TALLINN UNIVERSITY OF TECHNOLOGY
School of Business and Governance
Department of Economics and Finance

Lauri Kaijomaa

EVALUATING THE PERFORMANCE OF SMART BETA INVESTMENT FUNDS IN THE US STOCK MARKET

Bachelor's thesis
International Business Administration, Finance and Accounting

Supervisor: Karin Jõeveer, PhD

Tallinn 2020

I hereby declare that I have compiled the thesis independently
and all works, important standpoints, and data by other authors
have been properly referenced and the same paper
has not been previously presented for grading.
The document length is 9506 words from the introduction to the end of the conclusion.

Lauri Kaijomaa ……………………………
(signature, date)
Student code: 177672TVTB
Student e-mail address: lakaij@ttu.ee

Supervisor: Karin Jõeveer, PhD:
The paper conforms to requirements in force

……………………………………………
(signature, date)

Chairman of the Defense Committee:
Permitted to the defense
…………………………………
(name, signature, date)

TABLE OF CONTENTS

ABSTRACT

Passive investing has, for long, been a favored strategy among investors who prioritize easy diversification and low fees above all else. On the opposite side, actively managed funds attempt to generate excess returns over the market, with higher costs to compensate. Alongside the traditional passive or active investment strategies, the industry has seen combinations of the two emerge. This paper offers the reader a glimpse into one of these active-passive strategies, called smart beta, in the context of the United States' equity market. The reader is introduced to four different smart beta strategies and shown how each of them has performed during two time periods of different lengths. Both of the periods take place during years of rising markets. The four representative smart beta strategies are dividend, low volatility, value, and growth. The strategies will be compared with each other and against a common, passively managed benchmark index. The results of this paper reveal that none of the smart beta strategies in the sample were able to generate significantly different returns from the benchmark index. Additionally, none of the strategies in the sample had a significantly different risk profile from the benchmark index.

Keywords: Smart beta, the United States equity market, Fundamental factors, Passive-active strategies, Exchange-traded funds, Factor investing

INTRODUCTION

In the United States (US), mutual funds are the leading investment choice for a broad audience of individual investors. The Wall Street Journal writes that the most prevalent reason for this arises from the use of employer-sponsored retirement plans in the US, which often only offer mutual funds as their product choice for retirement savers (Ravo, 2019). Also, the same article notes that exchange-traded funds (ETFs), which are the main competitor for mutual funds, have grown from zero in 1992 to almost four trillion dollars in 2019. Overall, one might argue that the rising popularity of ETFs is well justified. ETFs usually follow a certain benchmark index, have relatively low management fees, and due to being exchange-traded, are liquid during trading hours. The downside of these passive index-following ETFs is their ability to deliver nothing more than the market-return of the underlying index. Conventional mutual funds, on the other hand, have attempted to provide excess returns over the market, or so-called “alpha” returns. The downside of mutual funds lies in their relatively high management fees and low liquidity compared to ETFs.

The author of this paper was curious whether the passive-active investment style of smart beta could be a middle-ground solution between the wholly active and passive strategies. The smart beta strategy is based on indices that have been constructed with a specific fundamental factor or multiple fundamental factors in mind. The fundamental factors represent a particular niche in the market, and portfolio construction is based on equity-specific characteristics. In traditional passive indexing, equities are selected to an index according to the size of their market capitalization. However, the conventional approach fails to take into account any other fundamental factors of the underlying equities, which may, in some cases, lead to inefficiency. In contrast, active managers of mutual funds have different approaches to portfolio creation, which are highly influenced by the theme and risk level of the specific fund. Smart beta places in between the two, being reliant on passive indices, but at the same time having the index based on some specific factors, which require the funds to be rebalanced from time to time.

This research area is significant due to the possibility of smart beta offering a solution that combines the elements of passive and active strategies in an efficient and low-cost manner. This paper attempts to answer the following questions that arise on the subject:

1) Can weighing indices based on the market capitalization of their underlying equities be considered inefficient?
2) Can investing based on fundamental factors create excess market returns?
3) Can the returns of the smart beta strategies be associated with better risk-reward levels relative to the market benchmark?
4) Should investors use smart beta strategies as additional components or sole components in their portfolio as a whole?

The factors associated with constructing a smart beta strategy are numerous. Hence, this paper has a focus on some of the most well-known approaches. The sample for this paper was chosen on the basis of availability, which led to four different strategies being examined. Two time periods of different lengths were chosen to test for differences and allow for all four strategies to be examined in detail. The first time period of 12 years took place between 2007 and 2019 and is later called by the author as the initial time period. The second period spanned seven years, between 2012 and 2019, and is subsequently called by the author as the alternative time period. The performance of the smart beta strategies and the representative ETFs is compared against a passive market benchmark. The author attempts to find a statistically significant difference between the returns of the smart beta ETFs and the market benchmark. The risk-reward characteristics of the smart beta ETFs have been measured with the Sharpe ratio, which is introduced later in detail.

During the first chapter, the reader is introduced to some theory and previous studies related to the subject. The second chapter covers the data collection and methodology part of this paper. In chapter three, the data will be implemented and analyzed with each sampled smart beta strategy covered. Additionally, comparisons and statistical significance tests are made between the smart beta funds and the market benchmark, followed by a discussion of the results. Finally, the conclusion chapter summarizes the contents and the findings of the paper, with the inclusion of some suggestions for future research.

1. THEORETICAL FRAMEWORK

1.1. Modern Portfolio Theory

Harry Markowitz introduced the financial industry to the expected returns–variance of returns (E-V) rule in his famous publication about portfolio selection. The E-V rule states that an investor should select a portfolio that has a minimum variance for a given expected return and maximum expected return for a given variance (Markowitz, 1952). In other words, the investor should seek a portfolio that offers the highest expected return with the lowest amount of variance. Alongside the introduction of the E-V rule, Markowitz rejected the hypothesis that an investor should aim only to maximize the discounted value of future returns. The said hypothesis implies that an investor should place all his funds in the security with the greatest discount value. An error with the previous assumption comes from not taking into account that the portfolio with the maximum expected return is not necessarily the one with minimum variance. Additionally, Markowitz points out that even though one single security might have a higher yield and lower variability than all other securities, the E-V rule leads to diversified portfolios in almost all cases. Markowitz made another critical notion in the same publication about how investors should diversify across different industries. His view was that industries with different economic characteristics exhibit lower relative covariances than closely related industries. He based the suggestion on the argument that when trying to minimize variance, it is necessary to avoid investing in highly covaried equities.

Several authors have examined Markowitz's original modern portfolio theory in retrospect. Mark Rubinstein assessed the condition of Markowitz's original work fifty years later, and in his paper, highlighted a vital understanding that Markowitz introduced the investor to in his original work. Rubinstein noted that Markowitz's suggestion that diversification does limit, but does not remove risk holds even to this day (Rubinstein, 2002). Rubinstein highlights in the same paper that the framework developed by Markowitz, enhanced by others, is still to this day used in portfolio management in the financial industry. Therefore, the importance of Markowitz's work cannot be stressed enough. In another retrospect paper on modern portfolio theory, Elton and Gruber point out some of the limitations of Markowitz's original work. They are critical about the E-V rule being sufficient, mostly in a simplified environment, which does not take into account other factors affecting portfolio performance (Elton & Gruber, 1998). Additionally, they note that the E-V rule focuses on a single-period setting in which all variables are adjusted to conform with a single period. Thus, it may not be sufficient for multi-period analysis.

1.2. Capital Asset Pricing Model

Two researchers, William Sharpe and John Lintner developed the Capital Asset Pricing Model (CAPM) in the late 1960s. Even to this day, it is still used for evaluating the cost of capital for companies or performance of portfolios for investment funds (Fama & French, 2004). Their original work marked the birth of the asset pricing theory and resulted in a Nobel Prize for William Sharpe. The CAPM formula attempts to derive the expected return of a given asset, taking into account the prevailing risk-free interest rate and a risk premium of the asset above the market return. The risk premium is represented by an asset's beta, which takes form as the asset's volatility relative to a market portfolio. The beta of a market portfolio is assumed to be 1

In 1992, Fama and French researched in the US market, where they examined the relationship between an asset's return and beta. Their results showed that over an almost fifty-year time period, there was not enough evidence to back up the claim of a positive relationship between the return and the beta of an asset (Fama & French, 1992). Later, in 2004, Fama and French, criticized some aspects of the CAPM theory in their newer publication. Their writings highlight that the calculations behind asset betas can be inconsistent and lead to errors in asset analysis. Besides, they point out that average asset returns do not take into account industry conditions, which can significantly have an impact on prevailing asset prices (Fama & French, 2004).

From the perspective of this paper, the critical introduction made by the CAPM theory is the presence of borrowing and lending at a risk-free rate. The importance of a risk-free rate lies in the opportunity cost that an investor is faced with when choosing between different investment opportunities. An investor should have a risk-free interest rate against which to compare portfolio performance. The amount of excess returns, or lack of returns, the portfolio has created can be analyzed with the risk-free rate. For assessing the risk-reward nature of an investment opportunity, the Sharpe ratio has been discussed further ahead, where the risk-free interest rate plays an important role as well.

1.3. Capitalization-weighted indices

Most of the popular stock market indices are weighted by the market capitalization (market cap) of the underlying equities in the given index. Weighting equities in an index by their market cap can be viewed as a simplified and almost entirely passive strategy. No fundamental factors need to be taken into account other than the size of the market cap of a certain company, which is the total value of the company's shares. For the distributor of the capitalization-weighted (cap-weighted) funds, the passive investment style equates to low transaction costs, since little to no active management needs to be done during the duration of the fund. The only occasion when trades are made is when the market cap of a target company falls below or rises above a set standard and is then let go from or added to the index. From an investor's point of view, this equates to presumably higher annual returns as lower expense ratios take up a smaller share of the total profits.

An article written by Haugen and Baker argues that market cap-weighted portfolios are inefficient investments. They claim that the argument holds even when the market is assumed to be informationally efficient, and when all investors are thought to rationally optimize the relationship between risk and expected return (Haugen & Baker, 1991). Additionally, they present results of their research where they tested the hypothesis of the market cap-weighted portfolios being inefficient. The results of their study showed that it was indeed possible to build portfolios, from the same securities that are included in the cap-weighted index, with the equal or greater return but significantly lower volatility than cap-weighted portfolios. For this paper, the findings of the Haugen & Baker study are relevant, since smart beta attempts to look away from cap-weighted strategies and offer investors more efficient portfolios based on different weighting schemes.

On the opposite side, an article written by Burton Malkiel in 2003 argues in favor of passive and cap-weighted indices (Malkiel, 2003). Malkiel bases his arguments on the fact that the markets are most of the time informationally efficient, and that passive management is efficient regardless of prevailing market conditions. Malkiel believes that no arbitrage opportunities are present, as the market truly is informationally efficient. What is more, he points out the fact that when one active investor gains, another loses. Therefore, based on Malkiel's findings, it can be argued that even for professional traders, consistent market outperformance is challenging to achieve.

1.4. Exchange-traded funds

Exchange-traded funds (ETFs) are one type of investment product offered in the market. In terms of a primary common goal to be achieved, exchange-traded funds are quite similar to the more traditional mutual funds. According to a paper that discusses ETFs and index funds, ETFs allow investors to own diversified portfolios in a low-cost way, through the use of economies of scale. In contrast to individual investors purchasing the underlying equities, economies of scale allow ETF providers to buy the underlying equities to the funds at a low cost when buying in large quantities (Kostovetsky, 2003). Gary L. Gastineau writes about the importance of ETFs in the equity market in his work in 2008. He highlights the higher liquidity and the availability of bid-ask spreads as the main points for their importance relative to traditional mutual funds (Gastineau, 2008). Gastineau's writings are relevant, since mutual funds are not tradeable intraday, as ETFs are. Thus, ETF investors do enjoy higher liquidity for their holdings through regular trading hours and prices set by market makers through bid-ask spreads.

From the perspective of beginner investors, mutual funds have long been the number one product offered for them by banks and other investment houses. Mutual funds often offer an easy start on investing with multiple risk levels and themes to choose from. However, since mutual funds are usually actively managed, the management fees they charge are relatively high. ETFs have risen to the spotlight as the solution for the more cost-conscious investors, who believe in easy and passive investment strategies. One crucial difference between ETFs and mutual funds is the nature of ETFs, usually being passively managed. Most ETFs are based on certain indices, and their goal is to replicate the given indices with as low tracking error as possible. Since market indices do not trade shares frequently, the funds that track them can charge next to nothing in annual fees from their investors as well.

1.5. Fundamental factors

The authors of an article published by the MSCI on factor investing, give factors the definition of being some underlying characteristics of individual equities. These characteristics seek to explain the levels of risk and returns associated with the equities (Bender, 2013). In the context of smart beta, factors are used as the building blocks of different strategies. This paper has focused on four different factors, which are growth, value, dividend, and low volatility. Due to the data collected for the study being based on real-life ETFs, with each of their fund managers, the specific criteria used by those managers when constructing their respective portfolios cannot be commented on a deeper level. The sampled four strategies are next presented in detail.

Growth is a strategy closely related to a more commonly known Momentum strategy. According to an article on fundamental factors, the momentum strategy attempts to generate excess returns with equities that have strong past performance (Bender, 2013). Asness (1995, 1997, as cited in Bender, 2013), in their research, confirmed earlier findings of the momentum strategy and additionally showed the tendency of winners and losers to revert over time. They also mention that empirical research has shown the momentum effect to be most prominent in the following 3-12 months of initiation, after which it will disappear. Based on this, one might argue that there exists a high probability of active momentum stock trading inside the fund, which may lead to higher annual fees and higher volatility. Sudden changes in the momentum direction are difficult to be predicted in an efficient or certain way.

Value-based strategies attempt to capture excess returns with equities that have low prices relative to their fundamental value (Bender, 2013). Value strategies are usually based on several ratios and figures related to fundamental analysis. Some examples include the price-to-earnings ratio, net sales, net profit, and price-to-book ratio. Value strategies aim to identify investment opportunities that offer an arbitrage opportunity in terms of low market price relative to their true fundamental value. In other words, the value strategy attempts to find equities that are priced at a discount in the prevailing market conditions, compared to their prospects on paper.

Dividend strategies aim to capture excess returns with equities that have higher-than-average dividend yields (Bender, 2013). As the name entails, the dividend factor is measured based on the dividend yields the selected companies are paying. Ang and Bekaert (2007, as cited in Bener 2013) in their research found out that the excess return predictability by the dividend yield is not statistically significant. Also, they noted that dividends are an unreliable indicator since the company itself can manipulate them. Along with these findings, it is essential to point out that dividends can offer the investor an extra benefit in terms of the time value of money when the received dividends are reinvested and are allowed to compound over long periods of time.

Low Volatility strategies aim to generate excess returns with equities exhibiting lower than average volatility or beta values (Bender, 2013). As the MSCI article claims, low volatility stocks and funds are controversial, since the basic principles in finance state that high volatility often translates to higher rewards. The same phenomenon can be traced back to modern portfolio theory and the CAPM as well. To this extent, low volatility should be an indication of lower returns. Interestingly, the MSCI article suggests an investor might use the low volatility strategy as a risk management tool for their portfolio as a whole. Another study, conducted by a French asset management company in 2013, suggested that a low volatility strategy could have a strongly positive or negative performance when the overall market is clearly in an upward or downward direction (Cazalet;Grison;& Roncalli, 2014). The same French study also concluded that an investor would choose to include the low volatility strategy in their portfolio based on how the investor personally views the future market conditions to be.

1.6. Smart Beta

An article written in the Financial Analysts Journal calls smart beta a disruptive innovation that has a high potential to affect the actively managed investment product-market in a significant way (Kahn & Lemmon, 2016). Furthermore, the authors of the article explain that essentially the ultimate goal of smart beta funds is to deliver either higher returns or lower risk, paired with lower costs than traditional mutual funds. Ultimately, Kahn and Lemmon argue that smart beta would be able to disrupt the investment fund industry, with only hedge funds and private equity funds left unaffected, due to their unique nature.

To better understand why smart beta could be a disruptive innovation, the idea behind smart beta is introduced in more detail. In a simple form, smart beta funds are a combination of passive and active strategies. Smart beta strategies are rule-based and rely on fundamental factors that have successfully been associated with excess risk-adjusted returns (Kahn & Lemmon, 2016). However, the strategies need to rebalance their investments at consecutive intervals to maintain the appropriate exposure to their desired factors. By being active in this sense, smart beta funds are under the risk of underperforming their relative benchmarks or a common market portfolio. In other words, smart beta strategies can be classified as active-passive strategies.

In 2014, one study on smart beta found out that according to their research in the US market, smart beta strategies were able to achieve higher Sharpe ratios relative to a cap-weighted index (Amenc;Goltz;Lodh;& Martellini, 2014). On the other hand, the smart beta strategy has received criticism in addition to its praise. One article in 2016 importantly points out the flaw of smart beta being rather new. The authors of the article mention that the excess returns received from some smart beta strategies are measured during a few market cycles and might be highly influenced by asset valuations overall (Arnott;Beck;Kalesnik;& West, 2016).

2. DATA AND METHODOLOGY

2.1. Data collection

The data for this paper was collected from the Thomson Reuters Eikon database, accessed at the Tallinn University of Technology. The Eikon database had a specified section for smart beta ETFs, from which all of the 29 available funds were chosen. Therefore, availability sampling was used as the sampling method for this paper. All the 29 funds were listed in the United States and represented multiple different smart beta strategies. Following the data collection, the data was organized and divided into smaller sections based on the strategy that each ETF was representing. The fundamentals behind the different strategies have been explained in further detail in chapter 1.5. For data organizing and analysis, the author used the help of Microsoft Excel.

From the 29 smart beta ETFs collected from the Eikon database, multiple different strategies were represented. Value, growth, dividend, low volatility, equal weight, replication, and hedged strategies were found in the sample. However, only the first four strategies had enough data to present sufficient evidence about the strategy for this paper. Hence, the ETFs representing equal weight, replication, and hedging were left out from the final sample. Therefore, the final sample consisted of nine ETFs representing value, seven representing growth, five representing dividend, and three representing low volatility. All but the low volatility ETFs had measurable data beginning in 2007. Thus, the alternative time period between the years 2012 and 2019 was created to analyze the returns of the low volatility strategy as well. Eventually, the addition of the alternative time period was welcomed, as it allowed for comparison of fund performance during two time periods of different lengths. The author was curious to see if the length of the time period had any significant effects on the performance of any of the strategies. One limitation regarding the data was that some ETFs reinvested their dividends, while others did not. Therefore, the closing prices were not adjusted for dividends, and the results do not take dividend payments into account.

In addition to the smart beta ETFs, data on a common benchmark index was collected. The results of the smart beta ETFs were to be compared with the results of the benchmark index. The benchmark index, in this case, takes the form of the market-return. The benchmark index used by the author was the Standard & Poor's 500 index (S&P), which consists of the 500 largest companies in the United States. Since this paper is concerned with smart beta ETFs, the ETF alternative of the S&P was used as well. Thus, the author used the SPDR S&P 500 ETF Trust (SPY), which tracks the S&P index, as the ETF variant of the benchmark fund.

2.2. Data interpretation

Monthly closing prices for each ETF were collected from the Eikon database, while percentage changes were used as the main variables for the analysis. The percentage changes stood for the difference between the closing prices of the current and the previous month. The ETFs were listed either on the NYSE Arca or the CBOE stock exchanges. Both exchanges are located in the United States. For the initial time period, the range of exchange dates was between January 31st, 2007 and December 31st, 2019. For the alternative time period, the exchange date range was situated between January 31st, 2012, and December 31st, 2019. Therefore, the initial time period spanned 12 years , while the alternative time period spanned seven years.

The phase that followed the data collection and organizing involved using the data to test for hypothesis and calculate returns and risk figures. Since the percentage changes in monthly prices involved both positive and negative numbers, the average returns were calculated with simple arithmetic mean. Another type of mean calculation could not have been used due to the presence of negative numbers. Since the returns were recorded on a monthly basis, the annualized return figures were obtained by multiplying the average monthly returns by 12. Additionally, as a measure of volatility, the standard deviations of each ETF were calculated on a monthly and annualized basis. The average monthly standard deviations were calculated with the simple formula for standard deviation. The monthly standard deviations were multiplied with the square root of 12 to annualize the results. Finally, the cumulative returns of the ETFs and the benchmark were calculated and displayed by an appreciation of one hypothetical dollar invested for the length of the given time period. The calculations were done by multiplying the hypothetical dollar with an equation of 1 plus the monthly percentage change in closing price.

After the initial calculations, the author moved on to analyze the data. The Sharpe ratios were calculated to formulate the risk-reward levels of each ETF and the benchmark. The Sharpe ratio has been discussed in more detail in chapter 2.3. To test for statistical significance, the author used a T-test to examine the differences between the ETFs and the benchmark. The hypothesized differences between average returns and average Sharpe ratios were tested. The T-test has been discussed in chapter 2.4 in further detail.

2.3. The Sharpe Ratio

The Sharpe ratio is often used to evaluate the efficiency of an equity, fund, or a portfolio. William F. Sharpe introduced the Sharpe ratio in 1966, in a paper called “Mutual Fund Performance”. In his first publication (Sharpe, 1966), Sharpe introduced a reward-to-variability ratio, later most commonly called the Sharpe Ratio. In this ratio, the expected return of a portfolio is subtracted from a risk-free interest rate, and the resulting figure is divided by the standard deviation of the portfolio’s returns. As Sharpe himself wrote (Sharpe, 1966), future return predictions cannot be obtained satisfactorily, and thus, the expected return and standard deviation of the portfolio must be substituted for its ex-post values, which are its average historical values. Therefore, the formula of the Sharpe ratio becomes a subtraction of ex-post returns from the risk-free interest rate, divided by the portfolio’s ex-post standard deviation. It is also understood from the same publication that the best portfolio will be the one with the highest Sharpe ratio. From a mathematical standpoint, a Sharpe Ratio can be considered adequate when it is above 1. If the calculated Sharpe Ratio is flat at 1, the risk-adjusted return of the portfolio is in accordance with its standard deviation. However, if the value of the ratio is below 1, the return of the portfolio equals its standard deviation. Thus, the investor has to accept a higher risk for the portfolio returns.

The nature of the Sharpe ratio has also been criticized. One paper concludes that the use of estimated values or historical values leads to errors in judgment (Lo, 2002). Additionally, the same paper notions that the Sharpe ratio should be used for comparison purposes only for funds withing the same type of investment style. For this paper, the Sharpe ratio is used to compare the passive-active smart beta ETFs against a passive benchmark. The reasoning behind the usage of the Sharpe ratio lies in the nature of smart beta to be closer to a passive than an active strategy.
The formula for the Sharpe ratio is as follows:

$$\boldsymbol{SR} = \frac{(\mu - R_f)}{\sigma}$$

μ – Mean ex– post portfolio returns over a given time period

R_f – Risk– free interest rate of the market

σ – Portfolio standard deviation

In this paper, the Sharpe ratio was calculated for each smart beta ETF, in addition to the benchmark index. Due to the sample consisting of monthly return data, the monthly standard deviation was not possible to be calculated. Therefore, the Sharpe ratios were calculated in an annualized form, using the average monthly returns and standard deviations for each year. The author chose to use the 10-year US Treasury Yield as the risk-free rate in the calculations. The decision was based on the common fact that the 10-year US treasury yield is often used in finance as the basic risk-free interest rate. The average rate of the yield was calculated separately for each year of the two time periods. After the Sharpe ratio calculations were completed, the ratios were used for hypothesis testing. The aim was to find evidence of a significant difference between the Sharpe ratios of the smart beta ETFs and the benchmark index. The tests for significance are examined in the next chapter.

2.4. T-test

The t-test was chosen as the statistical significance test for this paper since it can be used to compare the difference in means between two variables. The variables tested in this paper were the average returns and the average Sharpe ratios of the smart beta ETFs. These variables were tested for a difference relative to the respective figures of the benchmark index. To begin the t-tests, the author set a non-directional hypothesis, which led to the use of a two-tailed t-test. In other words, the null hypothesis was set with the assumption of no difference between the mean values of the smart beta ETFs and the benchmark index. On the opposite side, the alternative hypothesis assumed a significant difference between the means of the two variables. The two-tailed t-test assumes the difference to be either positive or negative relative to the mean. Hence it is not unidirectional. Additionally, the t-tests were conducted with the assumption of unequal variances between the respective independent variables.

A significance level of 95% was used, which left room for a 5% chance of falsely rejecting the null hypothesis. In statistical terms, a significance level of 95% is equal to an alpha level of 0.05. The t-test must generate a p-value below the level of alpha to reject the null hypothesis. Therefore, a p-value of less than 0.05 would be an indication of having enough evidence to back up the alternative hypothesis, which leads to the rejection of the null hypothesis. In other words, hypothesis testing aims to show that the sampled data has enough evidence to reject the null hypothesis.

3. RESULTS AND DISCUSSION

3.2. Smart beta strategies

3.2.1 Dividend

In chapter 1.5, dividend strategies are told to be based on companies that have paid consistent and higher than average dividend yields. A difficulty and a limitation regarding this paper comes from the fact that some dividend ETFs pay out dividends while others reinvest them. During the data collection, only prices not adjusted for dividends were exported. Therefore, the cumulative returns of the dividend funds do not take into account dividends paid out from the fund.

Table 1 displays the data of the dividend ETFs for the initial time period. Only three dividend ETFs had data covering the entire initial time period, hence two from the total of five dividend ETFs were excluded from the initial time period. The T-test results showed that none of the dividend ETFs had statistically different mean returns or mean Sharpe ratio from the benchmark index. The p-values for all the dividend ETFs were higher than 0.05 and did not reject the null hypothesis.

Table 1. Dividend ETFs, 2007-2019

Fund	Mean annual return	Mean annual standard deviation	Mean Sharpe Ratio	P-value (returns)	P-value (Sharpe)	Ending value of $1 invested
Benchmark	**7.3%**	**14.6%**	**0.72**	–	–	**2.24**
Vanguard Dividend Appreciation Index Fund ETF	7.2%	12.9%	0.64	0.99	0.89	2.28
Vanguard High Dividend Yield ETF	5.6%	14.1%	0.49	0.75	0.68	1.80
SPDR S&P Dividend ETF	5.3%	14.7%	0.36	0.73	0.50	1.73

Source: Compiled based on author’s calculations

Table 2 displays the results for the alternative time period, during which all of the sampled dividend ETFs were involved in the analysis. Similarly to the initial time period, the dividend ETFs showed no significantly different results from the benchmark during the alternative time period. Interestingly, during the alternative period, the Sharpe ratios of the ETFs were closer to 1 than they were during the initial time period. However, compared to the benchmark, the differences were not statistically significant.

Table 2. Dividend strategy, 2012-2019

Fund	Mean annual return	Mean annual standard deviation	Mean Sharpe Ratio	P-value (returns)	P-value (Sharpe)	Ending value of $1 invested
Benchmark	**12.4%**	**11.1%**	**1.32**	–	–	**2.56**
Vanguard Dividend Appreciation Index Fund ETF	10.9%	10.4%	1.13	0.77	0.77	2.28
Schwab US Dividend Equity ETF	10.5%	10.6%	1.07	0.72	0.70	2.21
Vanguard High Dividend Yield ETF	9.7%	10.3%	0.99	0.60	0.61	2.07
SPDR S&P Dividend ETF	9.2%	10.5%	0.81	0.55	0.41	2.00
iShares Core High Dividend ETF	7.6%	9.8%	0.70	0.36	0.31	1.77

Source: Compiled based on author’s calculations

For the dividend ETFs, it can be concluded that with this sample size, no statistically significant differences were found between the dividend smart beta ETFs and the benchmark index. The results showed that no single ETF had a p-value below the alpha, and thus, the null hypothesis was not rejected. Concerning both time periods, the statistical significance of the results was similar.

3.2.2 Low volatility

There ETFs were representing the low volatility strategy in the sample, with relevant monthly returns beginning in 2012. Therefore, the strategy was analyzed over the alternative time period only. From 2009 onwards, the market was recovering from the financial crisis and had a clear upward momentum, with no significant signs of slowing down. Therefore, 2012 was a great year to start investing, but with the influence of a strong bull market, the results of the period may be only applicable to similar market conditions in the future.

Table 3 displays the figures for the low volatility ETFs. The t-test on the low volatility strategy showed that none of the ETFs had a p-value less than the alpha of 0.05, which led the author to fail to reject the null hypothesis. Based on these results, the assumption was that there was no statistically significant difference present. Both the returns and the Sharpe ratios were close to the ones of the benchmark index. The low volatility ETF that was closest to rejecting the null hypothesis would have needed a significance level of below 82% to succeed in it.

Table 3. Low volatility strategy, 2012-2019

Fund	Mean annual return	Mean annual standard deviation	Mean Sharpe Ratio	P-value (returns)	P-value (Sharpe)	Ending value of $1 invested
Benchmark	**12.4%**	**11.1%**	**1.32**	–	–	**2.56**
iShares Edge MSCI Min Vol USA ETF	11.6%	8.6%	1.32	0.87	1.00	2.46
Invesco S&P 500 Low Volatility ETF	10.6%	9.0%	1.10	0.71	0.73	2.25
iShares Edge MSCI Min Vol EAFE ETF	5.4%	9.8%	0.46	0.18	0.21	1.48

Source: Compiled based on author’s calculations

In conclusion, the low volatility strategy was not able to achieve significantly different returns than the benchmark. However, the reader might have focused their attention on the standard deviations of the ETFs. Table 3 shows that the mean standard deviations of the ETFs were lower than that of the benchmark, in percentage terms. However, when examining the Sharpe ratios, which take into account both the returns and the standard deviations of the ETFs, no statistically significant difference was found to the benchmark.

3.2.3 Value

Nine value ETFs were included in the sample. All of them had monthly return data from the beginning of 2007, and thus, both time periods were taken into consideration. From the sample as a whole, the value strategy was the most represented strategy data-wise. As mentioned in chapter 1.5, the value strategy attempts to recognize companies whose market price does not reflect their fundamental value. This approach may be problematic due to there not being a single right way to determine a company’s fundamental value or the so-called intrinsic value. Additionally, during a strong bull market, it might be hard to find these so-called “undervalued companies” with which to achieve extraordinary returns.

Table 4 displays the performance of value ETFs during the initial time period. During this time, no statistically significant difference was found between the results of the value ETFs and the benchmark index. The reader may pay attention to the last ETF in the table, which had negative annual returns and a negative Sharpe ratio for the time period. However, only with a significance level below 80%, it would have rejected the null hypothesis. Therefore, the author considers the given fund an outlier in this sample.

Table 4. Value strategy, 2007-2019

Fund name	Mean annual return	Mean annual standard deviation	Mean Sharpe Ratio	P-value (returns)	P-value (Sharpe)	Ending value of $1 invested
Benchmark	**7.34%**	**14.62%**	**0.72**	–	–	**2.24**
iShares S&P Mid-Cap 400 Value ETF	7.33%	17.84%	0.42	1.00	0.58	2.09
Vanguard Mid-Cap Value Index Fund ETF	6.96%	16.96%	0.52	0.95	0.73	2.03
Vanguard Small-Cap Value Index Fund ETF	6.74%	18.87%	0.36	0.93	0.50	1.89
iShares Russell Mid-Cap Value ETF	6.39%	17.02%	0.45	0.88	0.63	1.88
Vanguard Value Index Fund ETF	5.57%	14.05%	0.49	0.75	0.68	1.80
iShares S&P 500 Value ETF	5.19%	15.74%	0.41	0.72	0.59	1.66
iShares Russell 1000 Value ETF	4.96%	15.07%	0.40	0.68	0.58	1.63
iShares Russell 2000 Value ETF	5.42%	19.11%	0.24	0.77	0.37	1.58
iShares MSCI EAFE Value ETF	-1.09%	18.98%	-0.08	0.21	0.15	0.69

Source: Compiled based on author’s calculations

Table 5 displays the results for the alternative time period. Regardless of the shorter time period, no value ETF had results that were significantly different from the benchmark. The value ETF with the lowest figures from the table stands out as an outlier during the alternative time period as well. Although not statistically significant with the given sample size, the difference in percentages can be seen relative to the benchmark.

Table 5. Value strategy, 2012-2019

Fund name	Mean annual return	Mean annual standard deviation	Mean Sharpe Ratio	P-value (returns)	P-value (Sharpe)	Ending value of $1 invested
Benchmark	**12.44%**	**11.06%**	**0.92**	–	–	**2.56**
Vanguard Mid-Cap Value Index Fund ETF	11.22%	12.06%	0.75	0.83	0.64	2.31
iShares S&P 500 Value ETF	10.84%	11.55%	0.75	0.78	0.57	2.25
iShares S&P Mid-Cap 400 Value ETF	11.12%	13.87%	0.64	0.83	0.39	2.25
Vanguard Small-Cap Value Index Fund ETF	10.78%	13.87%	0.62	0.79	0.38	2.19
iShares Russell Mid-Cap Value ETF	10.49%	11.73%	0.70	0.73	0.51	2.18
iShares Russell 1000 Value ETF	10.23%	11.00%	0.73	0.69	0.56	2.15
Vanguard Value Index Fund ETF	9.66%	10.28%	0.72	0.60	0.61	2.07
iShares Russell 2000 Value ETF	9.52%	14.78%	0.49	0.66	0.27	1.96
iShares MSCI EAFE Value ETF	2.89%	13.67%	0.05	0.13	0.12	1.17

Source: Compiled based on author’s calculations

On the whole, the value ETFs in the sample did not exhibit statistically significantly different mean returns or Sharpe ratios than the benchmark. No single p-value was below 0.05, and the null hypothesis was forced to be accepted. Even with a significance level of 90%, no single ETF would have been able to reject the null hypothesis and attain different results relative to the benchmark.

3.2.4 Growth

Lastly, the author examined the growth strategy. As mentioned in chapter 1.5, the growth strategy typically focuses on companies with strong past performance and assumes that the same performance, or better, could continue in the future. The final sample of this paper consisted of seven growth ETFs, which were examined through both time periods.

The results of the growth ETFs during the initial time period are presented in table 6 in cumulative dollar terms and mean annual return terms, the growth strategy achieved higher figures than the benchmark. However, in statistical terms, the returns and the Sharpe ratios were not significantly different from the benchmark. Most of the p-values presented in the table for both tested variables, are clearly in favor of the null hypothesis and far from the alpha.

Table 6. Growth strategy, 2007-2019

Fund name	Mean annual return	Mean annual standard deviation	Mean Sharpe Ratio	P-value (returns)	P-value (Sharpe)	Ending value of $1 invested
Benchmark	**7.3%**	**14.6%**	**0.72**	–	–	**2.24**
iShares Russell 1000 Growth ETF	10.0%	15.0%	0.99	0.65	0.68	3.12
Vanguard Growth Index Fund ETF	9.9%	15.4%	0.92	0.66	0.74	3.07
Vanguard Small-Cap Growth Index Fund ETF	10.3%	19.2%	0.77	0.66	0.93	2.97
iShares S&P 500 Growth ETF	9.4%	14.3%	0.92	0.71	0.75	2.95
iShares S&P Mid-Cap 400 Growth ETF	9.7%	17.1%	0.71	0.71	0.99	2.88
iShares Russell Mid-Cap Growth ETF	9.7%	17.3%	0.91	0.71	0.76	2.86
iShares Russell 2000 Growth ETF	9.6%	19.5%	0.65	0.74	0.91	2.67

Source: Compiled based on author's calculations

Table 7 exhibits that during the alternative time period, the results were not remarkably different from the initial time period. Interestingly, in dollar terms and percentage terms, the figures of the alternative time period were lower than they were in the initial time period. Nevertheless, the t-tests show that no p-value was even close to the alpha of 0.05, which forced the author to accept the null hypothesis again.

Table 7. Growth strategy, 2012-2019

Fund name	Mean annual return	Mean annual standard deviation	Mean Sharpe Ratio	P-value (returns)	P-value (Sharpe)	Ending value of $1 invested
Benchmark	**12.44%**	**11.06%**	**1.32**	–	–	**2.56**
iShares Russell 1000 Growth ETF	14.68%	11.76%	1.56	0.69	0.77	3.04
Vanguard Growth Index Fund ETF	14.34%	12.23%	1.43	0.74	0.89	2.95
iShares S&P 500 Growth ETF	13.92%	11.27%	1.47	0.79	0.83	2.88
iShares Russell Mid-Cap Growth ETF	13.61%	12.71%	1.38	0.84	0.94	2.77
Vanguard Small-Cap Growth Index Fund ETF	13.03%	14.28%	1.14	0.93	0.81	2.60
iShares Russell 2000 Growth ETF	12.97%	15.78%	1.01	0.94	0.66	2.54
iShares S&P Mid-Cap 400 Growth ETF	11.86%	12.69%	1.00	0.92	0.62	2.41

Source: Compiled based on author's calculations

Concluding the results of the growth ETFs, no statistically significant difference was found to the benchmark. However, it should be noted than in terms of cumulative returns and percentages, the final figures of the growth ETFs were almost always more positive than the figures of the other strategies. In a statistical context, this remark is irrelevant, since no statistical significance was found with the given figures.

3.3. Cumulative returns

As a small experiment, the author additionally conducted the t-tests for cumulative returns of the strategies. The author derived the cumulative returns of each ETF by calculating the growth in the value of one hypothetical dollar. The dollar was presumed to be invested at the beginning of the time period and held for the entirety of it. For easier interpretation, each smart beta strategy was represented by an equally weighted hypothetical portfolio, that the author had compiled based on the funds in the sample. In the equally weighted portfolios, each ETF of a given strategy got an equally sized weight in the representative portfolio as a whole. For example, each low volatility ETF represented a third of the weight of the entire equally weighted low volatility portfolio.

The two-tailed t-test was used in the same manner as for the non-cumulative return calculations. The non-directional null hypothesis assumed no significant difference between the mean values of the equally weighted portfolios and the benchmark. Table 8 represents the statistical significance of the cumulative growth of one dollar in the smart beta strategies and the benchmark during the initial time period. The test does not take the low volatility strategy into account, due to a lack of data for the initial time period. The results show that there is no statistically significant difference in the cumulative value of one dollar between the dividend strategy and the market benchmark. However, there seems to be a statistically significant difference between the benchmark, the value, and the growth strategies. In the case of the value strategy, the null hypothesis is rejected, and a negative difference to the benchmark is recognized. Contrarily, the growth strategy rejects the null hypothesis as well but shows evidence of a positive difference to the benchmark.

Table 8. Statistical significance, T-test, Value of $1, 2007-2019

	Average value of $1	**Difference to benchmark**	**P-value**	**H0**	**Ha**
Dividend	1.19	-0.06	0.167	Accept	Reject
Value	1.10	-0.14	0.001	Reject	Accept
Growth	1.55	0.31	0.000	Reject	Accept
Benchmark	1.25	0.00	-	-	-

Source: Compiled based on author’s calculations

Table 9 displays the statistical significance of the difference in cumulative returns during the alternative time period. The results show that with regards to the dividend, low volatility, and value strategies, the null hypothesis should be rejected, and the alternative hypothesis accepted. The test shows a significant negative difference between the cumulative returns of the three smart beta strategies mentioned and the benchmark. On the other hand, the cumulative returns of the growth strategy were close to the benchmark index’s, and the difference was not statistically significant. The null hypothesis was accepted in the case of the growth strategy.

Table 9. Statistical significance, T-test, Value of $1, 2012-2019

	Average value of $1	**Difference to benchmark**	**P-value**	**H0**	**Ha**
Dividend	1.51	-0.20	0.00007	Reject	Accept
Low volatility	1.48	-0.23	0.00001	Reject	Accept
Growth	1.79	0.08	0.21848	Accept	Reject
Value	1.59	-0.13	0.01234	Reject	Accept
Benchmark	1.71	0.00	-	-	-

Source: Compiled based on author’s calculations

Contrasting these findings with the ones presented at the beginning of chapter 3, the reader might be rather surprised. However, the author wanted to emphasize that the findings presented in the chapters before the cumulative returns are of higher relevant. For one, equally weighting the portfolios for each strategy does skew the final results. The equally weighted portfolio is an average of the results of the individual ETFs within the sampled strategy. The sample may not be fully representative, and outliers might be present. What is more, the cumulative returns assume the investor to hold their money for the specified time window and does not take into account inflation. Conclusively, a more realistic picture is drawn by the average returns and the risk levels observed of the funds from non-cumulative returns.

3.4. Expense ratios

Expense ratios represent the fees charged from the investors by the fund managers on an annual basis as compensation for the portfolio management of a given fund. From an investor’s point of view, low expense ratios create an illusion of more retained profits from the total returns of a fund. The said illusion may be appealing, but an important notion is that lower expense ratios do not equal higher returns automatically since numerous other factors affect the final returns of any investment fund. Passively managed funds can be considered to be one of the most cost-effective investment products available since they can keep their expense ratios low by following a certain passive index. On the other hand, actively managed funds charge higher expense ratios as compensation for the higher amount of trades executed in a similar time period. One author of an article on asset management fees, argues that the fees charged by active managers are exaggerated compared to the efficiency they are providing for their investors (Malkiel, 2013). The previous argument resonates with the idea behind smart beta, of bringing efficient returns to investors with low fees. Therefore, the passive-active approach of smart beta should place itself in the middle of the two strategies mentioned earlier, in terms of annual expense ratios.

Appendix 1 is compiled based on the prospectuses of the sampled ETFs and the author's calculations. It displays the expense ratios of each sampled smart beta ETF and the benchmark for the year of 2019. The ETFs are categorized by the strategy they represent. Additionally, the arithmetic average of all the smart beta ETFs is shown on the bottom. The table shows that the average smart beta fund from the sample has an expense ratio of 0.17 percent.

A study conducted by Morningstar in 2019, regarding 2018 fees, showed that the average expense ratio of active mutual funds in the US was 0.48 percent (Morningstar Research, 2019). The same study highlighted that the fees of US mutual funds had exhibited a steep decline since the year 2000 when it was reported that the average expense ratio of mutual funds was 0.93 percent. Then again, the average fees of passive funds were reported to be around 0.15 percent in 2018. The findings of the previously mentioned Morningstar study does place the sampled smart beta funds in a good light. The average fees of the smart beta funds were close to the average fees of entirely passive funds and lower than the average of 0.48 percent stated for active mutual funds. It should be noted that the Morningstar research averages were based on 2018 figures, while the author's data was based on the most recent 2019 prospectuses. Another interesting notion is that Vanguard seemed to offer lower expense ratios for its smart beta funds than the other asset managers.

3.5. Discussion

The purpose of this study was to examine how a randomly selected group of smart beta ETFs would perform when compared to a cap-weighted benchmark index. The time period was chosen under the availability of data and did not have other reasoning behind it. The study aimed to find evidence of a significant difference between the returns of the smart beta ETFs and the market benchmark. The smart beta ETFs sampled were tested independently, and any combinations of the different strategies were not created.

The results of this study showed that when testing for the significance of the difference in mean monthly returns, not enough evidence was found for the difference to be statistically significant. Therefore, the author was forced to accept the hypothesis that no smart beta strategy, in general, was able to overperform the returns of the chosen market benchmark.

However, when testing for differences in cumulative returns of the strategies and the benchmark, the author found some exceptions. During the initial time period, the value and the growth strategies both exhibited a statistically significant difference to the market benchmark. The value strategy delivered a significantly lower return and the growth strategy a significantly higher return than the benchmark. Additionally, during the alternative time period, all other strategies than the growth strategy exhibited a statistically significant difference to the benchmark. The difference, however, was negative and showed evidence of returns lower than the benchmark. Overall, the findings were surprising, since the author had a premise of all smart beta strategies exhibiting higher returns than the market benchmark.

Based on this paper's findings, the author attempted to answer the questions initially presented in the introduction chapter:

1) Can weighing indices based on the market capitalization of their underlying equities be considered inefficient?
Regarding investor psychology, the market cap-weighted indices can be considered inefficient if the investors assume the market to be informationally efficient. This remark was made by Haugen and Baker (1991). However, when considering the returns that the cap-weighted benchmark has produced during the periods chosen for this study, the conclusion might be different. The tests for statistical significance exhibit no evidence of a difference in the returns between the smart beta ETFs and the benchmark index. Therefore, based on these results, the market cap-weighted benchmark cannot be deemed inefficient.

2) Can investing based on fundamental factors create excess market returns?
Based on the results of this paper, no single smart beta strategy was able to generate statistically significant returns over the benchmark index during both time periods. However, in a hypothetical cumulative growth approach, the growth strategy exhibited a statistically significant difference

over the market benchmark during the initial time period of 2007-2019. Nevertheless, the premise that no excess returns are generated holds for this sample overall.

3) Can the returns of the smart beta strategies be associated with better risk-reward levels relative to the market benchmark?

The results of this paper show that no significant difference was found between the Sharpe ratios of the smart beta ETFs and the benchmark index. Strictly speaking, based on this sample size, it cannot be said that any enhanced risk-reward levels were found.

4) Should investors use smart beta strategies as additional components or sole components in their portfolio?

Based on the finding of this paper, no significant difference was found in the returns or the Sharpe ratios of the smart beta ETFs relative to the benchmark. Yet, due to the size of the sample in this study, the results should not solely be used for investment opportunity evaluation. However, one previously mentioned article pointed out that the low volatility strategy might be used as a portfolio risk management tool (Bender, 2013). This would suggest that at least some approach to smart beta might be used as an additional component to a portfolio as a whole.

Previous research on the topic of smart beta has found somewhat similar results. On a paper published in Advisor Perspectives in 2016, the authors similarly suggest that a longer testing period should be used for more relevant conclusions to be made on smart beta performance (Arnott;Beck;Kalesnik;& West, 2016). Additionally, the authors argue that rising overall valuations in the market may have caused high returns of smart beta funds, and they do not reflect the performance potential sustainably. The authors of a previously mentioned article by MSCI argued that smart beta has the potential to disrupt the traditional mutual fund industry (Bender, 2013). Their suggestion for the future is that active management will be divided between smart beta funds and pure alpha delivering mutual funds. Combinations of the two can be challenging to implement, they argue. The author of this paper agrees with these suggestions as well. The expense ratios compiled in Appendix 1 showcase how small the added expense for smart beta can be. Since the expense ratios of smart beta ETFs were closer to those of passive funds rather than active funds, the MSCI argument about the future can potentially hold. Finally, a paper written by Malkiel in 2014, also argues that the success of any smart beta strategy depends highly on the valuation of the securities at the time of the initial investment (Malkiel, 2014). His findings showed that smart beta funds rarely produced excess returns, and when they did, the added return came with an added risk.

The limitations of the study arise from smart beta overall being a newly adopted investment style. This results in limited amounts of pricing data available for all strategies. Another limitation arising from the sampled ETFs was that while representing a certain major smart beta strategy, some of them also exhibited characteristics of different market segments. For example, some of the sampled ETFs focused additionally on small-cap or mid-cap companies, instead of being purely value- or growth-oriented. Thus, the funds do not represent a raw mono-factor strategy essentially.

For future research, the author suggests the use of a more extended time period for the added statistical significance of the results. Additionally, the author suggests researching multi-factor smart beta strategies in addition to the mono-factor strategies presented here. It would be intriguing to find out if combinations of smart beta strategies could potentially create excess returns over a market benchmark. Finally, the author would suggest future researchers of the topic to analyze the possible effects of financial crisis' or black swan events on smart beta strategies. As the paper itself was written during a black swan event, the author would be curious to know whether smart beta strategies perform better or worse than the market when extraordinary events affect asset prices.

CONCLUSION

The author of this paper began the study with a premise that cap-weighted indices were inefficient investment options and that fundamental-based funds could create better returns during a longer time period. Therefore, this study aimed to find evidence that proves the inefficiency of cap-weighted indices and displays possible excess return capabilities of factor-based smart beta funds. The author focused solely on the United States stock market and used availability sampling to collect data for the study. The final sample of ETFs represented four different, and commonly known, smart beta strategies. These strategies were dividend, low volatility, value, and growth. The returns of the different ETFs and smart beta strategies as a whole were compared to a capitalization-weighted benchmark that took the role of the market return. The benchmark index used was the Standard & Poors 500 index, which is one of the most commonly used benchmarks in finance. The author chose to analyze the results during two time periods of different lengths. The reasoning behind the choice was twofold. Firstly, the author wanted to include all the sampled smart beta strategies in a relevant way to the analysis. Secondly, the author wanted to compare the returns of the smart beta strategies in the case of different timing of the initial investment.

The results of the study showed that on a monthly return basis, none of the sampled smart beta strategies were able to produce statistically significant returns over the market benchmark. However, when the cumulative returns of the strategies over the chosen time periods were examined, statistically significant results arose. During both periods of examination, the growth strategy produced either similar or significantly higher returns than the market benchmark. Conversely, the three other strategies exhibited signs of significant returns below the market benchmark. These findings were in line with previous research done on the subject.

For future research, the author suggests the use of a longer time period for analyzing the returns. As pointed out by previous research as well, there is yet only a little evidence of the long term success of the smart beta investment strategy overall. Additionally, future research would be encouraged to have the inclusion of different market conditions. The results for this paper were recorded during a rising market condition, where optimistic buyers possibly skew asset valuations. Therefore, a rising market does not show the true nature of the smart beta strategies, and the reactions to a sudden market downswing might be unprecedented. Finally, the author suggests future research to include multi-factor smart beta strategies to their samples. The performance characteristics of these types of hybrid-funds are yet rather unknown.

The author believes this research to be informative for investors considering alternatives to cap-weighted indices, or even financial professionals yet not aware of the smart beta investment style. This study should not, however, be used as a basis for any investment decisions due to its limited time span and a limited variety of strategy specific funds.

REFERENCES

Amenc, N., Goltz, F., Lodh, A., & Martellini, L. (2014). Towards Smart Equity Factor Indices: Harvesting Risk Premia without Taking Unrewarded Risks. *The Journal of Portfolio Management, Vol. 40, No. 4*, 106-122.

Arnott, R., Beck, N., Kalesnik, V., & West, J. (2016). *How Can "Smart Beta" Go Horribly Wrong?* Advisor Perspectives, Available at SSRN 3040949.

Bender, J. (2013). Foundations of Factor Investing. *Research Insight*, 2. Retrieved from msci.com.

Cazalet, Z., Grison, P., & Roncalli, T. (2014). The Smart Beta Indexing Puzzle. *The Journal of Index Investing 5.1*, 97-119.

Elton, E. J., & Gruber, M. J. (1998). Modern Portfolio Theory, 1950 to Date. *Department of Finance Working Paper Series 1998*, 1-35.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, 427-465.

Fama, E. F., & French, K. R. (2004). The Capital Asset Pricing Model: Theory and Evidence. *Journal of Economic Perspectives, Volume 18, Number 3*, 25–46.

Gastineau, G. L. (2008). Exchange-Traded Funds. In F. J. Fabozzi, *Handbook of Finance, Volume I. Financial Markets and Instruments, 6. Investment Companies, ETFs, and Life Insurence Products* (pp. 633-641). Wiley.

Haugen, R. A., & Baker, N. L. (1991). The efficient market inefficiency of capitalization-weighted stock portfolios. *The Journal of Portfolio Management*, 35-40.

Kahn, R. N., & Lemmon, M. (2016). The Asset Manager’s Dilemma: How Smart Beta Is Disrupting the Investment Management Industry. *Financial Analysts Journal*, 15-20.

Kostovetsky, L. (2003). Index Mutual Funds and Exchange-Traded Funds. *The Journal of Portfolio Management*, 80-92.

Lo, A. W. (2002). The Statistics of Sharpe Ratios. *Financial analysts journal 58.4*, 36-52.

Malkiel, B. G. (2003). Passive Investment Strategies and Efficient Markets. *European Financial Management, Vol.9, No. 1*, 1-10.

Malkiel, B. G. (2013). Asset Management Fees and the Growth of Finance . *Journal of Economic Perspectives, Vol. 27, N. 2*, 97-108.

Malkiel, B. G. (2014). Is Smart Beta Really Smart? *The Journal of Portfolio Management*, 127-134.

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance, Vol. 7, No. 1*, 77-91.

Morningstar. (2006). *Morningstar.com's Interactive Classroom*. Retrieved from Course 203: Understanding the News, The S&P 500: http://news.morningstar.com/classroom2/course.asp?docId=144045&page=4&CN=COM#

Morningstar Research. (2019, April). *Morningstar's Annual U.S. Fund Fee Study.* Retrieved from Morningstar: https://www.morningstar.com/lp/annual-us-fund-fee-study?con=17040&cid=CON_RES0077

Ravo, N. (2019, 10 6). *ETFs Get All the Buzz, but Mutual Funds Still Dominate. There's a Reason.* Retrieved from The Wall Street Journal: https://www.wsj.com/articles/etfs-get-all-the-buzz-but-mutual-funds-still-dominate-theres-a-reason-11570414020

Rubinstein, M. (2002). Markowitz's "Portfolio Selection": A Fifty-Year Retrospective. *The Journal of Finance*, 1041-1045.

Sharpe, W. F. (1966). Mutual Fund Performance. *The Journal of Business, Vol. 39, No. 1, Part 2: Supplement on Security Prices*, 119-138.

APPENDICES

Appendix 1. Annual expense ratios of the sampled funds, 2019

Full name of the fund	Annual management fee
Benchmark	
SPDR S&P 500 ETF Trust	0.10%
Dividend	
SPDR S&P Dividend ETF	0.35%
iShares Core High Dividend ETF	0.08%
Schwab US Dividend Equity ETF	0.06%
Vanguard Dividend Appreciation Index Fund ETF	0.06%
Vanguard High Dividend Yield ETF	0.06%
Low Volatility	
Invesco S&P 500 Low Volatility ETF	0.25%
iShares Edge MSCI Min Vol EAFE ETF	0.20%
iShares Edge MSCI Min Vol USA ETF	0.15%
Value	
iShares MSCI EAFE Value ETF	0.39%
iShares S&P 500 Value ETF	0.25%
iShares Russell 2000 Value ETF	0.24%
iShares Russell Mid-Cap Value ETF	0.24%
iShares Russell 1000 Value ETF	0.19%
iShares S&P Mid-Cap 400 Value ETF	0.18%
Vanguard Mid-Cap Value Index Fund ETF	0.07%
Vanguard Small-Cap Value Index Fund ETF	0.07%
Vanguard Value Index Fund ETF	0.04%
Growth	
iShares Russell 2000 Growth ETF	0.24%
iShares Russell Mid-Cap Growth ETF	0.24%
iShares S&P Mid-Cap 400 Growth ETF	0.24%
iShares Russell 1000 Growth ETF	0.19%
iShares S&P 500 Growth ETF	0.18%
Vanguard Small-Cap Growth Index Fund ETF	0.07%
Vanguard Growth Index Fund ETF	0.04%
Average	
Average smart beta ETF expense ratio	0.17%

Appendix 2. Non-exclusive license

A non-exclusive license for reproduction and for granting public access to the graduation thesis[1]

I, Lauri Kaijomaa

1. Give Tallinn University of Technology a permission (non-exclusive license) to use free of charge my creation,

Evaluating the performance of smart beta investment funds in the US stock market

supervised by Karin Jõeveer,

1.1. to reproduce with the purpose of keeping and publishing electronically, including for the purpose of supplementing the digital collection of TalTech library until the copyright expires;

1.2. to make available to the public through the web environment of Tallinn University of Technology, including through the digital collection of TalTech library until the copyright expires.

2. I am aware that the author will also retain the rights provided in Section 1.

3. I confirm that by granting the non-exclusive license no infringement is committed to the third persons' intellectual property rights or to the rights arising from the personal data protection act and other legislation.

[1] *The non-exclusive license is not valid during the access restriction period with the exception of the right of the university to reproduce the graduation thesis only for the purposes of preservation.*