MASTER'S THESIS I 2017

Smart Beta Factor Investing

Enhancing risk-adjusted returns with exposure to risk factors and empirical evidence of market inefficiencies

Alex Mikaelsson and Martin Nilsson

Lund University School of Economics and Management
Department of Economics
Supervisor: Thomas Fischer

Acknowledgements

First and foremost, we would like to extend our gratitude to Granit Fonder AB, who provided us with insight into the asset management industry, assistance in the data collection process as well as valuable advice and guidance during the course of this thesis. We would also like to acknowledge our supervisor Thomas Fischer, who provided us with much appreciated feedback throughout the process.

Abstract

In an attempt to bridge the gap between active and passive investing, Smart Beta strategies have become a popular alternative for investors given their systematic, rules-based approach to portfolio construction and historical tendency to capture market inefficiencies. In this thesis, we examine the performance of Smart Beta strategies versus the S&P 500 and the Euro Stoxx 600 index for time periods 1994-2016 and 2002-2016 respectively. The strategies analyzed are Value, Size, Sharpe-Momentum, Quality and Low Volatility. Given that factor investing and various rules-based strategies have previously been studied in academia, we fill the gap in the literature by providing our own variables to each factor as well as testing their performance across two geographical regions. The empirical analysis conducted in this thesis indicates that nine out of ten Smart Beta portfolios outperform their respective benchmark index on a risk-adjusted basis. We therefore conclude that Smart Beta strategies can serve as a superior alternative to passively investing in a cap-weighted index, which questions if markets are truly efficient from an asset allocation standpoint.

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1. Introduction

1.1 Background

The concept of utility is generally referred to as an abstract measurement of total satisfaction an individual receives from consuming a good or service. According to the neoclassical economic theory of utility optimization, rational individuals should then be willing to exchange these goods and services on the market in order to maximize their respective utility. From an investor perspective, utility is easier to define as rational individuals should behave in a risk-averse manner in order to achieve the highest amount of expected future return given the lowest amount of possible risk (Markowitz, 1952). This brings us to the more practical issue that investors face today, which is creating a portfolio of assets that generate returns in excess of the market. However, according to neoclassical theory, this should not be possible as long as markets are efficient (Fama, 1991). Financial markets should in theory be one of the most efficient markets today given how fast information is transferred and the speed at which prices adapt. The average time an investor held a security on the New York Stock Exchange in the 1960's was approximately eight years (NYSE, 2010) and with the introduction of automated trading and the increase in the amount of available information, average holding times have been reduced to weeks or days rather than years. The markets have arguably never been as quick in pricing as today, leaving little room for the everyday investor to compete for the ever-sought excess returns on the market. Nevertheless, investors always face the question of whether to trade on the market with their own knowledge in order to gain additional utility, known as active investing, or simply follow the market as a whole by investing in the market portfolio, more commonly known as passive investing (Bowen et. al., 1993). The question of which strategy is the best is still up for debate so in an attempt to bridge the gap between these two contrasting strategies, Smart Beta investing has become a popular alternative. Many investors believe Smart Beta strategies combine the best of both worlds, providing an alternative that expands the opportunities of portfolio construction. To quote research affiliates, who are renowned for being one of the global leaders in Smart Beta and asset allocation: "*Smart beta strategies are designed to add value by systematically selecting, weighting, and rebalancing portfolio holdings on the basis of factors or characteristics other than market capitalization*" (RA, 2017).

Despite the flashy name, Smart Beta is not a revolutionary strategy given that related concepts such as factor investing and rules-based strategies have been around in academia for decades. In the 1960's, Jack Treynor (1961), William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966) proposed the Capital Asset Pricing model (CAPM), which states that the return of an investment is a function of its exposure to the market factor, Beta. Expanding on this model, Stephen Ross (1976) proposed the Arbitrage Pricing Theory (APT), which allowed for several factors to explain asset returns. Since then, several studies have been conducted showing that exposure to factors such as Size, Value and Momentum have provided returns in excess of the market. The goal of Smart Beta is therefore to provide investors with exposure to factors that persistently drive returns, using a transparent and rules-based approach (Amenc et. al., 2015).

One of the first questions that come to mind when discussing the topic of Smart Beta is whether these strategies constitute an active or passive investment strategy. Smart Beta resembles passive investing in the implementation process, which as mentioned earlier, is systematic, rules-based and transparent. At the same time, it also resembles a form of active investing considering that the objective of Smart Beta is to increase risk-adjusted returns by providing exposure to certain factors. The diplomatic answer to the above question is that the Smart Beta is somewhere in between.

1.2 Thesis objective and disposition

The focus of this thesis is to identify whether Smart Beta investing can serve as a superior alternative to passively investing in a cap-weighted market portfolio. In order to test this, we will generate Smart Beta portfolios with exposure to risk factors widely acknowledged in academia such as Value, Size, Quality, Momentum and Low Volatility. We then measure the performance of these portfolios against traditional cap-weighted stock indices over time. We provide more width to the empirical analysis by examining the performance of our Smart Beta portfolios against both a U.S and European benchmark index. We find that nine out of ten portfolios exhibit superior risk-adjusted returns compared to their respective benchmark indices between 1994 and 2016 in the U.S. and between 2002 and 2016 in Europe.

The paper is divided into seven sections beginning with the introduction, which provides background on the subject of financial economics and Smart Beta strategies. Section two provides insight into previous studies relating to Smart Beta. Section three is dedicated to a more in-depth review of the theory analyzed in this thesis and their relation to Smart Beta. The fourth section offers a review of the factors analyzed in this thesis along with the variables underlying each factor. Section five explains the thesis data and methodology with insights into the security selection, weighting scheme and performance measurements. Section six presents the empirical results for our study followed by an analysis relating to previous studies. The last section is devoted to our own conclusions and suggestions to further research.

2. Theory

This section covers established theories within the field of Financial Economics on which Smart Beta investing has its roots. They are presented to provide background on contemporary asset pricing theories and serve as the basis for one of the thesis hypotheses this paper delves into: Are markets truly efficient? In this section, we cover the Efficient Market Hypothesis (EMH), the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT).

2.1 Efficient Market Hypothesis (EMH)

The concept of efficient markets was first introduced by Fama et. al. (1969) and theorized around how prices of securities and other assets adjust when new information is released to markets. An efficient market was originally defined as one that "*...adjusts rapidly to new information.*", but was revised two decades later as data transmission had become visibly seamless. This allowed Fama (1991) to redefine the hypothesis of prices to "*...fully reflect all available information*". The newer definition therefore fully disregards cases of asymmetric information in what contemporary financial economists refer to as efficient markets. In this sense, the hypothesis predicts that it is impossible to achieve excess returns through stock market expertise, since all available information is reflected in the price of securities. Furthermore, since all information to date is reflected in the price of a security, the only factor that can influence prices is tomorrow's news. Assuming that news are unpredictable, the hypothesis tells us that the market completely follows the idea of a random walk in the sense that all subsequent price changes will be a random step away from the last registered price of the security. This makes outperformance a game of chance and beating the market consistently is therefore an impossible feat according to the EMH, rendering smart beta investing a futile operation.

The EMH has been criticized over time where several contemporary financial economists point to irrational human behavior as one of the main antagonists of the theory. Robert J. Schiller (2000) discussed that investors tend to exhibit irrational exuberance, which refers to a situation where people develop misplaced confidence in the economy and financial markets. Periods of irrational exuberance are characterized by economic agents becoming less risk-averse, inflated asset prices, increased borrowing and herd behavior. Historical examples include the most recent financial crisis of 2007-2009, the dotcom bubble of the early 2000s and the period which led up to the great depression in 1929. Grossman and Stiglitz (1980) also posited that if financial markets are efficient, and if all information needed is reflected in the price of a security, then there would be no incentive for investors to spend money on research, which they obviously do. In this thesis, we attempt to outperform the market index to see if the EMH holds.

2.2 Capital Asset Pricing Model (CAPM)

In the 1960's Jack Treynor (1961), William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966) attacked the problem of optimal portfolio selection and introduced us to the perspective of the CAPM, which is defined as follows:

$$\bar{r}_a = r_f + \beta_a(\bar{r}_m - r_f) \qquad (1)$$

Where $\bar{r}_a$ is the expected return of asset a, r_f the risk-free rate of return, β_a the systematic risk factor Beta and $\bar{r}_m$ the expected return of the market. Stemming from Markowitz's (1952) portfolio theory, the CAPM provides a simple one-factor asset pricing model that attempts to capture excess market return. The theory argues that the expected return of any given security depends on its exposure the systematic risk factor. Subsequently, the only way an investor can earn higher return is to take on higher levels of risk. In other words, CAPM essentially captures the amount of risk premium, $(\bar{r}_m - r_f)$, investors demand in order to take on a riskier asset.

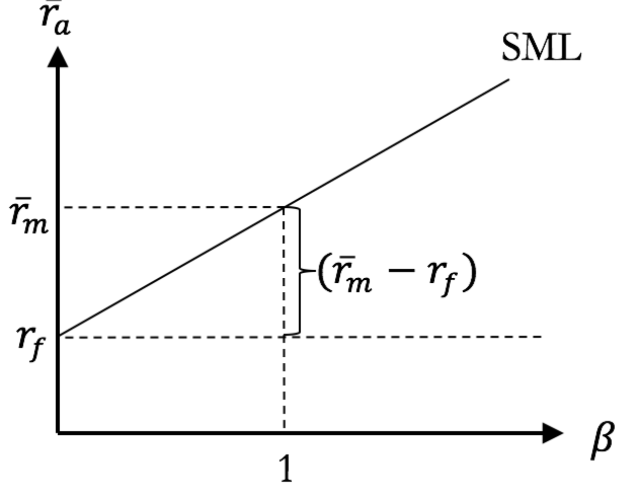


Figure 1: The security market line (Sharpe, 1999)

In technical terms, the model uses a setting with risk-averse investors who may invest in or borrow at the risk-free rate*, r_f, and are able to short any assets. Allowing for investments in the risk-free rate enables investors to secure any portion of its portfolio with a fixed return and thus marks a minimum level of return for other riskier assets. A security must therefore exhibit returns in excess of the risk-free rate for it to be an attractive investment. The risk level is captured by the asset's beta, β_a, where a higher beta represents a higher return at the cost of more risk.

* Risk-free rate is typically derived from the 3-month U.S. T-bill. (Appendix E)

The CAPM creates a linear security market line (SML), which shows the expected return contingent on the level of risk associated with each asset (Figure 1). A beta of one signals an expected return in line with the market and should any firm deviate from the SML, there will occur profitable opportunities due to arbitrage. The relationship between risk and return should cause the risk-adjusted return, or Sharpe ratio, to remain constant regardless of portfolio strategy.

Commonly iterated points of criticism towards the CAPM are its reliance on unrealistic assumptions, such as the assumption that investors have direct access to credit at risk-free rates. In fact, borrowing for an investor is likely more expensive than what the model suggests. Since most investors will not be able to borrow at the risk-free rate, the CAPM should therefore overestimate the expected return of an asset. Empirical evidence suggests that this is true such as Banz (1981), who claimed that the CAPM overestimates the expected return of large companies while underestimating the expected return of small ones. Mistrust against the CAPM coupled with the hunt for returns in excess of the market has investors searching for exposure to alternative risk factors other than the market. This inevitably has a connection to Smart Beta.

2.3 Arbitrage Pricing Theory (APT)

In 1976, Stephen Ross extended the CAPM framework by proposing the Arbitrage Pricing Theory (APT). This model builds on the CAPM's ability to price assets but instead incorporates several factors that explain returns other than exposure to the market factor. Ross suggested that there an infinite number of factors that have the ability to explain the return of an asset. The expected return of a portfolio according to APT is therefore captured by the following equation:

$$r_a = r_f + \beta_1 f_1 + \beta_2 f_2 + \cdots + \beta_n f_n \tag{2}$$

Where the rate of return, r_a, depends on the risk-free rate, r_f, the sensitivity of asset i's return to a factor, β_i, and the risk premium related to that factor, f_i. This captures the idea that variables influence the return of an asset in two steps. First, each specific influence (inflation, unemployment, firm-specific etc.) is determined. Second, the sensitivity to each specific influence is considered.

By allowing factors to be fluent and interchangeable, Ross' approach paved the way for economists to adopt multi-factor thinking into contemporary asset pricing models. The wide approach allowed the model to be more flexible in its assumptions and therefore applicable in a wider range of scenarios than its predecessor, the CAPM. However, what the model gains in customization it loses in utilization. The flexibility and namely the feature to capture any assetinfluencers requires rigorous research, and in extreme cases it is difficult to determine enough explanatory factors for it to have practical application. The idea of multi-factors naturally reached Smart Beta investing as well, and this paper leans on much of Ross's ideas as we use multiple underlying variables to create our factors.

3. Previous studies

In this section, we attempt to provide general results from previous, well-known studies relevant to this thesis. We start by examining famous papers within factor investing followed by more recent studies regarding Smart Beta.

3.1 Factor investing

Two professors and colleagues at the University of Chicago, Eugene Fama and Kenneth French (1993) established what constitutes one of the cornerstones in contemporary factor investing, namely the Fama and French three-factor model. This model expands on the CAPM by adding factors Value and Size. They proposed a regression model as follows:

$$r - R_f = R_f + B_3 \; x \; (R_m - R_f) + b_s \; x \; SMB + b_v \; x \; HML + \alpha \tag{3}$$

Where r is the return of the portfolio, R_f is the risk-free rate of return and R_m the return of the market portfolio. SMB stands for "small minus big" and states that by buying small cap stocks and shorting large cap stocks, investors can earn returns in excess of the market over the long run. HML stands for "high minus low" and essentially states that by buying Value stocks, i.e., stocks with low price-to-fundamental ratios, and shorting growth stocks, investors can also earn returns in excess of the market. Fama and French eventually discovered that a portfolios beta, i.e., exposure to the market factor, explained around 70% of excess returns. By adding the size and value factors to the CAPM, the model's explanatory power jumps to 95%. Put simply, small-cap and value stocks consistently outperform the market on a regular basis. Expanding on the three-factor model was Carhart (1997), who proposed a four-factor model to include a Momentum factor:

$$r - R_f = R_f + B_3 \; x \; (R_m - R_f) + b_s \; x \; SMB + b_v \; x \; HML + b_m \; x \; WML + \alpha \tag{4}$$

Where WML stands for "winners minus losers" and essentially states that by buying stocks that recently have exhibited high returns (winners) and selling (shorting) stocks that recently have exhibited poor returns (losers), investors can earn returns in excess of the market as a whole. Carhart described the Momentum factor as the tendency for prices to continue rising if they are going up and vice versa. He concluded that the Momentum factor successfully captures significant excess returns from stocks that have recently performed well.

Piotroski (2000), Novy-Marx (2014), Fama and French (2014) and Asness et. al (2014) are among some of the academic researchers that have studied the Quality factor. This factor attempts to identify securities that exhibit certain characteristics that constitute ”high-quality”, such as low leverage, high profitability and/or stable earnings (Piotroski, 2000). Asness et. al. concluded that high-quality stocks delivered consistent superior risk-adjusted returns compared to the market using a “quality-minus-junk” (QMJ) strategy, i.e. buying high-quality stocks and selling low quality stocks. They defined quality based on different measurements of leverage, growth and profitability.

Franzzini and Pedersen (2014) provided academic support for the outperformance of stocks exhibiting low volatility in their paper titled “Betting Against Beta”. They found that low-risk stocks outperformed high-risk stocks on a risk-adjusted basis over the long term. The motivation behind this was that since investors like high returns, but are often not able to use leverage, they instead overweight risky securities, which in turn pushes up their price thus lowering their expected return.

3.2 Smart Beta

Even though research has been conducted on various factors that could explain excess returns compared to traditional cap-weighted indices, the number of studies on Smart Beta is relatively scarce and a definitive definition of Smart Beta is still vague. There are, however, recent contributions that have helped explain the concept, namely the EDHEC (Ecole des Hautes Etudes Commerciales du Nord)-Risk Institute in their paper “Alternative Equity Beta Investing: A Survey” by Amenc, et al. (2015). This paper attempts to highlight potential benefits and risks of Smart Beta strategies, as well as expanding on the rationale and empirical evidence for certain Smart Beta factors including Value, Momentum, Low Risk, Size, Profitability and Investment.

Amenc and Goltz (2013) concluded that Smart Beta indices are likely to outperform cap-weighted indexes but are exposed to several types of risks including factor tilts (systematic risk), risks associated with specific inputs of a strategy and the risk of potentially severe underperformance over long periods of time.

There is another element aside from academia that is worth mentioning when it comes to Smart Beta. Research Affiliates LLC are one of the early adopters of Smart Beta asset allocation. The company provides asset managers and large fund managers with strategy consulting dedicated solely to various forms of Smart Beta. Hsu (2004) published on behalf of research affiliates the paper “Cap-Weighted Portfolios are Sub-Optimal Portfolios”, where he argues that capital pricing models may be misspecified. Research Affiliates’ presence within the field of Smart

Beta has influenced several global asset managers to provide investors the opportunity to invest in Exchange Traded Funds (ETF's) with Smart Beta exposure.

4. Factors

This section is dedicated to explaining and defining the Smart Beta factors analyzed in this thesis. These factors stem from previous academic research within factor investing.

4.1 Market

Factors can be defined as a set characteristics or fundamentals of securities that are important in explaining their performance and risk. According to the Capital Asset Pricing Model (CAPM) developed in the 1960's, stock performance is determined by one single factor, which is its exposure to the market portfolio, otherwise known as Beta. In this thesis, we may also refer to the market factor as the cap-weighted portfolio and will be used as a benchmark in terms of performance. The two market portfolios used in this thesis are the S&P 500 and the Euro Stoxx 600 index (also referred to as Stoxx 600 throughout this paper).

4.2 Value

Since its first appearance as a rules-based strategy in the 1930's (Graham and Dodd, 1934), the Value factor has been used in various forms. The strategy aims at identifying undervalued securities based on their price-to-fundamental ratios. Different types of measurements that have been examined extensively in academia include ratios such as sales-to-earnings, price-to-cash flows, price-to-earnings, price-to-book or book-to-market equity, as formalized by Fama and French (1993).

Sanjoy and Basu (1977) constructed a portfolio consisting of securities that expressed low price-to-earnings (P/E) ratios and found that they outperformed comparable indices over time. The economic intuition of the Value factor requires the investor to assume that a relatively low (high) fundamental value indicates that the asset is undervalued (overvalued), which is why various measures of price-to-fundamentals are commonly used when capturing value. The investor will typically invest in a portfolio of undervalued assets in relation to the market, expecting the portfolio to outperform the corresponding index until levels are in line with the rest of the market. The expected effect is therefore exponentially decreasing as it returns to market standards. This suggests that most excess returns occur early in the business cycle. Sanjoy and Basu also found that the Value factor exhibits a high level of sensitivity to the business cycle over the long run.

The explanatory power of dividend as a Value factor can be linked to several theories. Firstly, the *Dogs of the Dow* theory argues that dividends reflect the worth of a company and are relatively stable over time, while stock prices vary over the business cycle. Proponents of this theory therefore claim that high dividends relative to stock prices indicate the bottom of a business cycle. Thus, investors can ride the wave of the business cycle by picking out securities with high dividend-to-stock price ratios (Da Silva, 2001). The second theory follows a more behavioral line, where high dividend stocks appear overvalued compared to stocks not paying dividend, explained in the following example:

> "Assume two, ceteris paribus, identical firms with no underlying growth: Firm A follows a dividend policy of 100% of profits, while firm B decides not to pay any dividend. In the beginning, both firms enjoy the same amount of profits, 100, and have a share price of 1000, P/E is at 10 for both firms. One year later, profits remain at 100, letting firm A report a P/E of 10, but the P/E for firm B is lower. Why? Firm B is earning interest on the earnings from the first year, assuming an after-tax interest of 5% nets firm B 105 in profit, causing P/E to fall to 9.5" (Clemens, 2012).

The scenario creates an optical illusion, which makes a dividend paying firm appear relatively more expensive. The third theory attributes the explanatory power of dividend to differences in taxation between wage and capital gains, where dividends in most economies provide an alternative income less punished by taxes (Brennan, 1970).

4.2.1 Definition of the Value Smart Beta Factor

In this thesis, our Value Smart Beta factor will consist of four variables, including the price-to-earnings ratio (P/E), price-to-book ratio (P/B), price-to-cash flow ratio (P/CF) and dividend yield (these variables are further defined in Appendix B). Each security's Value score will be defined as the weighted average of their standardized variables (see Appendix A: Standardized score). The value score for security *i* is calculated as follows:

$$Value\ Score_i = (-1) * 0{,}25 * (Z_{PE_i}) + (-1) * 0{,}25 * (Z_{PB_i}) + (-1) * 0{,}25 * (Z_{PCF_i}) + 0{,}25 * (Z_{DivY_i}) \quad (5)$$

Where Z_{PE_i} is the standardized score of security *i*'s P/E ratio, Z_{PB_i} the standardized score of security *i*'s P/B ratio, Z_{PCF_i} the standardized score of security *i*'s P/CF ratio and Z_{DivY_i} the standardized score of security *i*'s dividend yield. We multiply the first three standardized variables by ***-1*** in order to obtain a higher (lower) score for a lower (higher) fundamental to price ratio. The top 100 value scores are selected and weighted according to our weighting scheme (section 5.2.2).

4.3 Size

Rolf Banz (1981) pioneered the Size factor, which targets comparatively smaller firms in order to capture excess returns relative to larger firms. There are several theories as to why smaller companies attain excess returns such as the exposure to default risk (Vassalou & Xing, 2004), liquidity issues (Yakov, 2002) and financial distress (Chan & Chen, 1991) but none seem to fully explain the increased returns earned by utilizing this investment form.

The main justification for size investing is the possibility of higher returns. Despite this, small cap stocks are usually accompanied by a greater level of risk. According to Fama and French (1993), small cap stocks have historically generated higher returns but the excess returns are not free, as small cap stocks tend to exhibit a higher level of risk. Investors should therefore be willing to ride out the "bad" times when size investing.

Exposure to the size factor is easily attained by using an equally weighted strategy, which involves equally weighting all constituents on an index. The strategy provides relatively larger exposure to the smaller firms, and less relative exposure to the larger firms. One thing to consider when size investing is that smaller companies naturally have a higher default rate than its larger counterparts making them more vulnerable to survivorship bias. Survivorship bias occurs when analyzing past performance and selecting firms that have not defaulted (Rohleder et. al., 2011). This essentially means neglecting firms that have defaulted during our sample, which in turn could inflate the level of performance.

4.3.1 Definition of the size smart beta factor

In our thesis, all constituents on our benchmark indices will be weighted as follows:

$$w_i = 1/N \tag{6}$$

Where w_i is the portfolio weight for security *i,* and N the total number of constituents on the benchmark index.

4.4 Sharpe-Momentum

Carhart pioneered the Momentum factor with his four-factor model in the 1997 paper titled "On Persistence in Mutual Fund Performance". The factor is meant to play on trends, where stocks with high recent returns tend to exhibit the same trend in the coming period and vice versa. Extensive research had been conducted earlier on the Momentum factor with significant results in terms of excess returns including Jegadeesh and Titman (1993) who monitored this factor on the U.S. stock market between 1965 and 1989. They showed that the strategy of buying high performing stocks and shorting losing stocks produced excess returns compared to the benchmark index over the same period. Despite the historical success of the Momentum factor, playing on trends is a short-horizon game. The effect reportedly dissipates in less than two years, which is why Jegadeesh and Titman (1993) suggested three-to twelve-month holding periods for securities. Momentum strategies therefore require frequent rebalancing, which could offset some of the returns in trading costs.

Economists have been unable to settle on a single underlying theory to interpret the success behind the momentum factor. Most research points towards behavioral economics, where Barberis et. al. (1998) traced the Momentum effect to irrational decision making during shorter periods due to news being incorporated slowly into prices. Overreactions in long series of good (bad) news can cause the stock price to reach higher (lower) levels than otherwise justified.

The original Momentum strategy only considers historical returns, which could lead to unwanted levels of risk. The Momentum strategy in this thesis therefore incorporates the Sharpe ratio, designed by William Sharpe (1966). The Sharpe ratio was introduced as a measure of reward-to-variability, which essentially captures the return in excess of the risk-free rate per unit of risk. The Sharpe-Momentum factor in this thesis therefore builds on a security's most recent return performance, adjusted for the volatility during the same time period.

4.4.1 Definition of the Sharpe-Momentum Smart Beta factor

Instead of only using past 12-month return performance like Carhart, we will also incorporate performance over the past six months and control for risk. We therefore define our Momentum Smart Beta factor as the weighted average of the standardized six- and twelve-month trailing Sharpe ratios. This is shown mathematically as follows:

$$Sharpe - Momentum\ Score_i = 0{,}5 * Z_{6M\ Trailing\ SR_i} + 0{,}5 * Z_{12M\ Trailing\ SR_i} \quad (7)$$

Where $Z_{6M\ Trailing\ SR_i}$ is the six-month trailing Sharpe ratio for security i and $Z_{12M\ Trailing\ SR_i}$ is the twelve-month trailing Sharpe ratio for security *i*. The top 100 Sharpe-Momentum scores are selected and weighted according to our weighting scheme.

4.5 Low Volatility

According to the risk-return principle, security's exhibiting low volatility should be associated with lower returns. Despite this, countless academic papers confirm that a portfolio of stocks with low volatility can outperform stocks with high volatility on a risk-adjusted basis and therefore disjoint the SML as conveyed by the CAPM (Chan et. al., 1999; Haugen and Baker, 1991). The outperformance is one of the most persistent anomalies found in the field of contemporary asset pricing but the lottery demand effect provides an explanation: High volatility stocks are more likely to give a high, lottery-like payoff. Should riskier payoffs be preferred by a majority of investors, the demand for high volatility stocks will be reflected in the price. The lottery demand effect runs the hypothesis that investors exhibit risk-loving preferences when it comes to the selection of stocks, and therefore low volatility stocks tend to be undervalued, which increases their potential return (Bali et. al., 2016).

The acknowledgement of the low-volatility anomaly should naturally remove any excess return it provides due to an increased number of investors following the strategy, but it has been an established pattern for 90 years, and continues to outperform high volatility stocks in more recent studies (Asness et. al., 2014).

4.5.1 Definition of Low Volatility Smart Beta factor

In this thesis, we define the Low Volatility Smart Beta factor as the one-year annualized volatility (Further defined in section 5.3.2). The 100 stocks exhibiting the lowest one-year daily return annualized volatility will be selected into the portfolio and weighted according to our weighting scheme.

4.6 Quality

While research is largely indecisive on why quality companies tend to yield excess returns, Campbell et. al. (2010) argued that cash flow fundamentals steer stock prices more than macroeconomic variables, meaning a well-run firm can gain a competitive advantage through careful capital management. This would in turn minimizes the risk of over-capitalization or over-leveraging, which subsequently affects the stock price positively. Quality stocks tend to perform better during bad times because if macroeconomic conditions start to deteriorate, more investors will become risk-averse and start investing in stocks with sound capital management. This would in turn push up the value of high quality stocks. This effect is the so called "flight-to-quality" (Asness et al., 2014).

Joseph Piotroski (2000) approached the quality factor by selecting a portfolio of securities using a broad accounting based fundamental analysis. Piotroski generated an F-Score, which determined the financial strength of a company by the sum of nine binary variables:

$$F_{Score} = F_{ROA} + F_{\Delta ROA} + F_{CFO} + F_{Accrual} + F_{\Delta Margin} + F_{\Delta Turn} + F_{\Delta Lever} + F_{\Delta Liquid} + F_{EQ-Offer} \quad (8)$$

Where F_{ROA} is given score 1 if return on assets is positive in the current year and 0 if negative, $F_{\Delta ROA}$ is given score 1 if the change in return on assets is higher in the current year than the previous year and 0 otherwise, F_{CFO} is given score 1 if cash from operations is positive in the current year and 0 if negative, $F_{Accrual}$ is given score 1 if accruals are positive in the current year and 0 if negative, $F_{\Delta Margin}$ is given score 1 if the change in the growth margin is higher in the current year than the previous year and 0 otherwise, $F_{\Delta Turn}$ is given score 1 if the asset turnover ratio is higher in the current year in relation to the previous year and 0 otherwise, $F_{\Delta Lever}$ is given score 1 if the leverage ratio is lower in the current year compared to the previous year and 0 otherwise, $F_{\Delta Liquid}$ is given score 1 if the Current ratio is higher in the current year and 0 it it's lower and $F_{EQ-Offer}$ is given score 1 if new shares aren't issued during the previous year and 0 otherwise. The highest quality stocks receive an F-Score of 9. This approach captures the multidimensionality of the quality factor but requires a large amount of data.

There are more simple approaches to define quality such as Novy-Marx (2013) who found that firms with high gross profitability earned returns in excess to the market benchmark over longer periods. This factor was also employed by Fama and French (2014), who integrated it into their 5-factor model. They defined quality as gross profitability divided total assets.

4.6.1 Definition of the Quality Smart Beta factor

Factors such as Momentum, Low Volatility and Value are relatively straightforward to understand whereas the multidimensionality of the Quality factor makes it harder to clearly define. Utilizing a simple, one-dimensional quality measurement such as Novy-Marx (2013) or Fama and French (2014) would be sufficient from an academic perspective but adopting Piotroski's comprehensive approach would limit the selection of usable securities in our analysis. We have therefore chosen to construct a Quality Smart Beta factor inspired by Piotroskis F-score and the quality approach of Bender et. al (2014) with a few variable modifications. Instead of assigning binary variables to our various quality variables like Piotroski, we use the standardized score approach as in previous portfolios (further described in section 5.2). Bender et. al (2014) argued that firms exhibiting low variability in earning-per-share over time can be perceived as "high quality". We therefore decided to incorporate this variable into our Quality Smart Beta factor.

More formally, we define the Quality Smart Beta factor in this thesis as the weighted average of the standardized scores of five variables. These include the debt-to-equity ratio to capture the leverage factor; return on assets (ROA), return on equity (ROE) and operating cash flow (CFO) capture the profitability factor complemented by earnings variability to capture earnings quality. These variables are further defined in Appendix B. Our quality score for a security, *i*, is calculated as follows:

$$Quality\ Score_i = (-0{,}2) \times Z_{DE\ Ratio_i} + 0{,}2 \times Z_{CFO_i} + 0{,}2 \times Z_{ROA_i} + 0{,}2 \times Z_{ROE_i} + (-0{,}2) \times Z_{EPSVar_i} \quad (9)$$

Where $Z_{DE\ Ratio\ i}$ is the standardized score of security i's debt-to-equity ratio, Z_{CFO_i} the standardized score of security i's operational cash flow, Z_{ROA_i} the standardized score of security i's return on assets, Z_{ROE_i} the standardized score of security i's return on equity and Z_{EPSVar_i} the standardized score of security i's earnings-per-share variability the past five years. The top 100 quality scores are selected into the portfolio and weighted according to our weighting scheme.

5. Thesis data and methodology

This section provides a description of the data and methodology used in this thesis. It starts by describing the data followed by the portfolio generation section, which is intended to explain the security selection, scoring and weighting process. This is then followed up by stating the various performance measurements used in the empirical analysis

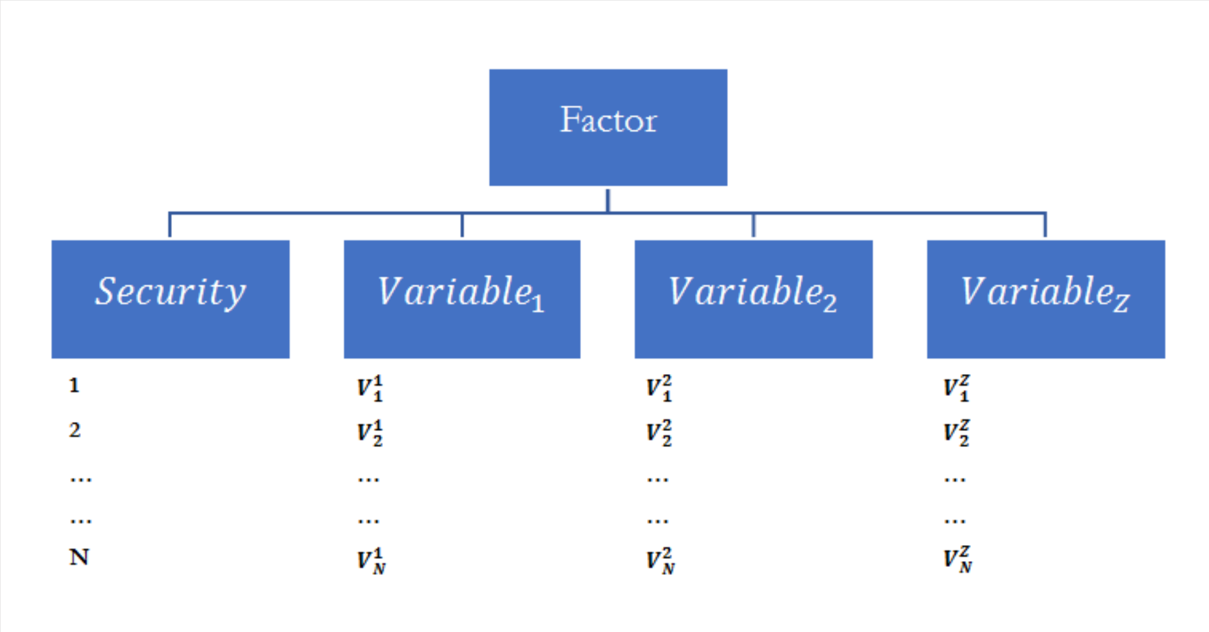
5.1 Thesis data

All data utilized in this thesis is collected from Bloomberg LP. Price data for all securities consists of daily closing prices quoted in U.S. Dollars from 1994-01-01 to 2016-12-31 for the S&P 500 and in Euros for the Stoxx 600 index from 2002-01-01 to 2016-12-31, adjusted for dividends. The S&P 500 is constructed to represent the broad domestic American economy through changes in the aggregate market value of the 500 stocks, which represent all major industries. The Euro Stoxx represents 600 large, mid and small cap companies across 18 different countries in the European region (Bloomberg LP, 2017). Factor-specific data is collected using Bloomberg's Watchlist Analytics (WATC) tool, which provides information on key ratios and measurements utilized in our security selection process. In rare cases, data on specific firms is interrupted by corporate actions such as mergers, acquisitions or default. If a security lacks more than 80% of its price data for a time period, it is excluded from the sample. Otherwise, the missing data is replaced by an index average, corresponding to the return of the market portfolio.

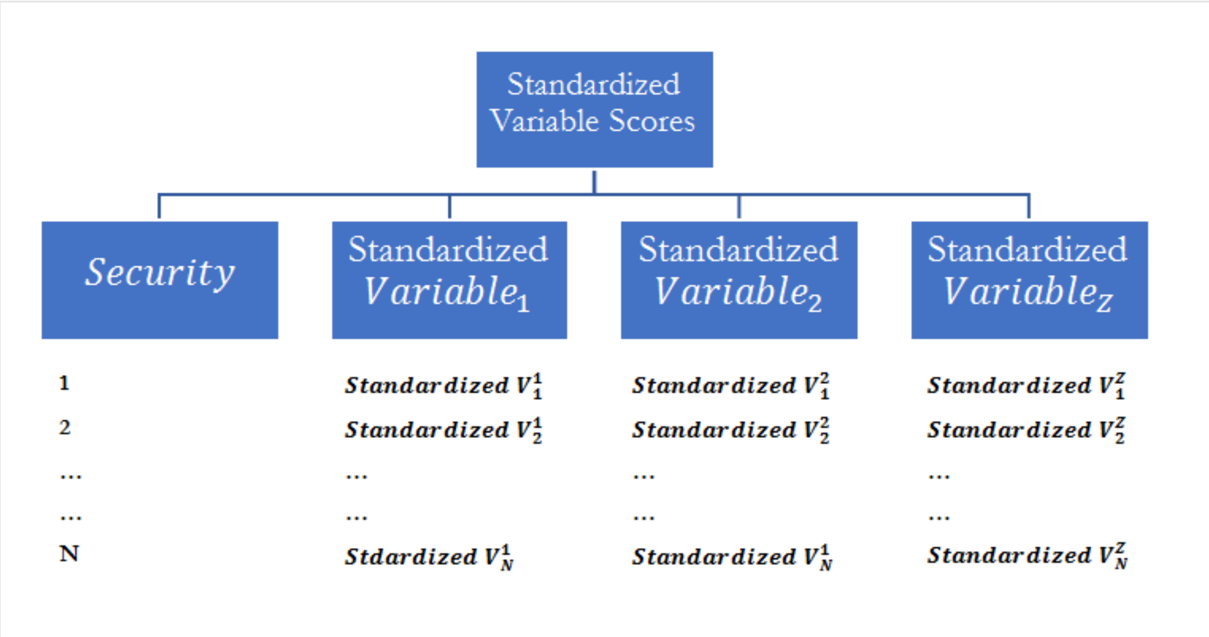
5.2 Portfolio generation

5.2.1 Scoring

Each Smart Beta factor has a different number of variables attached to it. Our Quality factor, for example, consists of data from five variables, including earnings variability, return on equity, return on assets, cash flow from operations and the debt-to-equity ratio. All of these variables are measured in different units, which creates a problem when attempting to generate a single factor-specific score for each security. To forego this problem, we standardize each security's respective variable in order to normalize all variables. We then take the average of all standardized scores for each variable to create a factor-specific score for each security (see Appendix A: Standardized scores). Each security is then sorted by their factor specific score and the top 100 scores are selected into the portfolio for weighting.



Graphic 1: Raw variable data is collected from Bloomberg for each security. The factors analyzed in this thesis are Value, Momentum, Low Volatility, Size and Quality. We do not score the Size factor since it's an equally-weighted strategy.



Graphic 2: Each security's variable is given a standardized score in order to normalize each variable.

The last step in the scoring process is to create a factor-specific score for each security. The factor-specific score for each security is the average of its standardized scores:

$$Factor\ Score_i = \frac{(StandardizedV_i^1 + StandardizedV_i^2 + \cdots + StandardizedV_i^Z)}{Z} \tag{10}$$

Where $Standardized\ V_i^1$ is the standardized score of variable 1 for security i, $StandardizedV_i^2$ the standardized score of variable 2 for security i and $StandardizedV_i^z$ the standardized score of variable Z for security i. This is then divided by Z, i.e., the number of variables associated with the factor.

5.2.2 Weighting

An outlier is an observation that has been given an abnormally large score and therefore threatens to skew the weights in the portfolio. Assigning exceptionally large weights to a single security in a portfolio is not necessarily an issue, since it reflects a firm with exceptionally large scores and should thus perform exceptionally well. The issue rather lies in that too much weight threatens to consume any diversification gains in the portfolio, adding unnecessary risk (Markowitz, 1952). While outliers are rare in our sample, we address the few cases by applying a two-step framework for weighting the 100 securities in each portfolio. To limit the effect of outliers we start by utilizing the Winsor method to make sure no factor-specific scores exceed a certain threshold limit (Dixon, 1960) (see Appendix A: The Winsor method). In this thesis, we Winsorize all factor-specific scores at $\pm$ 3 standard deviations from the mean. This means that if scores are above (below) the Winsor threshold, those observations will be given a score which represents three standard deviations above (below) the mean.

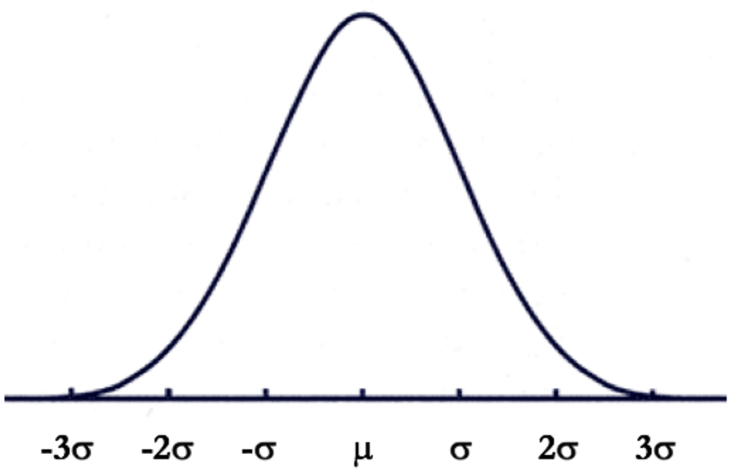


Figure 2: A normal distribution bell curve illustrating three standard deviations from the mean. In our first weighting step, if observations exceed the Winsor threshold, these observations are capped at three standard deviations.

To ease the weighting process, we assume the 100 securities in each portfolio is a large enough data sample to approximately assume they follow a normal distribution (Kish, 1965). Using normal distribution as an assumption in our sample is therefore justified as the potential bias it induces is negligible.

The second step consists of complying with rules established by the European Commission to ensure portfolios meet investor protection requirements in portfolio diversification and liquidity. The Undertakings for the Collective Investment of Transferable Securities (UCITS) limits individual weights in portfolios to five percent, and any exceeding weights are redistributed evenly according to the standardized score of the individual firms (see Appendix A: The UCITS framework).

The weight for each security in our portfolio is based on their factor-specific score and its contribution to the sum of all 100 scores:

$$w_i = \frac{Z_i^{winsor}}{\sum_{i=1}^{n} Z_i^{winsor}} \tag{11}$$

Where w_i denotes the weight for security *i*, and Z_i denotes the Winsorized factor specific score for security *i*.

5.3 Performance analysis

The performance of each Smart Beta strategy is measured against a benchmark index. Since the underlying values of individual firms change over time, the portfolio must be rebalanced frequently in order to maintain a portfolio that truly captures the desired factor. The portfolio generation, including weighting, is repeated quarterly, i.e. every four months. The performance measurements used are return, volatility, Sharpe ratio and excess return.

5.3.1 Portfolio Return

The cumulative return gathered as the return of asset i, R_i, times the weight attributed to that asset, w_i, summed for all securities in the portfolio.

$$R_i^P = \sum_{i=1}^{n} [R_i * w_i + R_{i+1} * w_{i+1} + \cdots + R_{i+n-1} * w_{i+n-1}] \tag{12}$$

Where daily returns for the portfolio are measured as follows:

$$R_i = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{13}$$

Where P_t is the closing price at time t and P_{t-1} the closing price at time t-1.

5.3.2 Daily Return Annualized Volatility

In this thesis, we refer to the portfolio's Daily Return Annualized volatility (or just Volatility) as the degree of daily return variation over the course of a year. This is defined mathematically as:

$$\sigma^P_{Annual} = \sigma^p_i \; x \sqrt{252} \tag{14}$$

$$\sigma^p_i = \sqrt{\frac{\sum_{i=1}^{N}(r_t - r)^2}{N-1}} \tag{15}$$

Where σ^p_i is the standard deviation of all daily returns observations during a year. We then multiply this number by the square root of 252 to arrive at the daily return annualized volatility.

5.3.3 Sharpe ratio (SR)

The Sharpe Ratio is defined as the return in excess of the risk-free rate per unit of risk The Sharpe ratio is mathematically defined as follows:

$$SR = \frac{(R^p_i - R_f)}{\sigma^p_t} \tag{16}$$

Where R^p_i is the portfolio return, R_f the risk-free rate of return as measured by the 3-month U.S. T-bill (Appendix E, Figure 27) and σ^p_t the volatility of the portfolio.

5.3.4 Excess returns

In this thesis, we define excess returns as the difference in return between the portfolio and its benchmark index. A portfolio's return in excess of the market portfolio $R^P_{e_T}$ is calculated as:

$$R^P_{e_T} = R^P_T - R^M_T \tag{17}$$

Where R^P_T is the return of portfolio P during time period T and R^M_T the return of the benchmark index M during time T.

6. Empirical analysis

The following results are measured from January 1st, 1994 to December 31st, 2016 for the S&P 500 and January 1st, 2002 to December 31st, 2016 for the Euro Stoxx 600. We have examined the performance of 5 different portfolios (Value, Momentum, Low Volatility, Size and Quality) versus their respective benchmark index in terms of total return, risk-adjusted return, volatility and excess returns.

6.1 Summary results

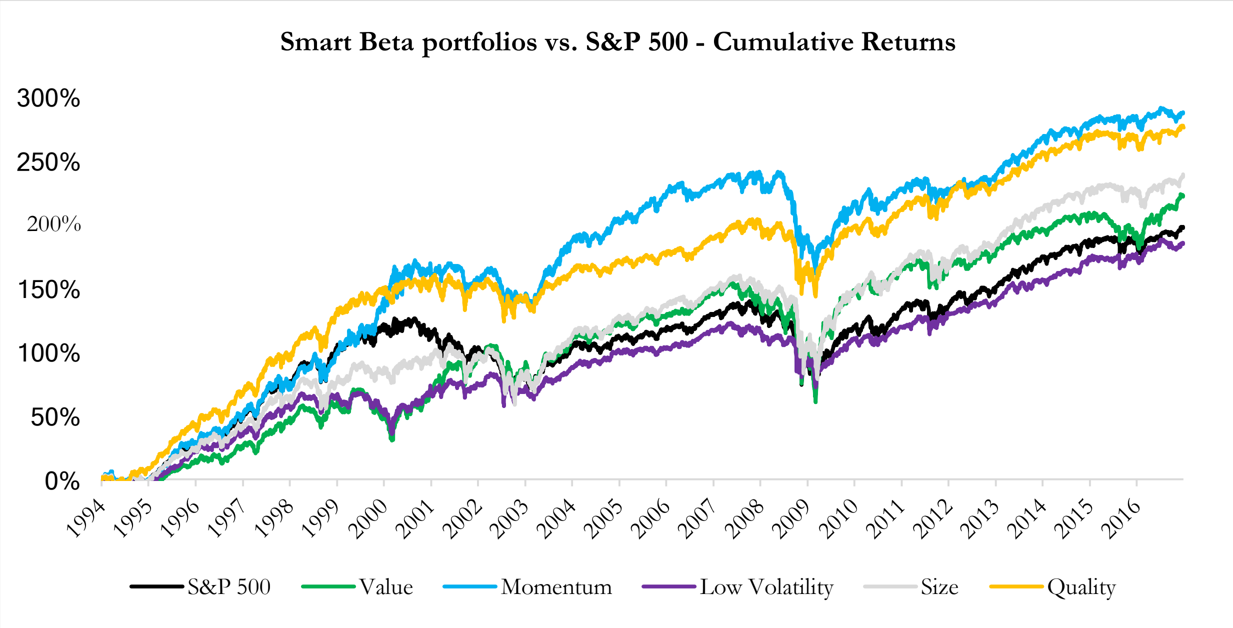


Figure 3: Cumulative returns for all portfolios, 1994 - 2016. S&P 500 in black for comparison.

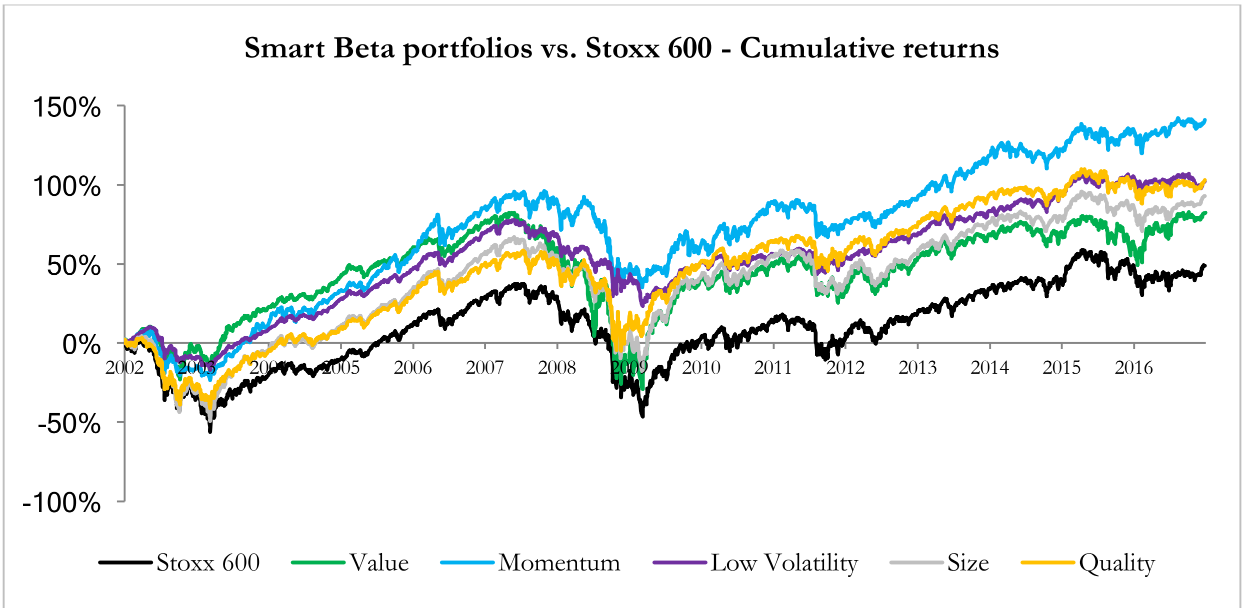


Figure 4: Cumulative returns for all portfolios, 2002 - 2016. Stoxx 600 in black for comparison.

Summary Statistics – Smart Beta portfolios vs. S&P 500						
Measurement	**S&P 500**	**Value**	**Momentum**	**Low Vol**	**Size**	**Quality**
Cumulative return	196,56%	221,10%	286,03%	184,49%	239,29%	275,57%
Return*	8,55%	9,61%	12,44%	8,02%	10,40%	11,98%
Sharpe ratio*	0,59	0,58	0,65	0,62	0,65	0,75
Volatility*	17,07%	17,16%	19,14%	12,68%	17,53%	17,06%
Excess returns*	-	1,07%	3,89%	-0,53%	1,86%	3,44%

*Table 1: Summary statistics for the smart beta portfolios on the S&P 500 from 1994 to 2016. S&P 500 included for comparison. Worst (red) and best (green) values for each performance metric are highlighted. * Denotes average annual.*

Summary Statistics – Smart Beta portfolios vs. Stoxx 600						
Measurement	**Stoxx 600**	**Value**	**Momentum**	**Low Vol**	**Size**	**Quality**
Cumulative return	49,08%	82,56%	141,32%	102,51%	98,16%	102,77%
Return*	3,27%	5,50%	9,42%	6,83%	6,54%	6,85%
Sharpe ratio*	0,38	0,61	0,78	1,05	0,83	0,70
Volatility*	18,55%	17,95%	15,42%	10,14%	12,11%	14,97%
Excess returns*	-	2,23%	6,15%	3,56%	3,27%	3,58%

*Table 2: Summary statistics for the smart beta portfolios on the Stoxx 600 from 2002 to 2016. Stoxx 600 included for comparison. Worst (red) and best (green) values for each performance metric are highlighted. * Denotes average annual.*

From a total return perspective, it is clear that the best performing Smart Beta strategy over both geographical regions was the Sharpe-momentum portfolio (Table 1, 2; Figure 3; 4). Both portfolios managed to outperform the U.S and European benchmark indices by roughly 90 and 92 percentage points respectively. Despite this, the Sharpe-momentum portfolio had a hard time outperforming the U.S benchmark index since 2006 as shown in the annual and cumulative excess returns (Figure 9, 10). For the U.S portfolio, most of the outperformance came between 1999 and 2005 where it outperformed by roughly 108 percentage points. Since 2006, the momentum portfolio has underperformed S&P 500 by about 15 percentage points and is also the second worst performer post financial crisis (Figure 5).

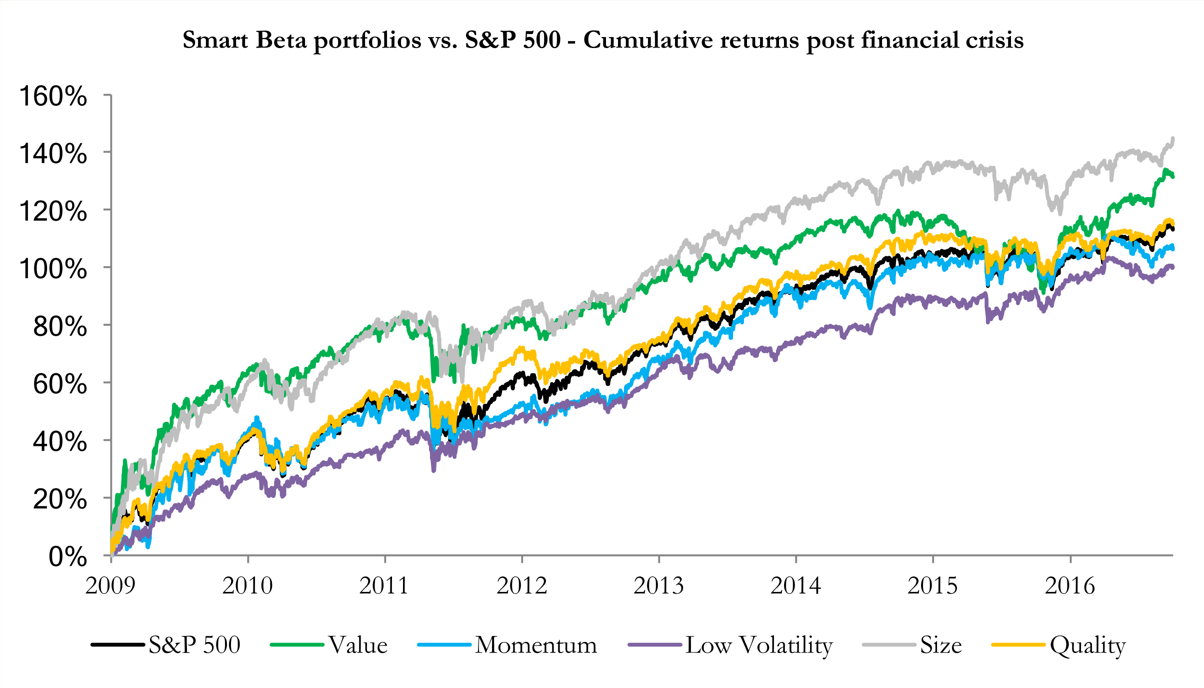


Figure 5: Cumulative returns post crisis for all portfolios, U.S.

Against the European benchmark, the outperformance in the Momentum portfolio has been more consistent. It manages to not only be the best performer over the entire period but also during the post financial crisis period, where it outperformed the benchmark by roughly 15 percentage points (Figure 6). As seen in figure 5 above, the size portfolio performs the best against the S&P 500 post crisis, exhibiting a total excess return of roughly 32%.

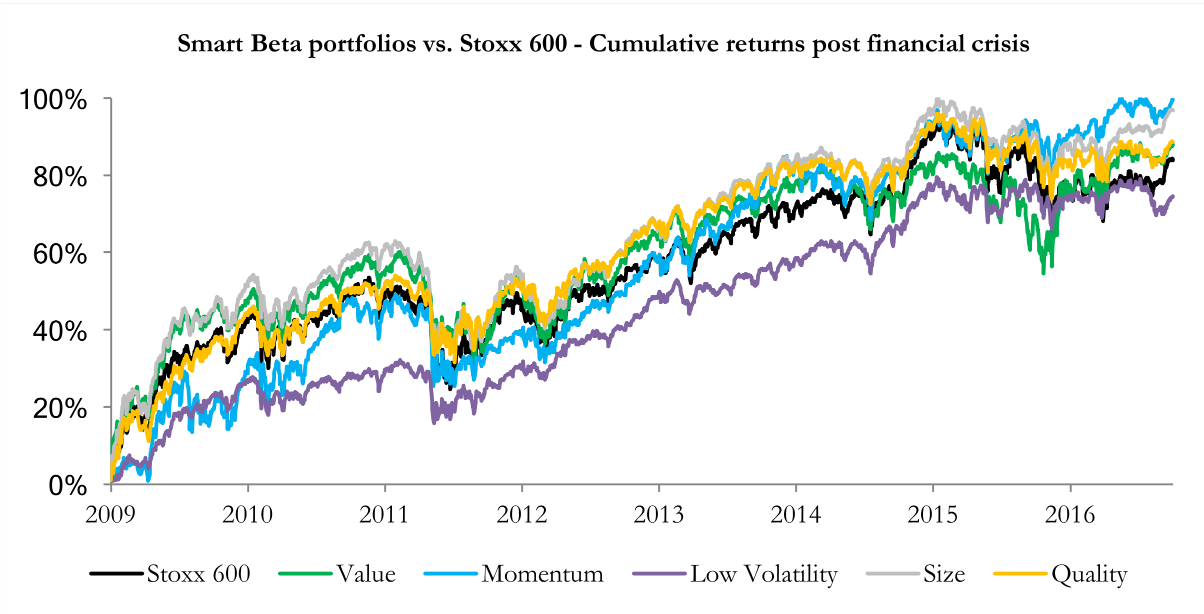


Figure 6: Cumulative returns post crisis for all portfolios, Europe.

The only portfolio that did not outperform the U.S benchmark in terms of total return during the whole period was the Low Volatility portfolio, which underperformed by roughly 12 percentage points. Even though the portfolio underperforms in terms of return, it exhibits significantly lower annualized volatility (12,68%) compared to the benchmark index (17,07%) and provides a slight upgrade in risk-adjusted return (0,62 versus 0,59). Another positive aspect of the low volatility portfolio is the evident trait of low drawdowns (Figure 3, 4). During bad economic periods, the Low Volatility portfolios seem to outperform the index as seen during years 2000-2002 and 2008 (Figure 11, 12). For the entire period, all of the portfolios managed to outperform the European benchmark, both in terms of total and risk-adjusted return. The post crisis period has seen only the Low Volatility portfolio underperform the benchmark index. The portfolio underperformed by roughly 13%.

The best risk adjusted performer in the U.S was the Quality portfolio, which exhibited an average annual Sharpe ratio of 0,75 compared to the S&P's 0,59. It was also the second best performer from a total return perspective (Table 1). The value portfolio exhibited the lowest Sharpe ratio (0,58). This can most likely be attributed to its large drawdowns during poor macro conditions since it outperformed the S&P 500 by about 23 percentage points over the whole period.

The best risk-adjusted performer in Europe was the Low Volatility portfolio, which exhibited an average annual Sharpe Ratio of 1,05 (Table 2). In terms of total return, it outperformed the Euro Stoxx 600 index by about 53 percentage points over the entire period and exhibits significantly less annualized volatility (10,14% versus 18,55%).

Figures 3 and 4 show clear signs of cyclical market trends for all portfolios, with peaks in early 2008 followed by large drawdowns due to the financial crisis. All smart beta portfolios showed varying behavior between years 1999 and 2003. The Value and Low Volatility portfolios both declined during the same time period between 1999 and 2000 whereas momentum and quality seemed to follow the S&P 500's trend, albeit with smaller drawdowns (Figure 3). The European portfolios seem to exhibit peaks and troughs during the same time periods, with drawdowns in late 2002, 2008 and 2015 (Figure 4).

6.2 Individual Portfolio results

6.2.1 Value

In terms of risk-adjusted returns, the value portfolio manages to outperform the benchmark index in Europe but not in the U.S (Table 1, 2). The varying results in the two benchmark indices could be explained by the underlying theory, which states that the value factor exhibits high sensitivity to the overall macro environment (Sanjoy and Basu, 1977). Seeing that our data on the European index starts in 2002 and the American equivalent begins in 1994, it is possible that the timing of the investment played a role in the risk-adjusted outperformance of the Value portfolio versus the Stoxx 600 index. This can be seen in figure 7, where the Value portfolio significantly underperforms the S&P 500 from 1994 to the trough in late year 2000.

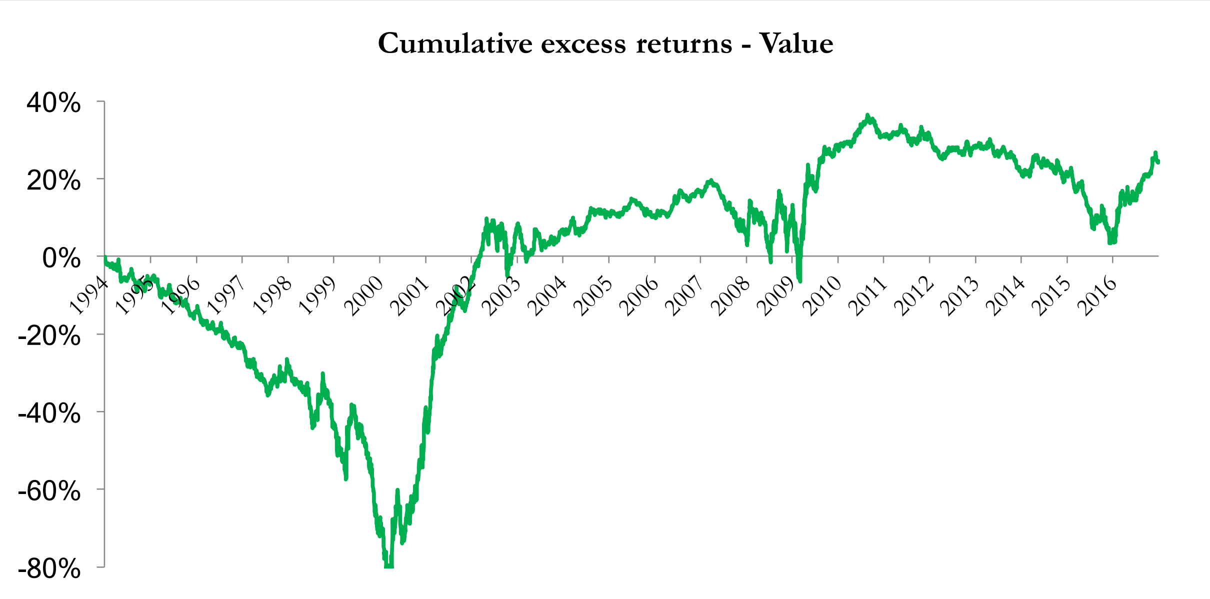


Figure 7: Cumulative excess returns for the Value portfolio versus the S&P 500 between 1994 and 2016.

Given that the U.S. and Europe roughly follow the same macroeconomic trends (Figure 3, 4), this period of underperformance could have affected the Value portfolio in Europe as well if data allowed us to measure from as early as 1994. Figure 8 below shows cumulative excess return for the Value portfolio in Europe. What is clear from this figure is the significant underperformance during the most recent financial crisis, which strengthens the argument that Value stocks tend to underperform during poor macroeconomic conditions. Figures 16 and 17 in Appendix D show that the Value portfolios exhibited higher levels of volatility during the most recent financial crisis.

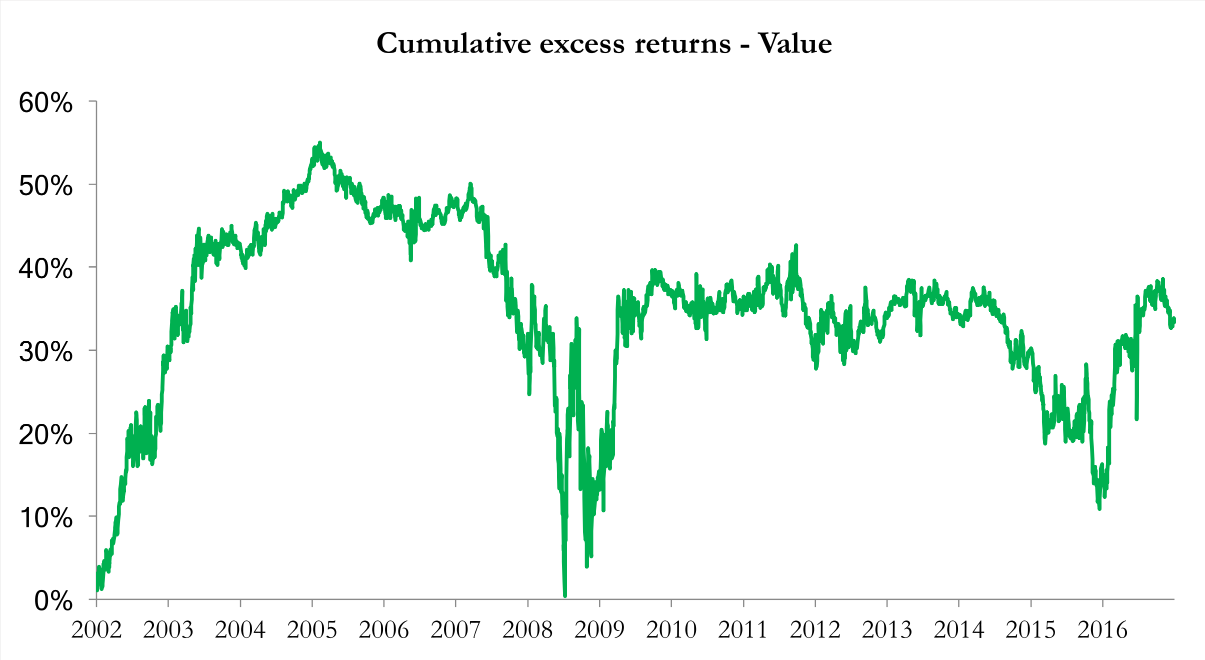


Figure 8: Cumulative excess returns for the Value portfolio versus the Euro Stoxx 600 between 2002 and 2016.

The overall results for the Value portfolio are in line with Fama and French (1993) who found that Value stocks tend to outperform the market as a whole over the long run (Table 1, 2). When studying figures 7 and 8, it seems as if the Value portfolio performs well during the early phases of the business cycle corresponding to the results of Sanjoy and Basu (1977). This is indicated by the outperformance from 2002-2005 and 2009-2011 across both geographical regions. The Value portfolio exhibited higher returns versus the S&P 500 in 61 of the 92 quarters examined, and in 37 of the 60 quarters on the European equivalent (Appendix C: Table 11, 19).

6.2.2 Sharpe-Momentum

The Momentum portfolios are the most impressive in the data set in terms of total return during the entire period. In 67 out of the 92 quarters examined, the Momentum portfolio outperformed the return of the S&P 500, and in 41 of 60 quarters on the European equivalent (Appendix C: Tables 11; 19). Seeing that Behavioral Economics attributes the momentum anomaly to irrational investor behavior i.e., overreaction to good or bad news, one could argue that our Momentum portfolios should exhibit much larger underperformance versus the benchmark than depicted in Figures 9 and 10. The Momentum portfolios also exhibited lower volatility during the most recent financial crisis (Appendix D, Figures 19, 20). A particularly interesting result from analyzing both Momentum portfolios are the differing results between years 2006 and 2016. The Momentum portfolio in the U.S clearly stagnates in terms of excess returns during this period but the outperformance remains relatively consistent in Europe.

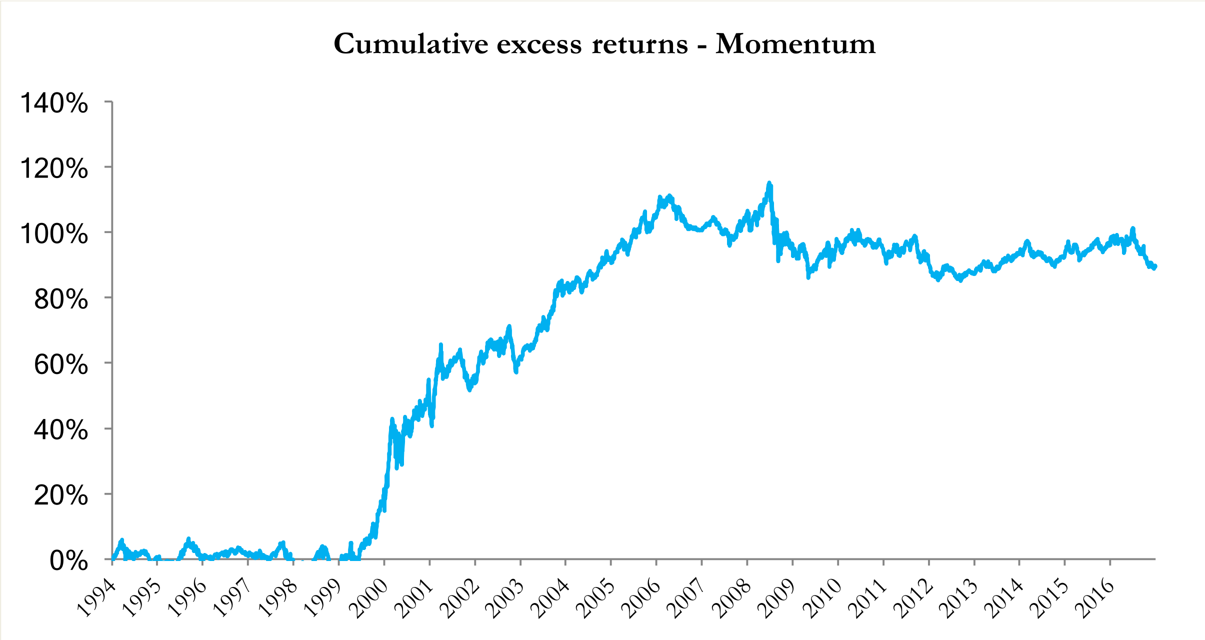


Figure 9: Cumulative excess returns for the Momentum Portfolio versus the S&P 500 between 1994 and 2016.

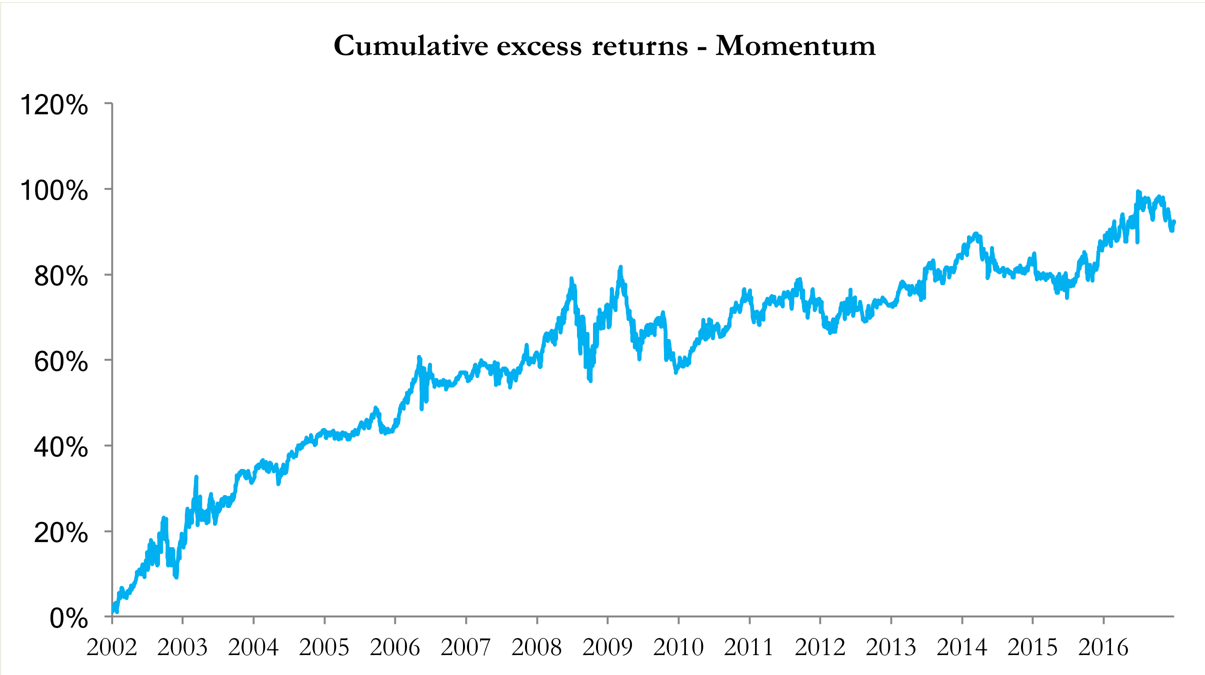


Figure 10: Cumulative excess returns for the Momentum portfolio versus the Euro Stoxx 600 index between 2002 and 2016.

Nevertheless, our results for the entire period are in line with Carhart (1997) as well as Jegadeesh and Titman (1993), who found that momentum stocks tend to exhibit excess returns compared to the market over the long run.

6.2.3 Low Volatility

Previous academic studies such Frazzini and Pedersen (2014), Chan et. al. (1999) and Haugen and Baker (1991) suggest that low volatility stocks tend to outperform high volatility stocks on a risk-adjusted basis because they are systematically undervalued due to risk-loving preferences among investors. This is in line with our results as both Low Volatility portfolios exhibit superior risk-adjusted returns relative to their benchmark indices. The portfolios also behaved according to expectations when it comes to volatility, where both portfolios exhibited the lowest annualized volatility over the entire period (Table 1, 2). Table 5 and 9 (Appendix C) shows the Low Volatility portfolio in the U.S. exhibiting the lowest daily return annualized volatility in every year between 1994 and 2016, with similar results for the European portfolio (See Appendix D for the annualized volatility of both Low Volatility portfolios throughout the time period). Another significant result is the outperformance during periods of economic turmoil such as the most recent financial crisis as seen in Figures 11 and 12 below.

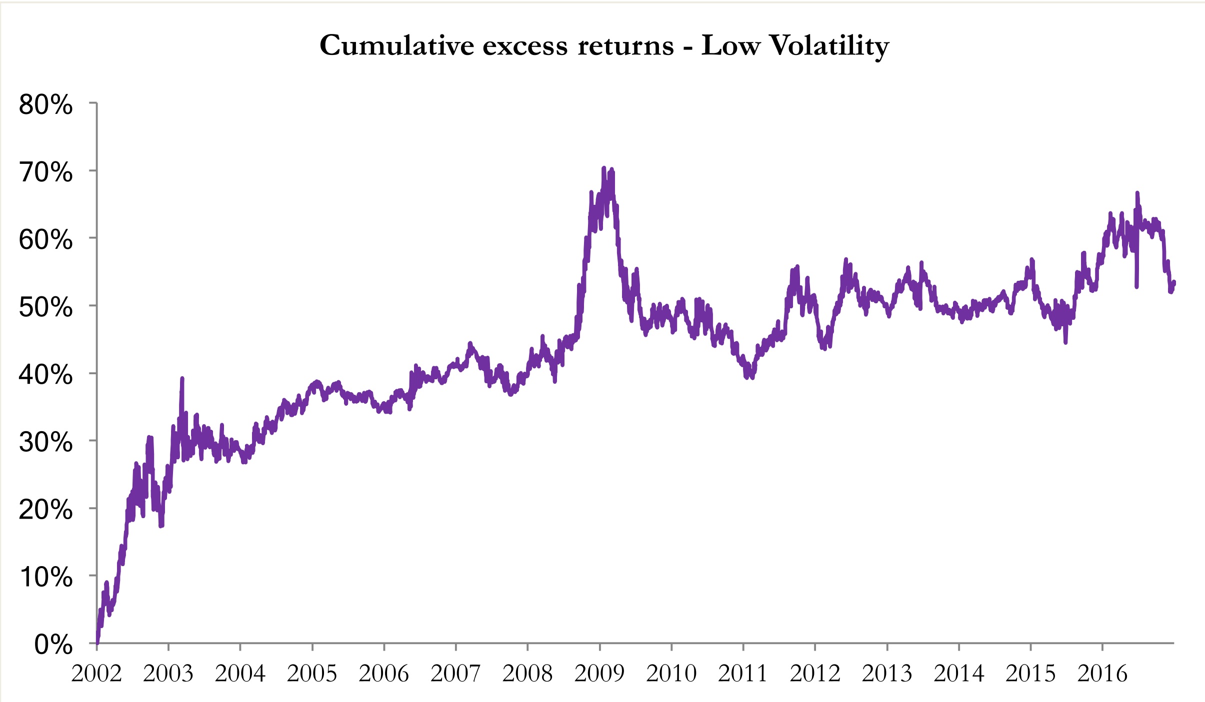


Figure 11: Cumulative excess returns for the Low Volatility portfolio versus the Stoxx 600 between 2002 and 2016.

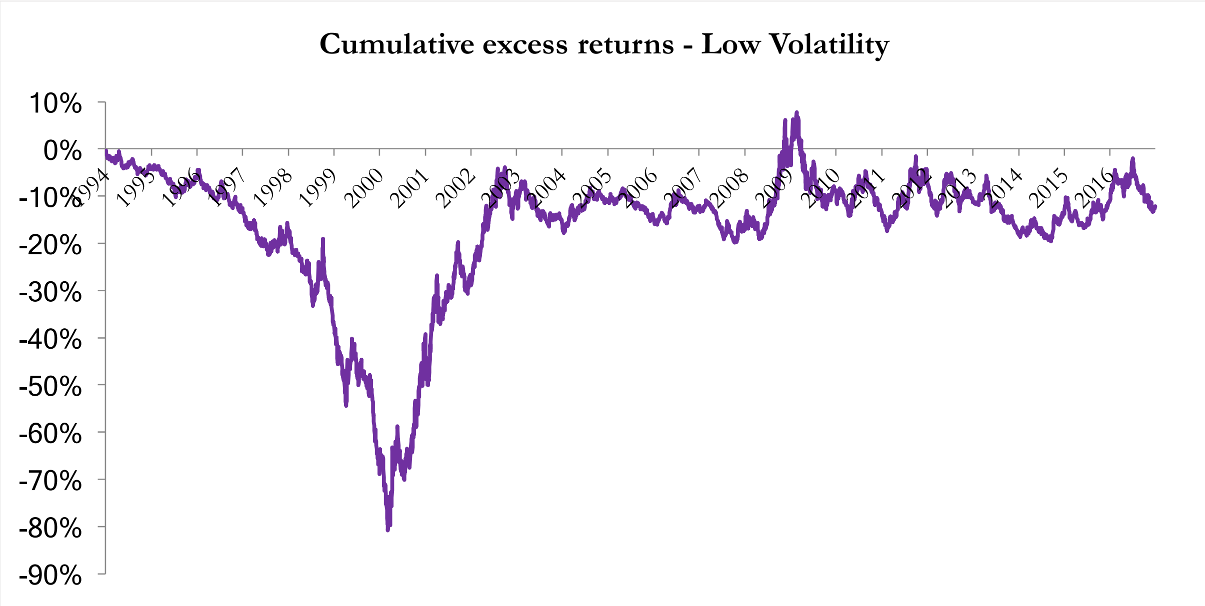


Figure 12: Cumulative excess returns for the Low Volatility portfolio versus the S&P 500 between 1994 and 2016.

In 62 out of the 92 quarters examined, the Low Volatility factor outperformed the return of the S&P 500, and in 32 of 60 quarters on the European equivalent (Appendix C: Tables 11, 19).

6.2.4 Size

Both Size portfolios outperform their respective benchmark indices in terms of total and risk-adjusted returns, which is in line with Fama and Fench (1993) who concluded that small cap stocks tend to outperform large cap stocks over the long run. Fama and French also established that even though smaller companies tend to outperform the market as a whole, they are exposed to greater levels of risk. This is evident in the U.S. but not in Europe, as the Size portfolio exhibited lower volatility during for the entire period (Table 1, 2). A reason for this could be the diversification effect as suggested by Markowitz (1952), since risk is spread out equally overall index constituents (See Appendix D for the daily return annualized volatility of both Size portfolios throughout the time period). As depicted in figure 13 and 14 below, both Size portfolios seem to exhibit underperformance in relation to their benchmark indices during poor macroeconomic conditions i.e., during the dot-com bubble of the early 2000's in the U.S. as well as the most recent financial crisis.

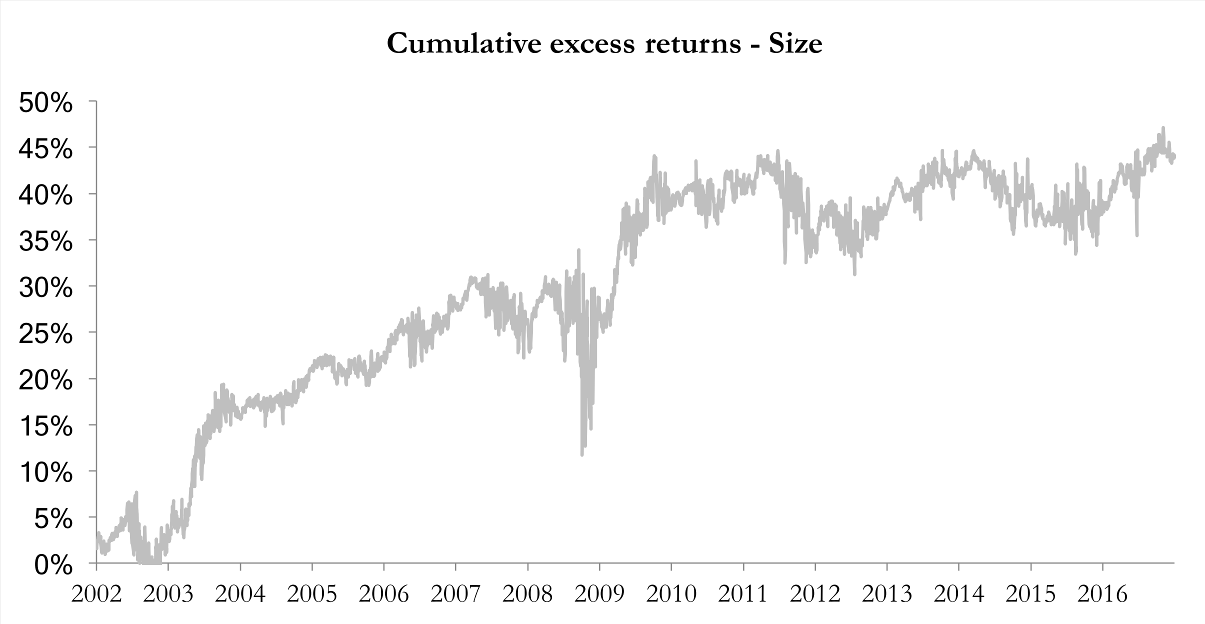


Figure 13: Cumulative excess returns for the Size portfolio versus the Stoxx 600 between 2002 and 2016.

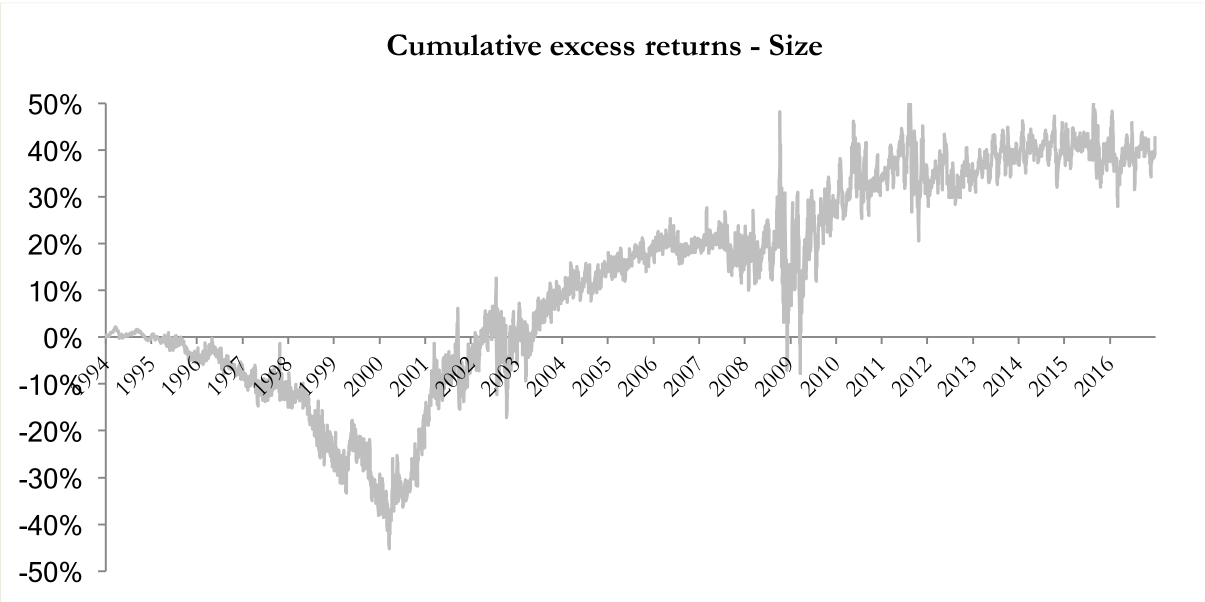


Figure 14: Cumulative excess returns for the Size portfolio versus the S&P 500 between 1994 and 2016.

Both Size portfolios perform particularly well in the post crisis period as seen in Figures 13 and 14 above. The outperformance during this period was about roughly 30% versus the S&P 500 and 12% versus the Stoxx 600 index. The Size portfolio outperformed the S&P 500 in 66 out of the 92 quarters examined. The corresponding result for Europe was 35 of 60 quarters (Appendix C: Tables 11, 19).

6.2.5 Quality

In line with the results of Asness et. al. (2014), the Quality portfolio exhibits superior risk-adjusted returns versus both benchmark indices (Tables 1, 2). As mentioned in section 4, the underlying reasons why quality stocks tend to outperform the market in risk-adjusted terms are unclear but Campbell et. al. (2010) argued that cash flow fundamentals steer stock prices more than macroeconomic variables meaning that a well-run firm can gain a competitive advantage through careful capital management. This would in turn minimize the risk of over-capitalization or over-leveraging, which subsequently affects the stock price positively.

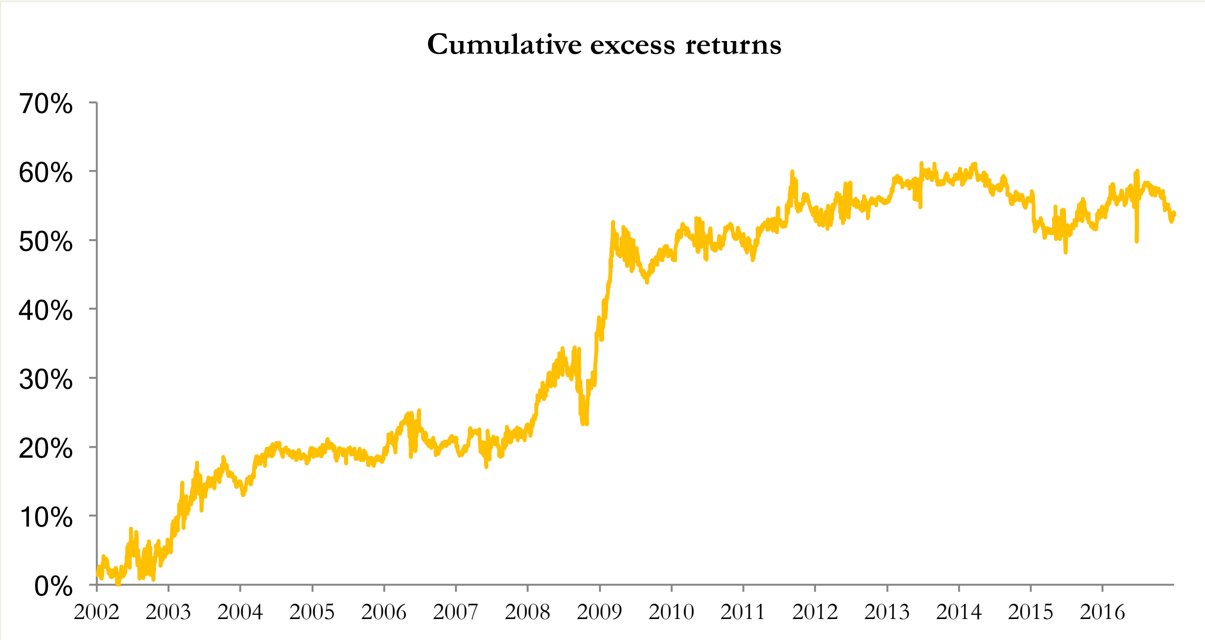


Figure 15: Cumulative excess returns for the Quality portfolio versus the Stoxx 600 between 2002 and 2016.

According to Asness et al. (2014), quality stocks tend to perform better during bad times because if macroeconomic conditions start to deteriorate, more investors will become risk-averse and start investing in less risky stocks. This would in turn push up the value of high-quality stocks. This effect is the so called "flight-to-quality" effect and is evident for both Quality portfolios in our analysis. This can be seen in figures 14 and 15 where both portfolios outperform their respective benchmark index during the most recent financial crisis as well as during the dotcom bubble of the early 2000's in the U.S. The results are also consistent with Asness et. al. (2014, who concluded that Quality stocks tend to outperform the market on a risk-adjusted basis over the long run.

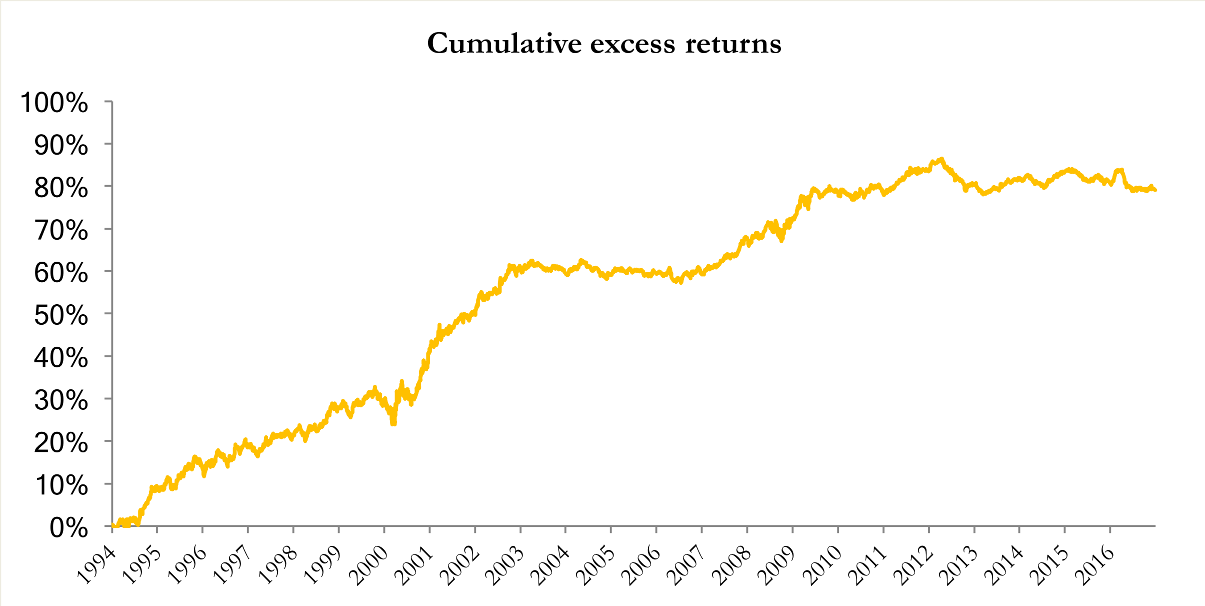


Figure 16: Cumulative excess returns for the Quality portfolio versus the S&P 500 between 1994 and 2016.

6.2.6 Portfolio correlation

Correlation Matrix						
	S&P 500	*Value*	*Momentum*	*Low Volatility*	*Size*	*Quality*
S&P 500	1					
Value	0,872231	1				
Momentum	0,885352	0,728588586	1			
Low Volatility	0,868248	0,869466357	0,765231016	1		
Size	0,018790	0,033352938	0,026106398	0,000814169	1	
Quality	0,973525	0,84195112	0,856633999	0,851596052	0,010752	1

Table 3: Correlation matrix for all portfolios, U.S.

Correlation Matrix						
	Stoxx 600	*Value*	*Momentum*	*Low Volatility*	*Size*	*Quality*
Stoxx 600	1					
Value	0,67669232	1				
Momentum	0,721489588	0,683531958	1			
Low Volatility	0,768505838	0,755981667	0,831248752	1		
Size	0,516431069	0,544309488	0,523920165	0,502933879	1	
Quality	0,819895803	0,822904911	0,856664972	0,884802083	0,565236191	1

Table 4: Correlation matrix for all portfolios, Europe.

As seen in tables 3 and 4, the Quality Smart Beta portfolio has the highest correlation with both benchmark indices. This could be explained by the underlying variables that we use to define our Quality factor (section 4.6). These variables are common characteristics among large cap stocks and considering that benchmark indices are market-cap weighted, the high correlation between Quality and both benchmark indices should be justified. The Size portfolios tend to exhibit the lowest correlation with the Quality and Low Volatility portfolios. This is in line with Fama and French (1993) who established that even though the Size factor tends to outperform the market as a whole, they tend to exhibit a higher level of risk. It is therefore plausible that the Size portfolio exhibits the lowest correlation with the Low Volatility portfolios. The correlation matrices show differing results from a geographical perspective. Besides the fact that we have a vast difference in the number of observations in each data set, both benchmark indices are also fundamentally different. The S&P 500 is constructed to represent the entire American economy whereas the Stoxx 600 represents 18 different countries in Europe (section 5.1). We can therefore expect to have a slight variance in portfolio behavior for each geographical region.

7. Conclusion

Based on the empirical analysis carried out in this thesis, we can conclude that 9 out of 10 Smart Beta portfolios outperformed their respective benchmark index on a risk-adjusted basis. This result suggests that exposure to Smart Beta factors can in fact lead to significant improvements in risk-adjusted returns. When attempting to analyze our results through the lens of academic theory and literature, we find that Smart Beta investing doesn't seem to always abide by the rules. This is particularly true when taking into account the widely accepted theory of efficient markets, which essentially implies that cap-weighted indices are mean-variance efficient, i.e. offer the best return-to-risk ratio given a specified level of risk tolerance. According to our results, exposure to Smart Beta factors has historically proven to be beneficial, both in total and risk-adjusted returns, which is in line with several previous academic studies within the subject.

The question if markets truly are efficient from an asset allocation perspective is highly dependent on the sample period analyzed. This is evident in our data set as we see some portfolios clearly stagnating in performance when examining the post crisis period. When drawing conclusions based on historical data, timing is certainly one of the main factors. The portfolios also exhibit different results across the two geographical regions we examine. As mentioned earlier, The S&P 500 and the Euro Stoxx 600 indices are fundamentally different in what they represent and thus, the differing results are to be expected. Another problem when analyzing historical data is the survivorship bias. This may have skewed the data set, especially when analyzing Smart Beta factors exposed to illiquid firms. In the real world, exposure to firms that default could be associated with costs that we cannot control for properly in our analysis. Since this paper compares Smart Beta strategies with passively investing in a cap-weighted index, one must account for the cost of active management and brokerage fees. While the brokerage fees of today do not offset the historical outperformance of Smart Beta strategies, the time and costs associated with actively constructing and rebalancing portfolios could. This may provide one of many explanations as to why markets remain inefficient given that investors face different financial and informational constraints, creating an uneven playing field.

The clear historical outperformance of Smart Beta strategies definitely questions if markets are efficient. Whether the explanation for this is behavioral or economic, our conclusion is that it's possible to outperform the market as a whole with exposure to certain risk factors over the long run. Despite this, we advise investors to be aware of the costs associated with Smart Beta investing and to remember that past performance is not an indicator of future results.

7.1 Suggested further research

The data set for the S&P 500 stretches back to 1994, while the corresponding data set for the Euro Stoxx 600 only goes back to 2002. A larger data set for the European index would yield more specified results, allowing for a more accurate comparison across geographical regions. We therefore suggest our method of portfolio evaluation to be conducted when more data is available.

In order to find out what drives each Smart Beta factor, further research should be conducted on how each Smart Beta portfolio performs in various stages of the business cycle. This can be done by regressing each portfolio on specific macroeconomic indicators such as GDP growth, inflation or unemployment.

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Appendix A

Standardized score

We rely on data of large indices carrying over 500 different firms. The large data pool allows us to assume that the values corresponding to individual firms follow a normal distribution* centered around a mean, μ, forming the classic bell-shaped curve below. Note that normal distribution implies that 68 percent of observations are within one standard deviation, 95 percent within two standard deviations and 99.7 percent are within three standard deviations from the mean (Altman and Bland, 1995).

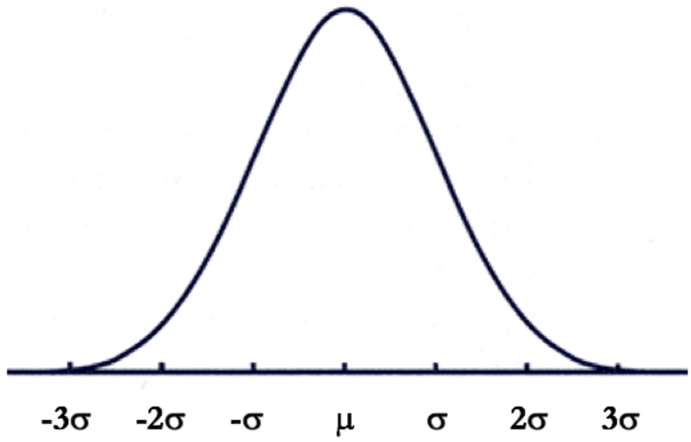

Figure 3: The normal distribution with centered mean and standard deviation ticks. See Altman and Bland (1995).

The standardized score is computed in two steps: First, the geometric mean of each underlying variable is calculated from the total pool of observations. This gives us an estimated center-value that will be used as the comparable value. Secondly, we assign individual standardized scores, z_i, to each underlying variable of interest by subtracting the underlying variable mean from the individual value, x. The last step involves dividing the difference between the underlying variables value and the mean value by the standard deviation of all underlying variables. This procedure gives us a standardized number, allowing us to treat all underlying variables similarly, regardless of any discrepancies in units.

$$z_i = \frac{x_i - \mu}{\sigma} \tag{18}$$

All standardized scores for each underlying variable are given equal weights, $\frac{1}{n}$, and added together to compile an overall standardized factor specific score, Z.

* Normal distribution is also known as Gaussian distribution (Altman and Bland, 1995).

$$Z_i = \frac{1}{n}(z_i + z_{i+1} + z_{i+2} + \cdots + z_n) \tag{19}$$

We now possess a large data set of firms with corresponding overall standardized scores based on selected underlying variables predetermined to reflect a Smart Beta factor. Lastly, the data set is sorted by scores, where the firms with the highest scores are on top of the list. The top 100 firms are selected to proceed to the weighting process, where it will be determined how much weight each firm will have in the final portfolio. The firms with scores below the top-100 are discarded.

The UCITS framework

An outlier is an observation that has been given an abnormally large score and therefore threatens to skew the weight in the portfolio. Assigning exceptionally heavy weights to a single firm in a portfolio is not necessarily an issue, since it reflects a firm with exceptionally large scores, and should thus perform exceptionally well. The issue rather lies in that too much weight threatens to consume any diversification gained in the portfolio, adding unnecessary risk. There are a few alternatives to solve this issue, but as in any data-altering practice, it induces bias in the sample. We therefore face a tradeoff between the vulnerability of outliers and bias. The path chosen in this paper is to accept the bias and follow the regulatory framework UCITS, established by the European Commission which is used by fund managers in the financial industry to ensure the portfolio meets investor protection requirements in portfolio diversification and liquidity (TIA, 2016).

The Undertakings for the Collective Investment of Transferable Securities (UCITS) states:

1. UCITS can invest in an absolute minimum of 16 assets: 4 holdings of up to 10% each plus 12 holdings of up to 5% each.

2. A UCITS fund may invest no more than 5% of its value in approved securities or money market instruments issued by any one body. This limit can be increased to 10% provided that the total value of any holdings between 5% and 10% does not exceed 40% of the fund.

3. No more than 20% of the fund as deposits with any one bank

4. No more than 20% of the fund invested in any one other fund

5. Up to 35% of the fund in any one bond issue provided the rest of the fund is invested in other types of assets; or a minimum of six issues if the fund is over 35% invested in Government bonds.

6. No more than 10% exposed in derivatives with another bank as counterpart

7. Hold no more than 20% of the voting shares of a company

8. Hold no more than 10% of the bonds issued by a company

9. Hold no more than 20% of the value of another fund

(TIA, 2016)

Since our data consist solely of securities, we can disregard bullet points 3-to-9, leaving us to adjust the portfolio according to rules 1 and 2. Rule one regulates diversification by setting a minimum number of securities in a portfolio, which we comply with by using portfolios of 100 securities. The UCITS rules thereby limits us through the second rule, which also regulates diversification, but by controlling for amount invested in a single entity. In cases of extreme outliers, our method will have to adhere to the UCITS 2nd rule, by allowing investments of no more than 5 percent in one stock.

The Winsor method

Applying the UCITS limitation to the portfolio raises another dichotomy. Either exclude outliers above the 5 percent threshold from the data set or invest exactly up until the five percent level and redistribute the excess funds. The first method is commonly known in statistics as trimming and is used when an outlier is considered a true anomaly which does not at all belong in the distribution. Our outliers are firms that have scored exceptionally well, we therefore wish to keep them without hurting the portfolio's diversification properties.

We apply two-step framework, a first step framework using the Winsor method, which is ultimately regulated by a second, framework consisting of the UCITS rules. Winsor is an applied statistic method designed to limit the effect of outliers by adjusting their value to an outer limit (Dixon, 1960). Our data set is Winsorized on the overall standardized scores of individual firms, and the limit is set to target scores that exceed three standard deviations from the mean. Finally, individual weights are limited to five percent, as by the UCITS framework, and any exceeding weights are redistributed evenly according to the standardized score of the individual firms.

The weight, i.e. amount invested in each firm is based on their score and its contribution to the sum of all scores:

$$w_i = \frac{Z_i^{winsor}}{\sum_{i=1}^{n} Z_i^{winsor}} \tag{20}$$

Where w_i denotes the weight for security *i*, and Z_i, denotes the factor specific score for security *i.*

Appendix B

Value variables

P/E Ratio

The price-to-earnings ratio (P/E) is defined as the ratio of a security's share price to its earnings per share (EPS). This is defined mathematically as:

$$\frac{P}{E} = \frac{Share\ price}{Earnings\ per\ share} \tag{21}$$

P/B Ratio

The price-to-book ratio is defined as the ratio between a security's current share price and it book value. This can also be referred to as the Market-to-book ratio. This is defined mathematically as:

$$\frac{P}{B} = \frac{Share\ price}{Book\ value} \tag{22}$$

P/CF Ratio

The price-to-cash flow ratio is the ratio between a security's share price and its operating cash flow. This is defined mathematically as:

$$\frac{P}{CF} = \frac{Share\ price}{Operating\ cash\ flow} \tag{23}$$

Dividend yield

A security's dividend yield or dividend price ratio is defined as ratio between a security's dividends per share and its share price. This is defined mathematically as:

$$Dividend\ yield = \frac{Dividends\ per\ share}{Share\ price} \tag{24}$$

Quality Variables

Return on assets (ROA)

Return on assets is the ratio between a firm's net income and total assets. ROA is an indicator of how profitable a firm is in relation to its assets. This is defined mathematically as:

$$ROA = \frac{Net\ income}{Total\ assets} \tag{25}$$

Return on Equity (ROE)

Return on Equity is the ratio between a firm's net income and shareholders' equity. This profitability measurement reveals how much a company generates in profit in relation to the amount of money shareholders have invested. This is defined mathematically as:

$$ROE = \frac{Net\ income}{Shareholders'equity} \tag{26}$$

Cash flow from operations (CFO)

Cash flow from operations or operating cash flow is a company's cash generation from revenue excluding costs such as investment in securities or long-term investment in capital. CFO is defined mathematically as:

$$CFO = EBIT + Depreciation - Taxes\ \pm\ \Delta Working\ capital \tag{27}$$

Debt-to-equity ratio (D/E Ratio)

The D/E ratio is defined as the relationship between a company total debt and total equity, which measures a firm's financial leverage. This is shown mathematically as:

$$\frac{D}{E} = \frac{Total\ debt}{Total\ equity} \tag{28}$$

Earnings per share variability (EPS Variability)

Earnings per share variability is defined as the standard deviation of the change in earnings per share growth during a period. In this thesis, we use EPS variability for the previous 5 years. This is defined mathematically as:

$$\sigma_{\Delta EPS\ Growth_{T-1:T-5}} \tag{29}$$

Appendix C
Annual winners and losers
a) S&P 500

Annual returns - Smart Beta portfolios vs. S&P 500						
Year	**S&P 500**	**Value**	**Momentu**	**Low Vol**	**Size**	**Quality**
1994	-1,07%	-8,00%	-0,41%	-5,28%	-1,12%	8,21%
1995	29,65%	21,89%	30,05%	27,80%	25,12%	33,99%
1996	19,10%	11,23%	19,73%	12,55%	17,89%	24,00%
1997	28,71%	23,56%	26,77%	24,43%	20,98%	31,40%
1998	25,64%	10,50%	22,74%	6,05%	13,76%	32,21%
1999	19,42%	-8,30%	43,09%	-10,79%	8,42%	20,56%
2000	-8,19%	22,10%	25,69%	18,34%	8,67%	3,50%
2001	-11,67%	22,95%	-9,74%	1,85%	1,66%	-1,85%
2002	-23,20%	-9,93%	-17,57%	-5,57%	-15,35%	-12,25%
2003	24,89%	24,09%	45,97%	18,73%	31,91%	23,16%
2004	9,26%	13,69%	17,96%	13,27%	15,80%	8,82%
2005	3,50%	2,79%	16,44%	0,61%	8,83%	3,72%
2006	13,25%	19,55%	9,19%	14,85%	12,39%	13,42%
2007	4,67%	-6,19%	9,20%	0,03%	0,50%	12,91%
2008	-40,18%	-35,08%	-49,02%	-23,80%	-42,52%	-36,45%
2009	24,66%	41,86%	24,76%	16,49%	38,49%	31,96%
2010	13,60%	16,26%	12,20%	9,74%	21,25%	13,41%
2011	2,71%	3,51%	-0,07%	10,71%	1,85%	7,67%
2012	13,44%	9,76%	8,85%	7,30%	15,45%	10,40%
2013	26,53%	20,23%	32,16%	19,54%	28,60%	27,79%
2014	11,41%	10,78%	10,31%	15,33%	14,43%	12,88%
2015	0,46%	-15,49%	4,50%	3,20%	-2,47%	-2,10%
2016	9,97%	29,35%	3,21%	9,12%	14,73%	8,20%

Table 3: Yearly annual returns for the smart beta portfolios on the S&P 500 from 1994 to 2016. S&P 500 included for comparison. Worst (red) and best (green) values for each year are highlighted.

Sharpe ratios - Smart Beta portfolios vs. S&P 500						
Year	**S&P 500**	**Value**	**Momentum**	**Low Vol**	**Size**	**Quality**
1994	-0,55	-1,22	-0,40	-1,10	-0,57	0,38
1995	3,08	2,10	2,28	3,45	2,55	2,93
1996	1,19	0,63	1,15	0,77	1,20	1,41
1997	1,30	1,48	1,05	1,57	1,04	1,39
1998	1,03	0,42	0,83	0,09	0,48	1,38
1999	0,81	-0,92	1,72	-1,25	0,25	0,91
2000	-0,64	0,84	0,56	0,73	0,14	-0,12
2001	-0,70	1,09	-0,72	-0,12	-0,09	-0,23
2002	-0,96	-0,45	-0,89	-0,38	-0,64	-0,58
2003	1,40	1,46	2,33	1,45	1,71	1,38
2004	0,71	1,25	1,15	1,35	1,16	0,70
2005	0,03	-0,04	0,93	-0,27	0,50	0,05
2006	0,84	1,67	0,30	1,29	0,69	0,77
2007	0,01	-0,60	0,25	-0,31	-0,24	0,54
2008	-1,02	-0,74	-1,27	-0,85	-1,02	-0,92
2009	0,90	0,95	0,86	0,97	1,11	1,23
2010	0,75	0,98	0,53	0,76	1,04	0,83
2011	0,11	0,14	0,00	0,65	0,07	0,34
2012	1,05	0,87	0,67	0,87	1,04	0,75
2013	2,40	1,79	2,38	1,91	2,34	2,49
2014	1,00	1,06	0,74	1,66	1,30	1,11
2015	0,03	-0,95	0,29	0,23	-0,16	-0,14
2016	0,74	1,65	0,23	0,80	0,95	0,58

Table 4: Yearly Sharpe ratios for the smart beta portfolios on the S&P 500 from 1994 to 2016. S&P 500 included for comparison. Worst (red) and best (green) values for each year are highlighted.

Annualized volatility - Smart Beta portfolios vs. S&P 500						
Year	**S&P 500**	**Value**	**Momentum**	**Low Vol**	**Size**	**Quality**
1994	9,82%	10,11%	11,83%	8,73%	9,67%	10,30%
1995	7,79%	7,75%	10,68%	6,42%	7,65%	9,67%
1996	11,76%	9,69%	12,69%	9,60%	10,61%	13,34%
1997	18,10%	12,43%	20,57%	12,28%	15,17%	18,90%
1998	20,25%	13,45%	21,65%	12,80%	18,54%	19,83%
1999	18,04%	14,20%	22,33%	12,44%	14,59%	17,31%
2000	22,18%	19,13%	35,43%	16,87%	18,60%	21,58%
2001	21,52%	17,86%	18,32%	13,28%	20,98%	22,73%
2002	25,97%	25,54%	21,66%	18,91%	26,68%	23,93%
2003	17,03%	15,84%	19,26%	12,21%	18,05%	16,09%
2004	11,07%	9,84%	14,46%	8,78%	12,45%	10,58%
2005	10,24%	10,57%	14,25%	9,43%	11,21%	10,49%
2006	10,02%	8,79%	14,49%	7,77%	10,95%	11,18%
2007	15,96%	17,80%	18,73%	14,22%	16,20%	15,71%
2008	40,89%	49,14%	39,77%	29,65%	43,02%	41,00%
2009	27,23%	43,99%	28,67%	16,83%	34,45%	25,91%
2010	18,01%	16,47%	22,83%	12,71%	20,27%	16,04%
2011	23,23%	25,51%	23,65%	16,37%	25,33%	22,30%
2012	12,74%	11,18%	13,12%	8,34%	14,78%	13,75%
2013	11,04%	11,26%	13,51%	10,22%	12,22%	11,12%
2014	11,35%	10,14%	13,89%	9,21%	11,10%	11,56%
2015	15,46%	16,42%	15,58%	13,54%	15,30%	15,43%
2016	13,07%	17,59%	12,84%	10,99%	15,26%	13,51%

Table 5: Yearly annualized volatility for the smart beta portfolios on the S&P 500 from 1994 to 2016. S&P 500 included for comparison. Worst (red) and best (green) values for each year are highlighted.

Excess Returns vs. S&P 500					
Year	**Value**	**Momentum**	**Low Vol**	**Size**	**Quality**
1994	-6,93%	0,66%	-4,21%	-0,05%	9,28%
1995	-7,76%	0,40%	-1,85%	-4,53%	4,34%
1996	-7,87%	0,63%	-6,55%	-1,21%	4,90%
1997	-5,15%	-1,94%	-4,28%	-7,73%	2,69%
1998	-15,14%	-2,90%	-19,59%	-11,88%	6,57%
1999	-27,72%	23,67%	-30,21%	-11,00%	1,14%
2000	30,29%	33,88%	26,53%	16,86%	11,69%
2001	34,62%	1,93%	13,52%	13,33%	9,82%
2002	13,27%	5,63%	17,63%	7,85%	10,95%
2003	-0,80%	21,08%	-6,16%	7,02%	-1,73%
2004	4,43%	8,70%	4,01%	6,54%	-0,44%
2005	-0,71%	12,94%	-2,89%	5,33%	0,22%
2006	6,30%	-4,06%	1,60%	-0,86%	0,17%
2007	-10,86%	4,53%	-4,64%	-4,17%	8,24%
2008	5,10%	-8,84%	16,38%	-2,34%	3,73%
2009	17,20%	0,10%	-8,17%	13,83%	7,30%
2010	2,66%	-1,40%	-3,86%	7,65%	-0,19%
2011	0,80%	-2,78%	8,00%	-0,86%	4,96%
2012	-3,68%	-4,59%	-6,14%	2,01%	-3,04%
2013	-6,30%	5,63%	-6,99%	2,07%	1,26%
2014	-0,63%	-1,10%	3,92%	3,02%	1,47%
2015	-15,95%	4,04%	2,74%	-2,93%	-2,56%
2016	19,38%	-6,76%	-0,85%	4,76%	-1,77%

Table 6: Yearly excess returns for the smart beta portfolios on the S&P 500 from 1994 to 2016. S&P 500 included for comparison. Worst (red) and best (green) values for each year are highlighted.

b) Stoxx 600

Annual returns – Smart Beta portfolios vs. Stoxx 600						
Year	**Stoxx 600**	**Value**	**Momentum**	**Low Volatility**	**Size**	**Quality**
2002	-34,53%	-4,58%	-15,91%	-9,36%	-31,78%	-28,31%
2003	14,22%	27,00%	27,16%	17,49%	27,53%	22,99%
2004	9,76%	19,41%	21,88%	19,50%	14,90%	14,60%
2005	21,55%	17,38%	22,63%	18,72%	22,59%	20,36%
2006	17,20%	16,75%	29,56%	22,97%	22,21%	19,86%
2007	1,12%	-16,56%	5,59%	-0,49%	-0,94%	2,90%
2008	-54,11%	-71,03%	-44,40%	-28,87%	-55,39%	-40,47%
2009	27,61%	51,18%	14,62%	10,69%	40,70%	38,81%
2010	9,97%	8,81%	27,33%	4,66%	12,31%	12,74%
2011	-9,53%	-15,87%	-11,76%	-1,46%	-15,55%	-6,54%
2012	14,63%	19,29%	13,91%	13,90%	19,10%	16,41%
2013	16,74%	16,82%	27,82%	15,92%	23,18%	20,24%
2014	5,14%	1,23%	3,83%	10,25%	4,32%	2,11%
2015	8,53%	-6,63%	13,21%	11,16%	8,76%	6,75%
2016	0,78%	19,36%	5,87%	-2,58%	6,21%	0,33%

Table 7: Yearly annual returns for the smart beta portfolios on the Stoxx 600 from 2002 to 2016. Stoxx 600 included for comparison. Worst (red) and best (green) values for each year are highlighted.

Sharpe ratios - Smart Beta portfolios vs. Stoxx 600						
Year	**Stoxx 600**	**Value**	**Momentum**	**Low Volatility**	**Size**	**Quality**
2002	-1,29	-0,34	-1,34	-1,15	-2,12	-1,46
2003	0,63	1,94	2,47	2,88	2,01	1,60
2004	0,74	2,56	2,09	3,87	1,90	1,52
2005	1,97	1,74	2,05	2,57	3,51	2,11
2006	0,98	1,06	1,57	2,36	2,17	1,31
2007	-0,21	-1,11	0,07	-0,45	-0,52	-0,10
2008	-1,52	-1,49	-1,59	-1,24	-2,46	-1,23
2009	1,14	1,72	0,68	0,96	2,09	2,09
2010	0,54	0,64	1,61	0,46	0,97	0,98
2011	-0,44	-0,78	-0,63	-0,12	-1,15	-0,36
2012	0,98	1,17	1,14	1,73	1,73	1,33
2013	1,39	1,44	2,16	2,05	2,57	2,06
2014	0,38	0,10	0,26	1,17	0,51	0,19
2015	0,43	-0,37	0,81	0,89	0,79	0,45
2016	0,02	0,85	0,41	-0,23	0,44	0,01

Table 8: Yearly sharpe ratios for the smart beta portfolios on the Stoxx 600 from 2002 to 2016. Stoxx 600 included for comparison. Worst (red) and best (green) values for each year are highlighted.

Annualized volatility – Smart Beta portfolios vs. Stoxx 600						
Year	**Stoxx 600**	**Value**	**Momentum**	**Low Volatility**	**Size**	**Quality**
2002	28,13%	18,39%	13,13%	9,59%	15,76%	20,54%
2003	20,89%	13,39%	10,60%	5,72%	13,17%	13,70%
2004	11,33%	7,03%	9,82%	4,68%	7,11%	8,70%
2005	9,30%	8,14%	9,47%	6,03%	5,53%	8,15%
2006	12,65%	11,19%	15,77%	7,68%	7,99%	11,46%
2007	15,87%	18,88%	17,44%	10,95%	10,37%	15,88%
2008	36,40%	48,55%	28,81%	24,31%	23,06%	33,96%
2009	24,10%	29,69%	21,37%	10,94%	19,38%	18,54%
2010	18,13%	13,57%	16,88%	9,75%	12,62%	12,92%
2011	21,99%	20,36%	18,60%	12,91%	13,60%	18,16%
2012	14,79%	16,47%	12,12%	8,00%	11,00%	12,30%
2013	12,04%	11,62%	12,84%	7,75%	8,99%	9,83%
2014	13,32%	11,85%	14,42%	8,73%	8,47%	10,83%
2015	19,76%	17,78%	16,28%	12,51%	11,08%	14,94%
2016	19,59%	22,36%	13,67%	12,56%	13,54%	14,68%

Table 9: Yearly annualized volatility for the smart beta portfolios on the Stoxx 600 from 2002 to 2016. Stoxx 600 included for comparison. Worst (red) and best (green) values for each year are highlighted.

Excess returns vs. Stoxx 600					
Year	**Value**	**Momentum**	**Low Volatility**	**Size**	**Quality**
2002	29,95%	18,62%	25,17%	2,75%	6,22%
2003	12,78%	12,94%	3,27%	13,31%	8,77%
2004	9,65%	12,12%	9,74%	5,14%	4,84%
2005	-4,17%	1,08%	-2,83%	1,04%	-1,19%
2006	-0,45%	12,36%	5,77%	5,01%	2,66%
2007	-17,68%	4,47%	-1,61%	-2,06%	1,78%
2008	-16,92%	9,71%	25,24%	-1,28%	13,64%
2009	23,57%	-12,99%	-16,92%	13,09%	11,20%
2010	-1,16%	17,36%	-5,31%	2,34%	2,77%
2011	-6,34%	-2,23%	8,07%	-6,02%	2,99%
2012	4,66%	-0,72%	-0,73%	4,47%	1,78%
2013	0,08%	11,08%	-0,82%	6,44%	3,50%
2014	-3,91%	-1,31%	5,11%	-0,82%	-3,03%
2015	-15,16%	4,68%	2,63%	0,23%	-1,78%
2016	18,58%	5,09%	-3,36%	5,43%	-0,45%

Table 10: Yearly excess returns for the smart beta portfolios on the Stoxx 600 from 2002 to 2016. Stoxx 600 included for comparison. Worst (red) and best (green) values for each year is highlighted.

Appendix D

Value

a) S&P 500

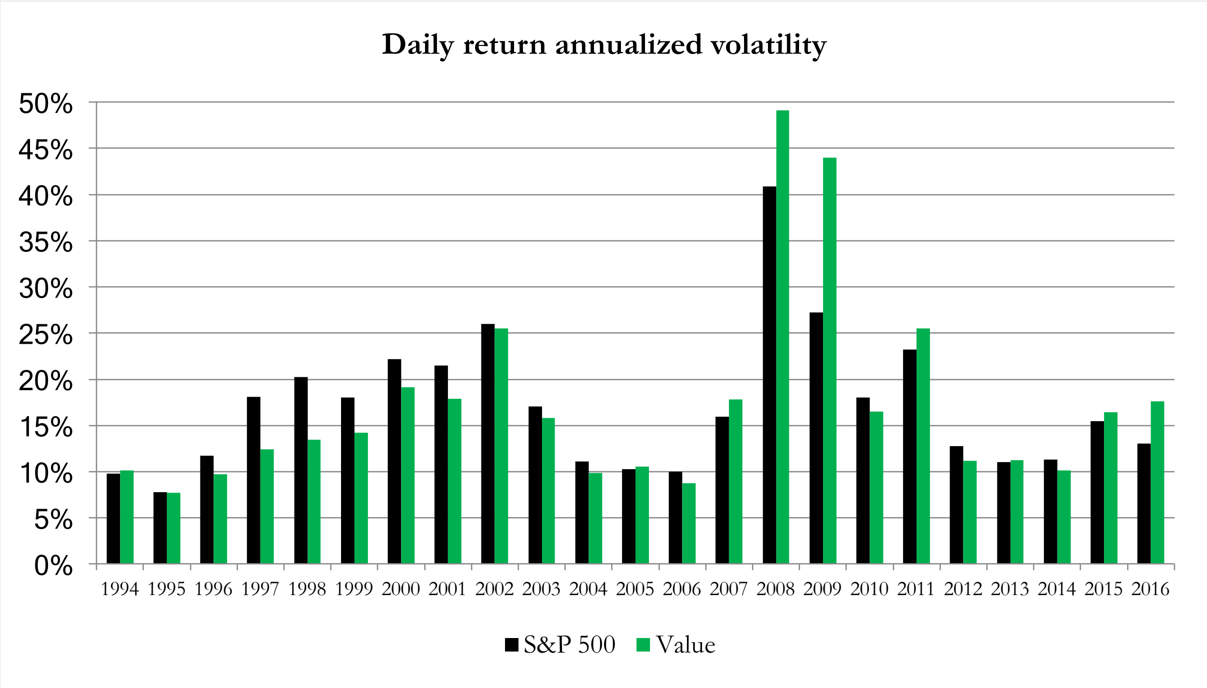

Figure 17: Daily return annualized volatility for the S&P 500 and the Value factor.

a) Stoxx 600

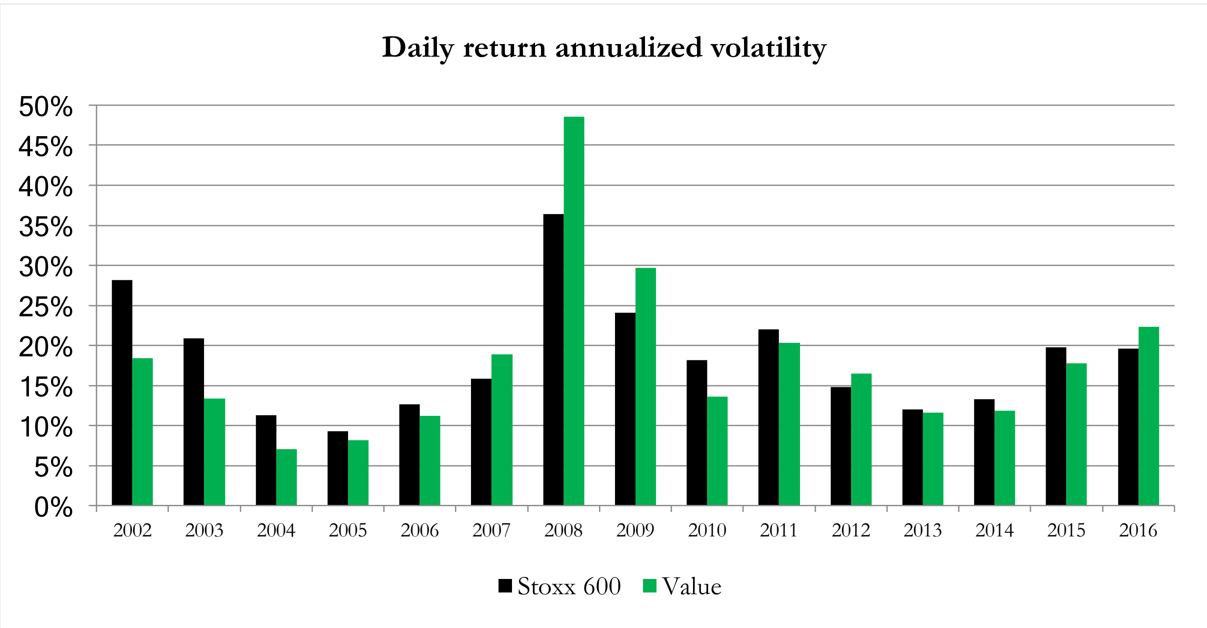

Figure 18: Daily return annualized volatility between 2002 and 2016 for the Stoxx 600 and the Value factor.

Momentum

a) S&P 500

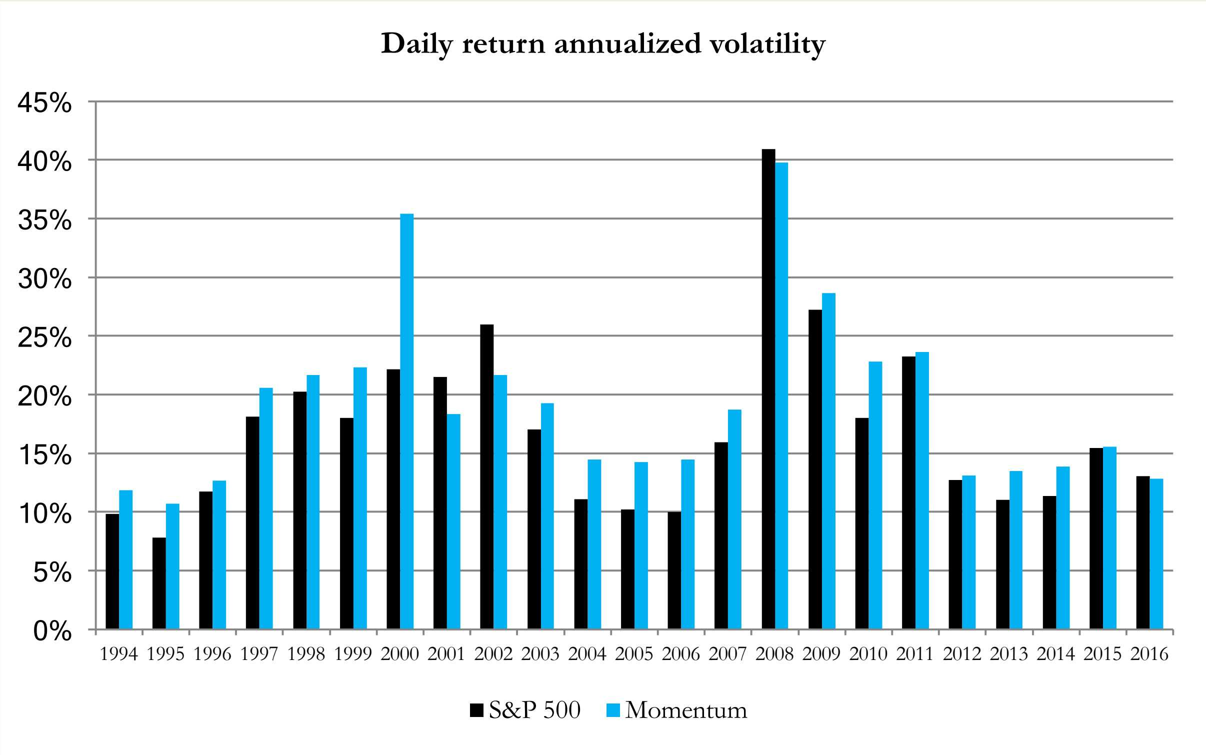

Figure 17: Daily return annualized volatility for the S&P 500 and the Momentum factor.

b) Stoxx 600

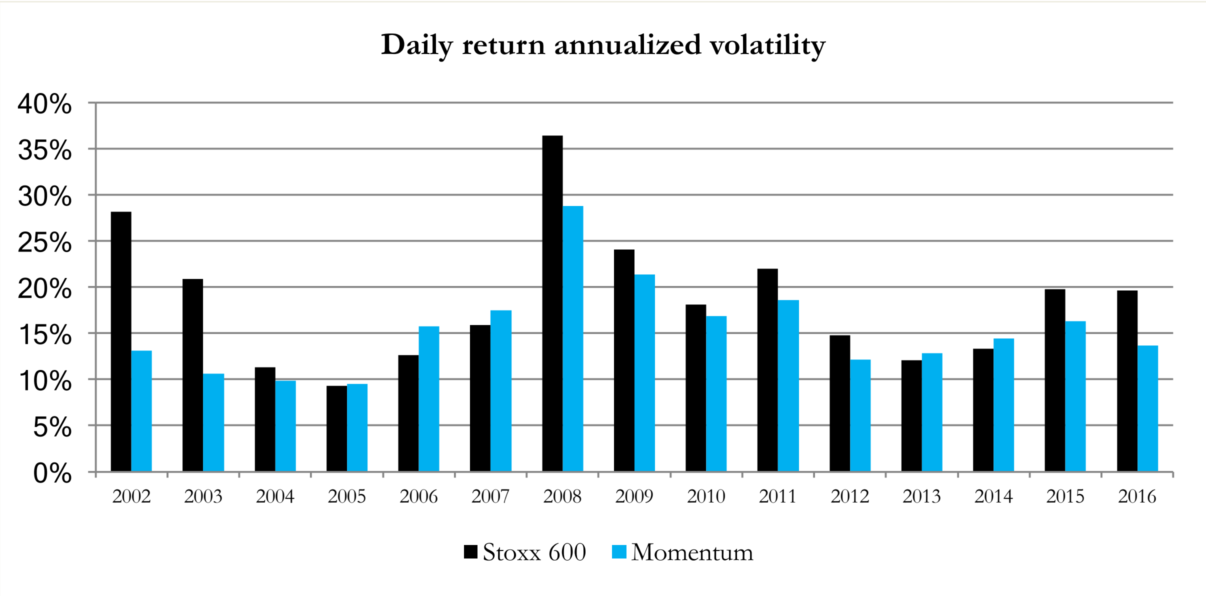

Figure 20: Daily return annualized volatility between 2002 and 2016 for the Stoxx 600 and the Momentum factor.

Low Volatility

a) S&P 500

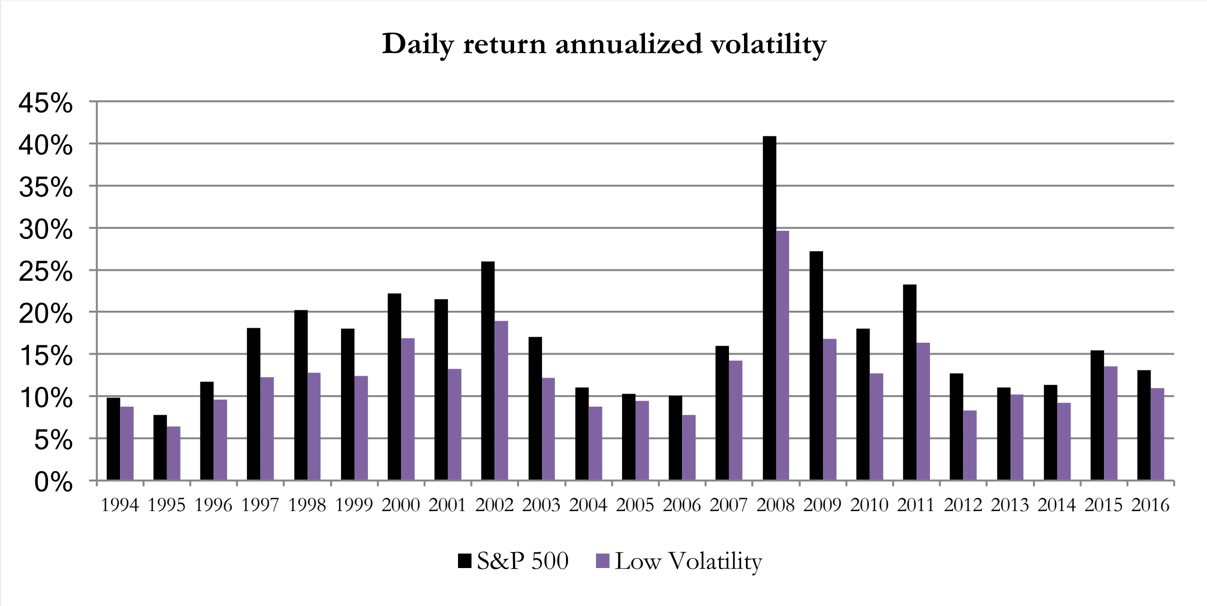

Figure 21: Daily return annualized volatility for the S&P 500 and the Low Volatility factor.

b) Stoxx 600

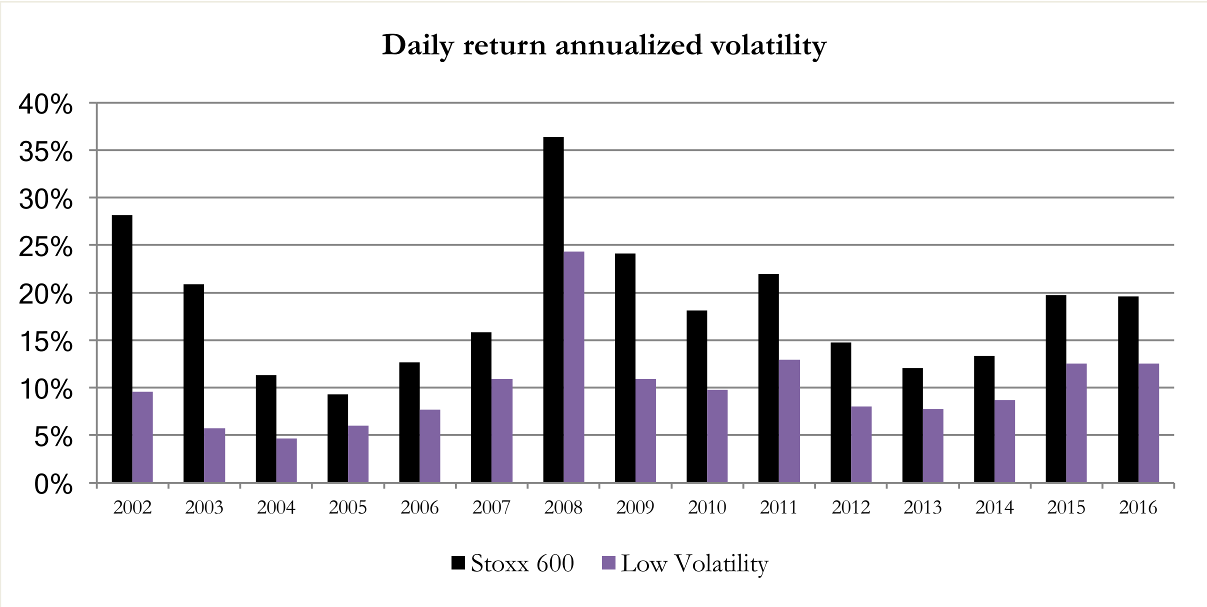

Figure 22: Daily return annualized volatility between 2002 and 2016 for the Stoxx 600 and the Low Volatility factor.

Size

a) S&P 500

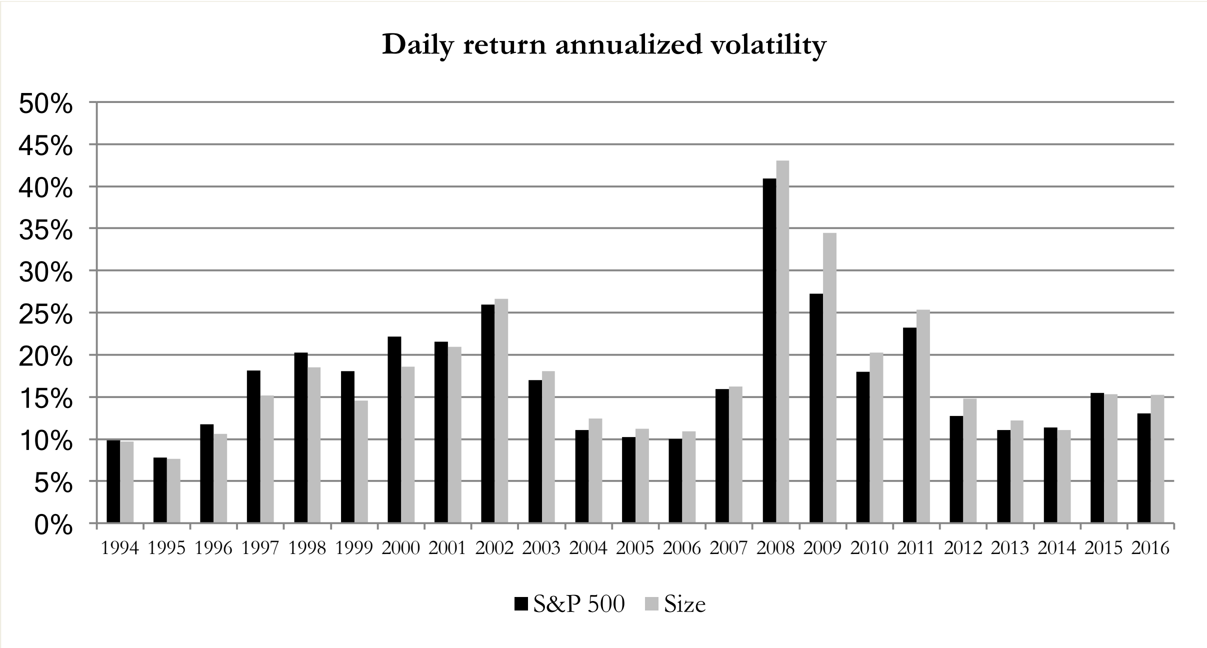

Figure 23: Daily return annualized volatility for the S&P 500 and the Size factor.

b) Stoxx 600

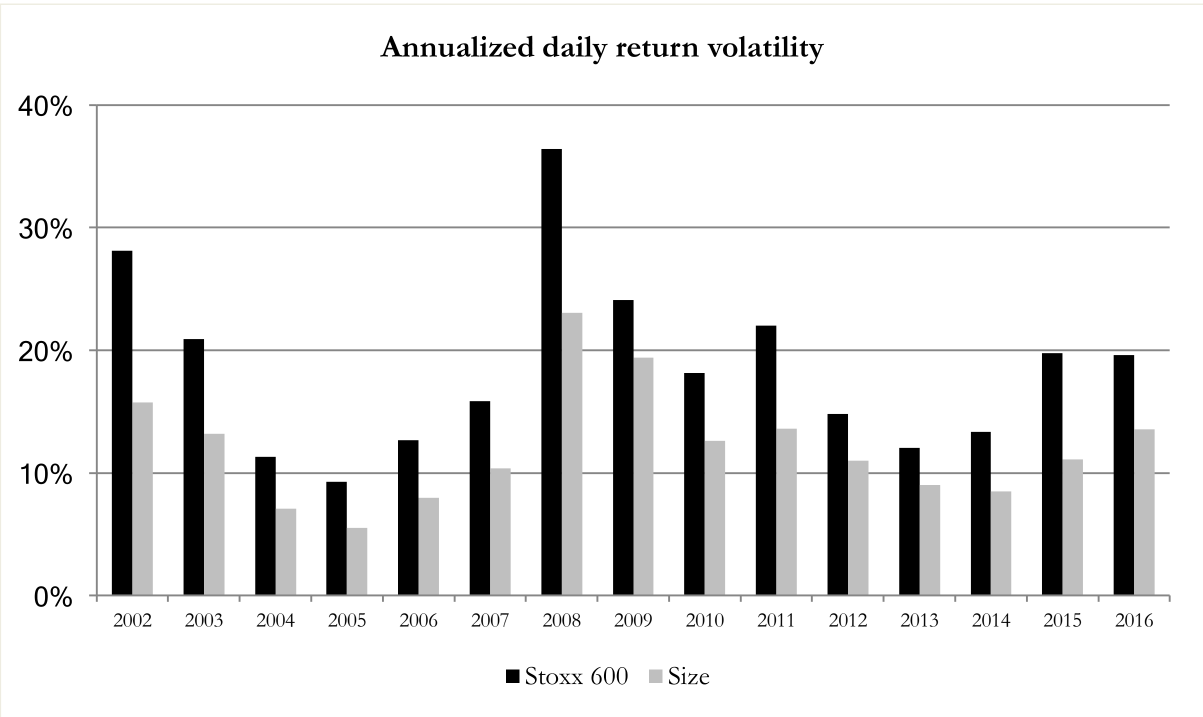

Figure 24: Daily return annualized volatility between 2002 and 2016 for the Stoxx 600 and the Size factor.

Quality

a) S&P 500

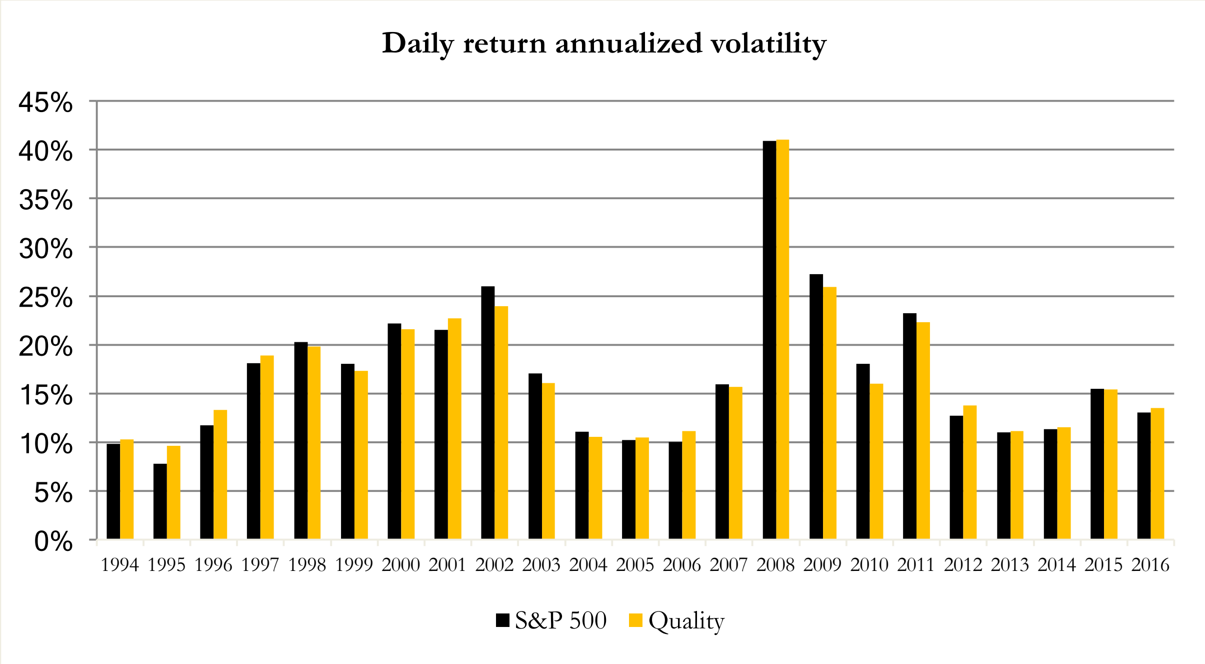

Figure 25: Daily return annualized volatility for the S&P 500 and the Quality factor.

b) Stoxx 600

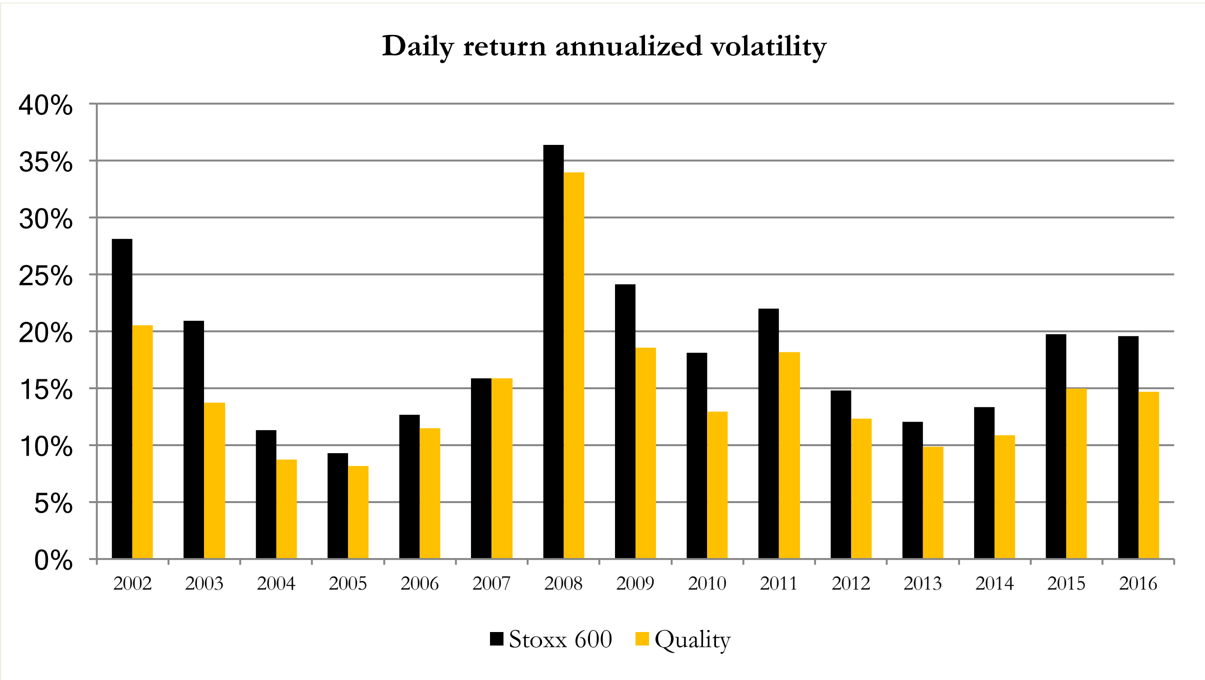

Figure 26: Daily return annualized volatility between 2002 and 2016 for the Stoxx 600 and the Quality factor.

Appendix E

Risk free rate of return

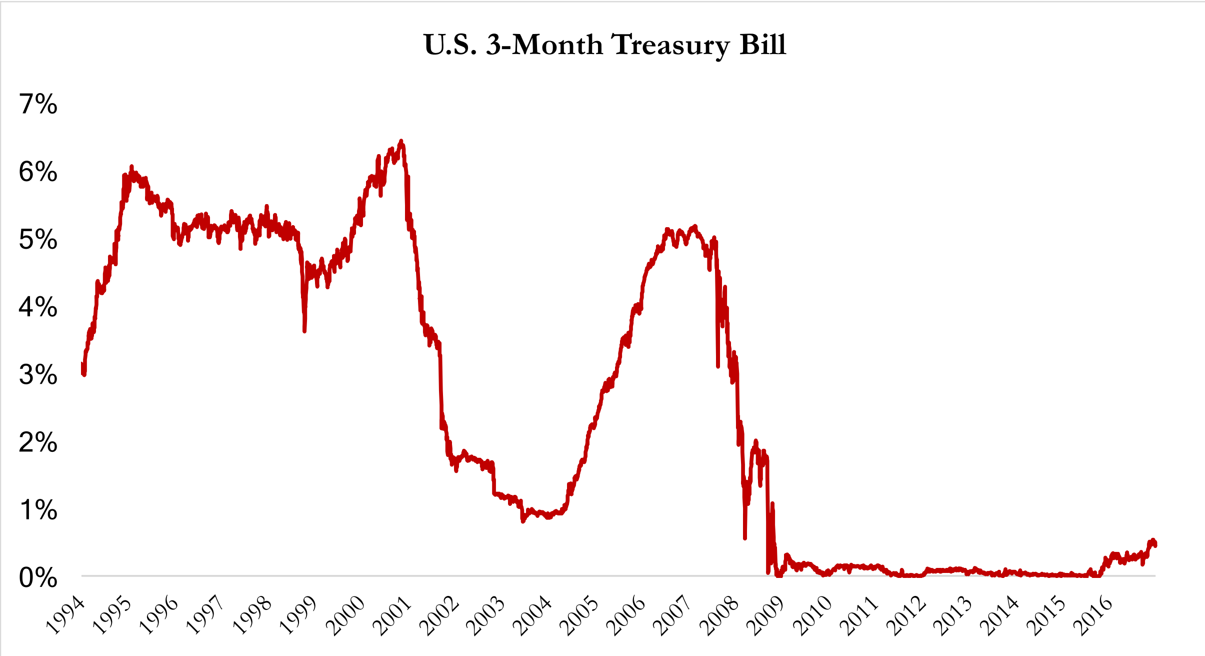

Figure 27: The U.S. 3-Month Treasury Bill between 1994 to 2016. The Treasury Bill is referred to as the risk free rate.