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Smart Beta Exchange Traded Funds

Empirical Study of the risks and returns of US-listed Smart Beta ETFs

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Author / Student ID**:**
Anders Øverland Nes / 102619

Supervisor:
Daniel Wekke Probst
Department of Accounting

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Executive Summary

Asset managers will forever be in the hunt for a sort of “holy grail” that could offer investors above-market returns at lower risk in an efficient and low-cost way. One of their latest efforts are commonly known as Smart Beta exchange-traded funds (ETFs). The investment approach implements a rule-based system for choosing and weighting assets based on factors associated with risk-premiums. From having practically zero dollars’ worth of assets under management in 2000, there are now more than $1 trillion in 2020 in the U.S. alone.

This thesis aims to provide an empirical study on US-listed Smart Beta equity ETFs and, thus, unmask some of the critical elements of the popular investment product. In a two-part analysis, the promise of outperformance and ability to provide intended factor exposures are investigated in the period between Jan-2007 and Mar-2020.

For the first part of the analysis, a sample of 60 domestic Smart Beta ETFs across six well-known and acknowledged factor-strategies is constructed. These strategies are Size, Value, Momentum, Low Volatility, Quality, and Multifactor. The Smart Beta ETFs are analyzed concerning both relative returns and risk-adjusted-performance over three-time frames; the entire period, “up” and “down” periods. For the second part of the analysis, a multivariate factor-based regression model is built by assessing factors from the AQR data library. From outputs of the regression model, it will be possible to judge whether the different Smart Beta portfolios have provided investors with the intended factor-exposures. The methodology is mostly based on previous studies on similar subjects as well as traditional financial theory, but have found the most inspiration in Glushkov (2015).

In line with Glushkov (2015), this thesis does not find any statistically significant evidence of Smart Beta ETFs outperforming either its benchmark indices nor a broad, cap-weighted market indices. Besides, Smart Beta ETFs are found to provide investors with statistically significant exposure to intended factor tilts. However, there is also evidence of significant unintended factor tilts that seem to more than offset the harvested risk-premiums from the intended factor exposures.

Keywords: *Smart Beta, Exchange Traded Funds, Factor-Models, Factor-Investing, Assessing Fund Performance, Factor Exposure Analysis, Expense Ratio, Fund-Flows, Market Cycles*

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1. Introduction

1.1 Background

The question of what drives stock returns has been a staple of modern finance. The oldest and most well-known model in financial theory is the Capital Asset Pricing Model (CAPM) which first became known in the 1960s through the works of Jack Treynor (1961) and William Sharpe (1964). According to the CAPM, stocks have only two main drivers: *market risk* and *company-specific risk*. The former is the risk that arises from exposure to the market and is captured by beta, i.e., the sensitivity of a stock's return to market movements. Because market risk cannot be diversified away, investors are compensated with returns for bearing this risk. In other words, the expected return to any stock could be viewed as a function of its beta relative to the market. In the decades that followed, academics and practitioners discovered other *factors*[1] that drive the returns of stocks.

Eugene Fama and Kenneth French (1992) demonstrated that besides the market factor, the *size* of a company and its valuation (i.e., *value*) are also important drivers of its stock price. This three-factor approach is an empirical approach, meaning that Fama and French worked backwards to explain the shortcomings of the traditional CAPM. Interestingly, Fama (1992) essentially discounts his previous work as he is claiming to generate excess returns based on companies with *good* price/book-ratios[2], although under the Efficient Markets Hypothesis (EMH) Fama (1970) proposed that to be impossible.

It was the EMH that essentially formed the intellectual basis for a style of investing that has become known as passive investing or index tracking. For several decades, market capitalization-weighted indices (e.g., S&P 500) have served as the foundation of the passive approach to investing. Many investors have long viewed these indexes as an efficient way to gain broad exposure to a wide variety of markets. On the contrary, active investing is for those who believe that there are inefficiencies in the marketplace and that it is possible to make systematic profits from trading. However, the current low-yield environment, increasingly volatile markets and central-bank interventions have made it challenging for active managers, and investors, to pick winners over losers. According to S&P Dow Jones (2019), more than 80 pct. of actively managed funds have underperformed their benchmarks

[1] Factors are characteristics relating to a group of securities that is important in explaining their returns and risk.
[2] The price/book-ratio measures the market's valuation of a company relative to its book value.

since 2001. As a result, active fund managers are increasingly losing out to passively managed mutual funds and exchange-traded funds[3] (ETFs), which have lower management fees and higher liquidity.

With the rise of passive investments, along with investors becoming more focused on how to harvest returns efficiently, factor-investing has increased in popularity among asset managers and providers of investment products. ETFs based on factor-strategies, or any index-based strategy that weights stocks by something other than market capitalization, are commonly referred to as Smart Beta ETFs (McGee, 2019). In other words, Smart Beta ETFs are rule-based indices that select stocks based on qualities or "factors" that empirical research suggests are associated with outperformance. Examples could be size, momentum, or value. According to data from Bloomberg, assets under management in U.S.-listed equity Smart Beta ETFs have gone from $28 billion in 2005 to almost $1 trillion in 2019 which is about 25 pct. of ETF assets under management in the U.S. combined (Gurdus, 2019).

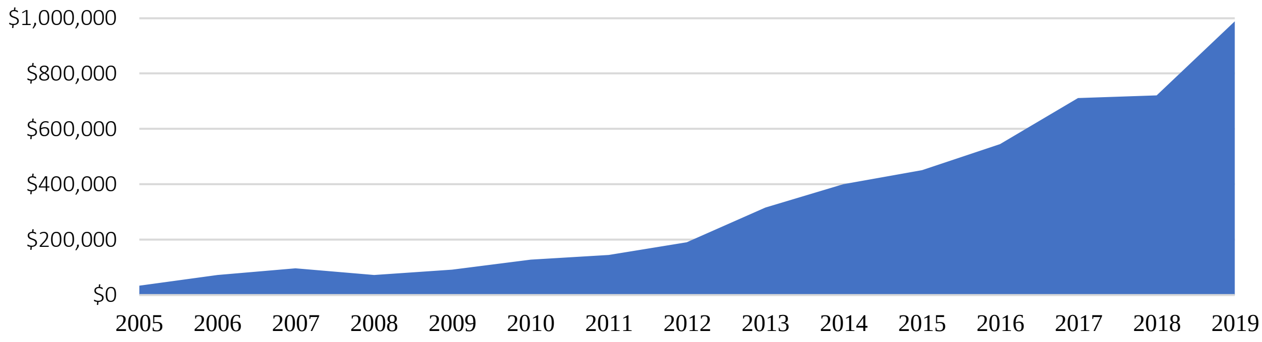

Figure 1 – U.S. listed Equity Smart Beta AUM ($million), source: Bloomberg

1.2 Motivation for Choice of Thesis Subject

Demand for ETFs in the U.S. has grown significantly. In the past ten years, the net share issuance of ETFs has totaled $2.3 trillion, with $311 billion issued in 2018 alone (ICI, 2019). As demands from investors has increased, the variety in investment objectives in ETFs has increased as well. One of the fastest-growing segments of the ETF-market in recent years is Smart Beta. These trends are supported by the overall positive attitude of investors, as 60 pct. (20 pct. in 2015) of surveyed asset managers in North America have adopted them (FTSE Russell, 2019). Besides, the Securities and Exchange Commission (SEC) is watering down its *exemptive relief rule*[4], which have often made the

[3] An exchange-traded fund (ETF) is a basket of securities that trade on an exchange, just like a stock.
[4] ETFs that meet certain conditions may go to market without the delay of obtaining an exemptive order.

come-to-market process long and tiring for ETF-issuers. According to Gurdus (2019), this relief could mean that ETFs are entering a new era that could expand Smart Beta ETFs even further.

According to the *Annual Smart-Beta Survey* from FTSE Russel (2019), the most common objectives for using Smart-Beta strategies, compared to traditional market-cap-weighted strategies, are **1)** return enhancement, **2)** cost savings, **3)** risk reduction and **4)** improved diversification.

According to Riding (2019), Smart-Beta ETFs have yielded less than their benchmarks between 2009 and 2018. Most factors tend to perform poorly during bull markets, so the decade-long rally could be one reason for the underperformance. In particular, the *value* factor has fared poorly as a result of the market being driven higher by *growth* and *momentum* stocks. As for costs, the expense ratio of Smart Beta funds costs investors about 0.39 pct. in fees on average. Compared to typical passive investment tied to cap-weighted indexed like S&P 500 (0.15 pct.), Smart Beta is more expensive. On the other hand, they are notably lower than an actively managed fund, which charges 0.90 pct. (McGee, 2019).

In terms of risk reduction and improved diversification, many investors believe that Smart Beta ETFs have the potential to deliver these features during different market cycles. In "down" periods, the ETFs could offer reduced volatility by tilting the portfolio towards defensive factors with negatively correlated risk-premia relative to the market (e.g., low-volatility or quality ETFs). In "up" periods, Smart Beta ETF strategies such as size and momentum may be better positioned to capture additional sources of risk-premia beyond the *bulk* beta offered by the market (Glushkov, 2015).

Another interesting thing to note about Smart Beta ETFs is the concern about the unintended risk exposures that they may cause. In other words, two Smart-Beta ETFs might say "value" on the label, but what's inside could be completely different. Asset managers at Robeco analyzed returns from the Russell 1000 Value index and found that the value factor only accounted for 36 pct. of index-returns. The remaining exposure was attributed to the market portfolio (23 pct.), the investment factor (21 pct.) and the low-volatility factor (20 pct.). This implies that the Russell 1000 Value index is not very suitable for investors seeking pure exposure to the value factor (Blitz, 2016).

1.3 Problem Statement

In order to address the mentioned objectives and the potential imperfections of Smart Beta ETFs, this thesis aims to provide further insights into the promise of investing in factor-based strategies through an empirical study of US-listed Smart Beta ETFs. Thus, the over-arching research question reads:

What should investors consider before investing in Smart Beta ETFs?

To answer the research question, the thesis has been operationalized into five sub-areas (highlighted in bold) which are equivalent to the main structure of the thesis itself:

- **Literature review:** from what foundations did Smart Beta ETFs prevail? What factors do they include? How are the factors defined? What studies have been made on similar subjects?
- **Data Sample:** what data is needed, and what is the rationale behind the final construction of the data sample? What considerations regarding data quality should readers be made aware of?
- **Methodology:** what (research) methods will the thesis rely on when **a)** evaluating performance and **b)** investigating factor exposures? What procedures are undertaken to mitigate issues related to data quality?
- **Analysis part I (performance analysis):** how does the performance of Smart-Beta ETFs **a)** compare with benchmark indices and broad, cap-weighted ETFs and **b)** how do they behave in "up" and "down" market cycles?
- **Analysis part II (factor exposure analysis):** is there evidence that US-listed Smart-Beta ETFs are providing significant exposure to their declared factor-strategies (i.e., index selections)?

Finally, the thesis will include a section that provides an overall **conclusion** to the problem statement and sets the stage for **further research** in the field.

1.4 Scope & Delimitations

The thesis covers US-domiciled Smart Beta exchange-traded funds (ETFs), which are benchmarked by domestic equity indices. The construction of the data sample, and the categorization of Smart Beta categories, are based on the "Smart Beta screener" of Bloomberg and supplemented with the more extensive Smart Beta taxonomy of Morningstar (Boyadzhiev, D.; Bryan, A.; Choy, J.; Johnson, B.;

Venkataraman, A., 2019). January 2007 was chosen as the initial record-date because it was the first date that return-data could be obtained for at least one Smart Beta ETF in all categories. Recordings ended in March 2020.

Academic and industry attention to Smart Beta ETFs has led to a surge in different labels that broadly encompass a similar approach to index investing. This thesis will use Smart Beta for convenience because it has been widely adopted by many in the industry.

Whether to account for costs related to transactions and tax is essential. Especially for the analysis on whether Smart-Beta ETFs have outperformed their benchmarks, as gross results may be eliminated when accounting for real-world transaction costs. In order for there to be a point in accounting for transaction costs, extensive amounts of data on historical trading costs in the U.S. should be at hand. As the author does not have access to this data, along with time and size constraints for the project, it was decided not to do a detailed analysis on this but rather do a very simplified comparison of expense ratios to account for possible impact on returns. The potential impact of taxation on investment returns will not be addressed for this thesis, but readers should be made aware that differences in taxation of dividends and capital income may have affected results.

Academics and practitioners have documented hundreds of individual factors, though few are widely accepted as being credible (Harvey et al., 2016). These are value, size, momentum, quality, and low volatility. Each of these factors has been vetted by multiple scholars and professional investors. More specific delimitations with regards to, for example, but not limited to, choice of method for evaluating performance and factor exposures, will be presented under the relevant sections.

2. Literature Review

This section introduces and reviews established theories within the field of financial economics which have set the foundation for factor investing and, subsequently, Smart Beta ETFs as we know it today. These are the Efficient Market Hypothesis (EMH), asset pricing models such as the Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT), and finally, factor-models such as Fama-French and Carhart. Furthermore, relevant findings from academic studies will be presented.

2.1 The Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH) was familiarized by Fama et al. (1969) and raised awareness of how prices of securities adjust when new information becomes available. Initially, an efficient market was described as a market that "*quickly adjusts to new information*" but was modified by Fama (1991) to "*all available information is reflected in current prices*" due to the rise of the internet and fast-paced data transmissions. Information entails what is currently known about securities as well as any future expectations. Thus, the EMH suggests that markets are consistent with the *Random Walk Hypothesis* by suggesting that only *new* information will move stock prices significantly, and since new information is unpredictable and happens at random, future price-movements are unknown and, hence, move randomly (Barack & Malkiel, 1974). In other words, generating alpha (i.e., achieve excess market returns) becomes a game of chance, and outperforming the stock market over time is considered impossible, rendering Smart-Beta investing a pointless operation.

Ever since it was introduced, the EMH has been one of the most disputed financial theories due to the complete disregard of asymmetric information and irrational behavior. Concerning the latter, the American economist Robert Shiller (2000) argued that investors tend to show irrational behavior and could more quickly than not become misled to develop over-confidence in financial markets. As a result, investors grow a higher risk-tolerance, asset-prices become inflated and borrowing (gearing) increases. These are also some of the predominant characteristics that led to economic recessions, such as the Dot-Com market crash in the early '00s and the global financial crisis of '07-09. In this thesis, it will be tested whether Smart-Beta ETFs can achieve excess gross returns compared to broad market indexes and thus, examine if the EMH holds[5].

[5] Not to get confused; it will also be tested whether Smart Beta ETFs an achieve excess gross returns compared to their declared benchmark indices.

2.2 Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) is famous for being the first, and most fundamental, factor model as it suggests that a single factor, market exposure (or beta), drives the risk and return of assets (Treynor, 1961; Sharpe, 1964; Lintner, 1965 & Mossin, 1966). **Equation 1** describes the framework;

$$\boldsymbol{r_a} = r_f + \beta_a(r_m - r_f) \tag{1}$$

r_a is the expected return of an asset, r_f is the risk-free rate of return (typically measured as a duration of government bonds), β_a is the systematic risk factor (i.e. beta) and r_m is the expected return of the market (e.g., broad market indexes). The equation relies on a string of assumptions related to investor behavior and market dynamics. It assumes that investors are rational and risk-averse, that they are able to invest in or borrow at the risk-free rate (r_f), short any asset and that there are no transaction costs. This CAPM-universe allows for investors to secure any portion of their investment portfolio with a fixed return. Hence, risky assets only become attractive if they are able to deliver excess returns of the risk-free rate. The riskiness of an asset is reflected by its beta which is that element of risk that cannot be diversified away. This market factor carries an associated risk premium, called the *equity risk premium*, which implies that the only way an investor is able to earn excess returns is by getting more exposure to risk. Essentially, the CAPM measures the amount of risk premium, $(r_m - r_f)$, investors demand to take on risky assets. Beyond the market factor, what are left to explain a stock's returns are *idiosyncratic*, or company-specific drivers (e.g., earnings).

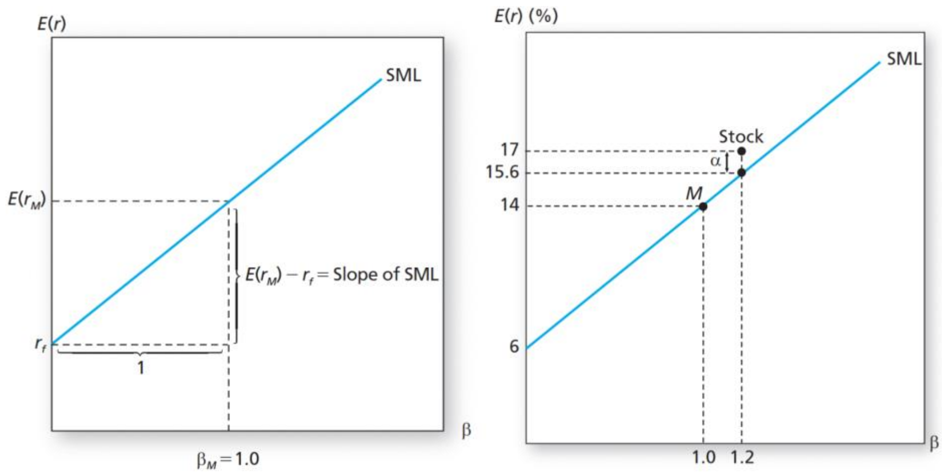

Figure 2 – The Security Market Line (SML), source: Bodie, Z.; Kane, A.; Marcus, A. (2014)

The Security Market Line (SML) is the visual or graphical representation of the CAPM. **Figure 2** displays the expected return of asset *i* as a function of systematic risk (or beta). As the market's beta is 1, the slope of the SML is the risk premium of the market portfolio. All fairly priced assets will plot on the SML in market equilibrium. In contrast, underpriced assets will plot above as they will produce an expected return in excess of their fair return stipulated by the SML (and vice versa). The difference between the fair and expected return on a stock is called *alpha* (Bodie et al., 2014).

As with the EMH, the CAPM has not been free from criticism due to its dependence on unrealistic assumptions. Examples of criticism include what is famously known as Roll's Critique (Roll, 1977). One of his main arguments is that the market portfolio is unobservable as it, realistically, would need to include all investable assets and that it is impossible to observe returns on all of them. Furthermore, Lakonishok and Shapiro (1984; 1986) found empirical evidence of an insignificant relationship between returns and beta. Following mounting evidence of CAPM defects, academics and investors began to move towards multi-factor models instead.

2.3 Arbitrage Pricing Theory (APT)

Stephen Ross (1976) presented an alternative framework to model the expected return of assets as a function of factor-betas, which became known as the Arbitrage Pricing Theory (APT). Opposed to CAPM's single-factor approach for explaining returns by exposure to the market factor (i.e., beta), the APT suggests that a multi-factor approach of macroeconomic factors (e.g., inflation) provides a better proxy. The expected return is shown in **equation 2**;

$$\boldsymbol{r_a} = r_f + \beta_{a,1} f_1 + \beta_{a,2} f_2 + \cdots + \beta_{a,n} f_n \tag{2}$$

r_a is the rate of return on an asset, r_f is the risk-free rate, $\beta_{a,n}$ is the sensitivity of the asset-return with respect to a factor, and f_n is the risk-premium.

Beta coefficients are estimated by linear regression. Investors would use the resulting rate of return to derive a *fair* stock price, and if the actual stock price differ from the expected end-of-period price, discounted at the rate derived from **equation 2**, arbitrageurs would quickly eliminate the mispricing and the stock price would move back to what is considered fair value. The approach of Ross (1976), which allowed factors to be interchangeable and, therefore, applicable in a wider variety of scenarios than the CAPM, laid the foundation for implementing what he called "multi-factor" methods into asset pricing models. On the other hand, what the APT benefits from its ability of customization, the indefinite number of factors could be considered a disadvantage as it would be difficult to find enough explanatory factors in order for it to have practical application.

2.4 Factor Models

As mentioned in **footnote 1**, factors could be any characteristic relating to a group of securities that is important in explaining risk and return. The way they work is to capture characteristics that are empirically persistent and have a relatively strong explanatory power in a "broad enough" subsection of stocks within a defined universe. Today, there are three main categories of factors. Apart from the macroeconomic model of Ross (1976), there are also statistical and fundamental models. For the purpose of this thesis, it is only the fundamental factors that are of particular interest.

Typical fundamental stock characteristics could be industry affiliation, financial ratios such as P/B, ROE and dividend yield, and much more. Apart from the market factor of the CAPM, independent studies conducted by Basu (1977) and Banz (1981) revealed that there is no linear relationship for a single-factor CAPM and that other factors than the market factor also contribute to returns. More specifically, Basu (1977) found empirical evidence to support that companies with low price-earnings ratios (P/E) gave higher returns compared to companies with higher P/E ratios than the traditional CAPM would predict. Four years later, Banz (1981) found that public companies of small size (i.e., small-cap) also tend to generate higher returns than companies of larger size (i.e., large-cap). The two factors would later be recognized as *value* and *size*, respectively.

Building on the CAPM, the multi-factor approach of Ross (1976) and the fundamental factors – value and size – Eugene Fama and Kenneth French (1992) developed a 3-factor model by adding value and size to the market factor. They intended to explain portfolio returns with these distinct risk-factors by econometric regression of historical stock prices using the expression in **equation 3** below.

$$\boldsymbol{r_p} - \boldsymbol{r_f} = \alpha + \beta_1\left(r_m - r_f\right) + \beta_2 SMB + \beta_3 HML + \epsilon \qquad \textbf{(3)}$$

r_p is the return of a portfolio, r_f is the risk-free rate, $r_p - r_f$ is the expected excess return of a portfolio, r_m is the return of the market portfolio, $\beta_{1,2,3}$ are factor coefficients, SMB stands for "*Small (market cap) Minus Big*" which is the size-premium and HML stands for "*High (book-to-market ratio) Minus Low*" which is the value-premium.

As a result of adding the value and size factors to the market factor, the model would adjust downwards for their tendency to outperform and thus, make it a better tool for evaluating the performance of portfolio managers. In terms of outperformance, there are a lot of arguments to be made as to whether it is due to market efficiency or inefficiency. Those who advocate for market efficiency is of the opinion that outperformance is explained by the higher risk that value and size stocks are accompanied by, which is a direct consequence of the higher cost of capital and more significant business risk. On the other hand, advocates for market inefficiency being the explanation for outperformance, argues that it is the market participants' incorrect valuation of these stocks that provides the excess return in the long run as the value adjusts (Hayes, 2020).

Carhart (1997) added another risk factor, namely *momentum*, to the Fama and French 3-Factor Model, which became known as the Carhart 4-Factor Model. Momentum is defined as the tendency of stock prices to continue to rise after an initial upward movement (and vice-versa), and is usually calculated by "subtracting the equal-weighted average of the lowest-performing firms from the equal-weighted average of the highest performing firms, lagged one month" (Carhart, 1997).

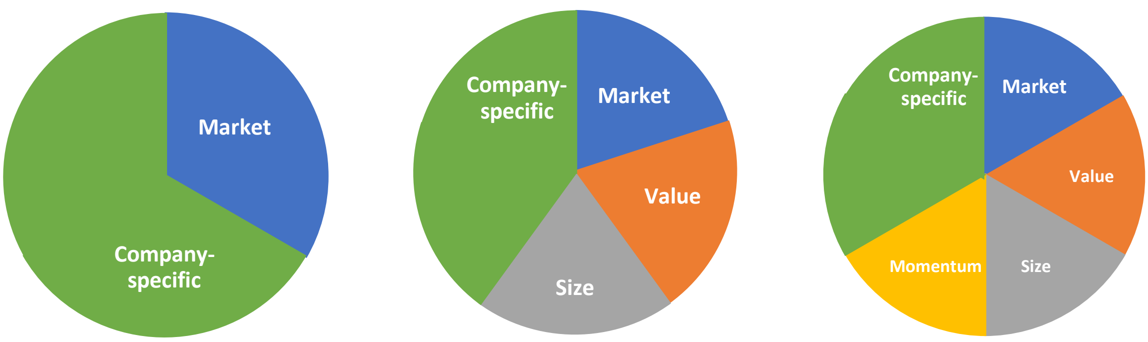

Figure 3 – The Evolution of Factor Investing, source: (Nielson, D., Nielsen, F., Barnes B., 2016)

As illustrated in **figure 3**, factor models have come a long way since the introduction of the CAPM. More recently, Fama and French (2015) published an extension to their 3-factor model by adding two more factors; *profitability* and *investment*. The profitability factor is measured as the difference in returns of companies with strong (high) and weak (low) operating profitability while the investment factor is measured as the difference in returns of companies that invest conservatively and those that invest aggressively. The new multi-factor model does not include the momentum factor that Carhart (1997) implemented, which is mainly due to Eugene Fama not being a supporter of momentum (Cliff Asness, 2016). While not refuting that the momentum risk-factor exists, Fama is of the opinion that the risk of equities in an efficient market will not change so drastically that it justifies recognizing the factor's part in it.

Asness, Frazzini, and Pedersen (2013; 2013; 2014) introduced a quality-minus-junk factor (QMJ), a betting-against-beta (BAB) factor and an alternative value factor (HML "devil"). They all followed the same methodology as Fama-French, extending the range of accepted factors. The QMJ-factor is constructed by going long high-quality stocks and short-sell low-quality stocks. Asness et al. (2014) define quality from different measures of profitability, growth and payout and use the resulting quality scores to construct the portfolios. The BAB-factor is a type of low-risk (defensive) investing and is constructed as going long low-beta securities and short-sell high-beta securities. The difference between the alternative value factor of Asness et al. (2013) and the value factor of Fama and French (1992), is that the prior uses *current* prices of book value and share price while the latter is constructed using lagged data (between 6-18 months). Asness et al. (2013) recommends using the HML "devil" factor only when using value and momentum together in a factor model.

2.4.1 Factor Zoo

The Fama-French 3-Factor Model became the start of an academic race to investigate new factors as research has, figuratively, exploded in line with advances in data and technology. Blackrock, the world's largest asset manager, highlights twelve factors of importance in their factor-based strategies. Between them and other significant institutional asset managers, there are hundreds more circulating – all of which are presumably *keys* to greater returns. Back in 2015, the research paper "*…and the Cross-Section of Expected Returns*" identified more than 300 risk factors from academic literature. The paper claimed that most of these newly-found factors are likely false or in lack of explanatory power as they question the t-statistic for significance (Harvey C., Liu, Y., & Zhu, H., 2016).

As a response, the working paper "*Taming the Factor Zoo*" collected and investigated 150 of them – with some examples being convertible debt and cash holdings. All factors that have emerged through academic research are based on different types of company characteristics, which could, in theory, capture *several* types of equity risk. Two portfolios that may seem different at first glance (e.g., one that overweighs small-cap-stocks and another that overweighs illiquid stocks) might as well expose investors to similar risk factors, whether they intend to or not. As such, many risk factors may be redundant (Feng G., Giglio, S., Xiu, D., 2020). That is not saying that all 300 factors are fake. It may be true that some of them truly deliver a significant risk premium, but they could merely be copying other essential factors.

2.6 Smart Beta

The purpose of Smart Beta ETFs is to improve returns and reduce risk through exposure to risk factors that have been found to explain additional sources of returns over time (i.e., value, size, momentum, etc.) in a low-cost, transparent and convenient manner (Jacobs & Levy, 2014). One could argue that the investment approach combines familiar characteristics of both passive and active investing (see **figure 4**), placing it at the intersection of the EMH and factor-investing.

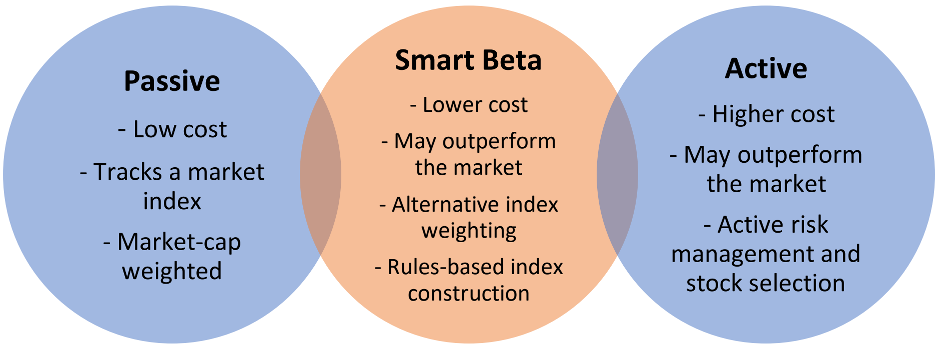

Figure 4 – Connection between passive, smart beta and active, source: (Invesco, 2018)

What Smart Beta ETFs attempts to do is to outperform the market portfolio by utilizing **1)** alternative index weighting and **2)** rule-based index construction. The former suggests equal-, fundamental- (i.e., stocks are weighted by measures of earnings etc.) or single-factor weighting (i.e., stocks are weighted by factors such as value or size) instead of the traditional market-cap weighting. Regarding rule-based constructions, it typically focusses on a single factor, or screens for multiple factors (Invesco, 2018).

Because of automated construction processes and systematic rebalancing at pre-determined intervals to maintain factor exposures, Smart Beta ETFs typically require less trading than actively managed funds. Thus, investors incur lower transaction-related fees. However, there is still much decision-making to be done, similar to the ones made by active managers, with regards to these processes. Which factor(s) should be targeted? How should the factor be captured? Should value be captured by book-to-price, earnings-to-price, or some other metric? Different from passive investing, Smart Beta is in need to rebalance portfolios through the use of systematic trading, as factor exposures of selected stocks change, so that the pre-determined weightings are upheld. Thus, asset managers need to make active decisions as to how frequently this rebalancing should occur. Also, like other active investing strategies, Smart Beta ETFs will deliver returns that differ from passive, cap-weighted indexes, for better or for worse (Jacobs & Levy, 2014).

2.7 Smart Beta Strategies & Factors

Many asset managers have definite differences in metrics to look for in stock-selection and how to weigh them in indexes. However, there is absolute uniformity in the fundamental understanding and purpose of most factors. Due to delimitations, this section will describe the selected factor-strategies that will be analyzed later in the thesis. Even though *growth* is not among the factor-strategies to be analyzed in the thesis, an explanation of the factor is provided because of its close connection to *value* and because it is evidently popular in many multifactor ETFs. Morningstar distinguishes between return-oriented and risk-oriented strategies, which explains the structure of this section.

2.7.1 Market Factor

Truly passive investing is portrayed by its focus on capturing beta through market-cap-weighted indexes as exposure to the market which, according to the CAPM, is a significant driver of returns. However, many would argue that CAPM-beta does not deliver excess returns as it measures only sensitivity to market movement and may instead be a risk-factor and not a risk-premium. Thus, exposure to market-beta alone is not a way to outperform the market and not a Smart-Beta strategy in its own right (Nielson et al., 2016). In this thesis, the market factor may also be referred to as the market portfolio, and it will be used as a benchmark in terms of performance as well as a measure of market exposure.

2.7.2 Return-Oriented

2.7.2.1 Size

The origins of the size factor, pioneered by Banz (1981), was briefly described in **section 2.4**. This strategy of holding stocks with lower market capitalization (i.e., small caps) instead of stocks with a high market capitalization (i.e., large caps) should, based on past performance, compensate investors with greater returns. The exact reason as to why, has been debated in academic circles for many years. Some claim that it is the exposure-to-default risk (Vassalou & Xing, 2004) or financial distress (Chan & Chen, 1991), while others claim that it is due to a higher level of information uncertainty (Ang, A., Hodrick, R., Xing, J., Zhang, X., 2006). In the efficient market view, Fama and French (1992) said that small-cap stocks have higher systematic risk, which allows higher return-premia. However, the empirically tested outperformance of size is not particularly steady. Due to the usually higher beta of small-cap stocks, it tends to outperform in bull-markets and underperform in bear-markets (Kula, G., Raab, M., Stahn, S., 2017).

2.7.2.2 Value

Origins of the value-factor were also briefly discussed in **section 2.4**. In relative terms, "cheap" or "expensive" stocks refers to ratios such as price-book, price-earnings as well as other fundamental data that has impact on the valuation of a stock. The value-factor has been around for many decades as its risk-premium was documented already in the early 1930s by Graham and Dodd (1934). Later, Graham (1955) argued that expensive stocks do not give as much room to beat expectations as cheap stocks, and consequently, cheap stocks have greater potential for generating excess returns. In more recent times, findings of Graham (1934; 1955) have found strong support in studies such as Fama & French (1998). In their study, they analyzed equity returns in 29 countries between 1975-1995 and concluded that the value-effect existed in several of these. On the other hand, Meredith (2019) points out that value-stocks in the U.S. has experienced a prolonged period of underperformance since 2007. Accordingly, underperformance is mostly due to a combination of capital-collapses in the financial sector along with a technological revolution which has led to a “growth-regime”. Also, Basu (1977) found that value exhibits a high level of sensitivity to market cycles over the long run.

2.7.2.3 Growth

The purpose of the growth-factor is to capture specific “growth” characteristics in stocks. In general, these traits usually mirror companies that have experienced rapid growth in revenues or earnings in recent years and that are expected to continue to grow at a higher rate than the average of peers. More specifically, growth is commonly captured by expected earnings growth, historical earnings growth, sales growth, growth in book value, and so forth. (Boyadzhiev et al., 2019). Investment products that follow growth- and value-strategies are, to some extent, based on the same type of ratios but with opposite target values. In research, growth-stocks are typically considered as expensive and, thus, regarded as the short-portfolio of value-stocks. If the value-factor generates positive excess returns, then excess returns from growth must be negative (Rabener, 2019).

2.7.2.4 Momentum

The momentum-effect is characterized by stocks that have performed strongly (weakly) in preceding periods, perform strongly (weakly) in future periods. In order to add value, stock-prices have to show trends over certain horizons. According to Boyadzhiev et al. (2019), the strategy is implemented by selecting stocks based on a timeframe of 3-12 months, subtracting the final month to account for possible short-term reversal effects. The factor was pioneered by Jagadeesh and Titman (1993). In their paper, they found significant evidence of generating excess returns between 1965-1985 through the momentum-strategy "*buy past winners and sell past losers*". According to Amenc (2015), no empirical literature has been successful in identifying a specific risk-factor that may explain this effect on stock-returns. The most commonly accepted theory is that investors tend to over-react to company information and that they are very much inclined to buy what others are buying (i.e., herding). Thus, while the size- and value-factors are associated with the Efficient Market Hypothesis, momentum is more a result of behavioral biases.

2.7.2.5 Quality

The primary objective of the quality-factor is to capture excess returns of stocks with relatively low debt, stable earnings growth, high/stable return on equity (ROE), and much more (Boyadzhiev et al., 2019). Having a lot of different "quality" metrics paired with subjective opinions as to their influence on returns, often results in confusion among investors and asset managers. With this in mind, Kalesnik and Kose (2014) found that only 9 of 40 commonly used metrics generated significant excess returns relative to the market portfolio. Furthermore, they found that profitability, measured as ROE, is the most frequently used "quality" metric. Not to get confused, the profitability-factor of the Fama-French 5-Factor Model is a subset of the quality-factor (Rabener, 2018). The robustness of the quality-factor is debated among academics. For example, Swinkels (2017) found that neither debt-to-equity, ROE, or gross profit metrics generated excess returns between 2000-2017, while NBIM (2015) states that there is evidence to suggest to they do. There is also no widely accepted explanation as to why high-quality should earn a risk-premium but Novy-Marx (2013) argues that statistical and measurement errors, behavioral biases, and constraints to investing are possible explanations.

2.7.2.6 Multifactor

According to Boyadzhiev et al. (2019), all Smart Beta ETFs that are constructed by "*more than one factor*" are considered a multifactor ETF. In order to reduce risk, and improve performance, issuers of multifactor ETFs should construct portfolios that consist of low-correlated factors. Bender et al. (2013) found that the momentum- and value-factor had lowest correlation as momentum tends to buy past winners and sell losers, whereas value tends to do the exact opposite. As an example, Jacobs and Levy (2014) points to the massive losses of momentum-strategies in 2008 and 2009 as a five-year bull-market suddenly collapsed while value-strategies captured by book-to-price performed relatively well. Polychronopoulos (2014) found that a portfolio with factor exposure to fundamentals, low-volatility, and momentum has generated higher risk-adjusted returns relative to the market portfolio between 1967-2013. However, there are challenges tied to this multifactor strategy. Difficulties in determining relative weighting when combining portfolios of different factor strategies, and that some of the holdings may overlap, may increase the overall risk – unintendedly.

2.7.3 Risk-Oriented

2.7.3.1 Low Volatility

The primary purpose of low-volatility strategies is to capture excess returns through exposure to stocks with "lower than average volatility, beta and/or idiosyncratic risk" (Boyadzhiev et al., 2019). Smart Beta ETFs using this strategy constructs their portfolios on metrics such as standard deviation (1-yr, 2-yrs, 3-yrs), market-beta and more. The low-volatility factor is in stark contrast to the intuition of CAPM that riskier stocks are compensated with higher returns than less risky stocks. Haugen and Heins (1972) were the first to publish evidence that low-volatility stocks in the U.S. generated excess risk-adjusted returns between 1926-1971. In more recent times, Jagannathan & Ma (2003) found evidence to support the risk-premium in a study of 300 stocks in the U.S. between 1990-2000. One of the most commonly accepted explanations for the historical outperformance is due to behavioral biases of investors and is called the "*lottery effect*". In other words, many investors tend to buy stocks with small expected losses but large expected gains even though there is a higher possibility of a loss than a gain. Thus, investors are compensated with a risk-premium to the market (Kula et al., 2017).

2.8 Previous Studies on Smart Beta

As popularity of Smart Beta ETFs has increased significantly over the years (ref. **figure 1**), numerous research publications have been made available by both academics as well as asset managers with the intent to demystify the construction, underlying risks and returns of the investment products.

One of the early adopters of Smart Beta investment products was Research Affiliates. In their article "*Fundamental Indexation*" they introduced a *new* way of thinking about traditional index-investing as they proclaimed that Smart Beta was a more transparent, systematic and efficient approach to stock selection and weighting that was different to the market-cap approach (Arnott, R., Hsu, J. & Moore, P., 2005). One notable critic has been Burton Malkiel (2014), who finds that returns of Smart Beta strategies are neither great nor consistent. More specifically, he showed that the performance of the Vanguard Value ETF and the Vanguard Growth ETF between 1992-2013 displayed similar levels of performance relatively but, individually, they have had significant cyclical variations in performance. He also adds that any excess returns generated by funds applying such strategies are due to taking on more risk. Furthermore, Malkiel (2014) was worried about the need for regular rebalancing, which increases transaction costs and thus, leads to higher expense ratios that could eventually "*eat up*" any gains. In 2017, however, Malkiel had a change of heart. The enhanced ability to deliver a Smart-Beta ETFs at low cost, coupled with tax efficiency, made him recognize that it may actually add value for investors (Stewart, 2017).

On behalf of the University of Pennsylvania, Glushkov (2015) published an empirical study of 164 domestic equity Smart Beta ETFs in the U.S. between 2003-2014. The purpose was to analyze relative performance and factor exposures. One of the main findings was that 8 of 13 Smart Beta strategies generated excess returns relative to the market. However, only value and low volatility did it after adjusting for risk. With regards to performance in "good" and "bad" market cycles, Glushkov (2015) found that multifactor ETFs generated greater returns during "good" cycles while dividends and low volatility performed best during downturns. Furthermore, the majority of Smart Beta ETFs were found to exhibit unintended factor exposure which may work to offset the return advantage from the intended factor exposures.

Jacobs and Levy (2014) share much of the same skepticism as Glushkov (2015) and argues that factors need to be combined in order to outperform. The reason, they explain, is that exposure to *one* factor may cause higher risk and, for some, undesirable sector exposure. An example that is reiterated is that solely investing in the momentum-strategy before the burst of the Dot-Com bubble in 2000, would result in excessive exposure to the technology sector. Hunstad and Dekhayser (2015) measured the differences between intentional factor risk exposures and unintended exposures of Smart Beta strategies, which underlined that the investment approach might have problems in this regard.

In addition to the disadvantages already discussed, Jacobs and Levy (2014) also points to several weaknesses in the structure of Smart Beta ETFs. They argue that being transparent and having a systematic, rule-based investment style will eventually lead to reduced flexibility, and the strategies may thus respond too late changes in market conditions. Furthermore, they add that transparency and systematic construction processes may result in "front-running" by opportunistic traders. Also, the surge in Smart Beta ETFs' popularity has led to concerns that factors have become over-crowded. According to Alford (2017), there are primarily two reasons as to why "factor crowding" would be a problem for Smart Beta investors. First, equities could face overvaluation and, thus, reducing the possibility of outperformance in the future. Second, rapid shifts in sentiment with regards to familiar equity factors could lead to large withdrawals which cause liquidity risk. Resulting selling pressure could trigger negative and/or more volatile excess returns from Smart Beta ETFs.

Although there is much skepticism as to how "smart" Smart Beta really is, there are also academics who have praised the investment approach and quantitatively proven that they do indeed live up to the hype. Chow et al. (2011) performed an empirical study on two portfolios (U.S. and global equities) of common Smart Beta strategies and did a risk-decomposition using a Carhart 4-Factor regression. Their results indicated that Smart Beta have the capability to give investors exposure to size and value factors in a more cost-efficient manner than to buy (or acquire) them directly, and that they are effective in improving essential risk-adjusted metrics such as Sharpe ratios and information ratios. Chow et al. (2011) supplements that even though Smart Beta ETFs are cost-effective, with regards to factor exposure, they are still considered costly to implement due to relatively high turnover rates and low capacity.

3. Data

This section provides a description, and justification, of the data that makes up much of the foundation of the thesis. It starts by describing the process of gathering data of assets under management (AUM) and monthly prices (NAV) of US-domiciled equity Smart Beta ETFs, followed by certain statistics about the data sample. After, the rationale behind the choice of a benchmark (market) index and risk-free rate is explained. For further references, Smart Beta will also be abbreviated to "SB" where fit.

3.1 Data Sample

3.1.1 Smart Beta ETFs & Factor-Returns

3.1.1.1 Overview & Descriptive Statistics

An overview of US-domiciled SB equity ETFs was downloaded from Bloomberg. The sample of 726 SB ETFS included fund names, exchange tickers and AUM. The number of funds, in the different categories, are exhibited in **table 1**.

	'05	**'06**	**'07**	**'08**	**'09**	**'10**	**'11**	**'12**	**'13**	**'14**	**'15**	**'16**	**'17**	**'18**	**'19**
Size	7	25	26	30	31	37	45	48	52	54	57	58	72	74	76
Value	14	18	22	24	26	31	35	37	38	42	44	45	48	50	53
Momentum	2	10	12	12	12	12	13	17	18	18	24	27	30	31	31
Low-Volatility							6	8	12	18	26	32	34	31	28
Quality	1	1	6	7	7	7	7	7	8	8	9	11	15	18	21
Multifactor	12	16	31	31	31	31	45	57	73	85	114	149	186	209	204
Total	**36**	**70**	**97**	**104**	**107**	**118**	**151**	**174**	**231**	**225**	**274**	**322**	**385**	**413**	**413**

Table 1 – Evolution of US-domiciled Equity Smart Beta ETFs by Category, source: Bloomberg

From looking at the table, it is clear that there are significant differences in the number of funds within each category and that some have limited historical data. These findings will have implications for the analysis, and further affect the ability to make astute conclusions from the findings.

Because the focus of this thesis is on the U.S. equity market, only funds that follow domestic equity indexes are retained. Individual benchmark indexes are gathered from issuers' prospectus/factsheet. In cases where it was difficult to obtain returns from the primary prospectus benchmark, a similar index of either S&P Dow Jones or FTSE/Russell was used instead. The sample is further reduced by only keeping ETFs with at least three years of return-data available. This screening process yields a final sample of 60 US-domiciled equity SB ETFs together with each its distinct benchmark. Full table of SB ETFs, its net assets per March 2020 and benchmarks are to be found in **appendix 9.1**. ETFs that had their primary prospectus benchmark replaced by another, are marked in bold font.

3.1.1.2 Monthly Prices (NAV)

Data of monthly prices are quoted in USD and collected from Bloomberg. The per-share price of a fund is represented by its net asset value (NAV) which is total net assets divided by outstanding shares (Morningstar, n.d.). The time window is from January 1st 2007 to March 31st 2020.

3.1.1.3 Factor-Return Data

The raw data of factor-returns from the market-risk premium (MKT), size (SMB), value (HML), momentum (MOM), low volatility (BAB) and quality (QMJ) are downloaded directly from the AQR data library[6]. The market (MKT) factor from the AQR data library is based on the CRSP Total Stock Market (TSM) Index which is comprised by publicly traded stocks across mega, large, small and micro-cap segments and thus, represents the *investable* stock market in the U.S. (CRSP, n.d.). This index will also be used in the definition of "up" and "down" periods in **section 4.3.2**.

3.1.2 Risk-Free Rate

The risk-free rate of return is also collected from the AQR Data Library and are based on the returns for a U.S. one-month (or four-week) Treasury Bill – which is a proxy for the risk-free return.

3.2 Data Considerations

3.2.1 Survivorship Bias

When doing empirical studies on fund-returns, it is important to consider the presence of *survivorship bias*. Malkiel (1995) describes the term as "*the difference in performance between survivors and non-survivors*". The dataset utilized for this thesis includes only SB ETFs that are active (i.e., survivors) and, thus, is not free of survivorship-bias. Glushkov (2015) argues that some of the most common reasons to terminate funds are due to inefficient capital-flows and/or performance. In other words, it

[6] https://www.aqr.com/Insights/Datasets

is only the "best" funds that survive and returns of surviving funds may be abnormal which may cause errors in results.

3.2.2 Data Sources

It is also important to note that only funds found in a screening of Smart Beta ETFs in Bloomberg are included. Nevertheless, Bloomberg is a recognized and credible source of fund data, and the data set is considered representative as it only includes ETFs that are categorized as Smart Beta in prospectus.

4. Methodology

With the purpose of answering the thesis' problem statement, and attached sub-questions, the analysis is divided into two sections: **1)** relative return analysis and **2)** factor exposure analysis. The methods, and underlying assumptions, that is being used to investigate the above-mentioned will be presented chronologically.

4.1 Philosophy of Science

Due to the nature of this thesis and its quantitative approach, the most obvious philosophy of science was, at least to the author, *positivism*. Positivism is based on the ontology that reality exists in *one* particular form, independent of whoever is the observer. The ontology of positivism is, therefore, realistic and the epistemology is purely objective, which is what this thesis strives for as well. The methodology of positivism is quantitative, and the concrete methodological plan is that scientific work consists of forming hypotheses, followed by controlled experiments to test the hypotheses. Data is collected by experiments or other quantitative methods. The aim is to uncover causal relationships in order to be able to say something about the future (Presskorn-Thygesen, 2012).

4.2 Forming Portfolios of Funds and Benchmark Indices

In order to make judgements and arguments on SB ETFs in general, portfolios of ten SB ETFs that follow the same strategies are created using an equal-weighting approach. The same thing is done for benchmark indices. It would have been preferred to use both an equal-weighting and size-weighting scheme to assess the robustness of results but due to time and size constraints for the thesis along with missing necessary data being unavailable, it would be difficult. **Equation 4** exhibits how returns on an equally weighted portfolio are calculated.

$$R_P = \sum \frac{1}{n} * R_i \tag{4}$$

R_P is the return of a SB category portfolio or benchmark portfolio at a given time, R_i is the periodic return of ETFs and benchmark indices during the same period, *n* is the number of funds by the end of the period.

4.2.1 Comparing Returns

4.2.1.1 Trailing Returns vs. Rolling Returns

Two of the most frequently used methods for comparing returns (i.e. relative returns) between a fund and its benchmark, are *trailing* and *rolling returns*. The former looks backwards from a specific date for the fund's annualized return over block-periods such as year-to-date, 1-year, 3-years and so on. Even though this is the most commonly used method of displaying performance, they are also criticized for being too simplistic. In other words, trailing returns may seem appealing in the short-term perspective, but the metric may actually mask the volatility of the fund over a longer time frame. Rolling returns operates in a way that it uses average annualized returns in overlapping periods, typically starting on the first day/month of the month/year and going as far back in the data-series as possible with the intention of displaying the frequency, and scale, of the fund's performance (Pak, 2011). In this thesis, the trailing returns method is applied for simplicity even though the author must acknowledge that using both methods could have been considered for a broader comparison. Block-periods that are used for the trailing returns are 1-year, 3-years, 5-years, 10-years and "since 2007".

4.2.1.2 Creating an "Investable" Market Portfolio

Comparing the performance of SB category portfolios with a pure market index would cause a particular bias in the estimates as the latter is not subject to management fees due to not being directly investible. Thus, the author has created an equal-weighted portfolio of three broad, market-cap-weighted ETFs that seeks to track the total stock market of the United States. When comparing the performance of SB portfolios, this market portfolio is viewed as more realistic than a pure market index such as the S&P 500. The three ETFs that make up this portfolio are the Vanguard Total Stock Market ETF (VTI), SPDR S&P 500 (SPY) and SPDR S&P 1500 Comps Stock Market ETF (SPTM). The underlying indexes are the CRSP US Total Market Index, the S&P 500 and the Russell 3000 Index, respectively. For later references, this portfolio will be referred to as the "TSM ETF portfolio", or simply, "market proxy (ETF)". A similar type of market portfolio has also been created concerning benchmarks indices. This covers the underlying indices mentioned above and is referred to as TSM Index Portfolio or "market proxy (indices)".

4.3 Relative Return Analysis

4.3.1 Calculating Returns

Returns of SB ETFs have to be calculated in order to investigate their (relative) performance. There are normally two different ways to calculate periodic returns; *arithmetic* and *geometric* average. The former measures the average of a return-series, where periods are equally weighted. By contrast, the geometric average measures the average rate of return by using the products of the terms. In other words, it takes several values and multiplies them together and sets them to the 1/nth power (Zucchi, 2019). Because geometric averages accounts for the compounding-effect that occurs from period to period, it tends to be a more accurate measure than the arithmetic average. The formula is presented in **equation 5** below.

$$\bar{\boldsymbol{r}}_{\boldsymbol{G}} = \sqrt[n]{(1+r_1)*(1+r_2)*\ldots*(1+r_n)} - 1 \quad \textbf{(5)}$$

Where monthly returns are measured as: $\boldsymbol{r_i} = \frac{NAV_t}{NAV_{t-1}} - 1$

r_G is the geometric mean of the portfolio return, *n* is the number of periods and r_n is the return in period *n*. When computing returns for SB category- and benchmark-portfolios, simple returns will be used. Log-returns are not applicable as they cannot be added across ETFs or indices of a portfolio in the same time period. This procedure would have given an inaccurate number because there is no real compounding element (Guan, 2018).

4.3.1.1 Excess Returns

In this thesis, excess returns are defined as the difference in return between SB category portfolios and the risk-free rate unless specifically stated otherwise. The same goes for benchmark indices. Both market- and factor-returns from the AQR data library are already in excess of the risk-free rate.

4.3.1.2 Benchmark-Adjusted Returns

Inspired by Glushkov (2015), the geometrically annualized difference between monthly returns of SB category portfolios and their respective benchmark portfolios are calculated. Thus, they would not have to be the exact difference between the portfolios.

4.3.2 Defining "Up" and "Down" Periods

There is a wide range of methods to define "up" and "down" periods in equity markets. According to Siegel (2014), moving averages has been used as a technical indicator since the 1930s and is still popular among researchers and investors. This thesis applies changes in the 10-month (roughly 210 trading days) simple moving average (SMA) of the CRSP TSM Index is applied. More specifically, monthly closing prices of the CRSP TSM Index is compared to its 10-month SMA. If the monthly closing price is greater than, or equal to, the 10-month SMA then it is defined as an "up" period – and vice versa. The time-series are exhibited in **figure 5**.

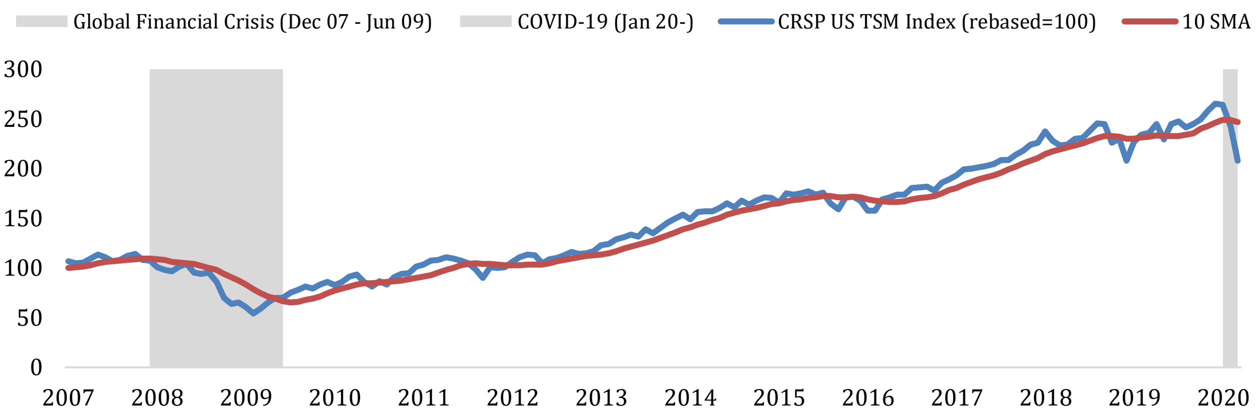

Figure 5 – CRSP TSM Index and 10-month SMA between Jan-2007 and Mar-2020, source: CRSP and own calculation

4.3.3 Risk-Adjusted Performance Analysis

It would not be sufficient to base a performance analysis of SB portfolios on returns alone. The risk that asset managers have taken over a given period to achieve returns are also important to consider as they may have significant impact on investments. There are many different risk-adjusted measures, and they are all slightly different from each other. This thesis will apply *Jensen's alpha*, *Sharpe ratio* and *Information ratio* as they are some of the most frequently used measures (Segal, 2019).

4.3.3.1 Jensen's Alpha

The term *alpha* (α) was coined by Michael Jensen (1968) who applied the CAPM framework in order to estimate a regression model on fund-returns (dependent variable y) and its intended benchmark (independent variable x). The output of that model provides alpha and beta estimates. Alpha is the *intercept* and is read as the difference between the fund's actual return and its expected return given the fund's level of risk, measured by beta. If alpha is positive, with significant t-statistics, it would indicate outperformance relative to the benchmark. For the analysis of "up" and "down" periods, the model also includes a dummy variable which takes on the values "1" and "0", respectively.

$$\boldsymbol{\alpha} = r_y - \beta r_x + \varepsilon_i \tag{7}$$

4.3.3.2 Sharpe Ratio

The purpose of the Sharpe ratio is to let investors isolate profits associated with risk-taking activities, and it does so by comparing investment-returns to the alternative investment of a risk-free asset (one-month U.S. treasury bill). Furthermore, it factors in the standard deviation (i.e., volatility) of returns so that the investor gets a sense of how much excess returns he/she is achieving in return for taking on additional risk associated of investing in something other than a risk-free instrument. The higher the value, the more attractive return (Sharpe, 1994). T-statistics are calculated to measure statistical significance of results and is equal to the SR multiplied by the square root of the number of returns.

$$\boldsymbol{SR_P} = \frac{r_p - r_f}{\sigma_p} \tag{8}$$

4.3.3.3 Information Ratio

Instead of using a risk-free investment for comparison, the Information ratio (IR) measures the return of a portfolio against a benchmark index, relative to the standard deviation of unsystematic risk (i.e. tracking error). If the IR is greater than zero, it indicates that the investment portfolio has generated excess returns of its benchmark index – and vice versa. The formula is exhibited in **equation 9**. Tracking Error (TE) is the standard deviation of the difference in return between the portfolio and a benchmark (Murphy, 2019). T-statistics are also calculated as it was with SR (Goodwin, 1998).

$$\boldsymbol{IR_P} = \frac{r_p - r_{bm}}{TE} = \frac{r_p - r_{bm}}{\sigma_{p,bm}} \tag{9}$$

4.3.4 Fund Flows

What Alford (2017) described in **section 2.8** as "factor crowding" is often referred to as "herding", or extreme capital flows into an investment strategy/product. To further supplement the performance analysis, this thesis will see if there could be any *observable* herding-effect on the performance of the SB portfolios. In a somewhat simplified manner, fund-flow data will be kept in mind when discussing results from the performance analysis in **chapter 5** to see if it *could* have any explanatory power on the portfolios. Data is gathered from Bloomberg and is presented in **section 5.1.2**.

4.3.5 Expense Ratios

All of the results from the performance analysis are based on net asset values (NAV). Because the NAV is calculated after deducting fees that ETFs charge their shareholders, returns are essentially *net-of-fee returns*. As the underlying indices of their benchmark portfolios are not directly investible, there are no fees to account for and, thus, returns are *gross-of-fees*. Comparing a portfolio that faces fees, and other real-world frictions that investable portfolios do, with a portfolio that does not, would certainly lead to a certain bias in favor of the latter – and possibly imply negative alpha. In order to understand the effect of fees, NAV of SB portfolios would have to be *grossed* up by an expense factor (Feibel, 2003). Unfortunately, historical expense ratios have not been able to attain for this thesis but only for the most recent year alone. Hence, expense ratios presented in **section 5.1.3** will be viewed in context with results from the performance analysis.

4.3.6 Criteria for Outperformance

To conclude on whether SB portfolios have outperformed their respective benchmark portfolios, they would have to fulfill four certain criteria. **First**, their benchmark-adjusted returns have to be positive on an annualized basis "since 2007". **Second**, they need to have generated positive alpha which is statistically significant over the entire sample period. **Third**, they must have a higher Sharpe ratio which is statistically significant over the entire sample period. **Fourth**, the Information ratio must be statistically significant and positive over the entire sample period.

SB portfolios need only to fulfill criteria **one** and **two** for them to have *outperformed* the portfolio of broad, cap-weighted ETFs (i.e., TSM ETF portfolio) as Sharpe and Information ratios have not been calculated for this portfolio.

4.4 Factor Exposure Analysis

This section will focus on the methodology used to measure factor exposures of the SB portfolios. As mentioned in **section 1.4**, five factors are used to explain returns: size, value, momentum, quality and low volatility. In order to do this, static regression analysis will give details on the average factor exposure, of the given equity factors, over the entire sample period.

4.4.1 Returns-Based Factor-Regression

The only required input for the return-based approach (top-down) is return-data for SB portfolios and academic factor portfolios. Preferably, there should be at least three years of monthly returns. The approach uses a regression analysis which explains the relationship between a dependent variable (fund-returns) and explanatory variables (risk-factors) over a pre-determined period of time (Israel & Ross, 2017). The factor model that forms the basis of the regression analysis, is based on the four-factor model of Carhart (1997) with certain modifications based on Asness, Frazzini and Pedersen (2013; 2014; 2017). More specifically, the traditional value-factor of Fama and French (1992) is replaced by the HML "devil" factor along with the inclusion of quality (QMJ) and low volatility (BAB). The final factor model is exhibited below.

$$\boldsymbol{r_p} - \boldsymbol{r_f} = \alpha + \beta_{MKT}\left(r_{MKT} - r_f\right) + \beta_{SMB}SMB + \beta_{HML_d}HML_d + \beta_{UMD}UMD + \beta_{BAB}BAB + \beta_{QMJ}QMJ + \epsilon$$

alpha (α) is the portion of a fund's returns that the factor regression model cannot explain and β_i is the beta-coefficients which shows the sensitivity of the portfolio to a 1-pct. change in factors. How to interpret beta-coefficients, and thus factor exposures, is exhibited in **table 2** below.

Risk-Factor	If the beta coefficient of the…
Market (MKT)	market (MKT) factor is equal to 1.0 that means that the portfolio would rise by 1 pct. for each gain of 1 pct. on the market portfolio. If the coefficient is greater than 1.0 it would imply that the portfolio is riskier than the market portfolio, and vice versa.
Size (SMB)	size (SMB) factor is positive, it would indicate that risk/returns could be explained by exposure to small-cap stocks and if it were negative it would indicate exposure to large-cap stocks.
Value (HML)	value (HML) factor is positive, it would imply that risk/return were due to exposure to value stocks and if it was to be negative then it would indicate exposure to **growth-**stocks.
Momentum (MOM)	momentum (MOM) factor is positive, it would imply that risk/return is due to the portfolio being exposed to market leading (or winning) stocks and in the opposite event it would imply a tilt towards laggards (or losers).
Low-Vol (BAB)	low-volatility (BAB) factor is positive, it would indicate that risk/returns could be explain by exposure to low-volatility stocks and if it were negative it would indicate exposure to high-volatility stocks.
Quality (QMJ)	quality (QMJ) factor is positive, it indicates that the fund's risk/return comes from stocks with robust (high) operating profitability and vice versa.

Table 2 –How to interpret the beta coefficients of a returns-based factor-regression, sources: Israel & Ross (2017), AQR

4.4.1.1 The Statistics of Regression Analysis

For the factor exposure analysis, beta is an important observation as it indicates how much a factor may have contributed to risk and returns. If regression results imply that a portfolio has a high beta coefficient to value, it does not necessarily mean that it is statistically different from a portfolio with a zero beta (i.e., statistically significant). To test the confidence level of alpha and beta estimates, it is essential to evaluate their t-statistics. If t-statistics are greater than two, one can say with 95 pct. confidence that the estimate is statistically different from zero (Israel & Ross, 2017). The numerical value of a t-statistic increases as more observations are added to the sample size as it allows for greater certainty about the estimates. Another essential measure to keep in mind is the explanatory power (or R2) of the model. The R2 measure indicates how much of the variance in returns is explained by the model's factors.

4.5 Statistical Diagnostics

Data presented in **chapter 3** is only a sample size of the Smart Beta ETF population. In order to form reliable assessments about parameters of a population, we need to examine whether the time-series fulfill certain conditions when performing statistical tests (e.g., regressions) as they are often *assumed* to be fulfilled (Keller, 2005). The regression model that form much of the analysis uses the Ordinary Least Squares method which is used to find a linear relationship between dependent and independent variables by drawing a straight line that fits all observations as good as possible. To produce reliable estimates, it *should* have **1)** error terms that are normally distributed, **2)** error terms with constant variance and **3)** zero correlation between error terms.

The following sub-sections will present certain statistical tests that have been used to see whether the data sample fulfills any of the three criteria above. Results of the diagnostics will be discussed briefly in **section 4.5.4**. All tests are carried out by using the statistical software of StataSE.

4.5.1 Jarque-Bera Test for Normality

The Central Limit Theorem (CLT) implies that the distribution of error terms approximates a normal distribution as the sample size grows larger. However, observations from stock market returns are often considered an exception to this rule (Keller, 2005). The reason for this is due to returns being prone to *tail-risk events* which is a result of stocks having more extreme returns than indicated by a normal distribution. The concept of tail risk suggests that the distribution of returns is skewed and has fatter tails (i.e. excess kurtosis). This thesis will be using the Jarque-Bera test to test whether the sample data have skewness and kurtosis matching a normal distribution. The data-series are said to follow a normal distribution if it has a skewness (S) of zero (i.e. symmetrical around the mean) and zero excess kurtosis (K). Deviations would indicate non-normality (Wooldrige, 2011). The JB test follows a chi-squared distribution with two degrees of freedom. If the chi-squared value is higher than 5 pct., then the null-hypothesis cannot be rejected, and error terms are said to be normal.

$$\boldsymbol{H_0}: \varepsilon \sim normal\ distribution \qquad \boldsymbol{JB} = \frac{n}{6}\left(S^2 + \frac{1}{4}K^2\right) \sim \chi^2(df = 2) \tag{10}$$

4.5.2 White's Test for Heteroscedasticity

The second condition implies that the variance in the error terms is constant and independent of the explanatory variables (i.e. homoscedasticity). On the other hand, heteroskedasticity results in lower precision in coefficient estimates and, thus, increases the likelihood of being further from the true population value. Evidence of homoskedasticity suggests that the regression model is well-defined and that the estimates provides a good explanation of variations in the dependent variable (Sajwan, R., Chetty, P., 2018). To test this, White's test for heteroscedasticity is applied (Wooldridge, 2011). The formula is exhibited in **equation 11** below, from where $\hat{u}$ is the estimated regression residuals, δ is the sensitivity to the independent variables and v is the residual.

$$\boldsymbol{H_0}: \varepsilon \sim homoscedatistic \qquad \boldsymbol{\hat{u}^2} = \delta_0 + \delta_1 x_1 + \delta_2 x_2 + \delta_3 x_1^2 + \delta_4 x_2^2 + \delta_5 x_1 x_2 + v \tag{11}$$

4.5.3 Breusch-Godfrey Test for Autocorrelation

The condition that error terms should not have any form for pattern, i.e. identically and independently distributed, is tested with the Breusch Godfrey Test. If there is a case of positive correlation in the estimated residuals, the t-test of an OLS regression could seem to be significant even though it is not – and vice versa (Wooldridge, 2011). To correct for autocorrelation, it is common to use the first difference, which is easily done by converting monthly prices into percentage-changes. As previously mentioned, excess returns have been calculated from historical prices of SB ETFs and benchmark indices. The test equation for the Breusch-Godfrey Test is exhibited in **equation 12**. The dependent variable is the estimated residual $\hat{u}$ as a function of its lags ρ and is also controlling for its original, structural x variables (Wooldridge, 2011).

$$\boldsymbol{H_0}: no\ autocorrelation \qquad \boldsymbol{\hat{u}_t} = \rho_1 u_{t-1} + \rho_2 u_{t-2} \ldots + \rho_q u_{t-q} + \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + \varepsilon_t \tag{12}$$

4.5.4 Results and Possible Implications

Table 3 shows the normality, heteroscedasticity and autocorrelation tests of the return-series for the regressions of both the performance and the factor exposure analysis. For the former, residuals have been estimated by regressing SB category portfolios on respective benchmark portfolios and for the latter, SB category portfolios have been regressed on the five risk-factors from AQR.

Source	Statistical Test	Size	Value	Momentum	Low-Vol	Quality	Multifactor
Factor Exposure Analysis	Jarque-Bera	0.9649	38.39	16.19	1.673	9.856	6.439
	Prob > χ^2	0.6173	0.0000	0.0000	0.4333	0.0072	0.0400
	Normal Distribution	**Yes**	**No**	**No**	**Yes**	**No**	**No**
	White	57.78	129.27	44.65	66.58	48.30	81.16
	Prob > χ^2	0.0005	0.0000	0.0177	0.0000	0.0071	0.0000
	Heteroscedasticity	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
	Breusch Godfrey	0.507	0.042	0.337	0.001	4.558	5.915
	Prob > χ^2	0.4763	0.8383	0.5615	0.9786	0.0328	0.0150
	Autocorrelation	**No**	**No**	**No**	**No**	**Yes**	**Yes**
Performance Analysis	Jarque-Bera	44.46	30.51	21.40	16.01	64.91	59.888
	Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.000
	Normal Distribution	**No**	**No**	**No**	**No**	**No**	**No**
	White	2.96	4.45	0.45	37.66	12.10	20.85
	Prob > χ^2	0.2273	0.1080	0.7966	0.0000	0.0024	0.0000
	Heteroscedasticity	**No**	**No**	**No**	**Yes**	**Yes**	**Yes**
	Breusch Godfrey	0.040	16.970	0.0360	0.3400	0.0090	0.4650
	Prob > χ^2	0.8406	0.0000	0.8497	0.5597	0.9254	0.4954
	Autocorrelation	**No**	**Yes**	**No**	**No**	**No**	**No**

Table 3 – Test results of statistical diagnostics described in **section 4.4**

As anticipated, there were not many return-series that proved to be of a normal distribution. It was realized that the normality-test was significant at the 5-pct. level for the return-series of size and low-volatility in the factor exposure analysis, while multifactor came close. The absence of normality in return-series was recognized by Jensen (1968), who declared a warning to interpret the respective tests as merely indicative. Apart from the return-series of size, value and momentum in the performance analysis, most did not display constant variances in the estimated residuals (i.e., homoscedasticity), but instead clusters of it over different periods. One of the consequences of this is that significance tests may not be very reliable. On a positive note, there is a considerable part of the return-series, which displays zero correlation in the estimated error terms.

5. Analysis Part I: Performance Analysis

Following the same chronological order as the methodology for the performance analysis, this chapter will present the results of calculations described in **section 4.2**. After that, results will be discussed in context of academic literature and other observations. The last part of this chapter will conclude on the most significant findings to provide a robust answer to **part 1** of the analysis:

*"How does the performance of Smart-Beta ETFs **a)** compare with benchmark indices and broad, cap-weighted ETFs and **b)** how do they behave in "up" and "down" market cycles?"*

5.1 Introduction

5.1.1 Chart of Cumulative Returns

In order to gain an overview of how the different SB portfolios have performed, their monthly excess returns have been rebased (=$100) in Jan-2007 to illustrate the growth of a $100- investment over the entire period (see **figure 6)**.

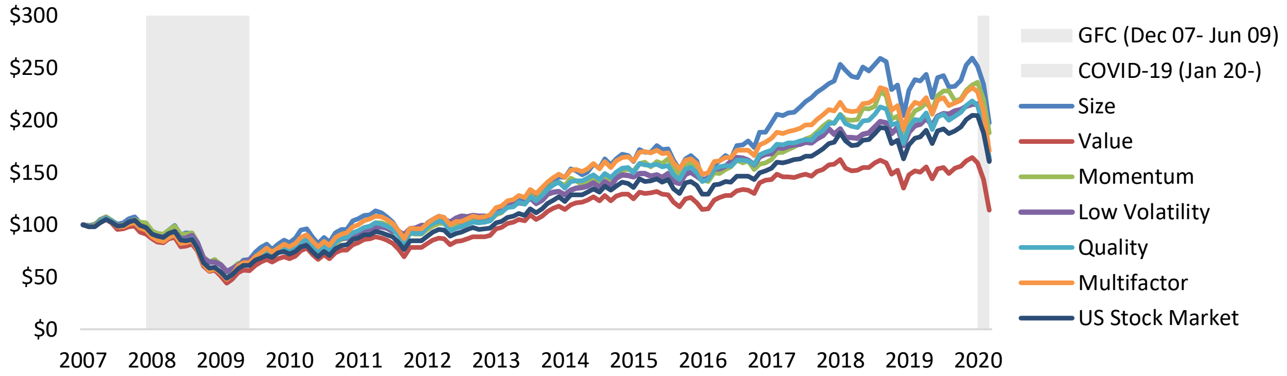

Figure 6 – Performance of SB ETF category portfolios compared to a proxy for the US stock market. Own calculations.

There are a couple of things that stand out from looking at **figure 6**. First, the SB portfolios seem to be relatively correlated, and very tightly so, up until the global financial crisis (GFC) ended in mid-2009. Since then, value has consequently been the worst-performing category. Any investor who went fully invested in this portfolio in Jan-2007, would have had to hold on for more than six years in order to recoup the initial amount paid and still significantly lag the market portfolio. The other five SB portfolios have all outperformed both value and the general market for the majority of the time period. Finally, size looks to have taken a strong leap relative to others, starting mid-2016, with more extreme price movements on both sides of the scale. The downturns after the outbreak of

COVID-19 are the most severe, collective downturn over a short period of time in the entire period. For most of the SB ETF portfolios, two-year gains were essentially wiped out in about two months while value witnessed nearly four years of gains being lost in the same period.

5.1.2 Fund Flows

As described in **section 1.1**., SB ETFs have been attracting an increasing share of capital flows into the overall ETF-market – especially since 2009. Despite value-themed ETFs having underperformed for nearly a decade, it has averaged more than 40 pct. of the total flows to the SB strategies of size, value, momentum, low volatility, quality and multifactor since 2007. According to Glushkov (2015), there is evidence to suggest that future fund flows are positively related to fund size and negatively related to expenses while *outflows* are heavily dependent on past performance. The fund-flow data displayed in **figure 7** will be used as a very simplified visual tool to validate what Alford (2017) characterized as being risks of factor-crowding in SB ETFs.

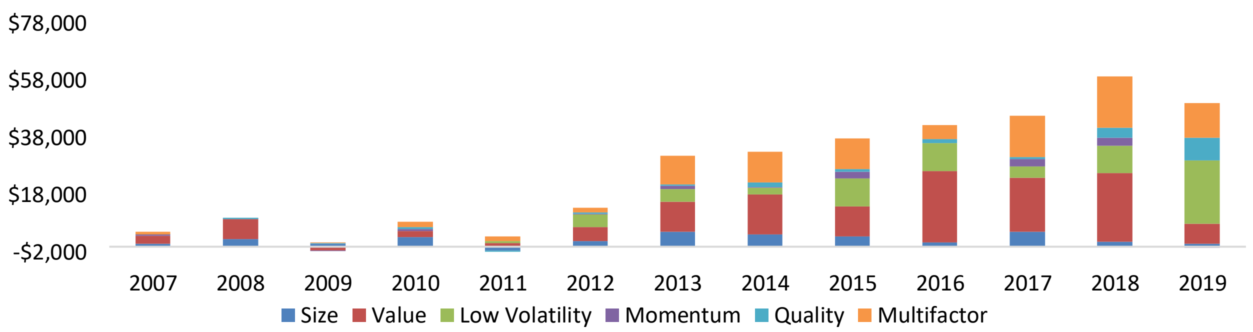

Figure 7 – Yearly Smart Beta ETF flows ($million). Includes only the chosen SB strategies of this thesis, source: Bloomberg

5.1.3 Expense Ratios

Average expense ratios are presented as an annual percentage of net assets in **figure 8**. When the results of the upcoming analysis is discussed in **section 5.4,** they will be seen in context with expense ratios for each SB portfolio. Readers are advised that fees should preferably be considered on a case-by-case basis due to significant differences between SB ETFs of similar categories. For an overview of SB ETFs and their respective expense ratios, please visit **appendix 9.1**. As illustrated in **figure 7**, momentum is one of the costliest SB strategies, mainly due to a high rate of turnover and low capacity. The multifactor strategy also has a relatively high expense ratio and could be due to its added complexity, which will depend on what factors the strategy combine.

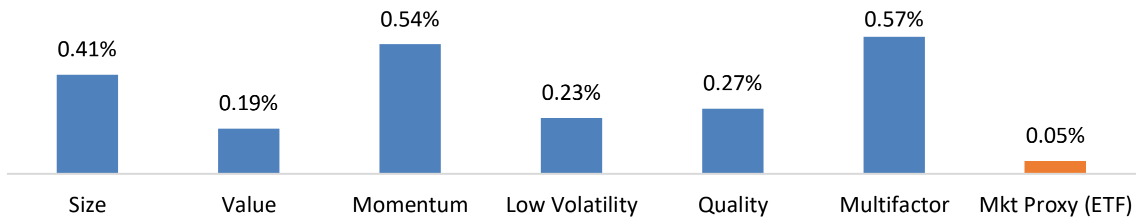

Figure 8 – Average annual expense ratios for each SB category portfolio and the TSM ETF portfolio, source: Morningstar.

5.2 Results of Relative Return Analysis

5.2.1 Summary Statistics

This sub-section will present summary statistics of the "entire sample period" along with the "up" and "down" sample periods. The chosen metrics are average annual return (AAR), volatility, monthly observations (i.e. count) and t-statistics. AAR and volatility are presented as annualized numbers for all periods tested. Asterisks (*, ** and ***) indicate statistical significance at different confidence levels (1-pct., 2-pct. and 5-pct.). Green and red colors are indicators of "best" and "worst" performers of each category, respectively.

5.2.1.1 The Entire Period

Summary statistics for the entire sample period are displayed in **table 4**. The period is based on 159 monthly observations of SB portfolios, benchmark portfolios, and market proxies for both ETFs and indices. The "count" statistic shows the number of monthly return-observations that cumulated into the calculation of the final portfolios for each category.

	Statistic	Size	Value	Momentum	Low-Vol.	Quality	Multifactor	Market	
SB Cat. Portfolios	AAR	7.19%	2.63%	6.14%	4.51%	5.37%	5.66%	4.91%	Mkt. Proxy (ETF)
	Vol.	19.54%	17.27%	15.67%	13.26%	16.71%	17.14%	15.46%	
	Count	1,590	1,590	1,410	854	1,098	1,555	477	
	t-stat.	4.64*	1.92**	4.94*	4.29*	4.05*	4.16*	4.01*	
Benchmark Portfolios	AAR	7.21%	4.56%	5.38%	4.92%	6.25%	6.07%	6.19%	Mkt. Proxy (indices)
	Vol.	17.45%	17.51%	15.26%	14.93%	16.48%	15.79%	15.48%	
	Count	1,512	1,551	1,590	1,434	1,509	1,551	477	
	t-stat.	5.21*	3.29*	4.45*	4.15*	4.78*	4.85*	5.05*	

Table 4 - Descriptive statistics for the entire sample period. AAR and volatility are annualized numbers. *P<0.01; **P<0.025; ***P<0.05 are indicative of whether results are significant at a 1-pct., 2.5-pct. and 5-pct. level, respectively.

5.2.1.2 "Up" Periods

From using the moving-average method described in **section 4.3.2**, there was 120 out of 159 months that was characterized as being "up" periods. Results are displayed in **table 5**.

	Statistic	Size	Value	Momentum	Low-Vol.	Quality	Multifactor	Market	
SB Cat. Portfolios	AAR	22.08%	15.84%	19.08%	13.92%	18.00%	18.84%	17.52%	Mkt. Proxy (ETF)
	Vol.	13.37%	10.84%	10.50%	8.52%	10.67%	10.77%	9.91%	
	Count	1,200	1,200	1,088	695	847	1,165	360	
	t-stat.	6.01*	5.32*	6.62*	5.95*	6.14*	6.37*	6.44*	
Benchmark Portfolios	AAR	21.00%	17.76%	18.12%	16.20%	19.32%	18.72%	18.84%	Mkt. Proxy (indices)
	Vol.	11.81%	11.09%	9.56%	9.21%	10.46%	10.08%	9.94%	
	Count	1,158	1,179	1,200	1,116	1,155	1,179	360	
	t-stat.	6.47*	5.83*	6.90*	6.40*	6.72*	6.76*	6.90*	

Table 5 - Descriptive statistics for "up" periods. AAR and volatility are annualized numbers. *P<0.01; **P<0.025; ***P<0.05 are indicative of whether results are significant at a 1-pct., 2.5-pct. and 5-pct. level, respectively.

5.2.1.3 "Down" Periods

From using the moving-average method described in **section 4.3.2**, there was 39 out of 159 months that was characterized as being "down" periods. Results are displayed in **table 6**.

	Statistic	Size	Value	Momentum	Low-Vol.	Quality	Multifactor	Market	
SB Cat. Portfolios	AAR	-38.64%	-37.92%	-33.84%	-24.48%	-33.60%	-34.80%	-33.96%	Mkt. Proxy (ETF)
	Vol.	28.09%	26.19%	22.24%	20.23%	25.15%	25.95%	22.69%	
	Count	390	390	322	159	251	390	117	
	t-stat.	-5.01*	-5.27*	-5.54*	-4.40*	-4.86*	-4.88*	-5.45*	
Benchmark Portfolios	AAR	-35.28%	-35.88%	-33.72%	-30.00%	-34.08%	-32.88%	-32.88%	Mkt. Proxy (indices)
	Vol.	24.98%	26.54%	22.55%	22.90%	24.53%	23.38%	22.66%	
	Count	354	372	390	318	354	372	117	
	t-stat.	-5.14*	-4.92*	-5.44*	-4.77*	-5.06*	-5.12*	-5.28*	

Table 6 - Descriptive statistics for "down" periods. AAR and volatility are annualized numbers. *P<0.01; **P<0.025; ***P<0.05 are indicative of whether results are significant at a 1-pct., 2.5-pct. and 5-pct. level, respectively.

5.2.2 Trailing Returns

Table 7 exhibits the trailing returns of SB portfolios, their benchmark portfolios, and the two market proxies for ETFs and indices. Portfolios are compared concerning annualized (geometric mean) excess returns over the periods of 1 year, 3 years, 5 years, 10 years, and since 2007. Benchmark-adjusted returns are also shown, which is the annualized difference in returns between SB portfolios and their respective benchmarks. When interpreting the results of **table 7**, it is crucial to keep in mind that trailing returns measure performance for just one block of time and, thus, suffer from a *recent-performance-bias*. This is especially important as the outbreak of COVID-19 caused massive losses in stock markets during the last two months of the data series. As a result, annualized results could be negatively skewed.

SB Category	Return Type	1 Year	3 Years	5 Years	10 Years	Since 2007
Size	SB Portfolio	-16.93%	-1.19%	3.09%	7.60%	5.41%
	Benchmark Portfolio	-13.90%	0.66%	4.43%	7.82%	5.84%
	Benchmark-adjusted	**-3.32%**	**-1.58%**	**-1.04%**	**0.05%**	**-0.09%**
Value	SB Portfolio	-24.18%	-8.00%	-2.65%	4.28%	1.06%
	Benchmark Portfolio	-23.24%	-6.28%	-0.88%	6.30%	2.99%
	Benchmark-adjusted	**-1.18%**	**-1.80%**	**-1.76%**	**-1.92%**	**-1.92%**
Momentum	SB Portfolio	-11.18%	3.48%	3.26%	8.67%	4.89%
	Benchmark Portfolio	-10.63%	1.36%	4.11%	8.42%	4.37%
	Benchmark-adjusted	**-0.95%**	**2.14%**	**-0.78%**	**0.31%**	**0.44%**
Low-Vol	SB Portfolio	-17.41%	-2.20%	1.69%	7.35%	3.82%
	Benchmark Portfolio	-17.07%	-1.94%	1.63%	7.12%	3.88%
	Benchmark-adjusted	**-0.38%**	**-0.30%**	**0.02%**	**0.02%**	**-0.40%**
Quality	SB Portfolio	-18.05%	-2.44%	0.84%	7.03%	3.94%
	Benchmark Portfolio	-15.14%	-0.45%	2.39%	8.32%	5.06%
	Benchmark-adjusted	**-3.34%**	**-2.04%**	**-1.56%**	**-1.22%**	**-1.04%**
Multifactor	SB Portfolio	-20.79%	-3.11%	0.09%	6.89%	4.30%
	Benchmark Portfolio	-14.41%	-0.48%	2.63%	7.76%	4.92%
	Benchmark-adjusted	**-7.03%**	**-2.40%**	**-2.33%**	**-0.69%**	**-0.40%**
Market	TSM ETF Portfolio	-11.76%	0.74%	2.92%	7.45%	3.88%
	TSM Index Portfolio	-10.67%	1.96%	4.21%	8.88%	5.21%

Table 7 – Annualized (geometric mean) excess (trailing) returns for six categories of SB ETFs, their respective benchmark portfolios, the benchmark-adjusted return and two market portfolios (i.e. TSM ETF and TSM Index) over one-, three-, five-, ten-year horizons and "since 2007" ending in March 2020.

5.3 Results of Risk-Adjusted Analysis

5.3.1 The Entire Period

Results of the risk-adjusted performance analysis are displayed in **table 8**. As mentioned in **section 4.3.3**, positive alpha would indicate excess returns, relative to its respective benchmark portfolio and TSM ETF portfolio, of that explained by the amount of market-risk over the time period. Thus, alpha would imply managerial skill. Beta is a measure of volatility with regards to the benchmark and TSM ETF portfolio. The results are supplemented with Sharpe ratios for both SB- and benchmark portfolios, while the Information ratio is provided for the SB portfolios. All metrics are annualized numbers. T-statistics are presented below each metric and asterisks (*, ** and ***) indicate statistical significance at different confidence levels (1-pct., 2-pct. and 5-pct.).

SB Category	Alpha wrt. Benchmark Portfolio	Alpha wrt. TSM ETF Portfolio	Beta wrt. Benchmark Portfolio	Beta wrt. TSM ETF Portfolio	Sharpe Ratio SB ETF Portfolio	Sharpe Ratio Benchmark Portfolio	Inf. Ratio SB ETF Portfolio
Size	-0.74%	1.22%	1.10	1.22	0.3679	0.4129	-0.0039
	-0.75	0.82	67.72*	43.80*	4.03*	4.52*	-0.04
Value	-1.87%	-2.73%	0.98	1.09	0.1520	0.2606	-1.7902
	-6.45*	-2.57*	205.98*	55.08*	1.66***	2.86*	-19.61*
Momentum	0.92%	1.42%	0.97	0.96	0.3921	0.3526	0.1490
	0.65	1.03	36.36*	37.29*	4.30*	3.86*	1.63***
Low-Vol	0.34%	0.66%	0.85	0.78	0.3400	0.3294	-0.0896
	0.31	0.44	39.89*	28.27*	3.72*	3.61*	-0.98
Quality	-0.93%	0.15%	1.01	1.06	0.3212	0.3791	-0.4648
	-1.77***	0.17	110.20*	65.73*	3.52*	4.15*	-5.09*
Multifactor	-0.87%	0.33%	1.07	1.08	0.3299	0.3844	-0.1554
	-1.31	0.33	88.87*	57.43*	3.61*	4.21*	-1.70***

Table 8 – Results of Jensen's Alpha regression, Sharpe Ratio and Information Ratio over the entire sample period. Numbers are annualized. *P<0.01; **P<0.025; ***P<0.05 are indicative of whether results are significant at a 1-pct., 2.5-pct. and 5-pct. level, respectively.

5.3.2 "Up" Periods

As previously mentioned, there were 120 out of 159 months that was defined as "up" periods. Results of the risk-adjusted performance analysis on this sample period is exhibited in **table 9**.

SB Category	Alpha wrt. Benchmark Portfolio	Alpha wrt. TSM ETF Portfolio	Beta wrt. Benchmark Portfolio	Beta wrt. TSM ETF Portfolio	Sharpe Ratio SB ETF Portfolio	Sharpe Ratio Benchmark Portfolio	Inf. Ratio SB ETF Portfolio
Size	-1.06%	0.17%	1.10	1.25	0.4773	0.5135	0.0960
	-0.98	0.10	46.80*	26.74*	5.23*	5.62*	1.05
Value	-1.48%	-2.44%	0.97	0.93	0.4198	0.4610	-0.5470
	-4.32*	-2.01**	120.07*	32.34*	4.60*	5.05*	-5.99*
Momentum	1.46%	2.80%	0.98	0.93	0.5258	0.5450	0.0639
	0.84	1.56	21.30*	19.94*	5.76*	5.97*	0.70
Low-Vol	-0.18%	1.00%	0.87	0.74	0.4720	0.5098	-0.2103
	-0.17	0.64	29.26*	18.07*	5.17*	5.58*	-2.30**
Quality	-1.43%	-0.15%	1.01	1.04	0.4882	0.5338	-0.2186
	-2.31**	-0.14	66.63*	38.79*	5.35*	5.85*	-2.39*
Multifactor	-0.80%	0.65%	1.05	1.03	0.5042	0.5357	0.0124
	-1.07	0.55	55.31*	33.97*	5.52*	5.87*	0.14

Table 9 - Results of Jensen's Alpha regression, Sharpe Ratio and Information Ratio during "up" periods. Numbers are annualized. *P<0.01; **P<0.025; ***P<0.05 are indicative of whether results are significant at a 1-pct., 2.5-pct. and 5-pct. level, respectively.

5.3.3 "Down" Periods

As mentioned earlier, there were 39 out of 159 months that was defined as "down" periods. Results of the risk-adjusted performance analysis on this sample period is exhibited in **table 10**.

SB Category	Alpha wrt. Benchmark Portfolio	Alpha wrt. TSM ETF Portfolio	Beta wrt. Benchmark Portfolio	Beta wrt. TSM ETF Portfolio	Sharpe Ratio SB ETF Portfolio	Sharpe Ratio Benchmark Portfolio	Inf. Ratio SB ETF Portfolio
Size	-0.72%	2.29%	1.04	1.21	-0.3975	-0.4079	-0.1758
	0.19	0.59	24.10*	26.24*	-2.51*	-2.55*	-1.10
Value	-2.48%	0.72%	1.12	1.14	-0.4174	-0.3905	-0.4449
	-0.07	0.25	25.19*	33.91*	-2.64*	-2.44*	-2.78*
Momentum	-1.85%	-1.32%	1.00	0.96	-0.4389	-0.4311	-0.0067
	-1.54	-0.44	13.91*	27.24*	-2.78*	-2.69*	-0.04
Low-Vol	0.76%	3.59%	0.73	0.83	-0.3492	-0.3780	0.2224
	0.07	0.77	14.00*	14.98*	-2.21**	-2.36*	1.39
Quality	1.11%	3.60%	0.95	1.10	-0.3863	-0.4007	0.0518
	-0.38	1.60	48.70*	41.35*	-2.44*	-2.50*	0.32
Multifactor	1.36%	3.48%	1.42	1.13	-0.3871	-0.4050	-0.1464
	1.08	1.27	30.15*	34.93*	-2.45*	-2.53*	-0.91

Table 10 - Results of Jensen's Alpha regression, Sharpe Ratio and Information Ratio during "down" periods. Numbers are annualized. *P<0.01; **P<0.025; ***P<0.05 are indicative of whether results are significant at a 1-pct., 2.5-pct. and 5-pct. level, respectively.

5.4 Overview of Outperformance Criteria

Regarding the outperformance criteria of **section 4.3.6**, an overview of whether SB portfolios have fulfilled any of these are displayed in **table 11**. Evaluations are based on the entire sample period, and benchmark-adjusted returns are judged by the block-period "since 2007". For benchmark-adjusted returns, "+" and "-" refers to whether the SB portfolio has generated positive or negative annualized differences in returns relative to the benchmark portfolio and the TSM ETF portfolio (i.e., market portfolio), respectively. For alpha, "+" and "-" refers to whether the SB portfolios have shown positive or negative alpha about the benchmark and TSM ETF portfolio, respectively. For the Sharpe and Information ratios, "+" and "-" indicate whether the SB portfolios have performed better or worse than the benchmark portfolio. Asterisks (*) indicate statistical significance at a 5-pct. level that only relates to alpha, Sharpe, and Information ratios.

SB Category	Benchmark-Adj. Returns: Benchmark Portfolio	Benchmark-Adj. Returns: TSM ETF Portfolio	Alpha wrt.: Benchmark Portfolio	Alpha wrt.: TSM ETF Portfolio	Sharpe Ratio: SB ETF Portfolio	Information Ratio: SB ETF Portfolio
Size	-	+	-	+	-*	-
Value	-	-	-	-*	-*	-*
Momentum	+	+	+	+	+*	+*
Low-Vol	-	-	+	+	+*	-
Quality	-	+	-*	+	-*	-*
Multifactor	-	+	-	+	-*	-*

Table 11 - Overview of outperformance criteria.

5.5 Discussion of Results

In this section, results will be discussed for each and all SB portfolios to give grounds for the chapter conclusion in **section 5.5**. Results that are not statistically significant at a 5-pct. won't be particularly emphasized and only mentioned when seen fit.

5.5.1 Size

From the summary statistics of **section 5.2.1**, it became evident that Size was the best-performing SB portfolio in the entire sample period as well as during "up" periods with average annual returns (AAR) of 7.19 pct. and 22.08 pct., respectively. Size also had the highest volatility in those periods (19.54 pct. and 13.37 pct.), which indicates that higher returns have been due to taking on more risk. As a result, the higher levels of risk may have caused Size to be the worst-performing SB portfolio during "down" periods with average returns of -38.64 pct. and 28.09 pct. in volatility. This finding is in line with Fama and French (1992). In their research paper, it was claimed that small-cap stocks tend to outperform large-cap stocks over time and even the market as a whole[7]. This outperformance, they iterated, is due to small-cap stocks having greater systematic risk (i.e., beta), which allows for a higher risk-premium.

[7] Whether the Size portfolio has harvested risk-premiums from being exposed to small-cap or large-cap stocks will be investigated in **chapter 6**.

The claim of Size having a higher beta than most, was backed up by results in **table 8** through **table 10**. Accordingly, results from the Jensen's alpha regressions showed that Size had the largest beta with regard to both the benchmark portfolio (1.10) and TSM ETF portfolio (1.22) during the entire sample period and during "up" periods. Size returned a lower Sharpe ratio (SR) than its benchmark portfolio during both the entire sample period (0.3679 vs. 0.4129) and the "up" periods (0.4773 vs. 0.5135) while it exhibited a slightly higher SR in "down" periods (-0.3975 vs. -0.4079). These results indicate that Size, in general, have provided lower excess returns than its benchmark per unit of risk. Results of the Information ratios (IR), which is the average differential return between SB portfolios and benchmarks, were all statistically insignificant at a 5-pct. level. The same goes for the estimates of alpha despite having a relatively large dataset.

When looking at trailing returns in **table 7**, the relatively good return properties of Size seem to have made it the SB portfolio with highest excess returns since 2007 (5.41 pct.). Compared to the TSM ETF portfolio (3.88 pct.), Size managed to deliver 1.53 pct. in excess returns and, thus, showed to have been superior to the market portfolio in that period. Despite delivering higher returns than most of the other SB portfolios, it only managed to deliver positive benchmark-adjusted returns (0.05 pct.) during the block-period of 10 years while having benchmark-adjusted returns of -0.09 pct. since 2007.

Regarding the possible influence of expense ratios on returns, a *very* simplified trial of *grossing* up the NAV-returns by an expense-factor of 0.41 pct.[8] to the returns of the Size portfolio, would actually change (from negative to positive) that it did deliver positive benchmark-adjusted returns of 0.33 pct. since 2007. Results for other negative block-periods would not change by doing this, and as such, it would indicate that expense ratios, at least alone, does not help to explain much of the deviation in returns between Size and its benchmark portfolio.

5.5.2 Value

If not *the* worst, Value was at least among the worst-performing SB portfolios in more or less every performance measure calculated in **section 5.2** and **section 5.3**. As for the entire sample period, **table 4** indicated that Value had delivered an average annual return (AAR) of 2.63 pct. which was 2.28 pct. less than the market proxy (ETF) and 1.93 pct. less than its benchmark portfolio. Also, Value had the second-highest volatility in the entire sample period (17.27 pct.) as well as during "up" (10.84 pct.)

[8] Calculations have been made in Excel to testify this.

and "down" (26.19 pct.) periods. In terms of trailing returns from **table 7**, Value was again the worst-performing SB portfolio in all block-periods having only produced 1.06 pct. in excess returns since 2007 and a devastating -24.18 pct. and -8.00 pct. over the last 1-year and 3-year periods, respectively. Moreover, Value delivered negative benchmark-adjusted returns for all block-periods.

From the risk-adjusted measures of **table 8**, the Jensen's alpha regression indicated that the portfolio has produced negative alpha of -1.87 pct. and -2.73 pct. with regard to its benchmark and the TSM ETF portfolio, respectively. Both numbers were significant at a 1-pct. level and also the lowest alpha of all SB-portfolios, regardless of significance. Based on the above mentioned, it did not come as any surprise that Value also had a lower Sharpe ratio than all of the other SB portfolios as well as its benchmark portfolio (0.1520 vs. 0.2606) which also culminated in an Information ratio of -1.7902.

These findings are in line with Meredith (2019), who also found Value to be underperforming since the beginning of 2007. For one, a technology-revolution has been at the forefront of the decade-long bull run through a significant boom in shares of major tech companies (e.g., Amazon and Apple) that have disrupted, and maybe even "ruined", the traditional retail sector which have been home to many value-stocks. This trend has led to a significant rotation from value- to growth-stocks[9] as the appetite for rapidly growing companies have surged (Lin, 2019). The underperformance of Value could also be explained by its high sensitivity to monetary interventions by central banks. As iterated throughout the thesis, interest-rates have been record-low since the Federal Reserve started its quantitative easing (QE) program after the financial crisis of 2008. Low-interest rates have been a significant contributor to boosted valuations ever since, leaving lower premiums on "cheap" stocks. With this in mind, an interesting observation from **figure 7** is that yearly flows to Value ETFs was drastically reduced from 2018 to 2019 (more than 3x).

Finally, with Value having the lowest expense ratio (0.19 pct.) and still underperform the way it has, it would be hard to argue that expenses have significant explanatory power with regard to deviations in returns between the SB portfolio and its benchmark.

[9] «Growth assets» are intangible which in many cases are not captured in book value and retained earnings.

5.5.3 Momentum

As mentioned in **section 2.7.2.4**, value and momentum are negatively correlated factors. Thus, with the recently discussed underperformance of Value in mind, it should not come as a surprise that the Momentum portfolio has been one of the best-performing SB portfolios in most categories. Over the course of the entire sample period, Momentum delivered an average annual return of 6.14 pct. (only beaten by Size and 1.23 pct. higher than the market) along the second-lowest volatility of 15.67 pct. (only beaten by Low Volatility). This indication of relatively high risk-adjusted returns is also backed by **table 8**, in which Momentum have the highest Sharpe ratio of all SB portfolios as well as for its benchmark portfolio (0.3921 vs. 0.3526). Both statistically significant at a 1-pct. level. Results also indicate that Momentum has the highest, statistically significant, Information ratio (0.1490). From the calculation of Jensen's alpha regression, it shows that the Momentum generated the highest alphas of 0.92 pct. and 1.42 pct. to its benchmark and TSM ETF portfolio, respectively. However, results are statistically insignificant and, thus, should be considered with caution. In terms of trailing returns, results from **table 7** indicate that Momentum delivered excess returns of 4.89 pct. since 2007 which was, again, only beaten by Size (5.41 pct.). It also displayed positive benchmark-adjusted returns over the block-periods of 3-years (2.14 pct.), 10-years (0.31 pct.) and since 2007 (0.44 pct.) – more than any other SB portfolio.

Performance measures calculated for the "up" periods were very similar to those of the entire sample and, thus, in agreement with Glushkov (2015) who also found momentum-stocks to thrive in upward-trending markets. Such an upward-trending market has been the case for most of the data sample of this thesis. As global growth, corporate earnings, and lower interest rates have lifted stocks steadily higher, Momentum has been one of the highest rewarded market participants of all SB portfolios. However, buying rising stocks works only well until it stops (Miskin, M., Roland, E., Wellman, R., 2019). One of the inherent risks of "buying the trend" is that it is often the highest-flying stocks, when conditions are favorable, that ends up with the worst drawdowns when markets are falling. This is in accordance with the findings of **table 6** and **table 10** as well. During what this thesis characterizes as "down" periods, Momentum have experienced the worst Sharpe ratio (-0.4389) as well as a negative alpha with regards to both its benchmark portfolio (-0.69 pct.) and TSM ETF portfolio (-0.11 pct.). However, both estimates of alpha were statistically insignificant.

An interesting observation from **table 7** is that, despite the stock-market crash of the last two months, Momentum is by far the best-performing SB portfolio over the most recent year (-11.18 pct.). On one hand, this would seem conflicted with Miskin et al. (2019), but according to Hajric (2020) there has been a shift which have resulted in momentum ETFs having many of the same traits as low-volatility ETFs. More specifically, MTUM[10] which is the largest momentum-ETF with regard to fund size, has seen an increase in allocations toward utility and real-estate stocks over the year. Those industries have typically been thought of as "safe havens" during downturns in the market. MTUM has reduced its holdings of financial companies over the same period and, thus, ended up having about 75 pct. of the same holdings as USMV[11] which is the largest low-volatility-ETF in terms of fund size.

Finally, by *grossing* up the NAV-returns of Momentum it would seem as though the portfolio have shown positive benchmark-adjusted returns for all block-periods in **table 7**. This result would indicate that the relatively high expense ratio of 0.54 pct. has *some* explanatory power regarding deviations in returns between the SB portfolio and its benchmark. Nevertheless, key-findings of the analysis seem to be aligned with both Carhart (1997) and Jagadeesh and Titman (1993), who claim that momentum-stocks outperform the market over the long run.

5.5.4 Low Volatility

From analyzing the different performance measures of Low Volatility, findings appear to be fairly in harmony with the research of Haugen and Heins (1972), and Jagannathan & Ma (2003). That being, low-volatility stocks tend to outperform in "down" periods and lag the market in "up" periods. From **table 4**, the Low Volatility portfolio averaged excess returns of 4.51 pct. over the entire sample period and 13.26 pct. in volatility. In terms of returns, this was the second lowest of SB portfolios and 0.40 pct. lower than the market portfolio (4.91 pct.). With more than three quarters of the sample period being characterized as "up" periods, it seems justifiable that Low Volatility have been lagging the market during this time. As a consequence of having the lowest volatility of all tested SB portfolios, Low Volatility had the third-highest Sharpe ratio (0.34), which was statistically significant at a 1-pct. level, as well as having a slightly higher Sharpe ratio than its benchmark portfolio (0.33). Results from the Jensen's alpha regression in **table 8** gave betas estimates of 0.85 and 0.78 with regard to its benchmark and TSM ETF portfolio, respectively – also in line with the strategy being more defensive

[10] iShares Edge MSCI USA Momentum Factor (ticker: MTUM)
[11] iShares Edge MSCI Minimum Volatility USA (ticker: USMV)

than most of its counterparts. Furthermore, alpha estimates were positive (0.34 pct. and 0.66 pct.) but statistically insignificant for all periods tested.

Results of trailing returns in **table 7** are also, to a certain degree, in line with some of the results that have been discussed. For example, the portfolio has delivered excess returns of 3.82 pct. since 2007 which is only higher than that of Value (1.06 pct.) and marginally lower than the market (3.88 pct.). As the portfolio also had slightly lower returns than its benchmark (3.88 pct.), negative benchmark-adjusted returns of -0.40 pct. since 2007 followed. If we were to exclude the financial crisis of Dec-07 through Jun-09, the annualized returns of the last 10-year period seems much higher (7.35 pct.) and the portfolio actually produced positive benchmark-adjusted returns.

More interestingly, **table 7** indicates that Low Volatility has been one of the worst-performers over the most recent year with an excess return of -17.41 pct. which is much worse than the market (-11.76 pct.) recorded in the same period. This significant difference in returns would seem strange compared to historical performance and its defensive risk-return profile. However, the abnormal negative performance of Low-Volatility can be attributed to sector biases. For example, the cruise operator Carnival Corporation (CCL) was not a particularly volatile stock before the outbreak of COVID-19 became clear, at which point the stock quickly declined by 75 pct. in just weeks. At the same time, a lot of (more) volatile technology stocks have been seemingly less moved by the global crisis than the average U.S. listed company (Kennedy, 2020).

Although Low-Volatility may have disappointed during the recent outbreak of COVID-19, it is just two data points and should not be given too much emphasis. In general, a weakness of empirically testing defensive strategies is that market-crashes, like the one just mentioned, does not happen very frequently. By including more data points for the "down" periods, 37 to be exact, **table 6** indicates that Low Volatility is the best-performing SB portfolio by a distance with *only* -24.48 pct. in average returns compared to -35.76 pct. for the remaining five SB portfolios and -33.96 pct. for the market. Regarding the expense ratio (0.23 pct.), it does not seem to result in any more periods of positive benchmark-adjusted returns by grossing up the NAV.

5.5.5 Quality

According to summary statistics for the entire period (see **table 4**), Quality has provided 5.37 pct. in average annual returns and 16.71 pct. in volatility since recordings started in 2007. On a risk-adjusted basis, this is better than the market (4.91 pct.) but less than its benchmark portfolio (6.25 pct.). All numbers are statistically significant at a 1-pct. level. Results are in agreement with the findings of Asness et al. (2013) in which it was claimed that quality-stocks exhibits superior risk-adjusted returns compared to the market in the long-run. From trailing returns of **table 7**, it becomes clear that Quality have posted negative benchmark-adjusted returns for all block-periods. Value (-1.92 pct.) was the only portfolio to have a worse benchmark-adjusted returns than Quality (-1.04 pct.) since 2007.

In terms of risk-adjusted performance for the entire period (see **table 8**), Quality was only one out of two SB portfolios to have statistically significant estimates of alpha (-0.93 pct.) with regard to its benchmark which is in line with previously discussed results. With betas of 1.01 and 1.06 with regard to its benchmark and TSM ETF portfolio, respectively, it becomes even clearer that Quality have a bad tracking error as it (in theory) should have moved in a "lock-step" to at least the benchmark. Furthermore, results of **table 8** indicates that Quality have a lower Sharpe ratio than its benchmark (0.3212 vs. 0.3791) along with the second-worst Information ratio (-0.4648). These results are also in harmony with Glushkov (2015).

Even though traits of the quality-factor are heavily debated in academic circles (see **section 2.7.2.5**), one of them is said to be that they should outperform the market in "down" periods. This is mainly due to the "flight-to-quality" effect. This is the effect of investors becoming more risk-averse when macroeconomic conditions start to worsen and, thus, invest in stocks that are perhaps low on leverage with strong foundations for stable earnings (Asness et al., 2013). The claim seems to be in accordance with findings of **table 6**, which shows that Quality has had the second highest average returns in "down" periods (-33.60 pct.) along with the second-highest Sharpe ratio (-0.3863) – only beaten by Low Volatility in both periods. On the other hand, Quality posted a loss of 18.05 pct. over the last 1-year period (see **table 8**) which is far worse than that of the market portfolio (-11.76 pct.). This is a very interesting observation to put in context with Arnott et al. (2016), in which they found that essentially all outperformance related to quality-stocks was due to the rising valuations. And with the very abrupt COVID-19 crisis causing a massive crash in the stock market, these seemingly inflated valuations have burst and caused damage to quality-stocks. By looking closer at the portfolio during March 2020, it was especially three ETFs that may have negatively skewed the overall performance of the portfolio. The common denominator of the ETFs (tickers: EZM, EES and XSHQ) is that they primarily invest in small- and mid-cap companies that *ticks* certain quality-marks. And, as evidence have shown, these segments have taken a much harder hit than large-cap companies (Direxion, 2020).

Regarding the expense ratio of 0.27 pct., which is relatively low compared to other SB portfolios, it does not seem like it would have made any significant difference to the benchmark-adjusted returns as they would still be negative even if gross-of-fees.

5.5.6 Multifactor

According to **table 1**, the number of US-listed multifactor ETFs have gone from 31 in 2007 to 204 in 2019 which is the biggest increase in all categories. Also, multifactor has been one of the SB strategies to attract the most fund flows since 2013 (see **figure 7**). As the name implies, multifactor SB ETFs offers investors exposure to not one, but several (often low-correlated) factors in order to give them more consistent returns while reaping the risk-premiums. In order to find explanations to the return-behavior of the Multifactor portfolio, it would be convenient to know exactly what factor-strategies the individual ETFs have intended to harvest risk-premiums from[12]. From **figure 9**, the most frequent combination of factors-strategies between ETFs in the Multifactor portfolio was of value and growth (7x). The three remaining ETFs have declared combinations of momentum and low volatility (2x) as well as momentum, quality and value (1x).

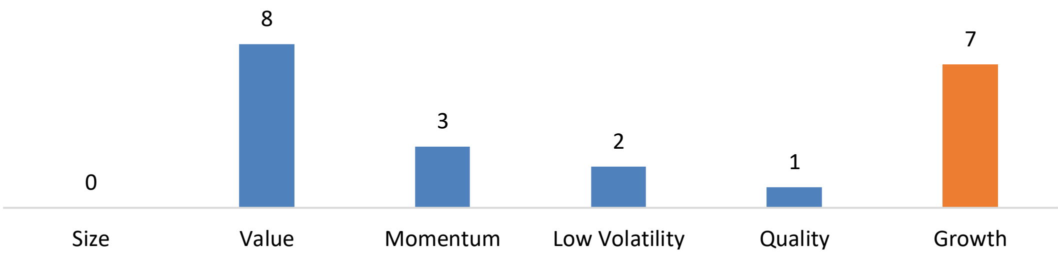

Figure 9 - Factor-strategies declared as intended index selection by SB ETFS in the Multifactor portfolio, source: Morningstar

From the summary statistics of **table 4**, the Multifactor portfolio have yielded excess returns of 5.66 pct. since 2007 together with 17.14 pct. in volatility. Compared to the market (4.91 pct.), Multifactor achieved higher returns but did it by taking on more risk (17.14 pct. vs. 15.46 pct.). In terms of trailing returns (see **table 7**), the portfolio showed 4.30 pct. in annualized returns since 2007 which was third best of all SB portfolios but lower than its benchmark (4.92 pct.). It is interesting that Multifactor did

[12] Whether the portfolio actually exhibit the intended factor exposures, will be analyzed in **chapter 6**.

not generate positive benchmark-adjusted returns in any of the block-periods and, more specifically, it yielded worst of all SB portfolios for the most recent 1-year, 3-year *and* 5-year periods.

Regarding the risk-adjusted performance (**table 8** through **table 10**), neither indicate that Multifactor provided statistically significant alphas in any of the periods that were tested. In terms of beta, the general consensus is that Multifactor had a beta higher than 1 with regard to both its benchmark and the market portfolio. Especially during the "down" periods, Multifactor had a statistically significant beta of 1.42 (!) compared to its benchmark portfolio which would to some degree explain the tracking error. It did, however, provide a slightly higher Sharpe during "down" periods than its benchmark (-0.3871 vs. -0.4050). As iterated before, "down" periods did only account for 39 months in the time-series and, thus, results should be considered with caution even if statistically significant at a 1-pct. level. On the other hand, findings are pretty much in agreement with Glushkov (2015) who also found Multifactor to underperform its benchmark portfolio, as well as the market, during "down" periods coupled with a beta significantly higher than 1 to its benchmark.

With the value-factor making up a substantial part of the strategy-combinations of the Multifactor portfolio which have proven to underperform in all periods tested, it would only seem natural that it has contributed negatively to performance of Multifactor as well. However, the value-factor have usually been combined with the growth-factor. The two factors are partially inverse of each other as there are not many stocks trading at low valuations *and* showing strong growth in sales. Thus, it is hard for both strategies to outperform at the same time and the combination is more of a risk-oriented move towards diversification. From the overall performance of the Multifactor portfolio, it seems as though the performance of growth-stocks has not been robust enough to offset the underperformance in the Value portfolio. As with Quality, the ETFs of the Multifactor portfolio with the most extreme downturns of the last two months have been directly exposed to the small- and mid-cap segments of growth- and value-stocks (tickers: FNX, FYX).

Finally, Multifactor is the SB portfolio with the highest average expense ratios (0.57 pct.). By grossing up NAV-returns, benchmark-adjusted returns since 2007 would seem to go from -0.40 pct. to 0.17 pct. but remain negative for all other block-periods. So, from this very simplified trial and the previous discussion of results, it would appear that the lack of outperformance cannot be explained by higher fees but rather unfortunate factor-combinations.

5.6 Chapter Conclusion

Based on the hype of Smart Beta, both in terms of marketing as well as capital in-flows, this chapter has come to some impressive results to indicate that the investment approach may not be so "smart" after all. Based on the criteria for outperformance in **table 11**, there is no significant evidence to suggest that SB portfolios have "outsmarted" benchmarks or broad, cap-weighted market portfolios over the entire period.

The overall impression is that SB portfolios find it challenging to keep up with the respective benchmark portfolios, which have indicated a relatively high tracking error. For the relative return analysis, only Momentum and Low Volatility delivered higher risk-adjusted average returns while being statistically significant at a 1-pct. level. Concerning benchmark-adjusted returns, Momentum was the only SB portfolio to achieve positive benchmark-adjusted returns since recordings started in 2007. Results of **section 5.3** did not manage to find any significant evidence of positive alpha, either – only Quality was suggested to have generated significant negative alpha.
Regarding performance relative to the market proxy (i.e., TSM ETF portfolio), SB portfolios seem to have done a much better job. In particular, four out of six SB portfolios achieved higher annualized excess returns than the market since 2007. The only two that did not were Value and Low Volatility. Again, there was only one that showed statistically significant, but negative, alpha, and that was Value.

One of the key takeaways from **section 5.2** and **5.3**, was that Momentum and Value was the best- and worst-performing SB portfolios, respectively. From the discussion in **section 5.5**, this was found to be very symptomatic of the financial climate we have been living in for the last decade or so. Global economic growth, rising corporate earnings along with lower interest rates and higher leverage, have provided substantial tailwind for Momentum and caused value-stocks to get even cheaper.

There were no big surprises concerning behavioral tendencies during "up" and "down" periods of the stock market. It was Size, Momentum, Multifactor, and Quality that did well on average when the general market was pointing upward, and there was no significant distress. During "down" periods, however, it was especially Low Volatility that stood out by performing significantly better than others while Momentum did just enough to outperform the market on a risk-adjusted basis. These findings are also in line with Glushkov (2015).

In terms of expense ratios, there is no questioning that they have a particular impact on returns, but it did not seem like management fees (etc.) could explain the deviations in returns. There was also something interesting to note from **figure 7** and the capital in-flows to SB portfolios. Over the last 5- and 10-year periods, Value and Multifactor have been the two SB portfolios to produce the worst annualized returns (see **table 7**). However, at the same time, they also attracted the most considerable amount of capital in new fund-flows. This *could* suggest that these strategies' profits may have been scraped away as a result of fund-flows chasing past performance. Another interesting observation from fund-flows is the extreme shift in 2019 towards Quality and Low Volatility. Figure **6** clearly shows that 2018 ended with sudden and severe downturns in the stock market, followed by periods of significant volatility. This may have led investors and asset managers to allocate funds to so-called "bond-proxies" such as low-volatility ETFs as well as quality-stocks.

6. Analysis Part II: Factor Exposure Analysis

This chapter will present results of calculations and tests described in **section 4.4**. Next, results of factor-regressions for all SB portfolios will be discussed in context of already mentioned academic literature and observations. The last part of this chapter will conclude on the most significant findings and try to provide a meaningful answer to the question set out for **part 2** of the analysis:

"Does US-listed Smart-Beta ETFs provide significant exposure to declared factor-strategies?"

6.1 Summary Statistics of AQR Factor Portfolios

As mentioned in **section 3.1**, factor portfolio returns are based on datasets acquired from AQR. Full sample summary statistics, along with a pairwise correlation, are shown in **table 12** below. T-statistics are provided, and asterisks (*, **, ***) indicate statistical significance at different confidence levels (1-pct., 2-pct. and 5-pct.). It is important to iterate that these factor portfolio returns are raw returns attributable to individual factors, and not to be *directly* compared to the NAV-returns of SB portfolios. This potential weakness, and probable implications to results, will be discussed in **section 6.4**.

Statistic	Market MKT	Size SMB	Value HMLd	Momentum UMD	Low Volatility BAB	Quality QMJ
AAR	6.46%	-1.11%	-3.71%	3.11%	3.81%	5.66%
Volatility	15.95%	7.42%	13.75%	16.57%	9.67%	8.89%
Count	159	159	159	159	159	159
T-Statistic	5.11*	-1.89***	-3.40*	2.37*	4.97*	8.03*
MKT	1					
SMB	0.4143	1				
HMLd	0.4641	0.4359	1			
UMD	-0.3872	-0.3777	-0.8518	1		
BAB	0.0142	-0.0588	-0.2583	0.3026	1	
QMJ	-0.6709	-0.5031	-0.5741	0.4884	0.0674	1

Table 12 – Descriptive statistics of factor portfolios and factor correlation matrix for the entire sample period. *P<0.01; **P<0.025; ***P<0.05 are indicative of whether results are significant at a 1-pct., 2.5-pct. and 5-pct. level, respectively. Annualized numbers.

6.2 Returns-Based Factor Regression

Results of the returns-based factor regressions described in **section 4.3.1** are exhibited in **table 13**. Estimates of alpha are annualized. T-statistics are provided below every metric, and asterisks (*, **, ***) indicate statistical significance at different confidence levels (1-pct., 2-pct. and 5-pct.). The adjusted r-squared (Adj-R2), a goodness-of-fit measure, indicates the explanatory power of the model.

SB Category	Alpha	MKT	SMB	HMLd	UMD	BAB	QMJ	Adj-R2
Size	1.57%	1.10	0.28	-0.24	-0.14	-0.11	-0.21	95.86%
	1.34	40.15*	5.52*	-5.11*	-3.72*	-3.15*	-3.91*	
Value	-3.73%	1.00	0.17	0.33	0.12	-0.01	0.16	98.11%
	-5.33*	61.54*	5.57*	11.53*	5.55*	-0.32	4.95*	
Momentum	-0.20%	0.95	0.37	-0.12	0.13	-0.02	-0.03	95.07%
	-0.19	39.87*	8.40*	-2.78*	4.11*	-0.79	-0.55	
Low Volatility	-3.23%	0.82	0.05	0.17	0.06	0.29	0.32	88.82%
	-2.47*	26.97*	0.92	3.14*	1.48	7.52*	5.28*	
Quality	-1.74%	1.03	0.24	0.06	-0.01	0.00	0.18	98.70%
	-3.11*	78.46*	9.93*	2.85*	-0.71	-0.13	7.10*	
Multifactor	-0.69%	1.00	0.31	0.07	0.00	0.00	0.08	98.29%
	-1.05	64.97*	10.92*	2.49*	0.00	0.17	2.71*	

Table 13 – Results from multiple, returns-based factor-regression. Alpha values are annualized. *P<0.01; **P<0.025; ***P<0.05 are indicative of whether results are significant at a 1-pct., 2.5-pct. and 5-pct. level, respectively.

6.3 Discussion of Results

In this section, results from the previous sections of this chapter will be discussed for each and every SB portfolio to give grounds for the chapter conclusion in **section 6.5**. Results that are not statistically significant at 5-pct. won't be particularly emphasized. Interpretations of regression coefficients will strictly follow the methodology described in **section 4.4.1**. If results are found unintuitive, chances are that it *could* be explained by factor design differences, constraints and/or different weighting. This will be further discussed in **section 6.4**.

6.3.1 Goodness-of-Fit and Alpha

With regard to the regression models' goodness of fit, all exhibit an adjusted r-squared of 88 pct. or more. This indicate that the six-factor model, as described in **section 2.4**, is capable of explaining variations in returns by the factors used in a satisfactory manner. The alpha (or intercept) parameter of the regression model is, again, interpreted as any active or excess return generated by the SB portfolio. From **table 13**, all but one alpha estimate is negative and only three of them are statistically significant at a 5-pct. level. Size is the only portfolio with positive alpha (1.57 pct.) but due to being statistically insignificant it is not very meaningful. Accordingly, there was not one single SB portfolio that was able to provide alpha after adjusting for AQR factors. However, as previously discussed, the factor portfolios of AQR does not account for implementation costs which makes results gross-of-fees. From comparing net-of-fees NAV-returns to gross-of-fees factor returns, it should not come as a surprise that alphas are negative.

6.3.2 Size

Regarding market risk (MKT), **table 13** shows that Size have a market beta of 1.10 which in theory would make it 10 pct. riskier, or more volatile, than the general market portfolio. This result is partly explained by the portfolio's exposure to the size factor (SMB) which is 0.28 and, thus, indicate a low-to-moderate tilt toward small-cap stocks. As discussed before, small-cap stocks tend to be more prone to price-swings due to lower liquidity and higher risk but that is also why they are supposed to harvest risk-premiums. Having a statistically significant beta coefficient of the SMB factor, and a tilt toward small-cap stocks, shows that Size have provided exposure to its intended factor. However, Size have also provided statistically significant exposure to all of the other factors at a 1-pct. level which may represent undesired risks for investors.

With a beta coefficient of -0.28 to the value factor (HMLd), the portfolio exhibits a low-to-moderate tilt toward growth-stocks. From **table 13**, the value-premium was found to be negative (-3.71 pct.) and, thus, Size have benefitted from the positive exposure to growth rather than value over the period. Size had a relatively weak, negative loading of -0.14 to the momentum factor (UMD) which indicates a tilt towards underperforming (or losing) stocks. This negative tilt toward UMD may have hurt the performance of the portfolio due to UMD averaging 3.11 pct. in annual excess returns. The same goes for the negative exposures to both the low-volatility factor (BAB) and quality factor (QMJ) of -0.11 and -0.21, respectively. Negative exposure to quality-stocks should not come as surprise as small-cap stocks often exhibit high leverage and so forth. This feature is also indicated by the pairwise correlation matrix of **table 12**, in which SMB and QMJ have a relatively strong negative correlation of -0.5031.

6.3.3 Value

Value have exhibited a market beta (MKT) of 1.0 which suggests that the portfolio moves in a "lock-step" with the market. This should have been a positive feature for Value as **table 12** indicate 6.46 pct. in market-risk premium. From **table 13**, Value have displayed a weak but positive beta coefficient 0.17 to the size-factor (SMB) which imply a tilt towards small-cap stocks. This tilt could be explained by the fact that many of the individual SB ETFs in the portfolio focus on value in small-cap indices such as the Russell 2000 index. More importantly, Value exhibit a positive, statistically significant beta coefficient to its intended value-factor (HMLd) of 0.33 which is also the factor exposure of the highest magnitude.

As previously discussed in the thesis, value-stocks have underperformed for most of the data sample and, thus, have become more frequently out-of-favor among investors. Consequently, value-stocks show weak momentum (UMD) which could explain the low-to-moderate 0.13 beta coefficient. Given the strong, negative correlation of -0.8518 between HMLd and UMD would immediately suggest that also the beta coefficient should be negative. Also, it is surprising that Value have a weak but positive exposure to the quality-factor (QMJ) as they tend to be expensive and should perhaps have displayed a negative quality-exposure.

6.3.4 Momentum

The Momentum portfolio have displayed a market beta (MKT) of 0.95 which implies that it is a little less risky than the market. Furthermore, the portfolio exhibit tilts toward small-cap stocks due to a relatively strong beta coefficient of 0.37 to the size-factor (SMB) as well as growth-stocks due to a weak but negative beta coefficient of -0.12 to the value-factor (HMLd). Momentum have seemingly benefitted from the negative exposure to HMLd as the value-premium was found to be very negative (-3.71 pct.). As should be expected, exposure to the momentum-factor (UMD) was positive (0.13) as well as statistically significant at a 1-pct. level which implies that the portfolio, on average, bought outperforming stocks or recent winners. However, the magnitude of the factor exposure was relatively small for a portfolio that has declared the momentum-factor as its intended target. At the same time, exposure to UMD have contributed positively to returns as the momentum-premium is indicated to be 3.11 pct. according to **table 12**. Lastly, exposures to both low volatility (BAB) and quality (QMJ) were statistically insignificant.

6.3.5 Low Volatility

From **table 13**, Low Volatility have a beta coefficient of 0.82 to the market (MKT). This result is in line with previous findings as low-volatility-stocks tend to lag the market portfolio in both “up” and “down” periods due to its defensive approach. Regarding the size (SMB) and value (HMLd) factors, the portfolio only exhibits a statistically significant value-coefficient of 0.17 which would indicate a slight tilt towards cheap, or undervalued, stocks. Moreover, Low Volatility has a relatively strong tilt towards stocks with robust (high) operating profitability which is indicated by the beta coefficient of 0.32 to the quality-factor (QMJ). Low-volatility stocks would often be considered as large, diversified companies with moderate growth and robust earnings which, intuitively, should reflect in a negative exposure to the size- and growth-factor as well as a positive exposure to quality. In that case, it is to some extent surprising that **table 13** did not find any significant exposure to SMB and that it indicated a weak-to-moderate tilt towards small-cap stocks.

Moving on to interpreting the beta-coefficient to the momentum-factor (UMD), Low Volatility does not seem to have any statistically significant co-movement. The findings of Hajric (2020), which was briefly discussed in **section 5.5.3**, involved a shift taking place in 2019 in which momentum and low-volatility ETFs had started to share similar traits. As this is supposed to have happened only recently, it makes sense that there is no statistically significant exposure to UMD over the entire period. Finally, the portfolio has displayed relatively strong and statistically significant exposure to the low-volatility (BAB) factor with a 0.29 beta coefficient. Accordingly, this result is indicative of exposure to stocks with little instability in price-movements and that the portfolio has provided investors with significant exposure to its declared factor-strategy.

6.3.6 Quality

The beta-coefficient of 1.03 to the market (MKT), shows that Quality is only slightly riskier than the market. Regarding the size (SMB) and value (HMLd) factors, the portfolio exhibits statistically significant exposures of 0.24 and 0.06, respectively. The moderate-to-strong tilt towards small-cap stocks could, at first, seem counterintuitive as small-cap stocks tend to be low on quality-metrics such as profitability, leverage, and market liquidity. Even though results are in line with Glushkov (2015), it qualifies for further investigation in **section 6.4**. Positive exposure to both the size (SMB) and value (HMLd) factors have not been beneficiary for the Quality portfolio as both have exhibited -1.11 pct. and -3.71 pct. in risk-premiums over the entire period.

Finally, the portfolio has shown a statistically significant exposure to its intended quality (QMJ) factor with a coefficient of 0.18 which indicate a moderate tilt towards robust stocks of companies with high profitability. The QMJ-factor have also shown to have a risk-premium of 5.66 pct. over the period and, thus, contributed well to the portfolio's overall performance.

6.3.7 Multifactor

As with Value, Multifactor exhibit a market beta (MKT) of exactly 1.0. The relatively high exposure of 0.31 to the size-factor (SMB), also statistically significant, is unexpected as **figure 9** indicated that none of the SB ETFs in the portfolio declared size as an intended index selection. With regard to the value factor (HMLd), the portfolio is suggested to have a beta-coefficient of 0.07, which is low-to-moderate and pretty much as expected due to it slight overweight towards value-stocks.

Table 13 suggests that the portfolio does not have strong exposure (0.08) to quality (QMJ) which is likely due to its relatively strong small-cap orientation. As previously mentioned, small-cap stocks tend to score low on quality-metrics. Regarding momentum (UMD) and low-volatility (BAB) factors, Multifactor does not have statistically significant exposure to any of them. Judging by **figure 9**, this would come a surprise due to momentum being a declared index selection in three out of ten SB ETFs in the portfolio.

6.4 Potential Weaknesses in Results

So far in **chapter 6**, the focus haven been on factor exposure analysis and how to interpret the output of the regression models. As touched upon in **section 6.3**, results can be highly influenced by differences in how AQR have formed their factors and how issuers of SB ETFs implement them in practice. Apart from AQR factors being gross-of-fees, there are also differences in investment universes to consider. That is, the factors of AQR span a much wider range of market capitalization. According to Israel and Ross (2017), they are strongly biased toward small-cap stocks as their investment universe includes more than five thousand stocks. Issuers of SB ETFs, however, would find it difficult to implement factor-strategies on micro-caps or stocks that reaches below a certain threshold in market capitalization because of liquidity issues. Glushkov (2015) adds that using different weighting schemes than market-capitalization (e.g., equal-weighting) would skew factor exposure towards small-caps. One of the *problems* this have caused for the factor exposure analysis is that all SB portfolios exhibit a relatively strong tilt toward small-cap stocks when we know that the majority of SB ETFs have been focused on mid- to large-cap stocks.

Another weakness of the analysis is that SB portfolios are constrained to long-only investments, while the academic factors of AQR are constructed using a long/short combination. Israel and Ross (2017) argues that long-short factor portfolios are able to capture the underlying characteristics of each factor more efficiently. Thus, SB portfolios are basically penalized when regressed on long-short factors as the regression model would assume that they are able to obtain returns in the same manner as long-short factor portfolios can.

Even though there usually is consensus in the fundamental understanding and purpose of most factors, there are many differences in specific metrics to look for in stock-selection. Also, asset managers and academics may argue whether it is best to use *one* or *multiple* metrics to capture a more robust equity factor. For example, AQR measures the value factor (HMLd) through book-to-price while iShares Russell 1000 Value ETF (IWD) combine earnings-to-price and book-to-price to identify *undervalued* stocks (iShares, 2020). In an empirical study of eight different strategies to capture the value-factor, Treussard (2018) found that the choice of what strategy (or strategies) to use would have yielded a significant difference in returns over 5-year periods between 1968-2017. He added that, due to mean-reversion, the choice of strategy did not really matter on investment outcomes over the long run.

6.5 Chapter Conclusion

In this chapter, the primary purpose was to identify whether US-listed Smart Beta ETFs have provided investors with significant exposure to declared factor-strategies (or index selections). Answering this question is essential for the over-arching problem statement since the leading argument investors have for buying Smart-Beta ETFs is to achieve exposure to rewarded risk factors. At the same time, they are also concerned about being exposed to unintended factors (Amenc, 2015). To provide a diligent answer, six well-known and acknowledged factors had been regressed on the SB portfolios to determine the extent of specific factor loadings.

The first key finding of this exposure analysis was that all SB portfolios, except for Low Volatility, have significant positive exposure to the size-factor (SMB) and, thus, indicate tilts toward small-cap stocks. From the discussion of potential weaknesses in results (**section 6.4**), it was suggested that this small-cap tilt was either due to AQR factor returns being *overly* exposed to micro and small-caps in their investment universe it could be due to using equal-weighting. Second, several SB portfolios seemed to have moderate or even vigorous exposures to counterintuitive factors. Some of these were the relatively strong loading of the Quality portfolio on the size-factor (0.24) and the moderate small-cap tilt (0.17) of the Low Volatility portfolio. Third, it was found that Multifactor had a relatively strong loading of 0.31 on the size-factor (SMB) while not having it declared as an intended index selection in any of the ten SB ETFs that formed the portfolio.

To summarize, the analysis in **chapter 6** gave mixed signals concerning the ability of SB portfolios to deliver exposure to intended factors. While all SB portfolios have provided investors with intended factor tilts, there is also a considerable amount of unintended risk-exposure to account for – some of which have weakened performance. Out of the six SB portfolios to be evaluated, only the Value (-3.73 pct.), Low Volatility (-3.23 pct.) and Quality (-1.74 pct.) portfolios displayed statistically significant, but negative, alphas. In other words, most of the SB portfolios would not be very suitable for investors seeking pure exposure to a specific factor.

7. Conclusion

The purpose of this thesis was to unmask some of the critical elements of Smart Beta ETFs, and aid possible investors of the future to understand its "uses and abuses". In a two-part analysis, the promise of outperformance and ability to provide intended factor exposures, have been investigated in the period between Jan-2007 and Mar-2020. This period was further split into three separate periods; the entire period, "up" and "down" periods.

From the performance analysis in **chapter 5**, regarding criteria for outperformance in **section 4.3.6**, there was not one SB portfolio that was able to fulfill all four criteria over the entire period. Momentum came close, but could not display statistically significant alphas. On the other hand, Value and Quality were the only ones to deliver on all criteria for *underperformance* relative to the market (i.e., TSM ETF portfolio) and the benchmark portfolio. Concerning the Value portfolio, it has been a repeated theme in the performance analysis that it is the worst-performing SB portfolio over the given period. This evidence is consistent with the idea that risk-premiums are highly time-varying and can have long periods of sustained negative performance.

By examining performance during "up" and "down" periods, it was interesting to find that there are no big surprises in the results. Concerning the summary statistics, Size, Momentum, Multifactor, and Quality did all perform well in "up" periods compared to the market portfolio but did it by taking on more risk. Only Momentum performed better than the market on a risk-adjusted basis. Regarding benchmark portfolios, only Size, Momentum, and Quality performed better in terms of total returns. However, none of the SB portfolios performed better than its benchmark on a risk-adjusted basis. During "down" periods, it was exceptionally Low Volatility that stood out by performing a lot better than others while Momentum did just enough to outperform the market.

In **chapter 5**, the performance was also seen in the context of both expense ratios and fund-flows. Regarding the former, it was noted that there is a significant distinction between gross-of-fees and net-of-fees performance as net asset value (NAV) are calculated net-of-fees and index-prices are gross-of-fees. In a very simplified experiment, NAV-returns was *grossed* up by an expense-factor. It was acknowledged that fees did play a significant part in deviations in returns, at least for some portfolios, but it was deemed that it could not explain deviations by fees only. Either way, results could indicate that Malkiel (2014) is right to recommend passive index funds due to the risk of fees "eating up" investment returns. Finally, the fund-flows exhibited in **figure 7** *could* suggest that "factor-crowding", put forward by Alford (2017), has led to lower returns for Value and Multifactor as a result of fund-flows chasing past performance.

For the factor exposure analysis in **chapter 6**, there were some interesting findings with regards to the magnitude of intended factor exposures as well as the number of unintended exposures. One of the key findings was that all SB portfolios, except for Low Volatility, were shown to have significant positive exposure to the size-factor (SMB) and, thus, indicate tilts toward small-cap stocks. For some of the SB portfolios, this factor tilt was somewhat unintuitive concerning the purpose of their investment strategies. For example, it does not make much sense that Quality have such a robust and positive loading on the size-factor for two reasons; **1)** the quality- and value-factor have a strong, negative pairwise correlation of -0.5031, according to **table 12** and **2)** small-cap stocks tend to score low on quality-metrics such as profitability, leverage, and market liquidity. It was suggested that excess tilt towards the size-factor could be due to the investment universe of AQR, or it could be due to using equal-weighting in calculating the SB portfolios. Moreover, it was found that Multifactor had a relatively strong loading of 0.31 on the size-factor. The more surprising thing about this was that Multifactor did not have the size-factor declared as an intended index selection in any of the ten SB ETFs that formed the portfolio.

Overall, the factor exposure gave mixed signals concerning the ability to deliver exposure to the intended factor tilts. While all SB portfolios have provided investors with intended factor tilts, some more than others, there is also a considerable amount of unintended risk-exposure to account for – some of which have led to weakened performance. Again, the size-factor, with a -1.11 pct. premium, could be a strong contributor of "unintended factor tilt gone bad" as it loads positively on every SB portfolio, and it even does so with a relatively high magnitude. In closing, most of the SB portfolios would not be very suitable for investors seeking pure exposure to a specific factor.

After analyzing both performance and factor exposures of six SB category portfolios, there is compelling evidence to suggest that Smart Beta might not be so "smart" after all.

There are primarily two types of risks investors should be aware of before investing in Smart Beta ETFs. First, **time horizon risk** is the risk of a lengthy drawdown and usually occurs when the economic environment is not very favorable to the specific risk factor. An example of this found through this thesis is the value-factor (for reasons described many times before). Even if it has been well documented that there have been a risk-premium associated with the value-factor for a very long time, the investor who now owns a value ETF may face the difficult decision of whether to hold or sell the factor-strategy that has, up until then, a strong history of success. Second, the **poor specification risk** of Smart Beta ETFs, which entails the significance of limiting unintended factor exposures as they may drag on investment gains.

7.1 Criticism & Suggested Further Research

As have been discussed many times in this thesis, there has been some limitations to the analyses as well as the data which may have caused problems to certain calculations or interpretations. There is a saying that "results reached are only as good as the data used". Hence, it is important to evaluate attributes of data along with the possible influence and/or bias it could have on results.

7.1.1 Historical Data

It should be iterated that the empirically tested performance of Smart Beta ETFs does not necessarily set the tone for future performance; however, while being short of better alternatives, historical data points must be considered adequate for this purpose. An idea for future studies could be to simulate future performance in order to supplement the analyses further. The time window that is used for this thesis is Jan-2007 to Mar-2020 and consists of 159 months of time series data. Between 2009 and 2018, there is no real market turbulence as the longest bull market in decades runs its course. Thus, it is only in the extremities of the data set we will find some real volatility (i.e., 2007/08, 2018/19, and 2020), and this could be a risk in that the period might not be representative of a "normal" market. On the other hand, Smart Beta ETFs is a relatively new investment product, which would mean that it would prove challenging to obtain data sets with a much longer horizon. However, it would be appreciated for future studies on the subject. One possible solution to this could be to create their portfolios by using similar scoring and weighting as issuers of commercial Smart Beta ETFs do. In that regard, one would be able to find factor-data for extensive periods.

7.1.2 Other Investment Regions

This thesis focuses on Smart Beta ETFs listed in the U.S. and only. It is therefore important to iterate that results are only indicative for U.S. markets and nothing more/less. A suggestion for future studies could be to do an empirical study on Smart Beta ETFs in Asia, Europe and less developed markets.

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8.2 Databases

AQR, AQR Capital Management, https://www.aqr.com/Insights/Datasets
Bloomberg, Bloomberg LP, Access provided by Copenhagen Business School (CBS)
Morningstar, Morningstar Inc., Morningstar Direct, Access provided by CBS
CRSP, Center for Research in Security Prices, http://www.crsp.org/products/investment-products

8.3 List of Figures

8.4 List of Tables

9. Appendix

Appendix 9.1: Table of Smart Beta ETFs per category, their respective benchmark, net assets ($m) and expense ratio (ER) of the fund, and its inception date.

SB Category and ETF (Ticker)	Benchmark (Index)	Net Assets ($m)	ER (%)	First Date
Size				
First Trust NASDAQ-100 Tech (QTEC)	**S&P 500 Information Tech**	**2,288.65**	**0.57**	**Apr-06**
First Trust NYSE Arca Biotechnology (FBT)	**S&P 1500 Health Care**	**1,820.83**	**0.57**	**Jun-06**
First Trust Capital Strength (FTCS)	**S&P 500**	**4,143.19**	**0.60**	**Jul-06**
Invesco S&P 500 Equal Weight (RSP)	S&P 500	16,104.80	0.20	Apr-03
Invesco S&P 500 Equal Weight (RYT)	S&P 500 Information Technology	1,672.00	0.40	Nov-06
SPDR S&P Bank (KBE)	S&P Banks Select Industry	1,159.52	0.35	Nov-05
SPDR S&P Biotech (XBI)	S&P Biotechnology Select Indstr	4,531.25	0.35	Jan-06
SPDR S&P Insurance (KIE)	S&P Insurance Select Indstr	576.19	0.35	Nov-05
SPDR S&P Metals & Mining (XME)	S&P Metals/Mining Select Indstr	328.79	0.35	Jun-06
SPDR NYSE Technology (XNTK)	NYSE Technology	324.44	0.35	Sep-00
Value				
Vanguard Value (VTV)	**Russell 1000 Value Index**	**88,953.63**	**0.04**	**Jan-04**
iShares Russell 1000 Value (IWD)	Russell 1000 Value	41,021.40	0.19	May-00
Vanguard Small-Cap Value (VBR)	**Dow Jones Small-Cap Value**	**31,591.55**	**0.07**	**Jan-04**
Vanguard Mid-Cap Value (VOE)	**Russell Mid Cap Value**	**21,269.54**	**0.07**	**Aug-06**
iShares S&P 500 Value (IVE)	S&P 500 Value	17,525.70	0.18	May-00
iShares Russell Mid-Cap Value (IWS)	Russell Mid Cap Value	11,724.67	0.24	Jul-01
iShares Russell 2000 Value (IWN)	Russell 2000 Value	9,394.23	0.24	Jul-00
iShares Core S&P US Value (IUSV)	S&P 900 Value	6,762.09	0.04	Jul-00
iShares S&P Mid-Cap 400 Value (IJJ)	S&P MidCap 400 Value	6,364.29	0.25	Aug-00
Invesco Dynamic Large Cap Value (PWV)	Russell 1000 Value	1,094.51	0.55	Mar-05
Momentum				
iShares Edge MSCI USA Mom Fctr (MTUM)	MSCI USA Momentum	10,179.75	0.15	Apr-13
Invesco DWA Momentum (PDP)	**Russell 3000 Growth**	**1,868.88**	**0.62**	**Feb-07**
Invesco DWA SmallCap Mom (DWAS)	**S&P SmallCap 600 Growth**	**252.32**	**0.60**	**Aug-12**
Invesco DWA Technology Momentum (PTF)	**S&P 500 Information Techn**	**214.19**	**0.60**	**Oct-06**
Invesco DWA Healthcare Momentum (PTH)	**S&P 500 Health Care**	**181.17**	**0.60**	**Oct-06**
Invesco DWA Consumer Staples Mom (PSL)	**S&P 500 Consumer Staples**	**166.24**	**0.60**	**Oct-06**
Invesco DWA Utilities Momentum (PUI)	**S&P 500 Utilities**	**154.77**	**0.60**	**Oct-05**
Invesco DWA Industrials Momentum (PRN)	**S&P 500 Industrials**	**104.08**	**0.60**	**Oct-06**
Invesco DWA Financial Momentum (PFI)	**S&P 500 Financials**	**63.78**	**0.60**	**Oct-06**
Invesco S&P SmallCap Momentum (XSMO)	**S&P SmallCap 600 Momentum**	**80.03**	**0.39**	**Oct-09**
Low-Volatility				
iShares Edge MSCI Min Vol USA (USMV)	MSCI USA Minimum Volatility	38,784.06	0.15	Oct-11
Invesco S&P 500 Low Volatility (SPLV)	S&P 500 Low Volatility	12,815.27	0.25	May-11
Invesco S&P MidCap Low Volatility (XMLV)	S&P MidCap 400 Low Volatility	3,773.76	0.25	Feb-13
Invesco S&P SmallCap Low Volatility (XSLV)	S&P SmallCap 600 Low Vol	2,417.82	0.25	Feb-13

SPDR SSGA US LargeCap LowVol (LGLV)	**S&P 500 Low Volatility**	**1,016.67**	**0.12**	**Feb-13**
SPDR Russell 1000 Low Vol Foc (ONEV)	Russell 1000 LV Fcsd Fctr	588.35	0.20	Jan-16
Fidelity Low Volatility Factor (FDLO)	**S&P 500**	**414.03**	**0.29**	**Oct-16**
InvescoS&P500 exRateSnsvLowVol (XRLV)	**S&P 500**	**326.92**	**0.12**	**May-15**
Invesco Defensive Equity (DEF)	**S&P 500**	**295.95**	**0.55**	**Dec-06**
SPDR SSGA US SmallCap LowVol (SMLV)	**Dow Jones Small-Cap**	**263.02**	**0.12**	**Mar-13**
Quality				
iShares Edge MSCI USA Quality Fctr (QUAL)	MSCI USA Sector Neu Quality	17,468.74	0.15	Jul-13
First Trust Capital Strength (FTCS)	**S&P 500**	**3,596.72**	**0.60**	**Aug-06**
Invesco S&P 500® Quality (SPHQ)	S&P 500 Quality	1,748.48	0.15	Dec-05
Fidelity Quality Factor (FQAL)	**Russell 1000 Growth**	**122.00**	**0.29**	**Oct-16**
JPMorgan US Quality Factor (JQUA)	**Russell 1000**	**144.20**	**0.12**	**Nov-17**
Invesco S&P MidCap Quality (XMHQ)	S&P MidCap 400 Quality	27.14	0.25	Oct-09
Invesco S&P SmallCap Quality (XSHQ)	S&P SmallCap 600 Quality	4.29	0.29	Apr-17
WisdomTree U.S. MidCap Fund (EZM)	Wisdom Tree MidCap earnings	587.90	0.38	Feb-07
WisdomTree U.S. SmallCap Fund (EES)	**Russell 2000**	**435.90**	**0.38**	**Feb-07**
WisdomTree U.S. LargeCap Fund (EPS)	**Russell 1000**	**361.50**	**0.08**	**Feb-07**
Multi-Factor				
First Trust Tech AlphaDEX (FXL)	**Dow Jones Technology**	**2,518.65**	**0.61**	**May-07**
First Trust Financials AlphaDEX (FXO)	**S&P 1500 Financials**	**1,989.71**	**0.63**	**May-07**
First Trust LrgCap CoreAlphaDEX (FEX)	**S&P 500**	**1,356.32**	**0.60**	**May-07**
First Trust Utilities AlphaDEX (FXU)	**S&P 1500 Utilities**	**1,250.23**	**0.63**	**May-07**
First Trust Health CareAlphaDEX (FXH)	**S&P 1500 Health Care**	**1,124.94**	**0.62**	**May-07**
First Trust MidCap CoreAlphaDEX (FNX)	**S&P MidCap 400**	**880.55**	**0.61**	**May-07**
First Trust SmlCap CoreAlphaDEX (FYX)	**Russell 2000**	**547.99**	**0.63**	**May-07**
Invesco S&P MidCap Momentum (XMMO)	Russell Midcap Growth	702.59	0.40	Mar-05
Invesco S&P SmallCap Momentum (XSMO)	S&P Smallcap 600 Growth	86.52	0.40	Mar-05
Invesco Dynamic Large Cap Growth (PWB)	Russell 1000 Growth	758.06	0.55	Mar-05

Appendix 9.2: 10 largest US-listed Smart Beta ETFs by size.

Name (ETF)	Ticker	Category	Benchmark	Size ($bil.)
Vanguard Growth	VUG	Growth	CRSP US Large Cap Growth	105.90
Vanguard Value	VTV	Value	CRSP US Large Cap Value	88.95
Vanguard Dividend Appreciation	VIG	Dividend	NASDAQ US Div Achievers Select	52.12
iShares Russell 1000 Growth	IWF	Growth	Russell 1000 Growth	51.84
iShares Russell 1000 Value	IWD	Value	Russell 1000 Value	41.02
iShares Edge MSCI Min Vol USA	USMV	Low Vol	MSCI USA Minimum Volatility	38.78
Vanguard High Dividend Yield	VYM	Dividend	FTSE High Dividend Yield	38.28
Vanguard Small-Cap Value	VBR	Value	CRSP US Small Cap Value	31.59
iShares S&P 500 Growth	IVW	Growth	S&P 500 Growth	25.94
Vanguard Small-Cap Growth	VBK	Growth	CRSP US Small Cap Growth	25.72

Appendix 9.3: Smart Beta ETF Portfolios (excess returns)

	Size	Value	Momentum	Low Volatility	Quality	Multifactor	US Stock Market
Jan-07	1.47%	1.53%	1.72%	-0.60%	2.87%	1.69%	1.36%
Feb-07	-0.80%	-1.21%	-0.68%	-1.27%	-1.35%	-3.58%	-2.23%
Mar-07	0.23%	0.40%	1.57%	0.71%	0.48%	1.04%	0.32%
Apr-07	5.42%	2.75%	3.26%	3.48%	3.75%	3.77%	3.77%
May-07	2.71%	3.31%	3.04%	3.12%	3.31%	3.32%	3.15%
Jun-07	-2.94%	-3.31%	-2.67%	-2.57%	-2.25%	-2.65%	-2.37%
Jul-07	-3.78%	-5.96%	-4.78%	-4.49%	-5.29%	-4.11%	-3.72%
Aug-07	1.24%	0.71%	0.61%	0.21%	0.30%	0.40%	0.99%
Sep-07	3.59%	1.72%	2.36%	3.28%	2.35%	2.67%	2.90%
Oct-07	1.96%	0.51%	2.78%	1.60%	1.96%	0.85%	1.31%
Nov-07	-5.11%	-5.76%	-2.92%	-4.74%	-5.77%	-5.00%	-4.50%
Dec-07	-2.05%	-2.26%	-0.51%	-3.04%	-0.46%	-1.88%	-1.58%
Jan-08	-6.08%	-4.40%	-7.37%	-5.50%	-6.56%	-6.51%	-6.11%
Feb-08	-2.65%	-4.16%	-2.45%	-1.96%	-2.78%	-3.98%	-2.91%
Mar-08	-1.68%	-0.84%	-0.64%	-1.48%	-1.53%	-1.93%	-1.54%
Apr-08	5.93%	4.63%	3.87%	4.31%	4.46%	4.67%	4.83%
May-08	4.31%	1.88%	3.74%	2.63%	2.97%	3.79%	1.68%
Jun-08	-9.14%	-9.99%	-7.26%	-7.34%	-7.84%	-8.50%	-8.64%
Jul-08	2.51%	0.21%	0.06%	0.31%	-0.79%	0.63%	-1.11%
Aug-08	-0.73%	2.35%	1.26%	3.27%	1.71%	1.89%	1.41%

Sep-08	-12.20%	-7.77%	-9.55%	-8.33%	-10.05%	-9.58%	-8.38%
Oct-08	-20.86%	-19.10%	-17.40%	-17.73%	-18.85%	-19.60%	-18.51%
Nov-08	-11.28%	-8.42%	-6.67%	-5.32%	-9.68%	-8.78%	-7.84%
Dec-08	3.98%	2.35%	3.49%	-0.40%	2.81%	3.69%	0.92%
Jan-09	-8.49%	-10.77%	-7.30%	-3.38%	-7.21%	-7.04%	-8.15%
Feb-09	-9.75%	-12.97%	-11.13%	-10.48%	-11.14%	-10.26%	-10.44%
Mar-09	10.96%	7.91%	5.50%	4.14%	7.86%	8.81%	7.64%
Apr-09	13.78%	13.53%	8.24%	6.45%	15.27%	14.32%	10.29%
May-09	7.89%	4.50%	2.57%	4.87%	5.64%	5.26%	5.51%
Jun-09	0.64%	-0.47%	1.71%	2.49%	-0.66%	0.52%	-0.32%
Jul-09	11.10%	8.82%	7.09%	5.58%	8.47%	8.00%	7.63%
Aug-09	5.64%	5.35%	1.69%	1.72%	2.51%	4.43%	3.64%
Sep-09	4.34%	3.92%	3.84%	3.60%	5.54%	5.62%	3.37%
Oct-09	-6.53%	-4.30%	-3.66%	-1.95%	-3.51%	-4.18%	-2.30%
Nov-09	6.68%	5.16%	3.75%	5.07%	4.81%	4.85%	5.84%
Dec-09	4.55%	3.15%	4.80%	0.67%	4.53%	6.05%	1.91%
Jan-10	-2.50%	-2.62%	-3.84%	-1.83%	-3.39%	-3.61%	-3.48%
Feb-10	5.09%	3.89%	3.40%	2.68%	3.26%	3.86%	3.42%
Mar-10	8.89%	6.51%	6.03%	3.94%	6.55%	6.81%	5.91%
Apr-10	1.17%	3.73%	2.97%	1.54%	3.25%	2.72%	1.80%
May-10	-8.56%	-8.02%	-6.21%	-6.01%	-6.61%	-6.01%	-7.95%
Jun-10	-6.56%	-6.47%	-5.82%	-0.64%	-5.91%	-6.50%	-6.01%
Jul-10	6.93%	6.66%	6.56%	6.21%	6.34%	6.23%	6.90%
Aug-10	-5.18%	-5.05%	-4.91%	0.03%	-5.15%	-4.87%	-4.64%
Sep-10	10.79%	8.34%	9.36%	5.44%	9.95%	10.59%	8.71%
Oct-10	3.43%	3.21%	3.99%	3.26%	4.06%	4.17%	3.90%
Nov-10	0.36%	0.40%	1.69%	-0.43%	1.10%	2.18%	0.34%
Dec-10	8.73%	6.63%	5.02%	2.58%	5.19%	5.46%	6.27%
Jan-11	1.57%	2.07%	1.08%	0.60%	1.55%	1.74%	2.11%
Feb-11	2.97%	3.93%	4.27%	3.47%	3.96%	4.02%	3.52%
Mar-11	0.43%	0.53%	2.60%	1.87%	1.04%	2.19%	-0.11%
Apr-11	3.75%	2.56%	3.17%	2.99%	3.13%	3.11%	2.84%
May-11	-1.58%	-1.23%	0.05%	0.37%	-0.98%	-0.72%	-1.22%
Jun-11	-3.55%	-2.40%	-2.08%	-1.44%	-1.90%	-2.64%	-2.12%
Jul-11	-4.60%	-3.71%	-4.22%	-2.74%	-3.27%	-3.86%	-2.19%
Aug-11	-9.00%	-6.84%	-6.27%	-0.37%	-6.15%	-6.66%	-5.79%
Sep-11	-9.70%	-9.02%	-8.74%	-3.04%	-8.75%	-8.54%	-7.75%

Oct-11	13.98%	12.27%	11.52%	6.19%	12.88%	12.27%	11.18%
Nov-11	-2.41%	-0.18%	-0.29%	0.80%	-1.03%	-0.75%	-0.35%
Dec-11	-1.29%	0.65%	-0.05%	2.57%	0.41%	-0.24%	0.31%
Jan-12	10.03%	4.75%	4.67%	0.10%	6.62%	5.43%	4.97%
Feb-12	3.11%	3.51%	3.72%	1.93%	3.59%	3.89%	4.15%
Mar-12	3.31%	2.29%	2.55%	2.00%	2.03%	2.56%	2.75%
Apr-12	-1.23%	-0.90%	-0.27%	1.31%	-1.69%	-0.98%	-0.69%
May-12	-8.63%	-6.11%	-5.45%	-2.60%	-7.34%	-6.90%	-6.08%
Jun-12	3.94%	3.89%	3.29%	3.82%	2.41%	2.82%	3.44%
Jul-12	-0.64%	0.42%	-0.47%	1.99%	1.26%	-0.03%	1.15%
Aug-12	3.09%	2.47%	2.59%	-0.45%	3.08%	2.91%	2.45%
Sep-12	2.88%	2.35%	2.02%	1.20%	1.88%	2.43%	1.97%
Oct-12	-3.32%	-0.53%	-1.22%	-0.53%	-0.95%	-1.91%	-1.81%
Nov-12	2.03%	0.43%	1.01%	-0.14%	0.83%	1.32%	0.65%
Dec-12	2.29%	1.49%	0.95%	-1.91%	1.38%	1.49%	0.37%
Jan-13	6.00%	6.63%	5.74%	5.44%	6.47%	6.43%	5.51%
Feb-13	0.07%	1.53%	1.71%	2.50%	1.03%	0.96%	1.15%
Mar-13	3.75%	3.97%	5.25%	4.53%	3.90%	4.18%	3.42%
Apr-13	0.64%	1.19%	1.12%	2.26%	0.75%	1.13%	1.71%
May-13	3.88%	2.36%	2.08%	-1.53%	3.99%	2.54%	2.41%
Jun-13	-2.67%	-1.19%	-0.99%	-0.35%	-1.46%	-1.21%	-1.87%
Jul-13	7.66%	5.41%	6.77%	4.50%	5.71%	5.75%	5.38%
Aug-13	-2.46%	-3.79%	-3.41%	-4.49%	-2.93%	-2.83%	-2.79%
Sep-13	4.53%	3.20%	4.36%	2.88%	3.94%	4.54%	2.97%
Oct-13	2.36%	4.19%	3.59%	4.60%	4.41%	3.70%	4.51%
Nov-13	3.90%	2.75%	3.70%	1.43%	3.51%	2.65%	2.77%
Dec-13	2.91%	1.58%	1.66%	0.24%	1.73%	2.27%	2.11%
Jan-14	-0.21%	-3.10%	-2.24%	-2.40%	-3.89%	-1.62%	-3.24%
Feb-14	5.78%	4.44%	4.82%	3.89%	4.54%	4.91%	4.63%
Mar-14	-1.55%	1.58%	-1.58%	1.25%	0.65%	0.06%	-0.10%
Apr-14	-2.40%	0.20%	-2.98%	0.38%	-0.12%	-1.40%	0.65%
May-14	1.55%	1.42%	1.70%	1.17%	1.79%	1.89%	2.12%
Jun-14	5.17%	2.82%	4.53%	2.35%	1.97%	3.22%	2.00%
Jul-14	-2.41%	-2.96%	-4.91%	-3.24%	-2.90%	-3.05%	-1.75%
Aug-14	5.99%	4.10%	6.07%	3.86%	4.20%	4.28%	4.03%
Sep-14	-3.46%	-3.85%	-3.35%	-3.08%	-2.70%	-3.58%	-2.13%
Oct-14	3.36%	3.24%	4.40%	5.97%	3.67%	3.83%	2.40%

Nov-14	2.69%	1.71%	2.02%	1.80%	2.52%	2.02%	2.68%
Dec-14	-0.71%	0.14%	0.35%	-0.43%	0.13%	0.63%	-0.56%
Jan-15	-3.29%	-3.44%	-0.72%	-0.50%	-3.16%	-1.99%	-2.99%
Feb-15	7.29%	5.10%	4.71%	1.96%	5.78%	5.00%	5.60%
Mar-15	-1.60%	-0.91%	0.71%	0.00%	-0.69%	0.16%	-1.66%
Apr-15	-0.02%	0.18%	-2.77%	-1.65%	-0.44%	-0.91%	0.67%
May-15	3.65%	1.11%	3.00%	0.63%	1.09%	1.65%	1.33%
Jun-15	-1.98%	-2.13%	-0.92%	-1.51%	-1.91%	-1.56%	-2.23%
Jul-15	0.15%	-0.38%	2.86%	2.66%	0.77%	1.07%	1.82%
Aug-15	-6.02%	-5.40%	-5.72%	-5.21%	-5.42%	-5.89%	-6.05%
Sep-15	-5.79%	-3.80%	-3.50%	-1.21%	-3.20%	-3.87%	-3.53%
Oct-15	6.66%	6.69%	5.17%	6.38%	7.15%	5.14%	8.37%
Nov-15	2.04%	0.82%	1.75%	1.11%	0.86%	0.92%	0.46%
Dec-15	-3.20%	-3.67%	-2.80%	-2.40%	-3.38%	-2.75%	-2.35%
Jan-16	-11.02%	-5.51%	-7.35%	-2.66%	-5.38%	-7.26%	-5.66%
Feb-16	1.15%	0.69%	-1.36%	1.12%	1.39%	0.47%	0.21%
Mar-16	8.49%	7.41%	6.06%	6.57%	7.18%	7.29%	6.31%
Apr-16	2.70%	1.64%	-0.58%	-0.13%	1.00%	0.34%	0.24%
May-16	2.96%	1.45%	2.63%	1.80%	0.91%	2.13%	1.84%
Jun-16	-1.94%	0.39%	1.75%	2.60%	-0.46%	-0.14%	-0.25%
Jul-16	7.97%	3.39%	4.04%	2.57%	3.58%	4.91%	3.94%
Aug-16	0.36%	0.68%	-1.41%	-0.54%	0.31%	0.04%	0.07%
Sep-16	2.01%	-0.46%	1.02%	-1.25%	-0.53%	-0.01%	-0.23%
Oct-16	-3.40%	-2.09%	-5.16%	-2.53%	-2.40%	-3.55%	-2.11%
Nov-16	8.48%	7.66%	3.56%	4.62%	5.89%	5.62%	4.19%
Dec-16	-0.04%	1.73%	0.51%	1.50%	1.54%	1.01%	1.32%
Jan-17	4.68%	0.82%	2.04%	0.49%	1.33%	2.19%	1.79%
Feb-17	4.24%	3.13%	3.87%	3.55%	3.24%	3.46%	3.70%
Mar-17	-0.59%	-1.33%	0.52%	-0.48%	-0.25%	0.03%	-0.36%
Apr-17	1.19%	0.02%	1.47%	1.08%	1.06%	1.44%	0.95%
May-17	0.26%	-0.82%	1.34%	0.81%	0.03%	1.12%	1.08%
Jun-17	2.57%	1.61%	1.93%	0.24%	0.86%	1.16%	0.32%
Jul-17	2.40%	0.95%	2.46%	1.28%	0.98%	1.74%	1.78%
Aug-17	1.69%	-1.51%	1.18%	-0.46%	-0.63%	0.33%	0.13%
Sep-17	2.24%	3.22%	2.42%	1.99%	3.40%	2.21%	1.76%
Oct-17	1.85%	0.92%	3.05%	1.77%	1.61%	2.35%	2.16%
Nov-17	1.79%	3.16%	2.41%	3.53%	3.76%	2.80%	2.98%

Dec-17	0.99%	0.25%	-1.06%	-2.47%	0.19%	-0.58%	0.55%
Jan-18	6.91%	2.83%	4.52%	2.50%	3.80%	4.15%	5.22%
Feb-18	-2.33%	-5.06%	-2.39%	-4.10%	-3.94%	-2.72%	-3.88%
Mar-18	-2.44%	-1.43%	-0.33%	-0.05%	-1.36%	-0.17%	-2.70%
Apr-18	-0.44%	0.29%	0.08%	-0.28%	-0.38%	0.17%	0.36%
May-18	4.20%	1.62%	5.51%	1.97%	3.17%	4.26%	2.49%
Jun-18	-1.44%	-0.13%	-0.38%	0.72%	0.16%	0.24%	0.05%
Jul-18	2.51%	2.96%	1.34%	3.10%	2.89%	1.61%	3.26%
Aug-18	2.28%	1.56%	6.41%	2.50%	3.55%	6.28%	3.20%
Sep-18	-1.27%	-1.30%	-1.56%	-0.69%	-0.91%	-0.69%	-0.32%
Oct-18	-10.39%	-6.87%	-10.11%	-5.28%	-7.42%	-9.49%	-7.39%
Nov-18	1.84%	2.41%	1.42%	3.32%	1.11%	2.08%	1.58%
Dec-18	-12.48%	-11.21%	-10.02%	-9.08%	-10.02%	-10.30%	-9.61%
Jan-19	11.75%	9.20%	8.79%	7.20%	8.76%	10.05%	8.24%
Feb-19	4.52%	2.97%	4.72%	3.65%	3.73%	4.62%	3.27%
Mar-19	-0.47%	-1.14%	1.17%	0.51%	-0.18%	-0.56%	0.88%
Apr-19	2.54%	3.63%	2.31%	2.82%	3.60%	2.84%	3.80%
May-19	-9.00%	-7.57%	-2.97%	-3.31%	-7.77%	-6.62%	-6.61%
Jun-19	8.61%	6.58%	6.40%	4.60%	6.42%	6.31%	6.35%
Jul-19	0.77%	0.88%	2.01%	1.24%	1.22%	1.36%	1.29%
Aug-19	-4.54%	-3.74%	0.18%	-0.47%	-2.98%	-3.09%	-2.10%
Sep-19	0.39%	3.43%	-4.27%	1.56%	1.95%	0.35%	1.23%
Oct-19	2.42%	1.57%	1.00%	0.66%	1.87%	1.31%	2.01%
Nov-19	6.20%	3.06%	3.77%	1.54%	3.12%	3.30%	3.60%
Dec-19	2.60%	2.03%	2.10%	0.93%	2.14%	1.73%	2.20%
Jan-20	-3.08%	-3.10%	1.13%	0.11%	-2.17%	-0.87%	-0.23%
Feb-20	-6.82%	-10.11%	-7.02%	-9.16%	-9.06%	-8.11%	-8.19%
Mar-20	-15.76%	-20.50%	-14.55%	-17.28%	-15.68%	-17.23%	-13.81%

Appendix 9.4: Benchmark Portfolios (excess returns)

	Size	**Value**	**Momentum**	**Low Volatility**	**Quality**	**Multifactor**	**US Stock Market**
Jan-07	2.07%	1.65%	1.29%	1.59%	1.44%	1.55%	1.35%
Feb-07	-1.68%	-1.11%	-1.98%	-1.71%	-1.93%	-1.10%	-2.22%
Mar-07	0.64%	0.78%	0.61%	0.58%	0.73%	0.94%	0.63%
Apr-07	5.88%	2.57%	3.91%	3.29%	3.31%	3.52%	3.66%
May-07	3.13%	3.29%	2.28%	3.20%	3.42%	2.86%	3.11%
Jun-07	-2.26%	-2.88%	-2.82%	-2.50%	-2.09%	-2.38%	-2.15%

Jul-07	-2.43%	-5.98%	-3.92%	-4.19%	-4.28%	-3.98%	-3.71%
Aug-07	1.97%	0.42%	1.32%	0.90%	1.08%	1.53%	0.99%
Sep-07	4.32%	1.82%	3.32%	2.80%	2.78%	2.73%	3.29%
Oct-07	3.86%	0.24%	2.00%	1.57%	1.74%	3.20%	1.47%
Nov-07	-4.90%	-5.79%	-4.25%	-5.01%	-5.57%	-4.84%	-4.78%
Dec-07	-0.04%	-1.46%	-1.55%	-1.11%	-0.92%	-0.69%	-0.94%
Jan-08	-8.43%	-4.32%	-6.38%	-6.07%	-6.35%	-7.47%	-6.40%
Feb-08	-1.79%	-4.25%	-4.47%	-3.30%	-3.28%	-3.30%	-3.28%
Mar-08	-1.31%	-0.70%	-0.57%	-0.73%	-0.80%	-0.87%	-0.77%
Apr-08	5.71%	4.82%	4.49%	5.15%	4.83%	5.10%	4.78%
May-08	5.44%	1.78%	1.06%	2.21%	2.75%	3.65%	1.61%
Jun-08	-5.95%	-9.90%	-8.79%	-8.15%	-8.09%	-6.72%	-8.48%
Jul-08	0.45%	0.55%	0.43%	-0.57%	-0.46%	-0.53%	-1.00%
Aug-08	-0.97%	2.41%	0.60%	1.58%	1.99%	1.62%	1.30%
Sep-08	-13.34%	-7.57%	-9.20%	-8.70%	-9.54%	-9.86%	-9.35%
Oct-08	-18.66%	-19.48%	-17.10%	-18.15%	-18.58%	-17.52%	-17.52%
Nov-08	-10.19%	-8.70%	-9.18%	-8.33%	-8.93%	-8.21%	-7.81%
Dec-08	3.67%	3.58%	1.29%	1.89%	2.72%	3.14%	1.51%
Jan-09	-4.19%	-11.15%	-10.43%	-8.65%	-8.57%	-6.04%	-8.40%
Feb-09	-8.83%	-13.05%	-12.15%	-10.91%	-10.66%	-10.24%	-10.55%
Mar-09	8.88%	8.67%	9.14%	8.23%	8.66%	7.98%	8.67%
Apr-09	10.00%	14.18%	10.86%	11.42%	12.77%	9.80%	10.15%
May-09	6.03%	4.29%	5.78%	4.43%	4.67%	3.69%	5.31%
Jun-09	2.44%	-0.29%	1.01%	0.38%	0.44%	2.18%	0.20%
Jul-09	8.01%	9.44%	7.43%	7.80%	8.29%	7.58%	7.62%
Aug-09	1.93%	5.49%	3.94%	3.61%	3.00%	2.27%	3.44%
Sep-09	4.40%	4.53%	3.40%	4.29%	4.74%	4.07%	3.98%
Oct-09	-3.85%	-4.34%	-3.16%	-3.29%	-3.24%	-3.39%	-2.37%
Nov-09	7.26%	5.01%	5.38%	5.09%	4.86%	4.77%	5.66%
Dec-09	4.48%	4.20%	2.52%	3.45%	4.48%	5.40%	2.50%
Jan-10	-4.90%	-2.73%	-3.36%	-3.42%	-3.70%	-4.06%	-3.56%
Feb-10	4.01%	4.03%	2.81%	3.40%	3.45%	3.13%	3.20%
Mar-10	6.56%	7.07%	6.24%	5.99%	6.69%	5.94%	6.16%
Apr-10	0.97%	3.72%	1.21%	2.18%	2.43%	2.36%	1.91%
May-10	-8.25%	-8.04%	-7.51%	-6.78%	-7.23%	-7.35%	-8.03%
Jun-10	-5.91%	-6.45%	-4.81%	-4.15%	-5.88%	-5.32%	-5.57%
Jul-10	6.30%	7.20%	6.57%	5.97%	6.53%	6.25%	6.98%

Aug-10	-5.61%	-5.07%	-4.96%	-3.83%	-5.42%	-4.99%	-4.73%
Sep-10	10.25%	8.92%	8.49%	8.22%	10.40%	9.73%	9.22%
Oct-10	3.42%	3.21%	3.16%	3.10%	4.01%	3.54%	3.84%
Nov-10	-0.08%	0.40%	-0.33%	0.25%	1.76%	0.71%	0.33%
Dec-10	7.68%	7.74%	6.09%	5.75%	6.19%	6.23%	6.67%
Jan-11	1.58%	2.09%	1.66%	1.05%	1.45%	1.72%	2.17%
Feb-11	2.75%	3.93%	2.71%	3.68%	4.17%	3.50%	3.80%
Mar-11	-0.24%	0.87%	0.24%	0.76%	1.11%	0.67%	-0.10%
Apr-11	3.52%	2.46%	3.18%	3.12%	3.24%	3.23%	2.91%
May-11	-1.56%	-1.24%	-0.72%	-0.32%	-1.14%	-0.80%	-1.23%
Jun-11	-2.69%	-2.28%	-1.85%	-1.83%	-1.65%	-1.97%	-1.81%
Jul-11	-2.46%	-3.60%	-2.64%	-2.86%	-2.61%	-2.54%	-2.22%
Aug-11	-7.64%	-6.80%	-5.19%	-3.75%	-6.21%	-5.89%	-5.90%
Sep-11	-8.16%	-8.63%	-6.72%	-6.54%	-8.20%	-7.73%	-7.57%
Oct-11	12.66%	12.22%	10.11%	9.75%	12.29%	11.42%	11.24%
Nov-11	-1.34%	-0.33%	-0.71%	-0.03%	-0.25%	-0.68%	-0.38%
Dec-11	-0.43%	1.63%	1.26%	1.32%	0.34%	0.56%	0.84%
Jan-12	7.33%	4.92%	4.13%	3.13%	5.77%	5.22%	4.81%
Feb-12	3.64%	3.61%	3.55%	2.68%	3.99%	3.50%	4.18%
Mar-12	3.57%	2.75%	3.93%	2.52%	2.68%	3.26%	3.08%
Apr-12	-1.08%	-0.96%	-0.59%	0.11%	-0.77%	-0.69%	-0.71%
May-12	-7.67%	-6.16%	-5.51%	-4.44%	-6.52%	-5.97%	-6.22%
Jun-12	4.30%	4.25%	3.86%	3.60%	3.35%	3.57%	3.94%
Jul-12	-0.04%	0.48%	0.86%	0.86%	0.33%	0.31%	1.07%
Aug-12	2.79%	2.42%	1.45%	1.20%	2.73%	2.28%	2.31%
Sep-12	3.04%	2.81%	2.01%	2.00%	2.22%	2.15%	2.54%
Oct-12	-2.86%	-0.46%	-1.20%	-0.99%	-1.85%	-1.83%	-1.84%
Nov-12	0.50%	0.53%	0.01%	0.44%	0.95%	0.25%	0.60%
Dec-12	1.42%	2.48%	0.99%	0.59%	1.32%	1.47%	1.05%
Jan-13	4.55%	6.73%	5.07%	5.43%	5.72%	5.43%	5.34%
Feb-13	0.01%	1.45%	1.46%	1.63%	1.23%	1.04%	1.24%
Mar-13	3.59%	4.32%	4.07%	4.31%	3.98%	4.22%	3.81%
Apr-13	0.59%	1.08%	2.09%	1.99%	1.03%	1.64%	1.71%
May-13	3.25%	2.40%	1.60%	-0.14%	2.74%	1.86%	2.26%
Jun-13	-2.89%	-0.99%	-1.29%	-0.77%	-1.27%	-1.32%	-1.35%
Jul-13	6.86%	5.65%	5.42%	4.95%	5.89%	5.85%	5.30%
Aug-13	-2.35%	-3.80%	-3.47%	-4.14%	-2.89%	-3.07%	-2.92%

Sep-13	3.68%	3.58%	3.19%	3.27%	4.43%	3.93%	3.46%
Oct-13	3.36%	4.22%	4.28%	4.26%	4.08%	3.70%	4.32%
Nov-13	3.76%	2.57%	2.97%	1.80%	3.16%	2.69%	2.86%
Dec-13	2.88%	2.46%	2.05%	1.70%	2.38%	2.19%	2.54%
Jan-14	-1.39%	-3.10%	-2.53%	-2.64%	-3.42%	-1.94%	-3.27%
Feb-14	4.74%	4.51%	4.18%	4.09%	4.79%	4.53%	4.59%
Mar-14	-0.67%	1.84%	0.61%	0.92%	0.35%	0.17%	0.58%
Apr-14	-1.72%	0.15%	-0.01%	-0.06%	-0.81%	-0.86%	0.27%
May-14	1.39%	1.39%	1.68%	1.36%	1.57%	1.60%	2.15%
Jun-14	4.48%	3.06%	2.24%	2.60%	2.94%	3.38%	2.32%
Jul-14	-1.70%	-2.87%	-2.53%	-3.31%	-3.01%	-3.06%	-1.82%
Aug-14	4.78%	4.05%	4.25%	3.89%	4.41%	4.48%	4.05%
Sep-14	-3.11%	-3.46%	-1.18%	-2.76%	-2.86%	-2.62%	-1.92%
Oct-14	2.69%	3.32%	3.97%	4.66%	3.82%	4.27%	2.60%
Nov-14	2.36%	1.67%	2.68%	2.00%	2.03%	1.99%	2.43%
Dec-14	-0.73%	0.96%	0.25%	0.69%	0.50%	0.67%	-0.14%
Jan-15	-3.76%	-3.50%	-2.34%	-1.43%	-2.46%	-1.91%	-2.89%
Feb-15	6.97%	5.05%	4.37%	3.52%	5.74%	4.68%	5.68%
Mar-15	-1.91%	-0.49%	-1.07%	-0.24%	-0.26%	-0.14%	-1.26%
Apr-15	0.97%	0.07%	-0.41%	-1.28%	-0.54%	-0.66%	0.57%
May-15	2.70%	1.10%	1.72%	1.07%	1.49%	1.76%	1.27%
Jun-15	-1.62%	-1.85%	-1.74%	-1.56%	-1.16%	-1.61%	-1.83%
Jul-15	0.71%	-0.28%	3.11%	2.28%	1.28%	2.05%	1.76%
Aug-15	-5.99%	-5.35%	-6.17%	-5.60%	-6.02%	-6.11%	-6.10%
Sep-15	-5.20%	-3.23%	-2.08%	-1.91%	-3.10%	-2.78%	-2.84%
Oct-15	7.48%	6.81%	6.77%	6.72%	7.35%	6.53%	8.02%
Nov-15	0.97%	0.79%	0.34%	0.76%	0.81%	0.71%	0.38%
Dec-15	-2.86%	-3.08%	-1.00%	-2.15%	-3.02%	-2.18%	-1.96%
Jan-16	-9.08%	-5.68%	-4.72%	-3.86%	-5.91%	-5.65%	-5.47%
Feb-16	0.37%	0.63%	-0.54%	0.50%	0.13%	-0.15%	-0.18%
Mar-16	8.66%	7.87%	6.35%	6.75%	6.97%	7.04%	6.86%
Apr-16	2.26%	1.86%	-0.05%	0.07%	0.42%	0.00%	0.49%
May-16	2.43%	1.38%	1.85%	1.85%	1.75%	2.27%	1.68%
Jun-16	-1.41%	0.59%	0.67%	2.10%	-0.25%	0.28%	0.15%
Jul-16	7.45%	3.64%	3.34%	2.67%	4.14%	4.41%	3.81%
Aug-16	-0.06%	0.72%	-0.16%	-0.62%	0.36%	-0.18%	0.11%
Sep-16	1.68%	-0.01%	-0.50%	-0.67%	-0.14%	-0.02%	0.04%

Oct-16	-2.69%	-2.11%	-1.48%	-2.41%	-2.78%	-2.58%	-2.13%
Nov-16	6.89%	7.43%	3.96%	4.06%	6.04%	5.09%	4.08%
Dec-16	0.90%	2.37%	2.27%	2.26%	1.98%	2.16%	1.86%
Jan-17	3.99%	0.80%	1.70%	1.01%	1.65%	1.85%	1.82%
Feb-17	4.07%	2.90%	4.28%	3.33%	3.02%	3.66%	3.68%
Mar-17	-0.68%	-0.93%	-0.28%	-0.41%	0.11%	-0.02%	-0.01%
Apr-17	1.11%	-0.01%	1.05%	0.87%	1.04%	1.07%	0.95%
May-17	0.26%	-0.88%	1.36%	0.70%	0.22%	0.72%	1.00%
Jun-17	2.43%	1.78%	1.24%	0.44%	1.06%	1.25%	0.69%
Jul-17	2.50%	1.13%	1.72%	1.39%	1.44%	1.63%	1.81%
Aug-17	1.30%	-1.55%	0.20%	-0.44%	-0.64%	0.15%	0.05%
Sep-17	1.96%	3.59%	2.16%	2.09%	3.24%	2.57%	2.19%
Oct-17	2.29%	0.76%	2.38%	1.83%	2.11%	2.58%	2.10%
Nov-17	1.57%	3.12%	2.92%	3.01%	3.23%	2.71%	2.87%
Dec-17	1.48%	0.93%	-0.08%	-0.49%	0.54%	-0.55%	0.89%
Jan-18	6.32%	2.98%	4.78%	2.98%	4.76%	4.29%	5.29%
Feb-18	-2.46%	-5.03%	-3.62%	-4.44%	-3.96%	-3.46%	-3.89%
Mar-18	-3.03%	-0.87%	-2.19%	-0.22%	-1.27%	-0.92%	-2.36%
Apr-18	0.05%	0.39%	-0.52%	-0.15%	-0.29%	0.20%	0.20%
May-18	4.03%	1.63%	1.74%	2.34%	3.41%	3.19%	2.44%
Jun-18	-0.90%	0.28%	0.07%	0.67%	0.46%	0.33%	0.45%
Jul-18	2.51%	3.12%	3.85%	2.74%	2.71%	2.95%	3.26%
Aug-18	2.74%	1.48%	3.04%	2.56%	3.84%	3.99%	3.16%
Sep-18	-0.80%	-0.72%	-0.45%	-0.74%	-0.89%	-0.97%	0.08%
Oct-18	-9.29%	-6.90%	-6.34%	-6.45%	-8.60%	-7.87%	-7.41%
Nov-18	0.86%	2.41%	2.09%	2.91%	1.68%	2.10%	1.76%
Dec-18	-9.94%	-10.60%	-9.52%	-9.20%	-10.12%	-9.73%	-9.45%
Jan-19	9.76%	9.07%	7.12%	7.82%	8.87%	8.32%	8.16%
Feb-19	4.02%	3.08%	3.34%	3.40%	3.83%	3.64%	3.14%
Mar-19	0.28%	-0.50%	0.43%	0.62%	0.32%	0.21%	1.37%
Apr-19	2.96%	3.55%	3.66%	2.97%	3.74%	3.52%	3.77%
May-19	-8.21%	-7.51%	-5.80%	-4.98%	-7.33%	-6.52%	-6.69%
Jun-19	8.47%	7.05%	6.24%	5.30%	6.90%	6.45%	6.77%
Jul-19	1.03%	0.68%	1.19%	1.02%	1.14%	1.18%	1.24%
Aug-19	-3.95%	-3.97%	-1.57%	-1.24%	-2.89%	-2.42%	-2.13%
Sep-19	0.95%	3.84%	1.61%	1.71%	1.52%	1.41%	1.57%
Oct-19	2.73%	1.33%	1.69%	0.94%	1.99%	2.06%	1.95%

Nov-19	5.27%	2.82%	3.24%	1.67%	3.44%	3.44%	3.53%
Dec-19	3.22%	2.76%	2.40%	1.86%	2.68%	2.72%	2.74%
Jan-20	-2.10%	-2.98%	0.44%	-0.14%	-1.07%	-0.13%	-0.24%
Feb-20	-7.77%	-10.11%	-8.98%	-9.22%	-8.77%	-8.59%	-8.38%
Mar-20	-14.94%	-20.12%	-13.38%	-16.29%	-15.30%	-14.57%	-13.38%

Appendix 9.3: AQR Equity Factors Monthly (USA)

Date	**Market (Mkt)**	**Size (Smb)**	**Value (Hml Devil)**	**Momentum (Umd)**	**Low Beta (Bab)**	**Quality (Qmj)**	**Riskfree Rate (Rf)**
Jan-07	1.52%	-0.01%	-0.34%	1.36%	1.38%	-0.33%	0.41%
Feb-07	-1.84%	1.38%	0.53%	-1.29%	1.17%	-0.51%	0.42%
Mar-07	0.86%	-0.50%	-0.58%	2.06%	0.08%	0.19%	0.42%
Apr-07	3.66%	-2.02%	-0.74%	0.04%	0.87%	-0.19%	0.41%
May-07	3.54%	-0.47%	0.06%	-0.29%	-1.03%	0.59%	0.40%
Jun-07	-1.91%	0.76%	-1.19%	0.17%	0.81%	1.09%	0.38%
Jul-07	-3.58%	-2.79%	-4.46%	2.91%	-0.64%	2.34%	0.39%
Aug-07	0.75%	-0.47%	-1.76%	-0.08%	-2.92%	1.36%	0.40%
Sep-07	3.73%	-2.48%	-2.82%	3.69%	1.40%	-0.79%	0.33%
Oct-07	2.28%	-0.06%	-5.15%	6.14%	0.21%	0.15%	0.31%
Nov-07	-5.31%	-2.95%	-1.76%	0.96%	-4.03%	3.64%	0.32%
Dec-07	-0.72%	-0.14%	-2.25%	5.42%	-2.49%	1.77%	0.26%
Jan-08	-6.53%	-0.37%	7.98%	-9.44%	-2.05%	-0.92%	0.27%
Feb-08	-2.46%	-0.14%	-4.28%	7.68%	2.25%	2.09%	0.16%
Mar-08	-1.23%	0.15%	-0.99%	2.19%	-6.73%	2.18%	0.15%
Apr-08	5.05%	-2.04%	-0.84%	0.92%	-2.13%	-1.25%	0.11%
May-08	2.22%	2.80%	-5.24%	3.46%	0.88%	1.21%	0.12%
Jun-08	-8.07%	-0.17%	-9.10%	11.09%	0.45%	3.28%	0.15%
Jul-08	-1.36%	2.53%	4.50%	-6.52%	-6.75%	0.68%	0.16%
Aug-08	1.08%	2.16%	3.71%	-5.18%	-1.36%	2.53%	0.14%
Sep-08	-9.88%	0.17%	1.81%	0.35%	-9.10%	3.47%	0.14%
Oct-08	-18.53%	-3.50%	-6.01%	7.33%	-5.05%	8.65%	0.08%
Nov-08	-8.47%	-5.40%	-7.63%	6.61%	-3.51%	7.92%	0.04%
Dec-08	2.14%	3.37%	5.38%	-6.25%	-7.64%	-0.29%	0.00%
Jan-09	-7.87%	2.86%	-5.39%	-1.23%	11.91%	3.29%	0.01%
Feb-09	-10.11%	-0.37%	-9.16%	4.57%	-0.32%	5.20%	0.02%
Mar-09	8.95%	-0.34%	7.65%	-10.24%	-2.65%	-3.07%	0.02%

Apr-09	11.04%	6.49%	27.00%	-34.56%	-7.87%	-6.90%	0.02%
May-09	6.59%	0.41%	6.13%	-14.45%	6.52%	-5.82%	0.01%
Jun-09	-0.31%	2.53%	-2.08%	5.42%	9.10%	3.08%	0.01%
Jul-09	8.22%	1.04%	5.99%	-4.71%	-3.62%	-4.39%	0.02%
Aug-09	3.19%	-0.03%	7.93%	-9.98%	-2.28%	-6.50%	0.02%
Sep-09	4.49%	2.49%	1.85%	-5.33%	-0.39%	-2.54%	0.01%
Oct-09	-2.77%	-3.17%	-1.64%	1.43%	0.82%	5.60%	0.01%
Nov-09	5.74%	-3.03%	-0.44%	1.39%	-1.21%	-0.29%	0.00%
Dec-09	2.83%	5.08%	0.07%	2.04%	0.95%	-0.33%	0.01%
Jan-10	-3.73%	1.04%	3.28%	-4.84%	1.01%	-0.48%	0.01%
Feb-10	3.56%	0.80%	0.84%	3.75%	0.72%	-0.75%	0.01%
Mar-10	6.45%	1.41%	2.07%	3.90%	1.54%	-2.97%	0.01%
Apr-10	2.14%	4.41%	2.74%	2.55%	1.49%	-3.53%	0.01%
May-10	-8.00%	-0.02%	-1.73%	-0.45%	-0.56%	2.44%	0.01%
Jun-10	-5.39%	-2.05%	-2.59%	-2.56%	2.31%	2.62%	0.01%
Jul-10	7.18%	-0.75%	1.94%	1.74%	-2.31%	-1.89%	0.02%
Aug-10	-4.48%	-2.34%	-1.50%	1.25%	1.61%	1.11%	0.01%
Sep-10	9.34%	2.95%	-1.38%	0.72%	-1.19%	-0.31%	0.01%
Oct-10	3.99%	0.59%	-1.85%	1.12%	2.06%	0.28%	0.01%
Nov-10	0.65%	3.22%	-1.13%	2.38%	-0.51%	-0.66%	0.01%
Dec-10	6.84%	1.07%	3.81%	-2.82%	-0.13%	-4.63%	0.01%
Jan-11	2.06%	-1.96%	1.09%	-0.50%	3.02%	-0.83%	0.01%
Feb-11	3.84%	1.33%	0.20%	1.99%	0.71%	-1.37%	0.01%
Mar-11	0.30%	1.74%	-1.57%	2.87%	0.43%	1.27%	0.01%
Apr-11	2.83%	-0.53%	-1.66%	0.11%	0.55%	1.44%	0.01%
May-11	-1.45%	-0.77%	-1.03%	-0.40%	1.42%	2.89%	0.00%
Jun-11	-1.88%	-0.70%	-1.03%	1.92%	0.41%	2.88%	0.01%
Jul-11	-2.32%	-0.68%	-1.79%	0.83%	-0.41%	0.66%	0.00%
Aug-11	-5.93%	-2.83%	-2.13%	0.05%	0.75%	5.96%	0.01%
Sep-11	-8.50%	-2.55%	-2.00%	-1.99%	2.04%	6.58%	0.00%
Oct-11	11.62%	2.64%	2.19%	-1.27%	-5.99%	-4.19%	0.00%
Nov-11	-0.62%	-0.07%	-1.25%	3.91%	0.62%	3.04%	0.00%
Dec-11	0.49%	-0.51%	1.45%	2.28%	1.26%	0.88%	0.00%
Jan-12	5.42%	2.72%	0.95%	-7.03%	0.71%	-3.56%	0.00%
Feb-12	4.25%	-1.34%	0.68%	0.10%	2.57%	-0.98%	0.01%
Mar-12	2.56%	-0.42%	-0.34%	2.19%	3.94%	0.56%	0.01%
Apr-12	-0.67%	-0.56%	-1.58%	3.25%	2.90%	0.51%	0.01%

May-12	-6.64%	-0.24%	-1.37%	6.75%	2.38%	3.14%	0.01%
Jun-12	3.81%	0.65%	0.43%	-0.57%	1.07%	-0.57%	0.01%
Jul-12	0.99%	-1.96%	-0.66%	3.13%	1.05%	0.61%	0.01%
Aug-12	2.70%	0.67%	1.21%	-2.72%	-0.87%	-0.54%	0.01%
Sep-12	2.65%	0.56%	1.25%	-1.79%	0.78%	-1.26%	0.01%
Oct-12	-1.47%	-1.13%	3.23%	0.48%	2.01%	-2.11%	0.01%
Nov-12	0.59%	0.44%	-0.93%	0.42%	-1.35%	1.29%	0.01%
Dec-12	1.23%	1.69%	2.85%	-2.06%	-1.07%	-2.45%	0.01%
Jan-13	5.56%	0.61%	1.15%	-0.96%	4.40%	-2.06%	0.00%
Feb-13	0.94%	-0.15%	-0.10%	2.06%	1.86%	0.47%	0.01%
Mar-13	3.69%	0.74%	-0.25%	1.85%	2.34%	-0.45%	0.01%
Apr-13	1.53%	-2.06%	-0.16%	1.07%	1.67%	-0.95%	0.01%
May-13	2.13%	2.31%	1.29%	-1.25%	-1.51%	0.21%	0.00%
Jun-13	-1.40%	1.19%	0.06%	0.64%	2.09%	1.36%	0.00%
Jul-13	5.43%	1.50%	0.66%	1.38%	1.81%	-1.05%	0.00%
Aug-13	-2.61%	-0.16%	-0.89%	-0.41%	-0.37%	0.86%	0.00%
Sep-13	3.77%	2.54%	-1.41%	3.15%	0.77%	-0.81%	0.00%
Oct-13	4.07%	-1.53%	0.74%	0.81%	2.88%	1.55%	0.00%
Nov-13	2.65%	1.07%	-0.54%	1.84%	1.94%	1.49%	0.00%
Dec-13	2.70%	-0.10%	-0.52%	1.16%	0.27%	-1.45%	0.01%
Jan-14	-3.03%	0.73%	-0.89%	0.73%	2.05%	-3.64%	0.01%
Feb-14	4.68%	0.19%	-0.94%	1.31%	-0.18%	-0.72%	0.00%
Mar-14	0.42%	-0.76%	3.45%	-1.95%	1.58%	1.51%	0.00%
Apr-14	0.10%	-3.62%	2.44%	-4.30%	0.19%	0.37%	0.00%
May-14	2.03%	-1.40%	-0.43%	1.17%	1.06%	0.18%	0.00%
Jun-14	2.88%	2.77%	-0.26%	0.58%	-0.37%	-1.82%	0.00%
Jul-14	-2.08%	-3.60%	0.20%	-0.04%	1.02%	1.11%	0.00%
Aug-14	4.13%	0.37%	-0.99%	0.92%	1.71%	-0.29%	0.00%
Sep-14	-2.51%	-3.94%	-2.51%	1.14%	2.48%	3.56%	0.00%
Oct-14	2.23%	2.06%	-2.41%	-0.20%	2.01%	4.24%	0.00%
Nov-14	2.21%	-2.63%	-3.00%	0.93%	2.30%	2.81%	0.00%
Dec-14	-0.28%	1.60%	-0.01%	1.11%	0.38%	0.25%	0.00%
Jan-15	-2.91%	-0.35%	-3.92%	5.35%	2.58%	-1.07%	0.00%
Feb-15	5.78%	1.14%	-0.21%	-3.22%	-2.06%	0.46%	0.00%
Mar-15	-1.02%	1.84%	-2.25%	3.45%	1.39%	0.12%	0.00%
Apr-15	0.88%	-1.32%	4.39%	-7.87%	-2.05%	-1.09%	0.00%
May-15	1.10%	0.07%	-3.42%	6.41%	2.68%	0.26%	0.00%

Jun-15	-1.88%	1.66%	-2.42%	3.43%	1.98%	2.38%	0.00%
Jul-15	1.14%	-3.81%	-5.73%	10.44%	4.95%	1.86%	0.00%
Aug-15	-6.08%	0.85%	2.00%	-1.65%	-1.54%	1.82%	0.01%
Sep-15	-3.45%	-3.44%	-2.52%	7.03%	5.58%	5.61%	0.01%
Oct-15	7.44%	-1.63%	0.54%	-2.93%	-1.02%	0.24%	0.00%
Nov-15	0.28%	1.60%	-2.64%	2.86%	1.32%	0.76%	0.01%
Dec-15	-2.32%	-2.82%	-3.52%	4.03%	2.59%	1.31%	0.02%
Jan-16	-5.94%	-3.49%	-0.61%	2.55%	0.73%	7.89%	0.01%
Feb-16	0.09%	0.85%	2.24%	-4.75%	-0.62%	2.53%	0.03%
Mar-16	7.13%	1.10%	7.13%	-5.48%	-2.50%	-2.19%	0.03%
Apr-16	1.20%	1.85%	8.51%	-6.07%	-2.63%	-4.89%	0.02%
May-16	1.49%	-0.77%	-3.68%	2.46%	2.20%	0.53%	0.02%
Jun-16	0.23%	-0.01%	-0.69%	4.85%	2.86%	0.78%	0.03%
Jul-16	3.87%	2.16%	-1.87%	-2.51%	2.35%	-0.08%	0.02%
Aug-16	0.29%	1.05%	1.39%	-3.49%	-1.85%	0.14%	0.02%
Sep-16	0.28%	1.55%	-0.35%	-0.34%	-0.16%	-3.14%	0.03%
Oct-16	-2.22%	-3.59%	2.65%	0.43%	1.11%	2.81%	0.02%
Nov-16	4.40%	4.35%	5.26%	-3.85%	-1.60%	0.62%	0.03%
Dec-16	1.86%	0.29%	2.79%	-0.55%	3.76%	1.47%	0.04%
Jan-17	2.16%	-0.64%	-0.53%	-0.29%	0.06%	-2.63%	0.04%
Feb-17	3.25%	-1.82%	-1.72%	-1.72%	1.86%	1.29%	0.04%
Mar-17	0.13%	0.62%	-2.60%	-0.88%	1.34%	0.78%	0.04%
Apr-17	0.81%	0.06%	-2.59%	0.17%	2.05%	2.39%	0.06%
May-17	0.78%	-2.87%	-4.79%	1.96%	2.36%	2.30%	0.07%
Jun-17	1.01%	2.25%	1.72%	-0.36%	0.06%	-1.36%	0.08%
Jul-17	1.91%	-1.42%	-0.23%	1.87%	0.18%	-0.73%	0.08%
Aug-17	0.02%	-1.36%	-2.73%	3.23%	-0.05%	-0.23%	0.09%
Sep-17	2.41%	3.60%	2.25%	-1.42%	-0.19%	-0.43%	0.08%
Oct-17	1.85%	-1.62%	-2.42%	5.42%	0.32%	2.16%	0.09%
Nov-17	2.77%	0.03%	-0.11%	-0.01%	2.01%	2.19%	0.09%
Dec-17	1.08%	-0.76%	1.68%	-2.40%	0.53%	-1.67%	0.10%
Jan-18	4.98%	-2.73%	-2.66%	3.69%	-0.01%	0.96%	0.11%
Feb-18	-4.07%	0.14%	-3.19%	4.06%	-1.95%	1.65%	0.12%
Mar-18	-2.04%	3.11%	0.83%	-0.92%	2.47%	-0.22%	0.14%
Apr-18	0.40%	1.10%	2.15%	-1.21%	0.10%	-1.52%	0.14%
May-18	2.60%	4.22%	-3.28%	2.47%	0.60%	-0.48%	0.15%
Jun-18	0.45%	0.87%	0.21%	-2.24%	2.38%	0.77%	0.16%

Jul-18	3.01%	-2.22%	0.25%	-1.41%	-0.36%	1.42%	0.16%
Aug-18	3.09%	1.07%	-4.83%	4.79%	-1.23%	1.09%	0.17%
Sep-18	-0.08%	-2.31%	-0.13%	0.11%	-0.62%	0.38%	0.17%
Oct-18	-7.67%	-3.22%	3.36%	-1.42%	2.11%	3.70%	0.18%
Nov-18	1.65%	-1.58%	-1.44%	-0.96%	-0.11%	1.48%	0.19%
Dec-18	-9.55%	-2.32%	-2.50%	2.50%	-0.04%	1.52%	0.19%
Jan-19	8.86%	2.65%	3.06%	-7.10%	-0.64%	-3.80%	0.20%
Feb-19	3.28%	2.53%	-2.83%	0.36%	0.01%	-0.29%	0.20%
Mar-19	1.08%	-3.16%	-2.55%	2.73%	0.32%	-0.63%	0.20%
Apr-19	3.67%	-1.60%	0.62%	-2.26%	-0.16%	2.29%	0.20%
May-19	-6.52%	-1.40%	-3.90%	8.53%	4.24%	-0.38%	0.20%
Jun-19	6.84%	-0.53%	-0.23%	-1.52%	-0.03%	0.30%	0.19%
Jul-19	1.02%	-1.02%	-1.01%	3.01%	2.12%	1.94%	0.17%
Aug-19	-2.31%	-3.14%	-5.26%	7.06%	2.40%	0.63%	0.17%
Sep-19	1.46%	0.14%	5.93%	-5.13%	-1.16%	1.77%	0.16%
Oct-19	1.77%	-0.31%	-2.39%	1.27%	-0.42%	0.51%	0.15%
Nov-19	3.54%	0.34%	-1.90%	-2.26%	-2.94%	-1.66%	0.13%
Dec-19	2.77%	1.56%	3.53%	-2.66%	-0.40%	-2.44%	0.13%
Jan-20	-0.33%	-2.93%	-8.37%	6.63%	4.12%	-0.77%	0.13%
Feb-20	-8.16%	0.09%	-3.03%	0.50%	-3.58%	-1.69%	0.13%
Mar-20	-14.50%	-7.31%	-14.60%	7.42%	-9.62%	7.30%	0.10%