ECONOMICS AND BUSINESS ADMINISTRATION FACULTY
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MASTER THESIS

SMART BETA STRATEGIJŲ TAIKYMAS IR VERTINIMAS	SMART BETA STRATEGIES APPLICATION AND ASSESSMENT

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INTRODUCTION

In modern economic conditions, the stock market is gaining an increasingly important role in the accumulation of investment resources. In order to achieve a positive result of investing in the securities market, by reducing the risk of investment operations and increasing their profitability, market participants create portfolios of securities. Portfolio risk and return management and portfolio optimization in constantly changing market is a main objective for portfolio managers, investors, financial advisers and etc.

A factor investing, or smart beta can be considered any of the characteristics of a securities group that are important in explaining their profitability and risk. There are three main categories of factors: macroeconomic, statistical and fundamental (Connor, 1995).

Currently, the most popular factors - value, growth, size, dividend yield, quality - have been studied for decades as part of the academic literature on asset pricing and practical research on portfolio constructing. The theoretical and methodological basis of this study is the works of leading experts on the formation and management of the investment portfolio.

The factor investing have a long story and have been investigated by various authors such as: Rosenberg and Marathe, who were among the first in 1976, who describe the importance of stock features explaining stock returns, which led to Barra factor risk model. Eugene Fama and Kenneth French in the early 1990s represent the three factors model, in 1997 the four factors models were characterized by Mark Carhart. Later in 2015 Eugene Fama and Kenneth French test the five-factor model. Different authors were investigating various factors during this time. Momentum factor were mentioned by Fama and French (2012), Griffin, Ji and Martin (2003), Lewellen (2002), Rouwenhorst (1998). Volatility - Ang A. et al (2006), Beveratos et al (2017), value – Piotroski (2000), Chan et al (2004), Cakici at el (2017), dividend yield – Seaton et al (2005), quality -Novy-Marx (2014). Also, in 2016 Kahn and Lemmon suggested that factor-based investment strategies, often referred to smart beta, represent a breakthrough innovation in the wealth management industry.

The novelty of the study consists, firstly, in the breadth of data coverage included in the analysis during the specified period from 1999 to 2020: two big crisis (2001, 2008) and low interest rate environment in US from 2008 till 2016. These periods allow to disclose the most profitable strategies during such periods in economy. Secondly, multivariance of the portfolio calculations permit to make comparable analysis between smart beta single factor portfolios against Markowitz portfolio and benchmark. Also, this study determines and build an effective methodology for the formation and management of the investment portfolio, taking into account specifics multiples. T**he problem** of particular topic is that investors and portfolio managers at all times making research in field of portfolio construction to achieve excessive return comparing to market and traditional indices. In last decades the most popular theme among investment professionals became smart beta approach and this approach exposure to their investment's portfolio.

The theoretical value of the study lies in the analysis and evaluation of existing methods for the formation and management of an investment portfolio, as well as the creation and verification of the practical smart beta applicability of investment portfolios in real market.

Practical value of this thesis is an evident for investors and portfolio managers of mutual and hedge funds, that such approach in portfolio construction have profitableness and help to design the portfolio according to investors targets based on predefined system of rules. And from this point of view could help to avoid human factor in decision making process.

Object of the research is to analyze the smart beta strategies performance during 1999-2020 period. **The aim** of the thesis is to evaluate smart beta various strategies of portfolio construction methodology in case of various US sectors using Nasdaq Composite Index constraints. Elaboration of the tools used in the literature under this thesis review, as well as identifying the possibility of the benefits of smart beta single factor strategies.

The tasks:

1. to analyze theoretical basis of investment management and smart beta global practice.
2. to analyze portfolio construction methodology based on smart beta approach.
3. to perform comparable analysis of smart beta single portfolios relative to traditional SPDR S&P 500 ETF Trust index and 1 Markovitz theory-based portfolio.

Research methods and tools. To make successful research, here would be used several different research methods: econometric, financial and mathematical tools considered in the literature review: comparable analysis, Markowitz's theory for building an optimal portfolio, factor investing methodology. In this research several external data sources used: Bloomberg, Morningstar fundamental library and QuantConnect LEAN Python engine for simulation real trading condition and build algorithm. These methods and tools bring necessary information to do correct conclusions and analyze limitations of this research.

Research consist of three chapters. First chapter analyze market efficiency hypothesis and disclose two opposite notions: efficient market and fractal market. Also, main market anomalies groups which observed in a market have been identified. Additionally, world practice of active and passive investment management review has been performed and analyzed main existing trends. Second chapter set out research workflow and factor-based portfolio construction methodology and research portfolio formation itself. Last chapter provide empirical result analysis of constructed portfolios.

1. SMART BETA: THEORETICAL BACKGROUND

1.1. Theoretical research in the field of investment portfolio management.

Portfolio investment allows to plan, evaluate, monitor the final results of all investment activities in various sectors of the stock market. The process of forming the securities portfolio can be decomposed into two main stages:

1. Identification of investment objectives (capital preservation, income generation, capital gains and etc.)

2. Definition of investment strategy.

Portfolio management is the ability to manage a set of securities so that they not only preserve their value, but also bring high returns. Let's look at the portfolio construction method existed before. The most important fact is that in earlier years investors seeking to maximize their return on investments and portfolio managers were rewarded for such portfolio performance as well. The managers using such technics:

1. Choosing the right entry and exit points (market timing)

2. Finding undervalued securities (stock prices)

This approach worked practically and theoretically during the first half of the 20th century and continuing to be used now. Decision to select the moment of purchase and sale of the security portfolio manager used technical and fundamental analysis. Technical analysis allows predicting price movements on repeated patterns basis. Fundamental analysis allows portfolio manager to find undervalued securities. Such securities whose market price are lower than the intrinsic value of the business could have a potential in the future. This fundamental analysis approach was well described in the works of B. Graham and D. Dodd (1934). But portfolio management continuing to evaluate, and many other approaches were discovered till now. To determine opportunity to use the smart beta approach in this study case it is needed to review the efficient market hypothesis theory to identify the theoretical confirmation of smart beta possibility seeking to generate excess return in the market.

Efficient market hypothesis.

In the academic literature, the Efficient Market Hypothesis dates back to 1965 when F. Fama published his Ph.D. “The Behavior of stock market prices”, which was later released in the same year under the title “Random Walks in Stock Market Prices”, the initial hypothesis postulates that the price of a security reflects all the information available on the market, that is, the future price of the paper is based on random walks and cannot be predicted by any means.

That means for investor and securities analysts, what all prices of financial assets individually selected at any given point of time through a meaningful investor's perception of all information at their disposal, reflect the internal and fundamental value of the assets. Thus, neither the technical analysis aimed to analyze price trends in the past, nor the fundamental analysis investigating the financial statements of companies, can provide with a sufficient degree of confidence the choice of relatively undervalued securities.

However, the term "efficiency" means that investors, compared to other investors, cannot obtain abnormal returns from capital market operations and cannot bit the market. The concept of market efficiency has profound implications for modern financial theory. This hypothesis has been repeatedly confirmed and at the same time repeatedly refuted. One of the causes of potential market inefficiency or price response to event reporting is delayed because investors are careless. This is a widely discussed topic in specialized literature: DeLong, Schleifer, Baker, Rubek, Wurgler, Della Vina, Pollet, Hirschleifer, Lim, et al. Returning over the course of the EMH is theoretically simple but has been proven to be very difficult to verify and provide an accurate result. Because economists have not agreed on any of the three forms of EMH, some researchers and eminent scientists have hypothesized that the reason why EMH does not support models is because the models themselves are biased and can lead to incorrect results (Titan, 2015).

For example, the hypothesis of an efficient market was supported by research: on the US stock market for the years 1962-1987; on the British stock market for 1965-1990; Brazilian Ibovespa stock index; by 18 indices of industrialized countries for 1970–1992, calculated by Morgan Stanley Capital International. But the following research has rejected the efficient market hypothesis: stock markets of Austria, Italy, Spain, Korea, Malaysia, New Zealand and Singapore for 1983–1998; an assessment of the profitability of the Australian stock market in 1876–1996, made by the McKenzie company; monthly data of stock markets of Japan and China; weekly quotes 30 Greek Blue Chips (ASE30) (Abdulin, 2015). These empirical research confirm what capital market can be also inefficient.

Fractal market hypothesis

From this point of view, we can analyze the alternative hypothesis which were provided by B. Mandelbort - Fractal Market Hypothesis. The fractal market hypothesis (FMH) were developed and applied to financial markets in E. Peters works. The main statements of the FMH are as follows (Nekrasova, 2015):

1. The market is stable when it is made up of investors with different investment horizons. This ensures a high liquidity of the financial markets.

2. When investors with long investment horizons stop participating in the market or become investors themselves in the short-term horizon, financial markets become unstable.

3. Prices are formed under the influence of information obtained from both technical analysis and fundamental information.

4. The liquidity of the financial markets is not associated with the volume of trading. Since the biggest financial crisis occurred, as a rule, in the context of large trading volumes.

5. The importance of information in financial markets is determined by the investment horizon of the investor. Given that investors with different investment horizons evaluate information differently, the distribution of information in the market will also be uneven.

6. The source of liquidity in financial markets are investors with different investment horizons, different sets of information and, therefore, with different perspectives of a fair price.

According to the Fractal Market Hypothesis, financial markets are characterized by varying degrees of elasticity, which can be defined as the ability to take and maintain form. This means that markets can change significantly in terms of their form and functions, and that they can maintain changes in the form of newly acquired properties, even if the reasons for such changes cease to exist. The elasticity of a financial market is a dual construction; it implies both the ability to change and the ability to retain (hold) the form for a prolonged period. All markets are elastic, but the degree of elasticity can change, so studying the relationship between variability and stability will allow to better understand the dynamics of the market (Nekrasova, 2015).

The Hurst exponent can be defined on the interval [0, 1], and is calculated within the following limits (Sviridov, 2016):

− $0 \leq H < 0{,}5$ – data is fractal, the FMH is confirmed, «heavy tails» of distribution, antipersistent series, negative correlation in instruments of value changes, pink noise with frequent changes in direction of price movement, trading in the market is more risky for an individual participant;

− $H = 0{,}5$ – data is random, the EMH is confirmed, movement of asset prices is an example of the random Brownian motion (Wiener process), time series are normally distributed, lack of correlation in changes in value of assets (memory of series), white noise of independent random process, traders cannot «beat» the market with any trading strategy;

− $0{,}5 < H \leq 1$ – data is fractal, the FMH is confirmed, «heavy tails» of distribution, persistent series, positive correlation within changes in the value of assets, black noise, the trend is present in the market

Smart beta anomaly.

Investment risk strategies can also be based on a variety of market anomalies that result in a return system with an acceptable level of risk. Some of these anomalies (calendar, technical and fundamental) are well described and verified at different times in developed and emerging capital markets (US, Western Europe, Canada, BRICS, etc.) (Singh, 2014, Atsin et al, 2015, Caporale, 2017).

Thus, the theoretical and empirical results of research on capital markets show that there have been many anomalies that are not predictable through modern tools of analysis and evaluation, as well as an explanation in the framework of the provisions of the neoclassical theory of finance. (Kozlova, 2016) The main idea of anomalies is to have a stable configuration or set of rules that allow portfolio manager or investor to generate higher return than efficient market hypothesis models, all other things being equal. Such definition closely related to smart beta definition, and from this side we can observe anomalies as a basis for smart beta strategy creating. Experts on this issue usually identify anomalies in three type: calendar, technical and fundamental (Singh (2014), Atsin et al (2015), Caporale (2017)).

Calendar anomalies.

Analysts point out such anomalies in terms of the impact of economic exposure as "January. Effect” or "New Year rally", when prices rising in January. "summer effect", where low profitability and trading activity in the region between May and October compared to profitability in November – April periods; “Turn-of-the-Month Effect”: when prices increase in the last week of December and the first half month of January, the last or the first day of the week and named as “Weekend Effect” (Latif et al, 2011).

Such evidence was provided in 1994. Presented by Agarwa and Tandon Research based on stock market data from Australia, Belgium, Brazil, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Luxembourg, Mexico, the Netherlands, New Zealand, Singapore, Sweden, Switzerland, United Kingdom, United States. 1987. and evidence of the lowest and negative returns on Monday in 9 of 18 countries; By the way, Friday's earnings are positive for all stock indices except the Luxembourg stock index. (Guidi, 2011). Also, in Engelberg, McLean and Pontiff (2018) academic research using a sample of 97 stock return anomalies, were found out that anomaly returns are 50% higher on corporate news days and six times higher on earnings announcement days. Such results could be explained by dynamic risk, mispricing due to biased expectations, or data mining.

Technical anomalies.

The second type of anomalies and the possibility of constructing investment strategies are associated with technical analysis, which allows to build and test various strategies. Therefore, it is assumed that the investors use past prices dynamics in the future, as well as the prices of financial instruments follow these trends. In 2001, Hons & Tonks studied trading tactics such as the impact of momentum in the US stock market from 1977 to 1996. According to the study, investors can gain an advantage by using momentum strategies, buying past winners and selling past losers. Investors can get abnormal profits. A portfolio is formed by organizing stock returns and ranking them. The highest rated shares are rated as losers, and the lower ones as a portfolio of winners. This approach shows that the return on the winner's portfolio is greater than the return on the loser's portfolio, because the winner's portfolio is riskier than the portfolio of the loser.

Fundamental anomalies.

Anomalies of fundamental analysis show that stocks with defined unified fundamental characteristics allow the investor to earn a systematic return on profitability. For example: the value premium is consistent with empirical evidence showing that value shares (stocks with high BM or EP ratios) have higher average returns than growth stocks (stocks with low BM or EP ratios). The stock duration anomaly follows evidence showing that low-duration stocks have higher average returns than high-duration stocks. A long-term change in the yield anomaly refers to a model in which stocks with low realized returns over the past 5 years have higher subsequent returns, while past long-term winners have lower future returns.(Maio, 2017) Fundamental anomalies also include value anomalies and small cap effect, low price to book, high dividend yield, low price to sales (P/S), low price to earnings (P/E) and etc. (Latif et al, 2011)

The last type on anomalies needed to be implement into this study – „bubbles" as an evidence of market inefficiency. Economic science has known about bubbles for quite some time. The collapse of a "bubble" of any kind also leads to crises and recessions, but economic cycles are regular fluctuations in the level of business activity from economic boom to economic recession with four clearly distinguishable phases: peak, recession, bottom and rise. In each historical period, the emergence and growth of "bubbles" is associated with the accumulation of excess capital and a shift in the direction of its investment from the production sector towards financial markets and speculation. (Rozkov, 2010) The boom of the so-called "dot-com" - companies that named the same as their Internet address, and which were displayed on the IPO in violation of the stringent standards that companies had to adhere to when entering the stock exchange, which resulted in the stock market in the period from 1995 until 2000, it was flooded with extremely overvalued papers of the technology sector, culminating in the fall of the NASDAQ index on March 10, 2000, more than one and a half times the opening level. (Chang et al, 2016). These crises were destructive; the near collapse of the American financial system in 2008 wiped out more than $11 trillion in household wealth. (Nelson, 2014). In table 3 provided the crisis impact on companies' capitalization during 2005-2010 period (Rubcov, 2011).

Table 1

Changes of capitalization of national companies at end of year

Country	2005	2007	2008	2009	2010
Great Britain	24%	26%	-52%	50%	9%
Germany	13%	72%	-47%	16%	11%
Canada	67%	48%	-53%	56%	35%
USA	19%	17%	-41%	28%	15%
Japan	55%	-5%	-25%	6%	19%
India	98%	229%	-64%	102%	25%
China	-22%	1014%	-60%	101%	13%
Russia	170%	151%	-74%	120%	31%
World	**33%**	**49%**	**-48%**	**43%**	**15%**
Median	**32%**	**56%**	**-51%**	**50**	**15%**

Source: Рубцов, Б. Б. (2011). Глобальные финансовые рынки: масштабы, структура, регулирование

As we can see from Table 1 the largest downfall among largest economies were in Russia, India and China exceeding the -60% declining threshold. For over economies it reached -51% on average. From this point of view in always changing market environment should be exist some methods allowing to manage risk and return and "catch" the right anomaly to implement it into strategy. The first quantitative portfolio managing basis were described by Henry Markowitz 50 years before.

Markowitz model

Modern portfolio theory is based on Markowitz's "Portfolio Selection", published in 1952 in the Journal of Finance. Even despite the criticism, this work still remains widespread among investors. The theory of an effective portfolio with Markowitz mean variance optimization is one of the most influential and important among modern investment works. First, this theory claims that investors seek to maximize their reduced expected returns. Therefore, the hypothesis that investors only want to maximize their present expected return can be rejected, since investors also consider the risk aspect. Risk in the model is measured by standard deviation. Moreover, since the maximization of profitability is not sufficient to meet the needs of the investor, Markowitz creates the rule of “expected return – standard deviation of returns”. According to this rule, an investor should diversify his investments among securities that provide the maximum expected return. The combination of various types of securities in a portfolio only partially reduces the standard deviation of expected returns, and only if these securities have a high degree of positive covariance. The covariance between stocks, the expected return and its standard deviation - what is needed for the practical use of the Markowitz model. And only if this information is available using quantitative calculations, is it possible to define a set of “effective portfolios” Following this rule, an investor should choose a portfolio from portfolios on the so-called “efficient portfolio frontier” (an efficient frontier consisting of portfolios that have the maximum mean (expected return) for a given variance of return (or standard deviation of returns) or the minimum variance of return for a given mean (expected return).). Accordingly, to Markowitz's portfolio theory on the efficient frontier dominate among other portfolios. (Trifonov, 2011, Glotova, 2018, Burkalcev, 2016, Marling, 2012).

To make an intermediate conclusion it is need to be stressed, what Markowitz model of portfolio construction does not have the free choice of an optimal portfolio in a whole, it is rather leading to the determination of a set of effective portfolios, each of which gives for portfolio manager the greatest expected return for a certain level of risk. This modeling will be used further for fluffiness of comparable analysis between various portfolios.

However so long as evidence of inefficiency in the market will be exist, here will be empirical researches in the field of opportunistic findings to determine the approach of how to use this inefficiency and investors irrational behavioral to earn excess returns based on variety of stocks or other financial instruments in portfolios. Next sections will describe the place of smart beta strategy beyond passive and active investment management.

1.2. Investment management: beyond passive and active.

Asset management industry has changed from active to passive investment strategies over the last few decades, but anyway in industry there are two main investment strategies: active and passive. Active management model involves careful tracking and immediate acquisition of instruments that meet the investment objectives of the portfolio, as well as a rapid change in the composition of the stock instruments included in the portfolio (Bodrova, 2012).

Therefore, the essence of an active strategy is that investors of an aggressive (active) type are buying securities in anticipation of a sharp increase in their market value. This strategy is associated with a significant degree of risk, but the expected results may be great. Thus, an active strategy involves the acquisition of the most profitable securities, the rapid rotation of the portfolio and getting rid of securities with low yields (Ahmedov, 2014).

Passive management involves the creation of well-diversified portfolios with a predetermined level of risk, calculated for the long term. Such an approach is possible with sufficient market efficiency, saturated with securities of good quality. The duration of the portfolio implies the stability of the processes in the stock market. (Bodrova, 2012)

Therefore, it can be said that passive management is based on the idea that the market itself will determine the level of yield of securities. Within the framework of passive management, it is possible to distinguish a “bought and hold” strategy, which consists in the fact that after forming a portfolio, the securities included in it are kept as long as possible, despite the current fluctuations in the market structure. Conservative investors are focused on getting a small but steady current income, or simply to preserve their assets with a small amount of risk. (Ahmedova, 2014)

Moving further into active and passive fund data. As of December 2017, passive funds accounted for 35 percent of combined U.S. MF and ETF assets under management (AUM), up from three percent in 1995, and 14 percent in 2005. This shift for MFs and ETFs has occurred across asset classes: Passive funds made up 45 percent of the AUM in equity funds and 26 percent for bond funds at the end of 2017, whereas both shares were less than five percent in 1995. (Anadu et al, 2018) According to Morningstar data in 2018 the market share of passive funds increased by to 2% in USA, from historical perspective the overall increase of growth in market share from 16% in 2006 to 37% in 2018 were achieved (Fig. 1). On the other side the market share of active fund decreased from 84% to 63% over this period. On average the passive funds asset under management year over year growth rate was around 16% against only 6 % for active fund during these 12 years (Fig.2).

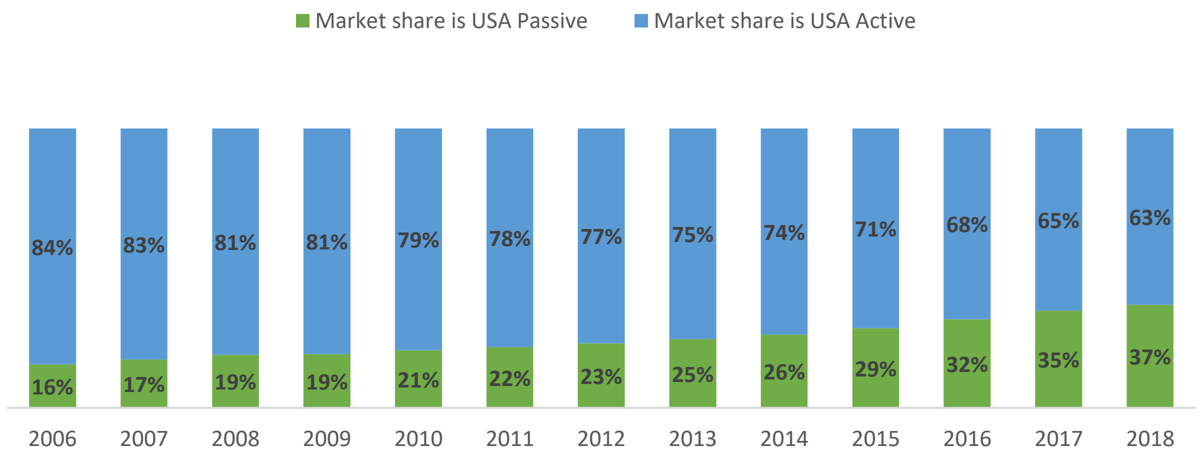


Figure 1 Passive and active market share is USA 2006-2018

Source: Morningstar

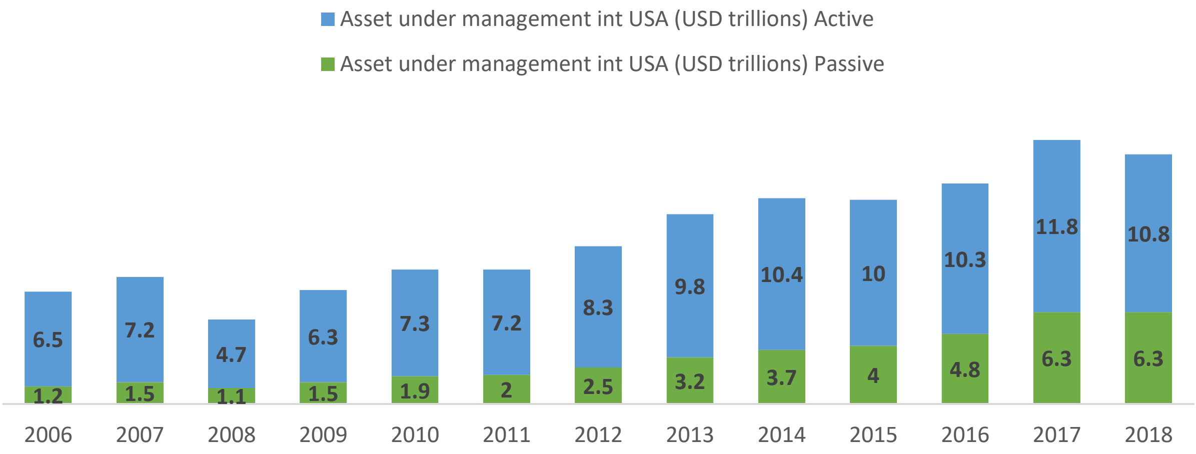


Figure 2 Passive vs Active funds asset under management in USA (USD trillions)

Source: Morningstar

Figure 3 shows the flow of USA money into active and passive fund for 2006-2018 period. In 2018, passive funds were attracted 453 USD billions in total inflows, however active funds suffered outflows of 304 USD billions. As you can see, since 2006 the inflows and outflows in active fund were very volatile and fluctuate between 304 USD billion of outflow and 338 USD billion of inflows, otherwise the passive fund has only positive inflows during this period. On average the passive fund attracted 252 USD billion year over year basis and twice as many compared to active funds with only of 110 USD billion on average. From 2006 to 2018 passive funds attracted 3.8 USD trillion of new investments, compared to only 583 USD billion for active funds.

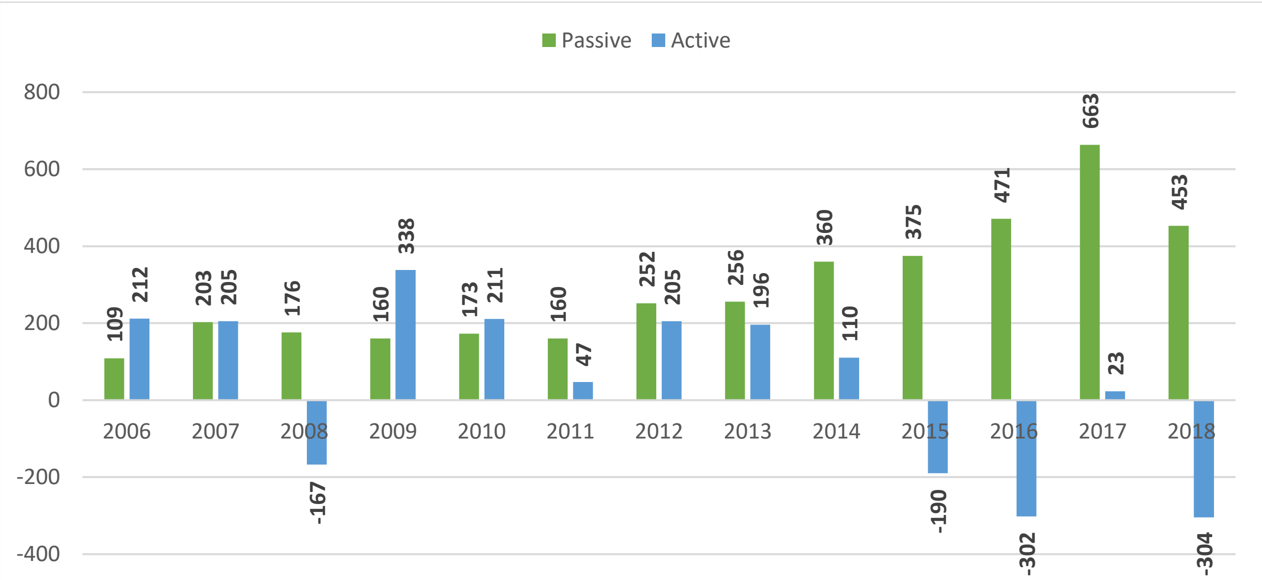
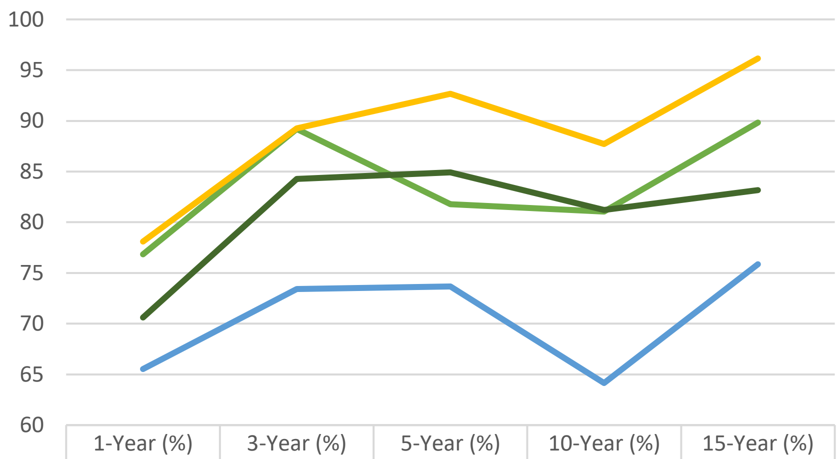


Figure 3 USA flow of funds into Passive and Active Funds, (USD billions)

Source: Morningstar

From international perspective we could investigate the SPIVA statistics, which include the comparison of various S&P indices (passive investment) versus other funds globally. The SPIVA (S&P Indices Versus Active) Scorecard tracks how qualified fund managers are doing compared to their respective indexes.(S&P Dow Jones Indices, 2018) The table below express the percentage of active international equity funds that underperformed their respective S&P benchmarks over one-, three-, five-, 10- and 15-year periods ending of 2018. For all periods only 20% of all international funds outperform their benchmarks As shown in Table 2 only ~24 % best active managed funds in International Small Cap funds category outperform their relative benchmarks. Also the problem here is that identification of next active fund leaders arise, because composition of that top quartile can change yearly, so this year’s leader is probably not going to lead the next year or vice versus (Soe, 2018).



	1-Year (%)	3-Year (%)	5-Year (%)	10-Year (%)	15-Year (%)
International Funds vs S&P International 700	76.84	89.19	81.78	81.07	89.83
International Small-Cap Funds vs S&P Developed Ex-U.S. Small Cap	65.52	73.42	73.68	64.15	75.86
Emerging Markets Funds S&P/IFCI Composite	78.1	89.27	92.67	87.72	96.15
Global Funds S&P Global 1200	70.61	84.26	84.92	81.2	83.16

Figure 4 International Equity Funds Outperformed by Benchmarks, %, 2004-2018
Source: S&P SPIVA

The main role to determine the total return of portfolio also impacted by various fees. By Morningstar U.S. Fund Fee Study provided in 2018 the asset-weighted average expense ratio has dropped every year since 2000. Investors are paying crudely half as much to own funds as they were in the year 2000, when the asset-weighted average fee stood at 0.93%; they're paying 40% less than they did a decade ago and about 26% less than they did five years ago. The asset-weighted average expense ratio of passive funds was 0.15% in 2018 (versus 0.25% a decade ago) compared with 0.67% for active funds (0.86% in 2008). This means active-fund investors are paying about 4.5 times more than passive-fund investors on each dollar, the widest disparity since 2000. The average active fund still charges about 1.8 times as much as the average passive fund. That's basically unchanged from 2017 and slightly higher than 2015, when the average active fund charged about 1.7 times as much as the norm for passive funds. Most smart beta funds are in US stocks. The average investors weighted active commission on US smart beta funds in 2018 year was 0.17%, which is higher than traditional passive funds with 0.08%, but significantly lower than active funds - 0.70%. Table 3 examine the total impact for wealth accumulation among 3 investment strategies taking into account latest fees and extrapolating them to 10, 20, 30, 40-year period. For illustrative purposes, I have assumed that a 30-year-old investor begins to save for retirement at age 70, a span of 40 years. Investors earns the $20 000 with assumption what annual compensation will grow at 2% rate. In Table 3 presented a comparison of hypothetical retirement plan accumulation if investor were invested 10% of his compensation each year in active, passive or smart beta funds assuming conservative scenario of 6% nominal annual return on equities.

Table 2

Total Wealth Accumulation by Retirement Plan

Compensation base	$20,000.00
Investment ratio, YoY	10%
Compensation base growth rate, YoY	2%
Expected inflation rate, YoY	2.50%

	Actively Managed Fund	Index fund	Smart beta
Gross annual return	6%	6%	6%
All-in cost	0.70%	0.08%	0.17%
Net annual return	**5.30%**	**5.92%**	**5.%**

Accumulation period, years	Actively Managed Fund	Index fund	Smart beta	Percentage of index fund investing: Actively Managed Fund	Smart beta
10	$29,167.65	$30,175.49	$30,026.90	96.66%	99.51%
20	$84,441.29	$90,416.99	$89,520.02	93.39%	99.01%
30	$184,868.35	$205,544.32	$202,382.48	89.94%	98.46%
40	$362,679.45	$419,988.60	$411,054.90	86.35%	97.87%

Present value for investment period, years	Actively Managed Fund	Index fund	Smart beta	Actively Managed Fund	Smart beta
10	$22,785.72	$23,573.04	$23,456.97	96.66%	99.51%
20	$51,532.06	$55,178.86	$54,631.47	93.39%	99.01%
30	$88,134.64	$97,991.75	$96,484.37	89.94%	98.46%
40	$135,072.93	$156,416.62	$153,089.43	86.35%	97.87%

Source: Author

From fees perspective the advantage provided by index fund in Table 3 constant 6% nominal annual return is significant in absolute value. By the retirement comes, when the investor for example in the 60 years old 205,544 USD would have been accumulated in the index fund versus 184,868 in active managed fund or 202,382 USD in smart beta fund. Comparing to index fund investor will accumulate approximately 10% less in active fund and only 1.5% less using smart beta funds. The discounted cash flow model represents the same results. This mean what in a long run in active strategies investor lose money paying higher fees to active managed funds, while for short terms investment such impact is only 3.4 % for 10-year accumulated wealth and 0.5% less in smart beta funds.

Moving forward to survey conducted in the 2018. In total of 185 various government organizations, corporations or private businesses, non-profit organizations or universities, unions or industry-wide pension schemes, insurance companies, sovereign wealth funds, healthcare organizations and family offices from various regions have been conducted a survey by FTSE Russel. All respondents have an estimated aggregate asset under management (AUM) over $3.5 trillion and were segmented into tiers by total AUM as follows: those with under $1B in total AUM (20%); those between $1B and $10B in total AUM (39%); and those with over $10B in total AUM (41%). The survey result presents some trends of smart beta strategies applying in investment industry for 5 years period.

Another 2018 survey provider - Edhec-Riks institute. This institute sample consist from 163 European high-ranking professionals: 33% executive managements, 33% - portfolio managers. 36% asset management firms AUM exceed 10 billion euro. Survey respondent's geographical allocation: 17 % from United Kingdom, 69% - European Union, 13% - Switzerland and 1% from other countries outside the EU.

Firstly, according to FTSE Russel (Fig.5), smart beta adoption rates globally have reached a record high of 48% in 2018. A comparison of smart beta adoption by region continues to reveal that Europe's adoption rate is the highest - 61%, because European asset owners started the earlier

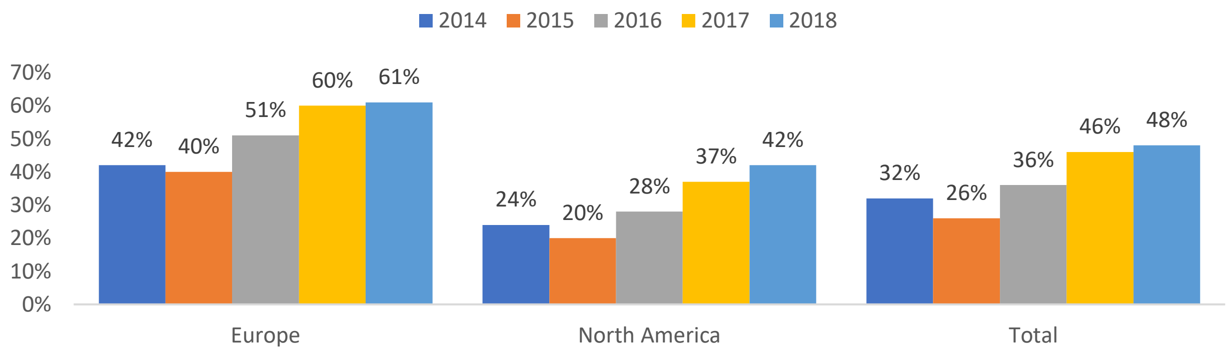


Figure 5 Smart beta adoption by region

Source: FTSE Russel

adoption of smart beta strategies. North American asset owners displayed the largest increase in smart beta adoption since 2014, with 42% reporting an existing allocation in 2018 – up from 26% in 2015. This figures also confirmed another survey provided by EDHEC-RISK Institute. Regarding to this survey, 67% of respondent used ETFs to invest in Smart Beta in 2018 versus 49% in 2014.

Secondly, regarding to FTSE Russel 2018 survey, the adoption rates are more evenly distributed between small - 39%, medium - 43% and large -56% asset owners (Fig. 6). Survey respondents vary by region and AUM tier each year, but the overall trend shows growth across all three tiers since 2014.

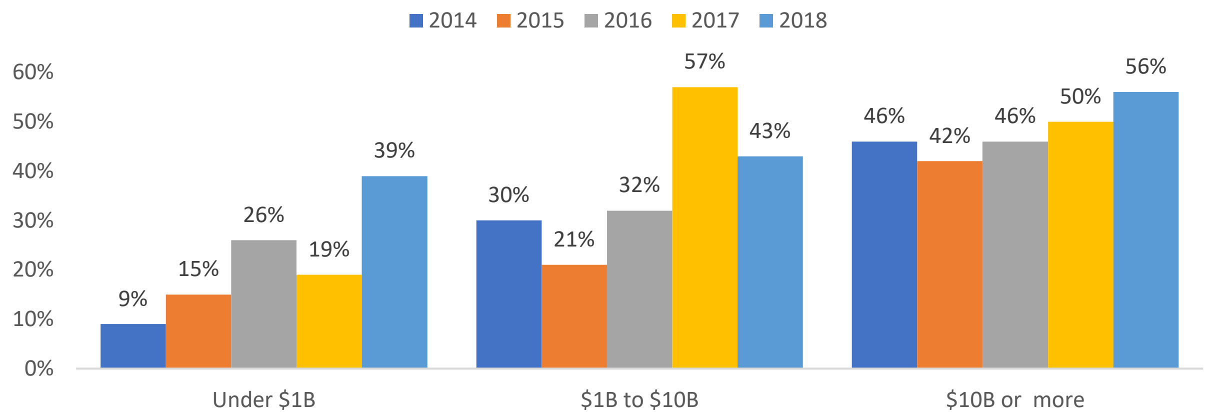


Figure 6 Smart beta adoption percentage by asset size

Source: FTSE Russel

According to Edhec-Risk institute survey results 73% of respondents decide that smart beta and factor investing indices offers significant potential for outperformance. 79% of them agreed that diversification across several weighting methodologies allowed risk to be reduced and added value. 90% of them agreed that smart beta and factor investing indices require full transparency on methodology and risk analytics, and 91% of them agreed that smart beta and factor investing indices allowed factor risk premia such as value and small cap to be captured. 50% of investors still plan to increase their use of ETFs in the future despite the already high maturity of this market and high current adoption rates.

Evaluation and application of environmental, social and governance considerations is gaining in popularity, with over half of asset owners implementing or evaluating ESG consideration in their investment strategy. Globally, regarding to FTSE Russel, among those who either have an existing smart beta allocation or plan to evaluate and/or implement one in the near future, 38% anticipate applying ESG considerations to a smart beta strategy.

In periods from 2016 to 2018 majority of asset owners used smart beta for long-term implementation: in 2016 – 58% of respondents, 2017-70%, 2018 - 58%. For both long term and short-term implementation only 39% in 2016, 27% - 2017 and 33% in 2018. Also, it should be stressed what 45 % of all respondent cite not knowing how to determine the best strategy or mix of strategies for entire portfolio.

In this sample of respondents were identified what the most widely used strategies. Table 4 results represent the main top three trends:43.2% of respondents use low volatility strategy, 42.5% - multifactor combination and 35.5% value.

Table 3

Most widely used smart beta strategies 2014-2018

Smat Beta strategies	**2014**	**2015**	**2016**	**2017**	**2018**	**Average**
Low volatility	49%	39%	46%	47%	35%	**43.2%**
Multi-factor combination		20%	37%	64%	49%	**42.5%**
Value		39%	41%	34%	28%	**35.5%**
Fundamentally weighted	41%	37%	30%	26%	19%	**30.6%**
High quality	16%	14%	22%	21%	19%	**18.4%**
Minimum variance		20%	19%	9%	16%	**16.0%**
Momentum	10%	18%	22%	16%	10%	**15.2%**
Maximum diversification	14%	12%	15%	10%	12%	**12.6%**
Equal weight	10%	14%	14%	6%	11%	**11.0%**
Dividend/ income/ yield	8%	8%	10%	10%	8%	**8.8%**

Source: FTSE Russel

I suppose that such breakdown in line with investor desire to invest more gently using more diversified portfolios from risk perspective. FTSE Russel survey top 3 objectives-initiated evaluation of smart beta strategies during the 2014-2018 periods confirmed this assumption:

1. Return enhancement
2. Risk reduction
3. Improve diversification

Also, the 70% of respondents in 2018 evaluating multi-factor combination of smart beta strategies. This strategy remains the most evaluated for last three years (Table 5). The top 3 strategies remain the same in strategy evaluation questionnaire, but the undisputed leader with 63,3% is multifactor strategies.

Table 4

Most commonly evaluated smart beta strategies 2016-2018

Smat Beta strategies	2016	2017	2018	Average
Multi-factor combination	46%	74%	70%	**63.3%**
Value	23%	44%	35%	**34.0%**
Low volatility	39%	44%	27%	**36.7%**
High quality	23%	25%	27%	**25.0%**
Fundamentally weighted	24%	23%	27%	**24.7%**
Dividend / income / yield	15%	19%	23%	**19.0%**
Momentum	23%	36%	19%	**26.0%**
Equal weight	14%	18%	15%	**15.7%**
Maximum diversification	19%	16%	12%	**15.7%**
Minimum variance	16%	14%	12%	**14.0%**
Risk parity	13%	15%	10%	**12.7%**

Source: FTSE Russel

Multi-factor index-based strategies are reported as the most commonly evaluated and the most widely adopted smart beta equity strategies, especially among more recent adopters of smart beta. Allocating to a single multi-factor product is far more common than allocating to multiple individual factor products. Among single factor strategies, value and low volatility persist as the most widely used and evaluated. Smart beta allocation less than 2 years – use 87% of respondents, Smart beta allocation 2 years or more – 39%. Among respondents with an existing smart beta allocation, 65% are currently evaluating additional allocations. Among the respondents who had previously evaluated smart beta and decided not to implement, 37% are now re-evaluating their smart beta options

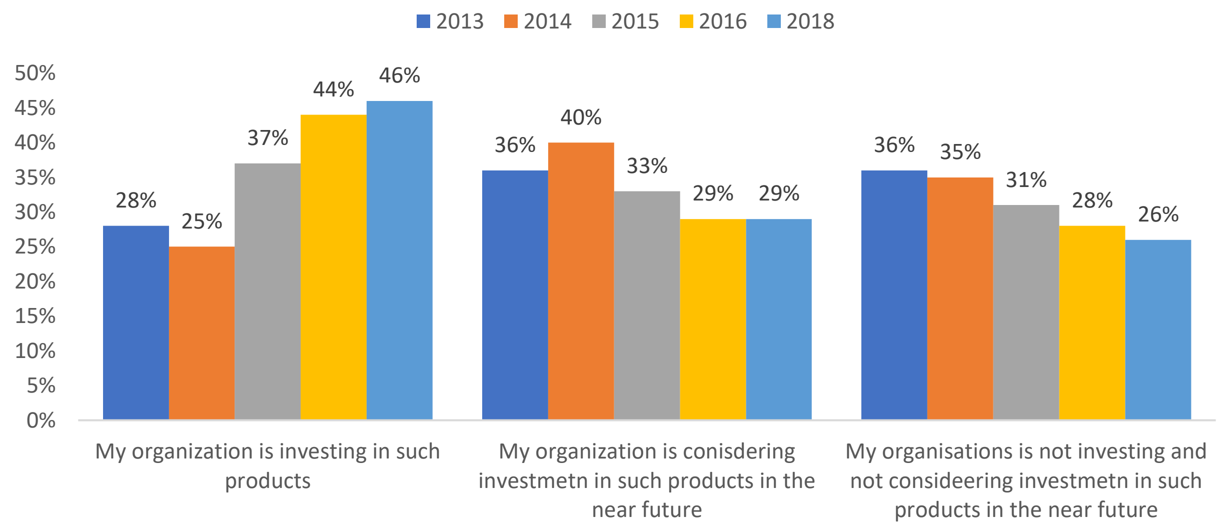


Figure 7 Use of products then track smart beta and factor investing indices

Source: Edhec-Risk institute

Also regarding to FTSE Russel survey data more than a half respondent, 58%, considering implementing asset allocation to multi-factor strategies, and only 20% - to single factors. However, regarding to Edhec-Risk institute survey responses in the planning of future used of Smart Beta strategies in 2018, where were top 3: diversification-based, multi-factor and a single factor strategy. Respondents plan to move towards more sophisticated strategies, than single-factor strategies. Also, in line with Edhec-Risk institute survey 2018 results respondents most frequently use Smart Beta exposures to harvest long-term premia (Figure 7). As you can see from 2013 year there is a positive trend increase by 18% of respondent who use smart beta based product in their portfolio of assets, also consideration stage remain quite stable for the recent years around 33%, also during this period 10% drop achieved in respondents who are not investing and not considering to invest into such product.

Despite this strong motivation and positive attitude for smart beta, more than 80% of respondents invest less than 20% of their total investments in smart beta and factor investing strategies. 90% of respondents declared that smart beta and factor investing indices required full transparency on methodology and risk analytics. Respondents are not fully satisfied with the level of transparency offered by existing smart beta and factor investing products and still see room for improvement.

1.3. Smart Beta global practice overview

Since the first stocks and bonds began to trade, investors were trying to understand what was driving forces of securities returns. By the 1930s, academics and practitioners began to systematically identify these return forces and call these driving forces factors. Factors reward investors for a long time. Leading institutional investors and active fund managers have for decades exploited their potential to generate excess returns. There are macroeconomic factors such as economic growth and inflation that may explain the return on asset classes such as stocks and bonds. For example, higher economic growth may lead to higher stock prices and higher inflation may lower bond prices. There are other factors that help explain excess returns in different asset classes: cost, acceleration, quality, smaller size (market capitalization), and minimum volatility. For example, the value of low-priced stocks has historically outperformed the broad equity market for a long time (Shores, 2015).

Investment decision making involve investors to a very important process what can be named as an asset allocation - one of the most important decisions investors have to make. One of the primary goals of the asset allocation process is to construct well-diversified portfolios that are designed to meet risk and return targets in a variety of market and macroeconomic environments. Goals, time horizon, and risk tolerance are the key factors that should be considered when investor trying to allocate portfolio of assets.(Donaldson et al, 2017) Thus, one of reason why smart beta has become one of most popular concepts in modern finance in last decades.

Smart beta concepts are not new at all - the idea of capturing systematic sources of returns has been around for decades. Previous work examining the role of systemic factors in increasing returns includes Fama and French, noting the explanatory power of two simple variables - the market capitalization of a security and its book to market ratio in their major white paper of 1992 and Mark Carhart, explaining how a steady engine of return on investment in 1997. (Shores, 2015).

Many academic studies of stock price anomalies were first carried out several decades ago and have stood the test of time. For example, Black, Jensen, Scholes (1972), Haugen and Hines (1975) recorded a lack of a positive relationship between risk and stock returns and did so over fifty years ago. These studies provide a solid foundation for the potential benefits of low risk investing and suggest that most recent studies by practitioners supporting this approach are in fact not consistent with the sample (Alford, 2016).

Despite its attractive name, Smart Beta is not a revolutionary strategy. Concepts such as factor investing, and rule-based strategies existed decades. In the 1960s Jack Traynor (1961), William Sharp (1964), John Lintner (1965) and Ian Mossin (1966) proposed the Capital Asset

Price Model (CAPM), which states that returns investments are influenced by market factors, beta. By expanding this model, Pricing theory (APT) was proposed by Stephen Ross (1976), which allowed factors explaining asset recovery (Rubenstein, 2011).

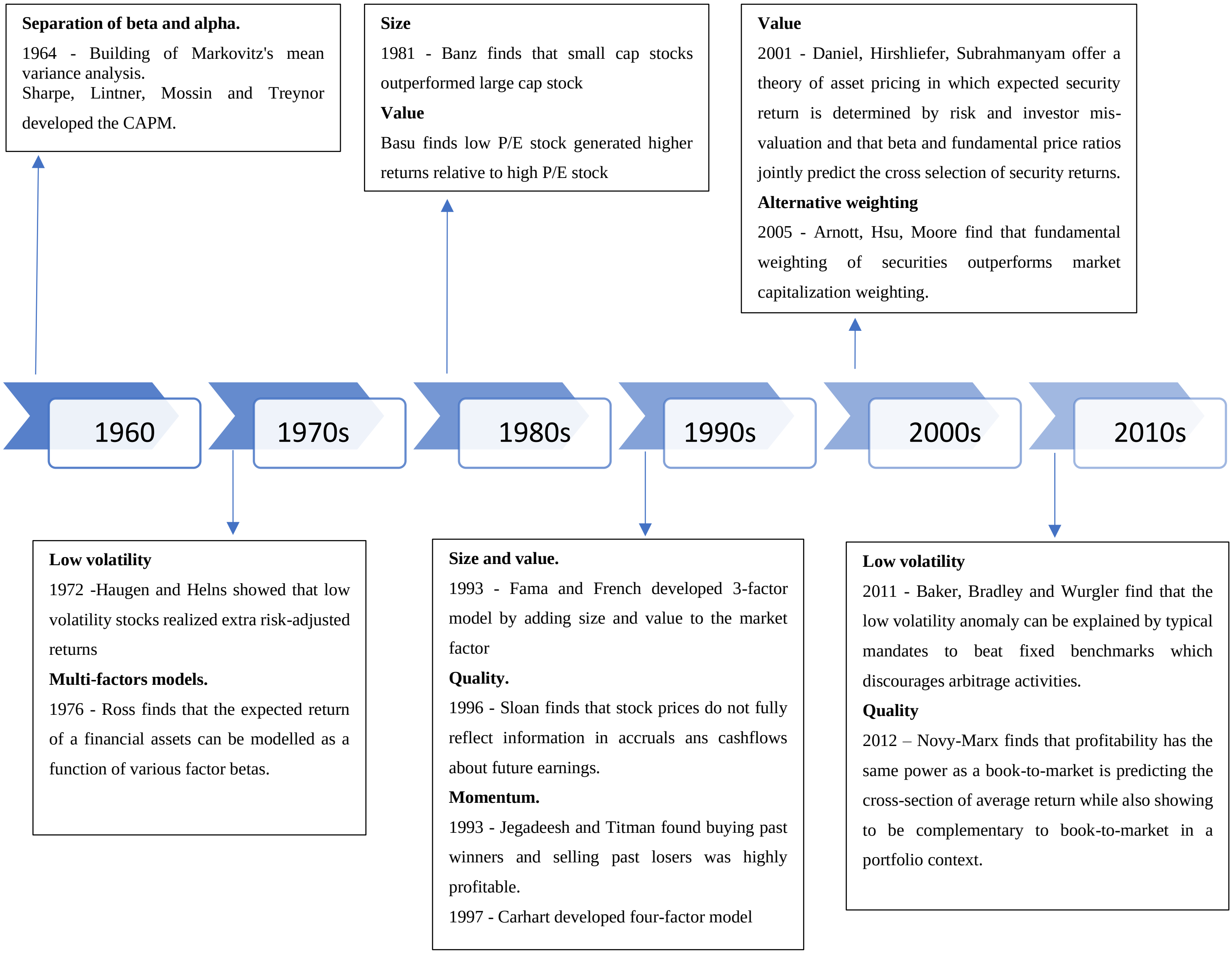


Figure 8 Academic progression of factor investing during 1960-2010

Source: Invesco

Since then, there have been several studies showing these Factors such as size, value, momentum and other resulted in higher return. As you can see in Fig. 8, factor investing have a very long history which could be started from Markowitz's mean variance portfolio implementation in 1964 and CAPM model development. Further the low volatility anomaly was described in 70's. After decade Size and Value factor were represented in Banz and Basu works with evidence of P/E significant impact on return. In 90's Fama and French developed 3-factor model by adding size and value to the market factor, Jegadeesh and Titman first time examine a momentum factor and Mark Carhart proposed the four-factor model by adding the monthly momentum to Fama and French 3 factor model. Since 2000 value, low volatility and quality factors were investigated in a new way by Daniel et al, Baker et al and Novy-Marx. Every ten years in factor investing appear new development and research by academics and practitioners.

Smart beta is a term the industry has broadly used to define non-market-cap-weighted strategies, also sometimes referred to as strategic beta, alternative beta, or advanced beta (Davidow, A. B. (2016).). Smart Beta is a generic term for indexes created using different methods that differ from the standard method of weighing index components based on their market capitalization. These indices reflect a variety of factors that influence academically recognized risk or reward factors, helping consumers gain more control over setting their portfolios toward specific investment goals (FTSE Russel, 2017).

According to Vanguard expert's smart beta – factor-based investing is a form of active management that aims to achieve specific risk or return objectives through systematic, rules-based strategies. Key due-diligence for constructing factor-based investments include factor selection, weighting methods, and all-in costs, which all together have a material impact on portfolio outcomes. (Grim et al, 2017).

The recognition of key drivers of risk and return or factors is at the heart of smart beta investing. Factors are investment characteristics that help explain the risk and return behavior of a security. For example, main factors recognized from Black Rock perspective in various markets represented in Table 6 (Shores, S., 2015):

Table 5

Different asset classes smart beta factors.

Equity	Fixed Income	Currency	Commodities
Value Momentum Size Quality Low Vol	Carry Curve Convexity Momentum	Carry Value Momentum	Carry Momentum

Source: Black Rock

Although stocks can be sorted in many ways, attention is typically paid to those factors with an extensive academic literature and empirical evidence of historical positive risk adjusted excess returns — in other words, certain factors that have "worked" in the past. In this paper, we focus on those most frequently addressed in the literature: value, momentum, quality, size, volatility, and liquidity. Based on Vanguard empirical calculation made from 1973 to end of 2016 for various factors it was empirically tested what different equity factors historically outperform the indexes on annualized excess return basis. Even though stocks can be sorted in different ways, they usually pay attention to factors that have extensive academic literature and empirical evidence of historically positive excess returns adjusted for risk, in other words, to some factors that "worked" in the past. These studies focus on topics that are commonly discussed in the literature: cost, momentum, quality, size, volatility, and liquidity. Based on empirical calculations of the Vanguard of various factors since 1973 until 2016 (Fig. 9), it was empirically confirmed that various factors have historically outperformed indices in terms of annual excess profits (Grim et al, 2017):

1. MSCI World Quality Index (USD) from 1975.10.30 1.3% excess return
2. MSCI World Minimum Volatility Index (USD) from 1988.05.31 – 1.5% excess return
3. MSCI World Momentum Index (USD) from 1973.05.31 – 2.6% excess return.
4. MSCI World Value Index (USD) from 1974.12.31 to 1997.10.30 and MSCI World Enhanced Value Index thereafter - 2.7% excess return
5. FTSE Developed Illiquidity Factor Index (USD) from 2001.09.30 - 2.7% excess return
6. MSCI World Small Cap Index (USD) from 2000.12.31 - 4.5% excess return

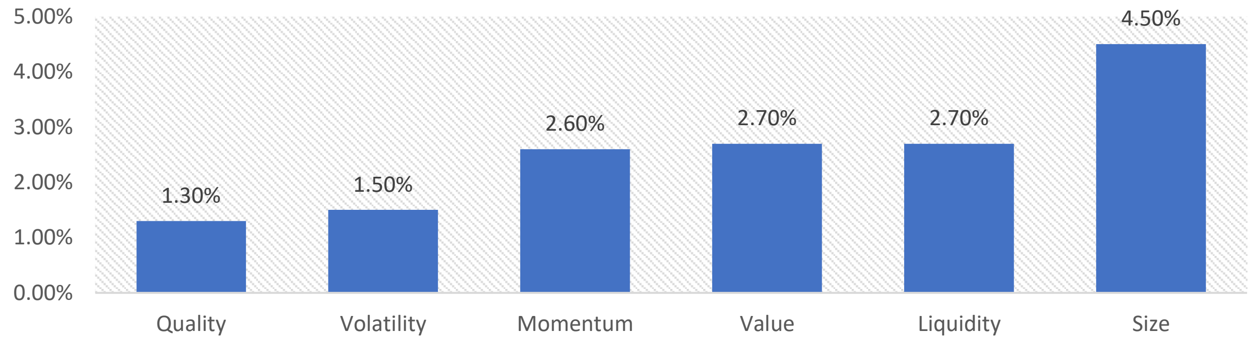


Figure 9 Annualized different smart beta strategies excess return, 1975-2016
Source: Vanguard

From historical perspective of smart beta funds applying in real life investing, according to Morningstar data, the size of the smart beta market as at June 2014 was $396 billion across 673 products in ETFs alone. The US holds around 91% of assets under management. (BNP Paribas asset management, 2015) Meanwhile, in Europe, the market has grown to just over $26 billion in less than 10 years.

According to Black Rock data as of December 2014, there were estimated more than 700 smart beta exchange traded products (ETPs) listed around the globe, comprising of $529 billion in assets. Morningstar in 2015 estimates that there is more than $558 billion, Cliffwater 2017 was estimated - approximately $600 billion in smart beta products. According to Morningstar 2015 data in strategic beta assets under management were nearly 1000 different exchange-traded funds (ETFs) globally based on smart beta strategies, which include most popular strategies as:

1. Equal weight
2. Low volatility
3. Dividend-oriented
4. Momentum
5. Fundamentally weighted strategies
6. Quality

The Table 7 below shows the major ETF asset classes split as of September 30, 2016, into 3 categories – smart beta, traditional beta and active/other. In the equity space, smart beta ETFs account for 13% of all ETF assets globally. By contrast, smart beta makes up only 1.1% of all global bond ETFs and 3.4% of all commodity ETF assets, and 13% of all equity's ETFs.

Table 6

ETF asset classes split: Smart Beta, Traditional Beta, Active

	Smart Beta	**Traditional Beta**	**Active/Other***	**Global ETF Market** Assets ($M)
Bonds	1.1%	94%	4.9%	666,287
Equities	13%	84.5%	2.5%	2,543,235
Commodities	3.4%	90.5%	6.1%	143,062
Other	3.8%	57.3%	38.9%	95,964

Source: Nasdaq

One of BIG4 representative, Earnst&Young, smart beta ETF global assets are expected to reach $ 1.2 trillion by 2020. compared with $ 0.6 trillion at the end of 2016. The only factor, especially the low volatility and dividend yield, remain in the spotlight. These funds are relatively easy to learn and have broad institutional attractiveness instead of mutual funds, making them a popular starting point for traditional asset managers. In Figure 10 we can see, what from 2001 to 2017 the amount of multifactor smart beta ETF increase significantly from 18 to 975, what equal to approximately 28% of compound annual growth rate, but the single factor compound annual growth rate reach approximately 45%, and increase from 1 to 371 ETFs. In fact, according to an article by the Financial Times, on December 27, 2017, smart beta funds reached the $ 1 billion milestone, indicating the growing popularity of the investment strategy. According to ETFGI, an industry data provider, in the first 11 months of 2017, exchange-traded funds and Smart Beta products raised $ 69 billion in net new assets.

Many scientific and practical works, which consider the features of investment based on equity factors, do not include various implementation costs in their results. These costs can significantly affect the performance of real-world portfolios. When evaluating the feasibility of an equity factor-based investment vehicle, it is important to consider these potential performance problems. Investors need to know which four key implementation problems can affect potential

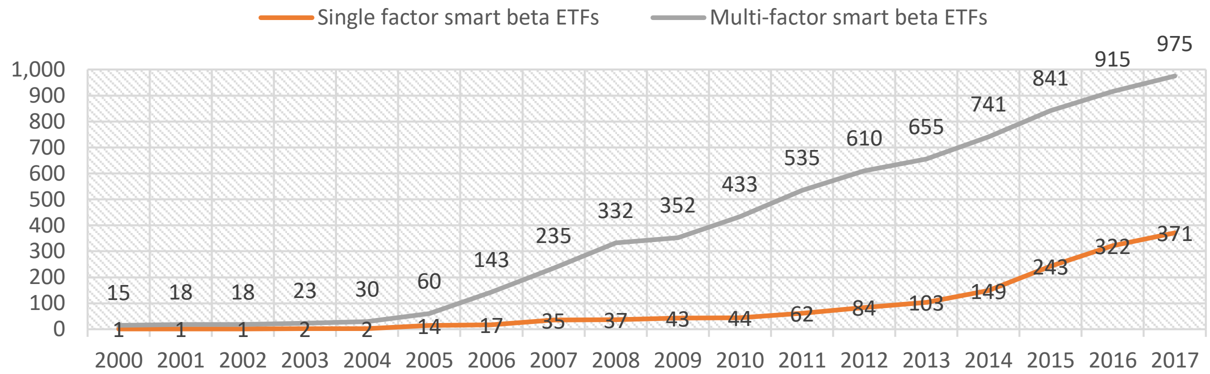


Figure 10 Growth of single and multi-factor smart beta ETFs number, 2000-2017

Source: Earnst&Young

returns compared to what is usually reported in an academic journal article and factor index returns (Grim et al, 2017):

1. Short-selling constraints.
2. Management and oversight expenses.
3. Transaction costs.
4. Taxes.

Regarding to all information mentioned in these 3 sections some intermediate conclusion can be made:

Smart Beta is not something new in portfolio construction it could be more related to new way of adoption of old concepts provided by Sharpe and developed in his works about CAPM model. New tools and data science could allow to make more complicated portfolio construction in factor investing field, where factor investing analyze possibility to use rule-based approach and it’s implementation into portfolio construction seeking to beat the market and earn excessive return. It was shown, what for last decades more and more single and multi-factor-based exchange traded fund were constructed and presented in the market with positive trends of AUM increased in such funds.

Smart beta – globally recognized strategies with positive trends of implementation among industry academics and professionals. Developing smart beta strategies offers exciting opportunities for investors and portfolio managers. Such strategies shall recognize stock portfolio development as a risk and profitability factor in the long run, what they were widely documented in the literature. One of the advantages in favor of smart beta strategies, for example, creating an equal weighting index. It means that this approach eliminates the index skewness for the securities with the highest market capitalization. When these stocks perform poorly, it will have a significant impact on the performance of the index relative to its components with the lowest specific gravity. Another potential advantage of using smart beta is increasing of portfolio return and better allocation of equity risk premium according to identified factor or anomaly implemented in strategy.

Smart beta lie in spectrum of market inefficiency, why it is can generate excessive returns. The main goal of the smart beta strategy is to outperform the traditional stock index by using special stock-option and special-purpose rules or fundamental ratios for the stocks included in the traditional index. The result is a "smart" fund, portfolio or new index with increased number of shares that are selected according to predefined rules. In addition, the portfolio manager using these formulated in advance index selection criteria strive to generate the result in outperformance the original index. This approach makes smart beta closer to passive investment than active. While passive funds keep extremely low fees, smart beta funds may be slightly expensive, but they are still cheaper than traditional active funds with possibility to generate excess return other their benchmarks.

Smart beta can be determined as the new way to use only the strengths of passive and active managements and avoid of their weaknesses. But it is important to remember that each of these strategies may differ from the other. For example, one manager of a value-based smart beta strategy may not evaluate this option as a manager of another smart-beta strategy that is also value-based. This approach sharply differs from traditional passive index funds, where two funds that copy an index do not theoretically differ from each other. Also, all investors and portfolio managers should keep in mind what wider participation of the mass in the market using similar strategies, as a rule, means lower expected premiums for all and the effect of anomaly can disappear at all.

2. RESEARCH OF SMART BETA PORTFOLIO SUBSTANTIATION

2.1. Research framework

2.1.1. Data mining and workflow

An empirical study was conducted to analyze hypotheses regarding their consistency based on stock market data. The study was conducted in the context of generally accepted works in foreign markets, which are formulated by generally recognized works on key strategies based on momentum effect, value, dividend yield, volatility, quality, and it outlines the key concepts and approaches that are implemented in these works.

As the main data for this work, daily quotes of closing prices for 1999-2020 period of Nasdaq exchange quoted securities have been used in QuantConnect platform for creating algorithm. In addition to directly used stock quotes, the following types of data were used for the necessary fundamental calculations, provided by Morningstar: dollar volume, Return on Equity (ROE), Debt to Equity (DOE), earnings per share growth rate (EPS growth), EV to EBITDA, market capitalization, Price to Earnings (P/E), trailing dividend yield, forward dividend yield, book value per share (P/B), free cash flow yield.

The initial investment amount for each portfolio is $ 1,000,000. It is distributed evenly among the stocks selected for the portfolio. To determine the number of shares of each company in the portfolio, the amounts received are divided by the market, price or equal value of the shares at the time the portfolio is created. Return at the end of the year is calculated by reference to changes in the market price of the shares.

Restriction rule: the stock amount in all constructed portfolios should not exceed 50 long only positions at all.

Benchmark set as SPDR S&P500. SPDR S&P500 is an exchange-traded fund incorporated in the USA. The ETF tracks the S&P 500 Index. ETF consist of a portfolio representing 500 stock in the S&P 500 Index. It holds predominantly large cap US stocks. This ETF is structured as Unit Investment Trust and pays dividends on quarterly basis (Bloomberg, Appendix A).

Invesco QQQ Trust ETF which track Nasdaq Composite Index have not been set as benchmark because of later incorporation date as of 1999-03-10 and by reason of not including financial companies in this ETF basket of securities. Universe of this research consist of all traded stocks on Nasdaq exchange.

The next important testing element is the choice of portfolio rebalancing techniques. With a full rebalancing, the stock selection changes at the beginning of each selected portfolio holding period. Partial rebalancing involves a review of the portfolio at a frequency of one month and year to determine the best strategies for the period under review. The rebalancing process is to maintain certain stock weights in accordance with the chosen method of portfolio formation. Due to price changes, stock weights change over time in portfolio. After preparing the sample for analysis, the portfolio formation algorithm will be used for research strategies. The calculations were carried out by writing a script in Python and using QuantConnect LEAN system to run developed code.

In this research only daily closing prices are used.

QuantConnect's LEAN engine manage portfolio and data feeds let concentrate on algorithm strategy and execution. All data is tweeted into strategy via event handlers, upon which algorithm developer can place trades. The general research algorithm scheme described as per below:

1. Universe selection define process of select assets and main filter and additional fundamental data filtering.
2. Creation of signal define a rule-based approach how stock will be selected from defined Universe.
3. Portfolio construction – characterize the position weight for securities which create signals.
4. Execution – place trades/orders to reach security position side under portfolio construction step.
5. Rebalancing procedure occur on monthly basis to make necessary correction in existing holding or add new stocks.
6. Calculate comparable ratio (annualized return).
7. Proceed hypothesis confirmation process.

2.1.2. Portfolio ratios for comparable analysis.

The simplest indicator for comparing the results of two portfolios is the accumulated yield. Even though this metric completely ignores the level of risk, psychological stress that the investor may have experienced during the dynamic rebalancing of the portfolio, it is considered traditional in the investment environment:

Equation 1
Source: Ross, S. A., Westerfield, R., & Jaffe, J. F. (2013). Corporate finance

$$\boldsymbol{Capital\ gain}(\%) = \left(\frac{\boldsymbol{Capital\ amount_1}}{\boldsymbol{Capital\ amount_0}} - \mathbf{1}\right) * \mathbf{100}\%$$

$Capital\ amount_1$*- this is the value of the portfolio at the end of the active management period;*

$Capital\ amount_0$ *– this is the value of the investment portfolio at the beginning of the period.*

Another indicator that evaluates portfolio returns, but already in annual terms, is Annualized Geometric Return, which is a cumulative return reduced to a period of one year using the compound interest formula. This metric can also be interpreted as the annual return that the investor received on average during the analysed period when using any strategy.

Equation 2
Source: Source: Ross, S. A., Westerfield, R., & Jaffe, J. F. (2013). Corporate finance

$$\boldsymbol{Annualized\ return}(\%) = \left(\left[\prod_{t=1}^{n}(\mathbf{1} + \boldsymbol{r_t})\right]^{\frac{1}{N}} - \mathbf{1}\right) * \mathbf{100}\%$$

r_1*-return of year t;*

N - duration of portfolio management (in years).

Therefore, traditionally comparing two investment portfolios uses the Sharpe coefficient (Sharpe. 1966). The Sharpe ratio is a metric that measures the profitability of a strategy or measure by unit of risk. The ratio is calculated as the average return for the period minus the risk-free interest rate divided by the standard deviation of yield.

Equation 3
Source: Sharpe, W. F. (1994). The Sharpe ratio

$$\boldsymbol{Sharpe\ ratio} = \frac{\boldsymbol{Annual\ return}}{\boldsymbol{\sigma_{annual}}}$$

σ_{anual} *– average annual standard deviation of the portfolio*

The Sharpe ratio is useful measure of the strategy's "quality", but it has its drawbacks. In fact, this metric only affects profitability data that is normally distributed. In the case of asymmetry (skewness), the coefficient gives a distorted result. Thus, with a positive tilt in portfolio returns, the Sharpe ratio will take lower values, while a negative slope will not fully take into account the risk of over-performance.

Despite the great popularity of the Sharpe ratio in the investment industry as a key indicator for comparing risk-return portfolios, it is not the only one. Therefore, when analyzing abnormally distributed returns, it is more appropriate to use the Sortino coefficient. It is a modification of the Sharpe ratio, where a one-sided standard deviation is used as a measure of risk, which takes into account only negative portfolio returns (Hoffman, 2013).

So, Dr. Frank Sortino proposed an alternative to this metric in the form of the Sortino ratio, which takes into account only the volatility of negative portfolio returns, thereby assessing the "negative" part of the risk:

Equation 4
Source: Rollinger, T., & Hoffman, S. (2013). Sortino ratio: A better measure of risk.

$$\boldsymbol{Sortino\ ratio = \frac{R - r_f}{\sigma_d}}$$

R = Actual or expected portfolio return

$\boldsymbol{r_f}$ *= risk free rate*

$\boldsymbol{\sigma_d}$ *= standard deviation of downside.*

This metric is widely used in practice in order to compare the performance of portfolio managers, as it seems to be a logical and universal assessment of the utility function of a potential investor. Traditionally, positive volatility does not cause negative emotions and stress for the investor, because it increases its wealth, therefore, it should not reduce the level of its usefulness.

Tracking error is a measure of financial performance that determines the difference between the return fluctuations of an investment portfolio and the return fluctuations of a chosen benchmark. The return fluctuations are primarily measured by standard deviations. Also, it is used as an input to calculate the information ratio.

Low errors indicate that the performance of the portfolio is close to the performance of the benchmark. High errors reveal that the portfolio's performance is significantly different from the performance of the benchmark. The high errors can indicate that the portfolio substantially beat the benchmark, or signal that the portfolio significantly underperforms the benchmark. (Ammann, 2001):

Equation 5
Ammann, M., & Zimmermann, H. (2001). Tracking error and tactical asset allocation.

$$\boldsymbol{Tracking\ error = \sqrt{\frac{\sum_{i=1}^{n}(R_p - R_B)^2}{N - 1}}}$$

R_p *- the return of a portfolio*

R_B *- the return of a benchmark*

Information ratio (or IR) – also called the appraisal ratio – main idea is to get the performance relative to a given reference portfolio. It measures the excess return of the fund over a given benchmark, divided by the standard deviation of the excess return – or more concretely, the degree of regularity in outperforming the benchmark (Cogneau, 2009):

Equation 6
Source: Cogneau, P., & Hübner, G. (2009). The 101 ways to measure portfolio performance.

$$\boldsymbol{Information\ ratio = \frac{Portfolio\ return - \ Becnhmark\ return}{Tracking\ error}}$$

Finally, it is worth looking at the transaction cost indicator, which will primarily be represented by a commission fee from the broker for each transaction executed. Using QuantConnect LEAN system in this research Interactive Brokers fixed fee model structure will be applied and calculated by below formula:

Equation 7
Source: Author

$$\boldsymbol{Total\ cost = \sum \frac{C \times N_i}{Capital\ gain} \times \frac{1}{T} + Fixed\ custodian\ annual\ fee}$$

C – broker's commission amount (dollar amount for securities buying);

$\boldsymbol{N_i}$ – the number of i purchased securities.

*$\boldsymbol{T}$ **–** time of investment held*

In every case of buying any security investor need to settle security to custody. Interactive Brokers offer several custodians and in this research State Street will be used. Fixed custody annual fee will be set as maximum of 0,84% as of State Street provided fee schedule for above USD 250 billion AUM (StateStreet, Fee Latter, 2020).

In this study the total risk measure will used maximum drawdown. Maximum drawdown is defined as the largest reduction in investment value over a period of time from last pick to lowest value before new high established. Usually indicated as a percentage of the maximum value.

Equation 9
Source: Author

$$\boldsymbol{Maximum\ drawdown} = \frac{Peak\ value\ before\ largest\ drop}{Peak\ value\ before\ largest\ drop - Lowest\ value\ before\ new\ high\ establshed}$$

2.1.3. Hypothesis conditions

Investing in the financial market involves building a portfolio of assets to diversify the risk. This problem is solved by portfolio theory, which provides tools to determine the optimal investor portfolio based on implied rules. A portfolio consisting of various exchange instruments such as equities, bonds, derivatives and other instruments available on the market can usually be used as a subject for investigation. Smart beta strategies lead to a higher return versus benchmark (market index), regardless of total expense ratio during the test period. Below are the hypotheses that have been tested during this study. The hypotheses were based on a review of existing literature on the topic of work from abroad. The following hypotheses will be presented in this paper:

Hypothesis 1.

Nasdaq Index acting in non-efficient environment and have Hurst exponent ratio ≠ 0.5 from 1995 to 2020.

$$\boldsymbol{H_0: H = 0.5}$$
$$\boldsymbol{H_1: H \neq 0.5}$$

Hypothesis 2.

For a strategy based on value factor, annualized expected excess return of 1% or larger is observed compared to the benchmark during the test period from 1999-2020.

Hypothesis 3.

For a strategy based on momentum factor, annualized expected excess return of 1% or larger is observed compared to the benchmark during the test period from 1999-2020.

Hypothesis 4.

For a strategy based on dividend yield factor, annualized expected excess return of 1% or larger is observed compared to the benchmark during the test period from 1999-2020.

Hypothesis 5.

For a strategy based on low volatility factor, annualized expected excess return of 1 % is observed compared to the benchmark during the test period from 1999-2020.

Hypothesis 6.

For a strategy based on quality factor, annualized expected excess return of 1% is observed compared to the benchmark during the test period from 1999-2020.

Hypothesis 7

For a strategy based on maximum Sharpe ratio, annualized expected excess return of 1% is observed compared to the benchmark during the test period from 1999-2020.

Conditions for hypothesis 2-7:

$$\boldsymbol{H_0}: \boldsymbol{r_B} \geq (\boldsymbol{r_P} - \boldsymbol{TC})$$

$$\boldsymbol{H_1}: (\boldsymbol{r_P} - \boldsymbol{TC}) - \boldsymbol{r_B} > \boldsymbol{r_E}$$

$$r_B - benchmark\ return$$

$$r_P - factor\ portfolio\ annualized\ return$$

$$TC - \ total\ costs$$

$$r_E - \ \ annualized\ expected\ excess\ return\ \%\ level\ for\ a\ given\ factor\ protfolio$$

Also constructed portfolios will be tested for effectiveness relative to the market SPDR S&P500 in terms of various risk-return ratios over the investigation period for the above mentioned factors.

2.2. Factors definitions.

2.2.1. Value

Fundamental analysis of the stock market plays a main role in investor activities. This investment-oriented analysis of the securities is aimed to predicting the basic parameters of the market in the future and based on the study of factors which affecting the dynamics of the market. Fundamental analysis is used by investors to assess the value of the company (or its shares), which reflects the state of affairs in the company, the profitability of its activities etc. Resulting value strategies which exploit the ratio of multiple measures of fundamental value over equity price in order to identify underpriced stocks.

Value has several dimensions: the stock price as a multiple of company earnings, price as a multiple of dividends paid, price as a multiple of book value, and other such “ratio descriptors.” Academics and investors differ on which best represents a value company, creating opportunity in the marketplace for a variety of investment products.(MSCI, 2017)

According to Fama and French „Value versus Growth: The international Evidence” sorts of stock in US and twelve major EAFE countries major markets on B/M, E/P, C/P and D/P produce large value premiums for 1975-1995 period.

In 2004 L K. Chan and J Lakonishok concluded, that a large body of empirical research indicates that value stocks, on average, earn higher returns than growth stocks. The composite value strategy described in their case study (in which value and growth were defined by BV/MV, CF/P, E/P, and S/P) could prompts the strong and growing interest in investing worldwide.

Also, according to Gray and Carlisle (2013) done survey for all possible variables that capture the premium of value and quality according to a large number of empirical evidence. The first is earnings yield as the inverse of price to earnings ratio. The second is enterprise yield (EBITDA/EV) defined as the acquirer's multiple. The third is a variation of the enterprise yield by substituting EBIT for EBITDA, which belongs to the Greenblatt's magic formula as a value measure combined with quality investing. Another variation is to substitute free cash flow or gross profit for EBITDA. The fourth is book to market ratio

From Morgan Stanley practitioners' side, who implementing such strategy in MSCI Enhanced Value Index. This index applies three valuation ratio descriptors on a sector relative basis:

1. Forward price to earnings (Fwd P/E);
2. Enterprise value/operating cash flows (EV/CFO);
3. Price to book value (P/B)

Value investing strategy finally can be determined as an investment strategy that buys or overweight stocks with low prices relative to their fundamentals determinants and underweights or shorts stocks with high prices relative to their fundamental's determinants. (Asness et al, 2015)

2.2.2. Momentum

Momentum investing remains one of the most puzzling market anomalies since the extensive analysis by Jegadeesh and Titman (1993). Although institutional investors may be able to use momentum strategies to earn excess profits, individual investors have more trading constraints and higher transaction costs.

The momentum effect is a price anomaly in the stock market where portfolios of stocks, bonds or other financial instruments, based on past performance (based on past performance or other indicators of investment performance), indicate excessive returns on a particular benchmark, such as the market. index or model constructs based on generally accepted factors that determine differences in return on assets (Teplova, 2013)

Momentum is a pervasive anomaly in asset prices. Jegadeesh and Titman (1993) find that previous winners in the US stock market outperform previous losers by as much as 1.49% a month. The Sharpe ratio of this strategy exceeds the Sharpe ratio of the market itself, as well as the size and value factors. Momentum returns are even more of a puzzle because they are negatively correlated to those of the market and value factors. From 1927 to 2011, momentum had a monthly excess return of 1.75%, controlling for the Fama and French factors. Momentum has been shown in European equities, emerging markets country stock indices, industry portfolios, currency markets, commodities, and across asset classes (Barroso, 2015). Jegadeesh and Titman (1993) document that strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate superior returns over various monthly holding periods. For instance, they show that a strategy that picks stocks based on their past 6-month returns and holds for a period of 6 months generates an average return of 12% per year. More importantly, they document that stock returns are predictable around quarterly earnings announcements (Naughton, 2008)

Moskowitz, Oui, and Pedersen (2012) showed that a simple trend-following rule provides profitability for the 58 liquid instruments considered by the authors. However, the strategy works on a specific time window, and a number of rules should be followed for selecting assets. Using Commodity Futures Trading Commission weekly data find out that speculators trade with time series momentum, being positioned, on average, to take advantage of the positive trend in returns for the first 12 months and reducing their positions when the trend begins to reverse.

But the remarkable performance of momentum comes with occasional large crashes. In 1932, the winners- minus-losers (WML) strategy delivered a -91.59% return in just two months. In 2009, momentum experienced a crash of -73.42% in three months. Even the large returns of momentum do not compensate an investor with reasonable risk aversion for the sudden crashes that take decades to recover from. For example, someone investing one dollar in the WML strategy in July 1932 would recover it only in April 1963, 31 years later and with considerably less real value. This puts the risk to momentum investing in an adequate long-run perspective. .(Barroso, 2015)

Often in studies, the following notation is used: 3-3, 3-6, 6-9, which means that the time period for the formation of portfolios of winners and losers is based on the first number of months (in our example, 3, 3 and 6 months), and the investment period (when the investor follows the momentum strategy) is fixed by the second digit (3, 6 and 9 months in the above example (Mikova, 2013). . Determinants of momentum strategy (Teplova, 2013):

- the period during which the "market winners" are selected (three, six, nine, 12 months);
- the criteria for the classification of shares or other instruments according to their success (only profitability with or without risk is analyzed);
- the share of successful companies in the momentum portfolio (all with above-average returns over the market period, or only 10% with the best performance from the stock sample under consideration);
- portfolio rebalancing principles and holding period.

2.2.3. Dividend yield

According to the survey of individual investors by Dong, Robinson and Velda (2005), first of all, investors gather for a cash dividend or, if this is not possible, to receive a dividend in the form of shares. Second, investors are not indifferent to the ongoing corporate dividend policy. Third, increased / decreased dividends indicate that the company's future position has improved / worsened, and investors do not believe that paying dividends resolves conflicts over the effective use of free cash flow.

Thus, Arnott et al. (2003), after analyzing 130 years of historical US stock market data, conclude that the traditional inverse relationship between dividend payout and firm growth prospects based on the Gordon model is vulnerable. Companies with high net profit dividends (payout ratio) systematically show higher profits in subsequent periods.

Also, worth mentioning is the article by Conover et al (2016), which examines the characteristics of dividend shares from an investor’s perspective. The empirical results of the authors show that the overall risk of the securities portfolio has been significantly reduced without a dramatic decline in returns. One of the main findings of the paper is the statistical dominance of issuers paying dividends irrespective of the size of the company (including small and mid-cap), the sector and the style of the investment portfolio. Thus, paradoxically, financial theory suggests the advantage of growth stocks in paying dividends over other non-dividend securities of this investment style, as traditionally companies in the growth phase reinvest undistributed profits to expand production and scale business.

2.2.4. Low volatility

Low-volatility investing has attracted considerable interest and substantial assets since the global financial crisis, but these concepts is not new at all. Minimum variance strategy was discovered by Henry Markowitz in 1952. In earlier 1970s the advantage of lo volatility of low beta stock has been analyzed by Black, Hauges and Heins. In 2007 Blitz and Vliet provide an empirical evidence that stocks with low volatility earn high risk-adjusted returns in terms of Sharpe ratios and in terms of CAPM alphas. The annual alpha spread of global low versus high volatility decile portfolios amounts to 12% over the 1986-2006 period

Total assets under management in low volatility strategies were at around USD 250 billion at the end of 2017. Total AUM in active low volatility products amounted to around USD 195 billion. These figures remain relatively small compared to the size of global equity markets. Therefore, low volatility is far from overcrowded and still has considerable growth potential (Robeco investment, 2019)

Historically, the low-volatility factor has outperformed the market during times of crises and market downturns. When embedded in portfolios, the defensive characteristics of the factor have tended to protect capital during turbulent markets. A low-volatility strategy can be constructed in two keyways: using either purely ranking-based (heuristic) approaches or optimization-based methods. The minimum volatility factor is one of the few factors that have performed well during turbulent markets, providing capital preservation when it is needed most. Yet it remains an anomaly as it has produced better-than-market returns over long time periods while offering less risk. (Alighanbari et al, 2016).

Some pitfalls what could be related to low volatility strategy implementation (Robeco, 2019):

1. Low volatility portfolio focusing only on past volatility and has a one-dimensional view of risk.
2. Due to its focus only on low volatility, a generic strategy tends to lag during an up market: this is called limited up-capture. Valuation risk is the risk of overpaying for low volatility stocks because the actual valuation is ignored.
3. Low volatility strategy can lead to high trading costs, because of high turnover. This high turnover is often the result of the optimization method used to construct portfolios.
4. Low volatility indices and portfolios constructed using the optimization method can heighten the concentration risk. This means that any sector-specific developments can have a large negative impact on total performance

2.2.5. Quality

Quality-based investment strategies aim to capture the documented excess returns of high-quality stocks over low-quality stocks characterized by low debt, stable earnings growth, and other "quality" metrics. Quality as an equity investing style refers to the idea that companies that are highly profitable, operationally efficient, safe, stable and well-governed tend to outperform the market average over the long run. Typically associated with buying profitable companies with low leverage and stable earnings (N. Quality investing is based on the idea that companies with healthier balance sheets make better use of their capital, have more stable operations and have outperformed their less efficient peers (BlackRock, 2018).

Novy-Marx (2013) argues that gross profit is the cleanest accounting measure of true economic profitability because this measure is relatively unaffected by accounting estimates for accruals and non-cash expenses such as depreciation and amortization The most commonly used definition is profitability as measured by the gross-profits-to-assets ratio. Author also provide the results what the stocks of profitable companies achieve better risk adjusted performance than less profitable companies.

The most commonly used quality metrics fall into three categories:

1. profitability measured by gross profits over assets, operating profit, ROA, ROE or ROIC;
2. safety or stability measured by a variety of solvency metrics such as debt/assets;
3. earnings quality measured by differences between cash and accounting items (accruals).

2.2.6. Equal weight

When comparing different portfolios, they can be compared with a naive equally weighted portfolio. If the portfolio does not outperform a simple well under predefined criteria, there may consider another different strategy or simply option for a such equal weights naive approach if all else fails. It can be expected that evenly balanced portfolios will tend to outperform the market when major companies perform poorly. This is because even small businesses will have the same weight in your portfolio versus large cap businesses. For example DeMiguel, Garlappi, and Uppal (2009), Duchin and Levy (2009), and Jacobs, Muller, and Weber (2014) compare the performance of equal-weighted portfolios to a number of optimized portfolios, and find that the such naive diversification rule performs better than other strategies based on optimization (Plyakha et al, 2012).

Need to point out, what Plyaha et al (2012) were provided equal, value, and price-weighted portfolios analysis from 100 stocks randomly selected from the constituents of the S&P 500 index over the past 40 years period. They found what equal-weighted portfolio with monthly rebalancing outperformed the value and price-weighted portfolios in terms of total mean return and four-factor alpha from the Fama & French and Carhart models. The total return of the equal-weighted portfolio was higher than that of the value and price-weighted portfolios by 271 and 112 basis points per year. The equal-weighted portfolio, however, had a higher standard deviation and kurtosis compared with the value and price-weighted portfolios. The volatility of the return on the equal-weighted portfolio was 17.90% a year, which was higher than the 15.83% and 16.46% for the value and price-weighted portfolios. However, the skewness of the equal-weighted portfolio was less negative than the skewness of the value and price-weighted portfolios. Sharpe ratio of the equal-weighted portfolio at 0.4275 was higher than those of the value and price-weighted portfolios - 0.3126 and 0.3966, respectively

2.3. Factor portfolios construction

2.3.1. Value portfolio construction

The investment rating of securities for value portfolio will be made in several stages. The first step is to collect data from Morningstar databases because this source provides systematized tables with the same financial and economic indicators for all issuers. The second stage introduces the concepts of ranking winners" and "looser" stocks.

A prerequisite for identifying "winners" stocks is the stock trading liquidity for every month and filtering only mostly traded stock on Nasdaq exchange. Based on the above, several restrictions are needed to determine the quality of the stock based on predefined criteria described below. The third step of the portfolio constructions the selection of significant variables (from those collected in the first stage) to determine the winners and losers' stocks. In order to build a model, it is necessary to select those variables that will have the greatest influence on the decision to include securities in the portfolio. From this point of view ratios associated only with value creation will be selected for only for top 50 stocks with long only positions:

Dividends – filter out if company paying dividend in last 3 months.

1 month return – stock with positive return for last month.

Book value per share - if the value of this exceeds the market value of one share, the company's shares are considered undervalued. Book value is used as an indicator of the value of a company's stock and can be used to predict the potential market price of a stock at a certain point in the future. It means that we expecting to have in portfolios only undervalued stock.

Free cash flow yield – it serves as an indicator of whether the company can pay and fulfill all of its obligations and make necessary capital investment. In fact, it is a reliable indicator of a company's financial stability. However, the possibility of manipulation of financial ratios by the management remains and this is a subject to influence from the accounting policy.

2.3.2. Momentum portfolio construction

Currently, in the academic literature, the generally accepted methods for building portfolios in the framework of momentum investment are decile/quantile described by Fama and French (1996) and Jegadeesh and Titman (1993) and weighted relative strength by Levy (1967).

The first approach involves classifying equities in descending order based on a selected criterion, such as the past 1-11 months, after which all securities are categorized as quantiles or deciles (i.e. five or ten portfolios with value equals number of shares). The upper quantile/decile forms part of the "winners" portfolio, the lower one the "losers" portfolio. Shares may be distributed in each group of portfolios on an equal basis (equal weighting) or according to the market capitalization of the issuing companies. The second approach also classifies all equities according to some criterion, such as past performance, and is split into two portfolios, where the first "winning" portfolio includes equities that have proven to be "better than the market" (e.g. and the second portfolio consists of equities that performed "below market". In the second method, the weight of the equity portfolio is determined in proportion to the deviation of the return of the stock from the average market level (weight of previously higher yields).

The second step in building momentum portfolio is the criteria by which shares are ranked. A common method is to track past monthly returns. These returns is considered as a 3, 6, 12 month follow-up period depending on the chosen strategy.

In this research will be realized the second approach method and only “Winners’’ will be the top 50 of all 100 stock selected in long positions with the highest values of the stock selection criteria in the ranking period. All the stocks satisfy the requirement that their returns exist at least 1, 3, 6, 12 months. Winners portfolios are equal weighted at formation and held for 1 month period and when rebalancing procedure repeated.

2.3.3. Dividend yield portfolio construction

All selected securities during portfolio selection checked if they have fundamental data. If such data do not exist portfolio will not be constructed at this year. All stock sorted by dollar volume to meet minimal liquidity criteria.

All stock samples also will be sorted by positive dividend yield synthetic ratio using trailing 12 month dividend yield multiplied by forward dividend yield, to rank more higher historical and forward looking yield having stocks.

Stocks with unusually high dividend yield (larger when 20%) were not selected to avoid distortions of results. Portfolio formed only 50 first securities which matched selection criteria. Dividend yield portfolios will be rebalanced annually with equal weighting scheme to avoid lack of data on shorter periods of rebalancing, because some of companies may have different dividend paying periods.

2.3.4. Low volatility portfolio construction

The main risk measure in the valuation of securities is volatility. Typically, increasing volatility of an asset is related to its declining value, but the increase in volatility of the market index corresponds to a fall in its stock price. Keep in mind that not only can falling prices cause volatility, but there is quite a lot of volatility in a growing up market. At the end of the each month, equally weighted portfolio of top 50 selected securities by ranking on the past one year volatility (standard deviation) of daily prices will be constructed.

2.3.5. Quality portfolio construction

Quality portfolio will be constructed in line with MSCI Quality index methodology. Quality growth companies have a tendency to have high ROE, stable earnings that are uncorrelated with the broad business cycle, and strong balance sheets with low financial leverage. The Quality score for each security is calculated by combining all scores of three fundamental variables, namely Return on Equity, Debt to Equity and Earnings growth.

The multiplication of last available Return on Equity and average 5 year Return on equity will be used to determine only highest Return on Equity having stock and exclude the one period effect in terms of last available Return on Equity. Debt on Equity used by normal condition calculated as Total Debt divided by Total Equity. Earnings growth used by normal condition as growth in the company's Normalized Basic EPS on a percentage basis.

2.3.6. Equal weights portfolio

This portfolio construction will be simplified in portfolios to equal weighting of all securities after selection phase is completed. The equal weighted approach will be applied for value, momentum, dividend yield, quality and volatility portfolios constructed in a previous step. After considering the above-mentioned criteria for building a portfolio, using a written script in Python, monthly returns of each strategy for the period from January 1999 to December 2020 will be analyzed. After portfolio calculations will be completed, hypothesis confirmation/rejection process and time analysis will be performed. I will be interested in the behavior of strategies dynamics over three periods from 1998 to 2020: three crisis (2001, 2008, 2020) and low interest rate environment from 2008 till 2016. The construction and analysis of the considered portfolios will help to understand the nature of the anomalies in the expected excess returns. It will also be possible to formulate other areas of research of potential factors that can explain deeper the resulting returns on such strategies.

3. SMART BETA STRATEGIES RESULTS EMPIRICAL ANALYSIS.

3.1. Hurst coefficient.

After performing 3 year rolling Hurst coefficient time series analysis (Table 7, Figure 11) null hypothesis has been rejected because of existing higher Hurst coefficient on analyzed period. As in provided table 97.14% of all time Hurst coefficient stayed in the zone higher then 0,5 also if applying more strict criteria > 0,55 and determine the time when Hurst coefficient in this zone, this time equal to 67,29%.

Table 7

Hurst coefficient time series analysis

Criteria	Observation in days	% of Observation	Criteria	Observation in days	% of Observation
> 0.5	5,610.0	97.14%	>0.55	3,886	67.29%
< 0.5	165.0	2.86%	>0.45 and <0.55	1,889	32.71%
	5,775.0	100%		5,775	100%

Source: Author

It can be stated what trend movement persist in this time series according not only to visual representation of Nasdaq Index in Figure 10, but also due to statistical substantiation of Hurst coefficient.

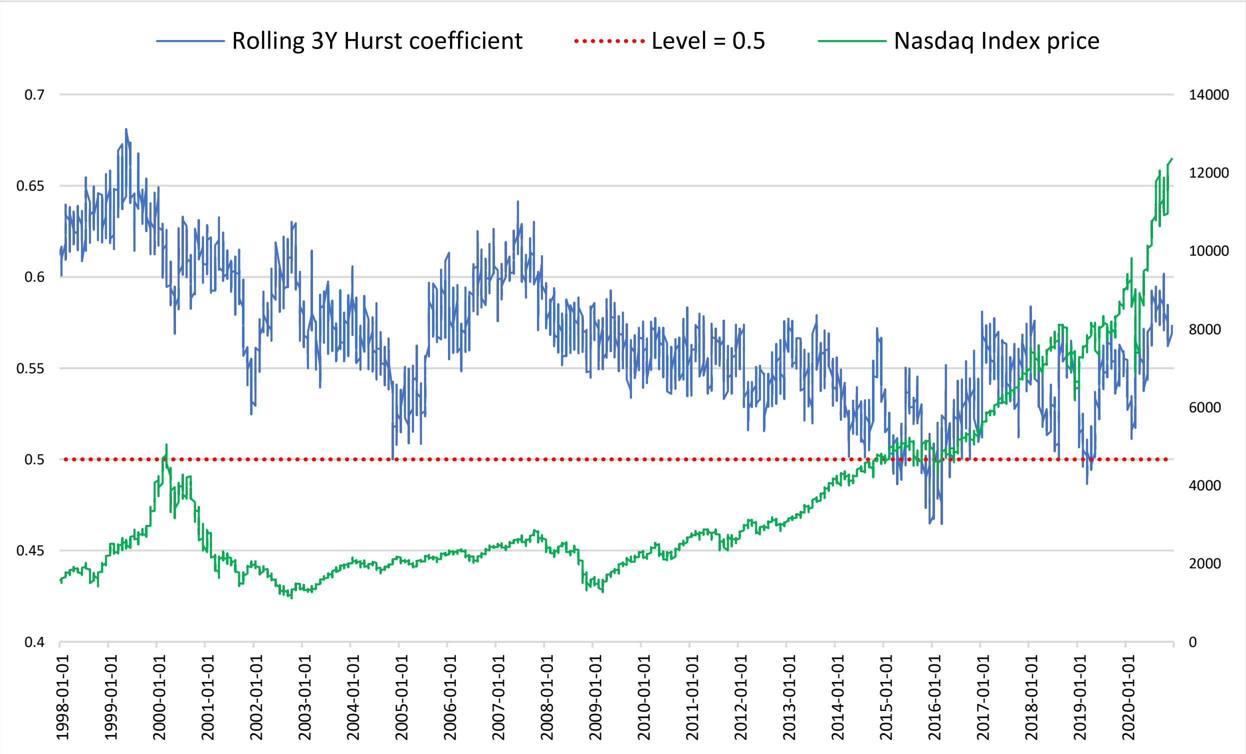


Figure 11 Nasdaq Index and 3-year Hurst coefficient

Source: Author

3.2. Value.

Null hypothesis for H #2 have been rejected. Strategy generated 822.21% of total return and 10.658% CAGR, 3.618% excess return and 2.743% excess return less cost, what satisfy hypothesis condition. Also, it should be highlighted, what excessive return have been earned with managing more risk which equal 0.24 annualized standard deviation for value factor comparing to 0.15 for benchmark. Maximum drawdown reached biggest value beyond 2002 and 2004. In first worst scenario maximum drawdown achieved 64% comparing to only 51% for benchmark. Sharpe and Sortino ratios higher then benchmark for 8.60 bps and 4.30 bps accordingly. Tracking error and Information ratio have positive difference of 11.3 bps and 53.3 bps accordingly. It means what developed strategy is able to outperform benchmark and can generate more consistent excess return compared to benchmark (Appendix B and Figure 12). Trading fee are very high compared to benchmark 0.095% and equal to 0.875% what will have significant impact on portfolio performance in long term. Strategy score is 45 and ranked 1 place amongst other.

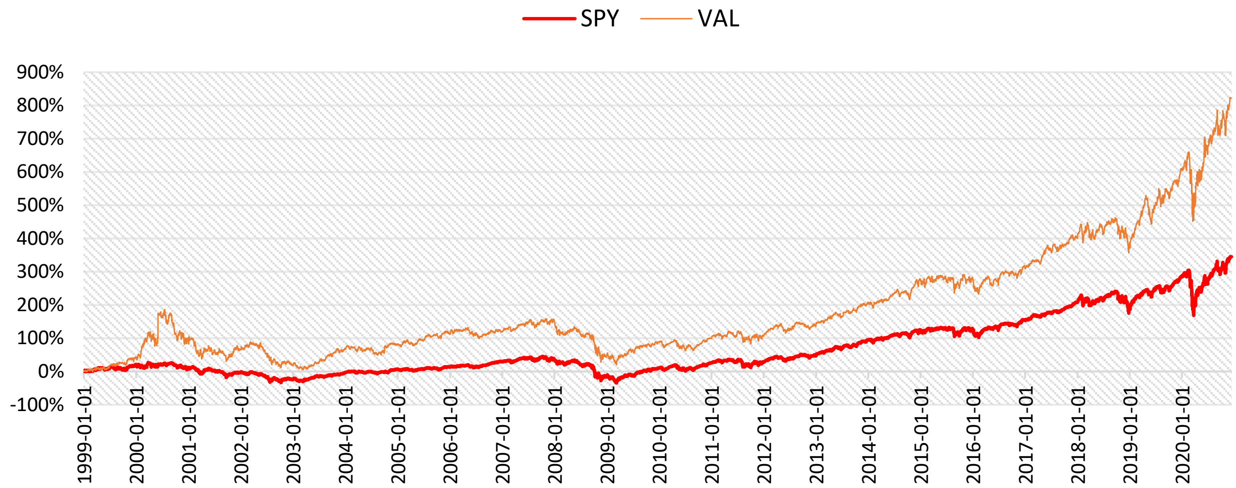


Figure 12 SPDR S&P 500 ETF vs value factor 1999-2020 total return

Source: Author

3.3. Momentum

Null hypothesis for H #3 have been confirmed 3 times of 4. Only strategy within 1-year momentum meet testing condition and generate 626.73% of total return and 9.464% CAGR, 2.424% excess return and 1.552% excess return less cost accordingly. 6-month and 3-month momentum generate positive excess return less cost and can be chosen as proper investing strategy, but do not pass hypothesis testing conditions. In case of 1-month momentum excess return less cost is negative and passive investment into benchmark is more appropriate choice.

Also it should be emphasized, what excessive return in case of 1-year have been earned with managing more risk which equal 0.24 annualized standard deviation for value factor comparing to 0.15 for benchmark. Maximum drawdown reached biggest value beyond 2002 and 2004. In first worst scenario maximum drawdown achieved 72% comparing to only 51% for benchmark. Sharpe and Sortino ratios vary against the benchmark for 4.70 bps and -9.00 bps accordingly. Negative Sortino difference shows, what benchmark passive investing can ensure more excess return for taken unit of risk. Tracking error and Information ratio have positive difference of 27.9 bps and 33.3 bps accordingly. It means what developed strategy is also able to outperform benchmark and can generate more consistent excess return compared to benchmark (Appendix B and Figure 13). Trading fee are remarkably high compared to benchmark 0.095% and equal to 0.872% what will have significant impact on portfolio performance in long term. 6, 3, 1 – month momentum strategies have not satisfied hypothesis condition, hence those strategies will be accounted only for strategy overall scoring purposes. 1year momentum strategy score is 52 and ranked 6 place amongst other, 6-month momentum score is 45 and 1 place. 3-month momentum rank is 5 and 1-month momentum is 9.

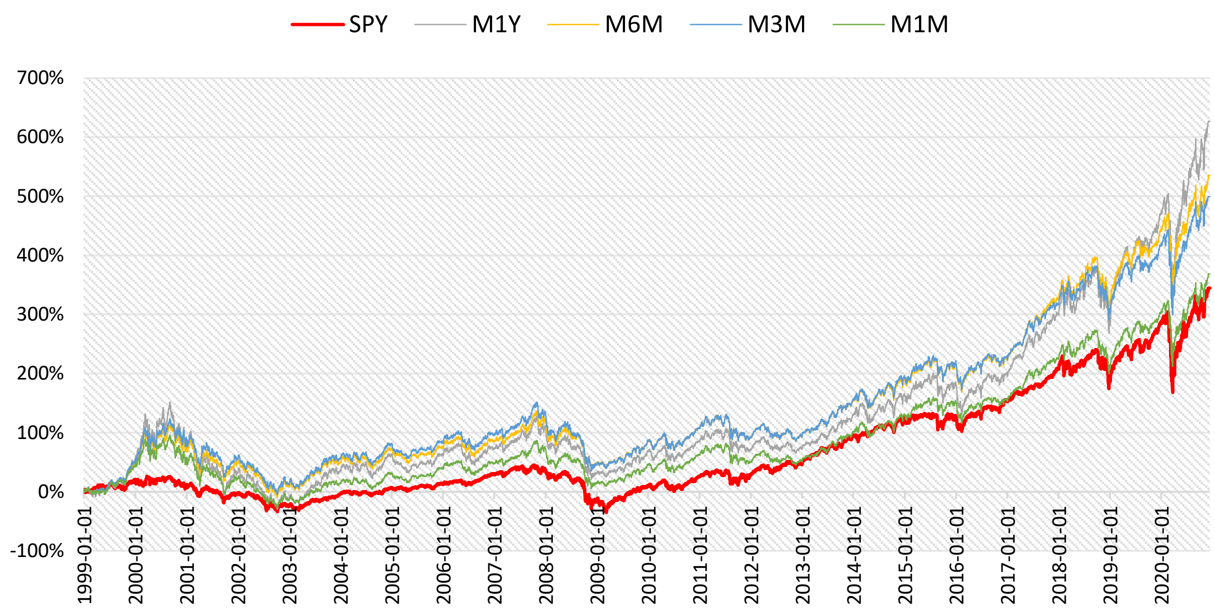


Figure 13 SPDR S&P 500 ETF vs momentum factor 1999-2020 total return

Source: Author

3.4. Dividend yield

Null hypothesis for H #4 have been confirmed. Strategy generated 482.78 % of total return and 8.357% CAGR, 1.317% excess return and 0.472%% excess return less cost, what do not satisfy hypothesis testing condition. Limitation taken into account – fundamental data for building dividend yield factor portfolio available only from 2008 year. It should be stressed, what excessive return have been earned with managing similar risk which equal 0.16 annualized standard deviation for value factor comparing to 0.15 for benchmark. Maximum drawdown reached biggest value beyond 2008 and 2009. In first worst scenario maximum drawdown achieved 49% comparing to only 51% for benchmark. Sharpe and Sortino ratios vary against the benchmark for 10.4 bps and -15.00 bps accordingly. Negative Sortino difference shows, what benchmark passive investing can ensure more excess return for taken unit of risk, but tracking error and information ratio have positive difference of 22.4 bps and 25.2 bps accordingly. It means what developed strategy is also able to outperform benchmark and can generate more consistent excess return compared to benchmark (Appendix B and Figure 14). Trading fee are very high compared to benchmark 0.095% and equal to 0.845% what will have significant impact on portfolio performance in long term. Strategy score is 46 and ranked 3 place amongst other.

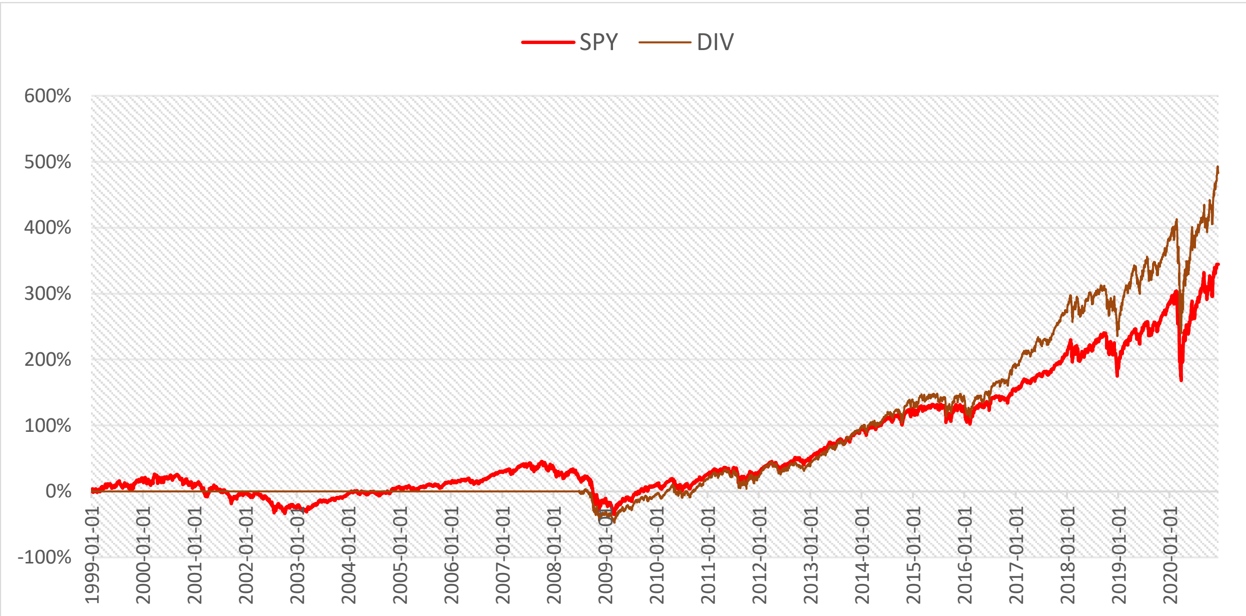


Figure 14 SPDR S&P 500 ETF vs dividend yield factor 2008-2020 total return

Source: Author

3.5. Volatility

Null hypothesis for H #5 have been rejected. Strategy generated 558.99% of total return and 8.357% CAGR, 1.935% excess return and 1.049% excess return less cost, what satisfy hypothesis testing condition. It should be stressed, what excessive return have been earned with managing similar risk which larger amount of risk equal to 0.24 annualized standard deviation for value factor comparing to 0.15 for benchmark. Maximum drawdown reached biggest value beyond 2008 and 2009. In first worst scenario maximum drawdown achieved 72% comparing to only 51% for benchmark. Sharpe and Sortino ratios vary against the benchmark for 10.4 bps and -15.00 bps accordingly. Negative Sortino difference shows as in previous strategies, what benchmark passive investing can ensure more excess return for taken unit of risk. Tracking error and Information ratio have positive difference of 22.4 bps and 25.2 bps accordingly. It means what developed strategy is able to outperform benchmark and can generate more consistent excess return compared to benchmark (Appendix B, Figure 15). Trading fee are very high compared to benchmark 0.095% and equal to 0.875% what will have significant impact on portfolio performance in long term. Strategy score is 60 and ranked 7 place amongst other.

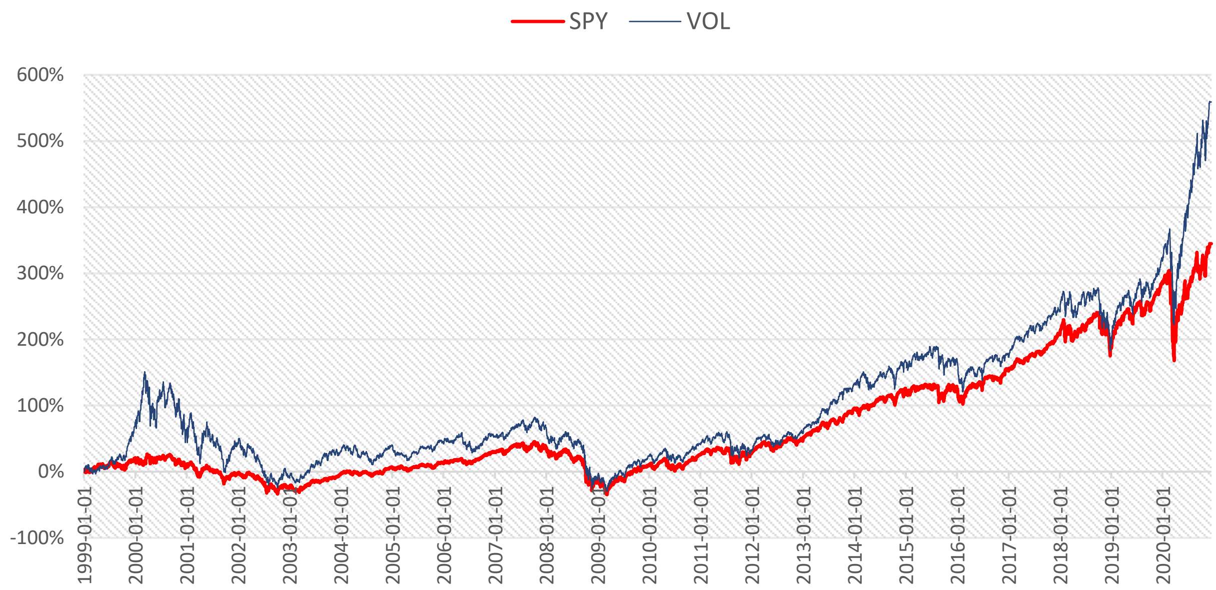


Figure 15 SPDR S&P 500 ETF vs volatility factor 1999-2020 total return

Source: Author

3.6. Quality

Null hypothesis for H #6 have been rejected. Strategy generated 856.07% of total return 10.840% CAGR, 3.800% excess return and 2.912% excess return less cost, what satisfy hypothesis testing condition. It should be stressed, what excessive return have been earned with managing larger risk which equal to 0.24 annualized standard deviation for value factor comparing to 0.15 for benchmark. Maximum drawdown reached biggest value beyond 2002 and 2004. In first worst scenario maximum drawdown achieved 70% comparing to only 51% for benchmark. Sharpe and

Sortino ratios vary against the benchmark for 7.8 bps and -2.2 bps accordingly. Negative Sortino difference shows as in previous strategies, what benchmark passive investing can ensure more excess return for taken unit of risk. Tracking error and Information ratio have positive difference of 12.0 bps and 56.7 bps accordingly. It means what developed strategy is able to outperform benchmark and can generate more consistent excess return compared to benchmark (Appendix B and Figure 16). Trading fee are very high compared to benchmark 0.095% and equal to 0.888% what will have significant impact on portfolio performance in long term. Strategy score is 51 and ranked 4 place amongst other.

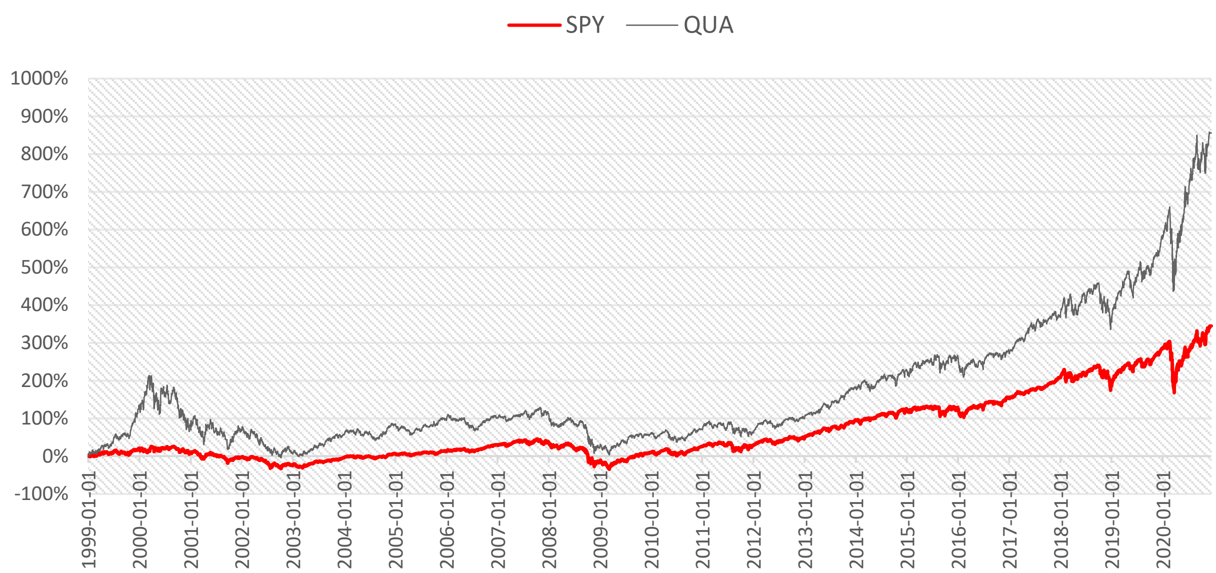


Figure 16 SPDR S&P 500 ETF vs quality factor 1999-2020 total return

Source: Author

3.7. Maximum Sharpe Ratio

Null hypothesis for H #7 have been confirmed. Strategy generated 472.82% of total return and 8.282% CAGR, 1.242% excess return and 0.298%excess return less cost, what do not satisfy hypothesis testing condition. It should be stressed, what excessive return have been earned likewise with managing higher risk which equal to 0.20 annualized standard deviation for this portfolio comparing to 0.15 for benchmark. Maximum drawdown reached biggest value beyond 2008 and 2009. In first worst scenario maximum drawdown achieved 62% comparing to only 51% for benchmark. Sharpe and Sortino ratios vary against the benchmark for 3.8 bps and -16.7 bps accordingly. Negative Sortino difference shows again as in previous strategies, what benchmark passive investing can ensure more excess return for taken unit of risk. Tracking error and Information ratio have positive difference of 25.2 bps and 27.5 bps accordingly. It means what developed strategy is able to outperform benchmark and can generate more consistent excess return compared to benchmark (Appendix B, Figure 17). Trading fee are remarkably high compared to benchmark 0.095% and equal to 0.944% what will have similarly significant impact on portfolio performance in long term. Strategy score is 65 and ranked 8 place amongst other. As we see the simple Markowitz optimization is still can give some excessive return comparing to set benchmark.

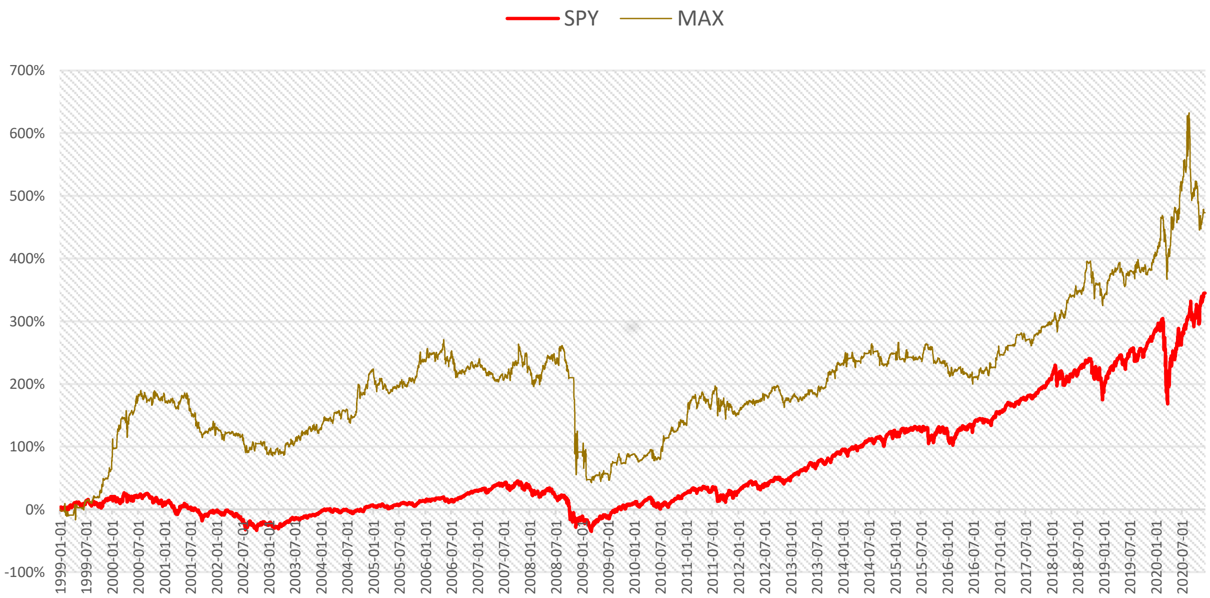


Figure 17 SPDR S&P 500 ETF vs maximum sharpe ratio 1999-2020 total return

Source: Author

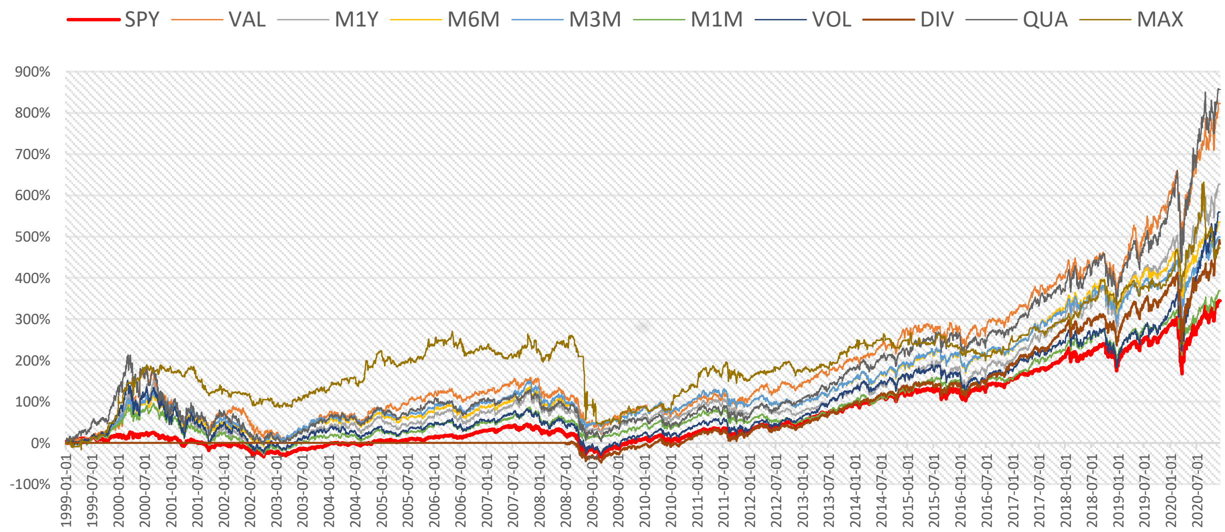


Figure 18 SPDR S&P 500 ETF vs factors 1999-2020 total return

Source: Author

After completed returns time series analysis it can be stated, that comparing to benchmark all strategies earn excess return and total return in all these cases described above in. Figure 18.

Analyzing four strategies which passed hypothesis conditions it can be highlighted what from total annual fees perspective strategies do not differ significantly. Value and Momentum 1Y only approx. 0.01% is less costly when Volatility and Quality, but significantly approx. 0.8% more expensive comparing to benchmark. Standard deviation is quite similar and equal to 0.24 and 0.25 accordingly. Maximum drawdown is different for Value and equal to 64% while three remaining strategies exceed 70% level and benchmark maximum loss only 51%. Sharpe and Sortino for Value also shown greater levels 0.5 and 0.63 against similar ratios for Momentum 1Y, Volatility and Quality. Strategies have been scored (Table 8, Appendix B) in line with their ratios and intuition behind these ratios in below table. The winning strategy should collect the smallest amount of point from 10 ratios, points are from 1 to 10.

Table 8

Strategy (only passed hypothesis) places determined by ratios scoring

Strategy	Place	Annualized return
Value factor	**1**	**10.658%**
Quality	**2**	**10.840%**
SPDR S&P 500 ETF Trust	**3**	**7.040%**
Momentum 1Y	**3**	**9.464%**
Volatility 3M	**5**	**8.975%**

Source: Author

After adjusting annualized compounding return for total percentage annual cost level only one 1-month momentum strategy do not generate excess return after cost. 4 null hypotheses from total 9 have been rejected and empirical evidence of factor effect have been observed according to testing conditions. Despite this in, below table provided overall score of all strategies (Table 9).

Table 9

Strategy (all strategies) places determined by ratios scoring

Strategy	Place	Annualized return
Value factor	**1**	**10.658%**
Momentum 6M	**1**	**8.794%**
Dividend yield	**3**	**8.357%**
Quality	**4**	**10.840%**
Momentum 3M	**5**	**8.503%**
Momentum 1Y	**6**	**9.464%**
Volatility 3M	**7**	**8.975%**
SPDR S&P 500 ETF Trust	**7**	**7.040%**
Maximum Sharpe	**8**	**8.282%**
Momentum 1M	**9**	**7.292%**

Source: Author

CONCLUSIONS AND RECOMMENDATIONS

After theoretical research it can be examined that main fact why the smart beta strategies were presented in this paper is it's ability to earn excessive returns in a market. However, market, as whole, can be represented as a very efficient universe according to Efficient market hypothesis, where there is not any additional possibility to earn more than market can furnish and anyone cannot predict the future movements.

But at the same moment alternative Fractal market hypothesis allow us to determine that with investment horizons increasing longer-term fundamental information dominates in a market and this will ensure that there is enough liquidity for market participants to make trades. But if an event occurs that creates uncertainty on the validity of the fundamental information, long-term investors either stop participating in the market or start trading based on a short-term information. Thus, the prices reflect a blend of short-term technical trading and long-term fundamental valuation. It is likely that short-term price changes will be more volatile than previous ones.

The main market trend reflects changes in expected earnings based on a changing economic fundamental environment. Short-term trends are more likely to be the result of crowd behavior. There is no reason to believe that the length of short-term trends is associated with a long-term fundamental trend. For myself, this hypothesis most closely describes market actions in real terms.

Further, the anomaly definition was described to understand the nature of anomaly factor and it's relationships in the market. Academic research in this field confirmed that in various period anomalies have positive effect on returns and negative impact in case of "bubbles". The understanding of how anomaly can work in a market, can give advantage for investor to make investment decision more rule-based and make it before the positive or negative event can occur.

It was identified what asset management split into two mainstreams: passive and active. It was shown, that according to Morningstar data for last decade there is a huge outflow from active management to passive. Also, some statistics prove that approximately 20% of all international active management fund outperform the market all periods from 3 to 15-year. It was discovered what management fee downward trend exist but stay quite huge exclusion between active and passive with smart beta funds. For this reason, the wealth accumulation plan was created to check the dollar and percentage return for 30-year period. The model results that in case of constant 6% return and due to different fees structure investor will accumulate approximately 10% less in active fund and only 1.5% less using smart beta funds comparing to index funds.

According to survey results provided by FTSE Russel and Edhec-Risk institute were established the upward trend of smart beta implementation among asset management industry professionals. Three main top 3 objectives: return enhancement, risk reduction and improve diversification remain in line with smart beta usage of low volatility, multi-factor combination and value strategies.

Hypothesis about inefficiency in Nasdaq exchange stocks universe have been confirmed using rolling 3-year Hurst coefficient. Approximately 97% of time coefficient indicate a persistency in a market and from this point of view we can conclude that factor which grab more longer trend anomaly can have positive return or excess returns. Momentum strategies excess returns confirms this statement under this research conditions.

1. 1-year momentum with excess return of 2.424%
2. 6-months momentum with excess return of 1.754%
3. 3-months momentum with excess return of 1.463%
4. 1-months momentum with excess return of 0.252%

Under this research and developed codes all strategies total return beat SPDR S&P 500 ETF Trust, but it need to stress what comparable benchmark consist of large capitalization stock of all sectors, while our portfolios have all stock available and size effect also may have an impact on achieved returns. Size factor not covered by this thesis, but should be taken into consideration in further analysis. Also is should be stressed that portfolio size (number) of selected securities may have an impact on returns due to marginal efficiency principle.

Total transaction cost formed by trading and custody fee made significant impact to portfolio performance for long term investors. Costs managing and trading turnover reduction can give investor an opportunity to increase returns. 1 month momentum strategy after cost adjusting earn less that SPDR S&P 500 ETF and maximum Sharpe, dividend yield and 3-month momentum earn approximately 0.5% more. In this case SPDR S&P 500 ETF strategy may be prioritized against these 3 strategies because of involving additional staff and resources for managing and administration. Hence investor could choose SPDR S&P 500 ETF or any other ETF as simplest method to invest.

After completed scoring for passed and not passed hypothesis testing conditions Value scored best among all strategies and stand in line with most commonly evaluated smart beta strategies for 2016-2018 survey results. Quality and Volatility according to research get into top five, that is in line with most widely used smart beta strategies for 2014-2018 results. It can be treated as an evidence of algorithm correctness and achieved results confirmed existing trends in investment management industry.

Value, Long term momentum, Volatility, Quality and Dividend yield portfolios outperform the SPDR S&P 500 ETF and this outperformance in line with market practice seen in theoretical part. According to scoring table Value, Long term momentum (6-month) and Dividend yield are most valuable strategies. These top 3 strategies can be developed further to construct multifactor portfolio.

On the other hand of this research algorithmic trading as a process should be reviewed. One of the most major benefits of using algorithmic trading is the velocity it offers. Algorithms can analyze various parameters and technical indicators in a second and trade immediately. Increased speed becomes very important, as investors can capture price changes as soon as they occur. When algorithm is working it required minimum human intervention and all logic applied in this algorithm will be realized very quickly, insights or signals will be generated accordingly to set logic or trading idea like Momentum or Value or etc.

Due to the fact that process became automated, it allow to minimize human emotion impact and eliminate psychological element and let investor follow initial strategy and plan. Asset selection, order execution, in’s and out’s became step-by-step instructions defined in advance.

Several issues arise when investor will try implement algorithmic trading. First of all investor need to have technical background and know-how to program an idea. Secondly, it is extremely possible that the strategies formulated on paper may not turn out to be profitable and effective during live trading. Another thing which should be stressed, what investor need to have resources and technology to access data and be able to generate signals when going live based on data received from external party.

Last but not least thing is that algorithms are programmed instructions and they cannot recognize the situations and circumstances like human minds do. An investor could understand the irrational behavior of the market and respond accordingly. However, the algorithms recognize ideal situations only defined by human. They fail in the irrational markets and can become inaccurate under away-from-normal situations. Artificial intelligence component in portfolio construction model could cover this topic on deeper level and ensure ability for model to learn. But from other side this component may overfit the model and desirable results may not be achieved. This step can be examined in further research.

The main **recommendation**s to algorithm code developing is to include risk management step. It should manage risks on overall portfolio or separate security level. Several option could be realized during developing process:

1. Trailing sell-limit order technique for single security and its value may be set as 1 or 2 standard deviation or fixed percentage of position. This order will move along with

security price movements and liquidate stock position when opposite movement occur.

2. Fixed sell-limit technique for single security. Value also can be set as percentage of 1 or 2 standard deviations or fixed percentage from opened position.
3. Portfolio maximum drawdown technique will ensure liquidation of all portfolio at predetermined level of drawdown for all portfolio. It will be extremely useful during short term drop during long term market turbulence.
4. Sector exposure can allow to avoid overweight one sector or industry.
5. Asset reallocation technique can allow to move capital from one asset class to another (exp.: switching between equity and fixed income classes).

Portfolio construction step can be improved by constructing multifactor portfolio and make additional analysis between various multifactor weighted portfolios and different rebalancing periods. Rebalancing step can be set to 3 and 6 months or another to test less and more frequent rebalancing impact on portfolio.

General algorithm described in research provide only general view of how portfolio can be constructed for various investors purposes. Investor targets will depend on investment horizon, desirable return and acceptable risk. Also we need to keep in mind regulations and tax obligations which can arise after going live with constructed portfolio. It should be stressed what all smart beta strategies constructed portfolios use the historical data sample to discover factors. These factors can be integrated into strategy and portfolio managers and investors need to avoid the historical figures “trap” and always should know what is behind the figures they use.

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SMART BETA STRATEGIES APPLICATION AND ASSESEMENT

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Master Thesis

Finance and Banking Programme

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SUMMARY

Size: 68 pages, 20 figures, 10 tables, 91 references, 2 annexes

The purpose of this work is to conduct a comprehensive study of the development and application of key actual Smart Beta investment strategies in various sectors of US stock market using NASDAQ stock exchange constraints. Smart Beta, also known as a “Strategic Beta", "Alternative Beta", and "Factor Investing", is a set of investment strategies based on alternative rules that determine the weight of the portfolio rather than the traditional strategies weighted by capitalization. Such strategies may allow to gain an advantage over market inefficiency that are not available for traditional capitalization weighted strategies. Smart beta strategies, as a partly passive investment representative, are cheaper than active management, hence portfolio managers does not require daily decision-making, but require only to recalculate weights according to predefined rules. This study provides an empirical research of Smart Beta strategies what are capable to generate excessive return.

In the course of this study, 4 hypotheses were confirmed what smart beta strategies allows to get a higher return while maintaining a fairly acceptable risk level in relation to the market adjusted to total trading and custodian fess. Portfolios based on these strategies were measured against the return on profitability compared to the market portfolio benchmark SPDR S&P 500 ETF Trust as broadly used benchmark in industry. For this purpose, 9 single factor portfolios were formed and tested on historical data using on NASDAQ exchange traded stocks from 1999-01-01 to 2020-12-02.

All portfolios were analyzed and compared against each other, additional ratios such as CAGR, standard deviation, maximum drawdown, Sharpe, Sortino, tracking error, information ratio profit/loss ratio, standard annualized deviation and total fees were calculated for additional comparable analysis.

SMART BETA STRATEGIJŲ TAIKYMAS IR VERTINIMAS

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SANTRAUKA

Apimtis: 68 puslapiai, 20 paveikslų, 10 lentelių, 91 literatūros šaltiniai, 2 priedai

Šio darbo tikslas - atlikti išsamų pagrindinių faktorinių “Smart Beta” investicinių strategijų konstravimą ir taikymą JAV akcijų rinkos Nasdaq biržoje prekiaujamų akcijų. „Smart Beta“, taip pat žinoma kaip „Strateginė beta“, „Alternatyvioji beta“ ir „Faktorinis investavimas “, yra investicijų strategijų rinkinys, pagrįstas alternatyviomis taisyklėmis, kurios nustato akcijų svorius portfelyje, atvirkščiai nei tradicines strategijas, kuriuose svoriai įvertinami pagal kapitalizaciją. Tokios smart beta strategijos gali leisti įgyti pranašumų prieš rinkos neefektyvumą, kurie nėra prieinami tradicinėms svertinėms pagal kapitalizaciją strategijoms. Smart beta strategijų taikymas yra pigesnės nei aktyvus valdymas, nes iš portfelio valdytojų nereikalaujama kasdieninio sprendimų priėmimo, tačiau reikalauja portfelio svorių perskaičiavimo pagal iš anksto nustatytas taisykles.

Šio tyrimo metu buvo patvirtintos 4 hipotezės, kad Smart Beta strategijos leidžia pasiekti didesnės grąžos, kartu išlaikant priimtina svyravimo riziką sukoreguota į numanomas išlaidas. Šiomis strategijomis pagrįsti portfeliai buvo lyginami su SPDR S&P 500 ETF Trust. Šiuo tikslu buvo suformuoti 9 vienfaktoriniai portfeliai, o istoriniai duomenys buvo patikrinti nuo 1999-01-01 m. iki 2020-12-02 m.

Visi portfeliai buvo išanalizuoti ir palyginti vienas su kitu. Palyginamajai analizei buvo apskaičiuoti papildomi rodikliai, tokie kaip Šarpo rodiklis, Sortino rodiklis, atitikties paklaida, „information ratio“ standartinė deviacija ir bendros metinės išlaidos.

ANNEXES

Annex A SPDR S&P 500 ETF trust information and total dividend gross return

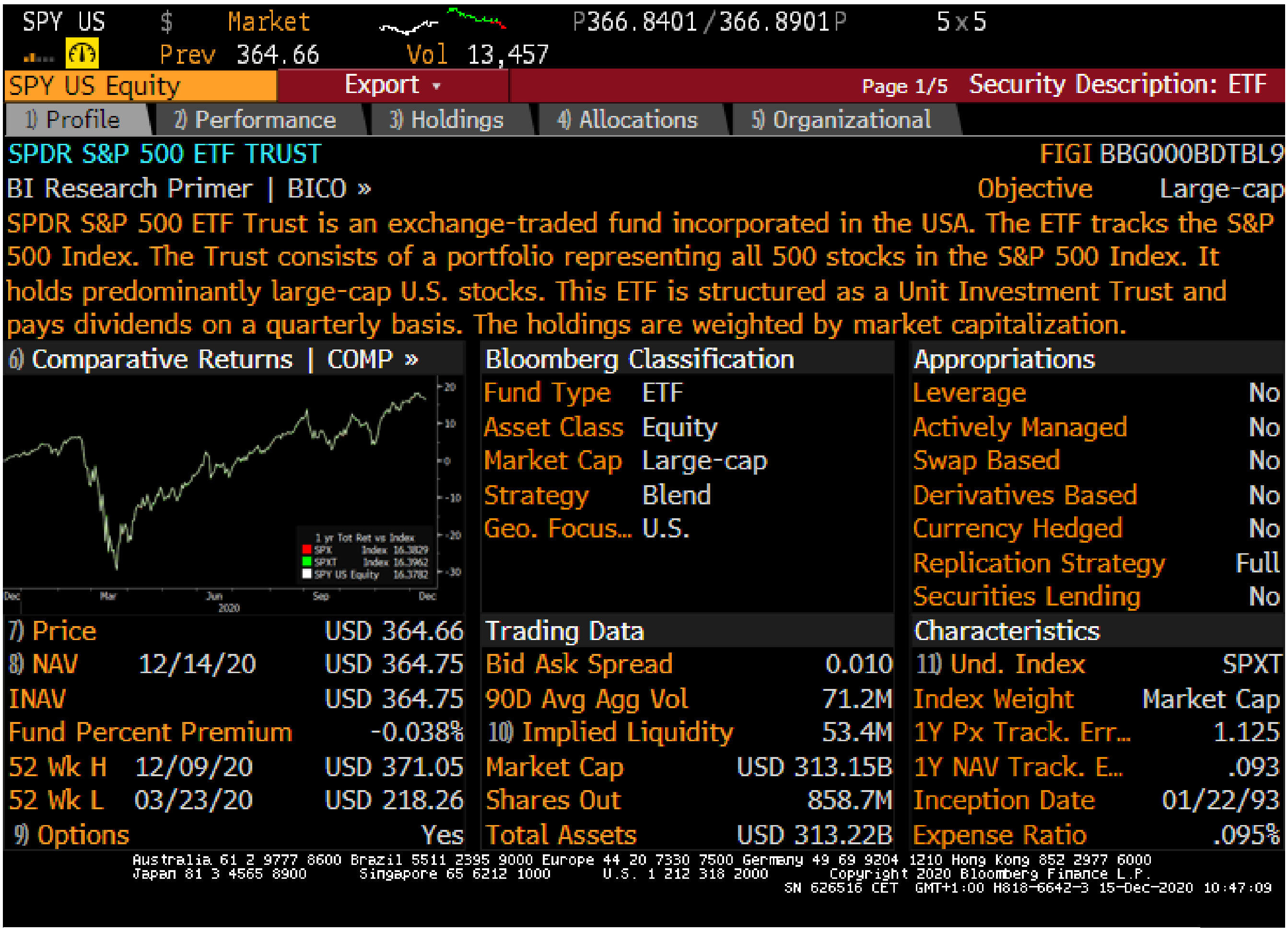

Figure 19 SPDR S&P 500 ETF general information.

Source: Bloomberg

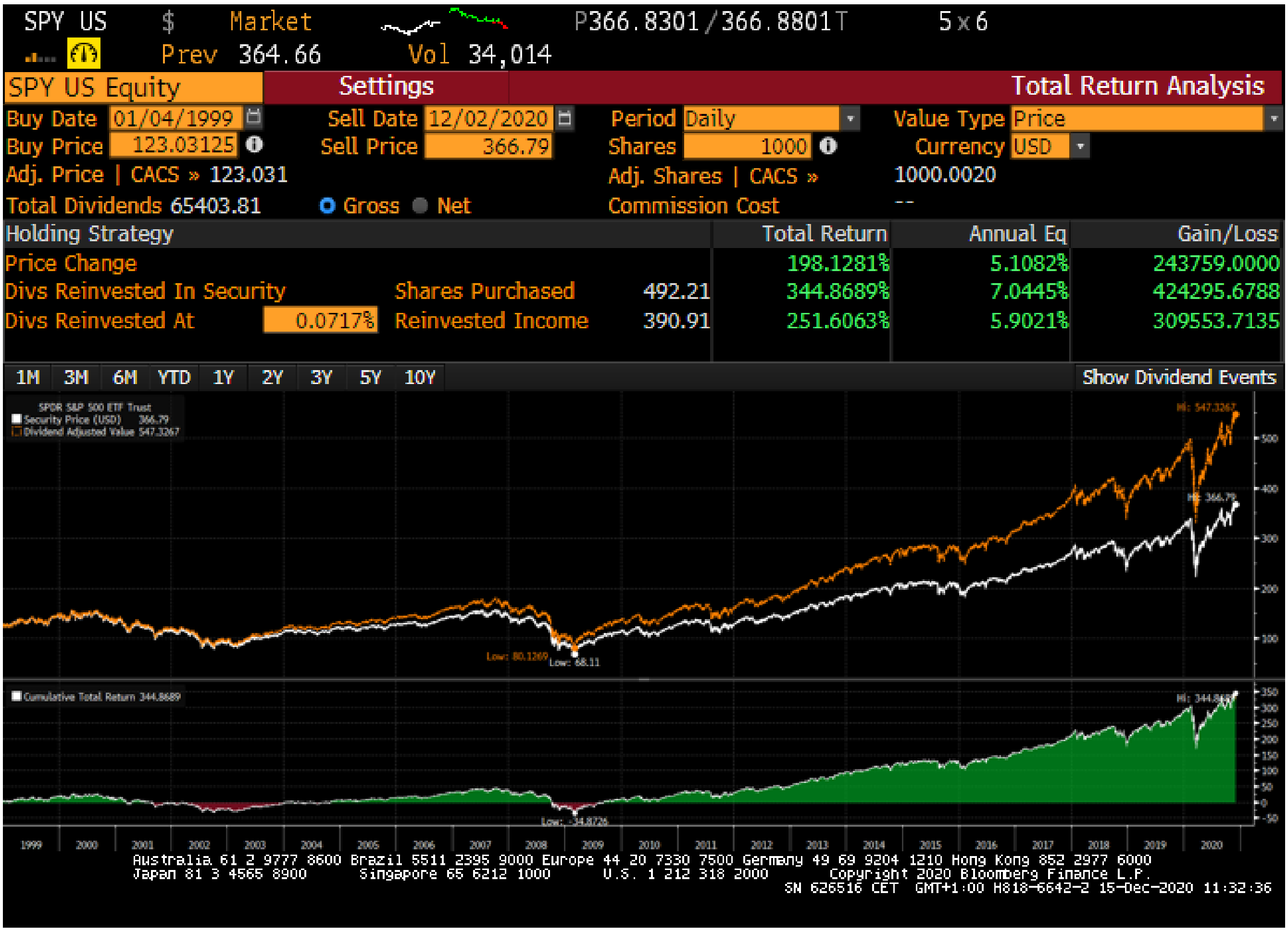

Figure 20 SPDR S&P 500 ETF return breakdown

Source: Bloomberg

Annex B Smart Beta strategies 1999-2020 period results analysis

Table 10

Smart Beta strategies 1999-2020 period results analysis

Main information	SPDR S&P 500 ETF Trust	Value factor	Momentum 1Y	Momentum 6M	Momentum 3M	Momentum 1M	Volatility 3M	Dividend yield	Quality	Maximum Sharpe
Is the null hypotheis rejected?		YES	YES	NO	NO	NO	YES	NO	YES	NO
Excess return	-	**3.618%**	**2.424%**	**1.754%**	**1.463%**	**0.252%**	**1.935%**	**1.317%**	**3.800%**	**1.242%**
Excess return less cost		**2.743%**	**1.552%**	**0.890%**	**0.596%**	**-0.615%**	**1.049%**	**0.472%**	**2.912%**	**0.298%**
Annualized return	7.040%	**10.658%**	**9.464%**	**8.794%**	**8.503%**	**7.292%**	**8.975%**	**8.357%**	**10.840%**	**8.282%**
Stdev	0.15	0.24	0.24	0.19	0.18	0.19	0.25	0.16	0.25	0.20
Max. Drawdown	51%	64%	72%	58%	57%	62%	72%	49%	70%	62%
Sharpe Ratio	0.41	**0.50**	**0.46**	**0.49**	**0.48**	**0.42**	**0.43**	**0.51**	**0.49**	**0.45**
Sortino ratio	0.59	**0.63**	**0.50**	**0.60**	**0.58**	**0.49**	**0.44**	**0.43**	**0.57**	**0.42**
Tracking Error	0.02	**0.14**	**0.30**	**0.26**	**0.26**	**0.49**	**0.32**	**0.25**	**0.14**	**0.28**
Information Ratio	(0.22)	**0.31**	**0.11**	**0.06**	**0.05**	**0.02**	**0.11**	**0.03**	**0.35**	**0.06**
Profit/Loss Ratio	89%	**66%**	**56%**	**50%**	**50%**	**26%**	**74%**	**111%**	**69%**	**112%**
Average annual trading fees	0.000%	**0.035%**	**0.032%**	**0.024%**	**0.027%**	**0.027%**	**0.046%**	**0.005%**	**0.048%**	**0.104%**
Custodian annaul fess	0.095%	0.840%	0.840%	0.840%	0.840%	0.840%	0.840%	0.840%	0.840%	0.840%
Total annual fees	0.095%	0.875%	0.872%	0.864%	0.867%	0.867%	0.886%	0.845%	0.888%	0.944%
Total trading fees	0.000%	1.01%	0.94%	0.70%	0.77%	0.79%	1.33%	0.06%	1.39%	3.01%
Capital gain	345%	**822%**	**627%**	**535%**	**499%**	**368%**	**559%**	**483%**	**856%**	**473%**
Equity	$ 4,381,216.00	**$9,222,098.38**	**$7,267,870.25**	**$6,351,341.10**	**$5,989,205.52**	**$4,682,564.74**	**$6,589,936.68**	**$5,827,810.90**	**$9,560,668.56**	**$5,728,199.82**
Total Fees	$ -	$ 93,414.25	$ 68,353.08	$ 44,580.12	$ 46,242.82	$ 37,140.57	$ 87,329.79	$ 3,773.80	$ 133,026.78	$ 172,522.35

Source: Author

Continued of Table 10

Additonal information	SPDR S&P 500 ETF Trust	Value factor	Momentum 1Y	Momentum 6M	Momentum 3M	Momentum 1M	Volatility 3M	Dividend yield	Quality	Maximum Sharpe
Maximum stocks qty in portfolio		50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00
Strategy comments	Total gross dividend return	Long direction signals	Long direction signals	Long direction signals	Long direction signals	Long direction signals	Long direction signals	Long direction signals	Long direction signals	Long direction signals
Rebalancing	No	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Yearly	Monhtly	Monhtly
Sharpe Ratio		8.6	4.7	7.7	6.6	1.0	1.8	10.4	7.8	3.8
Sortino ratio		4.3	-9.0	1.0	-0.7	-9.7	-15.0	-15.7	-2.2	-16.7
Tracking Error		11.3	27.9	24.1	24.0	46.7	29.5	22.4	12.0	25.2
Information Ratio		53.3	33.0	28.1	27.1	23.5	32.6	25.2	56.7	27.5
Strategy rank	**7**	**1**	**6**	**1**	**5**	**9**	**7**	**3**	**4**	**8**

Scoring and Ranking	SPDR S&P 500 ETF Trust	Value factor	Momentum 1Y	Momentum 6M	Momentum 3M	Momentum 1M	Volatility 3M	Dividend yield	Quality	Maximum Sharpe
Annualized return	10	2	3	5	6	9	4	7	1	8
Stdev	1	7	7	4	3	4	9	2	10	6
Max. Drawdown	2	7	9	4	3	6	9	1	8	5
Sharpe Ratio	10	2	6	4	5	9	8	1	3	7
Sortino ratio	3	1	6	2	4	7	8	9	5	10
Tracking Error	10	9	3	5	6	1	2	7	8	4
Information Ratio	10	2	3	5	7	9	4	8	1	6
Profit/Loss Ratio	3	6	7	8	8	10	4	2	5	1
Total trading fees	1	7	6	3	4	5	8	2	9	10
Capital gain	10	2	3	5	6	9	4	7	1	8
Strategy score	**60**	**45**	**53**	**45**	**52**	**69**	**60**	**46**	**51**	**65**