combined portfolio is estimated based on the equal-weighted returns of the scaled factor strategies. The alpha parameter in the combined strategy is set to 6% as in the momentum strategy. This is done such that volatility is kept as stable as possible. The results of the combined strategy with other alpha parameters can be found in appendix 28.

# 4. Results

In this chapter, a walk-through of the results of the implementations for the various strategies is given. This includes the analyses of the momentum and value premium along with the combination of these strategies. We show how hedging systematic risk and volatility targeting affects the strategies and compares the strategies' historical performance with the equal-weighted Russell 3000 benchmark.

## 4.1 Performance of Momentum Strategies

The results of backtesting price, idiosyncratic, and alpha momentum strategies are shown in the following sections. The analysis includes the performance of the classic versions of the strategies and when controlling for market risk and volatility.

### 4.1.1 Momentum Decile Portfolios

Following the methodology, the stocks are sorted in decile portfolios based on their momentum score in the formation period. In figure 4.1 below, the cumulative returns for the deciles portfolios of the common price momentum measure are illustrated. In these, no costs are included. In appendix 4, the same graph for the other momentum measures is shown. As can be seen, there is a general tendency for portfolios in the higher deciles to have a higher return than lower decile portfolios. This is the case for the momentum deciles of all the different measures.

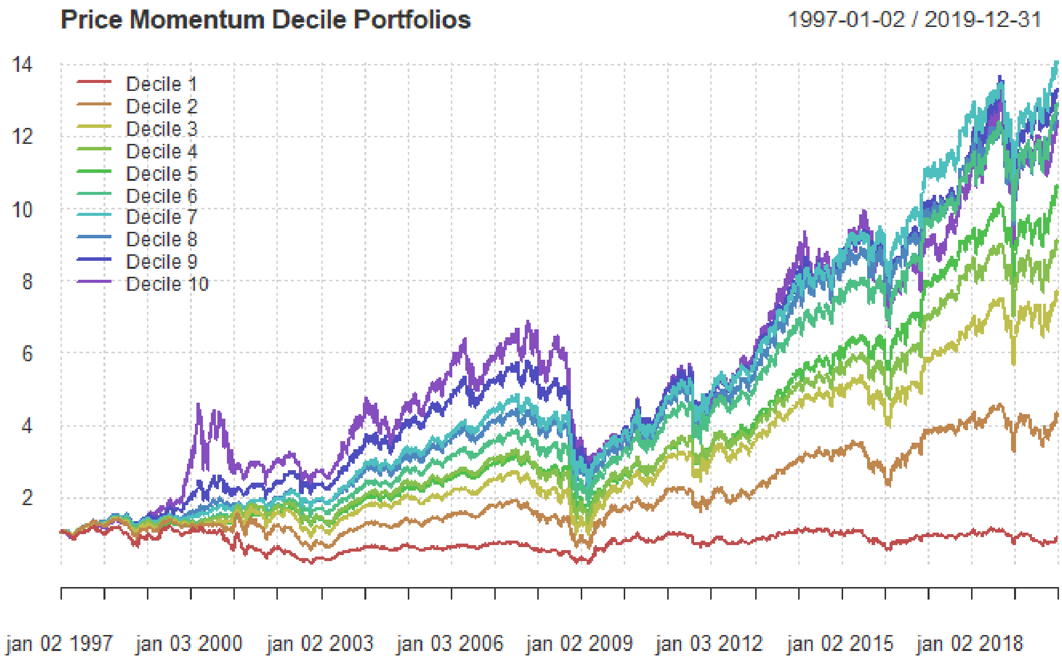



Figure 4.1: Decile Portfolios

The lowest decile portfolio has a much smaller return than the rest of the portfolios and is by far the worst-performing portfolio. For the top deciles, the difference in performance is less clear. The top decile is among the best performing but does not accumulate the highest return. There are a few cases where the portfolios crash, and the top decile portfolios are profoundly affected. For example, the period around the Dot-com bubble in 2000 causes a severe crash in the top decile portfolios, after a period of substantial increases. This follows the reasoning of high systematic factor exposures in momentum investing as described by K. D. Daniel and Moskowitz (2014) and will be evident in the examination of the time-varying beta further below. The general conclusion from the graph is that, in general, the higher decile portfolios perform better than, the lower decile portfolios. This is the case for all types of momentum, as is evident when examining the plots for the other deciles portfolios in appendix 4. To further explore the deciles, the annualized returns, standard deviation, and Sharpe-ratio are calculated as follows:

$$r_{annualized} = \Pi_i^n (1 + r_i)^{\frac{252}{n}} - 1 \quad (4.1)$$

$$\sigma_{annualized} = \sqrt{252} * \sigma_{daily} \quad (4.2)$$

where 252 is an approximation of the annual trading days, $n$ is the number of observed returns, and $\sigma$ the standard deviation:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x-\bar{x})^2}{n-1}} \tag{4.3}$$

Annualized returns and volatility are used to calculate the Sharpe Ratio via:

$$SR = \frac{\overline{r_p - r_f}}{\sigma[r_p - r_f]} \tag{4.4}$$

The risk-free rate is set such that it matches the investment rate for the liquidity buffer mentioned in the cost calculations. The results are shown in table 4.1 below. The table shows the calculation for the top and bottom decile for each momentum type. In appendix 5, a table containing these calculations for all momentum decile portfolios is shown.

Table 4.1: Low and High Deciles for Momentum Strategies

| | Price Momentum | | Idiosyncratic Momentum | | Alpha Momentum | |
|---|---|---|---|---|---|---|
| | Lowest Decile | Highest Decile | Lowest Decile | Highest Decile | Lowest Decile | Highest Decile |
| Ann. Ret | -0.0052 | 0.1154 | 0.0615 | 0.1284 | 0.0088 | 0.1094 |
| Ann- Std Dev | 0.3335 | 0.2682 | 0.2459 | 0.2297 | 0.3018 | 0.2968 |
| Ann. Sharpe Ratio | -0.0606 | 0.3674 | 0.1847 | 0.4845 | -0.0216 | 0.3119 |

From table 4.1, it is clear that there is a large spread between the performance of the lowest decile portfolio and the top one for all of the different momentum strategies. Thus, there is evidence that a strategy going short the bottom decile and buying the top decile should show positive returns. For both price and alpha momentum, the bottom deciles all have annualized returns close to 0%, while the top deciles have annualized returns close to 11%. The spread in performance is slightly smaller for idiosyncratic momentum, but the annualized return for the top decile portfolio is still more than double that of the lowest decile. There is also a tendency for the lowest deciles to have slightly higher volatility (measured by the standard deviation) than the higher deciles. This difference might be because of the negative correlation between return and volatility. The lower deciles generally have lower returns than the higher deciles. If underperformance is caused by the stocks in the decile having negative returns, it can lead to higher leverage. When the market value of equity decreases, the leverage ratio increases, which leads to higher uncertainty for equities with declining market value and lower for those with increasing value (Hull, 2018). In this paper, we have not adjusted the short and long leg contribution of volatility in the long/short strategies. Therefore time-varying volatility in these long and short legs leads to a difference in the risk contribution from these at different points in time. The difference in the annualized returns and volatility results in the top deciles portfolio having a superior return per unit of risk as measured by the Sharpe ratio.

The cumulative returns for the non-beta-neutralized long/short momentum strategies are shown in the graph below. In this graph, costs, and interest on cash, as described in the methodology, are included in the returns.

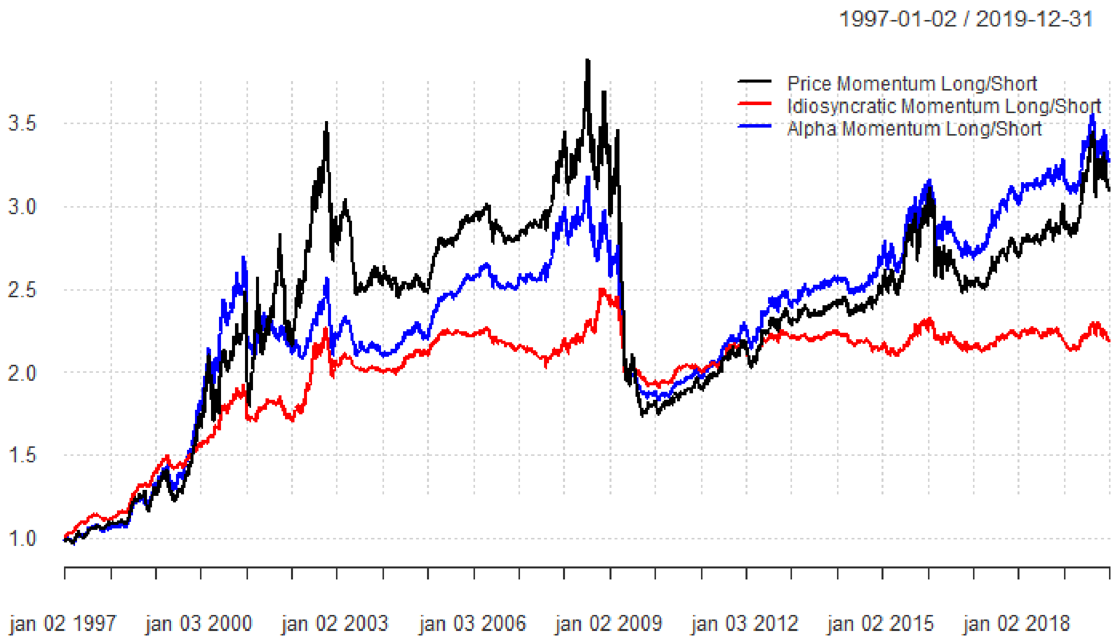



Figure 4.2: Momentum Long/Short Strategies

In figure 4.2, it is evident that all the momentum long/short strategies are correlated and generally rise and crash at the same time. All the long/short strategies generate a positive return over time, but they also experience severe crashes. These crashes follow the well-known problems with time-varying systematic risk exposure as described by K. D. Daniel and Moskowitz (2014) and lead to the returns being negatively skewed. In appendix 6, a table of the return distribution characteristics is provided, and here it is shown that all three strategies exhibit negative skewness and fat tails. The global financial crisis in 2007-2008 is apparent in all strategies, and their market exposure results in a severe crash following this period. The idiosyncratic momentum strategy, which adjusts for both volatility and systematic risk factors, exhibits a crash less extreme than the others, following the results of Blitz et al. (2017) and Hanauer and Windmueller (2019). However, as it is also present in their implementation of idiosyncratic momentum in the US market, the performance stagnates after the crisis. This stagnation leads to a substantial decrease in its Sharpe ratio compared to the period before 2010. In appendix 6, a table with Sharpe ratios for the strategies from the period leading up to 2010 is shown, and in this period, the idiosyncratic strategy outperforms other momentum measures. The metrics for the full period are shown in table 4.2 below, where the maximum drawdown is also introduced.

The maximum drawdown is a measure of the largest cumulative loss, i.e. the largest relative distance from peak to trough over the entire trading period (Pedersen, 2019). As such, the drawdown and maximum drawdown can be formulated as equation 4.5 and 4.6 below.

$$Drawdown = min(0, \frac{p_t - p_{max}}{p_{max}}) \tag{4.5}$$

$$Maximum\ Drawdown_T = Max_{t \leq T}(Drawdown_t) \tag{4.6}$$

| | Price Momentum Long/Short | Idiosyncratic Momentum Long/Short | Alpha Momentum Long/Short | Benchmark |
|---|---|---|---|---|
| Annualized Return | 0.0502 | 0.0346 | 0.0527 | 0.0983 |
| Annualized Std Dev | 0.1150 | 0.0508 | 0.0854 | 0.2225 |
| Annualized Sharpe | 0.2987 | 0.3733 | 0.4306 | 0.3670 |
| Worst Drawdown | 0.5542 | 0.2400 | 0.4255 | 0.6283 |

Table 4.2: Momentum Long/Short Returns

Table 4.2 shows that all of the strategies have lower annual returns than the benchmark but also lower volatility. Despite the large momentum crashes, the maximum drawdowns are lower across all momentum strategies. The maximum drawdown ranges from 24% to 55% across the momentum measures compared to 62% for the benchmark. The classical price momentum has a lower Sharpe ratio than the benchmark (0.2985 versus 0.3670) over the measured period and does not have a return high enough to compensate for its associated risk. For Idiosyncratic momentum, it is marginally higher than the benchmark with a Sharpe of 0.3733, but the two Sharpe ratios are so close that the difference might as well be a result of chance. Alpha momentum is the best performing strategy in terms of Sharpe ratio with 0.4306 and has the highest return of the momentum strategies, but not the highest volatility. The volatility is different across all the strategies, with the lowest being 5.08% for idiosyncratic and the highest being 11.50% for price momentum. However, all the annualized standard deviations are much lower than the 22.25% for the benchmark portfolio.

The difference in momentum performance is due to the fact that the different measures are not perfectly correlated. Idiosyncratic momentum is the strategy with the lowest correlation to the other momentum measures as visible in figure 4.2 and can be seen in the correlation matrix in appendix 6. The correlation for idiosyncratic momentum and the other strategies is below 0.7 when evaluated across the whole period. Price and alpha momentum are more correlated and have a correlation of 0.75. The correlations are calculated with the Pearson correlation coefficient.

$$\rho = \frac{\text{cov}(X,Y)}{\sigma_x \sigma_y} \tag{4.7}$$

with

$$cov(X,Y) = \sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) \tag{4.8}$$

However, the correlation for the whole period does not provide a complete description of the co-movements over time. The correlations vary significantly across time. In appendix 6, a plot of the rolling two years correlations is illustrated. The correlations, most notably between price and alpha momentum, show large variations. The correlation between alpha and price momentum across time ranges from a minimum of 0.1 to a maximum of 0.97 when measured over rolling two-year periods. Thus, the momentum measures are overall highly correlated but have times of large differences in their returns.

As previously mentioned, there is also a considerable variation in the systematic risk exposures for the strategies. In the plot below, 12 months rolling betas for the portfolios are illustrated. These are calculated ex-post via the simple standard beta formula and with daily observations.

$$\beta_i = \frac{Cov[r_i, r_m]}{Var[r_m]} \tag{4.9}$$

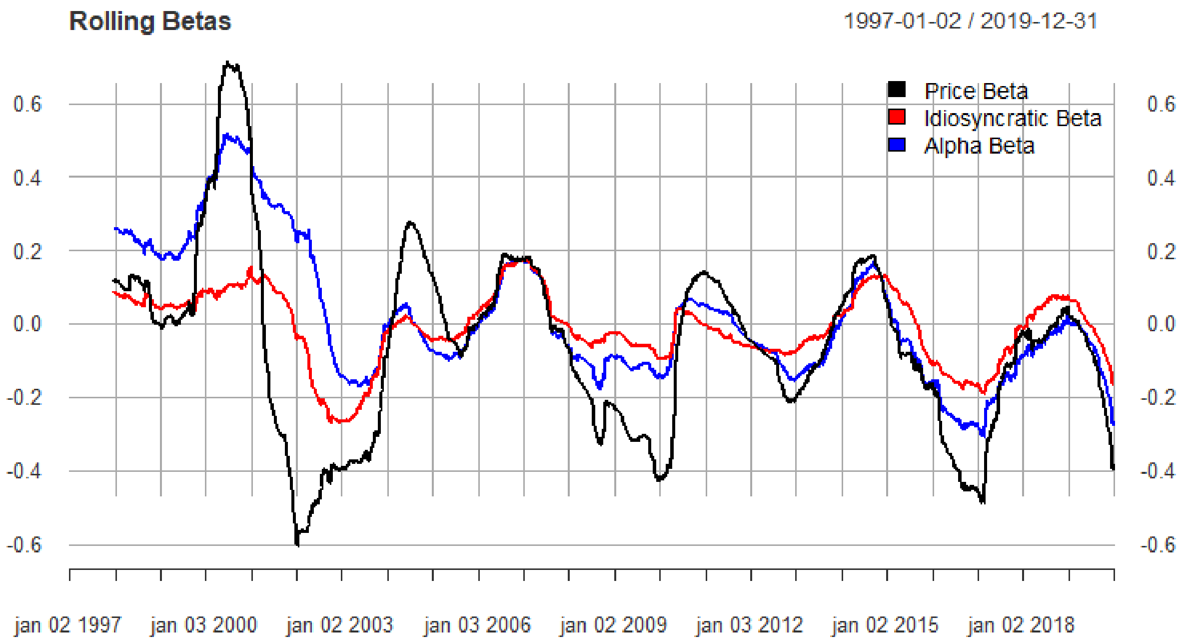



Figure 4.3: 12 Months Rolling Beta

As the strategies have equal weight in the long and short legs, the betas generally fluctuate around 0. Although over time, these betas vary and follow the problems of momentum described by Huhn and Scholz (2013), K. D. Daniel and Moskowitz (2014), and Blitz et al. (2017). They all show that the systematic risk i.e., the market exposure has large temporal variations. Prior to crises, for example, the Dot-com bubble and the Global Financial Crisis, the strategies load beta before crashing. During the crisis, the beta turns negative before a bull market reappears. This leads to large crashes, as shown in figure 4.2. However, the magnitude of the crashes follows the systematic risk exposure to a large degree. Price momentum, which has the largest time-variance in its beta, also experiences the most severe crashes. These crashes are not as heavy for the alpha strategy and even smaller for the idiosyncratic momentum. Idiosyncratic momentum has a maximum drawdown of only 24% and is also much less exposed to market risk. For both the alpha and idiosyncratic momentum versions, where the non-systematic return components are used, the beta exposure is decreased, and therefore the large drawdowns are reduced. Alpha momentum does not remove the market exposure to the same degree as the idiosyncratic counterpart, and all of the strategies in general still suffers from crashes to some degree. To further illustrate how these changes in systematic risk are realized, the rolling betas of the long and short legs are shown for price momentum in figure 4.4 below. The corresponding plots for idiosyncratic and alpha momentum are presented in appendix 6. They show similar tendencies, but as these strategies have reduced factor exposure, it is less significant than in the plot below.

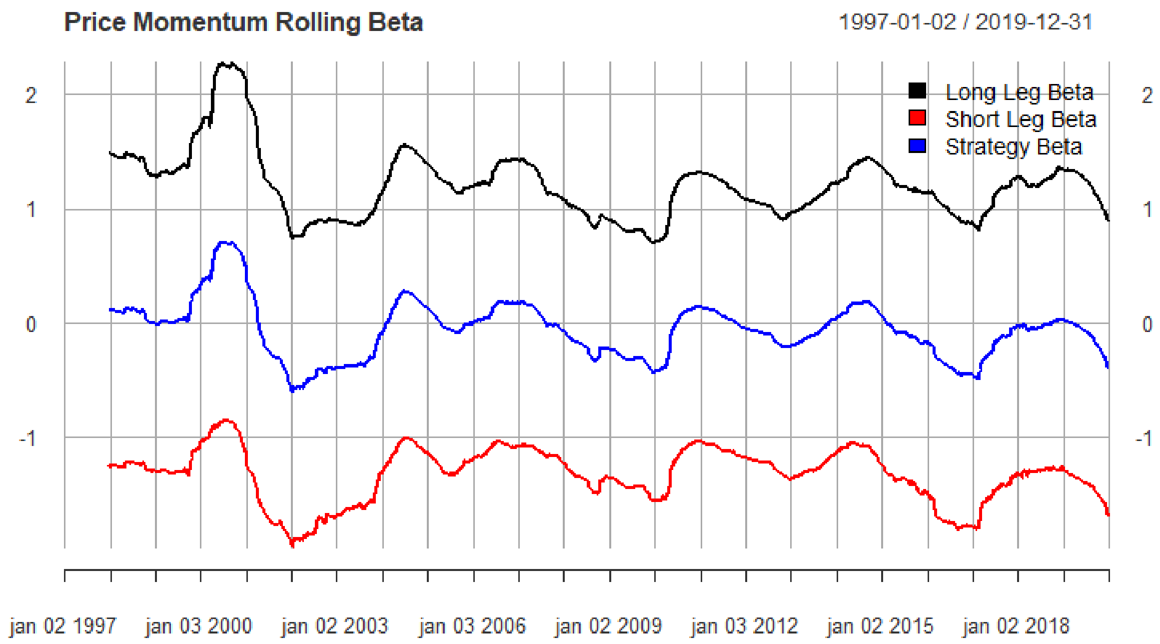



Figure 4.4: Price Momentum Long and Short Beta

It is clear that in bull markets, the long leg beta tends to increase, whereas the short leg beta becomes less negative, leading to an increase in the strategy beta. When a bear market has been persistent, the opposite happens. There is a high beta loading before financial crises, causing significant drawdowns. These drawdowns are then prolonged because of the negative beta loading at the start of the bull market. In figure 4.4, this is evident as the absolute beta values of the legs tend to be negatively correlated and thereby pushing the beta-risk above zero leading up to the Dot-com bubble and Financial Crisis and below zero during the bear markets. The changes in systematic risk happen such that the strategy has positive beta where markets crash and negative beta as markets start to rise. This exposure leads to large drawdowns and indicates that the crashes could be reduced by minimizing this variance in the systematic risk.

### 4.1.2 Momentum Beta Neutralised

The following section validates the positive effect of minimizing systematic risk in momentum trading. This has a positive effect on momentum crashes as the strategies do not take on unwanted market risk around periods of financial turmoil. This section, therefore, introduces beta-neutralized versions of the previously examined momentum strategies.

The alpha and idiosyncratic strategies are an extension of the classical price momentum, and in their momentum scoring already account for systematic risk. However, as shown in the previous section, they still take on market risk at bad times. To overcome this, further control of this exposure is introduced. As mentioned in the methodology, the momentum strategies are beta neutralized via Fama-Macbeth regressions, which adjusts the momentum-scores across different betas. By making the adjustment, the long and short legs consist of balanced beta portfolios. The ex-ante betas are estimated over a very short time period i.e., a 3-months rolling window such that changes in market environments are captured quickly. In figure 4.5, the resulting ex-post estimates of beta for the strategies before and after the neutralization is shown. The limits on the y-axis are set, such that it is easy to compare the difference in the resulting betas to figure 4.3.

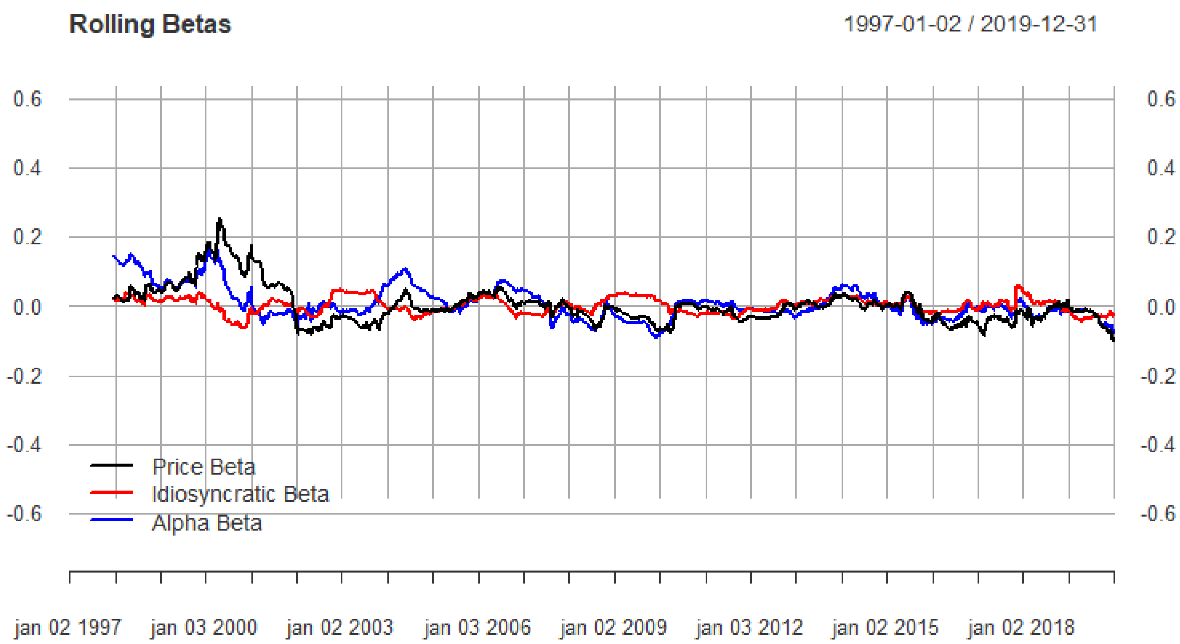
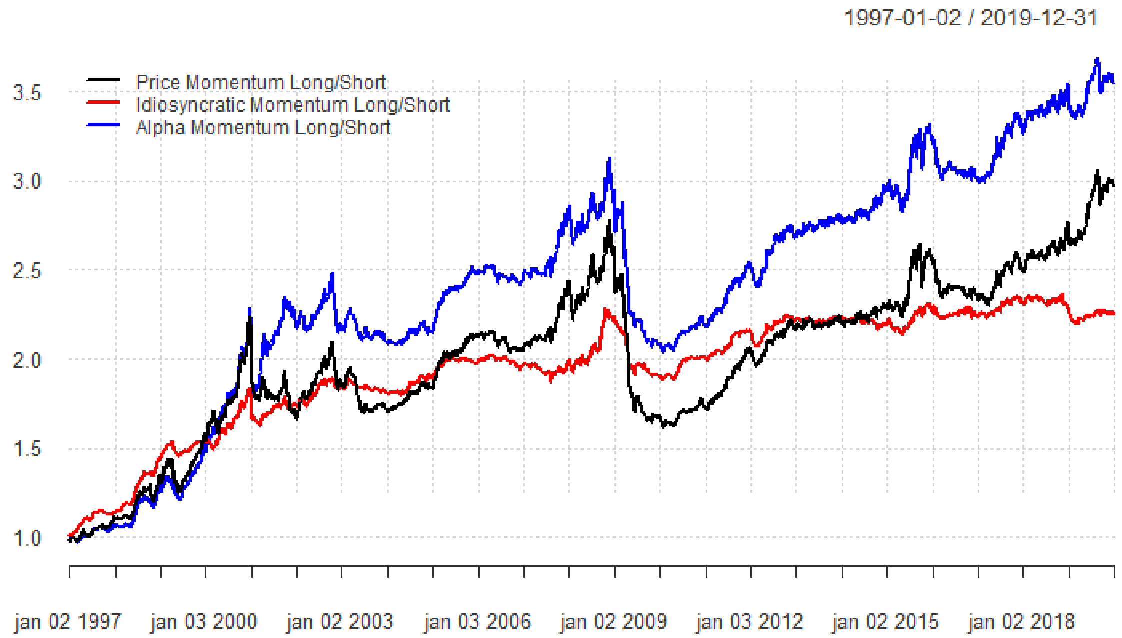



Figure 4.5: Rolling Beta of Neutralised Portfolios

From figure 4.5 is evident that the variance in the systematic risk is much smaller than for the initial momentum strategies. Across time the deviations from beta values of zero are less and smaller. The standard deviation for the rolling beta of the alpha momentum strategy goes from 0.1781 before neutralization to 0.0469 after and is thus much more stable over time. The standard deviations for all of the rolling betas with and without the neutralization are shown in appendix 7. Even though all of the strategies remain closer to a zero beta through time, the systematic risk is not completely removed. All the momentum strategies still have significant betas, which is shown in the CAPM regressions in appendix 8. These are estimated using equation 2.9, but with an alpha term and excess return on the equal-weighted benchmark as the market factor. All the betas are notably less significant than before the neutralization, however, not insignificant for any of the momentum factors. Prior research has also shown that it is very difficult to completely remove all systematic risk from the momentum anomaly (Hollstein et al., 2019). Hence, the resulting momentum strategies still experience some severe crashes after the beta neutralization, albeit these are less severe than without limiting this factor exposure. The performance of the beta neutralised strategies are shown in figure 4.6 and table 4.3 below.

Figure 4.6: Beta Neutralised Momentum Portfolios




| | Price Momentum Long/Short | Idiosyncratic Momentum Long/Short | Alpha Momentum Long/Short | Benchmark |
|---|---|---|---|---|
| Annualized Return | 0.0484 | 0.0360 | 0.0565 | 0.0983 |
| Annualized Std Dev | 0.0714 | 0.0404 | 0.0661 | 0.2225 |
| Annualized Sharpe | 0.4563 | 0.5031 | 0.6128 | 0.3670 |
| Worst Drawdown | 0.4190 | 0.1756 | 0.3482 | 0.6283 |

Table 4.3: Neutralised Momentum Long/Short Returns

In comparison with the strategies before neutralization, as shown in figure 4.2 and table 4.2, the momentum crashes for all momentum variations have been reduced as a result of the beta neutralization. For example, the maximum drawdown of the alpha momentum strategy has gone from 43.1% to 34.8%. This drawdown is realized around the GFC, where market exposure has been lowered, confirming the positive effect. All of the Sharpe ratios are now higher than the equal-weighted benchmark, and reducing the systematic risk in the momentum premium thus greatly enhances the performance. The idiosyncratic momentum is still the strategy with the lowest risk and drawdowns, while the opposite is the case for classical price momentum. Alpha momentum lies somewhere in between, and the annualized standard deviation is slightly higher than that of idiosyncratic momentum, but it also has higher returns. Moreover, alpha momentum continues to perform after the Global Financial Crisis, where the idiosyncratic momentum stagnates. The Sharpe ratio for the alpha momentum strategy is now 0.6128, almost twice the market's 0.3670. Thus, the momentum premium is revived when the systematic beta exposure is lessened, and all portfolios show better historical performance than the equal-weighted market portfolio.

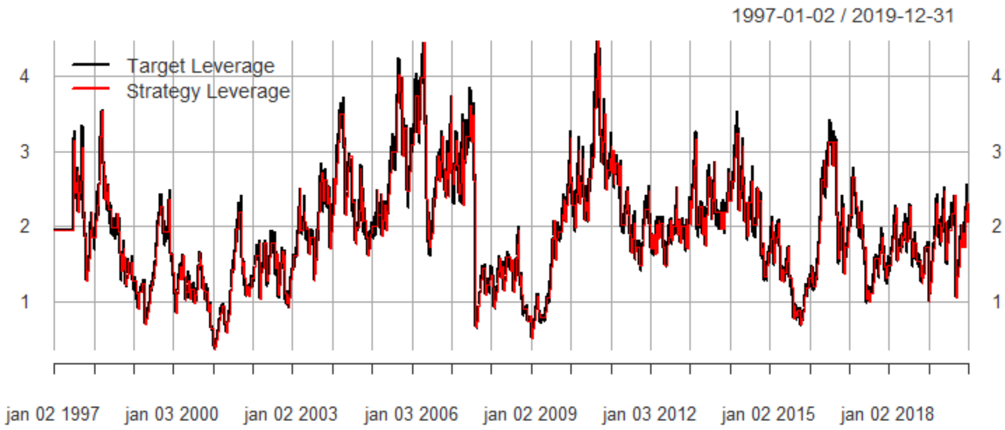
In the following section, the focus is laid on further improving the alpha momentum, which historical performance in the above results has shown to be superior to the other momentum measures. However, these improvements of volatility scaling have been tested for the other measures and show the same positive results when applied to price and idiosyncratic momentum.

### 4.1.3 Momentum Volatility Scaled

In this section, we verify the positive effect that volatility scaling has on the risk and performance of momentum. Here the focus is laid on alpha momentum, and we show that its performance is enhanced by the use of leverage and risk targeting.

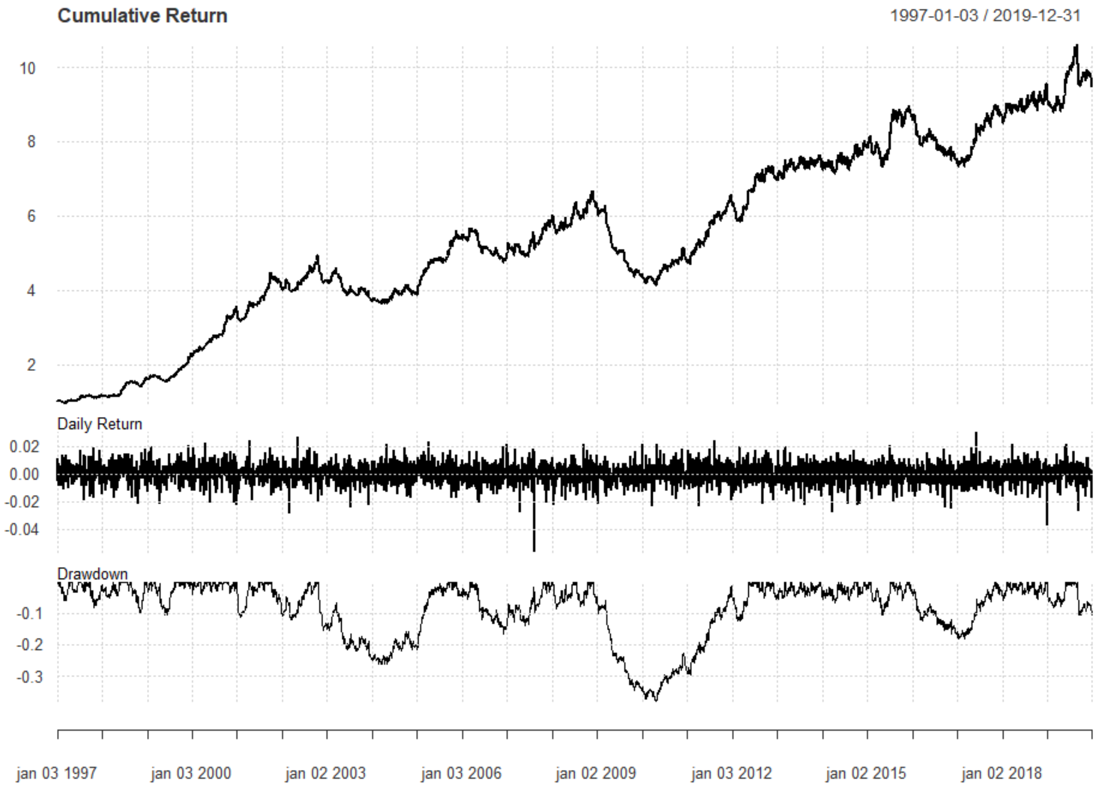
As mentioned in the methodology, the targeted risk is set to an annualized volatility of 10%. The implication of the applied constant volatility scaling is a momentum strategy that increases leverage in stable periods and decreases leverage when the momentum factor has high volatility. In figure 4.7 below, the leverage across time is shown for the alpha momentum with a 10% volatility target adjusted according to the I-GARCH volatility forecast. The alpha in the I-GARCH is 6% and thus has a center of mass of 16.67 days. Please note that the sideways movement, in the beginning, is because the model does not have a long enough history to estimate the leverage. Instead, we have set the leverage for this period to the average leverage over time. This leads to a small look-ahead bias, however, the period is very short and has a minor impact on the analysis.

Figure 4.7: Alpha Momentum Leverage Across Time




The black line in figure 4.7 shows the targeted leverage across time, while the red line is the actual leverage taken. This difference is present because the strategy only trades when there is a 10% difference between the forecasted target leverage and the current leverage, such that trading costs are reduced. The mean leverage for the beta-neutralized alpha momentum strategy is 1.92 when the volatility target is set to 10%. The dynamic leverage fluctuates around this level over time and increases to over 4 in the periods of stable momentum returns and decreases below 1 in volatile times. For example, the leverage decreases massively during the Dot-com bubble and the Global Financial Crisis, where the volatility forecasts for momentum portfolios are high. Before and after these periods, the leverage increases as the strategy returns stabilize. The increase in leverage will, of course, lead to a substantial increase in trading costs. Therefore, this has to be offset by an increase in returns. The cumulative return of the resulting strategy, including the increased cost due to leverage, is illustrated in figure 4.8 and in the second column of table 4.4.

Figure 4.8: Alpha Momentum with 10% Volatility Target




| | Unscaled Alpha Momentum | Scaled Alpha Momentum | Benchmark |
|---|---|---|---|
| Annualized Return | 0.0565 | 0.1027 | 0.0983 |
| Annualized Std Dev | 0.0661 | 0.1034 | 0.2225 |
| Annualized Sharpe | 0.6128 | 0.8322 | 0.3670 |
| Worst Drawdown | 0.3482 | 0.3809 | 0.6283 |

Table 4.4: Scaled Momentum Long/Short Returns

There is a negative relation between momentum returns and volatility, as described by K. D. Daniel and Moskowitz (2014). Therefore, when the leverage is adjusted by the forecasted volatility, it creates a better risk-adjusted return. This improvement is evident from the table above, where the scaled strategy shows a Sharpe ratio of 0.83, compared to 0.61 for the unscaled version. The drawdown is slightly higher 38.1% compared to 34.8% for the unscaled version, albeit this is affected by increased volatility across the whole period when the risk target is set to 10%. In appendix 9, the metrics for the strategy where the volatility target is set to 6.6% is shown. This lower volatility is close to the full-period standard deviation of the unscaled strategy. Here, the strategy has a lower maximum drawdown of 26.5% with a constant 6.6% volatility targeting. This shows that the higher drawdown for the scaled strategy with a 10% risk target is a consequence of a higher overall risk appetite. For a given level of volatility, risk targeting does not increase the risk of momentum crashes but lowers it.

The Sharpe ratio for the 10% scaled strategy is double the size of the equal-weighted benchmark. The two strategies now have annualized returns, which are almost equal. The annualized return is 10.25% for the scaled momentum strategy and 9.83% for the benchmark. However, the annualized standard deviation is 10.34% for the momentum strategy and 22.3% for the market portfolio. Thus, scaling the strategy results in momentum having approximately the same return as the market but half the overall risk. In appendix 10, subsets of the monthly and yearly returns of the scaled momentum strategy are shown.

The one very sizeable downward spike in the daily returns in figure 4.8 is not a loss specific to momentum strategies, but to long/short quantitative trading strategies in general. The large negative return occurs in August 2007 in a period known as the Quantmare (A. E. Khandani & Lo, 2007). The subprime crisis led to funds being in need of capital and to cut down risk. As equity constituted some of the more liquid parts of the quantitative portfolios, these positions were closed to raise capital. The long and short positions in market-neutral factor strategies were closed, leading to substantial negative returns in many equity factors while the overall equity marked remained unaffected (A. Khandani & Lo, 2008). This is why the most substantial one-day negative return (-5.6%) occurs on the 8th of August 2007 for this quantitative long/short strategy, albeit the crash is not specific to momentum. As the crash was a matter of short term liquidity problems, the factor strategies started rebounding on the 10th of August. However, the deleverage caused by the increasing volatility reduces the following positive return for the volatility scaled long/short momentum strategy.

The variance in momentum's risk is much more stable for the constant volatility strategy than for the unscaled, as the strategy is scaled up and down quickly by the I-GARCH. This is illustrated in the plot below, where the realized volatility of the strategy is shown. The realized volatility is calculated from the 1-year rolling standard deviation of the scaled strategy and is annualized. The Quantmare also affects the realized volatility of the strategy. The spike in the realized volatility in August 2007 is caused by the Quantmare, as the massive deleveraging of the portfolio happens after the first significant increases in volatility. The deleveraging and increased volatility are shown in appendix 12. As the realized volatility is calculated by a rolling standard deviation with equal weight on the observations, this shock is persistent for some time.

Figure 4.9: Scaled Momentum Strategy Realized Volatility

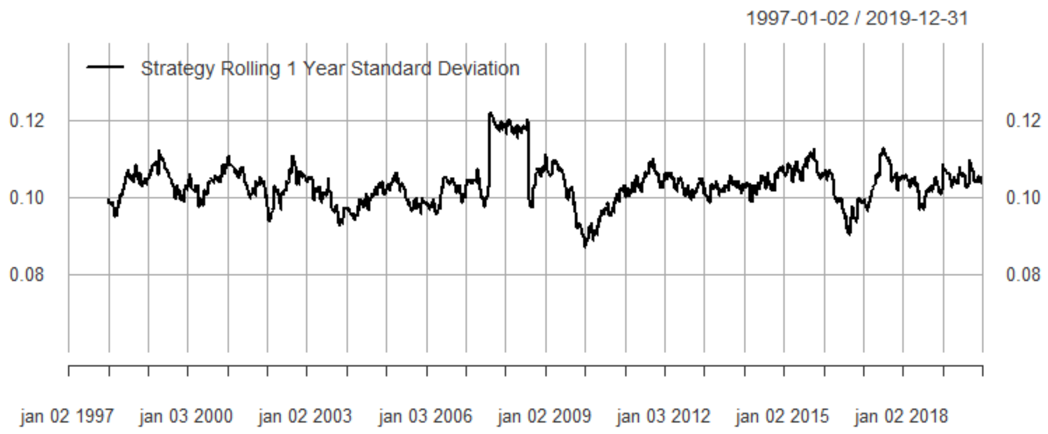



Figure 4.9 shows that the volatility fluctuates around the mean value of approximately 10% volatility. The standard deviation of the rolling annualized volatility is 2.22% for the unscaled strategy, while it is 0.05% for the scaled version. The risk of the scaled strategy remains much more stable over time, which limits the negative effect that rising volatility has on momentum returns.

As a measurement of the factor exposures from the volatility scaled strategy, a Carhart four-factor regression is run on the excess returns. The resulting model estimates are shown in table 4.5 below.

Table 4.5: Carhart Four Factor Regression

| Momentum Strategy | Estimate | t value | $\Pr(> \lvert t \rvert)$ |
|---|---|---|---|
| Alpha | 0.0002 | 2.9135 | 3.59E-03 |
| Beta | 0.0993 | 16.0127 | 1.68E-56 |
| HML | -0.0402 | -3.2259 | 1.26E-03 |
| SMB | -0.1431 | -10.5279 | 1.10E-25 |
| UMD | 0.3426 | 37.3790 | 4.27E-274 |

The factor returns are obtained from Kenneth French's data library and are based on a bigger trading universe. Therefore the results could vary slightly if the factor returns were realized in the same trading universe. Worth noticing is that all of the factor coefficients are significant. Thus the beta neutralization has not entirely removed the market risk, nor have the alpha based momentum removed exposure to other factors. The beta is positive, with a coefficient of 0.1 and highly significant. However, when the excess return is only regressed on the excess return of the benchmark (market factor), the beta coefficient is -0.003 and insignificant. This is shown in appendix 13. The strategy has significant negative exposure to the value factor (HML), which follows the historical negative correlation between momentum and value returns (Asness, Moskowitz, & Pedersen, 2013). There is also a negative exposure to size as the SMB coefficient is -0.14 and highly significant. This makes sense as stocks with high momentum are stocks that have increased their value over the formation period, while the opposite is the case for stocks with low momentum. Thus the momentum strategy tends to buy firms with increasing market cap and shorting those with decreasing market cap leading to a slightly negative relationship with the size factor. The UMD factor is largely positive, which is expected, as this factor corresponds to the price momentum strategy of Jegadeesh and Titman (1993) implemented on the entire US stock market. Despite the slightly different structure of the alpha momentum measure, it is still highly related to classical price momentum. The scaled alpha strategy has a largely positive UMD coefficient of 0.34, which is highly significant. The strategy also has a significant alpha and therefore have returns, which cannot be explained by its Carhart factor exposure. The daily alpha is 0.0002, which corresponds to approximately 5% abnormal returns yearly.

### 4.1.4 Momentum Performance Summary

In our implementation of quantitative momentum strategies, we have shown that the most simple version of price, idiosyncratic, and alpha momentum did not perform far better than the market from 1997-2019. Price momentum had a lower Sharpe ratio in the backtest, while it was slightly higher for idiosyncratic and alpha momentum. However, some parts of the bad performance can be attributed to time-varying market risk. By reducing the market exposure via beta neutralization, the performance across all momentum measures are improved and outperform the benchmark. The alpha momentum is the best performing momentum measure as it provides high returns compared to its risk in the backtests. However, the return per unit of risk is further enhanced when utilizing constant volatility scaling. This is done by increasing leverage in stable periods and descaling in highly volatile periods. With beta neutralization and constant volatility scaling, the final momentum strategy shows superior performance in relation to the initial momentum strategies and the benchmark. The strategy has a Sharpe ratio of 0.83, a maximum drawdown of 38%, while the benchmark has a Sharpe ratio of 0.37 and a maximum drawdown of 63%. Thus, the backtest shows that risk-managed momentum strategies have had an excellent performance in the US market from 1997-2019, and the momentum factor shows to be consistently beating the market.

## 4.2 Performance of Value Strategies

This section shows the results of the implementation of the value strategies. This includes both the performance of value with and without quality measures. Beta neutralized and volatility scaled portfolios are introduced, and the performance is compared to the benchmark portfolio.

### 4.2.1 Value Tertile Portfolios

Before the fundamental ratios (B/M, D/P, E/P) are sorted into tertiles, each ratio is divided into GICS sectors. Thus, the tertile sort is based on each of the 11 sectors for each of the three initial value measures. In figure 4.10 below, the sort of two GICS Sectors, 10: Energy and 15: Materials are shown. The highest and lowest tertile for all sectors and value measures are provided in appendix 14.

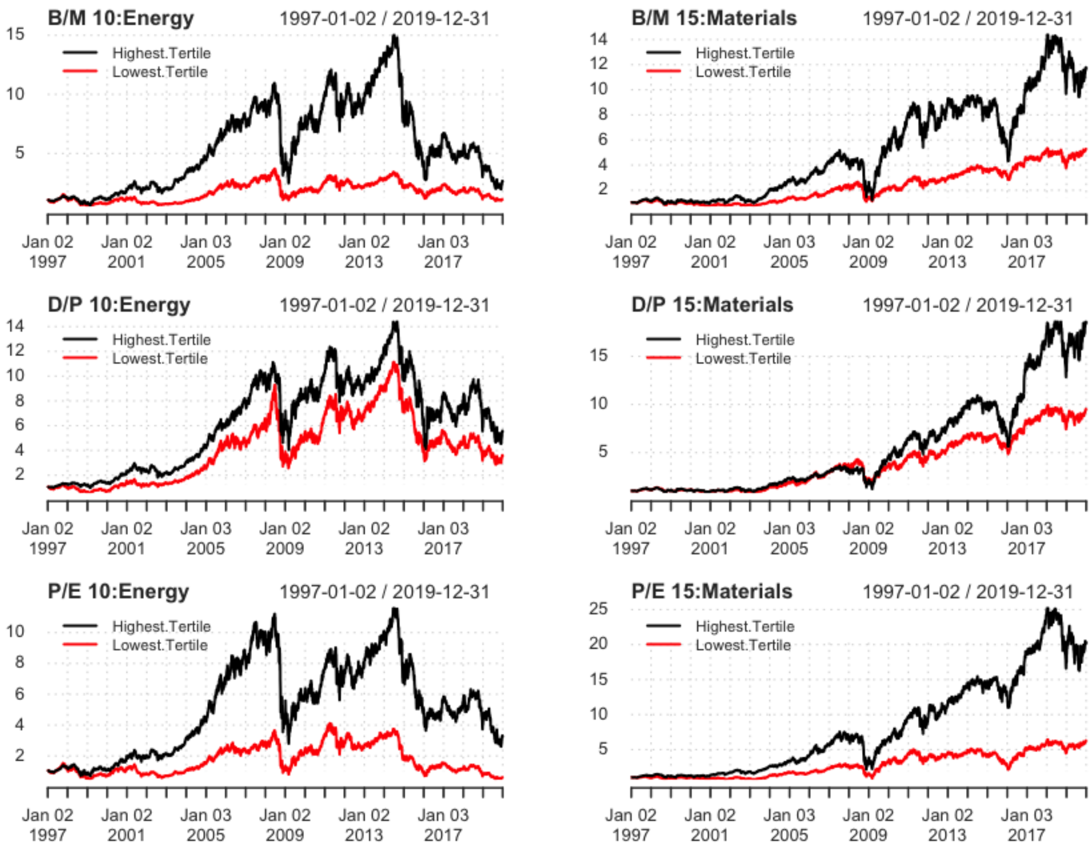



Figure 4.10: GICS Tertiles

From figure 4.10 and the figures in appendix 14, a clear tendency of the highest tertile to outperform the lowest tertile is apparent. However, the degree of outperformance varies across the sectors and measures, as is apparent when comparing the P/E for Sector 15: Materials, and D/P for Sector 10: Energy. The highest tertile for the dividend yield in Energy still outperforms the lowest tertile, but the difference between the two tertiles are much smaller than for the P/E in Materials. Sector 50: Communication Services is the only sector where the lowest tertile notably outperforms the highest tertile.

For all the sectors and measures, a crash is observed during the Great Financial Crisis. This matches the performance for the value portfolios tested by Hlavaty (2016). The severity of the crash depends on the type of sector, for example, the decline of Sector 30, 35, and 55, (Consumer Staples, Health Care, and Utilities) are less steep compared to sector 25 and 10 (Consumer Discretionary and Energy). The increase and the subsequent decline in communications and IT around 2000 can perhaps be attributed to the dot-com bubble. Here companies with internet-based activities saw a quick increase from the late 1990s in their stock price, followed by a rapid decrease in late 2000. The after-cost performance for each of the individual value measures can be viewed in appendix 15.

The plot below shows the performance when combining the dividend yield, book-to-market, and P/E using the described z-score approach.

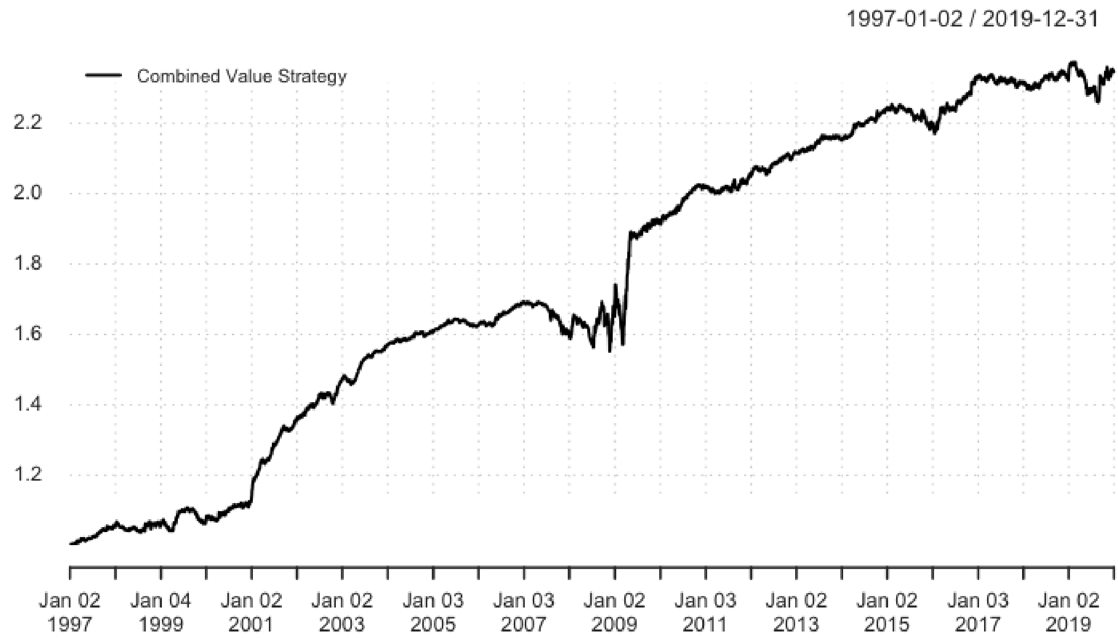



Figure 4.11: Performance of Long/Short Value Strategy

As is evident from figure 4.11, the value composite long-short strategy overall has a positive performance, ending with a cumulative return of approximately 130%. The strategy generally performs very well with large surges in the performance right after the dot-com bubble in the early 2000s and after the GFC around 2010. Furthermore, the absence of large drawdowns is also noticeable. When observing table 4.6, the worst drawdown of the long/short strategy is quite low and is at 9.73%. This supports the overall stable performance, as can be seen from the low annualized volatility of 3%. The annualized return for the short-leg of the strategy is negative. This indicates that shorting the lowest tertile of the three value measures sorted on the GICS sectors yields a negative return. This also explains the colossal maximum drawdown of 93.44%, since the cumulative return of the portfolio keeps on declining.

| | Combined Value Strategy | Long-leg | Short-leg | Benchmark |
|---|---|---|---|---|
| Annualized Return | 0.0378 | 0.1606 | -0.1109 | 0.0983 |
| Annualized Std Dev | 0.0302 | 0.2175 | 0.2007 | 0.2225 |
| Annualized Sharpe | 0.7336 | 0.6577 | -0.6198 | 0.3670 |
| Worst Drawdown | 0.0973 | 0.5068 | 0.9344 | 0.6283 |

Table 4.6: Value, Long & Short-leg Returns, and Benchmark

According to table 4.6, both the long and short leg has a much larger annualized standard deviation than the long/short strategy. The combination of both the long and short leg results in a strategy with low volatility. The combination of the low standard deviation of 3.0% and the annual return of 3.8% results in an annual Sharpe-ratio of 0.7336. When observing the Sharpe-ratio of the long and short leg, it is not apparent how a combination of a negative and positive Sharpe-ratio yields a higher Sharpe than only the long leg. One explanation stems from the historical correlation between the returns of the long and short legs, which is $-0.96$. The negative correlation stems from the opposite market movements. If the prices of the stocks included in the trading universe generally increase, the long-leg yields a positive return, whereas the short-leg yields a negative. As a result of the strategy being dollar-neutral, the positive return for the combined value strategy indicates that the stocks selected based upon the highest tertile of a value composite outperform the lowest tertile.

From appendix 15, the annualized volatility of the individual factors are 3.82% for B/M, 3.56% for P/E, and 2.72% for the D/P. The volatility of the value composite is thus lower than the book-to-market and P/E, but not lower than the dividend yield. However, the volatility of the value composite is lower than the equal-weighted average of the three factors. This supports the evidence of Asness et al. (2015), where the creation of a value composite leads to more stable returns than for the individual factors.

A comparison between the previously described equally-weighted benchmark and the combined value strategy also appears in table 4.6. It is evident that the benchmark has a higher annualized return (9.8%) and higher volatility (22.3%), which yields a lower Sharpe-ratio (0.3670), and thus a lower compensation per unit of risk than for the value strategy. The worst drawdown of the benchmark is higher than for the value strategy. Hence the crash risk is lower for the value strategy.

The value strategy exhibits a positive skewness, as can be observed in appendix 16, meaning that the distribution of the daily returns has a fat right tail. When comparing the skewness to the momentum strategies, the opposite is observed, i.e., negative skewness. These results are similar to those of Rabener (2017b), where a negative skew is present in a long/short momentum portfolio, and a positive skew in a long/short value. Value portfolios are known to behave as long call options on the market (Chibane & Ouzan, 2019). Therefore, the dynamics of the value are very different from the classic momentum strategies. The negative skew and crash risk in momentum mimics the behavior of written call options on the market during crises (K. D. Daniel & Moskowitz, 2014).

The value strategy is shown to outperform the market. However, this does not imply that it is without flaws, and several adaptions of this type of strategy are often applied.

### 4.2.2 Introducing Quality Measures

When using the composite value measure, an uncertainty is present of whether or not the securities in the upper tertile are value stocks for the right reason. If the companies are fundamentally flawed, the traded price might be a correct reflection of the intrinsic value. This issue is the previously described value trap, and according to Asness, Moskowitz, and Pedersen (2013) and Piotroski (2000), it can be mitigated by introducing quality measures. The performance, when including the three quality ratios, debt/assets, gross profit margin, and return on assets in the strategy, i.e., the QARP-factor, is shown in figure 4.12.

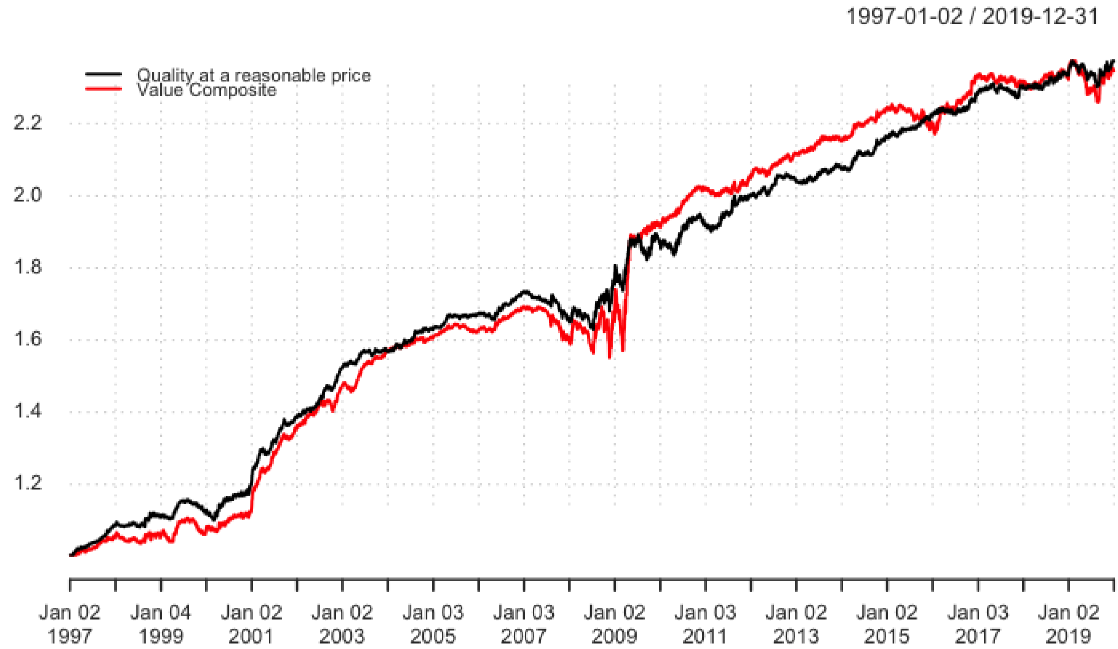



Figure 4.12: Performance of Long/Short QARP Strategy against Value

Following figure 4.12, the performance of the long/short QARP generally follows the pure value strategy. The declines and increases that are present, especially during the GFC, are not as apparent in QARP. The QARP premium is more stable, with less sudden crashes and surges. This stability translates into the volatility, as can be observed in table 4.7, where the standard deviation of the QARP strategy is lower than value. Furthermore, the annualized return is very comparable to the value strategy, as is also apparent from figure 4.12. However, introducing the three quality measures has slightly improved the return. The lower volatility and slightly increased return translate into a higher annualized Sharpe-ratio. The results show that the return of the QARP strategy yields a better risk-adjusted return than the value composite strategy.

| | QARP L/S | Value L/S | Benchmark |
|---|---|---|---|
| Annualized Return | 0.0384 | 0.0378 | 0.0983 |
| Annualized Std Dev | 0.0236 | 0.0302 | 0.2225 |
| Annualized Sharpe | 0.9621 | 0.7336 | 0.3670 |
| Worst Drawdown | 0.0610 | 0.0973 | 0.6283 |

Table 4.7: QARP L/S, Value L/S and Benchmark Performance

In appendix 18, the performance of the individual legs can be observed. When comparing the long and short leg of the QARP with the value legs in table 4.6, it can be seen that the return of the short leg is worse for QARP compared to value. The long leg of QARP overall outperforms the long leg of value, with a lower drawdown, higher return, and lower volatility resulting in a higher Sharpe.

When comparing the QARP factor to the benchmark, the same results as with the value composite can be seen. The return, volatility, and maximum drawdown of the benchmark are higher, but the corresponding Sharpe-ratio is lower. When creating a dollar-neutral long/short strategy based upon a tertile sort of the QARP factor, where the lowest QARP tertile is sold, and the highest QARP tertile is bought a Sharpe ratio of 0.9621 is obtained. The Sharpe-ratio is higher than both the composite value strategy and the benchmark, which indicates that a higher return per unit of risk has been received.

To investigate whether the outperformance of the QARP is due to systematic risk exposure the strategy beta is estimated. This is done by estimating the yearly rolling beta for the QARP strategy and can be seen in the graph below.

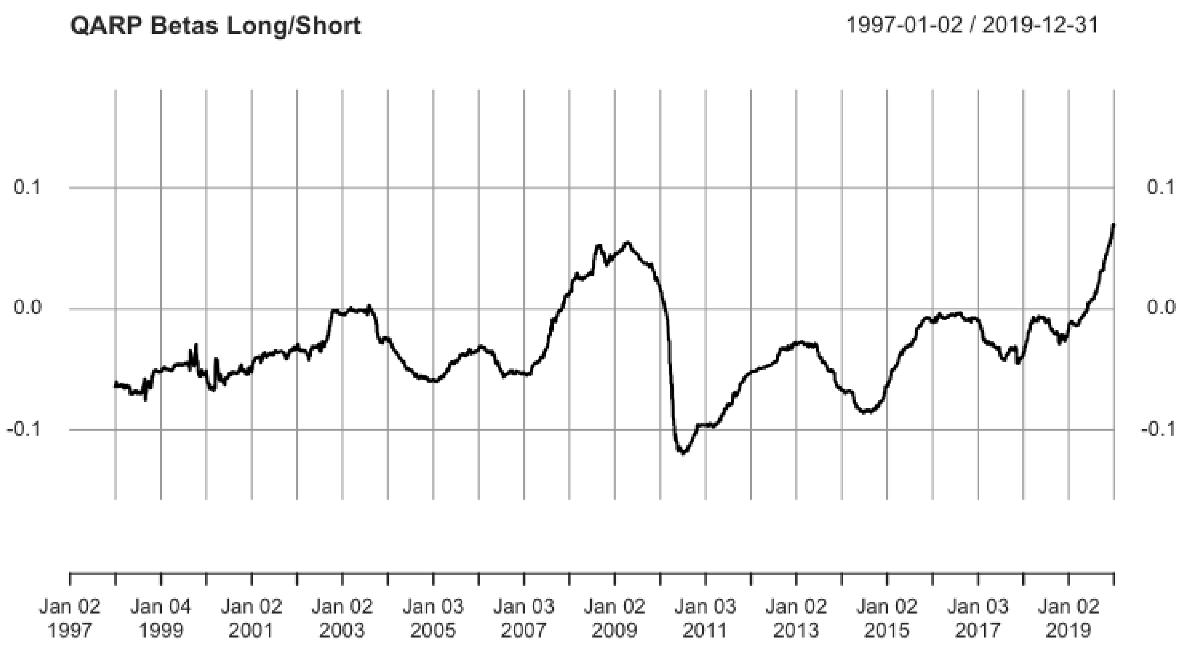



Figure 4.13: QARP Long/Short Rolling Beta

The 12-month rolling betas are generally negative when the whole period is observed and usually very close to 0. When comparing the betas in figure 4.13 with the betas for momentum in figure 4.4 or appendix 6, it is observed that the QARP-factor is not loading as much beta. The beta never exceeds a value of 0.1 in the trading period. Moreover, only in the aftermath of the GFC does the beta dip below $-0.1$. During the financial crisis, it seems that the QARP-factor slightly loads up on beta. The betas of the short and long leg can be observed in appendix 19. Although the systematic risk exposure is lower for the QARP strategy, it still shows slight temporal variation, which can be diminished.

### 4.2.3 QARP Beta Neutralized

In order to stabilize the market exposure, the beta-neutralization methodology used in the momentum strategies is also applied to the QARP strategy. The QARP z-scores will thus be adjusted by the residuals based on a linear regression between the z-scores and the corresponding betas.

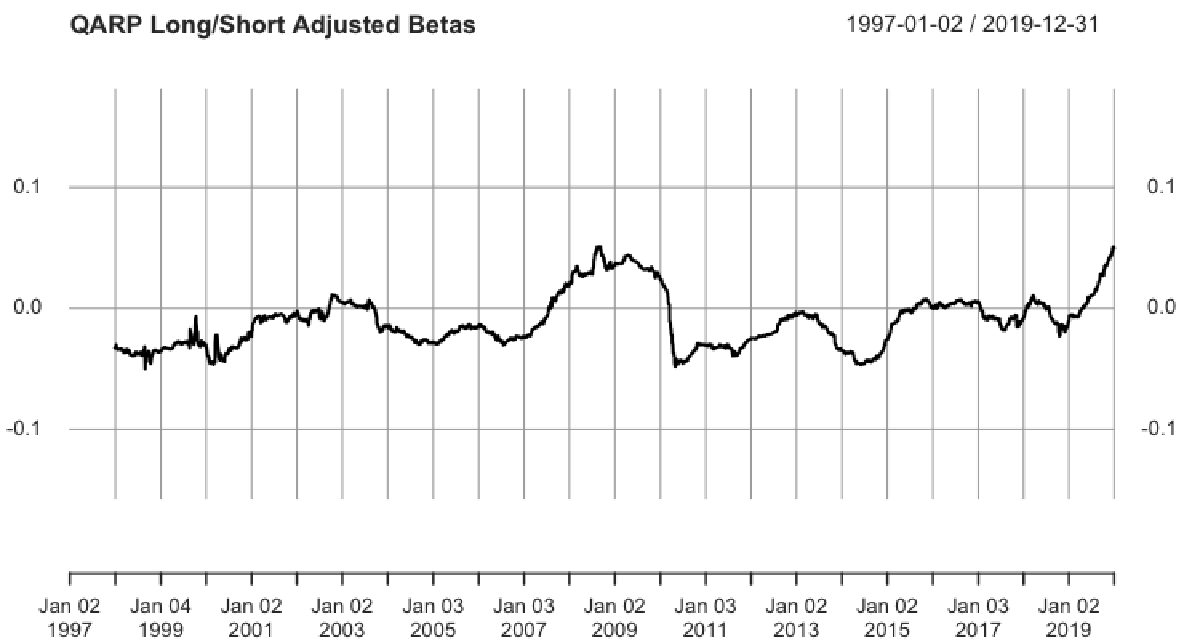



Figure 4.14: QARP Beta Neutralized Long/Short Rolling Beta

When comparing figure 4.14 and 4.13, it is apparent that the residual adjustment limits the beta exposure. The slight loading of negative beta after the GFC has been reduced. Generally, the beta adjustment has caused a decrease in the betas in periods with positive betas, and an increase in the betas in periods with negative beta. Furthermore, the average beta decreases from −0.033 to −0.011 when the strategy is beta neutralized. The standard deviations of the betas also decrease from 3.54% down to 2.17%. Not only does the exposure to systematic risk decrease on average over the period, but the systematic risk also becomes more stable.

In appendix 20, CAPM regressions are run, following the same methodology as in momentum. From the appendix, it is apparent that before the QARP-factor has been beta neutralized, the systematic-risk component is highly significant. After the neutralization, the p-value increases. However, it is still significant at the 5% significance level. This supports a reduction of the systematic risk exposure followed by introducing beta neutralization in the QARP strategy. The performance of the beta neutralized QARP strategy is shown below.

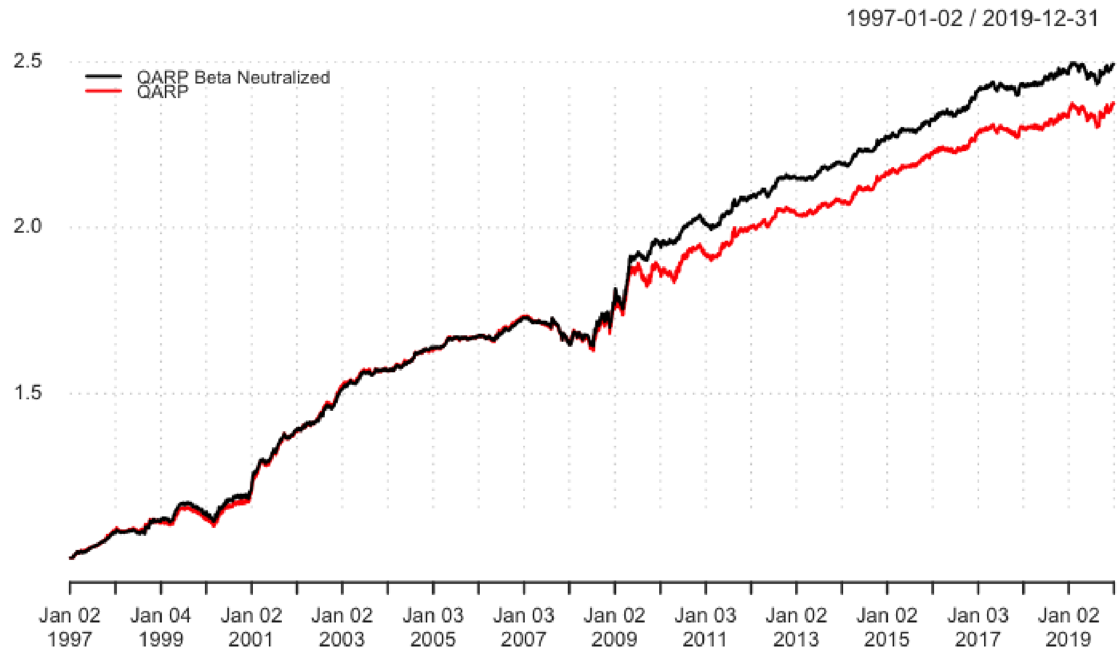



Figure 4.15: QARP Beta Neutralized L/S against QARP L/S

The effect of the beta neutralization in the performance of the strategy can be seen from figure 4.15. The performance up until the GFC is almost identical. However, around mid-2009, a slight disparity between the two strategies emerges. As a result of the decrease the systematic risk exposure, the total return variation has lessened. The total return variance follows equation 2.10, and this is lower when the market component shrinks. The return variation would still consist of the variation in the value and quality factors, but the market risk has been reduced. The decrease in total return variation is supported by table 4.8 below since the annualized standard deviation of the beta-neutralized QARP strategy has decreased relative to the QARP.

| | QARP Beta Neutralized | QARP | Value | Benchmark |
|---|---|---|---|---|
| Annualized Return | 0.0406 | 0.0384 | 0.0378 | 0.0983 |
| Annualized Std Dev | 0.0206 | 0.0236 | 0.0302 | 0.2225 |
| Annualized Sharpe | 1.2051 | 0.9621 | 0.7336 | 0.3670 |
| Worst Drawdown | 0.0504 | 0.0610 | 0.0973 | 0.6283 |

Table 4.8: Performance of the Beta Neutralized QARP compared to previous strategies and benchmark

The performance metrics of the beta neutralized QARP are better than that of the standard QARP. The annualized return has increased slightly from 3.8% to 4.1%, and the standard deviation has decreased from 2.4% to 2.1%. The increase in return and decrease in risk naturally leads to a higher Sharpe-ratio. Therefore, the beta-neutralized QARP strategy is the best performing strategy in comparison to the benchmark and the unadjusted strategies.

### 4.2.4 Volatility Scaled Value

In the following section, the beta neutralized QARP is addressed as value. As mentioned, the QARP factor is an extension of the pure value factor (Asness, Frazzini, & Pedersen, 2013), (Piotroski, 2000). As seen from the previous section, this addition does not radically alter the value strategy's attributes.

The volatility scaling methodology is applied in order to maintain volatility close to the target of 10%. To achieve this, the strategy is levered according to ex-ante forecasted volatility based on the I-GARCH-model. As mentioned in the leverage methodology, the alpha parameter in the I-GARCH model of value is different from momentum. An increase in the I-GARCH's alpha decreases the center of mass for the volatility. This increases the speed of adjustment in the volatility forecast and limits the tail risk exposure. As shown, value is positively skewed. Therefore the limitation of tail risk can lead to a decrease in the performance. Thus, the alpha parameter is set to 1%, such that the average center of mass is 100 days. The average leverage of the value strategy across the traded period is shown below in figure 4.16.

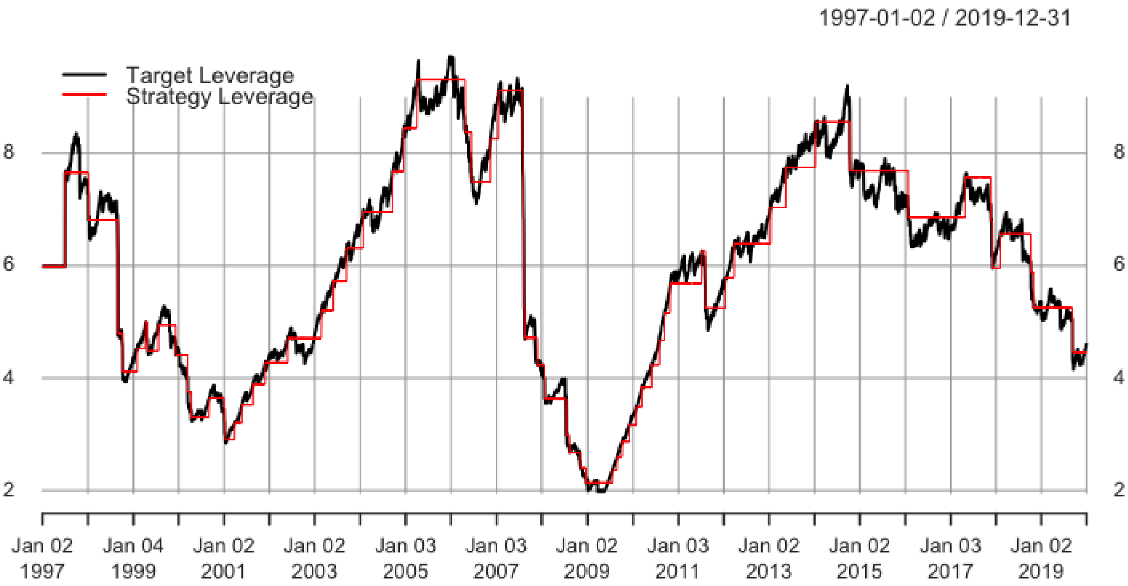
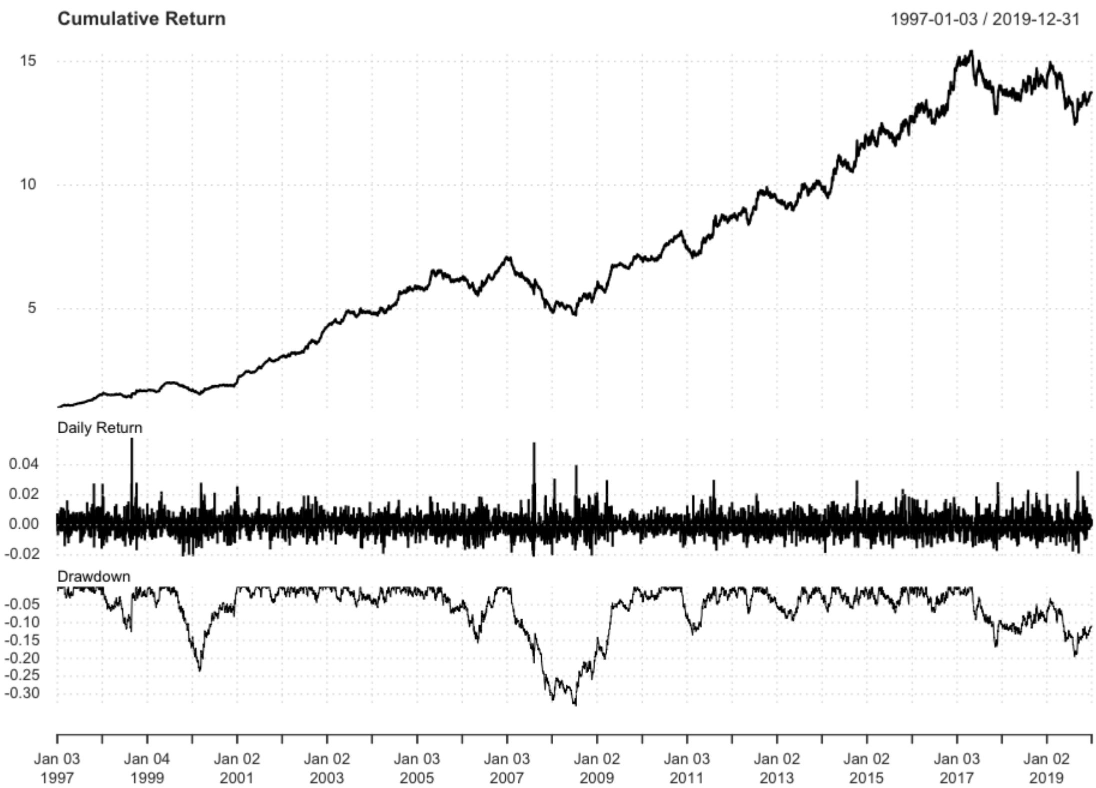



Figure 4.16: Value Leverage Across Time

As with momentum, it is necessary to mention the constant leverage at the beginning of the traded period. In the first six months, not enough observations are present to forecast the volatility, and the average leverage for the value strategy of 5.97 is used. The black line shows the target leverage, whereas the red line shows the actual leverage of the strategy. The leverage is only adjusted when the difference between the target leverage and current leverage exceeds 10%. The difference in the alpha parameter is notable in figure 4.16, where the leverage is adjusted less frequently compared to momentum. As a result of the longer time horizon, the fluctuations in the leverage decreases. As mentioned, the mean leverage of the strategy is 5.97, with a volatility target of 10%. An explanation for the general leverage stems from the average volatility, which is 2% for the beta neutralized strategy. Hence, a considerable amount of leverage is needed to increase the volatility and hit a 10% target. The dynamic leverage fluctuates over the traded period. However, the absolute values of the leverage are generally high, which can be attributed to the low volatility of the value strategy. In periods with high volatility, the strategy levers down. The large decrease in leverage is thus an indicator of periods with high volatility. These periods are usually followed by stable periods, where the leverage increases incrementally. The implementation of dynamic leverage leads to higher trading costs. In figure 4.17 and table 4.9

the performance of the volatility scaled value is analyzed and compared to the values before the introduction of a risk target.

Figure 4.17: Performance of Volatility Scaled Value




| | Vol Scaled Value | Unscaled Value | Benchmark |
|---|---|---|---|
| Annualized Return | 0.1209 | 0.0406 | 0.0983 |
| Annualized Std Dev | 0.1018 | 0.0206 | 0.2225 |
| Annualized Sharpe | 1.0215 | 1.2051 | 0.3670 |
| Worst Drawdown | 0.3334 | 0.0504 | 0.6283 |

Table 4.9: Volatility Scaled Value Long/Short Returns

The cumulative return of the scaled long/short value strategy over the 23 years is 1,278%. The risk-adjusted return deteriorates as a result of the volatility scaling, and the Sharpe ratio decreases from 1.21 down to 1.02. An explanation for the decrease in performance might be found in the previously mentioned decrease of tail risk when volatility scaling. The positive skewness of the beta neutralized strategy shown in appendix 16 is observed to be 0.99, whereas when volatility scaling, the skewness decreases to 0.60. Hence, the decrease in tail risk adversely affects the value strategy. The worst drawdown increases from 5.0% in the unscaled value to 33.3% in the scaled. However, an increase in the drawdowns is to be expected following the approximate five-fold increase in annualized volatility.

Even though the scaled strategy has a lower risk-adjusted return than the unscaled, the volatility scaled value strategy is superior on all metrics compared to the benchmark. The annualized return of value is larger (12.10% versus 9.83%) and the annualized standard deviation is under half that of the benchmark (10.18% versus 22.25%). The scaled strategy has returns similar to the benchmark but with half the risk. Therefore the Sharpe of 1.02 is much higher than the market's 0.37. In appendix 21, all of the monthly and yearly returns for the scaled strategy is shown.

The large decrease in leverage in figure 4.16 and the very notable daily return in figure 4.17 occurring in the middle of 2007 is a result from the previously referenced Quantmare (A. E. Khandani & Lo, 2007). The Quantmare crash is the driver of the largest negative one-day return of −2.14% for the strategy. As a consequence of the lower alpha-parameter for value, the change in leverage is slower compared to momentum, following appendix 12. The strategy did not heavily reduce the leverage during this period despite the increase in volatility. When the market rebounded on the 10th of August occurred, the strategy was still highly levered, and the 2nd largest daily increase of 5.51% is observed.

As a result of the low alpha-parameter, the speed of the leverage-adjustment is slow. This leads to more fluctuations in the realized volatility, as can be seen from figure 4.18.

Figure 4.18: Scaled Value Strategy Realized Volatility


The volatility generally stays inside the $8\% - 12\%$ range. Although, there exist periods where the realized volatility is above this range. For example, the Quantmare in August 2007, where volatility increases above 12% and is followed by volatility below 8%. The higher variance in the volatility creates a trade-off between keeping the volatility close to the risk target and preserving the large positive returns.

When comparing figure 4.16 and 4.7, it is evident that the lower alpha parameter leads to a more delayed leverage adjustment. These delayed leverage adjustments lead to more fluctuating volatility compared to momentum, which is evident when comparing figure 4.18 and 4.9. In appendix 22 the performance and realized volatility of different volatility scaled value strategies with varying alpha parameters are shown.

A linear regression is run using the Carhart four-factor model to measure the factor exposures of the scaled value strategy. This is based upon data from Kenneth French's data library to try and explain the scaled value returns. The estimates etc., are shown in table 4.10 below.

| Scaled Value | Estimate | t-value | Pr(> $\|t\|$) |
|---|---|---|---|
| Alpha | 0.0005 | 6.2991 | 3.21e-10 |
| Beta | -0.0856 | -13.5106 | 5.64e-41 |
| HML | 0.1189 | 9.3501 | 1.22-20 |
| SMB | -0.0216 | -1.5246 | 0.1274 |
| UMD | -0.2562 | -27.3809 | 2.59e-155 |

Table 4.10: Carhart Four Factor Regression on the Value Strategy

The coefficient of the momentum factor, UMD, is $-0.2562$ and significant. This confirms the negative value and momentum relationship described by Asness, Moskowitz, and Pedersen (2013). Additionally, this result follows the regression performed for the scaled momentum strategy, which shows a significant negative exposure to the HML factor in table 4.5.

The exposure to the HML factor is positive and significant. One might expect that the increase of the returns in the HML portfolio, would explain a larger part of the returns in the value strategy. However, it is important to note that the scaled value strategy is a composite of three different value measures in addition to three quality measures. In contrast, the HML factor only consists of the book-to-market ratio. Thus, this strategy is very different, but the HML factor still captures a significant part of the returns.

From table 4.10, the exposure to the SMB factor is negative and insignificant. Since the size coefficient is insignificant, it cannot be determined whether or not the true relationship between size and value is negative or positive. The universe of the securities in Kenneth French's data library consists of all stocks in the CRSP database, and the number of stocks is larger than the trading universe of the strategy. This can considerably affect the size factor since the stocks in the SMB portfolios in the Kenneth French data might not be included in the tradeable universe.

The systematic risk exposure measured by the beta coefficient of $-0.0856$ is highly significant. When the excess returns of the strategy are regressed on only the benchmark index, the coefficient is $-0.0258$. This coefficient is also significant, as can be seen from appendix 23.

Finally, the daily alpha is also significant, with a coefficient of 0.0005. The Carhart factor model cannot explain the entirety of the returns from the volatility scaled value strategy. The daily alpha corresponds to an annualized abnormal return of approximately 12.95%.

### 4.2.5 Value Performance Summary

In our implementation of quantitative value strategies, we have shown that creating a composite based upon three value measures, book-to-market, dividend yield, and price/earnings, has an excellent performance. The composite has a larger Sharpe ratio than the benchmark index, and thus the compensation per unit of risk is better for the value composite as opposed to the benchmark. Furthermore, the introduction of quality measures has a positive impact on the performance and lowers the strategy's risk. To limit the QARP strategy's exposure to systematic risk, a residual adjustment is applied. The residual adjustment causes the strategy's systematic risk to decrease. However, the beta-coefficient remains significant, and the systematic risk is not completely removed. This reduction has a positive effect on the performance, with an increase in the risk-adjusted return of the strategy. Moreover, when scaling the strategy to hit a volatility-target of 10%, the performance slightly deteriorates. This is because the value strategy is positively skewed, and the dynamics resemble buying call options on the market. The volatility scaling cuts of tail risk, which reduces the Sharpe ratio from 1.21 to 1.02 in unscaled strategy. However, the scaled value is still superior to the benchmark. The results provide evidence that quantitative value and other fundamental alterations have been a source of a high return premium over the last decades.

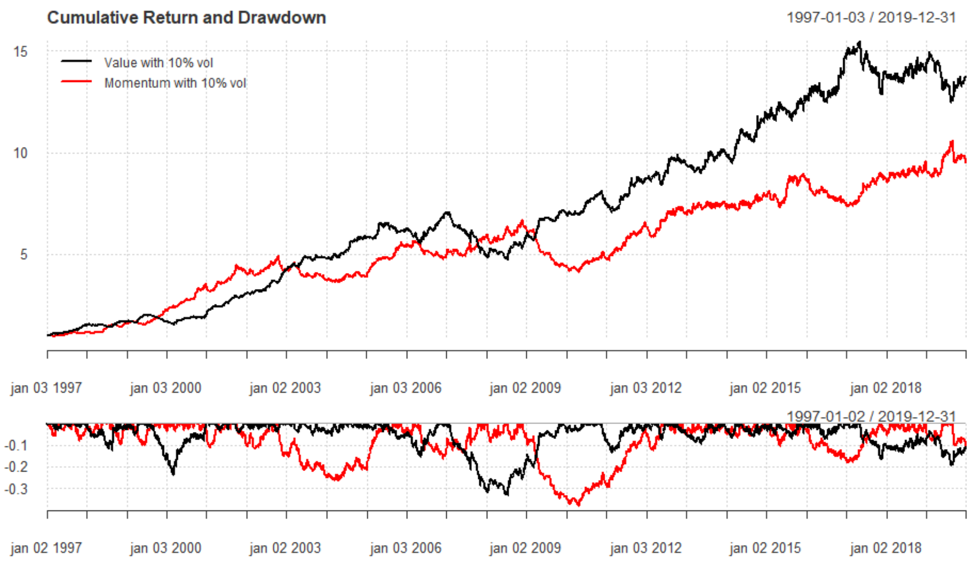
## 4.3 Combining Value and Momentum

As the dynamics of the value and momentum strategies are very different, the two strategies often perform at different times. Therefore a combination of the strategies can be used to minimize risk and improve portfolios. In this section, we evaluate the momentum, value, and benchmark strategies in relation to each other and validate how combining value and momentum can improve performance.

### 4.3.1 Value and Momentum Correlation

From the previous sections, it is evident that both value and momentum strategies provide substantial risk-adjusted returns compared to the market factor. However, the two strategies are very different in nature, and it is a well-known fact that the momentum and value factors are negatively correlated (Asness, Moskowitz, & Pedersen, 2013). This is also clear from figure 4.19 below, illustrating the performance of the two volatility scaled value and momentum portfolios. The value factor generally increases as momentum decreases and vice versa.

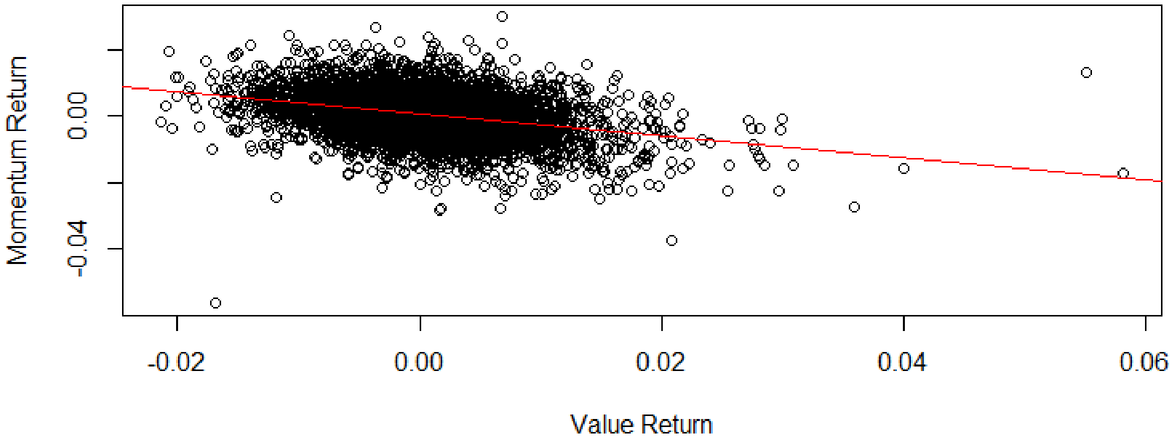
Figure 4.19: Value versus Momentum




Both strategies have high returns over the periods. However, the strategies perform poorly at different points in time. This is visible from the drawdowns, and when one factor is experiencing extensive losses, the other strategy tends to perform well. The value strategy has its most significant drawdown at the beginning of the Global Financial Crisis, where the momentum strategy still shows positive returns. The momentum strategy suffers in the aftermath of the crisis. Here value on the other has started to increase again. The two strategies have a negative correlation -0.32 across the whole period. This correlation, of course, changes over time, and therefore the magnitude of the opposing movements may vary. In appendix 24, the one-year rolling correlation of the two strategies is shown. The correlation between the two strategies fluctuate around the full period correlation but vary over time. However, the correlation is not positive over any one-year rolling period. Moreover, the correlation becomes increasingly negative from 2015 and is -0.65 at the end of 2019. The increasing negative correlation can be a slight problem in a combined portfolio as the short position in one factor can match a long position in another factor. In cases of very high negative correlation, it could be attractive to apply intersectional factor portfolios instead. However, in the period analyzed, this problem is not critical for the combined strategy.

A non-perfect negative correlation in returns offers an excellent opportunity to reduce risk as bad periods in one strategy can be offset by positive returns in the opposing strategy. In the figure below, a scatterplot illustrates this negative relationship between momentum and value returns. The y values are the daily return of the momentum strategy, and the x values are the corresponding value returns on the same day.

Figure 4.20: Momentum vs Value Strategy Returns




The red line in figure 4.20 is the result of a linear regression of the momentum strategy returns on the value returns. The regression estimates can be found in appendix 25 with both strategies as the dependent variable. These coefficients are approximately the same as the full-period correlation as $\beta = \rho_{xy}\frac{\sigma_y}{\sigma_x}$ and both the applied value and momentum strategies have a standard deviation very close to 10%. It is clear that momentum's return tends to be higher when value's return is low and lower when value's return is high. The outlier in the bottom left corner of the figure, where momentum return is -5.6%, and the value return is -1.7% is because of the Quantmare in 2007. This observation is from the 8th of August during the Quantmare. In the opposite end, the outlier in the top right corner of the figure also happens during the Quantmare, namely the 10th of August, where the quantitative long/short strategies rebound. Thus, both strategies experience large positive returns on that date. As the value strategy adjusts its leverage slower, this rebound is more prominent for the value strategy. Without these two outliers, the negative correlation is even more valid. It strongly indicates that the two strategies can be used to provide insurance against each other while preserving positive returns.

### 4.3.2 Combined Strategy

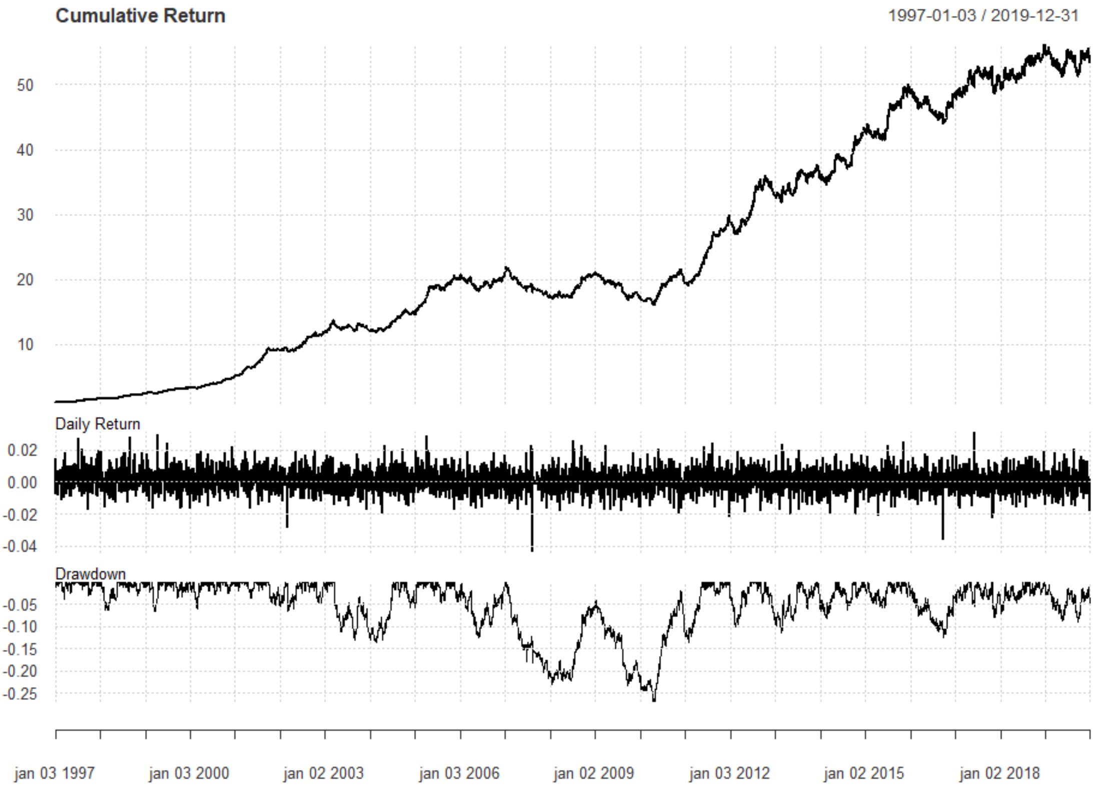
The combination of value and momentum creates a strategy with much lower risk but preserves a high return and therefore creates an even better Sharpe ratio. In table 4.11, the performance of a strategy with equal weight in the 10% volatility momentum and value strategies are shown along with the benchmark and non-combined factors.

Table 4.11: Value and Momentum Combined

| | Combined | Value | Momentum | Benchmark |
|---|---|---|---|---|
| Annualized Return | 0.1157 | 0.1209 | 0.1027 | 0.0983 |
| Annualized Std Dev | 0.0596 | 0.1018 | 0.1034 | 0.2225 |
| Annualized Sharpe | 1.6571 | 1.0215 | 0.8322 | 0.3670 |
| Worst Drawdown | 0.1187 | 0.3334 | 0.3809 | 0.6283 |

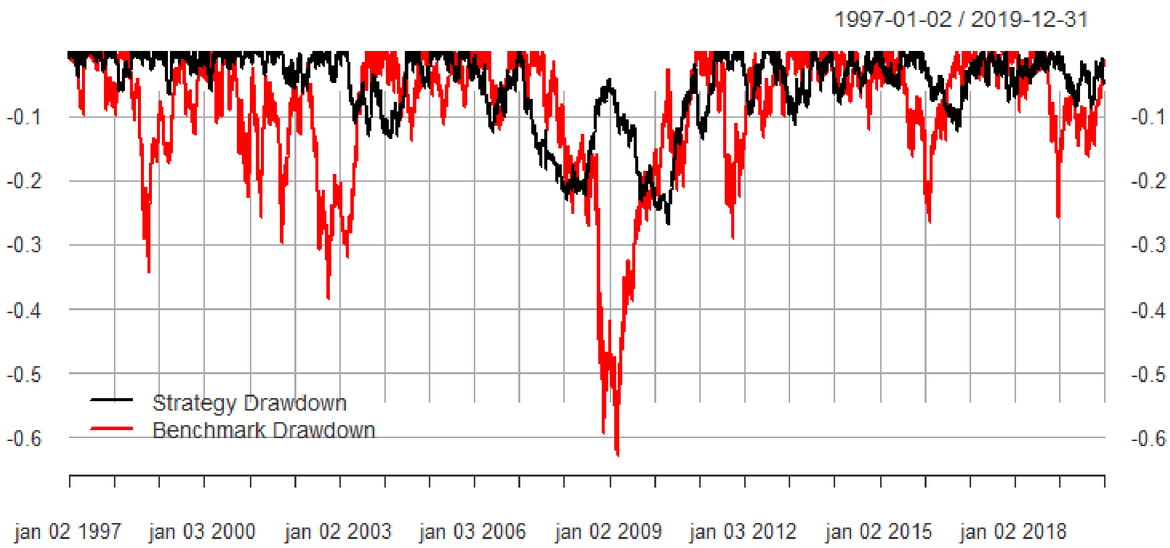
Table 4.11 verifies that the combination of the two strategies leads to an improvement in the risk-adjusted return. The negative correlation among the strategies induces a much lower standard deviation of approximately 6% compared to the targeted 10% for the individual strategies. Both strategies provide high returns, and therefore the annualized return for the combined strategy is 11.6%, which, together with the smaller standard deviation, leads to a Sharpe ratio of 1.66. This Sharpe ratio is considerably larger than any of the individual strategies and almost four times bigger than the benchmark's Sharpe ratio. Moreover, the maximum drawdown is now only 12% for the strategy. However, the lower standard deviation of the combined strategy does not comply with the 10% risk target. Therefore the volatility adjustments are also applied to this strategy. A graph showing further leverage on the strategy is illustrated in appendix 26. For the combined strategy, the alpha in the I-GARCH is set to 6%. This way, the volatility fluctuation is kept at a minimum. The results of the strategy are shown in figure 4.21 below.

Figure 4.21: Combined Value & Momentum Strategy with 10% Volatility




The strategy has a cumulative return of 5,232% from the beginning of 1997 to the end of 2019, with an annualized rate of return of 18.88%. At the same time, the benchmark, which corresponds to investing in an equal-weighted market portfolio, accumulated 762% with an annualized return of 9.83%. The combined value and momentum strategy exhibits its most significant negative return during the Quantmare in 2007. This is because both of the strategies are affected by this event, as also shown in figure 4.20. The strategy has two periods of large drawdowns, each stemming from crashes in one of the factors. Despite minimizing drawdowns, the two factor does not completely offset each other's risk. The first crash happens in 2007 at the beginning of the financial crisis, which was a bad period for the value factor, see figure 4.17. The second large drawdown is in the aftermath of the financial crisis, where momentum crashes as it is evident from figure 4.8. The two periods of large drawdowns, however, are more substantial in the individual strategies, as the opposing factor reduces the magnitude of the drawdown. Moreover, the combined strategy performs excellently in the period where the stock market crashes the most. This is shown in figure 4.22 below, where the drawdown of the combined strategy is plotted against the drawdown of the benchmark. Each of the monthly returns can be found in appendix 27 along with the graphs for shorter time periods.

Figure 4.22: Combined Strategy vs Benchmark Drawdown




The drawdowns are much more extreme for the benchmark strategy in the period from 1997 to 2019. The maximum drawdown of 62.8% for the benchmark comes in between the two major drawdowns of the strategy. This illustrates that the value crash happens at the beginning of the crisis, and the momentum crash in the aftermath. The yearly return for 2007 and 2009 is -15.9% and -18.3% for the strategy, while the benchmark shows returns of -3.3% and 49.9%. However, in the middle of the crisis in 2008, where the benchmark declines by 38.5%, the combined strategy shows great performance with a return of 20.1%. In general, the movements of the combined strategy are not profoundly affected by market movements. The market risk is significant when running a CAPM regression on the returns. However, when controlling for exposure to other factors and running a Carhart four-factor regression on the returns, the market beta is not significantly different from zero, as shown in the table below.

Table 4.12: Carhart Four Factor Regression

| Combined Strategy | Estimate | t value | Pr(> $\|t\|$) |
|---|---|---|---|
| Alpha | 0.0006 | 7.2403 | 5.06E-13 |
| Beta | 0.0095 | 1.3655 | 0.1721 |
| HML | 0.0648 | 4.6466 | 3.45E-06 |
| SMB | -0.1221 | -8.0218 | 1.25E-15 |
| UMD | 0.0786 | 7.6565 | 2.23E-14 |

Table 4.12, shows that the strategy, of course, has a positive exposure to the high-minus-low and up-minus-down factors. As previously mentioned, the composition of these factor portfolios is different from our factor strategies, which is why the coefficients are low. The coefficients for HML and UMD have also been reduced from the individual strategy regressions shown in tables 4.5 and 4.10. Moreover, the significant negative exposure to the size factor from momentum persists in the combined strategy. The combined strategy produces a daily alpha of 0.0006, which is highly significant and corresponds to an annualized abnormal return of 16.32%, which is higher than for any of the individual factor strategies.

### 4.3.3 Performance and Risk Analysis

To further evaluate the performance and risk of the momentum, value, combined, and benchmark strategies, more metrics are introduced and calculated. The performance metrics are described below:

Sortino Ratio:
The Sortino ratio is an extension of the Sharpe ratio, but instead of using the standard deviation of the return to measure performance, the semi-standard deviation is applied. This is also called the downside risk and is measured in relation to the minimum acceptable return, which is often the risk-free rate of return (Bacon, 2010).

$$Sortino\ Ratio = \frac{\overline{(R_p - MAR)}}{\sigma_D} \tag{4.10}$$

where

$$\sigma_D = \sqrt{\sum_{t=1}^{n} \frac{min[(R_p - MAR), 0]^2}{n}} \tag{4.11}$$

with $MAR = Minimal\ Acceptable\ Return$, which we set to the match the investment rate for the liquidity buffer (LIBOR overnight -10bps) which is also used as the risk-free rate in the Sharpe ratio.

Appraisal Ratio:

The appraisal ratio measures the risk-adjusted returns by Jensen's alpha divided by the idiosyncratic risk (Munk, 2018). Here we calculate Jensen's alpha with the rate earned on the liquidity buffer as the risk-free rate.

$$Appraisal\ Ratio = \frac{\alpha}{\sigma_\epsilon} \tag{4.12}$$

where $\sigma_\epsilon$ is derived from the specific risk component in equation 2.10 and alpha is calculated as follow:

$$\alpha = \bar{R}_p - (R_f + \beta_m(\bar{R}_m - R_f))$$

M-squared:

M-squared is the return adjusted for the risk of the market. The M-squared adjusts return, such that the risk for the portfolio and the benchmark is the same. Thus returns of strategies with different levels of risk are comparable (Bacon, 2010).

$$M^2 = (R_p - R_f) * \frac{\sigma_b}{\sigma_p} + r_f \tag{4.13}$$

These performance metrics, along with the annualized returns and Sharpe ratios, are shown in table 4.13 below.

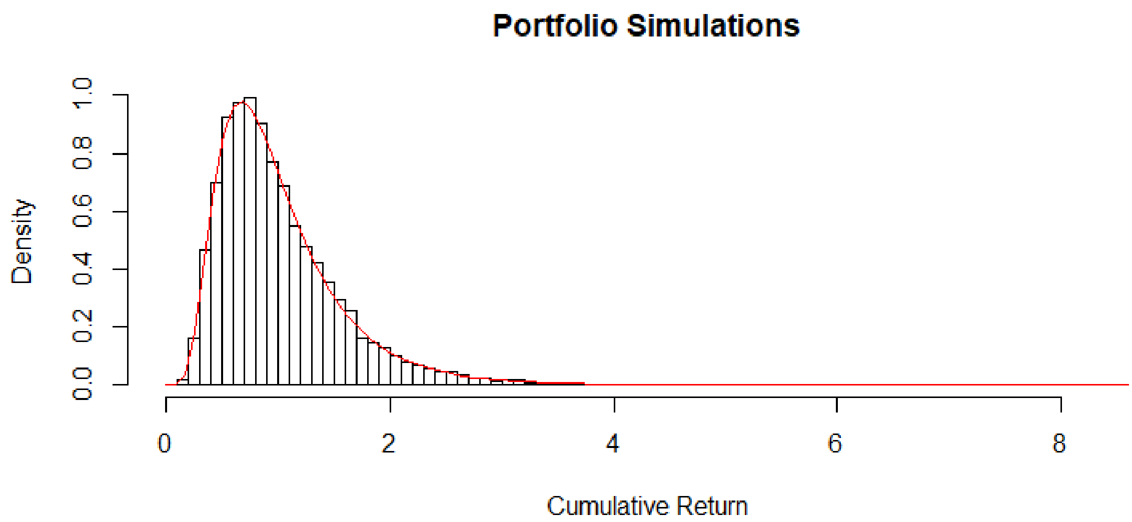
Table 4.13: Return Metrics

| | Momentum | Value | Combined | Benchmark |
|---|---|---|---|---|
| Annualized Return | 0.1027 | 0.1209 | 0.1888 | 0.0983 |
| Annualized Sharpe Ratio | 0.8322 | 1.0215 | 1.6651 | 0.3670 |
| Annualized Sortino Ratio | 1.1884 | 1.6064 | 2.5751 | 0.5207 |
| Appraisal ratio | 0.8488 | 1.0612 | 1.7152 | NA |
| M-squared | 0.2035 | 0.2463 | 0.3917 | 0.0983 |

From table 4.13, it is clear that the combined strategy performs better than any of the individual strategies and the benchmark. The Sharpe ratio of the combined strategy is 1.66 compared to 0.83 and 1.02 for the individual strategies. The outperformance is also present when risk is measured on downside risk and excess return in relation to the benchmark. Moreover, the factor and combined portfolios are better than the benchmark strategy across all comparable metrics. When the returns are adjusted by the benchmark's volatility, the strategies all have a yearly return, which is more than double that of the benchmark. Thus, evidence is given that both value and momentum provide higher excess returns than simply investing in the market, but that this can be improved even further by combining the two factors. The combined strategy ranks highest on all of these return metrics.

To verify that the excess return on the factors strategies are not a result of chance simulations of the cumulative return of 10.000 random long/short portfolios are shown in figure 4.23. These portfolios each month randomly selects and buys 200 stocks and randomly shorts 200 stocks. Trading costs are not deducted from the portfolio returns in the simulations. Hence the cumulative returns are slightly higher than they would be if one traded the random portfolios. Furthermore, the strategies are scaled ex-post each year to match the 10% volatility target of the factor portfolios.

Figure 4.23: Cumulative Return Distribution of Random Portfolios




The bins constitute the empirical distribution, and the red line is a fitted lognormal distribution. The wealth index is set to start at 1 in figure 4.23, and therefore the mean of the final wealth is very close 1 as the portfolios are long/short. It is evident from the figure that obtaining cumulative returns matching the individual and combined factor portfolios by chance is almost impossible. The highest cumulative return out of the 10.000 simulated long/short portfolios is 750%. This is much lower than for the scaled strategies. Here the cumulative returns were equal to 846%, 1,278%, and 5,232% for the momentum, value, and combined strategies. Thus, one should not expect to see long/short portfolios that by pure randomness show performance matching the factor strategies.

The metrics in table 4.13 are based on the evaluation of returns. Below, the focus is put on the riskiness of the strategies. This is done using several risk metrics.

Drawdowns:
The worst drawdown, formulated in equation 4.6, is used. The maximum drawdown is furthermore extended, such that it measures the maximum drawdown over a timeframe of 3-months, i.e., $T$ in equation 4.6 is set to 3 months. As referenced, the maximum drawdown measures the relative difference between peak and trough, but it does not take the amount of time it takes to hit the trough into account. As such, by limiting the timeframe to 3-months, the results for different strategies become more comparable. The average drawdown, formulated in equation 4.14, and the average length of the drawdown, expressed by equation 4.15, are used. The average drawdown measures the average drawdown from the last peak. The average length of the drawdowns measures the time in days it takes for the strategy to recover and reach a new peak (Bacon, 2010).

$$Average\ Drawdown = \frac{1}{n} \times \sum_{i=1}^{n} DD_i \tag{4.14}$$

$$Average\ Drawdown\ Length = \frac{1}{n} \times \sum_{i=1}^{n} Duration_{DD_i} \tag{4.15}$$

Where $DD_i$ is the i-th drawdown in percentage, $n$ is the number of drawdowns, and $Duration_{DD_i}$ is the duration of the i-th drawdown measured in days.

Standard & Downside Deviation:
The standard deviation of the strategies is shown in equation 4.3. However, it can be argued that investors prefer upside risk, and the increase in the standard deviation as caused by higher returns can be categorized as positive volatility. The downside deviation is used as a measure

of negative volatility. The downside deviation, as formulated by Bacon (2010), is shown in equation 4.11.

Value-at-Risk & Expected Shortfall:

Another measure of the downside risk is to use Value at Risk (VaR). VaR measures the expected minimum loss when exceeding different confidence levels. In this paper, a confidence level of 99% is used. The VaR, therefore, represents the minimum loss expected in 1% of the observations. The VaR is not a measure of the worst loss, but it serves as an indicator of what amount the losses exceed in 1% of returns. The Expected Shortfall (ES) measures the expected loss of the average values that are more extreme than those measured by the VaR. The VaR and ES formulas are shown in equation 4.16 and 4.17 respectively. The VaR and Expected Shortfall measures in this paper assume normality in returns to simplify the metrics. Modifications to the VaR and ES estimation exists, which accounts for differing distributions, but they are not utilized in this paper.

$$VaR = \bar{R} - \sqrt{\sigma^2} \cdot z_c \tag{4.16}$$

$$ES = \bar{R} - \sqrt{\sigma^2} \cdot \frac{1}{c}\phi(z_c) \tag{4.17}$$

where $z_c$ is the z-score of the confidence interval in the standard normal distribution, $\phi$ is the Gaussian density function, $\sigma^2$ is the variance of the returns, $\bar{R}$ is the mean of the returns.

Beta:

Finally, the systematic risk component of the strategies is defined by utilizing the previously referenced CAPM-regressions. Here, the excess returns of the benchmark are regressed on the excess returns for each strategy to measure the systematic risk. By construction, the beta of the benchmark is equal to one.

Table 4.14: Risk Metrics

| | Momentum | Value | Combined | Benchmark |
|---|---|---|---|---|
| Worst Drawdown | 0.3809 | 0.3334 | 0.2685 | 0.6283 |
| Worst 3-month Drawdown | 0.1861 | 0.1823 | 0.1338 | 0.5170 |
| Average Drawdown | 0.0256 | 0.0176 | 0.0142 | 0.0285 |
| Average Drawdown Length (Days) | 33 | 23 | 18 | 25 |
| Annual Std Dev | 0.1034 | 0.1018 | 0.1026 | 0.2225 |
| Annual Downside Dev | 0.0724 | 0.0647 | 0.0663 | 0.1568 |
| Daily VaR (99%) | -0.0147 | -0.0144 | -0.0143 | -0.0321 |
| Daily ES (99%) | -0.0170 | -0.0166 | -0.0165 | -0.0369 |
| CAPM Beta | -0.0033 | -0.0258 | -0.0255 | 1 |

From these metrics, it is evident that the combined strategy is less risky than the individual strategies. The worst overall and three-month drawdowns are notably smaller for the combined value, being 0.2685 and 0.1338, respectively. The decrease in drawdowns is further supported by the lower average drawdown and drawdown length. The lower metrics indicate that the combined strategy on average does not crash as hard, and the duration in days of the decreases are reduced when compared to the momentum and value strategy. Since the strategies are volatility scaled to an average long-term target of 10%, the strategies are all close to this level. Hence, the downside deviation for the three strategies is very similar, but momentum is slightly higher than value and combined. When measuring tail risk under the normality assumption using VaR and ES, the combined strategy exhibits the smallest losses at the 99th percentile. In 1% of the observations, the daily loss is more than 1.43% and has an average size of 1.65%. The systematic risk, as measured by the CAPM beta-estimate, is lowest for the volatility scaled, beta neutralized momentum strategy. The systematic risk of the combined strategy is significant but very close to 0, as shown in appendix 29. The low beta coefficient indicates that exposure to the market factor is minimal.

### 4.3.4 Combined Portfolio Summary

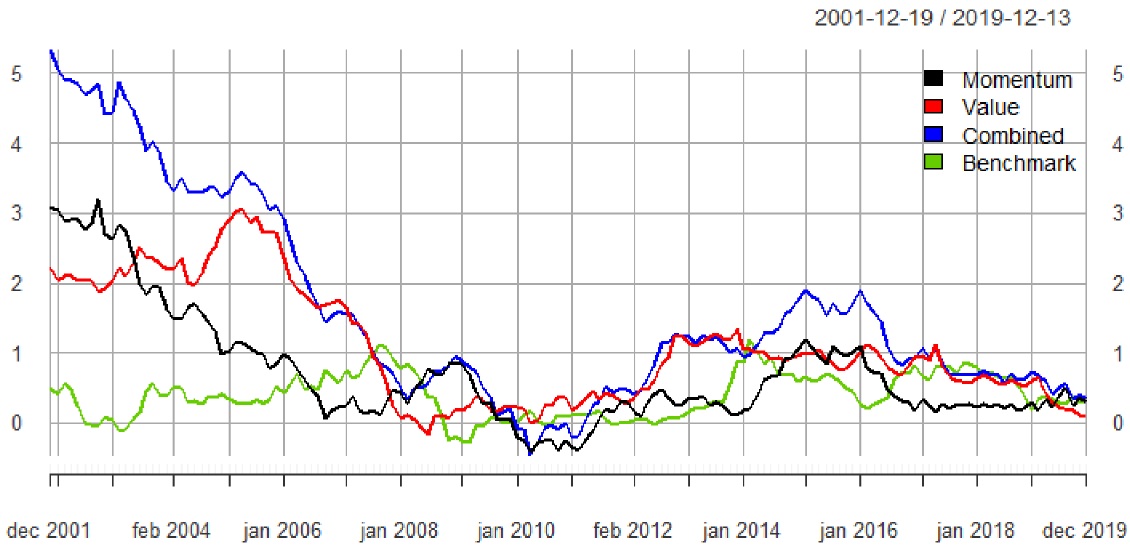
It is shown that the empirical value and momentum portfolios have a negative correlation. Therefore, combining the value and momentum strategy results in a higher risk-adjusted return. The negatively correlated strategies cause an increase in the Sharpe ratio following the decrease in risk. The Carhart four-factor exposure shown in table 4.12 of the 10% volatility scaled combined strategy shows an insignificant exposure to the market factor. As expected, both the HML and UMD factor exposure is significant and positive, whereas the size exposure is negative and significant. The Carhart four-factor model cannot explain the entirety of the strategy's return since significant alpha is observed. The combined strategy has a higher return than both the value strategy and momentum strategy. However, the standard deviation is close to halved compared to the individual strategies. When the performance is analyzed in table 4.13 using the selected metrics, the outperformance of the combined strategy becomes apparent. The combined strategy exhibits outstanding performance compared with the value, momentum, and benchmark strategies. Moreover, none of the random portfolios simulations in figure 4.23 are close to the cumulative return of approximately 5000%. This comparison shows that it is highly improbable that the performance of the combined or individual strategies is due to chance. Furthermore, the risk metrics show that the combined strategy has the lowest risk of all the strategies. The systematic exposure present is significant but very limited.

From the results, it is evident that both value and momentum strategies outperform the benchmark. However, when combining this into a single portfolio, synergy effects are obtained, and the performance is remarkably enhanced.

## 4.4 Performance Decay

In this section, a short discussion on the results of the strategies' performance is provided. As shown, the factors have provided a great source of returns over recent decades. However, the performance is not persistent and stable across the whole period. Therefore it is reasonable that some might question the continued performance of the factors. The analyzed period is very short, and therefore it is not possible to make any reliable conclusions regarding a decay in performance. Nonetheless, it should not be neglected that there is a time variance in the factor performance, and in the analyzed time-period, the factors perform better in the beginning. In figure 4.24, five-year rolling Sharpe ratios of the momentum, value, combined, and benchmark portfolios are illustrated.

Figure 4.24: Five-Year Rolling Sharpe Ratios




The rolling Sharpe ratios for the different strategies are generally higher than the benchmark across time. However, while the Sharpe ratio of the benchmark portfolio appears stationary over time, the Sharpe ratios for the other portfolios do not. The Sharpe ratios are extraordinarily high for the strategies at the beginning of the period. However, they normalize and remain closer to the benchmark Sharpe ratio around and after the financial crisis. Hence, it is reasonable that there is an ongoing debate about whether the value and momentum factors are dead. These discussions have been highly prevalent for the value factor. This makes sense, as it is evident from figure 4.24 that this strategy has the lowest five-year Sharpe ratio at the end of the period. There are several hypotheses as to why this decay is present. A plausible reason is an increase in the importance of intangible assets. Lev and Srivastava (2020) show that since the 1980s, firms have massively increased investments in intangible assets. When the value factor originated, physical assets constituted the major parts of the firms' market value. However, nowadays, much more of the firm's actual value lies in its intangible assets such as RD, IT, brand, etc. Expensing intangibles assets leads to the reported value measures being understated, and the classic value measures become flawed. Hence, this change in the structure of value investing can have caused a decline in returns.

Nevertheless, the period analyzed in this paper is not long enough to conclude that this decay in performance will be persistent. Moreover, the overall Sharpe ratios for the period after the financial crisis are still higher than for the benchmark. It is natural for factors to have fluctuating performance. In a recent paper, Israel, Laursen, and Richardson (2020) argue that a temporal variance in the importance of fundamental information can explain the previous years' downturn in the value factor. They argue that this relevance of fundamental information has been low across recent years, and that is why value has suffered. This reasoning gives a plausible explanation for the variation. Moreover, the argument justifies the considerable temporal variation in factor performance, which is highly evident when a longer look-back history is applied. The declines in Sharpe ratios might be a result of the natural drifts in the factors which tend to show a cyclical pattern (Cazalet & Roncalli, 2014). In appendix 30, five-year rolling Sharpe ratios of the value, momentum, and market factors from Kenneth French's data library are illustrated[1]. The graphs show the Sharpe ratios since 1968 and verify the temporal changes in factor performance. It is evident from these graphs that it is normal for the factor to show periods of declining performance. Moreover, it is shown in appendix 30 that the period shown in figure 4.24 is not abnormal. The decay in performance follows that of the past factor fluctuations, and such performance decays are not atypical in the long-run. Of course, there is no certainty in the world of finance, and it is not given that the recent decrease in the Sharpe ratios will rebound as in the past. However, it is normal that factors show a decline in the premium at times. Therefore, we do not conclude that the factor premiums will continue at a lower level or increase in the future. Although it is safe to say, from the evidence given in the prior sections, that over the whole period analyzed in this paper, both value, momentum, and combined portfolios have provided a great source of returns.

[1]Please note, that these factors are constructed in a bigger trading universe and using pure value and price momentum. They will, therefore, vary from the factor strategies applied in the paper.

# 5. Conclusion

In this section, we conclude on the results and findings of the thesis in relation to the specified problem statement in section 1.1. Moreover, we briefly mention some topics that further research could dig deeper into. This future work could shed light on some interesting aspects of such strategies as those applied in this paper.

## 5.1 Findings

In this paper, we have evaluated the performance of systematic fundamental and momentum driven strategies in the US equity market over the last decades. The results show that classic and simple quantitative momentum strategies have provided a source of positive returns with a low, but highly time-varying beta. However, simple long/short portfolios with classic, idiosyncratic, and price momentum do not provide risk-adjusted returns that are extraordinary compared to long exposures to the market premium. As momentum strategies exhibit time-varying systematic-risk exposure and negatively skewed returns with fat tails, the crash risk is high. The momentum dynamics mimic written call options in periods of financial turmoil. However, the idiosyncratic and alpha momentum adaptions of classic price momentum lower the strategy's drawdowns, albeit large crashes are still present. Further control of the market exposure and application of constant volatility scaling to momentum strategies is shown to enhance performance and reduce the crashes. Risk-adjusted momentum strategies, where beta neutralization and a constant risk targeting are employed, results in a much higher Sharpe ratio than for the unadjusted strategies. Moreover, risk-adjusted momentum delivers returns comparable to the equal-weighted market portfolio but with half the risk. Hence the results show that the performance of practical momentum factor strategies have been excellent in the past decades.

The results show that value strategies also provide an alternative to the market risk premium as a source of returns. The implementation of a pure value strategy produces better risk-adjusted returns than the benchmark portfolio in the backtest. Nonetheless, avoiding value pitfalls by adding quality measures and applying beta-neutralizing techniques improves the strategy's performance compared with the pure value strategy. On the other hand, volatility scaling has a negative impact on the value factor. The returns of value strategies are positively skewed and resemble the behavior of buying call options. As the constant risk-scaling cuts of tail-risk, it does not improve performance. The volatility scaling lowers the risk-adjusted returns despite utilizing a slightly slower speed of adjustment than in the momentum strategy. Even though the 10% risk target induces a minor reduction of performance, the adjusted value strategy results in a better performance than the unadjusted value strategy. Furthermore, the adjusted strategy provides risk-adjusted returns higher than the equal-weighted market portfolio and higher than the momentum strategy. Therefore, it is evident that the systematic fundamental strategies applied in this paper have achieved high risk-adjusted returns and have shown strong performance in the US across the last 23 years.

In addition to the tremendous individual performance of the factor strategies, this paper also provides evidence of the synergy effects that arise when combining the adjusted value and momentum. The negative relationship between the strategies can be used to minimize the drawdowns of each factor. As both factors have high returns but tend to perform well in different periods, a combination of these strategies leads to superior performance. The volatility scaled combined portfolio strategy show returns that are higher than any of the isolated factors. Moreover, the annualized returns for the combined portfolio is more than double the benchmark/market portfolio, but with only half overall volatility.

The overall results of this paper have shown that both individual quantitative fundamental and momentum driven strategies have provided great performance in the US equity market over the past decades. The performance is superior to the market portfolio and provides reliable alternatives to simple market investments. Furthermore, combining value and momentum strategies takes advantage of the high risk-adjusted returns present in both strategies while utilizing the negative correlation to offset risk. Therefore a combined factor portfolio has shown exceptional performance that exceeds the individual factor strategies and the benchmark in past decades.

## 5.2 Future Work

In future research, it could be beneficial to evaluate specific aspects of the quantitative strategies. We have focused on broader perspectives when implementing the trading strategies. However, there are subjects within this type of quantitative trading which could be interesting to examine deeper.

Beta hedging is a very challenging subject within quantitative finance. There does not exist a universal approach, and it is compelling to dive deeper into this. An in-depth analysis of different beta estimation methods might provide better forecasts of the strategies' systematic risk exposure. Furthermore, alternative beta neutralization methods could be studied and compared on their ability to limit systematic risk. Further research could include other methodologies such as beta stratification or a sequential selection of securities with comparable betas.

Another intriguing subject is how to best forecast the volatility of quantitative strategies. An expansion of the volatility estimation could be included in future work. The volatility in this paper is estimated ex-ante by an I-GARCH model with varying alpha-parameters. The volatility estimates are impactful since they decide the level of leverage. It could be beneficial to investigate the impact of different estimation methods and how these influence the volatility and leverage.

To create a combined portfolio of factor strategies, we use the combined approach. This is done to explicate the individual return contributions of the different factors. However, the impact of this choice could be studied by implementing other methods. A very different portfolio would be constructed by combining different factors using an intersectional or sequential model. Such portfolios might not have the same transparency in performance, but on the other hand, they do not run the risk of trading opposite positions. This can be beneficial when the negative correlation among factors runs rampant. Therefore it is not given that the combined approach is optimal. Other methods might be able to integrate the different factors in a more favorable way.

# 6. References


AQR Capital Management. (2017). *Systematic versus discretionary.*

Asness, C. S. (1997). The interaction of value and momentum strategies. *Financial Analysts Journal*, *53*(2), 29–36. doi: 10.2469/faj.v53.n2.2069

Asness, C. S., Frazzini, A., Israel, R., & Moskowitz, T. J. (2015). Fact, fiction, and value investing. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2595747

Asness, C. S., Frazzini, A., & Pedersen, L. H. (2013). Quality minus junk. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2312432

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance*, *68*(3), 929–985. doi: 10.1111/jofi.12021

Bacon, C. R. (2010). *Practical portfolio performance measurement and attribution.* Wiley.

Barroso, P., & Maio, P. F. (2016). Managing the risk of the betting-against-beta anomaly: Does it pay to bet against beta? *SSRN Electronic Journal*. doi: 10.2139/ssrn.2876450

Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, *116*(1), 111–120. doi: 10.1016/j.jfineco.2014.11.010

Basu, D., & Stremme, A. (2007). Capm and time-varying beta: The cross-section of expected returns. *SSRN Electronic Journal*. doi: 10.2139/ssrn.972255

Berkshire Hathaway. (1989). *Berkshire hathaway - 1989 letter to shareholders.*

Blitz, D., Hanauer, M. X., & Vidojevic, M. (2017). The idiosyncratic momentum anomaly. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2947044

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82. doi: 10.1111/j.1540-6261.1997.tb03808.x

Cazalet, Z., & Roncalli, T. (2014). Facts and fantasies about factor investing. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2524547

Chibane, M., & Ouzan, S. (2019). Value bubbles. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3412459

Christensen, J. I. (2015). *Value and momentum – a winning combination.*

CUSIP. (n.d.). *Structure of identifiers.* Retrieved from `https://www.cusip.com/identifiers.html`

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance*, *53*(6), 1839–1885. doi: 10.1111/0022-1082.00077

Daniel, K. D., & Moskowitz, T. J. (2014). Momentum crashes. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2486272

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics*, *7*(2), 197–226. doi: 10.1016/0304-405x(79)90013-8

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47*(2), 427–465. doi: 10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56. doi: 10.1016/0304-405x(93)90023-5

Fama, E. F., & French, K. R. (1997). Value versus growth: The international evidence. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2358

Frazzini, A. (2006). The disposition effect and underreaction to news. *The Journal of Finance*, *61*(4), 2017–2046. doi: 10.1111/j.1540-6261.2006.00896.x

Frazzini, A., & Pedersen, L. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1–25. doi: 10.1016/j.jfineco.2013.10.005

Fusai, G., & Roncoroni, A. (2011). *Implementing models in quantitative finance: methods and cases.* Springer.

Greenwich Associates. (n.d.). *Institutional equity trade commission rates hold steady amid volatility and market structure reform.* Retrieved from `https://www.greenwich.com/press-release/institutional-equity-trade-commission-rates-hold-steady-amid-volatility-and-market?fbclid=IwAR37xyXRdvAJrkzhLj9zmK91_JzHY_VgC0cqw1kE3-A-Lc6Z5XMwoicSSe8`

Haghani, V., & Dewey, R. (2016). A case study for using value and momentum at the asset class level. *The Journal of Portfolio Management*, *42*(3), 101–113. doi: 10.3905/jpm.2016.42.3.101

Hanauer, M. X., & Windmueller, S. (2019). Enhanced momentum strategies. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3437919

Harvey, C. R., Hoyle, E., Korgaonkar, R., Rattray, S., Sargaison, M., & Hemert, O. V. (2018). The impact of volatility targeting. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3175538

Hlavaty, L.-B. C. K., Smith. (2016). Value everywhere. *J.P. Morgan*.

Hollstein, F., Prokopczuk, M., & Simen, C. W. (2019). Estimating beta: Forecast adjustments and the impact of stock characteristics for a broad cross-section. *Journal of Financial Markets*, *44*, 91–118. doi: 10.1016/j.finmar.2019.03.001

Huhn, H. L., & Scholz, H. (2013). Alpha momentum and price momentum. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2287848

Hull, J. (2018). *Options, futures, and other derivatives, ninth edition, global edition.* Pearson Education Limited.

Israel, R., Laursen, K., & Richardson, S. A. (2020). Is (systematic) value investing dead? *SSRN Electronic Journal*. doi: 10.2139/ssrn.3554267

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of Finance*, *45*(3), 881–898. doi: 10.1111/j.1540-6261.1990.tb05110.x

Jegadeesh, N., & Titman, S. (1993, Mar). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, *48*, 65–91. doi: 10.2307/2328882

Johnson, T. C. (2002). Rational momentum effects. *The Journal of Finance*, *57*(2), 585–608. doi: 10.1111/1540-6261.00435

J.P. Morgan. (1996). *Riskmetrics—technical document.* Retrieved from `https://www.msci.com/documents/10199/5915b101-4206-4ba0-aee2-3449d5c7e95a`

Kahneman, D., & Tversky, A. (1977, Jan). Prospect theory. an analysis of decision making under risk.
doi: 10.21236/ada045771

Kapadia, N. (2011). Tracking down distress risk. *Journal of Financial Economics*, *102*(1), 167–182. doi: 10.1016/j.jfineco.2011.05.004

Khandani, A., & Lo, A. (2008). What happened to the quants in august 2007?: Evidence from factors and transactions data.
doi: 10.3386/w14465

Khandani, A. E., & Lo, A. W. (2007). What happened to the quants in august 2007? *SSRN Electronic Journal*. doi: 10.2139/ssrn.1015987

Kok, U.-W., Ribando, J., & Sloan, R. (2017). Facts about formulaic value investing. *Financial Analysts Journal*, *73*(2), 81–99. doi: 10.2469/faj.v73.n2.2

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, *49*(5), 1541–1578. doi: 10.1111/j.1540-6261.1994.tb04772.x

Lev, B. I., & Srivastava, A. (2020). Explaining the recent failure of value investing. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3442539

Moreira, A., & Muir, T. (2017). Volatility-managed portfolios. *The Journal of Finance*, *72*(4), 1611–1644. doi: 10.1111/jofi.12513

Moskowitz, T. (2010). Explanations for the momentum premium. *AQR Capital Management*.

MSCI. (n.d.). *Sp dow jones indices and msci announce further revisions to the global industry classification standard (gics®) structure in 2016.*

Munk, C. (2018). *Financial markets and investments.*

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance*, *53*(5), 1775–1798. doi: 10.1111/0022-1082.00072

Pazaj, E. (2019). The value-momentum correlation: An investment explanation. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3476844

Pedersen, L. H. (2019). *Efficiently inefficient: how smart money invests and market prices are determined*. Princeton University Press.

Perchet, R., Carvalho, R. L. D., Heckel, T., & Moulin, P. (2015). Predicting the success of volatility targeting strategies: Application to equities and other asset classes. *The Journal of Alternative Investments*, *18*(3), 21–38. doi: 10.3905/jai.2016.18.3.021

Piotroski, J. D. (2000). Value investing: The use of historical financial statement information to separate winners from losers. *Journal of Accounting Research*, *38*, 1. doi: 10.2307/2672906

Piotroski, J. D., & So, E. C. (2012). Identifying expectation errors in value/glamour strategies: A fundamental analysis approach. *Review of Financial Studies*, *25*(9), 2841–2875. doi: 10.1093/rfs/hhs061

Rabener, N. (2017a, Jul). *Factors volatility-based risk management.* Retrieved from https://www.factorresearch.com/research-factors-and-volatility-based-risk-management

Rabener, N. (2017b, Jun). *Market factor volatility.* Retrieved from https://www.factorresearch.com/research-market-factor-volatility

Rabener, N. (2018a, Jan). *Multi-factor models 101 - top-down vs bottom-up.* Retrieved from https://www.factorresearch.com/wp-content/uploads/FactorResearch_Multi-Factor_Models_2018_01.pdf

Rabener, N. (2018b, Feb). *Research: Value factor - intra vs cross-sector.* Retrieved from https://www.factorresearch.com/research-value-factor-intra-vs-cross-sector

Russell, F. (n.d.). *Index factsheet.* Retrieved from https://research.ftserussell.com/Analytics/FactSheets/temp/2da396f2-710a-42a4-9bfe-afb5f76552ce.pdf

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics*, *80*(2), 309–349. doi: 10.1016/j.jfineco.2005.04.005

Scholes, M., & Williams, J. (1977). Estimating betas from nonsynchronous data. *Journal of Financial Economics*, *5*(3), 309–327. doi: 10.1016/0304-405x(77)90041-1

Shaikh, V., Chaudhry, K., Hanif, A., & Khan, A. (2015). Beta: An alternative outcome. *J.P. Morgan*.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, *40*(3), 777–790. doi: 10.1111/j.1540-6261.1985.tb05002.x

Turner, D. (2017, Sep). *Hedge fund administrators do more for smaller fees.* Institutional Investor. Retrieved from `https://www.institutionalinvestor.com/article/b14zbcyrtg5kr0/hedge-fund-administrators-do-more-for-smaller-fees`

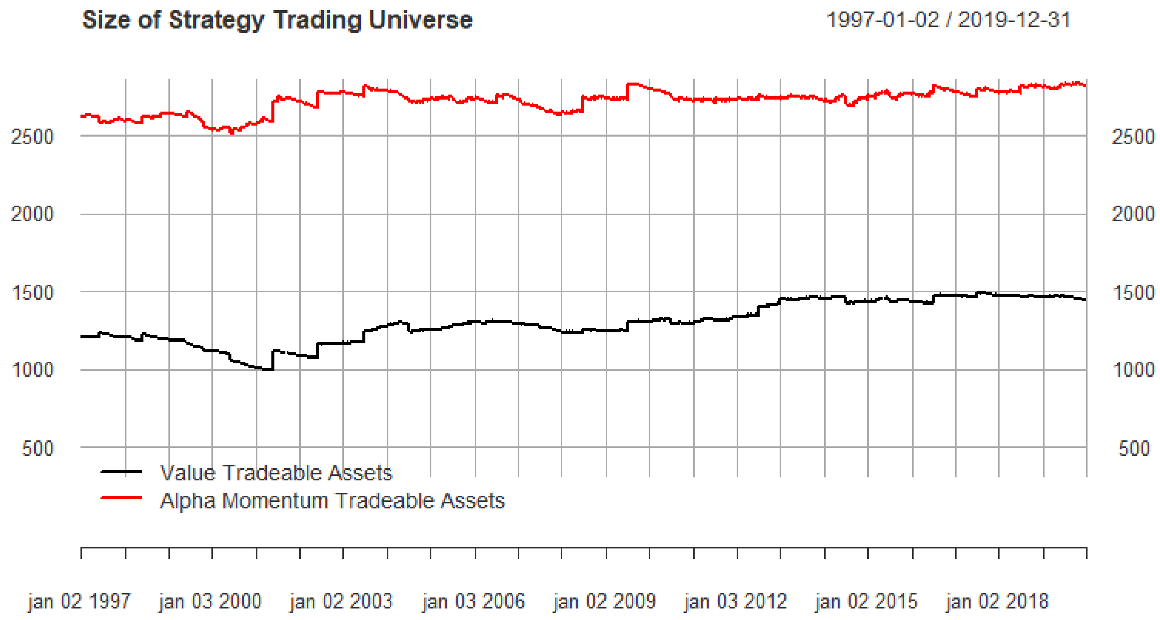
Vasicek, O. A. (1973). A note on using cross-sectional information in bayesian estimation of security betas. *The Journal of Finance*, *28*(5), 1233–1239. doi: 10.1111/j.1540-6261.1973.tb01452.x

Zhang, H. B. (2004). Dynamic beta, time-varying risk premium, and momentum.

Zhang, W., & Skiena, S. (2010, 01). Trading strategies to exploit blog and news sentiment..

# Appendix A. Figures and Tables

## A.1 Number of Tradeable Assets

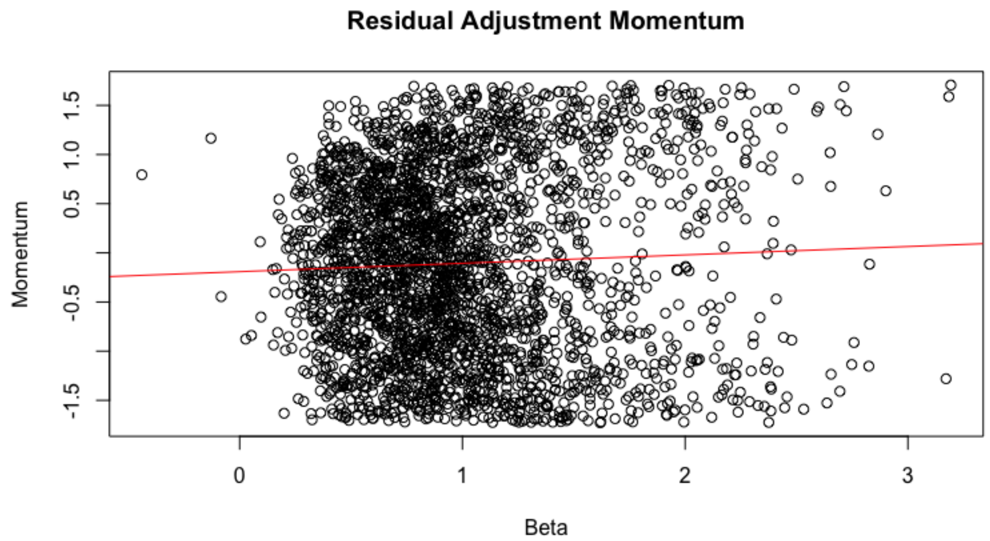


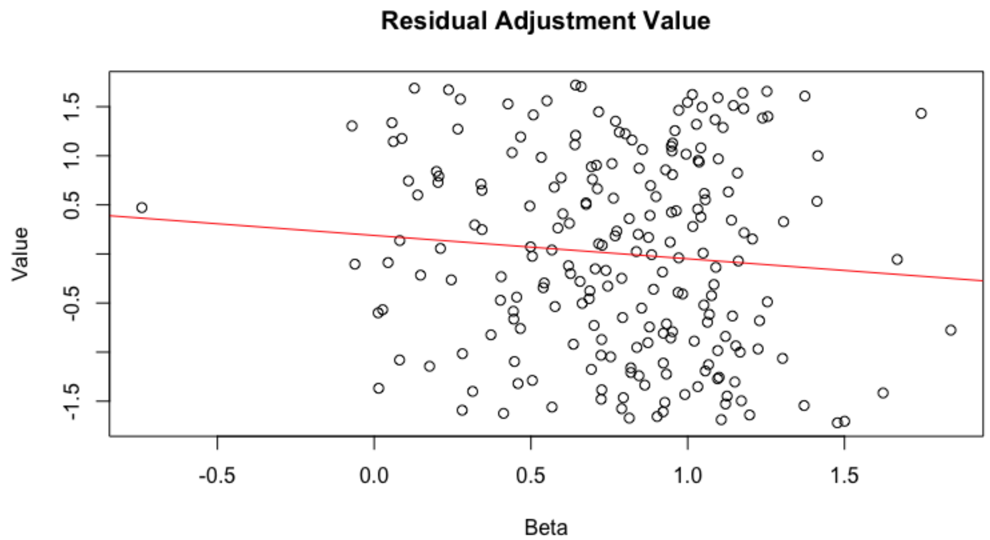
## A.2 Benchmark Returns

| Return in % | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Full Year |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1997 | 3.88 | -1.78 | -5.19 | -0.12 | 11.60 | 6.02 | 5.69 | 1.55 | 6.97 | -4.11 | 0.17 | 1.07 | 27.41 |
| 1998 | -0.72 | 7.96 | 4.10 | 0.93 | -5.01 | 0.61 | -6.60 | -19.20 | 7.22 | 6.07 | 5.86 | 4.85 | 2.54 |
| 1999 | 0.55 | -6.37 | 0.98 | 9.60 | 2.69 | 6.44 | -2.39 | -3.91 | -0.94 | 1.09 | 5.30 | 6.80 | 20.28 |
| 2000 | -2.87 | 5.45 | 4.43 | -3.76 | -3.27 | 10.77 | -2.06 | 7.06 | -4.05 | -4.67 | -11.92 | 5.22 | -1.96 |
| 2001 | 15.84 | -9.71 | -7.98 | 10.27 | 3.35 | 3.82 | -4.37 | -4.41 | -14.69 | 8.12 | 10.15 | 6.53 | 12.68 |
| 2002 | -1.79 | -4.17 | 8.53 | -1.42 | -4.78 | -4.78 | -13.22 | -0.02 | -8.99 | 5.31 | 12.28 | -5.60 | -19.53 |
| 2003 | -2.81 | -3.45 | 0.97 | 10.64 | 12.28 | 3.13 | 6.07 | 4.30 | -0.88 | 8.12 | 3.54 | 3.03 | 53.51 |
| 2004 | 4.08 | 1.29 | 0.24 | -4.18 | 1.02 | 3.72 | -6.47 | -0.43 | 4.32 | 2.30 | 8.17 | 3.96 | 18.59 |
| 2005 | -4.02 | 1.22 | -2.57 | -5.39 | 5.96 | 3.65 | 6.15 | -1.74 | 0.32 | -2.62 | 4.61 | 0.22 | 5.07 |
| 2006 | 7.22 | 0.19 | 3.67 | 0.18 | -4.59 | 0.22 | -2.97 | 3.03 | 1.29 | 5.62 | 2.83 | 0.85 | 18.32 |
| 2007 | 1.67 | -0.56 | 0.85 | 2.18 | 3.67 | -1.31 | -6.30 | 1.51 | 1.72 | 1.77 | -7.40 | -0.54 | -3.32 |
| 2008 | -5.70 | -3.93 | -0.35 | 3.93 | 3.59 | -10.71 | 3.84 | 3.81 | -8.49 | -22.38 | -13.18 | 6.59 | -38.51 |
| 2009 | -9.91 | -12.83 | 12.89 | 23.76 | 6.84 | 1.82 | 10.20 | 4.00 | 6.07 | -6.45 | 2.82 | 7.36 | 49.86 |
| 2010 | -2.99 | 4.40 | 8.13 | 5.77 | -7.90 | -7.35 | 6.79 | -7.41 | 12.40 | 4.08 | 2.90 | 8.54 | 27.70 |
| 2011 | 0.05 | 4.68 | 2.10 | 2.45 | -1.71 | -2.36 | -3.59 | -9.10 | -10.93 | 14.99 | -1.13 | 0.71 | -6.04 |
| 2012 | 8.10 | 3.00 | 2.69 | -1.76 | -7.30 | 5.04 | -1.42 | 3.05 | 3.70 | -2.16 | 0.78 | 3.32 | 17.39 |
| 2013 | 6.37 | 0.92 | 4.67 | 0.03 | 4.16 | -0.05 | 6.90 | -3.22 | 5.95 | 2.60 | 4.04 | 2.51 | 40.37 |
| 2014 | -2.24 | 4.69 | -0.19 | -3.37 | 0.69 | 5.24 | -5.31 | 4.55 | -5.30 | 5.30 | -0.03 | 2.64 | 5.96 |
| 2015 | -4.03 | 6.44 | 0.83 | -1.03 | 1.24 | 0.18 | -1.62 | -5.62 | -5.51 | 6.36 | 2.37 | -4.47 | -5.66 |
| 2016 | -9.41 | 0.30 | 9.23 | 2.98 | 1.21 | -0.28 | 5.42 | 1.72 | 1.96 | -4.73 | 10.10 | 2.64 | 21.42 |
| 2017 | 0.36 | 1.86 | 0.47 | 0.72 | -1.99 | 4.09 | 0.52 | -1.10 | 6.23 | 0.23 | 3.25 | 0.31 | 15.69 |
| 2018 | 2.43 | -4.23 | 1.28 | 1.02 | 5.10 | 1.16 | 1.28 | 3.63 | -1.92 | -9.99 | 1.17 | -11.95 | -11.93 |
| 2019 | 11.27 | 5.19 | -1.80 | 3.08 | -8.31 | 6.61 | -0.39 | -5.16 | 3.15 | 1.39 | 4.68 | 4.49 | 25.18 |

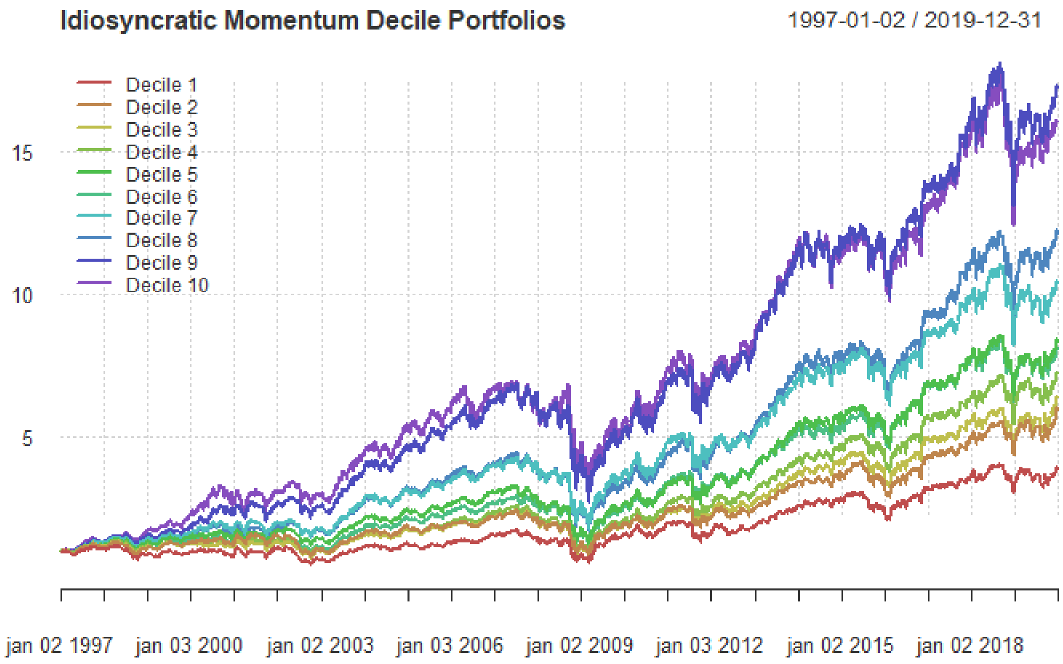
## A.3 Linearity Between the Beta and Scores

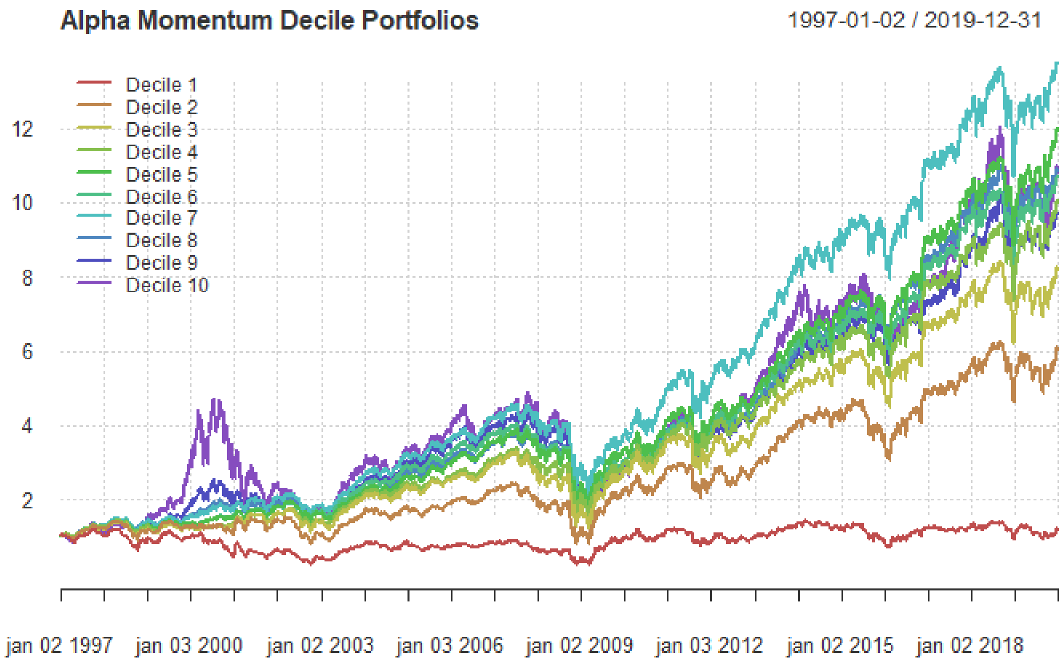
In the graphs below, the residual adjusted scores are defined as the distance between the individual observations and the fitted red line. Since value is beta neutralized on a sector level, the number of observations , the number of observations per sector is smaller than for momentum.



## A.4 Idiosyncratic and Alpha Decile Portfolios



## A.5 Momentum Deciles

Price Momentum Deciles

| | Decile 1 | Decile 2 | Decile 3 | Decile 4 | Decile 5 | Decile 6 | Decile 7 | Decile 8 | Decile 9 | Decile 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Ann. Return | -0.0052 | 0.0655 | 0.0927 | 0.1009 | 0.1082 | 0.1177 | 0.1220 | 0.1167 | 0.1191 | 0.1154 |
| Ann. Std Dev | 0.3335 | 0.2690 | 0.2364 | 0.2161 | 0.2042 | 0.1963 | 0.1926 | 0.1956 | 0.2129 | 0.2682 |
| Ann. Sharpe Ratio | -0.0606 | 0.1836 | 0.3224 | 0.3897 | 0.4480 | 0.5133 | 0.5453 | 0.5104 | 0.4800 | 0.3674 |

Idiosyncratic Momentum Deciles

| | Decile 1 | Decile 2 | Decile 3 | Decile 4 | Decile 5 | Decile 6 | Decile 7 | Decile 8 | Decile 9 | Decile 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Ann. Return | 0.0615 | 0.0814 | 0.0841 | 0.0899 | 0.0970 | 0.0958 | 0.1075 | 0.1151 | 0.1321 | 0.1284 |
| Ann. Std Dev | 0.2459 | 0.2309 | 0.2268 | 0.2218 | 0.2203 | 0.2193 | 0.2196 | 0.2188 | 0.2208 | 0.2297 |
| Ann. Sharpe Ratio | 0.1847 | 0.2816 | 0.2984 | 0.3309 | 0.3650 | 0.3611 | 0.4131 | 0.4486 | 0.5205 | 0.4845 |

Alpha Momentum Deciles

| | Decile 1 | Decile 2 | Decile 3 | Decile 4 | Decile 5 | Decile 6 | Decile 7 | Decile 8 | Decile 9 | Decile 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Ann. Return | 0.0088 | 0.0817 | 0.0959 | 0.1056 | 0.1142 | 0.1087 | 0.1210 | 0.1096 | 0.1040 | 0.1094 |
| Ann. Std Dev | 0.3018 | 0.2417 | 0.2177 | 0.2038 | 0.1981 | 0.1941 | 0.1988 | 0.2090 | 0.2309 | 0.2968 |
| Ann. Sharpe Ratio | -0.0216 | 0.2703 | 0.3646 | 0.4360 | 0.4916 | 0.4736 | 0.5231 | 0.4440 | 0.3782 | 0.3119 |

## A.6 Initial Long/Short Momentum Statistics

Momentum Long/Short Return Distribution Characteristics

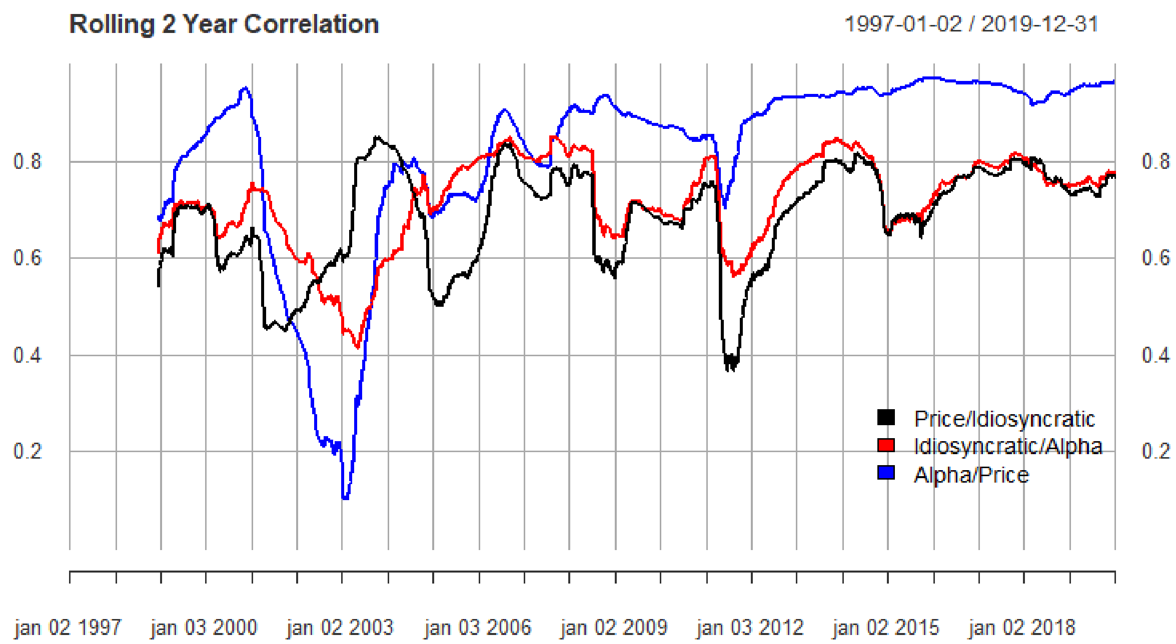
| | Price Momentum Long/Short | Idiosyncratic Momentum Long/Short | Alpha Momentum Long/Short |
|---|---|---|---|
| Daily Std Dev | 0.0072 | 0.0032 | 0.0054 |
| Skewness | -0.6982 | -0.3314 | -0.4571 |
| Excess kurtosis | 6.5875 | 3.9834 | 5.5173 |

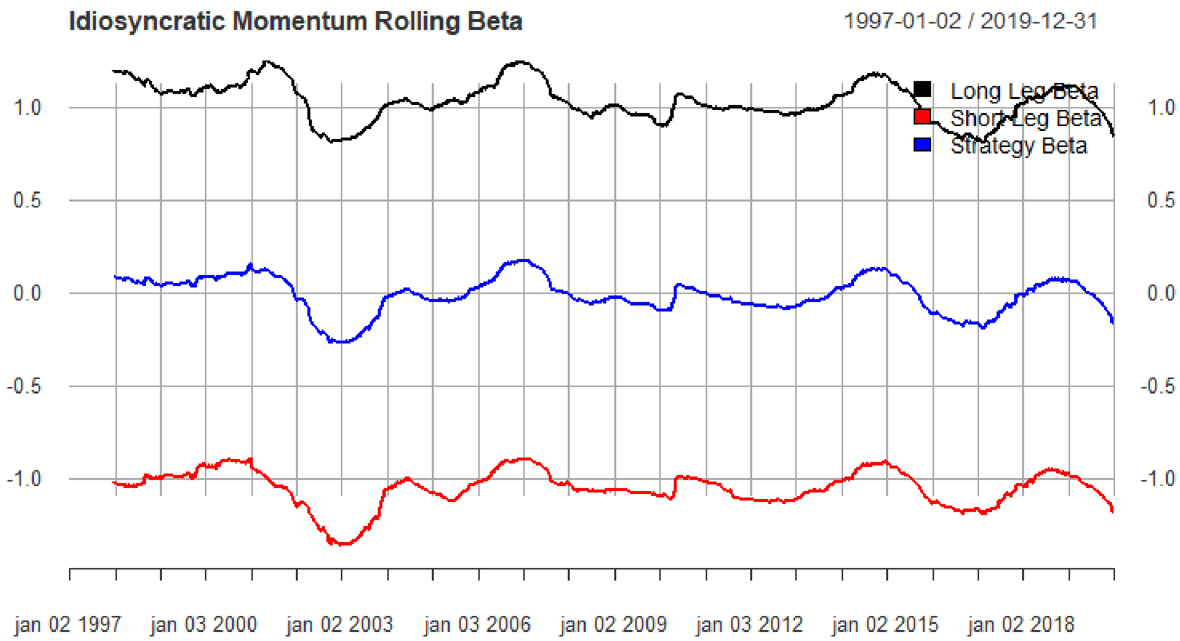
Performance until 2010

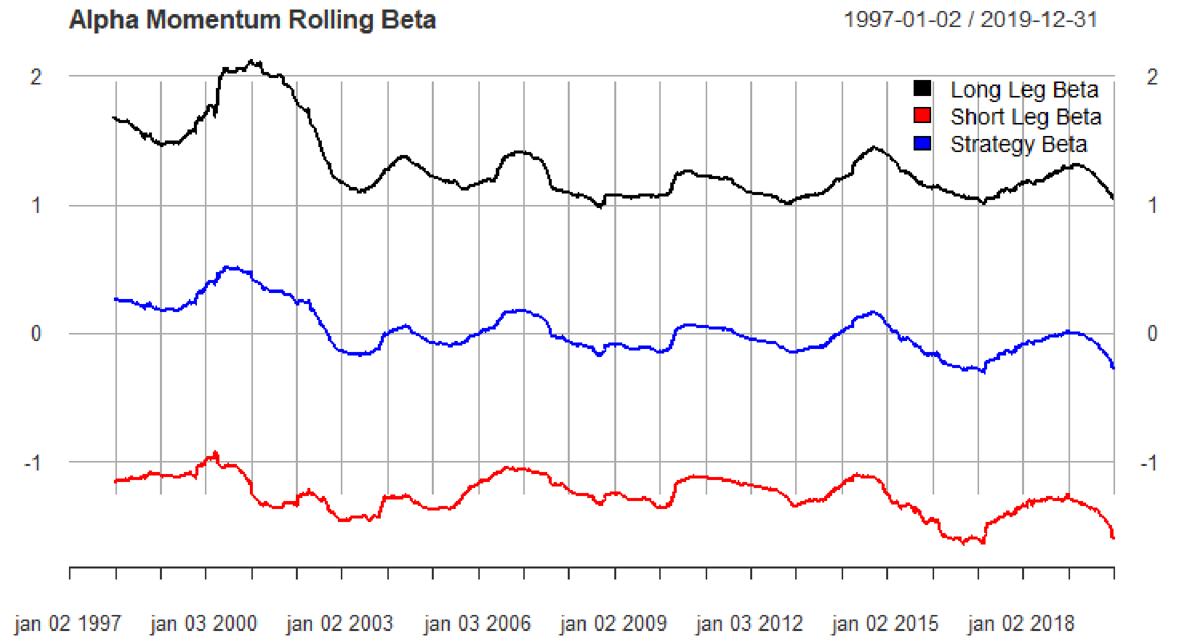
| 1997-2010 | Price Momentum Long/Short | Idiosyncratic Momentum Long/Short | Alpha Momentum Long/Short |
|---|---|---|---|
| Annualized Return | 0.0469 | 0.0512 | 0.0498 |
| Annualized Std Dev | 0.1290 | 0.0550 | 0.0918 |
| Annualized Sharpe | 0.2411 | 0.6413 | 0.3689 |
| Worst Drawdown | 0.5542 | 0.2400 | 0.4255 |

Correlation Matrix

| | Price Momentum | Idiosyncratic Momentum | Alpha Momentum |
|---|---|---|---|
| Price Momentum | 1.0000 | 0.6580 | 0.7488 |
| Idiosyncratic Momentum | 0.6580 | 1.0000 | 0.6727 |
| Alpha Momentum | 0.7488 | 0.6727 | 1.0000 |




Idiosyncratic Momentum Rolling Beta
1997-01-02 / 2019-12-31
Long Leg Beta
Short Leg Beta
Strategy Beta
1.0
0.5
0.0
-0.5
-1.0
jan 02 1997
jan 03 2000
jan 02 2003
jan 03 2006
jan 02 2009
jan 03 2012
jan 02 2015
jan 02 2018


Alpha Momentum Rolling Beta
1997-01-02 / 2019-12-31
Long Leg Beta
Short Leg Beta
Strategy Beta
2
1
0
-1
jan 02 1997
jan 03 2000
jan 02 2003
jan 03 2006
jan 02 2009
jan 03 2012
jan 02 2015
jan 02 2018

## A.7 Standard Deviation of Rolling Betas

| Standard Deviation | Price Beta | Idiosyncratic Beta | Alpha Beta |
|---|---|---|---|
| Without Neutralisation | 0.2457 | 0.0968 | 0.1781 |
| With Neutralisation | 0.0535 | 0.0223 | 0.0469 |

## A.8 CAPM Regressions Momentum

Non-Neutralised Strategies

| Price Momentum | Estimate | t value | Pr(> $\|t\|$) |
|---|---|---|---|
| Alpha | 1.82E-04 | 2.0030 | 4.52E-02 |
| Momentum | -1.58E-01 | -24.3974 | 3.21E-125 |

| Idiosyncratic Momentum | Estimate | t value | Pr(> $\|t\|$) |
|---|---|---|---|
| Alpha | 5.06E-05 | 1.2195 | 2.23E-01 |
| Beta | -3.76E-02 | -12.7044 | 1.71E-36 |

| Alpha Momentum | Estimate | t value | Pr(> $\|t\|$) |
|---|---|---|---|
| Alpha | 1.15E-04 | 1.6275 | 1.04E-01 |
| Beta | -2.10E-02 | -4.1761 | 3.01E-05 |

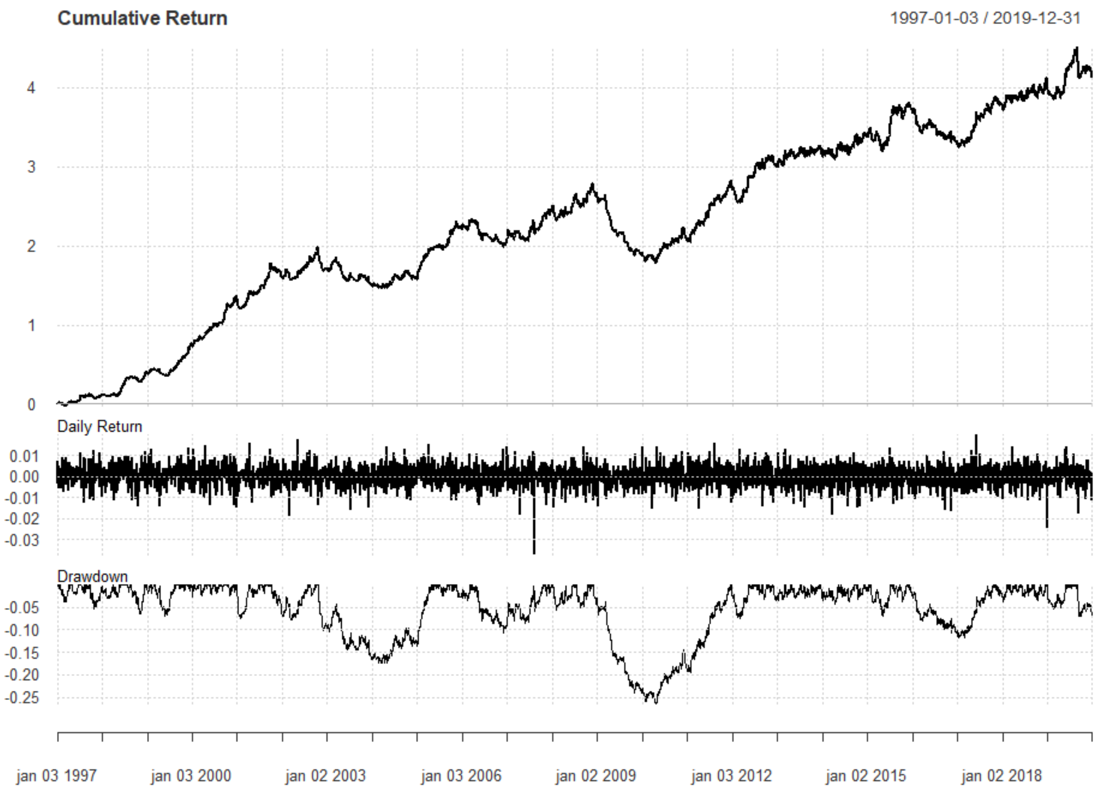
Beta Neutralised Strategies

| Price Momentum | Estimate | t value | Pr(> $\|t\|$) |
|---|---|---|---|
| Alpha | 9.23E-05 | 1.5611 | 0.1186 |
| Beta | -1.30E-02 | -3.0851 | 0.0020 |

| Idiosyncratic Momentum | Estimate | t value | Pr(> $\|t\|$) |
|---|---|---|---|
| Alpha | 3.34E-05 | 0.9977 | 0.3185 |
| Beta | 6.91E-03 | 2.8990 | 0.0038 |

| Alpha Momentum | Estimate | t value | Pr(> $\|t\|$) |
|---|---|---|---|
| Alpha | 1.21E-04 | 2.2167 | 0.0267 |
| Beta | -1.42E-02 | -3.6557 | 0.0003 |

## A.9 Momentum Scaled with 6.6% Volatility Target

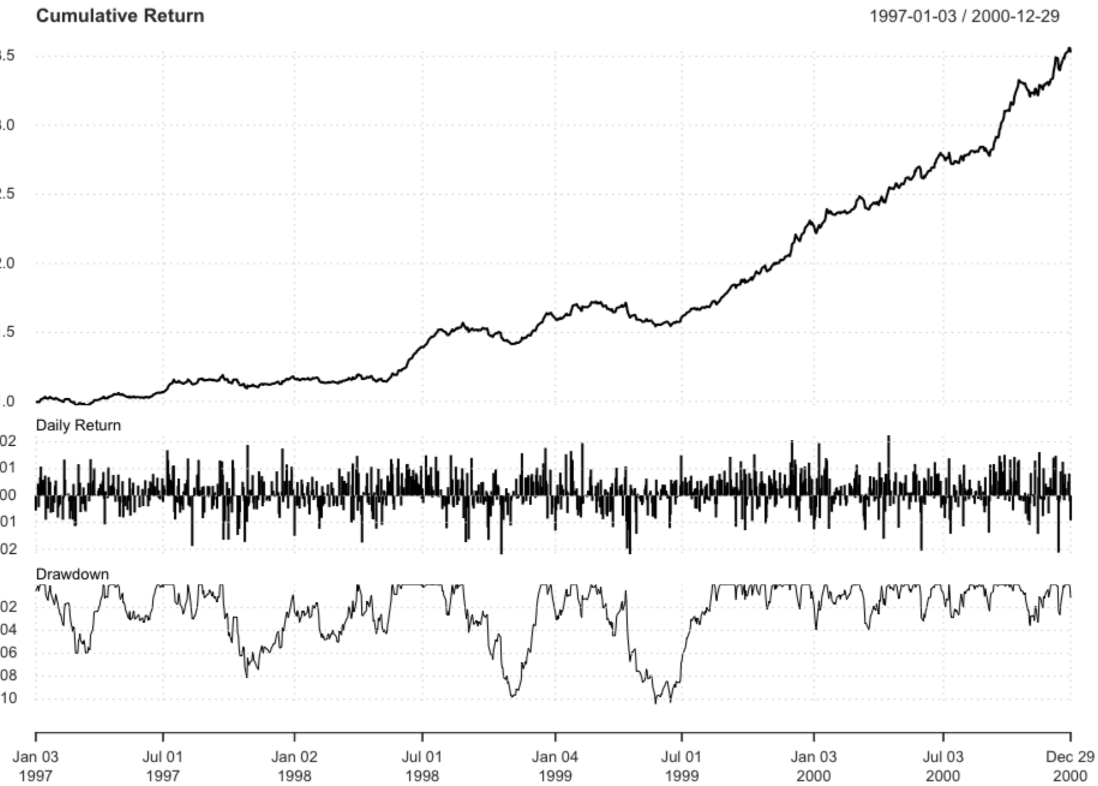



| | Unscaled Alpha Momentum | Scaled Alpha Momentum | Benchmark |
|---|---|---|---|
| Annualized Return | 0.0565 | 0.0736 | 0.1091 |
| Annualized Std Dev | 0.0661 | 0.0683 | 0.2153 |
| Annualized Sharpe | 0.6128 | 0.8409 | 0.4289 |
| Worst Drawdown | 0.3482 | 0.2648 | 0.6283 |

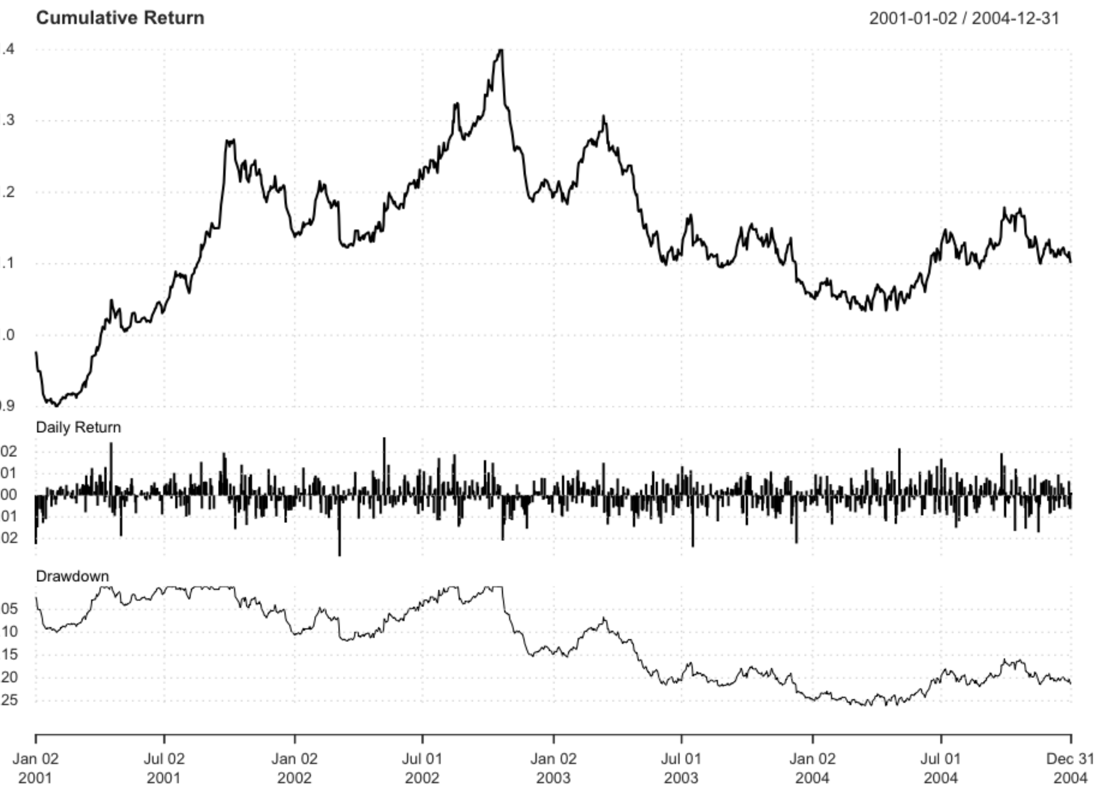
## A.10 Scaled Momentum Strategy Returns

| Return in % | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Full Year |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1997 | 2.56 | -5.17 | 3.88 | 4.84 | -2.90 | 3.95 | 5.89 | 1.86 | 0.45 | -4.07 | 0.93 | 5.39 | 18.19 |
| 1998 | -1.20 | -2.28 | 4.54 | -2.66 | 5.66 | 13.53 | 8.26 | 1.48 | -0.06 | -6.07 | 2.88 | 9.82 | 37.30 |
| 1999 | 4.52 | 1.20 | -2.42 | -4.82 | -2.28 | 3.10 | 4.80 | 5.63 | 5.06 | 3.96 | 5.69 | 11.87 | 41.50 |
| 2000 | 2.43 | 2.45 | 1.46 | 5.49 | 4.49 | 3.45 | -1.52 | 3.25 | 9.47 | 4.85 | 1.72 | 6.59 | 53.62 |
| 2001 | -10.07 | 1.50 | 7.22 | 5.98 | -1.38 | 0.80 | 5.12 | 5.65 | 11.12 | -3.92 | -1.41 | -5.15 | 14.33 |
| 2002 | 4.00 | -0.46 | -3.16 | 1.04 | 2.22 | 3.67 | 3.43 | 1.01 | 4.09 | -1.53 | -9.33 | 0.07 | 4.31 |
| 2003 | 1.70 | 4.80 | -1.53 | -5.15 | -5.53 | -0.59 | 1.42 | -2.97 | 3.53 | -1.07 | 0.23 | -6.12 | -11.34 |
| 2004 | -0.01 | -0.36 | 1.24 | -2.89 | 3.82 | 3.05 | 1.55 | -1.39 | 5.29 | -2.50 | -0.46 | -2.65 | 4.40 |
| 2005 | 8.88 | 7.24 | 1.70 | 3.46 | 0.94 | 0.52 | -0.29 | 1.46 | 6.22 | 2.75 | 1.02 | -1.02 | 37.61 |
| 2006 | 1.16 | 1.38 | 1.40 | -2.37 | -4.96 | -0.58 | -0.42 | -3.26 | 1.48 | -1.63 | -3.44 | 2.54 | -8.67 |
| 2007 | 4.78 | -2.89 | 4.32 | -4.37 | -0.26 | 2.32 | 7.44 | -3.31 | 3.02 | 4.61 | 2.23 | 1.46 | 20.28 |
| 2008 | -5.73 | 1.95 | 0.27 | 0.72 | 0.69 | 8.11 | -1.45 | -2.16 | 3.69 | 2.89 | 2.80 | -3.94 | 7.33 |
| 2009 | -2.35 | -1.20 | -5.56 | -8.49 | -2.06 | -2.03 | 0.53 | -5.92 | -4.31 | -3.86 | 2.45 | -2.94 | -30.78 |
| 2010 | -4.08 | 3.30 | -0.71 | -1.54 | 5.41 | 5.16 | -1.33 | 3.13 | -0.57 | 2.27 | 5.43 | -6.81 | 9.15 |
| 2011 | 2.75 | 2.15 | 5.87 | -0.37 | 2.19 | 5.60 | 2.38 | 2.96 | -1.72 | 3.86 | 3.74 | 0.56 | 34.11 |
| 2012 | -4.31 | -3.66 | 3.14 | 2.74 | 6.81 | 1.59 | 4.23 | 1.28 | -0.55 | 2.80 | -0.60 | -2.79 | 10.54 |
| 2013 | 0.70 | 1.63 | 1.72 | 1.06 | -2.04 | 0.75 | 2.18 | -1.41 | 1.43 | -0.43 | 0.28 | -2.90 | 2.88 |
| 2014 | 2.29 | 0.19 | -2.21 | 0.02 | 3.14 | -0.95 | -2.49 | 3.55 | 5.08 | -1.73 | 1.14 | 0.02 | 8.00 |
| 2015 | 2.51 | -4.37 | 2.52 | -7.24 | 4.16 | 4.38 | 8.61 | -1.65 | 2.94 | -1.53 | 2.45 | -1.61 | 10.62 |
| 2016 | -2.32 | -5.21 | -0.71 | 0.96 | 1.08 | -0.37 | -2.53 | -2.18 | -0.28 | -0.23 | 0.24 | -3.06 | -13.84 |
| 2017 | -0.72 | 0.00 | 0.93 | 2.91 | 5.05 | 1.34 | 0.92 | 5.63 | -2.00 | 4.20 | -1.73 | -1.13 | 16.11 |
| 2018 | 2.14 | 1.80 | -1.00 | -1.04 | 1.97 | -1.26 | 0.31 | 3.37 | -1.62 | 2.78 | -3.14 | 5.57 | 9.96 |
| 2019 | -6.08 | -0.26 | 1.70 | -1.89 | 8.25 | 2.46 | 1.51 | 3.42 | -8.25 | 3.50 | -0.56 | -3.76 | -1.08 |

## 1997-2000

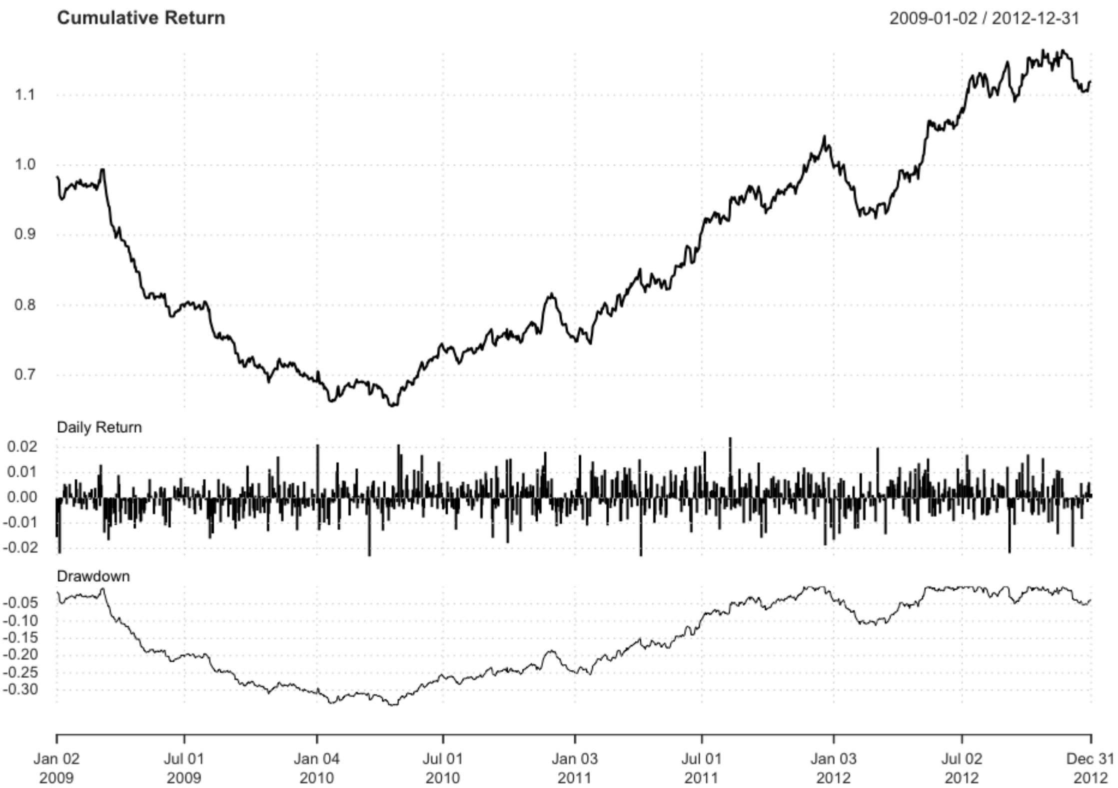



## 2001-2004

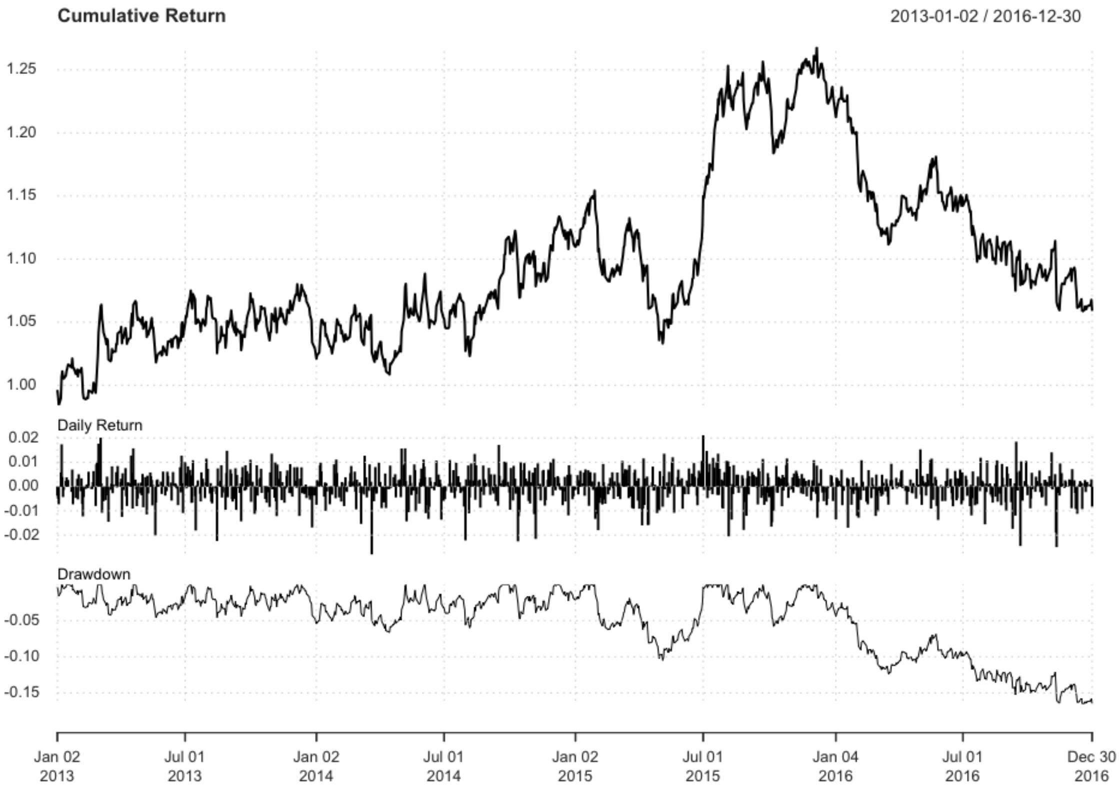


**2005-2008**

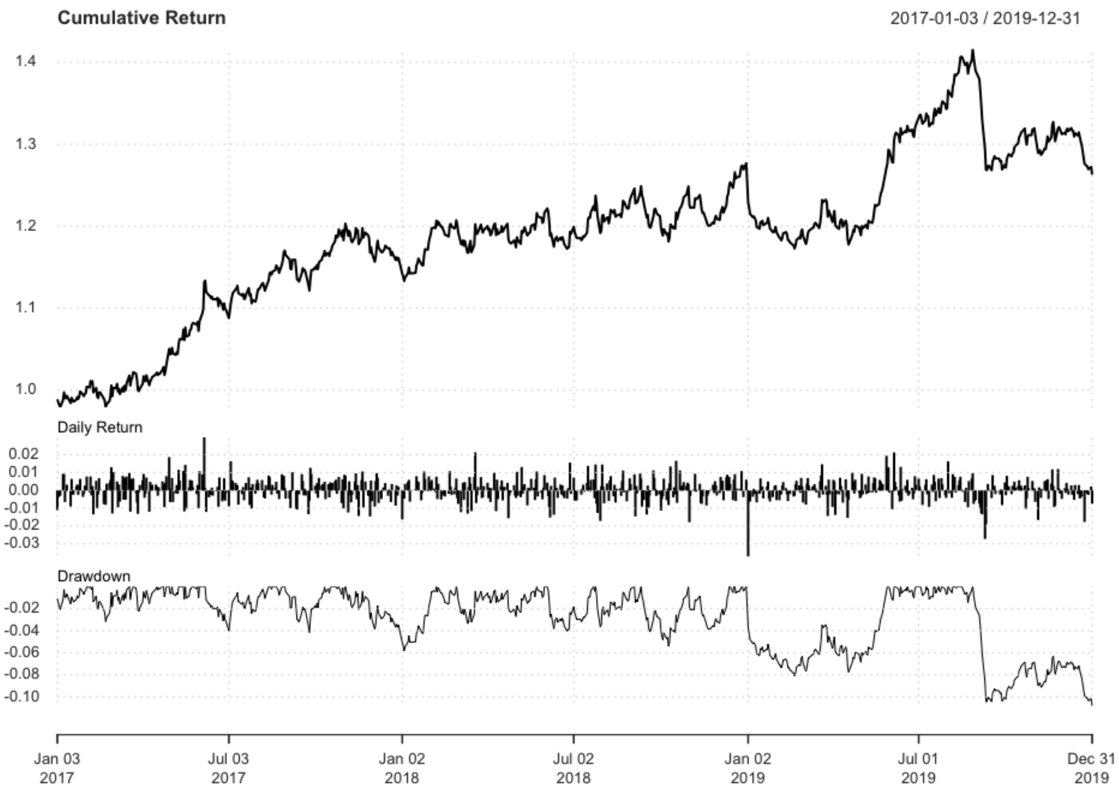

**2009-2012**



## 2013-2016



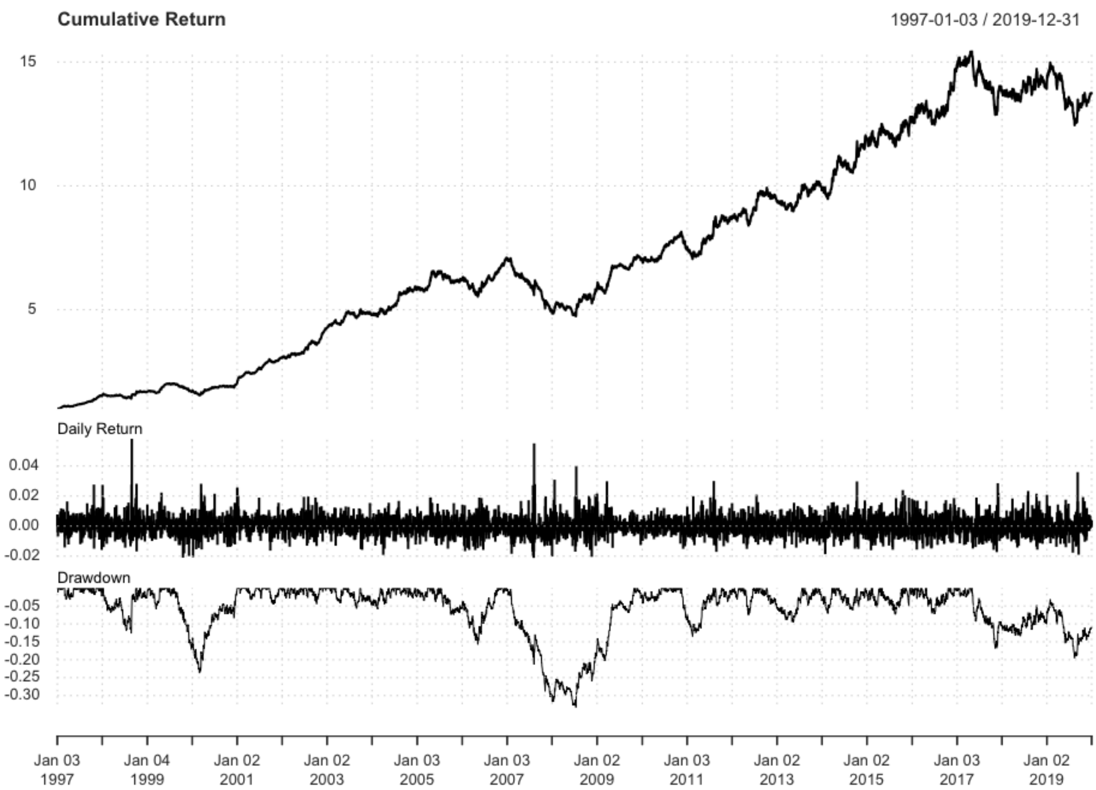

## 2017-2019

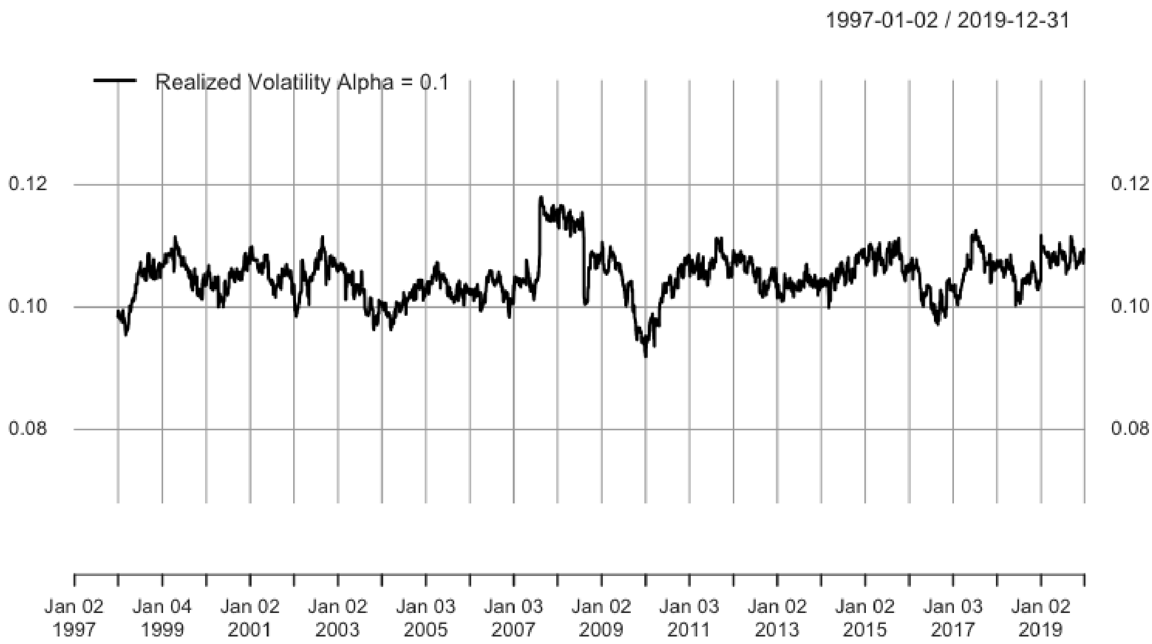


## A.11 Volatility Scaled Momentum with Different Alphas

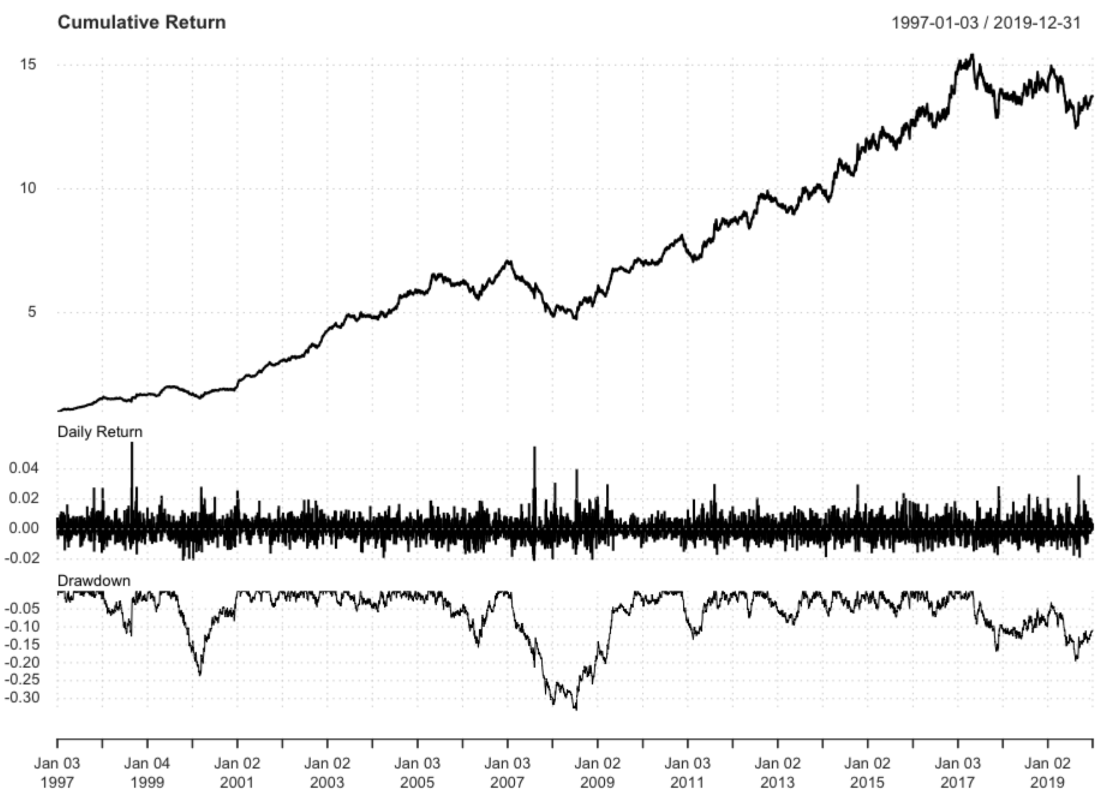
| Scaled Momentum Strategy | Alpha = 0.1 | Alpha = 0.06 | Alpha = 0.01 | Alpha = 0.001 | Estimated Alpha |
|---|---|---|---|---|---|
| Annualized Ret | 0.10213 | 0.10274 | 0.09776 | 0.08532 | 0.11953 |
| Annualized Std Dev | 0.10525 | 0.10341 | 0.10172 | 0.10261 | 0.10133 |
| Annualized Sharpe | 0.81193 | 0.83215 | 0.79779 | 0.6715 | 1.01241 |
| Worst Drawdown | 0.3844854 | 0.3809252 | 0.353502 | 0.4571964 | 0.3933402 |

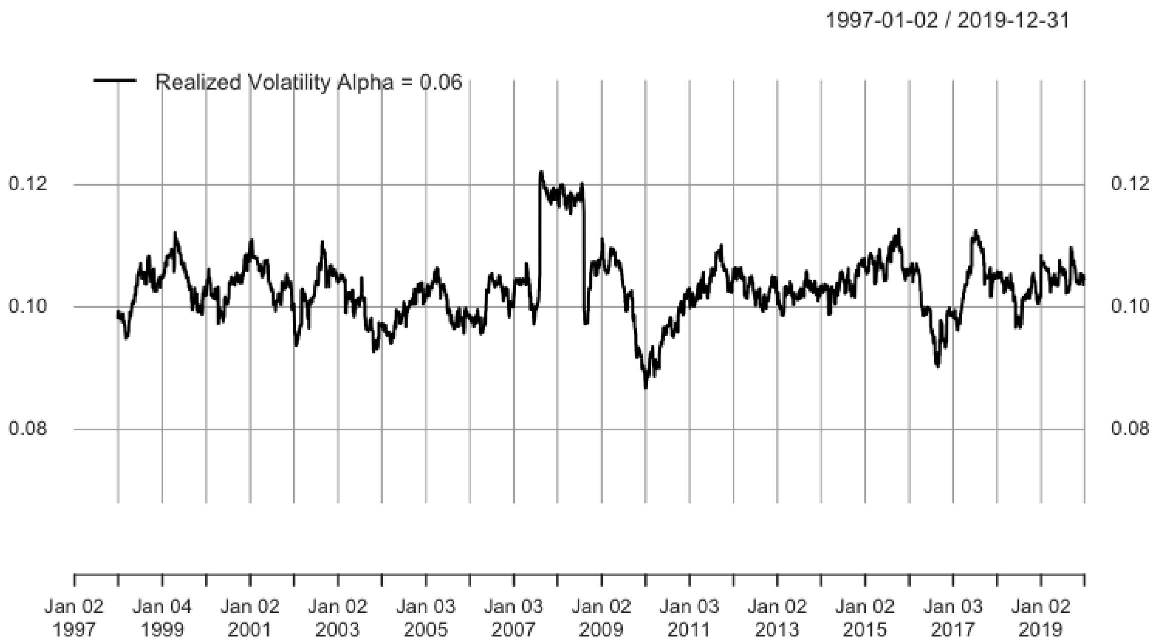
### Alpha = 0.1



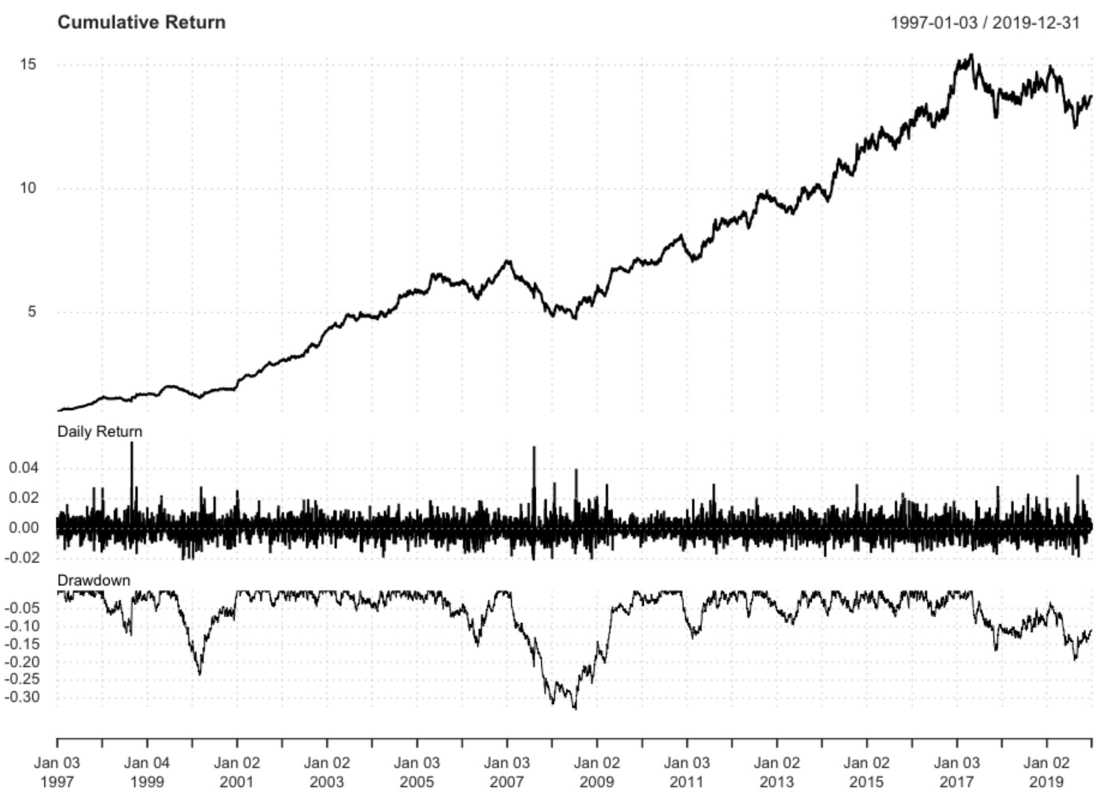

1997-01-02 / 2019-12-31
Realized Volatility Alpha = 0.1
0.12
0.10
0.08
Jan 02 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

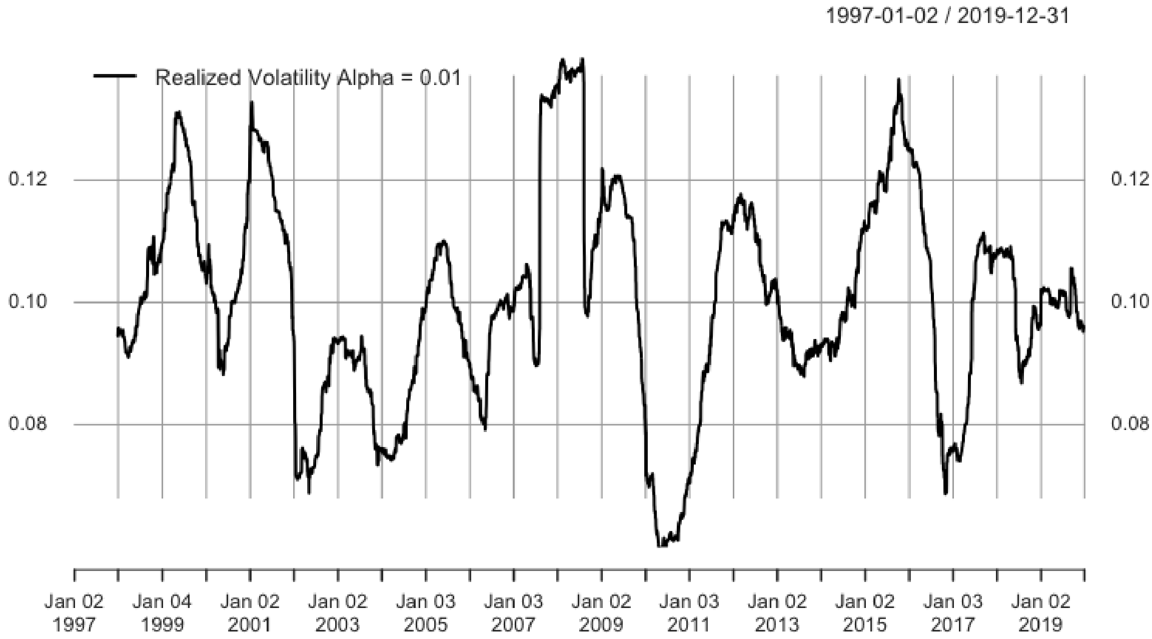
**Alpha = 0.06**


Cumulative Return
1997-01-03 / 2019-12-31
15
10
5
Daily Return
0.04
0.02
0.00
-0.02
Drawdown
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
Jan 03 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

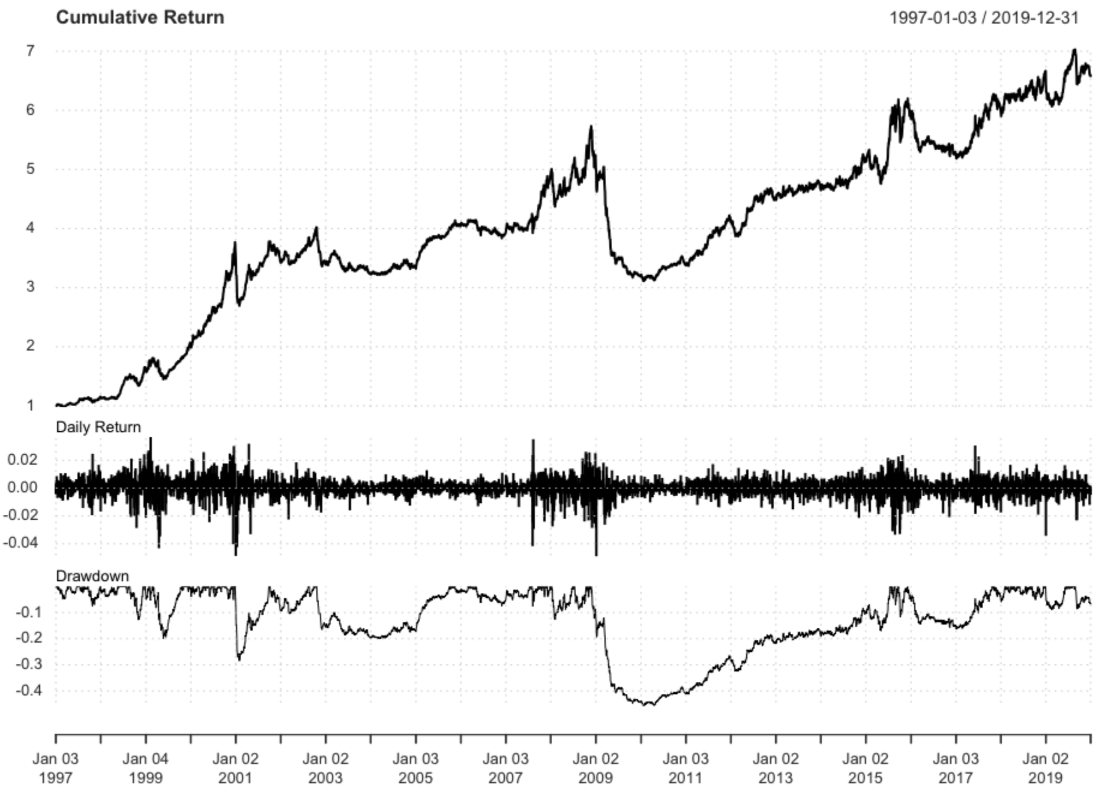

1997-01-02 / 2019-12-31
Realized Volatility Alpha = 0.06
0.12
0.10
0.08
Jan 02 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

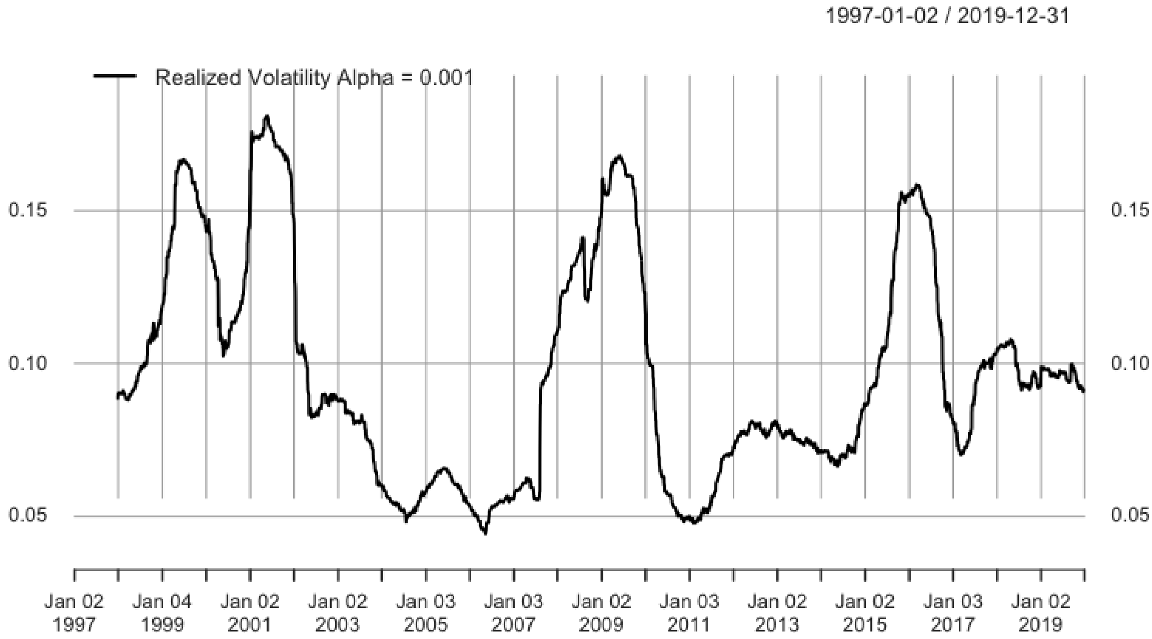
**Alpha = 0.01**


Cumulative Return
1997-01-03 / 2019-12-31
15
10
5
Daily Return
0.04
0.02
0.00
-0.02
Drawdown
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
Jan 03 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019


1997-01-02 / 2019-12-31
Realized Volatility Alpha = 0.01
0.12
0.10
0.08
Jan 02 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

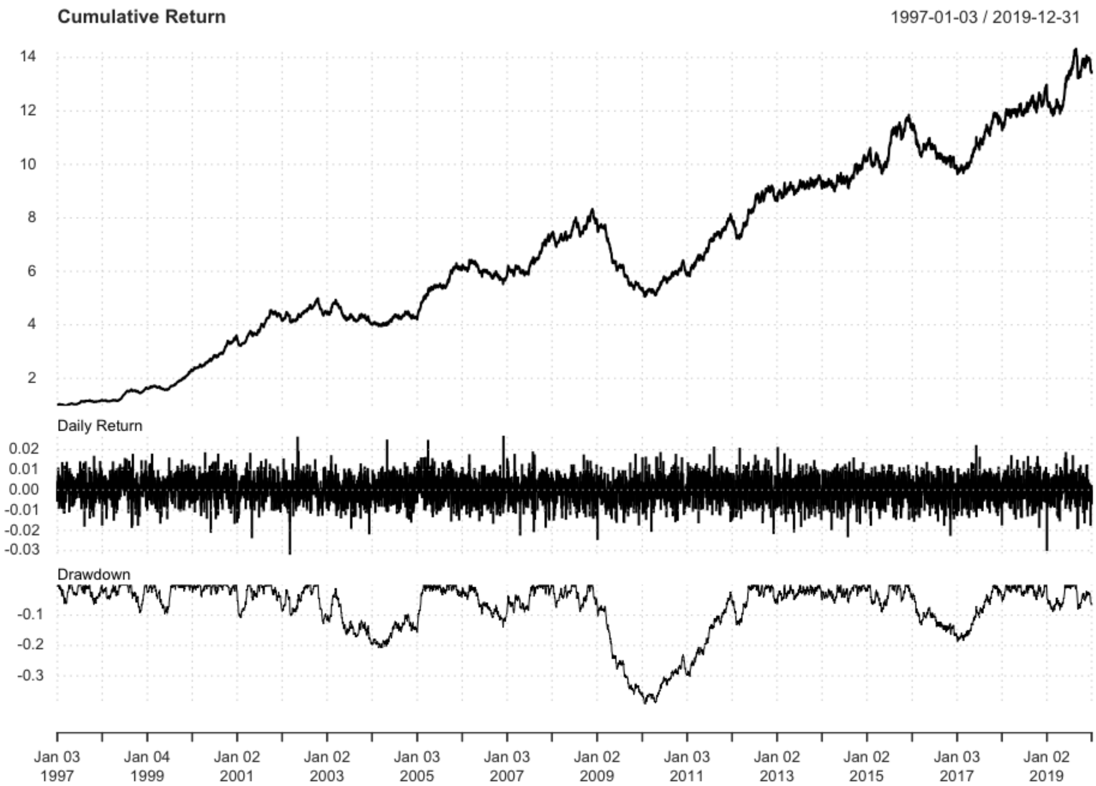
**Alpha = 0.001**

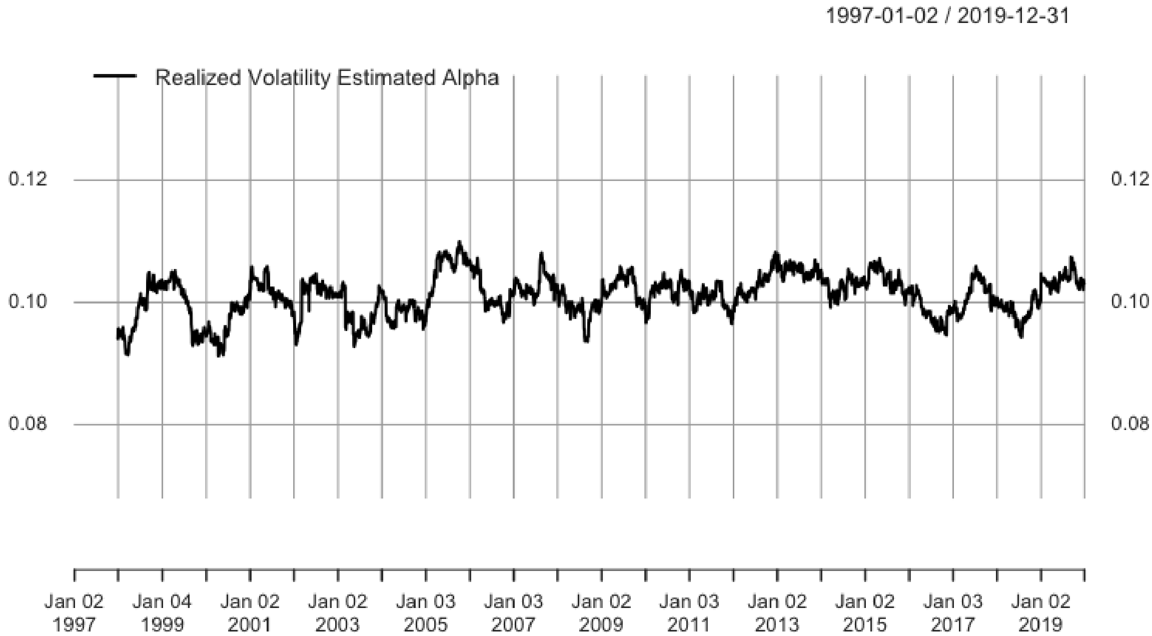

Cumulative Return
1997-01-03 / 2019-12-31
Daily Return
Drawdown
Jan 03 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019




## Estimated Alpha

The alpha is based upon a yearly reestimation of the parameter in the I-GARCH model

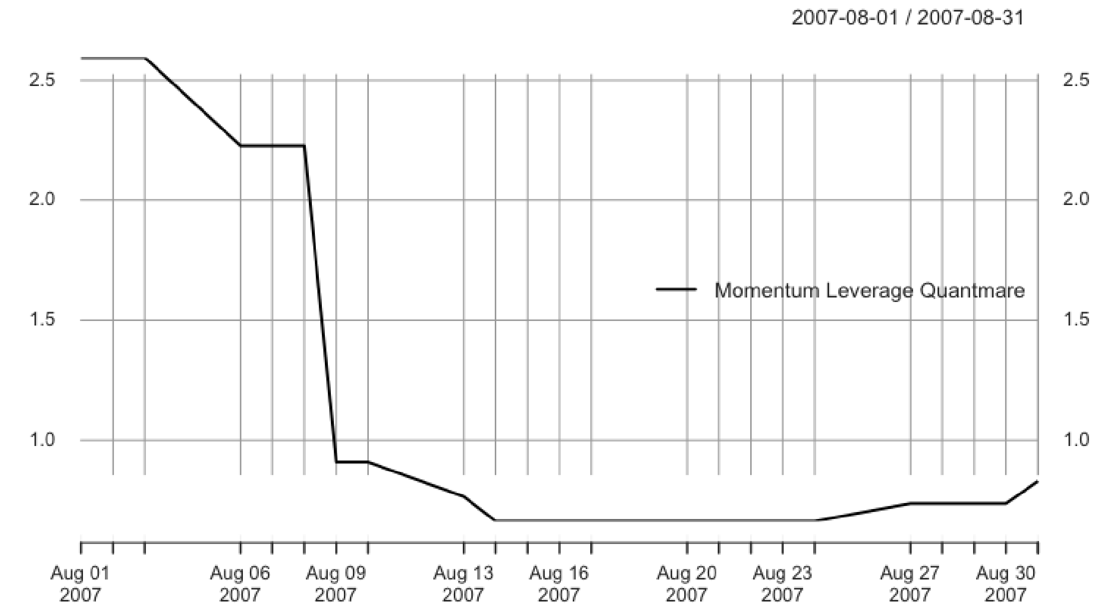


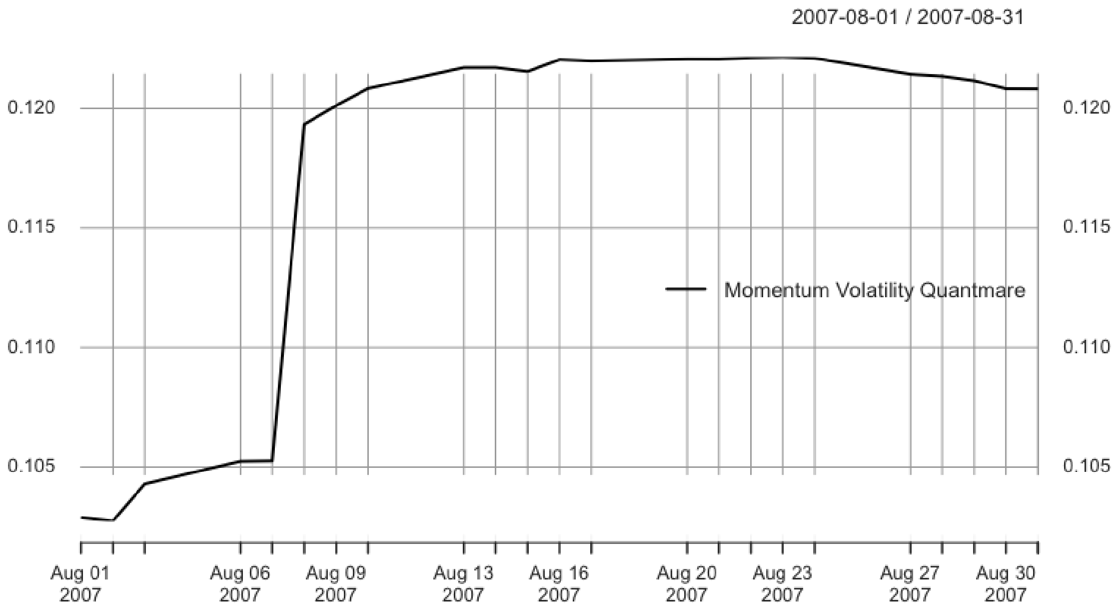


1997-01-02 / 2019-12-31
Realized Volatility Estimated Alpha
0.12
0.10
0.08
Jan 02 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

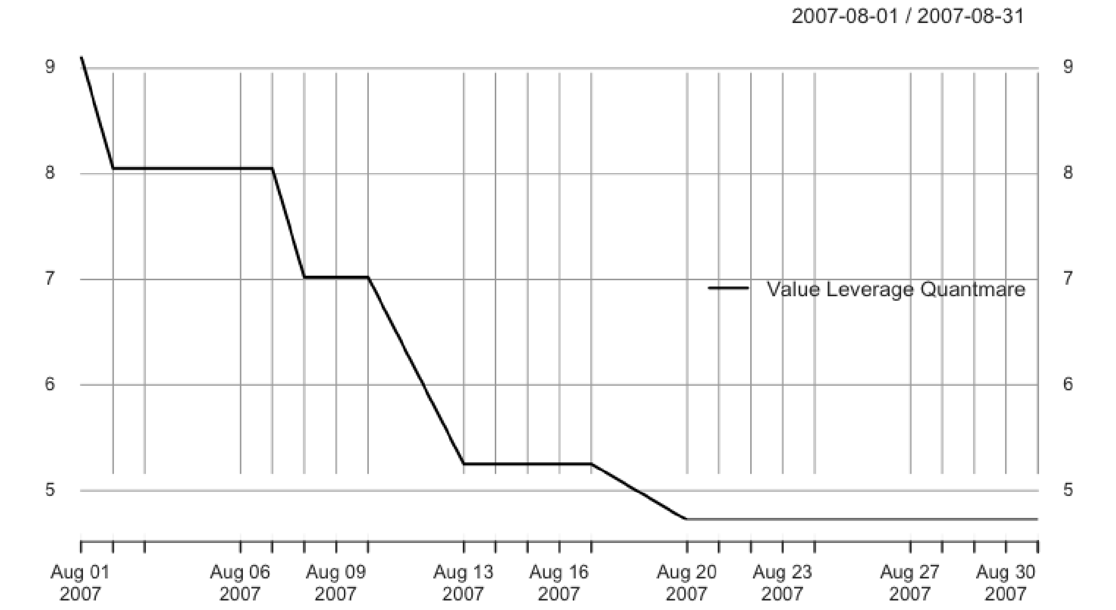
## A.12 Quantmare Leverage and Volatility

### Momentum

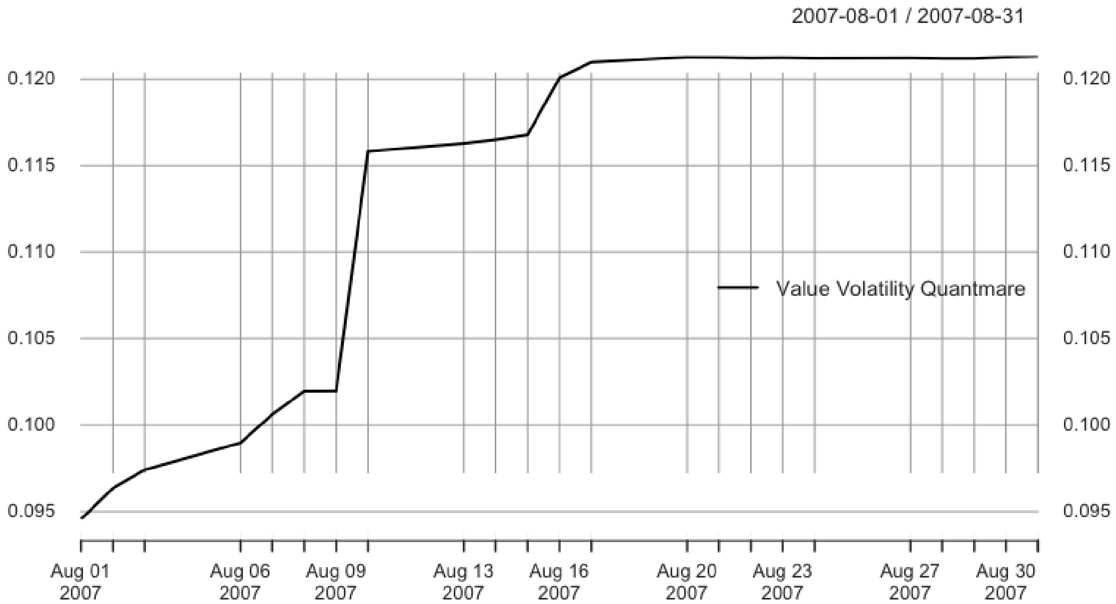


## Value



2007-08-01 / 2007-08-31
9
8
7
6
5
Value Leverage Quantmare
Aug 01 2007
Aug 06 2007
Aug 09 2007
Aug 13 2007
Aug 16 2007
Aug 20 2007
Aug 23 2007
Aug 27 2007
Aug 30 2007

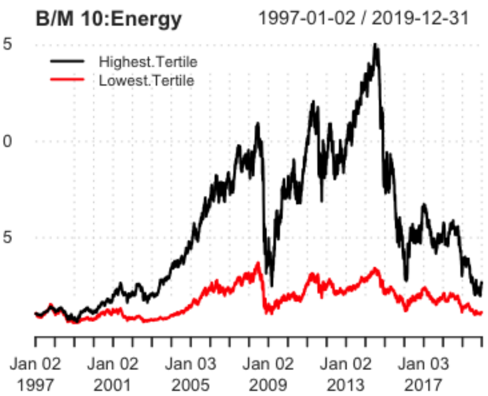



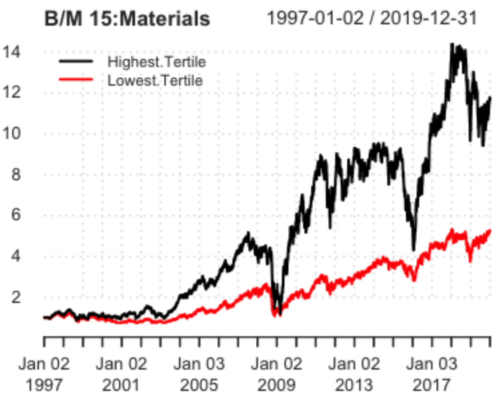
2007-08-01 / 2007-08-31
0.120
0.115
0.110
0.105
0.100
0.095
Value Volatility Quantmare
Aug 01 2007
Aug 06 2007
Aug 09 2007
Aug 13 2007
Aug 16 2007
Aug 20 2007
Aug 23 2007
Aug 27 2007
Aug 30 2007

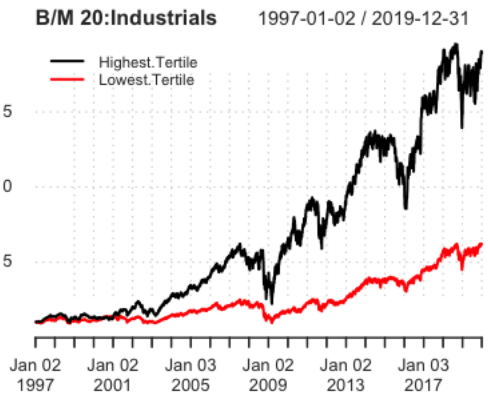
## A.13 CAPM Regression Volatility Scaled Momentum

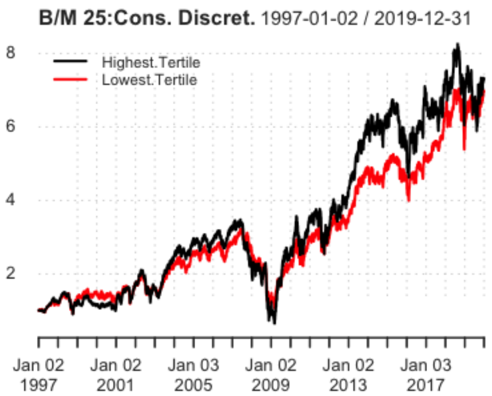
| Momentum Strategy | Estimate | t value | Pr(> $\|t\|$) |
|---|---|---|---|
| Alpha | 0.0003 | 3.8573 | 0.0001 |
| Beta | -0.0033 | -0.5454 | 0.5855 |

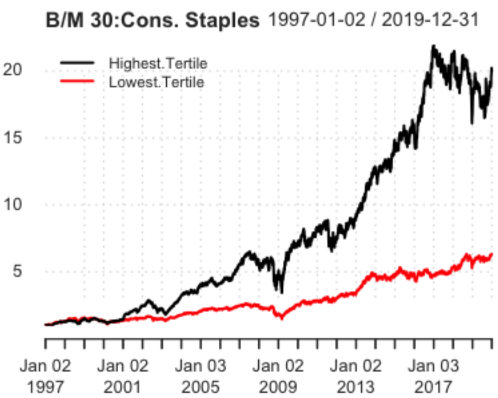
## A.14 Performance of GICS-divided Tertiles

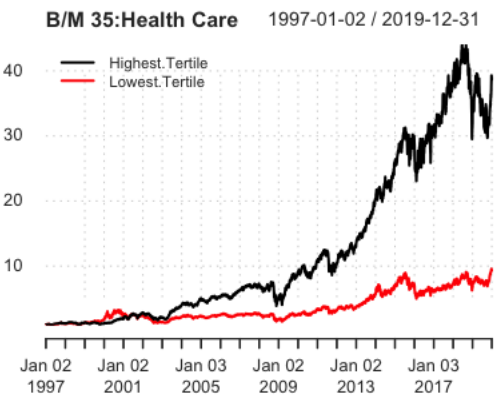


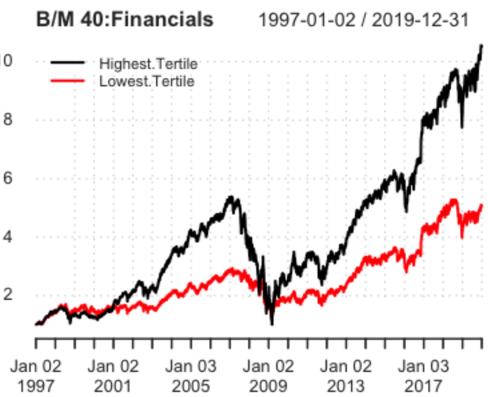



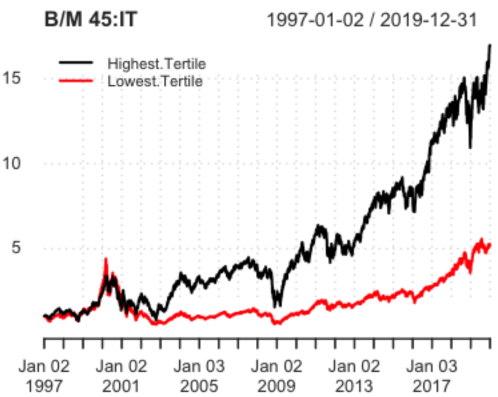



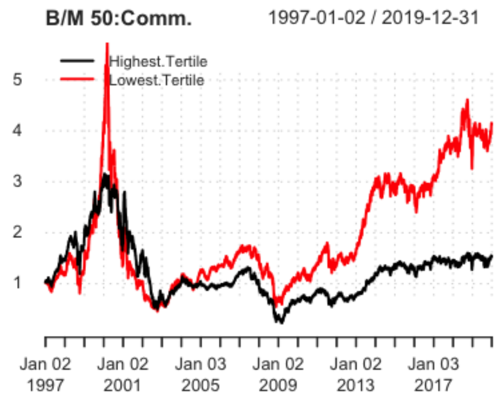



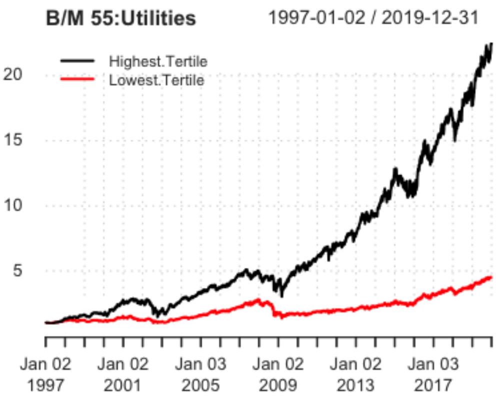



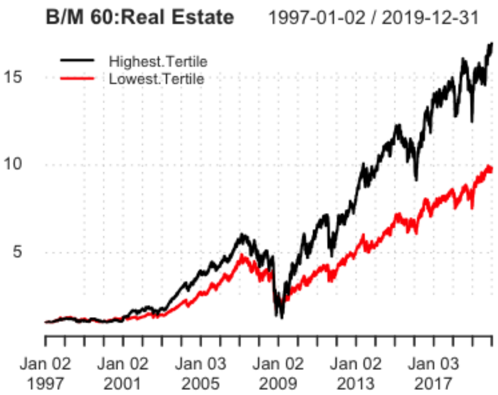



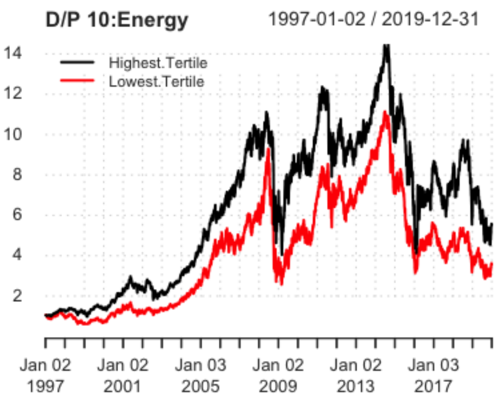



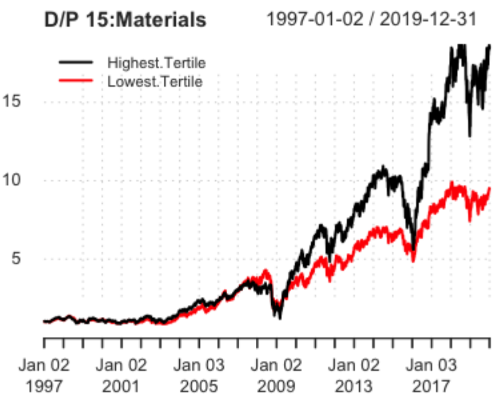



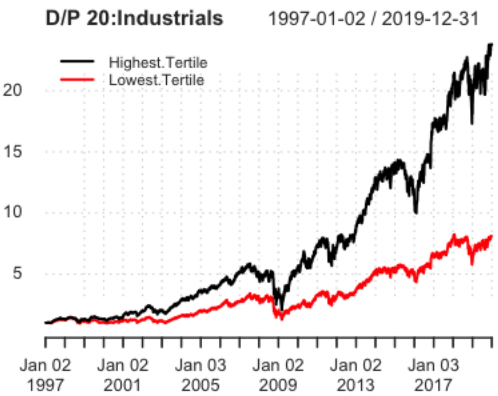

B/M 50:Comm.
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
1
2
3
4
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

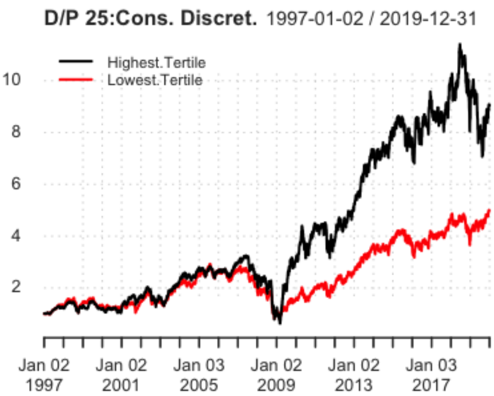

B/M 55:Utilities
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
5
10
15
20
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

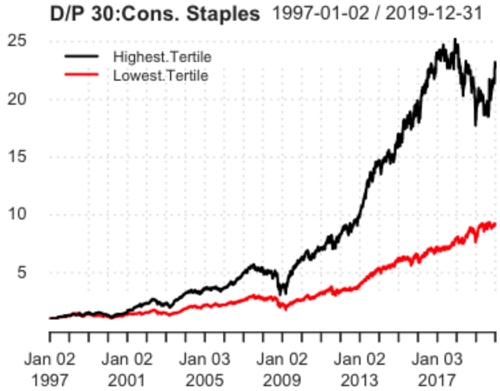

B/M 60:Real Estate
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
5
10
15
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

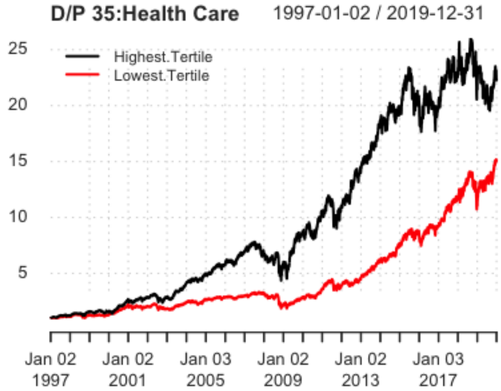

D/P 10:Energy
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
2
4
6
8
10
12
14
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

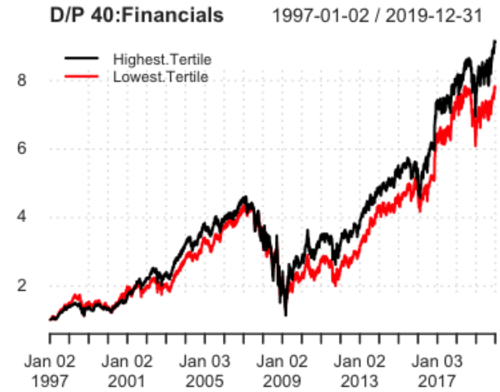

D/P 15:Materials
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
5
10
15
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

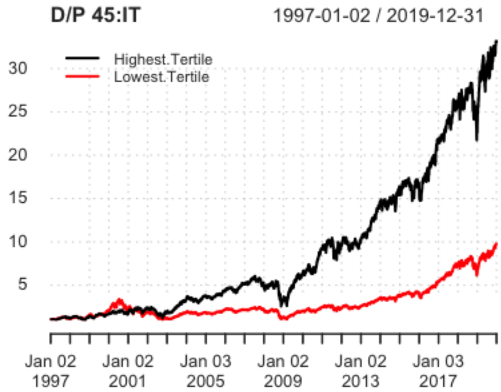

D/P 20:Industrials
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
5
10
15
20
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

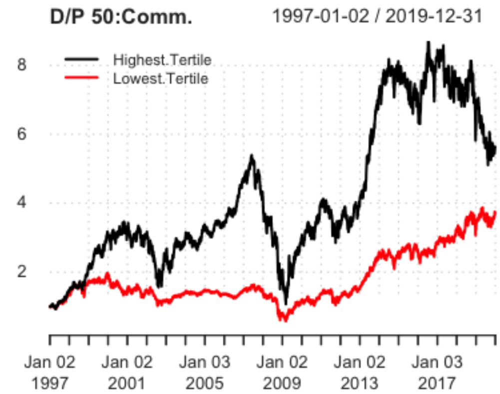

D/P 25:Cons. Discret.
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
2
4
6
8
10
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

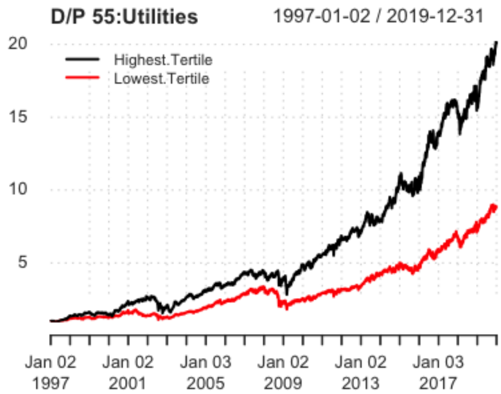

D/P 30:Cons. Staples
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
25
20
15
10
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

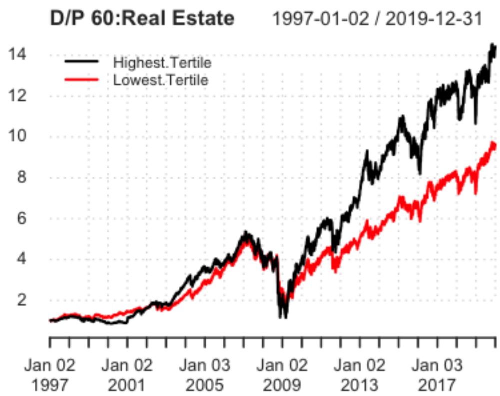

D/P 35:Health Care
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
25
20
15
10
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

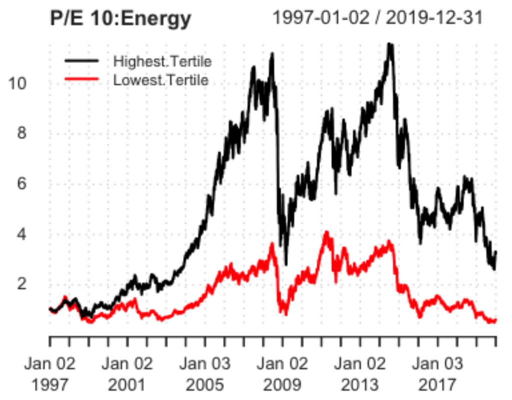

D/P 40:Financials
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
8
6
4
2
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

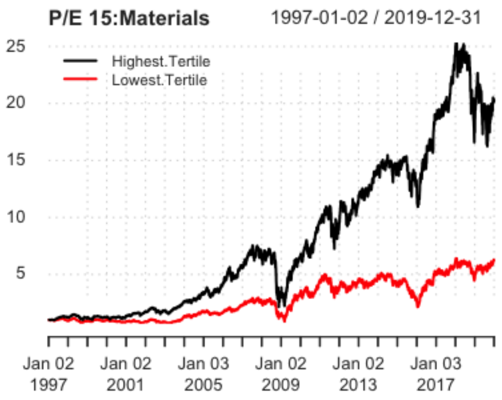

D/P 45:IT
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
30
25
20
15
10
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

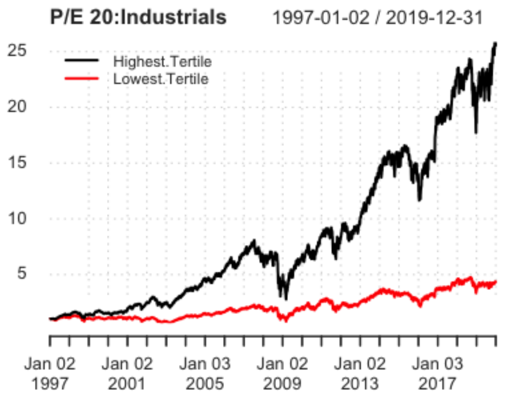

D/P 50:Comm.
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
8
6
4
2
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

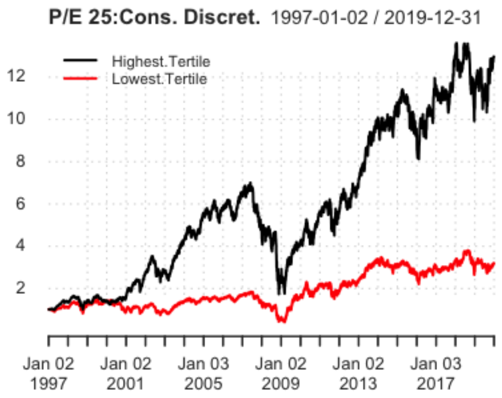

D/P 55:Utilities
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
20
15
10
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

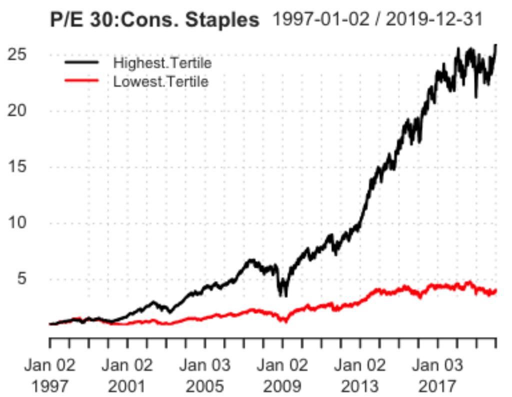

D/P 60:Real Estate
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
14
12
10
8
6
4
2
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

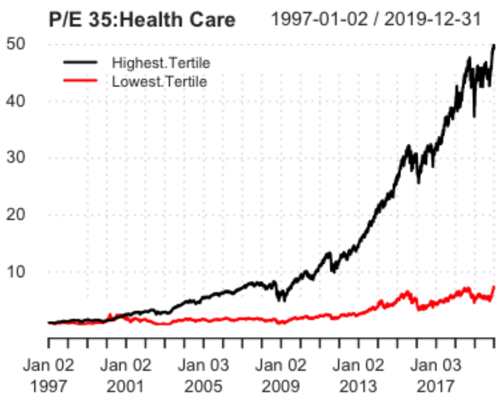

P/E 10:Energy
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
10
8
6
4
2
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

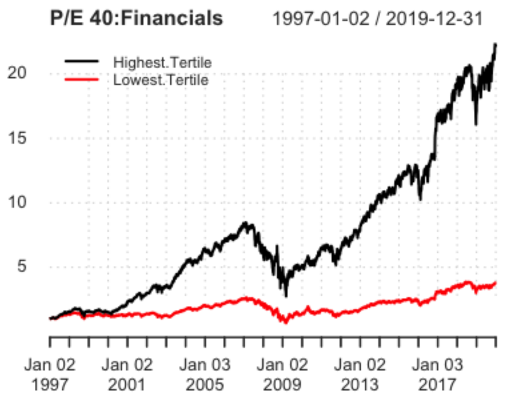

P/E 15:Materials
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
25
20
15
10
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

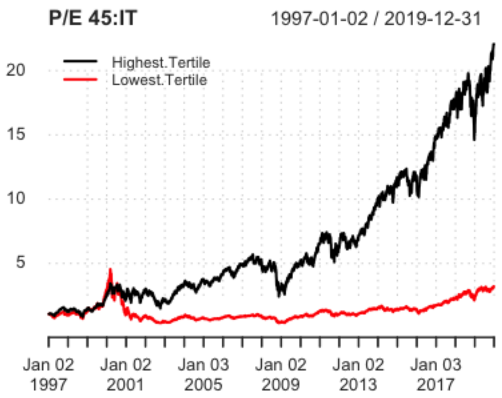

P/E 20:Industrials
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
25
20
15
10
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

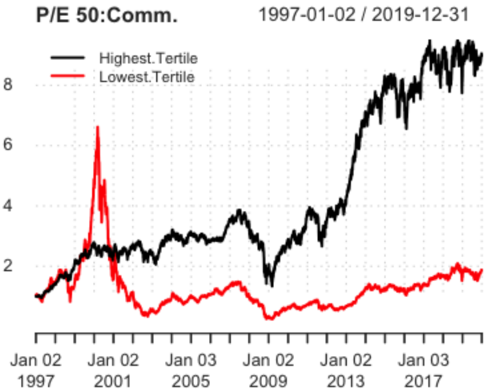

P/E 25:Cons. Discret.
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
12
10
8
6
4
2
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

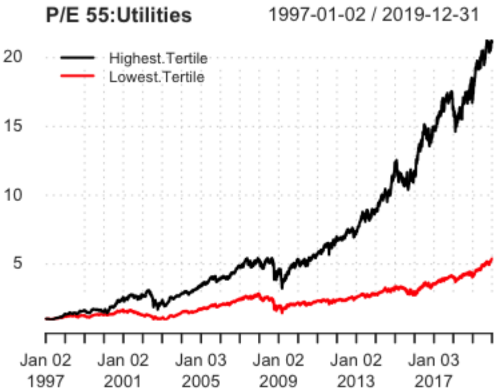

P/E 30:Cons. Staples
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
25
20
15
10
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

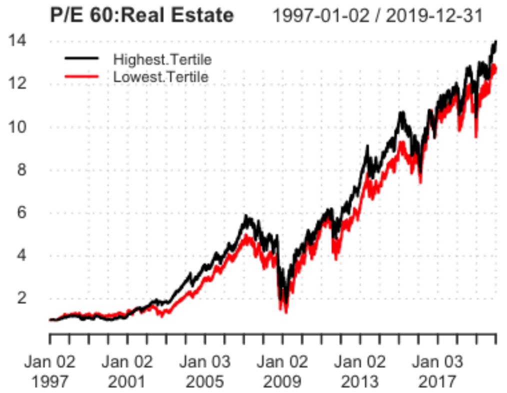

P/E 35:Health Care
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
50
40
30
20
10
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017


P/E 40:Financials
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
20
15
10
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017


P/E 45:IT
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
20
15
10
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017


P/E 50:Comm.
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
8
6
4
2
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017


P/E 55:Utilities
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
20
15
10
5
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017


P/E 60:Real Estate
1997-01-02 / 2019-12-31
Highest.Tertile
Lowest.Tertile
14
12
10
8
6
4
2
Jan 02 1997
Jan 02 2001
Jan 03 2005
Jan 02 2009
Jan 02 2013
Jan 03 2017

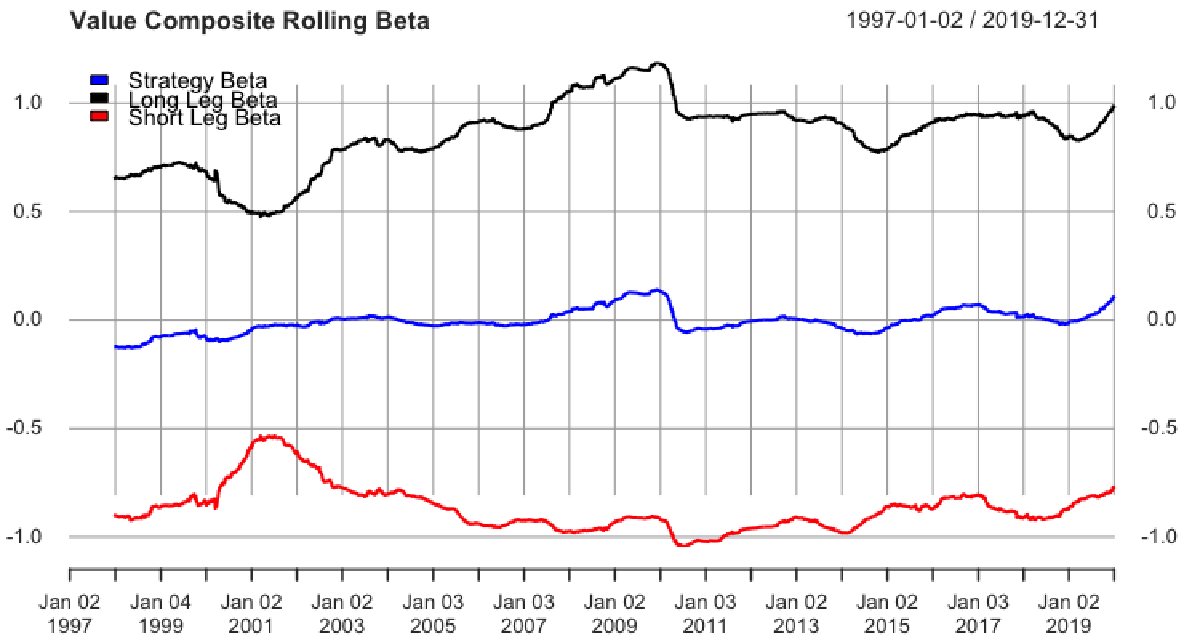
## A.15 Individual Performance of Value Measures

| | Book-to-Market | P/E | Dividend Yield |
|---|---|---|---|
| Annualized Return | 0.0325 | 0.0414 | 0.0225 |
| Annualized Std Dev | 0.0382 | 0.0356 | 0.0272 |
| Annualized Sharpe (Rf=1.52%) | 0.4416 | 0.7212 | 0.2585 |
| Worst Drawdown | 0.1261 | 0.1654 | 0.0791 |

## A.16 Characteristics of the Value strategies

| | Value | QARP | QARP Beta Neutralized | Scaled Value |
|---|---|---|---|---|
| Daily Std Dev | 0.0019 | 0.0015 | 0.0013 | 0.0064 |
| Skewness | 1.0162 | 0.7673 | 0.9920 | 0.5995 |
| Excess kurtosis | 17.0346 | 6.2451 | 7.7983 | 3.2941 |

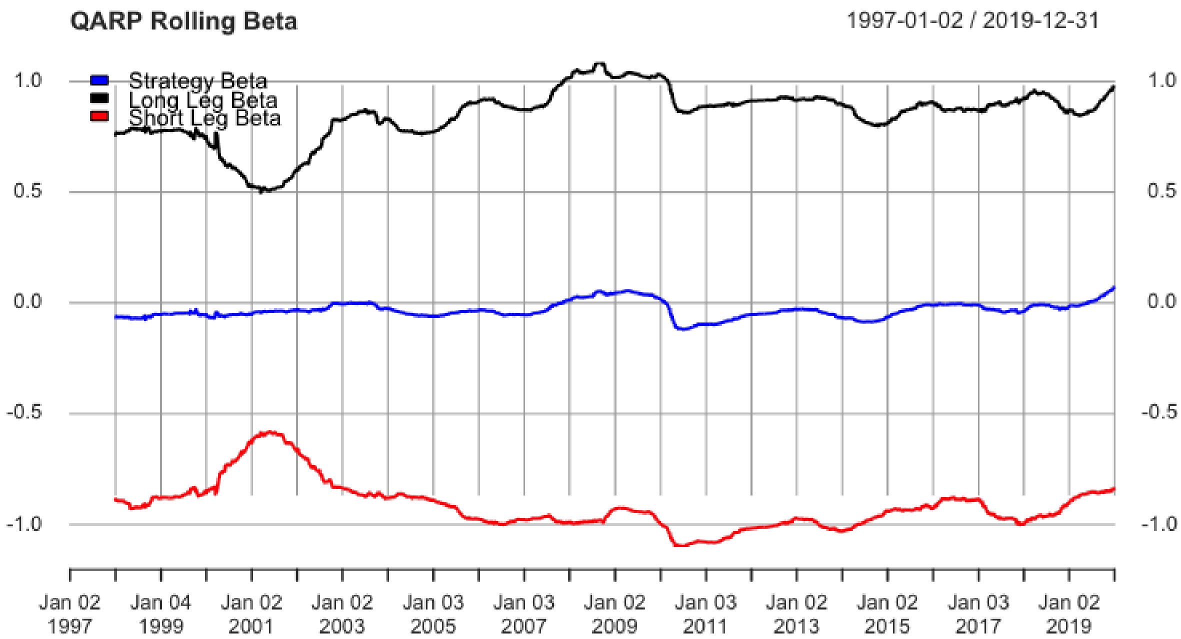
## A.17 Rolling Yearly Betas of the Value Composite Strategy



## A.18 Detailed Performance of the QARP strategy

| | QARP L/S | Long | Short |
|---|---|---|---|
| Annualized Return | 0.0384 | 0.1651 | -0.1133 |
| Annualized Std Dev | 0.0236 | 0.2065 | 0.2094 |
| Annualized Sharpe | 0.9621 | 0.7998 | -0.6053 |
| Worst Drawdown | 0.0610 | 0.6184 | 0.9387 |

## A.19 Rolling Yearly Betas of the QARP Strategy



## A.20 CAPM Regressions Before/After Neutralization for Value

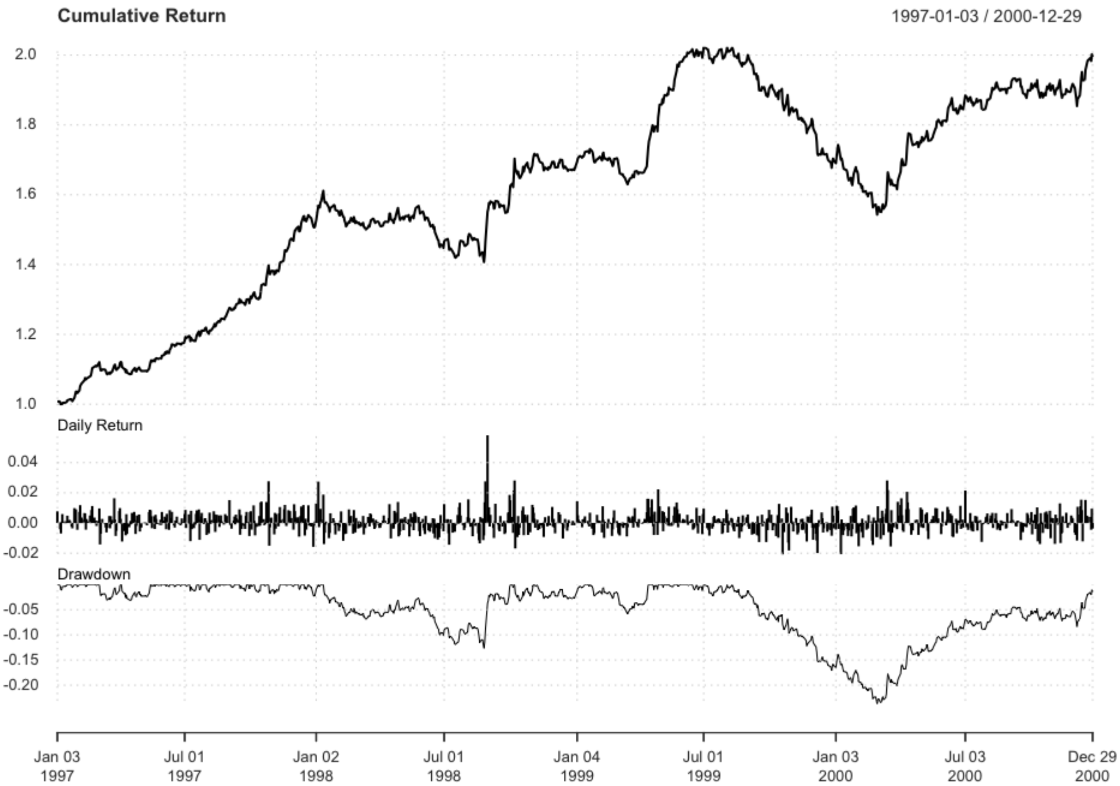
| QARP Before Neutralization | Estimate | Std. Error | t-value | Pr(>$\|t\|$) |
|---|---|---|---|---|
| Alpha | 3.75E-05 | 1.93E-05 | 1.9391 | 0.0525 |
| Beta | -1.17E-02 | 1.38E-03 | -8.5062 | <2E-16 |

| QARP After Neutralization | Estimate | Std. Error | t-value | Pr(>$\|t\|$) |
|---|---|---|---|---|
| Alpha | 4.04E-05 | 1.70E-05 | 2.3711 | 0.0178 |
| Beta | 2.90E-03 | 1.21E-03 | 2.3915 | 0.0168 |

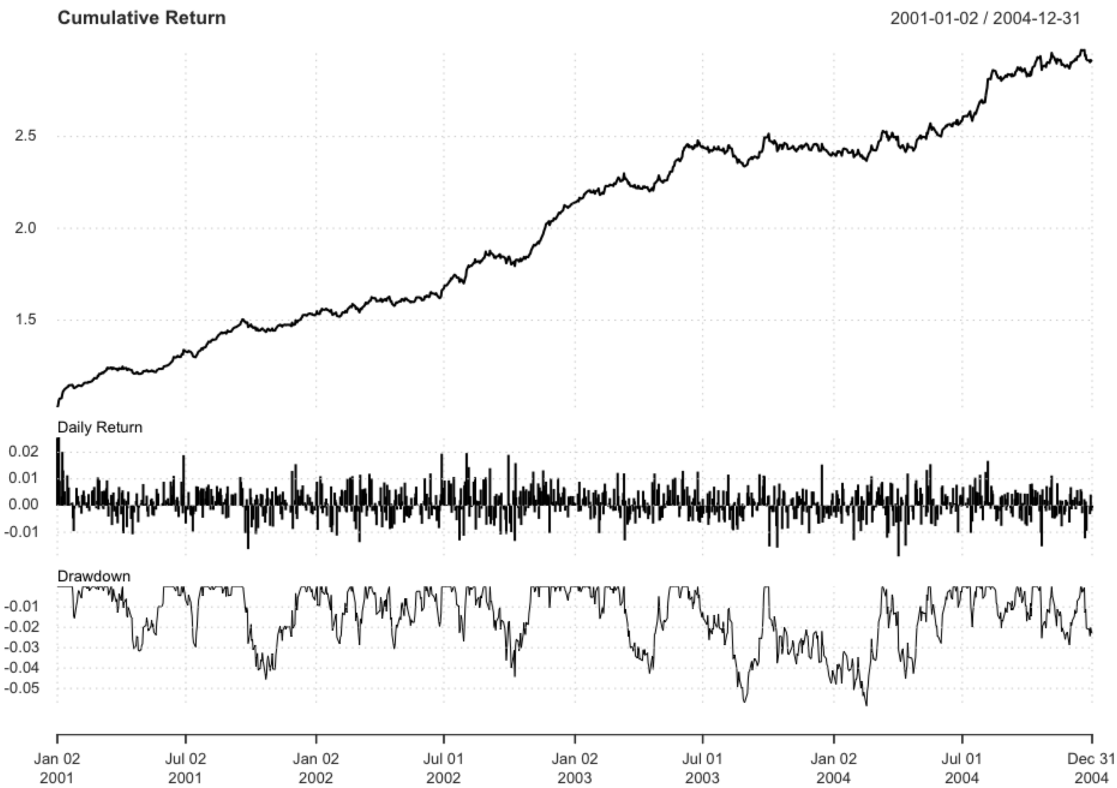
## A.21 Scaled Value Strategy Returns

| Return in % | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Full Year |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1997 | 3.18 | 7.55 | -0.25 | -0.76 | 3.68 | 3.21 | 3.75 | 3.08 | 2.58 | 7.17 | 6.69 | 2.25 | 50.76 |
| 1998 | 3.19 | -2.05 | -0.19 | 0.43 | 1.31 | -6.46 | 0.43 | 6.69 | 1.37 | 5.80 | 1.85 | -1.39 | 10.83 |
| 1999 | 1.31 | 0.57 | -2.52 | 11.96 | 6.53 | 1.27 | -0.59 | -0.18 | -5.12 | -3.15 | -0.56 | -6.60 | 1.60 |
| 2000 | -1.09 | -7.24 | 5.70 | 5.48 | 3.52 | 2.61 | 0.04 | 3.11 | -0.15 | -0.06 | 0.69 | 4.33 | 17.51 |
| 2001 | 14.39 | 4.73 | 3.36 | -2.39 | 2.35 | 8.16 | 1.69 | 5.63 | 1.76 | -1.05 | 1.82 | 3.60 | 52.66 |
| 2002 | -0.17 | 2.86 | 2.27 | 0.02 | 0.31 | 3.33 | 4.03 | 7.56 | -0.82 | 1.04 | 9.36 | 4.92 | 40.10 |
| 2003 | 2.92 | 1.83 | -1.04 | 3.13 | 3.40 | 3.18 | -0.75 | -3.52 | 6.81 | -2.57 | -0.17 | -0.69 | 12.75 |
| 2004 | -0.99 | 1.59 | 2.38 | 0.22 | 0.78 | 2.96 | 3.85 | 5.57 | -0.15 | 2.73 | -0.73 | 0.88 | 20.60 |
| 2005 | -0.32 | -0.94 | 3.38 | 9.74 | -2.75 | 2.67 | -2.89 | -0.06 | -2.39 | -0.65 | 0.44 | 0.85 | 6.65 |
| 2006 | 0.46 | -4.19 | 0.40 | -4.31 | 0.26 | 4.31 | 4.48 | -1.06 | 3.60 | 4.17 | 2.18 | 3.70 | 14.31 |
| 2007 | 0.10 | -7.24 | -2.21 | -0.52 | -3.87 | -0.85 | -4.96 | 3.74 | -3.94 | -7.72 | -1.87 | -4.73 | -29.65 |
| 2008 | 4.60 | -1.37 | -0.24 | -0.55 | -0.19 | -5.88 | 6.97 | 4.24 | 4.09 | -1.42 | -1.25 | 7.54 | 16.82 |
| 2009 | 1.18 | -2.24 | 4.23 | 11.43 | 1.35 | 0.13 | -0.34 | -1.13 | 1.38 | 4.93 | 0.96 | -1.63 | 21.34 |
| 2010 | 0.86 | -2.13 | 0.46 | -0.50 | 1.96 | 6.12 | 0.94 | 2.11 | 1.47 | 1.51 | -1.33 | -5.74 | 5.41 |
| 2011 | -2.32 | 0.59 | -1.50 | 3.29 | 3.14 | 3.03 | 0.89 | 4.73 | 2.64 | 1.35 | -2.09 | 1.74 | 16.31 |
| 2012 | 1.57 | 0.32 | 1.94 | -1.19 | -3.18 | 6.34 | 5.09 | 0.78 | -0.35 | 0.40 | -1.55 | -1.74 | 8.32 |
| 2013 | -0.07 | -1.38 | -1.60 | 1.44 | -0.06 | 4.74 | 3.69 | -0.70 | -1.18 | 0.85 | 1.62 | -2.34 | 4.87 |
| 2014 | -1.42 | -0.24 | 5.90 | 4.07 | 4.34 | -2.49 | 0.77 | -3.29 | 2.02 | 6.53 | 0.92 | 2.53 | 20.84 |
| 2015 | -1.67 | 1.21 | -0.90 | 6.80 | -2.82 | -1.29 | -2.06 | 2.11 | 1.32 | 2.00 | -0.27 | 1.65 | 5.86 |
| 2016 | 2.11 | 2.36 | 0.54 | 0.99 | -2.26 | -3.50 | 2.42 | 2.40 | -1.76 | 5.75 | 1.03 | 7.02 | 17.92 |
| 2017 | 0.28 | 1.31 | -0.40 | 2.39 | -7.20 | 4.24 | -2.80 | -3.47 | 0.50 | -5.46 | 2.21 | 2.22 | -6.66 |
| 2018 | -0.95 | -0.49 | 1.18 | -1.56 | -0.87 | 4.88 | 0.07 | -3.20 | 1.55 | 1.36 | 1.42 | -2.52 | 0.62 |
| 2019 | 6.25 | -1.63 | -2.80 | 1.64 | -8.93 | 3.83 | -2.98 | -3.94 | 4.77 | 0.95 | -0.07 | 3.01 | -0.94 |

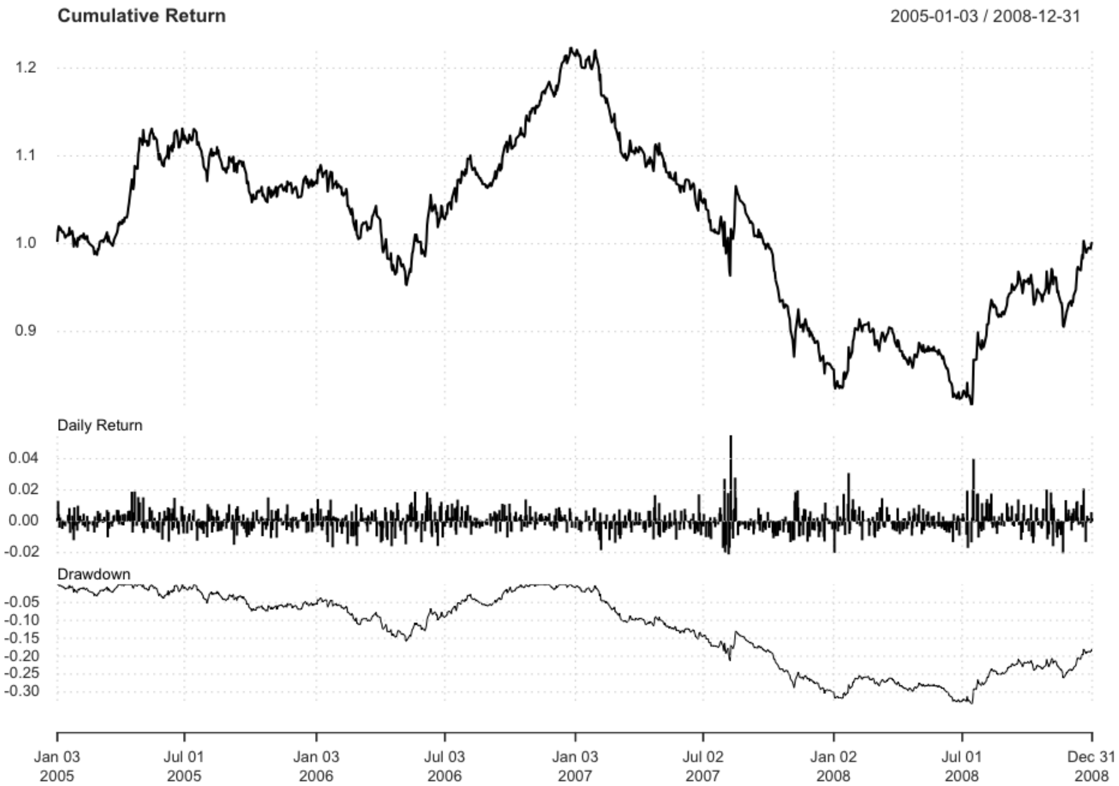
## 1997-2000



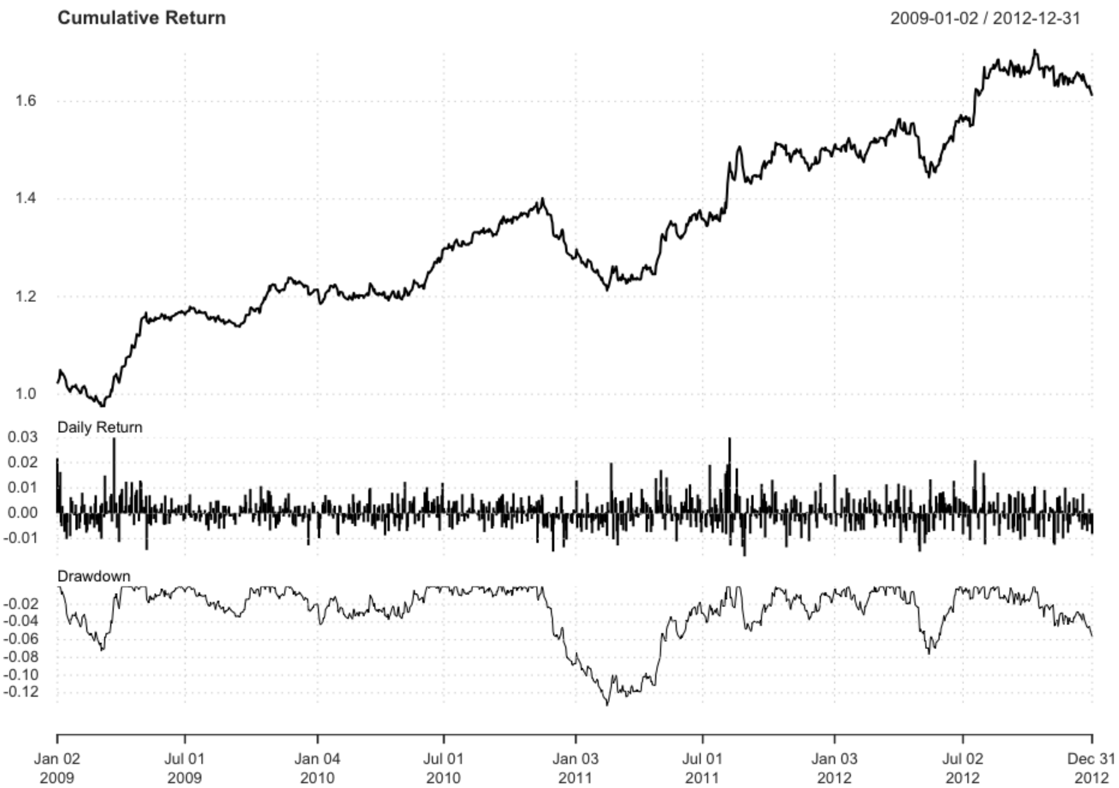

## 2001-2004



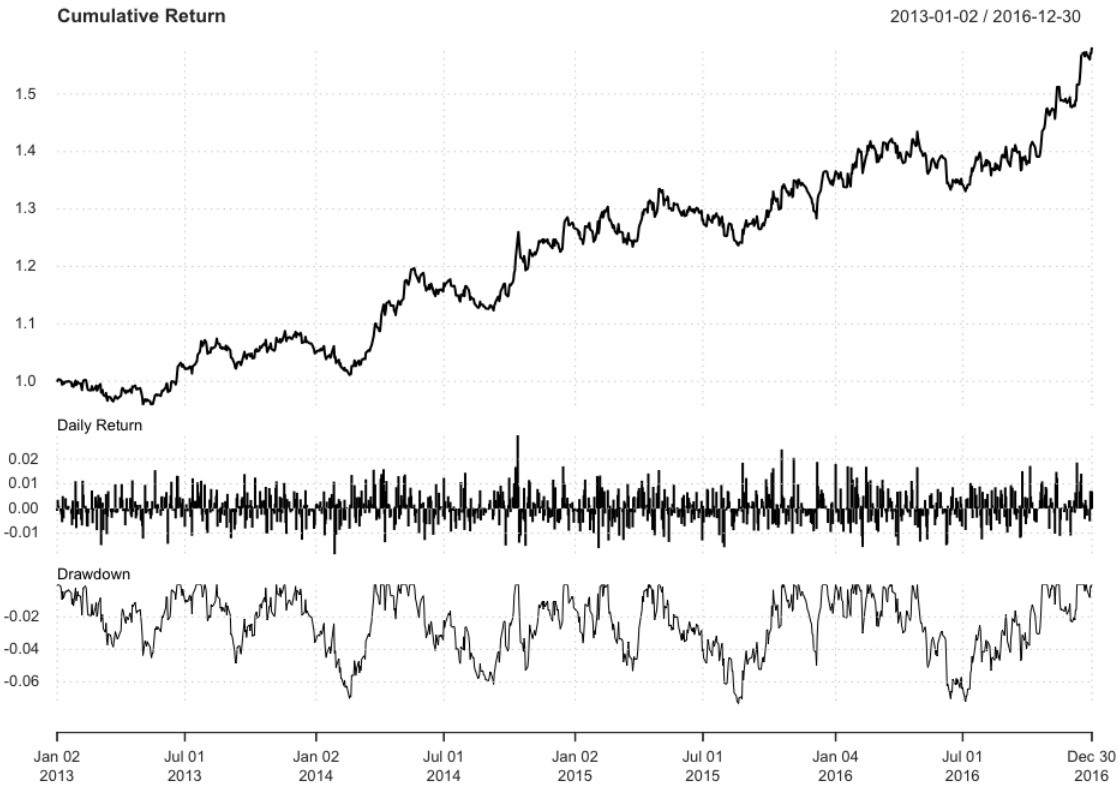
**2005-2008**



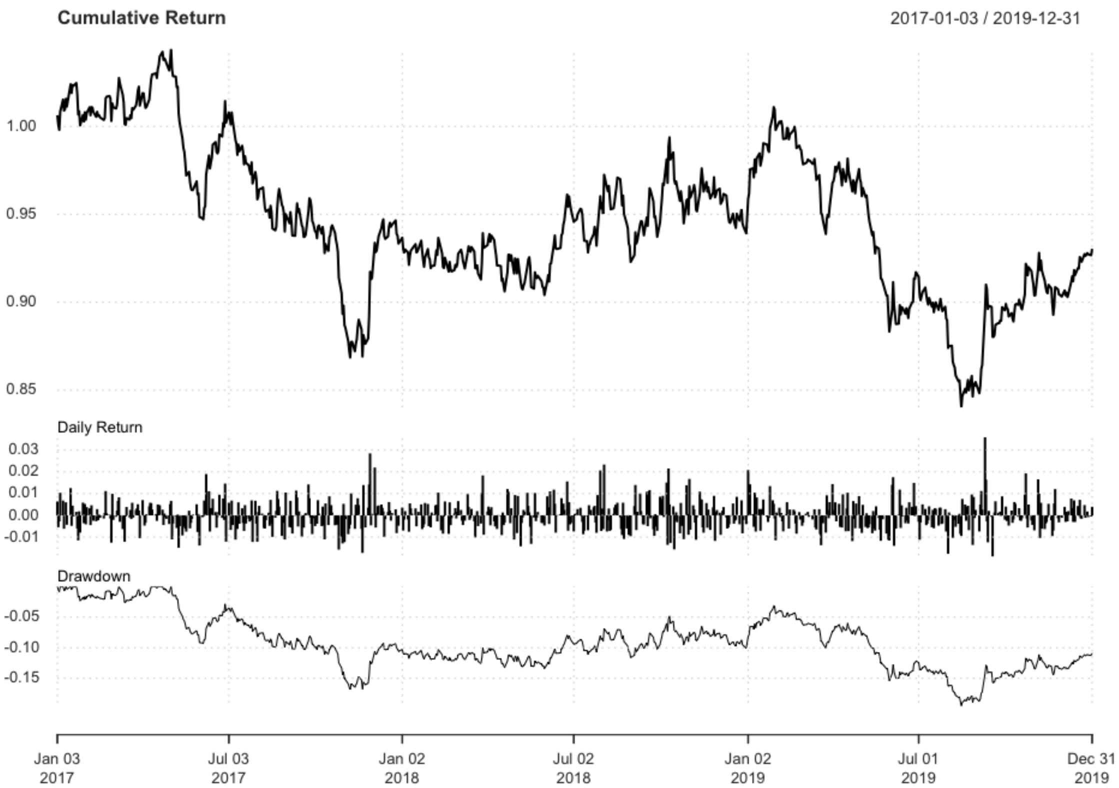

**2009-2012**



**2013-2016**



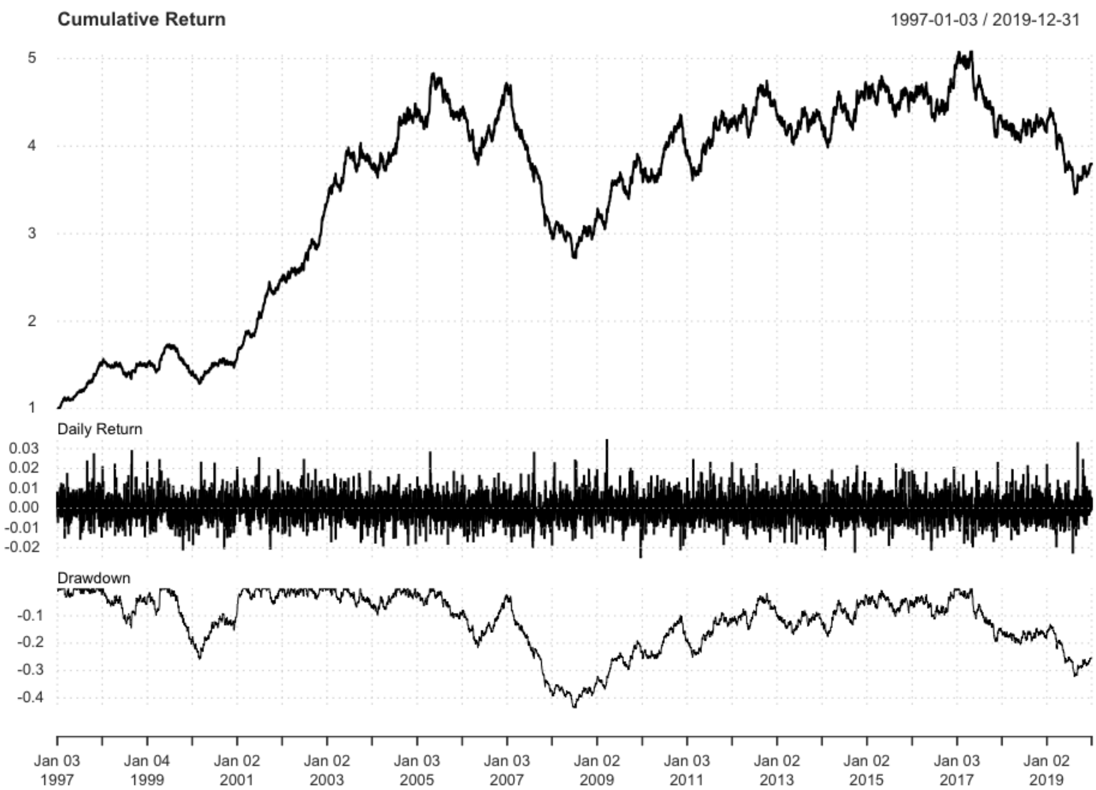

**2017-2019**

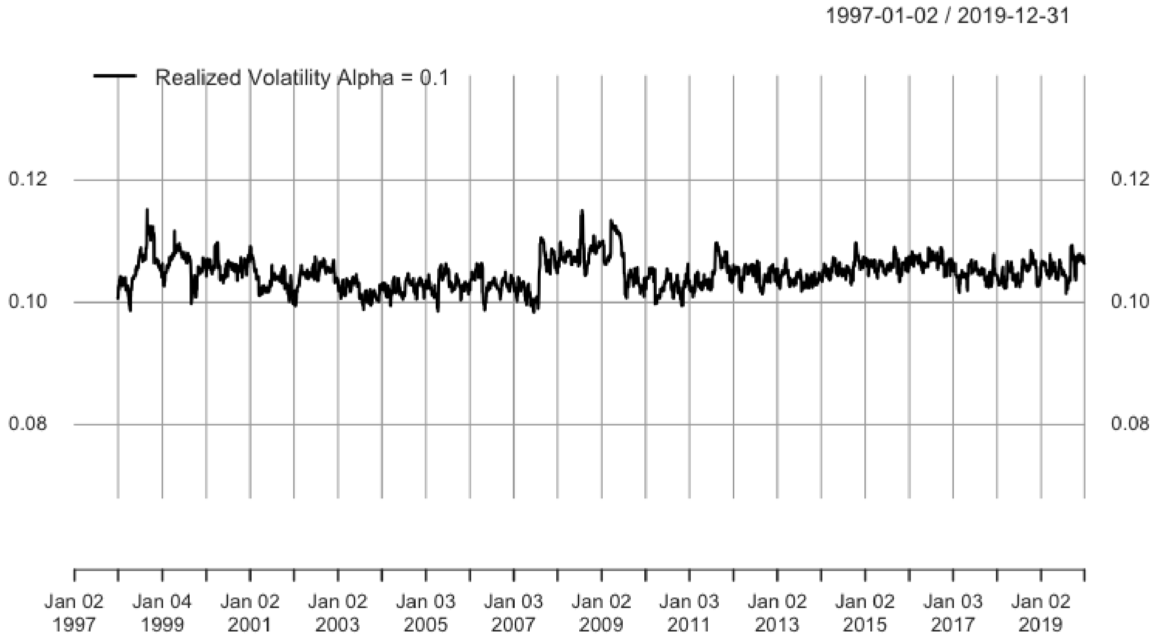


## A.22 Volatility Scaled Value with Different Alphas

| Scaled Value Strategy | Alpha = 0.1 | Alpha = 0.06 | Alpha = 0.01 | Alpha = 0.001 | Estimated Alpha |
|---|---|---|---|---|---|
| Annualized Ret | 0.0600 | 0.0940 | 0.1209 | 0.1295 | 0.1125 |
| Annualized Std Dev | 0.1049 | 0.1025 | 0.1018 | 0.1032 | 0.1001 |
| Annualized Sharpe | 0.4187 | 0.7555 | 1.0215 | 1.0889 | 0.9557 |
| Worst Drawdown | 0.4367 | 0.3766 | 0.3334 | 0.3410 | 0.3574 |

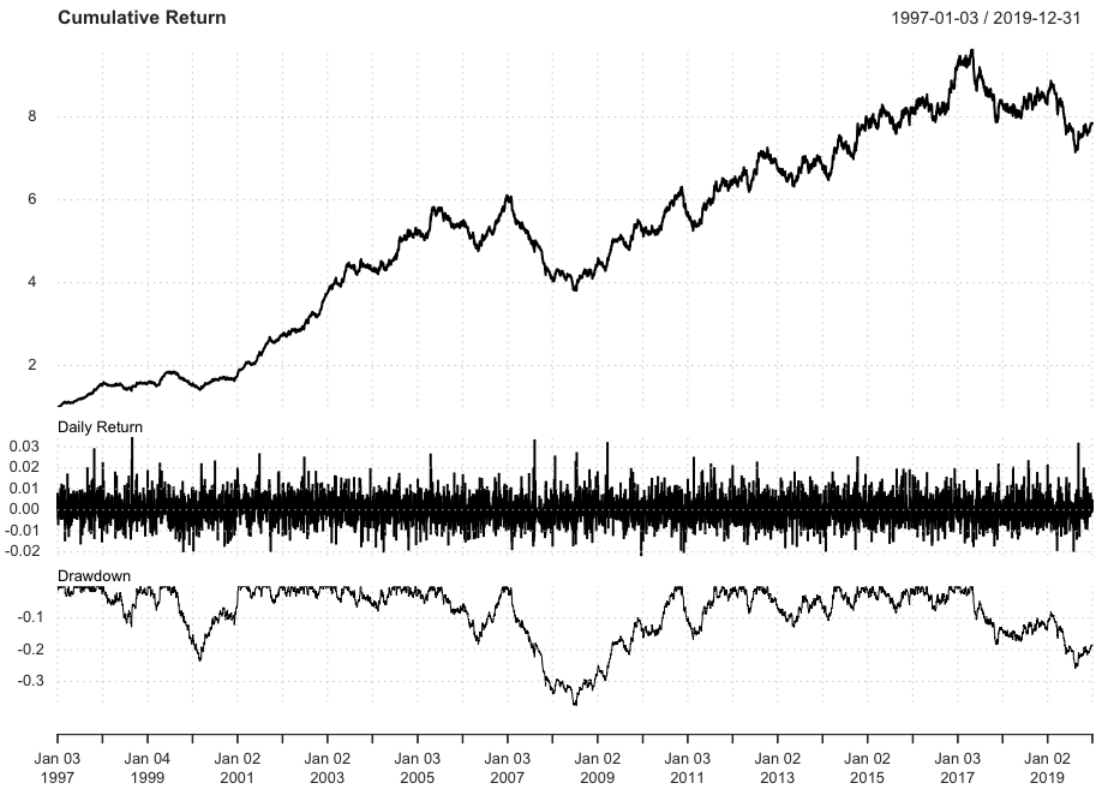
### Alpha = 0.1



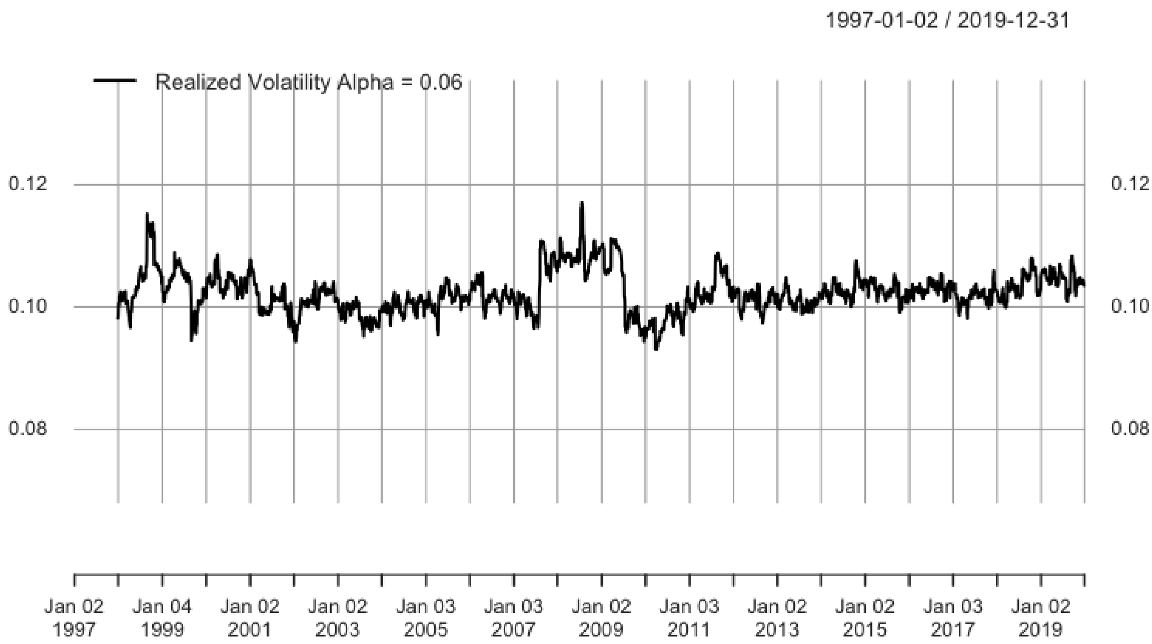


1997-01-02 / 2019-12-31
Realized Volatility Alpha = 0.1
0.12
0.10
0.08
0.12
0.10
0.08
Jan 02 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

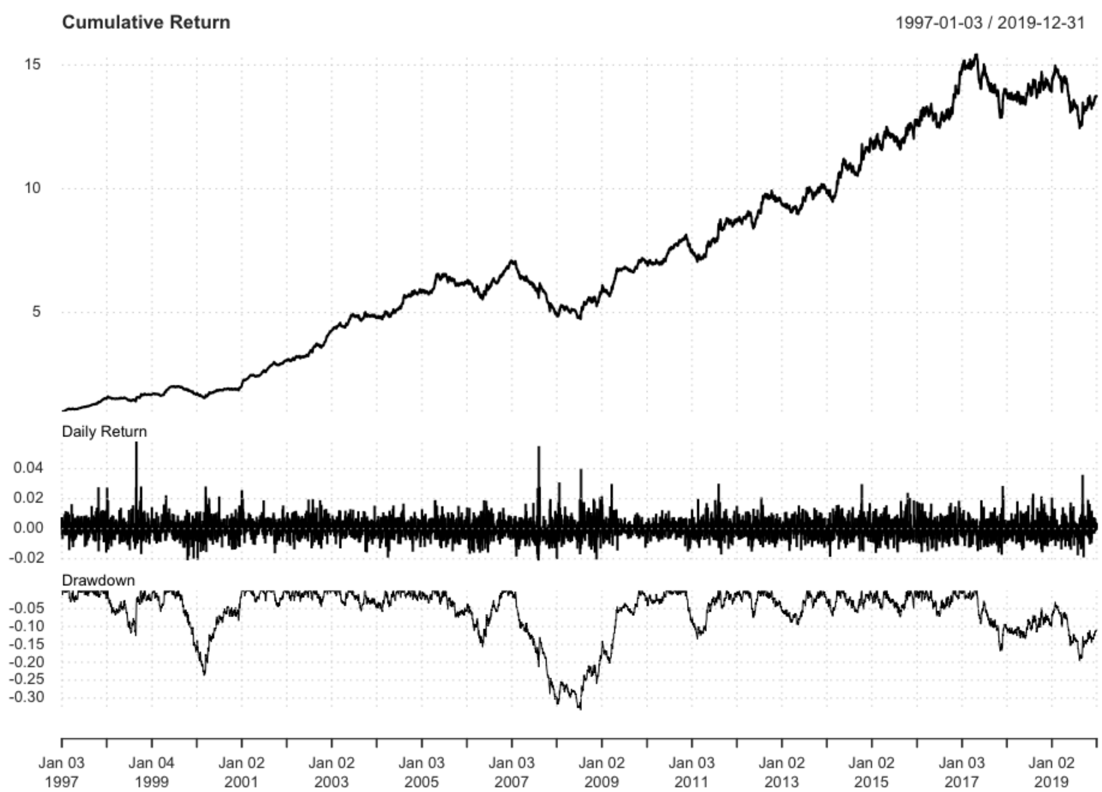

**Alpha = 0.06**

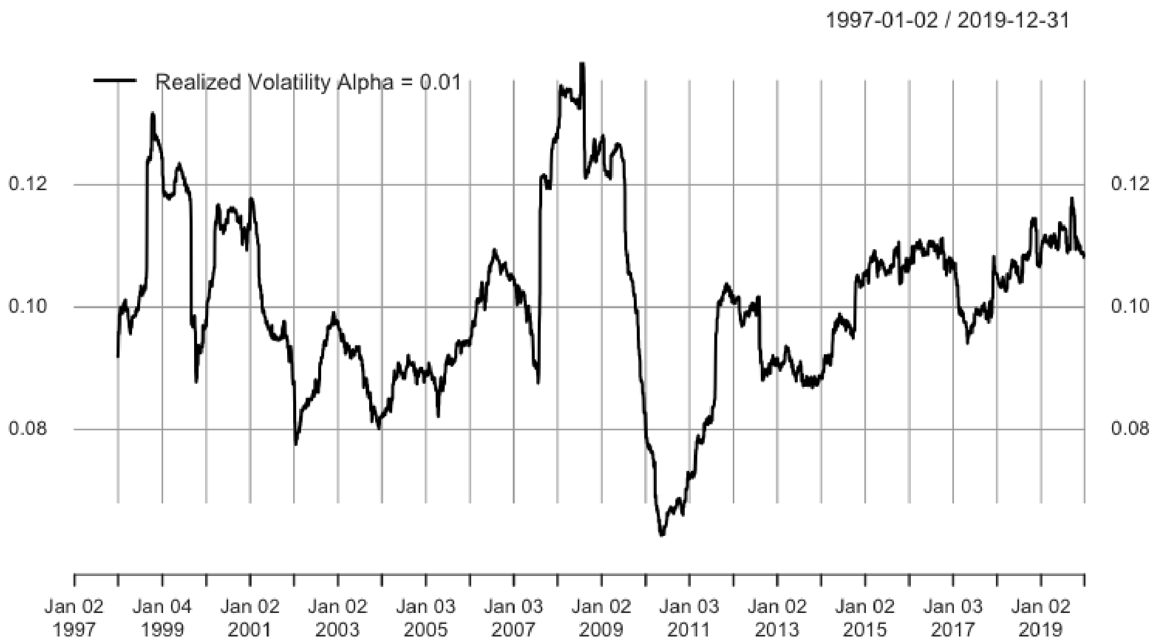


Cumulative Return
1997-01-03 / 2019-12-31
8
6
4
2
Daily Return
0.03
0.02
0.01
0.00
-0.01
-0.02
Drawdown
-0.1
-0.2
-0.3
Jan 03 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

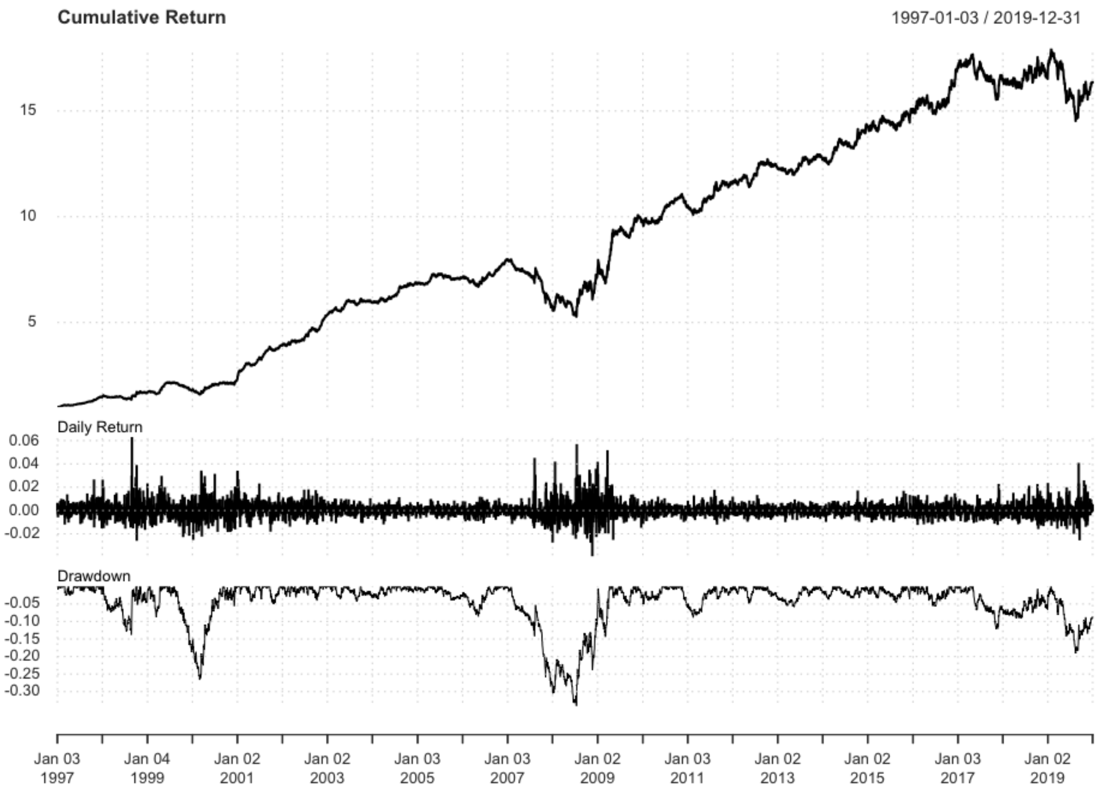

1997-01-02 / 2019-12-31
Realized Volatility Alpha = 0.06
0.12
0.10
0.08
0.12
0.10
0.08
Jan 02 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

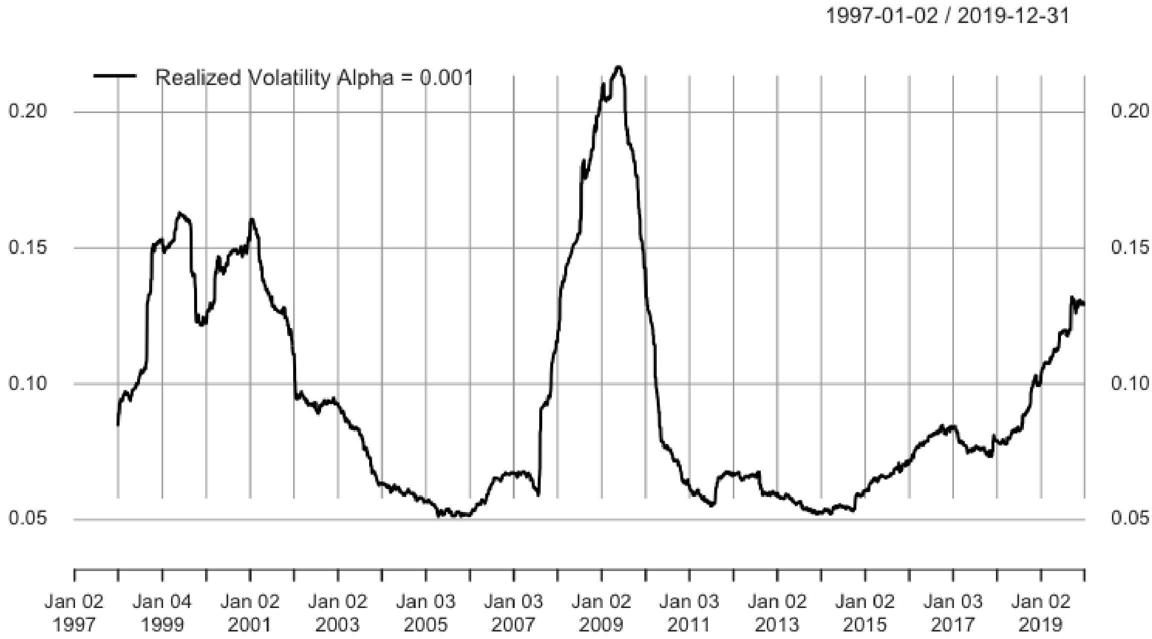
**Alpha = 0.01**


Cumulative Return
1997-01-03 / 2019-12-31
15
10
5
Daily Return
0.04
0.02
0.00
-0.02
Drawdown
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
Jan 03 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019


1997-01-02 / 2019-12-31
Realized Volatility Alpha = 0.01
0.12
0.10
0.08
Jan 02 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

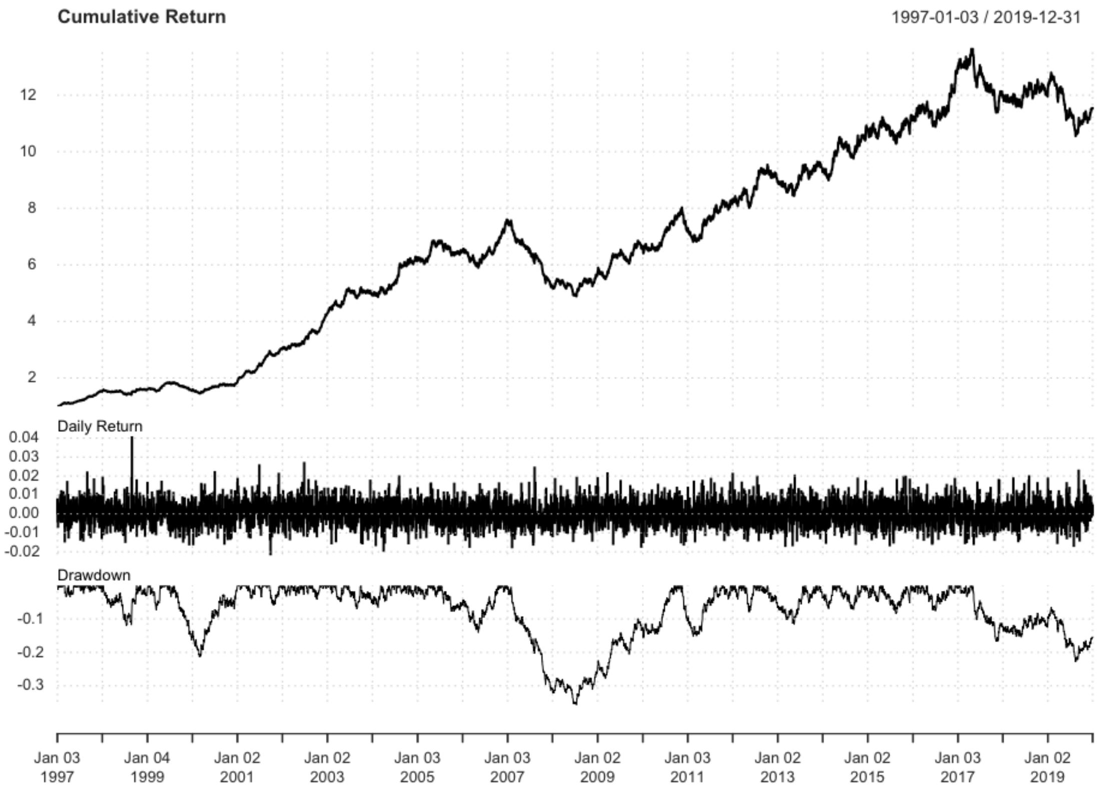
**Alpha = 0.001**

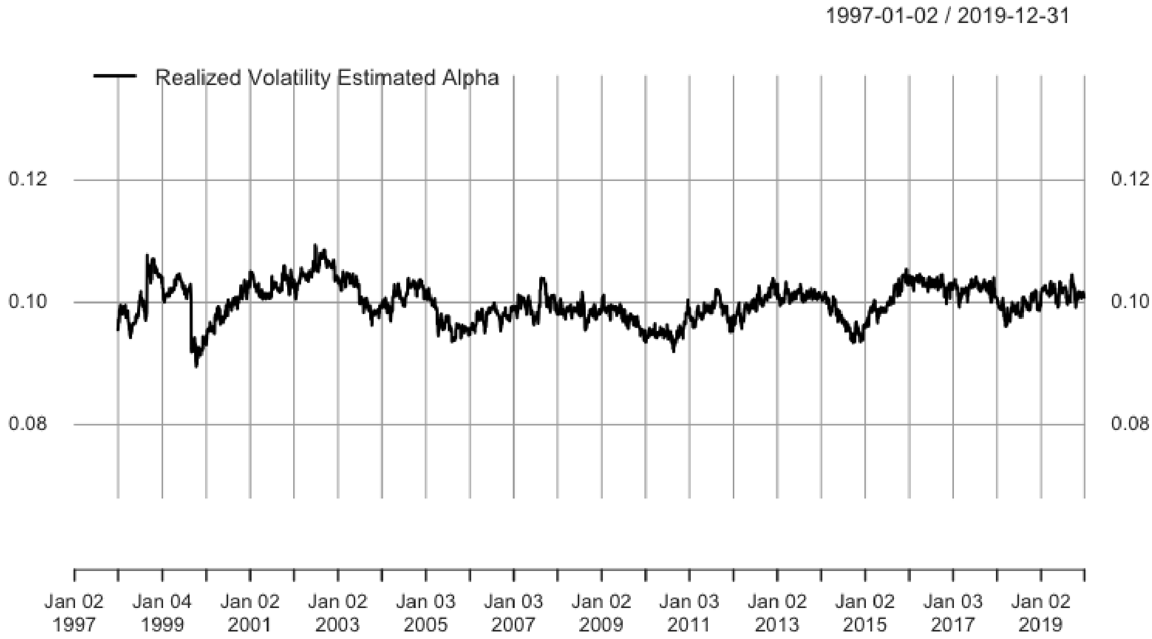

Cumulative Return
1997-01-03 / 2019-12-31
15
10
5
Daily Return
0.06
0.04
0.02
0.00
-0.02
Drawdown
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
Jan 03 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019




## Estimated Alpha

The alpha is based upon a yearly reestimation of the parameter in the I-GARCH model

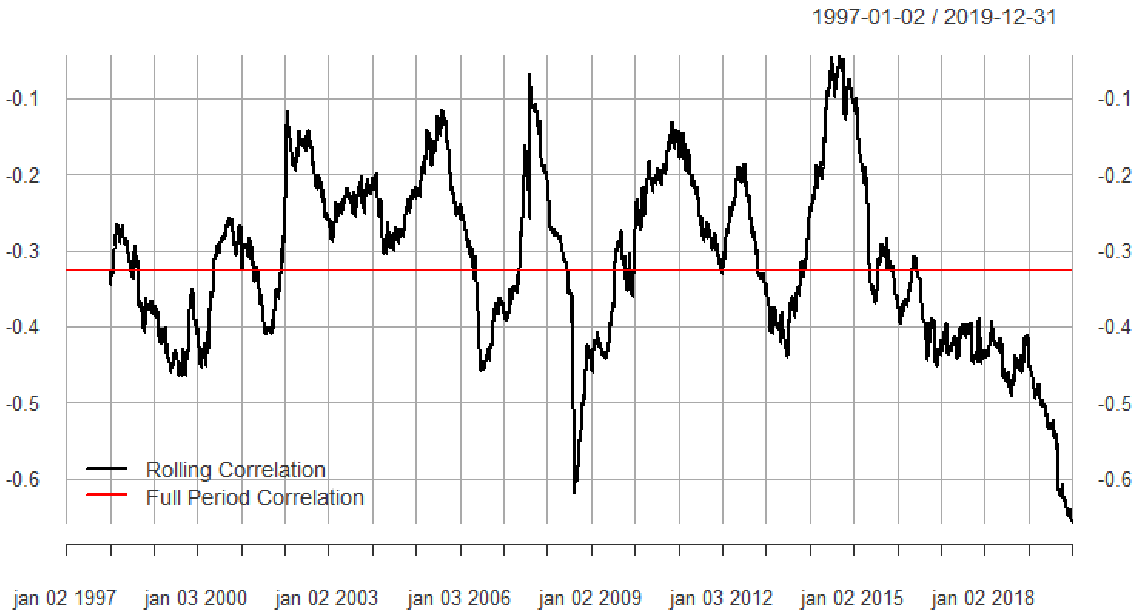



1997-01-02 / 2019-12-31
Realized Volatility Estimated Alpha
0.12
0.10
0.08
Jan 02 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

## A.23 CAPM Regression Volatility Scaled Value

| Scaled Value Strategy | Estimate | t value | $\Pr(>|t|)$ |
|---|---|---|---|
| Alpha | 0.0004 | 4.8147 | 1.51197e-06 |
| Beta | -0.0258 | -4.3027 | 1.71481e-05 |

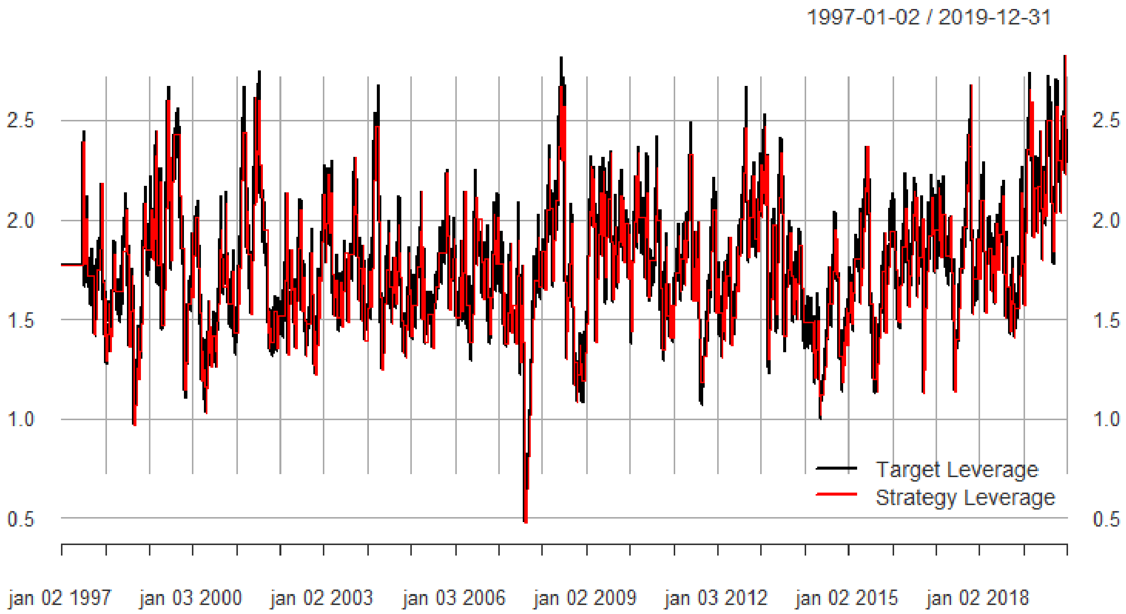
## A.24 Value & Momentum 1-year Rolling Correlation



## A.25 Momentum vs Value Daily Returns

| Momentum ∼ Value | Estimate | t value | Pr(> $\|t\|$) |
|---|---|---|---|
| Intercept | 0.0006 | 6.9668 | 3.60E-12 |
| Beta Value | -0.3299 | -26.1256 | 2.52E-142 |
| **Value ∼ Momentum** | **Estimate** | **t value** | **Pr(> $\|t\|$)** |
| Intercept | 0.0006 | 7.5694 | 4.34E-14 |
| Beta Momentum | -0.3197 | -26.1256 | 2.52E-142 |

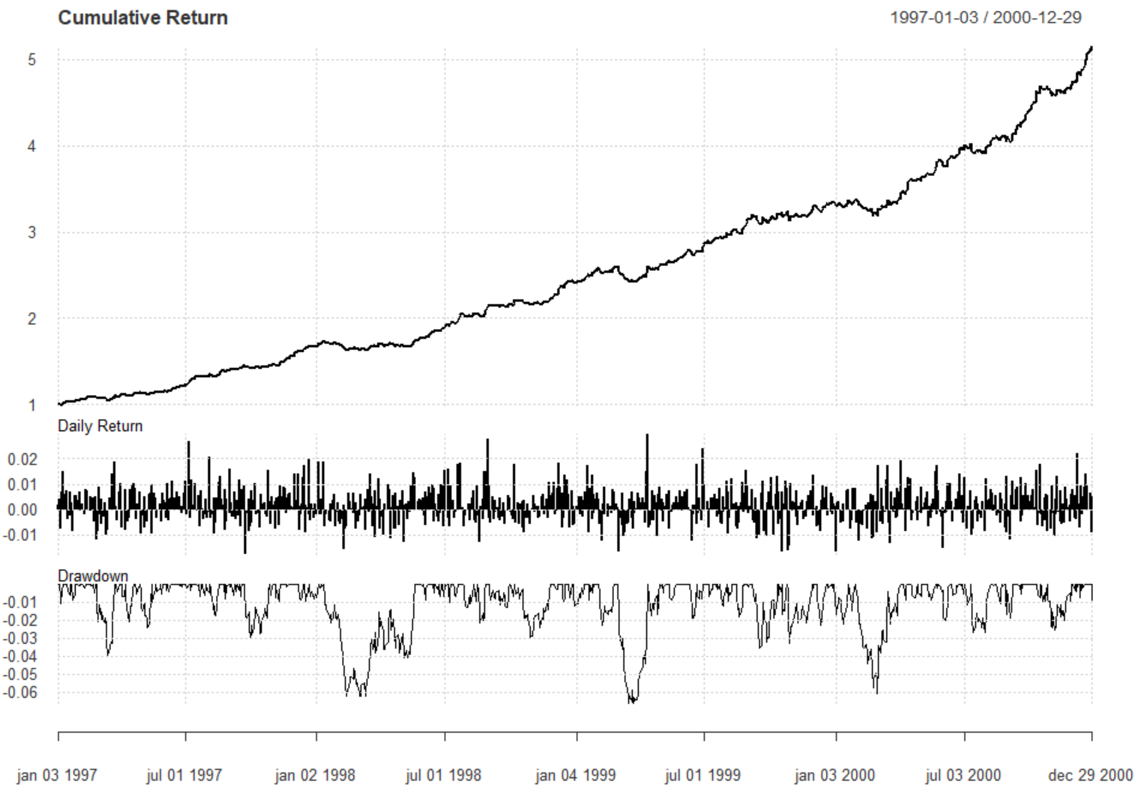
## A.26 Further Leverage on Combined Strategy



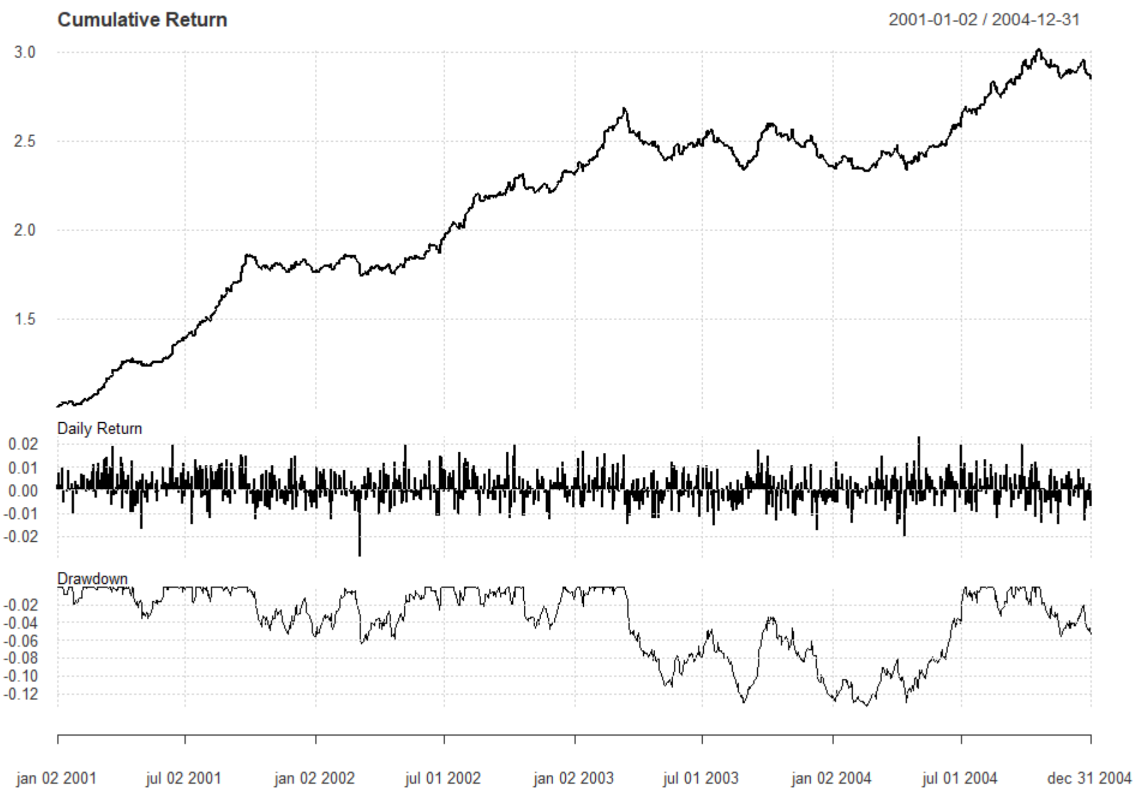
## A.27 Combined Strategy Returns

| Return in % | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Full Year |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1997 | 5.05 | 1.70 | 3.12 | 3.48 | 0.50 | 6.31 | 9.17 | 4.39 | 2.62 | 2.36 | 6.79 | 7.62 | 67.57 |
| 1998 | 1.75 | -3.47 | 3.96 | -1.91 | 5.69 | 5.69 | 7.77 | 5.92 | 0.74 | -0.14 | 3.92 | 7.92 | 44.07 |
| 1999 | 5.67 | 1.56 | -5.19 | 6.44 | 3.58 | 4.53 | 3.73 | 6.35 | -0.56 | 1.06 | 3.17 | 3.62 | 38.94 |
| 2000 | 1.00 | -5.22 | 5.28 | 6.70 | 5.76 | 3.81 | -1.31 | 4.95 | 7.37 | 4.85 | 1.88 | 8.40 | 52.03 |
| 2001 | 1.80 | 6.32 | 12.66 | 3.30 | 0.52 | 10.27 | 7.58 | 10.92 | 11.10 | -3.64 | 0.05 | -1.42 | 75.89 |
| 2002 | 2.83 | 1.52 | -2.37 | 0.51 | 1.94 | 5.88 | 5.84 | 6.19 | 2.67 | -0.33 | -0.96 | 4.10 | 31.10 |
| 2003 | 4.55 | 6.91 | -2.01 | -2.10 | -1.71 | 1.79 | 0.55 | -5.89 | 10.50 | -3.40 | 0.01 | -5.31 | 2.61 |
| 2004 | -1.12 | 1.14 | 4.16 | -3.29 | 3.23 | 5.05 | 4.57 | 3.23 | 4.56 | 0.39 | -0.96 | -1.67 | 20.57 |
| 2005 | 6.29 | 4.92 | 4.58 | 11.04 | -1.54 | 2.37 | -2.75 | 1.18 | 3.32 | 1.79 | 1.88 | -0.41 | 37.05 |
| 2006 | 1.52 | -2.28 | 1.12 | -5.82 | -3.47 | 3.15 | 3.74 | -3.77 | 4.51 | 2.06 | -1.59 | 5.71 | 4.20 |
| 2007 | 4.45 | -8.24 | 1.37 | -4.52 | -3.20 | 0.03 | 1.39 | -2.12 | -0.38 | -2.62 | 0.28 | -3.10 | -15.96 |
| 2008 | -1.33 | 0.24 | 0.35 | -0.03 | 0.18 | 2.02 | 5.16 | 1.42 | 7.42 | 0.63 | 0.66 | 2.03 | 20.07 |
| 2009 | -0.96 | -4.04 | -1.89 | 1.73 | -1.02 | -2.16 | -0.10 | -6.91 | -3.23 | 0.62 | 3.02 | -4.62 | -18.27 |
| 2010 | -2.64 | 0.82 | -0.32 | -2.16 | 7.18 | 10.18 | -0.46 | 5.11 | 0.29 | 2.78 | 2.58 | -9.44 | 13.27 |
| 2011 | 0.46 | 2.15 | 3.76 | 2.63 | 5.19 | 8.49 | 3.01 | 6.48 | 0.45 | 3.77 | 1.37 | 2.62 | 48.31 |
| 2012 | -2.28 | -2.81 | 4.22 | 1.21 | 2.08 | 6.45 | 9.12 | 2.39 | -1.50 | 3.03 | -2.70 | -4.80 | 14.34 |
| 2013 | 0.45 | -0.07 | 1.23 | 2.14 | -2.29 | 5.99 | 4.59 | -1.70 | -0.59 | 0.03 | 1.57 | -3.70 | 7.50 |
| 2014 | 0.58 | -0.10 | 1.75 | 2.71 | 5.00 | -2.02 | -1.81 | -0.01 | 6.30 | 3.93 | 1.07 | 1.90 | 20.69 |
| 2015 | 0.61 | -2.72 | 1.35 | -1.11 | 1.26 | 2.84 | 5.63 | 0.40 | 2.83 | 0.56 | 1.71 | 0.02 | 13.95 |
| 2016 | -0.23 | -2.84 | -0.21 | 1.98 | -1.08 | -3.39 | -0.60 | -0.16 | -2.62 | 4.57 | 1.15 | 3.80 | 0.02 |
| 2017 | -0.75 | 0.93 | 0.52 | 4.75 | -2.55 | 4.15 | -1.58 | 1.57 | -1.49 | -2.38 | 0.16 | 0.60 | 3.69 |
| 2018 | 1.17 | 1.38 | 0.30 | -2.40 | 0.52 | 3.23 | 0.42 | 0.17 | 0.07 | 3.32 | -1.43 | 2.93 | 9.93 |
| 2019 | -0.31 | -2.29 | -1.97 | -0.56 | -1.60 | 6.46 | -1.83 | -0.71 | -3.73 | 5.42 | -0.86 | -1.63 | -4.04 |

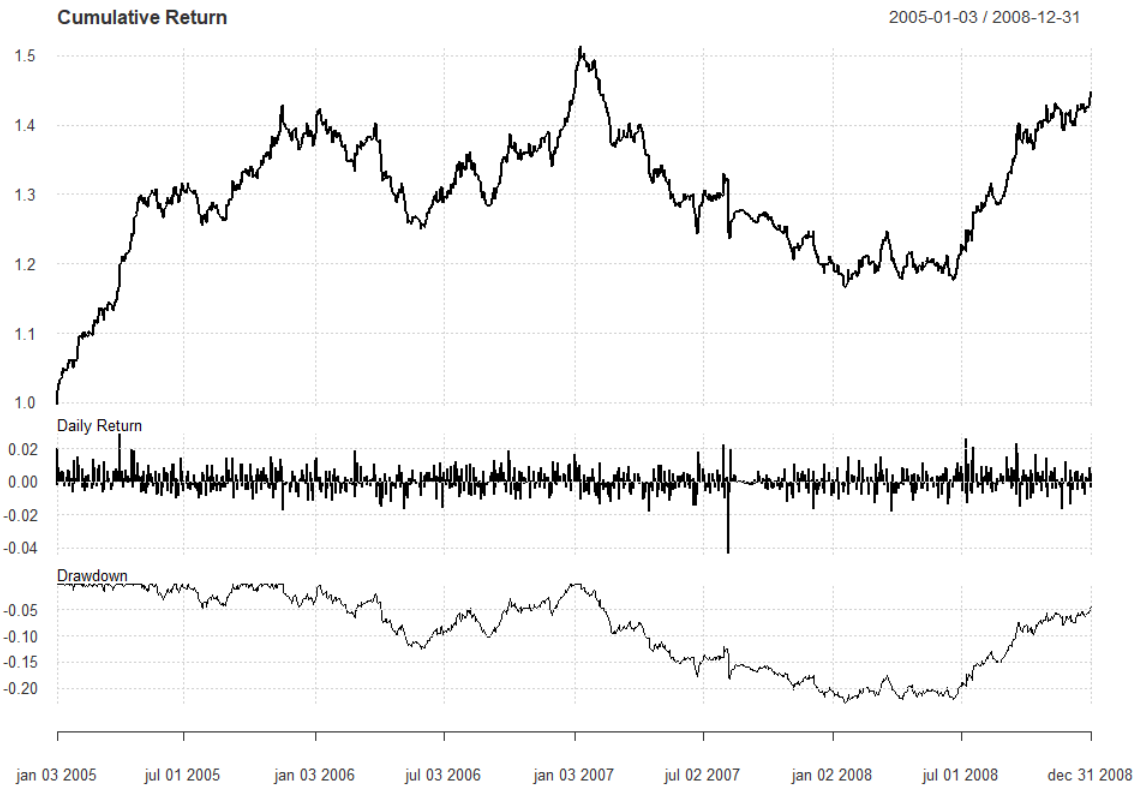
## 1997-2000



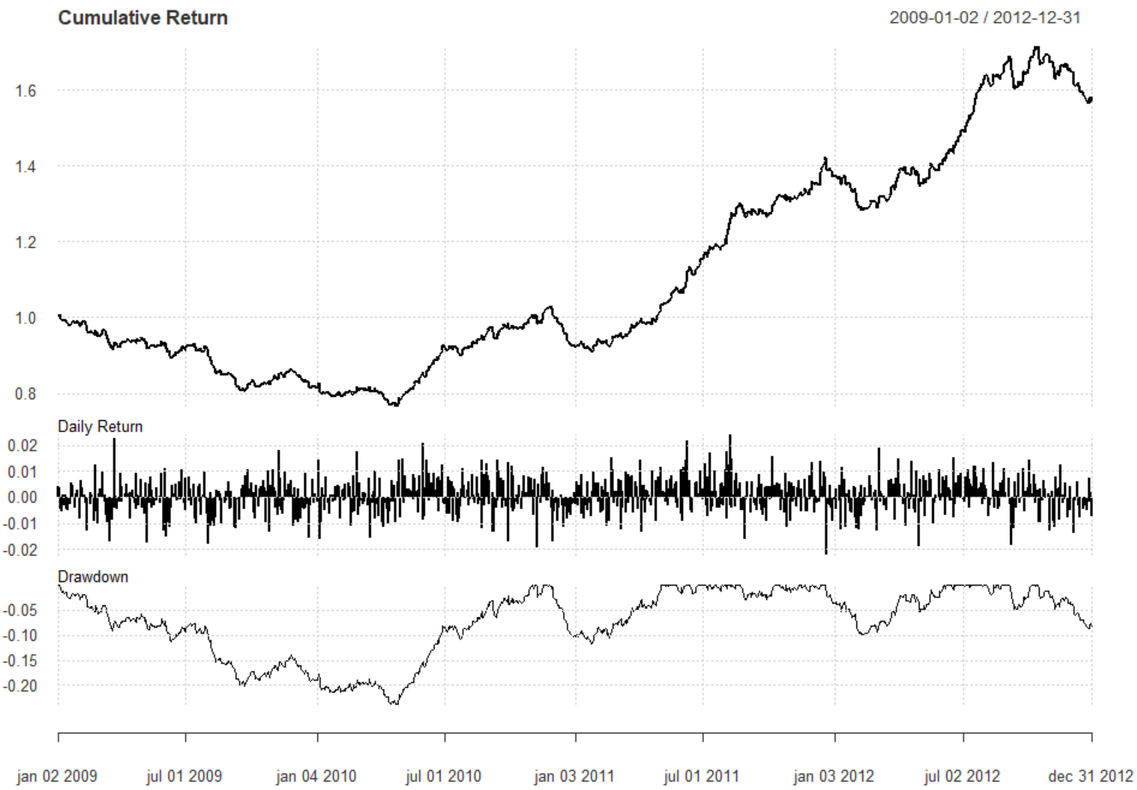

## 2001-2004



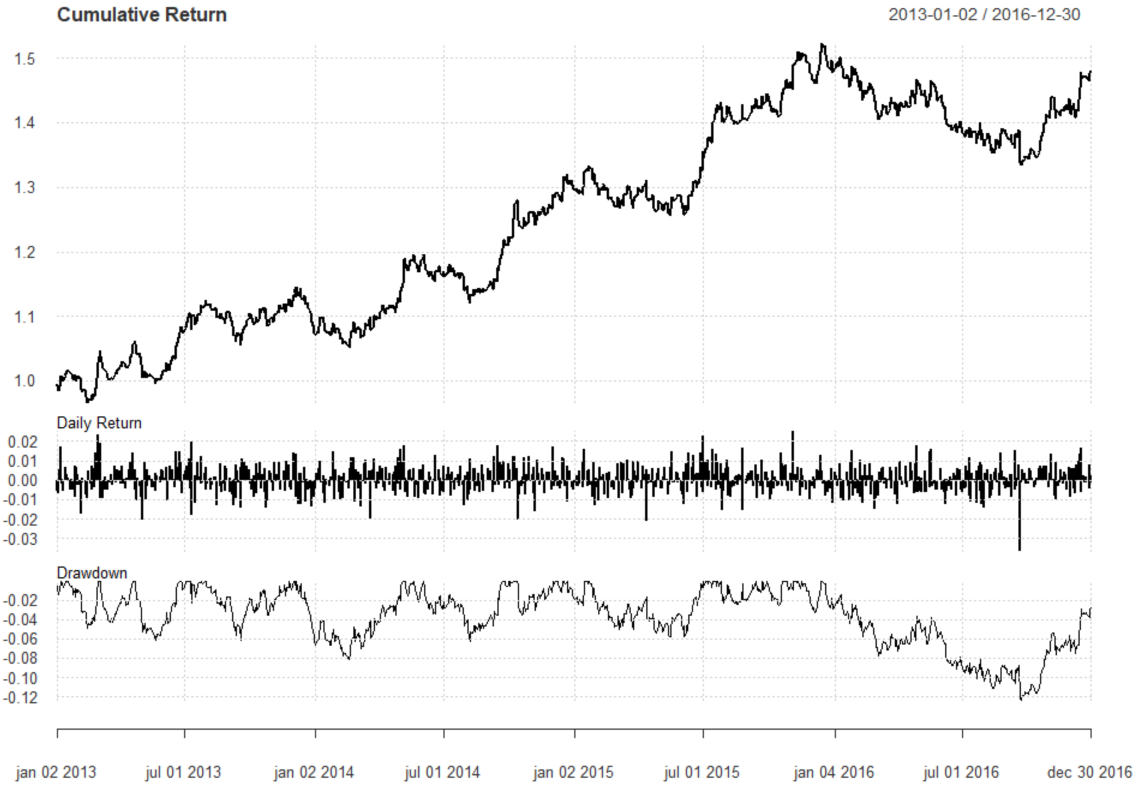
**2005-2008**



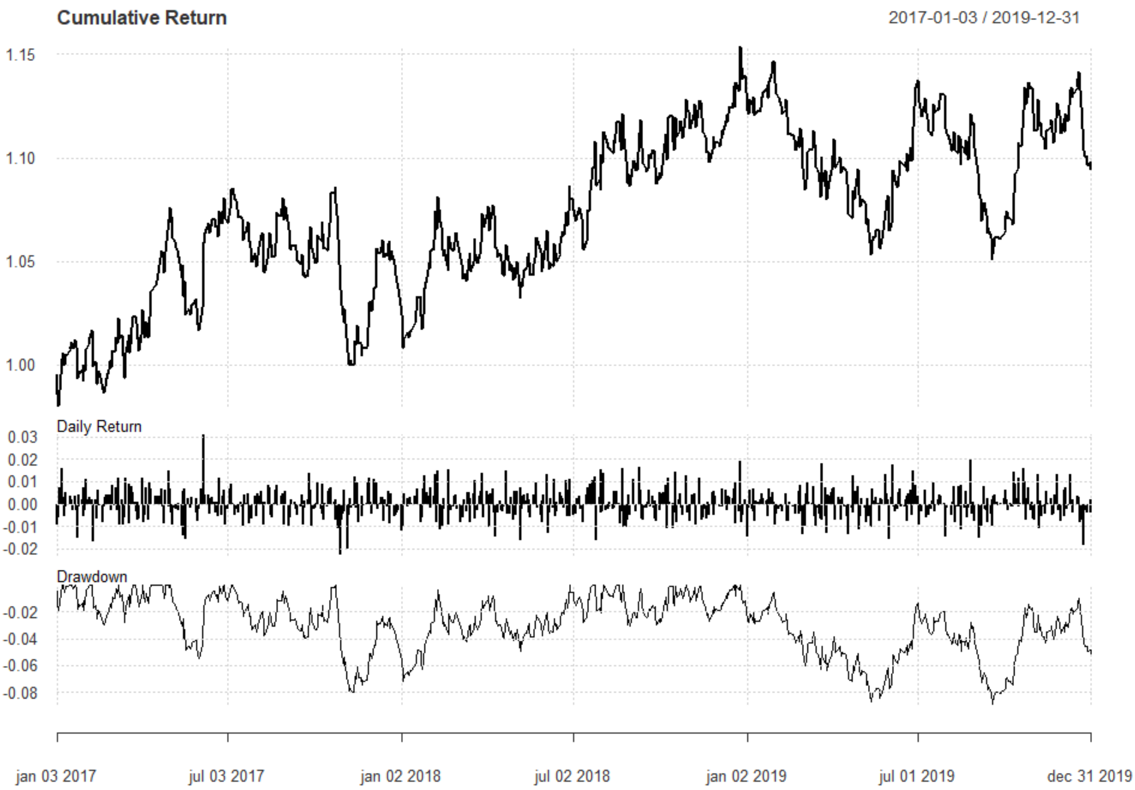

**2009-2012**



**2013-2016**



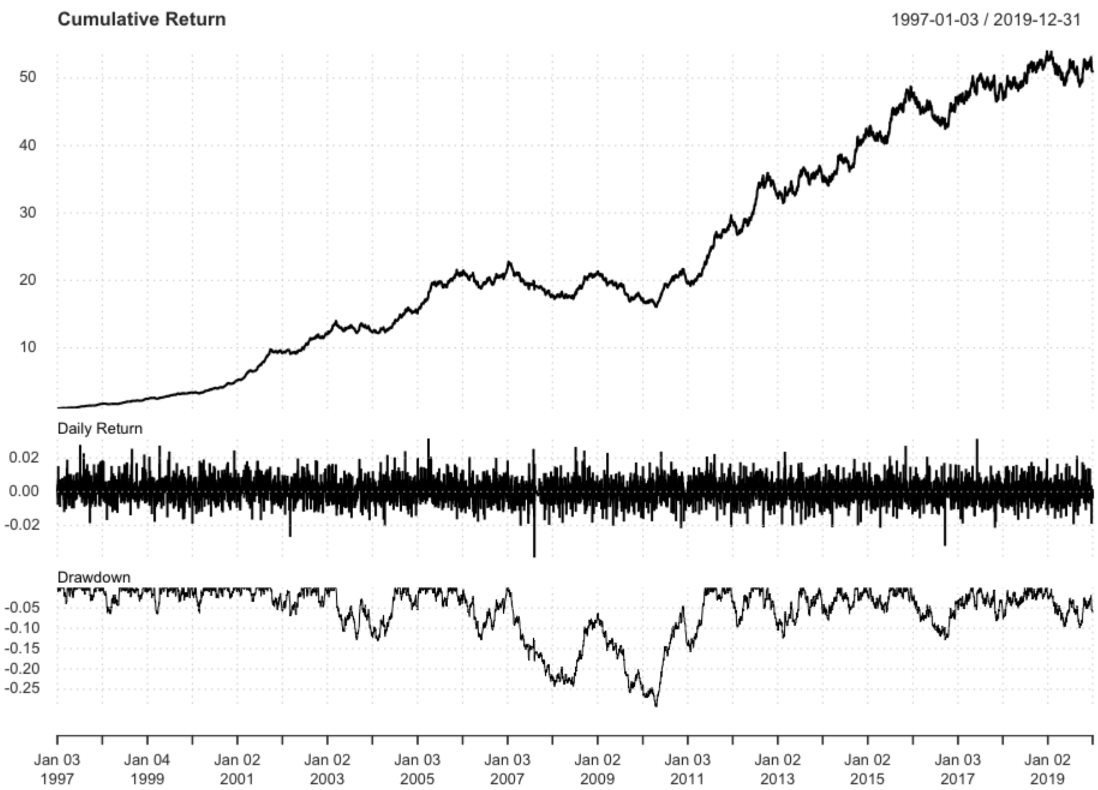

**2017-2019**

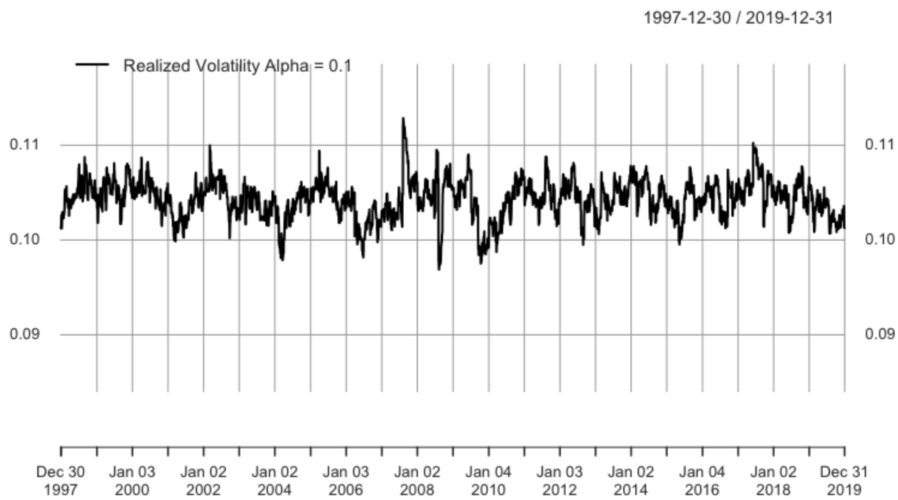


## A.28 Volatility Scaled Combined Strategy with Different Alphas

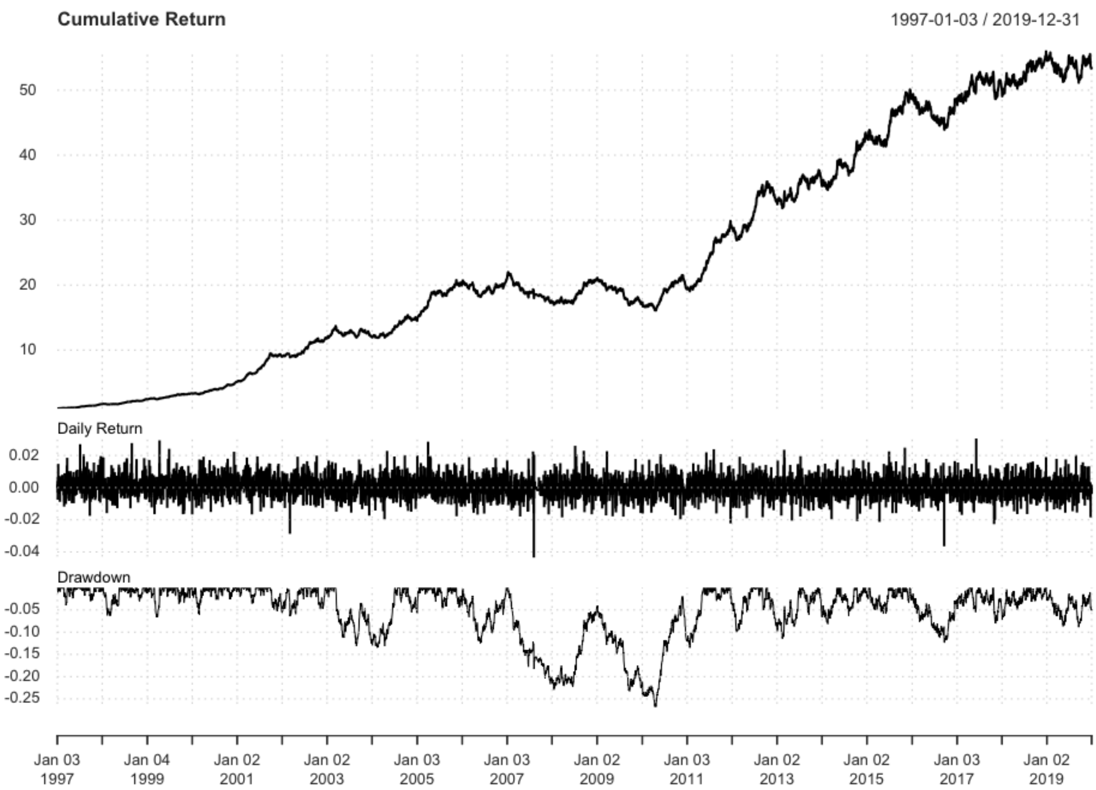
| Combined Strategy | Alpha = 0.1 | Alpha = 0.06 | Alpha = 0.01 | Alpha = 0.001 | Estimated Alpha |
|---|---|---|---|---|---|
| Annualized Return | 0.1864 | 0.1888 | 0.1860 | 0.1917 | 0.1915 |
| Annualized Std Dev | 0.1046 | 0.1026 | 0.1004 | 0.1001 | 0.1027 |
| Annualized Sharpe | 1.6102 | 1.6651 | 1.6742 | 1.7351 | 1.6889 |
| Worst Drawdown | 0.2939 | 0.2685 | 0.2179 | 0.2094 | 0.2387 |

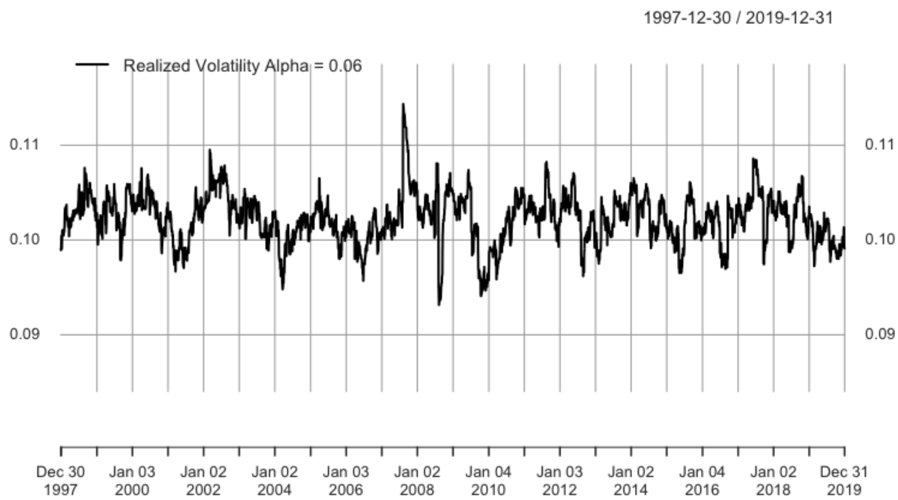
**Alpha = 0.1**


Cumulative Return
1997-01-03 / 2019-12-31
50
40
30
20
10
Daily Return
0.02
0.00
-0.02
Drawdown
-0.05
-0.10
-0.15
-0.20
-0.25
Jan 03 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

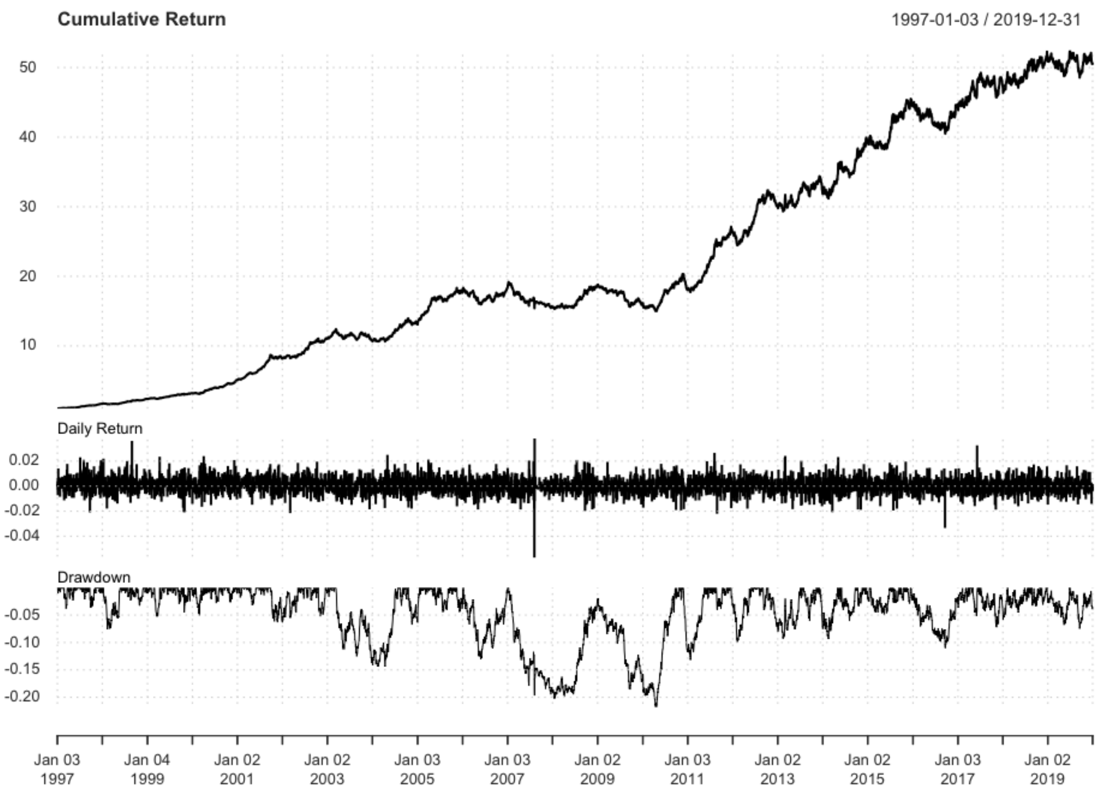

1997-12-30 / 2019-12-31
Realized Volatility Alpha = 0.1
0.11
0.10
0.09
Dec 30 1997
Jan 03 2000
Jan 02 2002
Jan 02 2004
Jan 03 2006
Jan 02 2008
Jan 04 2010
Jan 03 2012
Jan 02 2014
Jan 04 2016
Jan 02 2018
Dec 31 2019

**Alpha = 0.06**

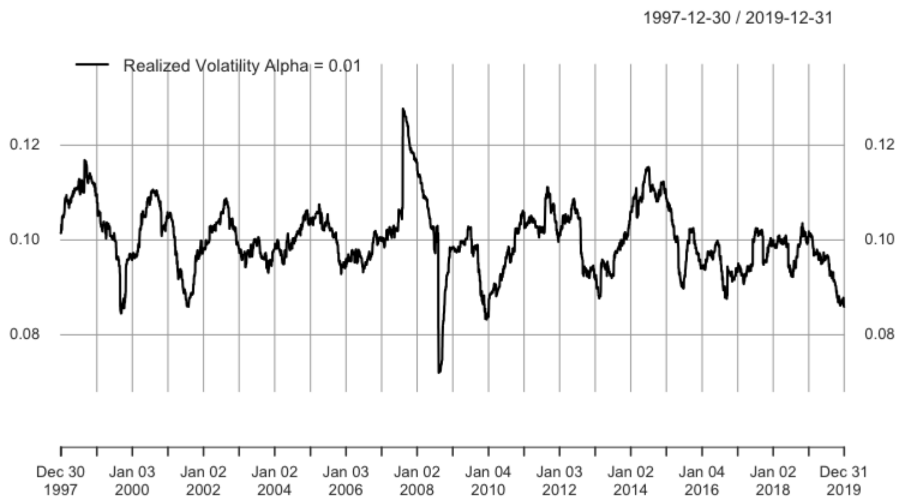

Cumulative Return
1997-01-03 / 2019-12-31
50
40
30
20
10
Daily Return
0.02
0.00
-0.02
-0.04
Drawdown
-0.05
-0.10
-0.15
-0.20
-0.25
Jan 03 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019


1997-12-30 / 2019-12-31
Realized Volatility Alpha = 0.06
0.11
0.10
0.09
Dec 30 1997
Jan 03 2000
Jan 02 2002
Jan 02 2004
Jan 03 2006
Jan 02 2008
Jan 04 2010
Jan 03 2012
Jan 02 2014
Jan 04 2016
Jan 02 2018
Dec 31 2019

**Alpha = 0.01**

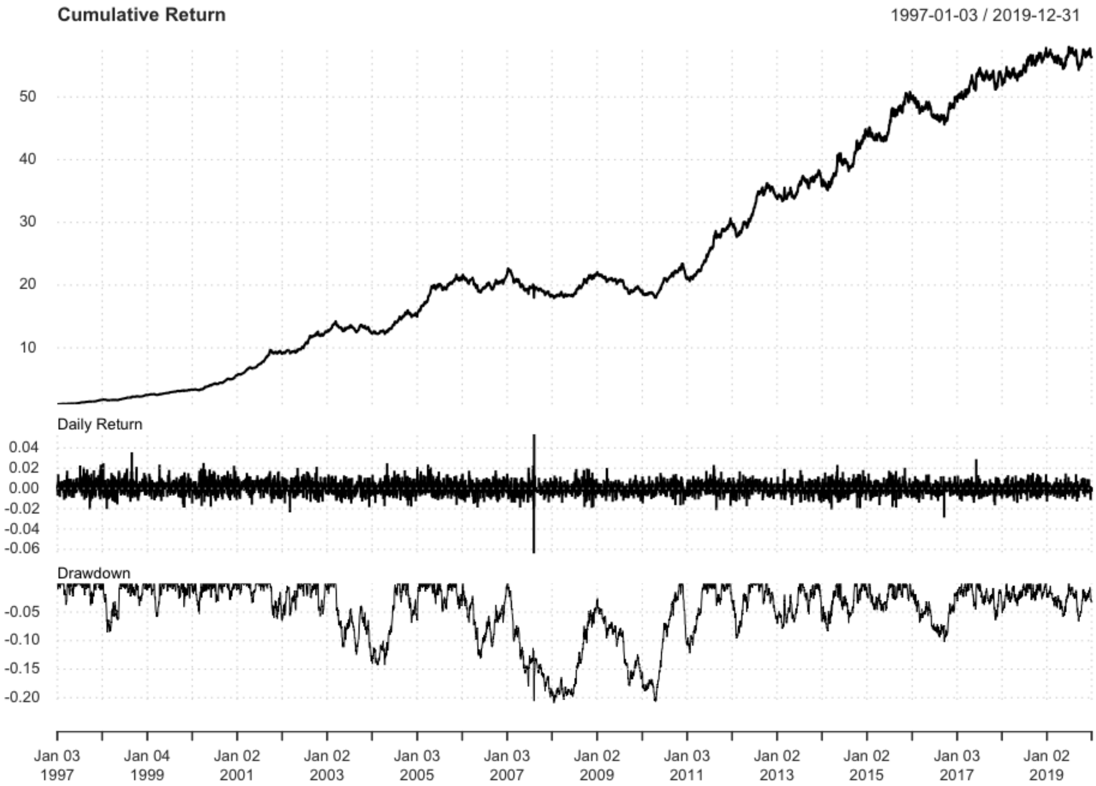


Cumulative Return
1997-01-03 / 2019-12-31
50
40
30
20
10
Daily Return
0.02
0.00
-0.02
-0.04
Drawdown
-0.05
-0.10
-0.15
-0.20
Jan 03 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

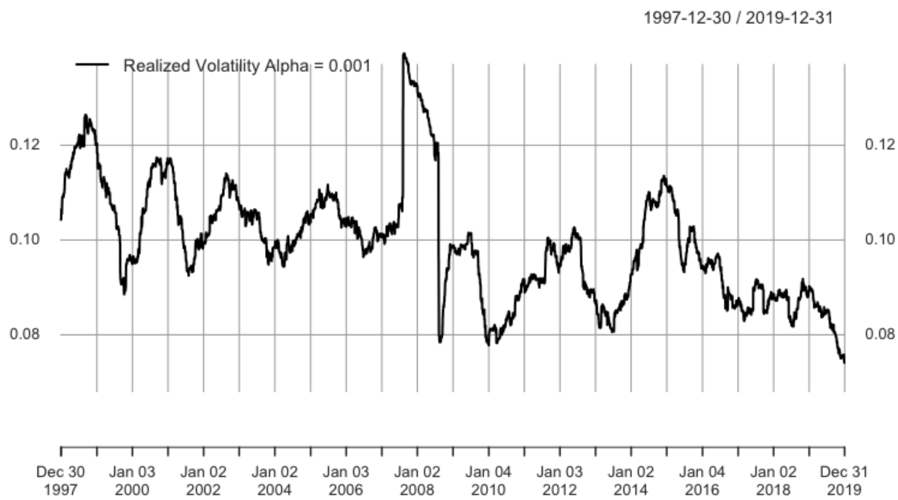



1997-12-30 / 2019-12-31
Realized Volatility Alpha = 0.01
0.12
0.10
0.08
Dec 30 1997
Jan 03 2000
Jan 02 2002
Jan 02 2004
Jan 03 2006
Jan 02 2008
Jan 04 2010
Jan 03 2012
Jan 02 2014
Jan 04 2016
Jan 02 2018
Dec 31 2019

**Alpha = 0.001**



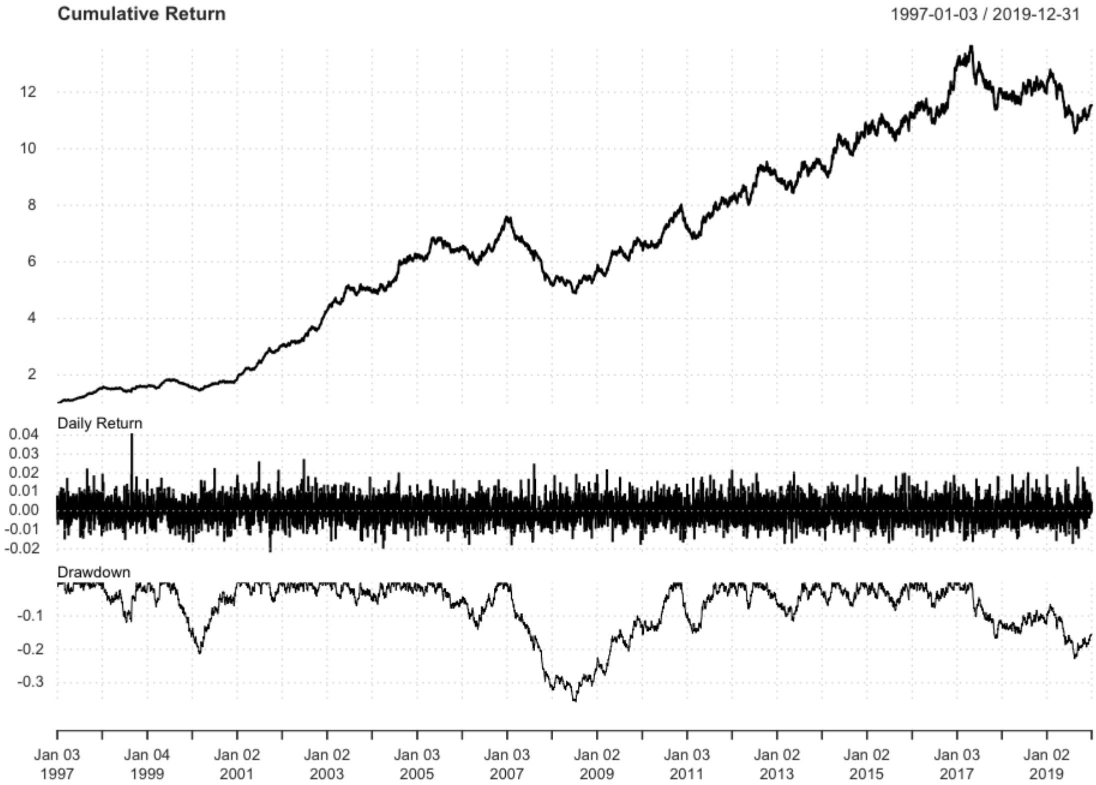
Cumulative Return
1997-01-03 / 2019-12-31
50
40
30
20
10
Daily Return
0.04
0.02
0.00
-0.02
-0.04
-0.06
Drawdown
-0.05
-0.10
-0.15
-0.20
Jan 03 1997
Jan 04 1999
Jan 02 2001
Jan 02 2003
Jan 03 2005
Jan 03 2007
Jan 02 2009
Jan 03 2011
Jan 02 2013
Jan 02 2015
Jan 03 2017
Jan 02 2019

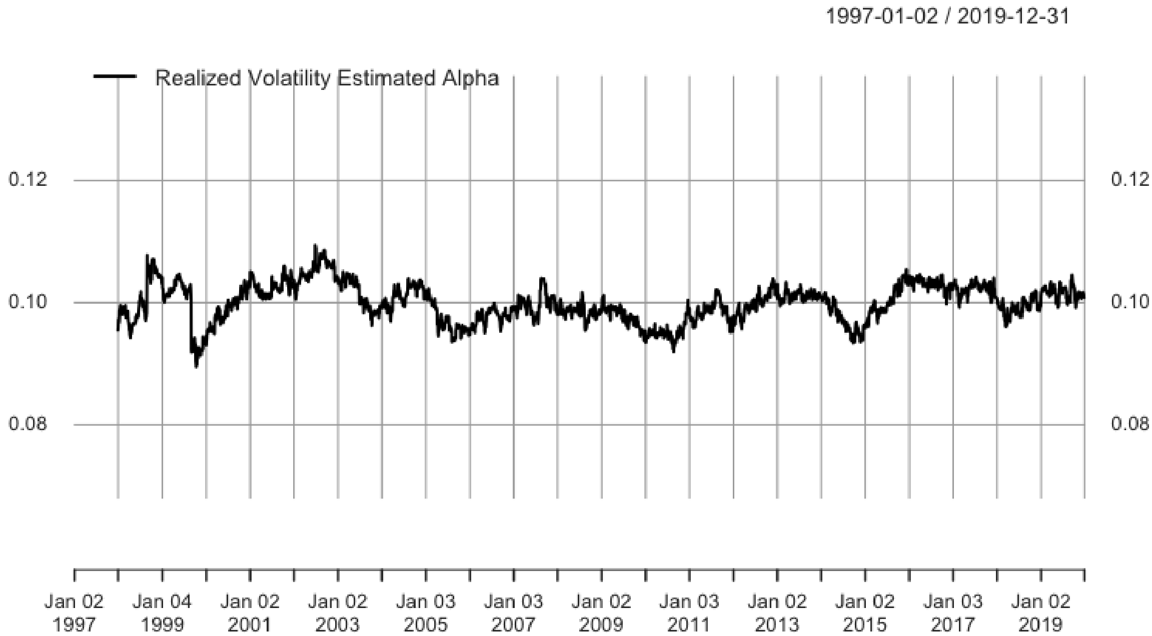



1997-12-30 / 2019-12-31
Realized Volatility Alpha = 0.001
0.12
0.10
0.08
Dec 30 1997
Jan 03 2000
Jan 02 2002
Jan 02 2004
Jan 03 2006
Jan 02 2008
Jan 04 2010
Jan 03 2012
Jan 02 2014
Jan 04 2016
Jan 02 2018
Dec 31 2019

## Estimated Alpha

The alpha is based upon a yearly reestimation of the parameter in the I-GARCH model



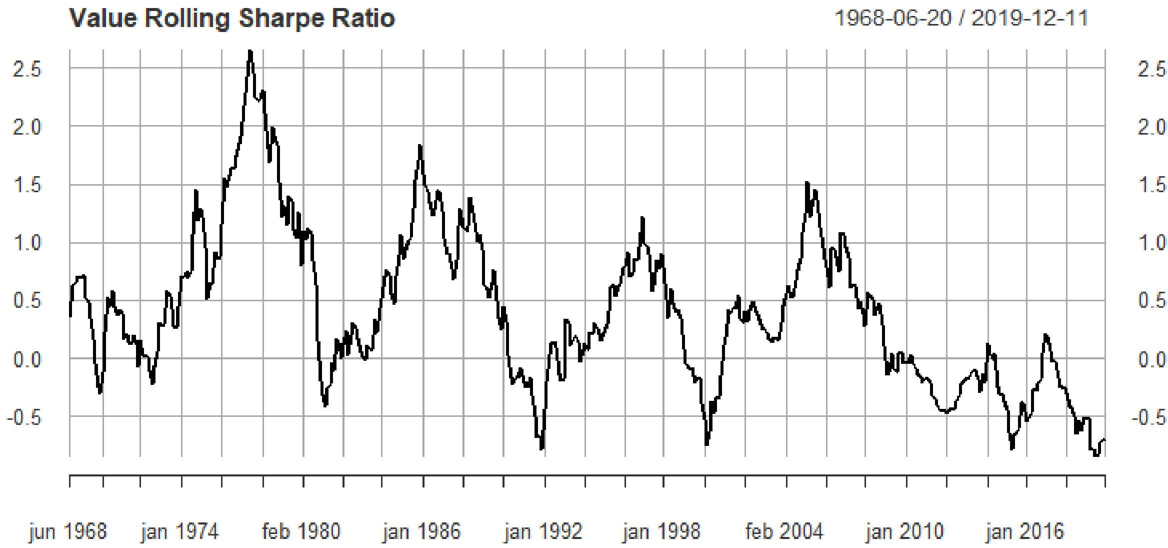



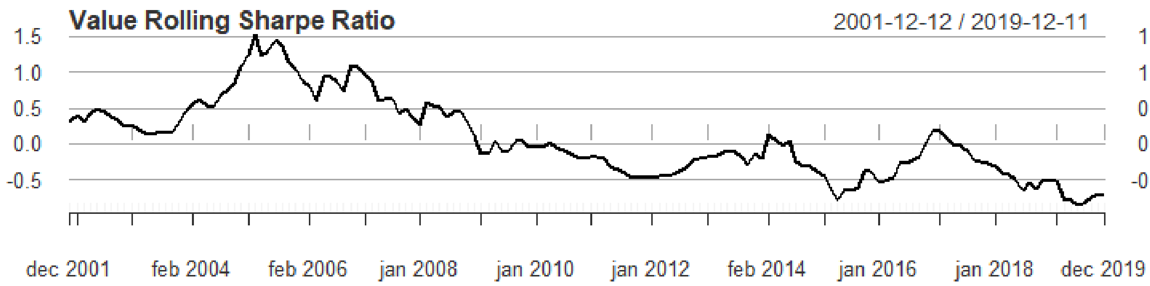
## A.29 CAPM Regression Volatility Scaled Combined Strategy

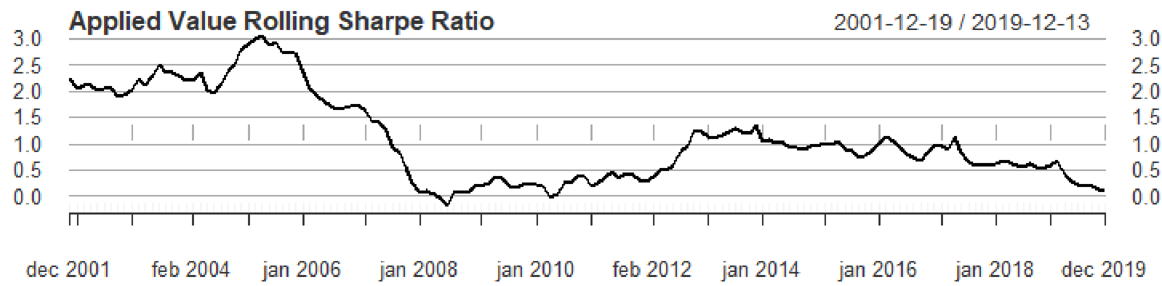
| Scaled Combined Strategy | Estimate | t value | Pr(> $\|t\|$) |
|---|---|---|---|
| Alpha | 0.0006 | 7.5358 | 5.6011e-14 |
| Beta | -0.0255 | 4.2212 | 2.4670e-05 |

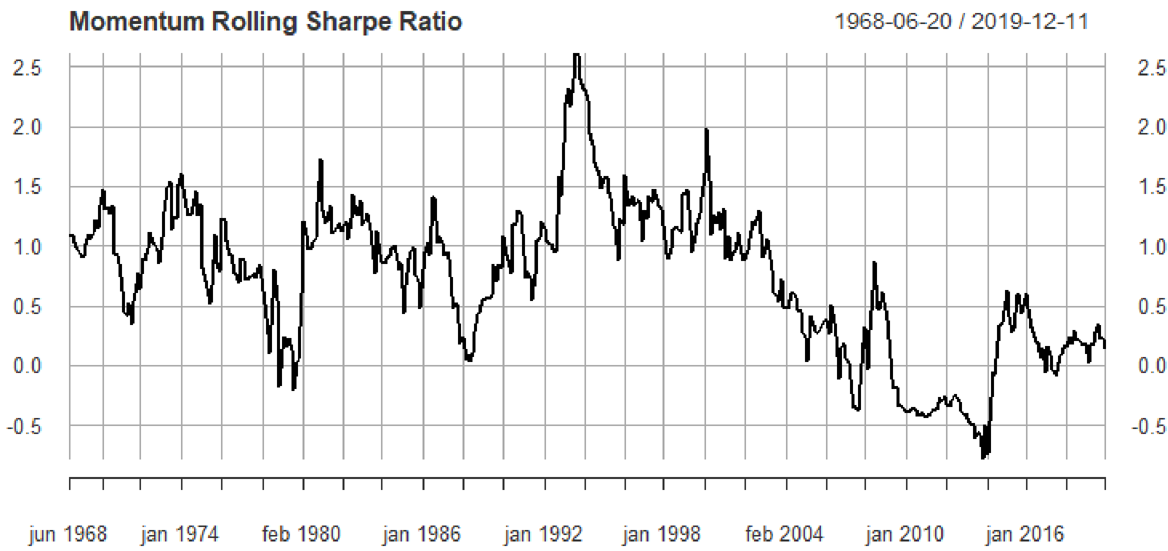
## A.30 Historical Five-Year Rolling Factor Sharpe Ratios

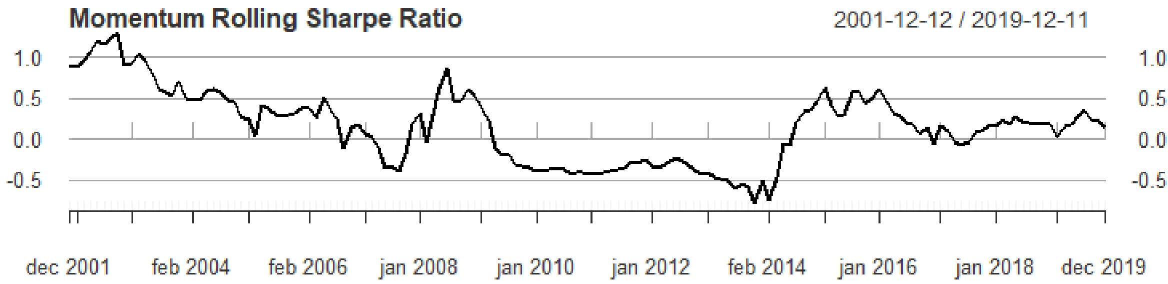
The plots below show the historical five-year rolling Sharpe ratio of the value, momentum and market premium. The factor data was obtained from Kenneth French's data library. The graphs with the applied factors constitutes the factor strategies applied in this paper.

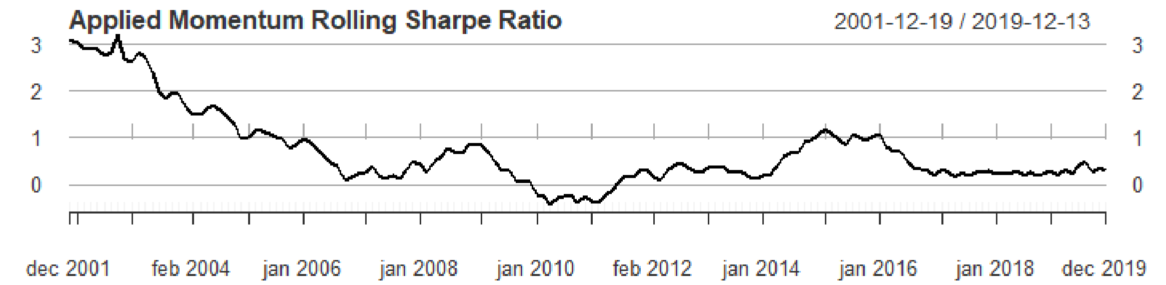


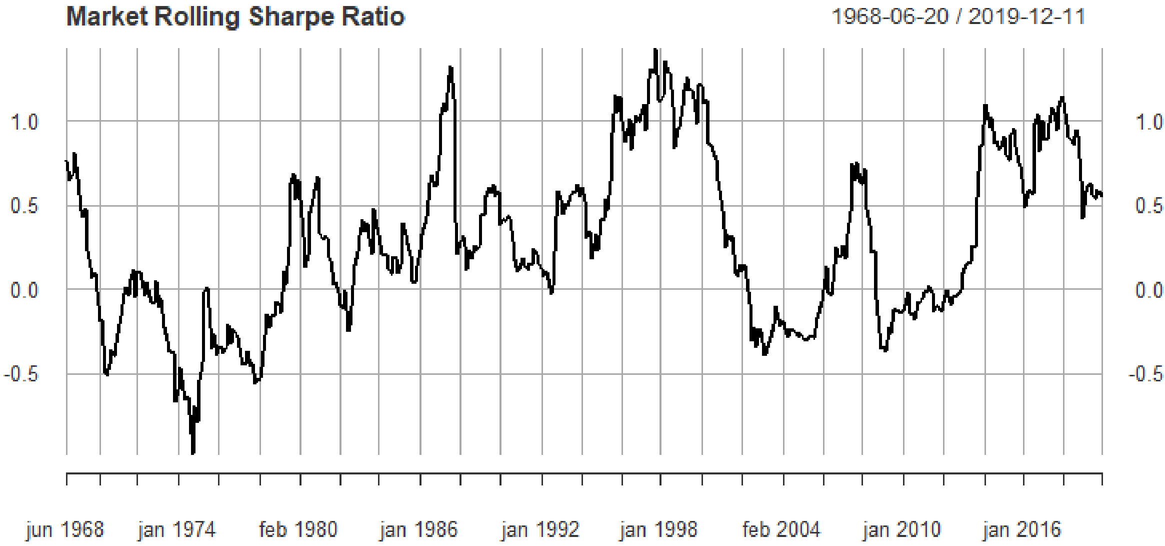



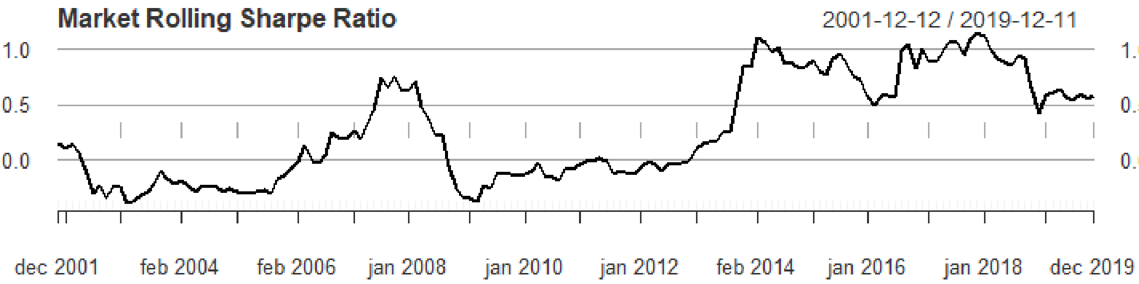



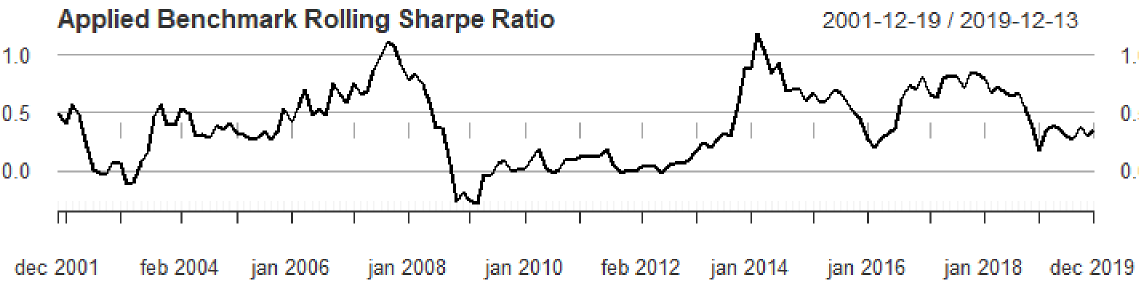

Momentum Rolling Sharpe Ratio
1968-06-20 / 2019-12-11
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
jun 1968
jan 1974
feb 1980
jan 1986
jan 1992
jan 1998
feb 2004
jan 2010
jan 2016


Momentum Rolling Sharpe Ratio
2001-12-12 / 2019-12-11
1.0
0.5
0.0
-0.5
dec 2001
feb 2004
feb 2006
jan 2008
jan 2010
jan 2012
feb 2014
jan 2016
jan 2018
dec 2019


Applied Momentum Rolling Sharpe Ratio
2001-12-19 / 2019-12-13
3
2
1
0
dec 2001
feb 2004
jan 2006
jan 2008
jan 2010
feb 2012
jan 2014
jan 2016
jan 2018
dec 2019


Market Rolling Sharpe Ratio
1968-06-20 / 2019-12-11
1.0
0.5
0.0
-0.5
jun 1968
jan 1974
feb 1980
jan 1986
jan 1992
jan 1998
feb 2004
jan 2010
jan 2016


Market Rolling Sharpe Ratio
2001-12-12 / 2019-12-11
1.0
0.5
0.0
dec 2001
feb 2004
feb 2006
jan 2008
jan 2010
jan 2012
feb 2014
jan 2016
jan 2018
dec 2019


Applied Benchmark Rolling Sharpe Ratio
2001-12-19 / 2019-12-13
1.0
0.5
0.0
dec 2001
feb 2004
jan 2006
jan 2008
jan 2010
feb 2012
jan 2014
jan 2016
jan 2018
dec 2019

# Appendix B. Code and Data Folder

The data and R-code used to create the strategies, and the plots are attached as a zip folder. Before running any scripts, the working directory file "Working Directory.R" needs to be changed, so that the file path leads to the unpacked zip-folder.

The collected data is located in the "data"-folder, which includes the prices, historical constituents, fundamental data, etc. The raw data is stored in excel or CSV files, whereas the processed data is stored in RData files, which can be found in the corresponding "RData"-folder inside the "data"-folder.

The code is located in the "Code"-folder, which is divided into several subfolders. The codes used to sort the portfolios in "Quantile_ports". The code written to create and analyze the strategies is in the "Port_analysis"-folder. The functions explicitly written for portfolio analysis is also included. The data processing scripts are in "data.processing", these include the processing of each individual fundamental ratio, price processing, etc. Finally, some of the functions we have written to assist us are located in the "functions"-folder.

Our collection of literature is also included in the file.