UNIVERSITY OF GOTHENBURG
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Graduate School

Fundamental Indexation Smart Beta Strategy on the Swedish Market

Enhancing risk-adjusted performance with Fundamental Indexation

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Abstract

Smart Beta strategies' ability to combine the benefits of active- and passive investing has caught the attention of the Asset Management industry – propelling a surge in new Smart Beta products. These strategies offer a novel approach to factor investing by not weighting assets according to the typical cap-weighting scheme, instead applying weighting methods such as fundamental indexation, yielding a new dimension to factor-oriented strategies. This thesis examines the Fundamental Indexation Smart Beta strategy on the Swedish market by comparing the constructed portfolios versus the OMX Stockholm All-Share index from 2006 to 2021. The aim is to investigate whether risk-adjusted cross-sectional returns can be found using a heuristic portfolio generation procedure based on previous literature of the Capital Asset Pricing Model, Factor Investing, and contemporary Smart Beta research. Value, Low Volatility, Quality, and Momentum are the chosen Smart Beta portfolios. The portfolio generation procedure is divided into three steps: screening, scoring, and weighting. The findings reveal significant outperformance in three out of four Smart Beta portfolios versus the benchmark index on a risk-adjusted basis.

Key terms: Smart Beta, Fundamental Indexation, CAPM, EMH, Value, Quality, Momentum, Low Volatility, Factor Investing

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1. Introduction

Smart Beta strategies are among the fastest growing passive-active strategies within the Asset Management industry (Martellini & Le Sourd, 2019). Despite their popularity, there are few studies on the topic and the literature is quite ambiguous in explaining its meaning. Smart Beta has served as an umbrella term for similarly related concepts such as Advanced Beta, Alternative Beta, ActiveBeta, Anti-Beta, Factor Investing, Strategic Beta, and Scientific Beta. However, its meaning is quite simple. Smart Beta strategies aim to break the link between the price of securities and their weight in a portfolio – instead weighting them using alternative schemes such as equal weighting, minimum variance, or fundamental indexation (Arnott & Kose, 2014).

In order to evaluate Smart Beta strategies one needs first to understand factor investing. A simple analogy is that factors can be seen as nutrients in a diet. Just like a human being needs a well-balanced diet to function properly, an investment portfolio needs to be diversified to optimize its risk-adjusted performance. As illustrated in Figure 1, a meal is based on ingredients that contain nutrients, in the same way a portfolio is based on assets that contain factors. For example, similar to salmon containing protein and fats, the stock Evolution Gaming contains quality- and momentum characteristics (Ang, 2014).

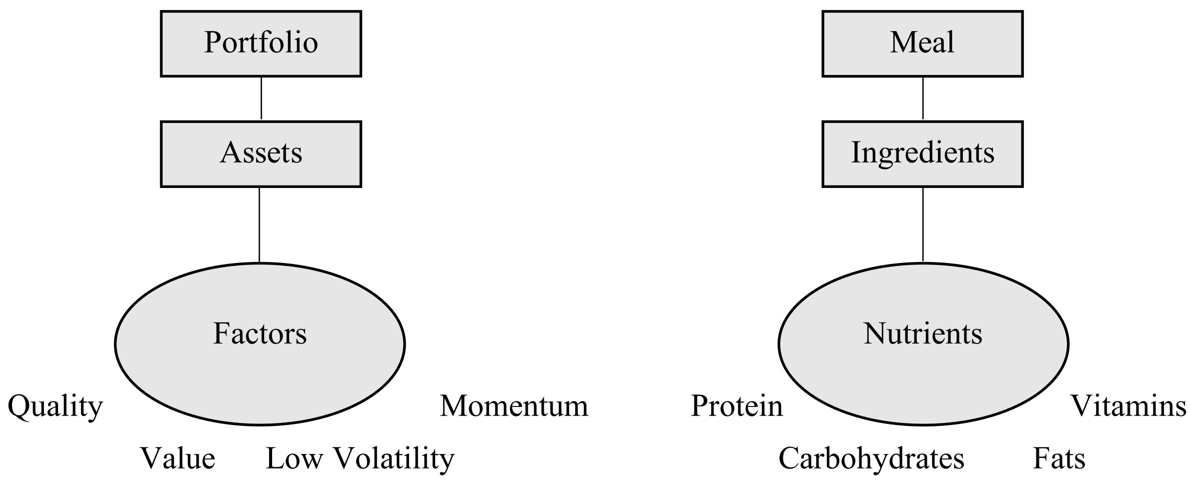

Figure 1: Nutrient & Factor Analogy
Source: Ang, 2014

Factor investing builds upon the framework established in the Capital Asset Pricing Model (CAPM), which was introduced in the 60s by Treynor (1961), Sharpe (1964), Lintner (1965), and Mossin (1966). Since then, the model has been continuously expanded upon, such as in the famous Fama & French (1993) three-factor model, which introduced the Value- and Size factors. Four years later, Carhart (1997) introduced their four-factor model by adding Momentum. Moreover, examples of contemporary research are given by Hou et al. (2012), who studied an investment-based asset pricing model which stems from the q-theory of investment; Novy-Marx (2013) who studied the Value- and Quality factors; and Bali et al. (2016) who studied the Low Volatility factor. These are some of the studies discussed further in the previous research section and throughout the paper.

The purpose of this thesis is to construct Fundamental Indexation Smart Beta portfolios using Swedish securities during the period April 2006 to February 2021 and compare these versus the OMX Stockholm All-Share index to determine whether cross-sectional returns can be found. The chosen Smart Beta portfolios are Value, Low Volatility, Quality, and Momentum.

2. Theory

This section covers well-known theories within finance on which Smart Beta strategies have their roots. Starting with Modern Portfolio Theory, followed by the Capital Asset Pricing Model (CAPM), and concluding with the Efficient Market Hypothesis (EMH).

2.1 Modern Portfolio Theory

Harry Markowitz (1952) established the underpinnings for Modern Portfolio Theory, which in turn has served as the framework for the famous Capital Asset Pricing Model (CAPM). He outlined an investment framework that maximizes portfolio returns while simultaneously minimizing investment risk. This is achieved by eliminating the idiosyncratic risk (diversifiable risk), which leaves investors only exposed to the systematic risk (undiversifiable- or market risk). In addition, Markowitz supposes that all investors are rational and risk-averse, meaning that investors always prefer the mean-variance efficient portfolio (maximizing expected return relative to risk level). Other vital assumptions are access to the same information, market efficiency, and the normal distribution of returns (Markowitz, 1952).

Markowitz (1952) also emphasized the importance of diversification and proposed that compiling stocks uncorrelated with each other creates a diversification effect that minimizes the overall portfolio risk. The figure below illustrates this concept.

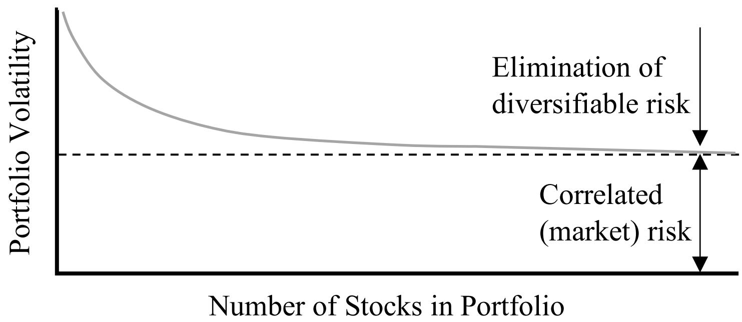

Figure 2: Diversification effect
Source: Berk & DeMarzo, 2017

There are many studies with differing opinions on the number of securities required to obtain a well-diversified portfolio. For example, Evans & Archer (1968) concluded that ten stocks were enough, while Statman (1987) believed that at least thirty stocks were required.

2.2 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) was introduced in the 60s by Jack Treynor (1961), William F. Sharpe (1964), John Lintner (1965), and Jan Mossin (1966) where the relationship between systematic risk and expected return for securities was studied. To arrive at a CAPM equilibrium, a few necessary assumptions have to be met. These have been summarized by Elbannan (2015):

- All investors take a position on the efficient frontier, maximizing the utility from investments. Investors are risk-averse, utility maximizers and make investment decisions solely on said investment's risk- and return profile. At what point on the efficient frontier investors lie is based on their trade-off between risk and return.
- Investors can borrow or lend at a given risk-free rate of return.
- All investors have homogenous expectations about the future, which implies the same expectations of future rates of return.
- All investors hold investments for the same period.
- Investors can buy or sell portions of any security or portfolio.
- No tax- or transaction costs are associated with buying or selling assets.
- No inflation or changes in interest rates exist.
- Capital markets are in equilibrium, all investments are fairly priced, and investors have no power to influence prices.

If these assumptions hold, each investor will strive towards the same portfolio – the one with the highest Sharpe ratio. This implies that every investor will demand the same efficient portfolio of risky assets, which can then be complemented by risk-free assets to match each investor's risk preferences. Hence, the sum of all the investors' portfolios (the efficient tangent portfolio) will be equal to the market portfolio. This is governed by basic supply and demand mechanics. For example, if a stock is not part of the efficient portfolio no investor will hold that stock, producing a downward shift in demand and a decreasing price up until a certain point when the stock becomes attractive again. In this way, the prices in the market will constantly adjust so that the efficient- and market portfolios coincide and demand equal supply. Figure 3 on the next page demonstrates the outcome when following the CAPM rules mentioned above. All investors will choose a portfolio that lies on the Capital Market Line (CML) by owning the market portfolio, which is the tangent portfolio plus some risk-free securities (Berk & DeMarzo, 2017).

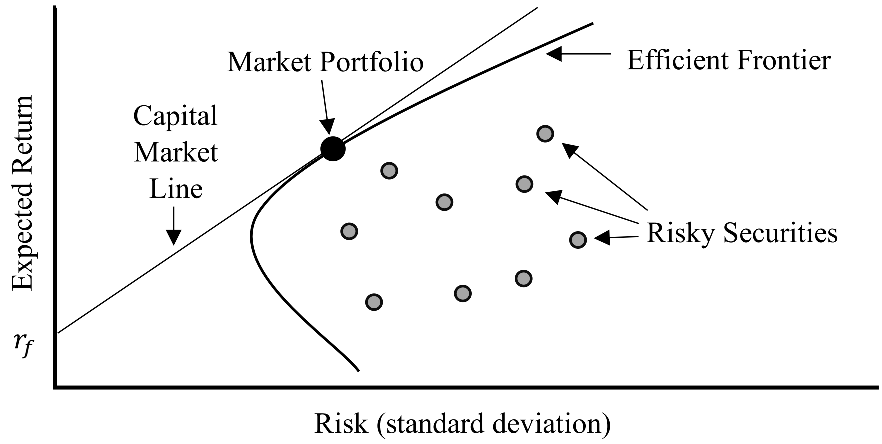

Figure 3: The Capital Market Line
Source: Berk & DeMarzo, 2017

The CAPM equation is illustrated below:

$$E[R_i] = r_f + \beta_i(E[R_{Mkt}] - r_f) \tag{1}$$

Where $E[R_i]$ is the expected return, r_f is the risk-free return, β_i is the beta of the security and, $E[R_{Mkt}] - r_f$ is the expected market risk premium. The equation shows that the expected return is solely explained by beta, indicating that the only way to receive a higher return is through higher risk-taking. Beta measures the volatility in relation to the market and captures a stock's sensitivity to systematic risk. The market has a beta of 1, and stocks with higher betas than the market will be more sensitive against market movements and vice-versa for stocks with lower beta than the market. According to CAPM, all assets are correctly priced and positioned on the Security Market Line (SML). A stock positioned above the SML is considered undervalued due to the "too high" expected return – implying a "too low" stock price compared to the fair CAPM value. Conversely, a stock positioned below the SML is considered overvalued due to the "too low" expected return – implying a "too high" stock price compared to the fair CAPM value (Bodie et al., 2014).

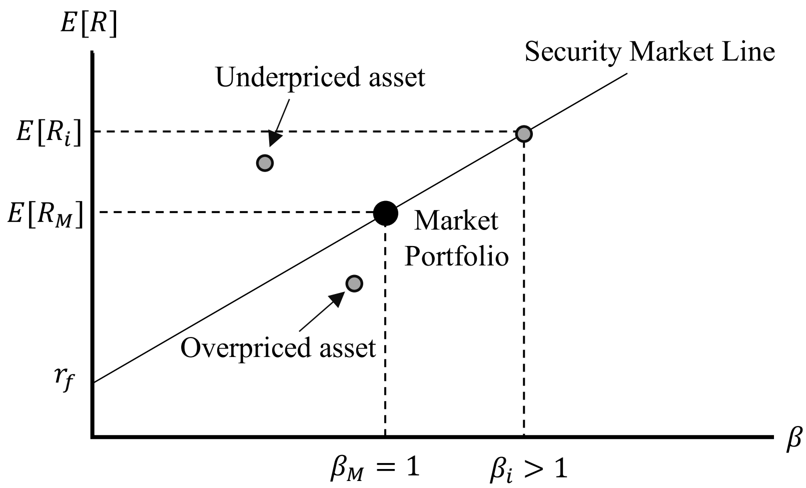

Figure 4: Security Market Line
Source: Berk & DeMarzo, 2017

2.3 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) was introduced by Fama et al. (1969), who posited an efficient market to be "a market that adjusts rapidly to new information." However, twenty years later and in a completely different landscape with abundant data, Fama (1991) re-defined and heavily strengthened the definition of an efficient market – "a market that fully reflects all available information." Hence, assuming this statement to be true would render the ability to outperform the market over time pointless since all information is already reflected in the stock price. Therefore, according to contemporary EMH research, Smart Beta strategies are ill-fated.

Fama (1970) divides the EMH framework into three characterizations of market efficiency: weak, semi-strong, and strong. Weak form efficiency suggests that current stock prices reflect all information contained in historical stock prices. An example of a strategy that challenges this assumption is the Momentum strategy, relying solely on historical stock prices. Semi-strong form efficiency expands on weak form efficiency by considering public information. Examples of strategies that challenge semi-strong efficiency are Value- and Quality strategies, relying on fundamental analysis. Lastly, strong form efficiency expands on semi-strong form efficiency by incorporating private information. Trading on private information is commonly called insider trading and is a criminal act. Despite being punitive, strong form efficiency has been challenged, as evidenced in the empirical study by Keown & Pinkerton (1981), who found abnormal returns before M&A announcements.

Since its inception, the EMH has received a fair share of criticism where several financial economists pinpoint investors' irrationality as one of the main critiques. For example, Shiller (2000) found that investors tend to exhibit irrational exuberance, which refers to situations where people push security prices higher, in a frenzied fashion, to heights difficult to justify by fundamental valuation. Historical examples of this were seen in the IT bubble of 2000 and the 2008 financial crisis. Another compelling criticism was presented by Grossman & Stiglitz (1980), who argued that if the market is so efficient, why would anyone pay for security analysis?

3. Literature Review

This section will delve into relevant previous research associated with Smart Beta strategies. Firstly, an introduction of factor investing will be presented, followed by contemporary research on Smart Beta and its evolution. Lastly, finishing with the individual selected factors chosen in this thesis.

3.1 Factor Investing

The starting point for any research essay covering factor investing should begin with arguably the most influential paper ever written on the subject, namely the "Common risk factors in the returns on stocks and bonds" (Fama & French, 1993). In this paper, the Nobel Laureate Eugene F. Fama and his colleague Kenneth R. French developed the famous Fama-French (FF) three-factor model, which builds upon the CAPM framework by adding the Size- and Value factors. They proposed a regression model as follows:

$$R_{it} - R_{ft} = \alpha_{it} + \beta_1(R_{Mt} - R_{ft}) + \beta_2 SMB + \beta_3 HML + \varepsilon_{it} \tag{2}$$

Where $R_{it} - R_{ft}$ is the excess return of the portfolio, and $(R_{Mt} - R_{ft})$ is the return of the market minus the risk-free rate. These variables are the constituents of the original CAPM formula. The novelty of FF's work is the addition of SMB – "Small Minus Big" and HML – "High Minus Low." SMB is the difference in returns between portfolios consisting of small-capitalization and large-capitalization stocks, this factor captures the size premium. The assumption is that small firms have positive exposure to this factor while large firms have negative exposure. Hence, in other words, FF suggests that investors can earn risk premiums above that of the market over the long run by buying small-cap stocks and shorting large-cap stocks. HML is the difference in returns between portfolios consisting of firms exhibiting high book-to-market ratios (value stocks) and those consisting of firms with low book-to-market ratios (growth stocks), this factor captures the value premium. The assumption is that value stocks have positive exposure to this factor while growth stocks have negative exposure. Hence, in a similar fashion to the conclusion in SMB, investors can expect higher risk premiums than the market over the long run by buying value stocks and shorting growth stocks. Furthermore, the Fama-French three-factor model bumped up the explanatory power, i.e., the portfolio beta's explanatory capabilities of the excess returns, of the original CAPM framework by 25 percentage points from 70- to 95% (Fama & French, 1993).

Carhart (1997) built upon the Fama-French three-factor model by adding a fourth factor to the model – Momentum:

$$R_{it} - R_{ft} = \alpha_{it} + \beta_1(R_{Mt} - R_{ft}) + \beta_2 SMB + \beta_3 HML + \beta_4 MOM + \varepsilon_{it} \qquad (3)$$

Carhart defines the momentum factor, MOM, as the proclivity for securities that have performed well or poorly in the recent past (three to twelve months) to continue doing so in the near future. Hence, following the momentum and buying stocks that have performed well – "the winners" and shorting stocks that have performed poorly – "the losers," investors can earn risk premiums above the market. Carhart concluded that incorporating the momentum factor into the pre-existing three-factor model framework established by FF, resulted in a slight improvement in the model's explanatory power (Carhart, 1997).

FF (and to some extent Carhart) laid the groundwork and summarized much of the state-of-the-art understandings of the cross-section of returns as of the mid-1990s. Since then, however, it has become increasingly apparent that the existing models fail to explain a wide range of cross-sectional anomalies. Prominent examples include post-earnings-announcement drift, momentum, and the negative relations of average returns with net stock issues, financial distress, and idiosyncratic volatility. To illuminate and minimize these anomalies, Hou et al. (2012) produced a new multifactor model, called the q-factor model, based on investment-based asset pricing, which in turn stems from the q-theory of investment – *Tobin's Q*. They proposed a regression model as follows:

$$E[r^i] - r^f = {\beta^i}_{MKT} E[MKT] + \beta^i_{ME} E[r_{ME}] + \beta^i_{\Delta A/A} E[r_{\Delta A/A}] + \beta^i_{ROE} E[r_{ROE}] \qquad (4)$$

Where MKT is the market excess return, r_{ME} is the difference in returns between portfolios consisting of small-market equity stocks and those consisting of large-market equity stocks (size factor), $r_{\Delta A/A}$ is the difference in returns between portfolios consisting of low-investment stocks and those consisting of high-investment stocks (investment factor), and lastly, r_{ROE} is the difference in returns between portfolios consisting of high return on equity stocks and low return on equity stocks (ROE factor). Hence, there are similarities and a few alterations to the FF and Carhart models.

Hou et al. (2012) found that their q-factor model was significantly more effective in explaining many anomalies that the FF and Carhart models could not. For example, higher explanatory effectiveness on anomalies related to idiosyncratic volatility, earnings surprise, financial distress, composite issuance, net stock issues, investment, and ROE. The work by Hou et al. (2012) summarizes much of the current literature on the cross-section of returns as of the early 2010s, and their key contribution is to provide a new workhorse factor model.

Novy-Marx (2013) found that profitability, measured by gross profits-to-assets, exhibits approximately the same explanatory power of predicting the cross-section of average returns as book-to-market. Profitable firms outperform unprofitable firms in terms of return generation, despite observing considerably higher valuation ratios. He also found that when controlling for profitability, the performance of value strategies is dramatically increased, most notably for the largest, most liquid stocks. These results may be hard to comprehend using popular explanations of the value premium, as profitable firms have longer cash flow durations, are less prone to distress, and experience decreased levels of operating leverage. Lastly, he also found that when controlling for gross profitability, the earnings-related anomalies are illuminated.

The work by Hou et al. (2012), and especially the work by Novy-Marx (2013), pointed out some significant flaws in the framework developed by FF. To address these issues, FF developed a new and improved version of their three-factor model by adding two additional factors – profitability and investment. This five-factor model aims to fill the gap of unexplained expected returns from the variation in average returns related to profitability and investment. They proposed a regression model as follows:

$$R_{it} - R_{ft} = \alpha_{it} + \beta_1(R_{Mt} - R_{ft}) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \varepsilon_i \qquad (5)$$

Where CMA (conservative minus aggressive) measures the difference in returns on diversified portfolios of securities of high and low investment companies. RMW (robust minus weak) measures the difference in returns on diversified portfolios of securities with weak and robust profitability. FF found that their new five-factor model outperforms the three-factor model on all metrics, and it generally outperforms other models as well. They did find one peculiar exception, however, namely that when omitting the factor "HML" from the model, no loss in the description of average returns was observed (Fama & French, 2014).

3.2 Smart Beta

The concept of Smart Beta is relatively new, and there is no definitive definition for it which has created a vague and mysterious impression. This lack of clarity is partly due to the scarcity of research on the topic and its evolution. The term Smart Beta was coined in 2007 by the founders – Towers Watson, a leading global investment consulting firm based in London. Their definition is:

"Smart Beta is simply about trying to identify good investment ideas that can be structured better, whether that is improving existing beta opportunities or creating exposures or themes that are implementable in a low cost, systematic way" – (Towers Watson, 2013)

A similar concept was introduced by Rob Arnott – later called the "godfather of Smart Beta," and his colleges Jason Hsu and Philip Moore at Research Affiliates. They published the article "Fundamental Indexation" in 2005, which introduced a new index investing method. They created a rules-based approach to security selection and weighting that utilized a fundamental approach instead of the popular cap-weighted approach (Arnott et al., 2005).

Rob Arnott and Ergin Kose at Research Affiliates defined Smart Beta as "a category of valuation-indifferent strategies that consciously and deliberately break the link between the price of an asset and its weight in the portfolio, seeking to earn excess returns over the cap-weighted benchmark by no longer weighting assets proportional to their popularity, while retaining most of the positive attributes of passive indexing" (Arnott & Kose, 2014).

The definition presented by Arnott & Kose is closest to what most researchers today perceive as Smart Beta strategies. Hence, in short, Smart Beta strategies are a combination of active- and passive investing where one implements a systematic investment approach that targets specific attributes of securities and weights them with alternative weighting schemes. How is this different from Factor Investing strategies? Well, there are two distinct differences. Firstly, using Fundamental Indexation Smart Beta strategies as an example, one assigns security weights based on individual factor scores (where each factor represents the underlying characteristics of a company) instead of using market capitalization. Secondly, Smart Beta strategies are usually long-only, while Factor Investing strategies combine long- and short positions (Research Affiliates, 2021)

Martellini & Milhau (2018) at the Ecole des Hautes Etudes Commerciales du Nord (EDHEC) Risk Institute found that Smart Beta portfolios reduce the unrewarded risk and improve the risk-adjusted performance by deviating from the typical cap-weighting scheme instead implementing a smart weighting scheme.

Similar results were found by Cai et al. (2018), who studied five different Smart Beta strategies: fundamental indexation, risk parity strategy, equal weighting, mean-variance optimization, and minimum-variance. They compared these strategies to the Shanghai Stock Exchange (SSE 50 Index) and SSE sector indices and found outperformance across the board, with higher returns and Sharpe ratios for each alteration of portfolio weighting against the benchmark.

3.3 Selected Factors

This section will provide a summary of influential previous research on each of the selected factors. The factors are Value, Low Volatility, Quality, and Momentum.

3.3.1 Value

With its early roots in the highly influential book "Security Analysis" by Graham and Dodd (1934), the Value factor is arguably one of the most covered and recognized factors in academia and beyond. Its core premise is that stocks trading below their intrinsic value outperform stocks trading above their intrinsic value. In practical terms, this implies that investors would utilize different fundamental ratios (e.g., price-to-earnings, debt-to-equity, return on equity, and more) in trying to find cross-sectional returns (Novy-Marx, 2013). Prominent examples of fundamental ratios from academia can be found in Fama & French (1993), where they used price-to-fundamental ratios such as price-to-earnings, price-to-book, sales-to-earnings, price-to-cash flows, and book-to-market equity.

Results of outperformance from using value-oriented strategies have been observed in older studies. For example, Basu (1977) found that by constructing a portfolio consisting of securities with low price-to-earnings ratios and comparing it to a portfolio of randomly selected securities from the NYSE with the same overall level of risk, between September 1956 to August 1971, outperformance was observed. Rosenberg et al. (1985) came to the same conclusion but by using the price-to-book ratio.

However, as evidenced by Fama-French's five-factor model mentioned in the Factor Investing section, no loss in the description of average returns was observed when omitting the value factor. Hence, the effectiveness of the value factor might have lost some of its prudence when comparing it to newer factors.

3.3.2 Low Volatility

The fundamental concept of "higher risk higher return" is something most investors take for granted. Despite this, numerous academics have found evidence disproving this idea. The earliest finding dates back to the 1970s where Haugen & Heins (1972) studied US stocks in two time periods, 1926 to 1971 and 1946 to 1971, who found that low volatility stocks delivered higher returns than high volatility stocks. Moreover, Ang et al. (2006) found that securities with high volatility compared to the Fama-French three-factor model produced abnormally low average returns. Additionally, Blitz et al. (2013) studied emerging markets and found that the relation between risk and return was flat or even negative. But, perhaps the most substantial evidence was found in the comprehensive study by Baker & Haugen (2012), who studied every country's equity market in the world (where data is available) and found outperformance of low volatility stocks in all markets.

Moreover, Bali et al. (2016) arrived at the same result using a different approach – the lottery demand effect. They speculated that high beta (high risk) stocks function similar to a lottery, with erratic high returns. Accounting for the popularity bias of these stocks, i.e., preferred by most investors, the price will increase due to the demand shock. The premise of their work states that investors are risk-takers which pushes the price of high beta stocks upwards, producing a void for higher possible returns in low beta (low risk) stocks which are now considered undervalued.

One would naturally expect that the knowledge of this anomaly would remove any excess returns it produces, as it should lead to an increase in the number of investors adopting this strategy. Nevertheless, the pattern has been observed for the last 90 odd years and continues to outperform high volatility stocks in more recent studies. This extremely controversial deviation has put sensible theory on its head and has left academics and investors baffled (BMO Global Asset Management, 2016).

3.3.3 Quality

Previous literature is divided over what variables constitute the Quality factor. Novy-Marx (2013) uses a simple definition – gross profits-to-assets. He found that this simple ratio is as reliable as price-to-earnings and price-to-book ratios are to the value factor. Hsu et al. (2019) established a more comprehensive definition where they identified a list of seven characteristics that they believe define the Quality factor. These are profitability, investment, growth, capital structure, earnings stability, accounting quality, and payout/dilution.

Piotroski (2000) approached the quality factor by breaking it into three parts using a simple accounting-based fundamental analysis strategy. The first step is to identify a company's profitability by the variables ROA, CFO, and the variabilities of these. The second step is to measure the leverage, liquidity, and source of funds by looking at the variability in debt-to-asset and liquidity ratios as well as any occurrence of rights issues. The last step in identifying the overall quality is to measure the operating efficiency by looking at the variability in the decomposition of ROA, which is gross profit margin and asset turnover. This process concluded in a separation of future winners and losers, which may provide some guidance in finding cross-sectional returns.

Campbell et al. (2009) studied whether the characteristics of companies' cash flows influence security prices more than macroeconomic factors. They found this to be true, implying that an efficiently managed firm could obtain a competitive edge via prudent capital management. In other words, companies with superior internal governance tend to earn excess returns compared to those with poor governance. This relationship is perhaps strongest and most apparent in market downturns, where investors become increasingly risk-averse and seek stocks with quality characteristics such as sound capital management. This phenomenon is called "flight to quality" (Brooke et al., 2018).

The recent work by Brooke et al. (2018), who studied Australian firms, supports the thesis of flight to quality and also found the link between superior governance and outperformance of peers in market downturns.

Asness et al. (2019) found, using data from 25 countries, persistent outperformance of high-quality stocks when comparing them to the market by implementing a "quality-minus-junk" strategy. This strategy entails going long high-quality stocks and selling low-quality (junk) stocks. Their definition of quality is "characteristics that investors should be willing to pay a higher price for."

3.3.4 Momentum

Jegadeesh & Titman (1993) were the pioneers of the Momentum strategy. They found that by buying past winners and selling past losers on the New York Stock Exchange with a holding period of 6-months, they generated significant excess returns of 12.01% on average per year between the period 1965 to 1989. Furthermore, they suggest an average holding period of 3- to 12 months due to the dissipative effect of abnormal returns after 2- to 3 years. Conrad & Kaul

(1998) and Lee & Swaminathan (2002) found similar results with overperformance in the US stock market.

The cross-sectional returns discovered from using the Momentum strategy have propelled a search for an explanation of this anomaly. This has led to the creation of a new realm within finance – Behavioral Finance (Dhankar & Maheshwari, 2016)

Barberis et al. (1998) traced the Momentum effect to two groups of pervasive regularities (motivated by two important phenomena within psychology – conservatism and representativeness heuristic): overreaction of stock prices to a series of good or bad news, and underreaction of stock prices to news such as earnings announcements. They proposed that investors pay disproportionate attention to the strength of evidence they are presented with and neglect this information's statistical weight. The supposition is that earnings announcements should explain a larger part of the variation in the price of a security than good or bad news. However, their evidence pointed to the opposite conclusion.

In more recent research, Asness et al. (2013) demonstrated the ubiquity of momentum profits by implementing the Momentum strategy in eight markets across different asset classes and found extensive evidence on the return premia. Fama & French (2012) tested the strategy in developed markets in North America, Europe, Japan, and the Asia Pacific regions, where they found strong momentum returns in all regions except Japan.

4. Data and Methodology

This section will cover data generation, the portfolio creation procedure, the weighting methodology, and ending with a description of the performance measurement.

4.1 Data

The data used in this thesis is retrieved from Bloomberg, consisting of daily closing prices from the OMX Stockholm All-Share Index (OMXSGI) spanning from 2006/04/01-2021/02/05, adjusted for dividends. OMXSGI reflects all shares listed on OMX Nordic Exchange Stockholm and aims to represent the status of the broad Swedish economy and changes in the market. The 15-year time period is chosen as it provides substantial data and offers insight into two market downturns – the 2008 financial crisis and the recent coronavirus crash of 2020. Using Bloomberg's Watchlist Analytics (WATC) tool and filtering out the factor-specific variables, one obtains the raw data that serves as the foundation for the screening process. For each portfolio, the top 40 stocks that exhibit the highest scores will be selected. The weight for each stock will then be assigned depending on their contribution to the total sum of factor scores. In rare cases of misleading data, e.g., due to corporate actions such as spin-offs which produce unintended consequences yielding unreasonably high factor-specific scores, the data will be analyzed and adjusted when needed[1]. The portfolios will be rebalanced yearly every 1st of April[2]. A glimpse of the final result of this process is seen in the figures below (complete portfolios can be observed in Appendix C).

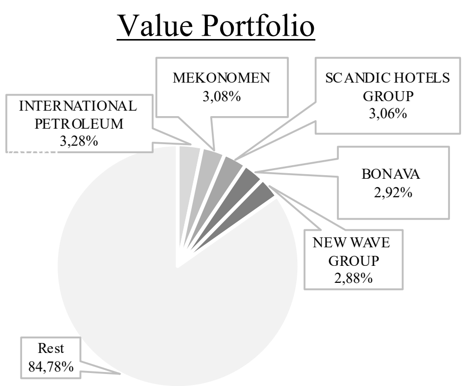

Figure 5: Value – Smart Beta Portfolio of last rebalancing period 2020/04/01 – 2021/02/05

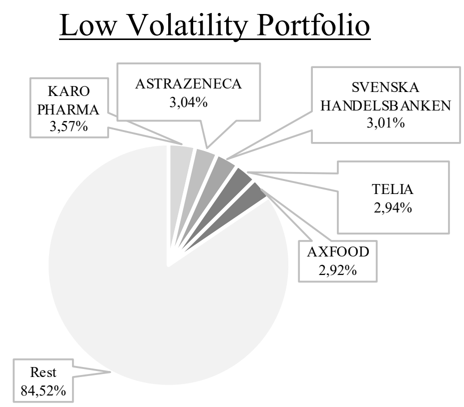

Figure 6: Low Volatility– Smart Beta Portfolio of last rebalancing period 2020/04/01 – 2021/02/05

[1] E.g., in 2018, SCA had a ROA and a ROE of 128% and 228%, respectively, due to a spin-off. This led to an unreasonably high factor-specific score which did not capture the true value.
[2] Companies on regulated Swedish stock markets tend to report their year-end financial numbers within two months after the fiscal year has ended. This means that in April one can be assured that all companies have reported their year-end numbers.

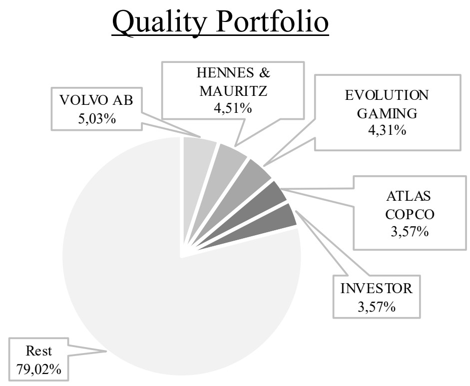

Figure 7: Quality – Smart Beta Portfolio of last rebalancing period 2020/04/01 – 2021/02/05

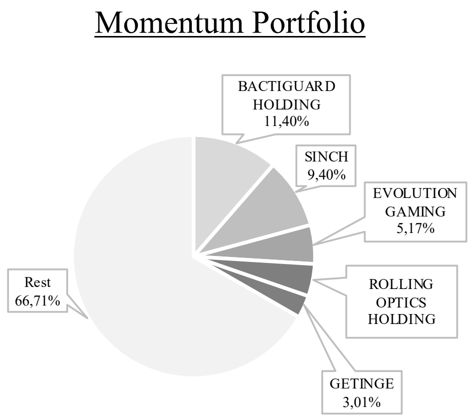

Figure 8: Momentum– Smart Beta Portfolio of last rebalancing period 2020/04/01 – 2021/02/05

4.2 Portfolio generation

The portfolio generation procedure is divided into three steps. The first step is to screen out stocks based on their factor-specific variables. The second step is to standardize these variables and receive factor scores for each stock. When a portfolio of 40 stocks has been found, the final and last step is that each stock receives a weight based on its factor score. This process is detailed below, and yearly rebalancing of each Smart Beta portfolio takes place 1st of April.

4.2.1 Screening, scoring, and weighting method

The first step in this process is screening. The screening tool provides the factor-specific variables for the stocks in each Smart Beta portfolio. This is illustrated in the graph below:

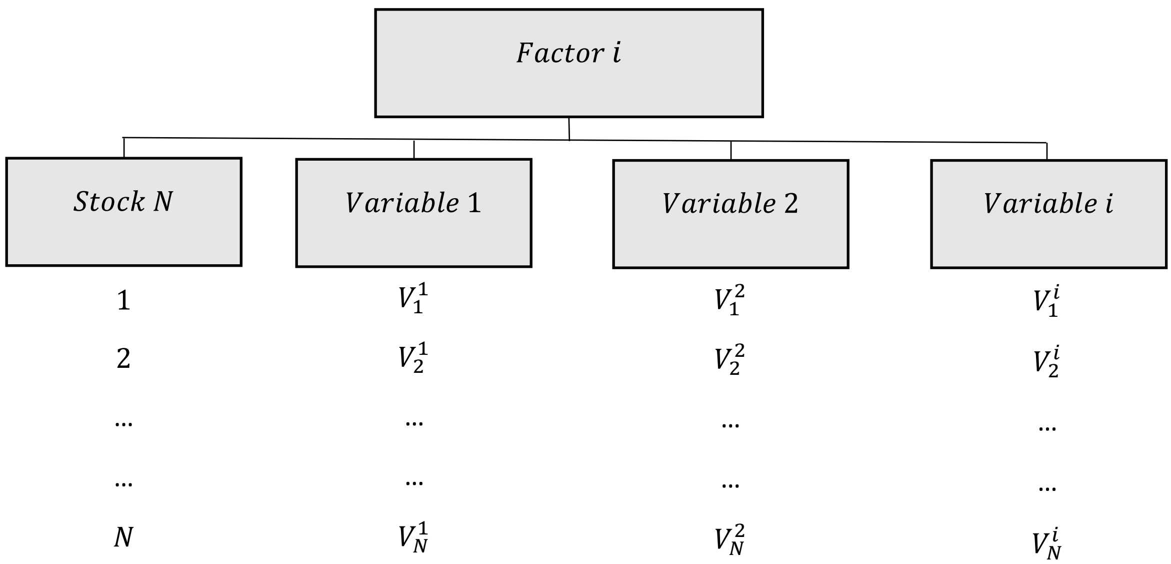

Figure 9: Step 1 – Raw data collected from Bloomberg. The factors are Value, Quality, Momentum and Low Volatility (see Appendix C for details)

To begin the ranking process a framework needs to be established that neutralizes all variables, putting them on an even scale. Drawing inspiration from Asness et al. (2019), this second step is done by standardizing them according to equation (6), resulting in standardized scores (see Appendix B for more details).

$$Z_N^i = \frac{V_N^i - \mu_i}{\sigma_i} \tag{6}$$

Where Z_N^i is the standardized score for variable i of stock N, V_N^i is the raw data for variable i of stock N, μ_i and σ_i are the cross-sectional mean and standard deviation of variable i.

When all variables have been standardized, one obtains the factor score according to the equation below:

$$Factor\ Score_N^i = \frac{(Z_N^1 + Z_N^2 + Z_N^i)}{n}, \qquad n = number\ of\ variables \tag{7}$$

Where $Factor\ Score_N^i$ is the score for each stock in the Smart Beta portfolios obtained by taking the sum of all standardized scores (Z_N^i) and dividing it by the number of variables that each factor contains. A visual representation of this process is observed in figure 10. The 40 highest scoring stocks is then selected into their respective Smart Beta portfolio (see Appendix D for specific examples on the scoring procedure).

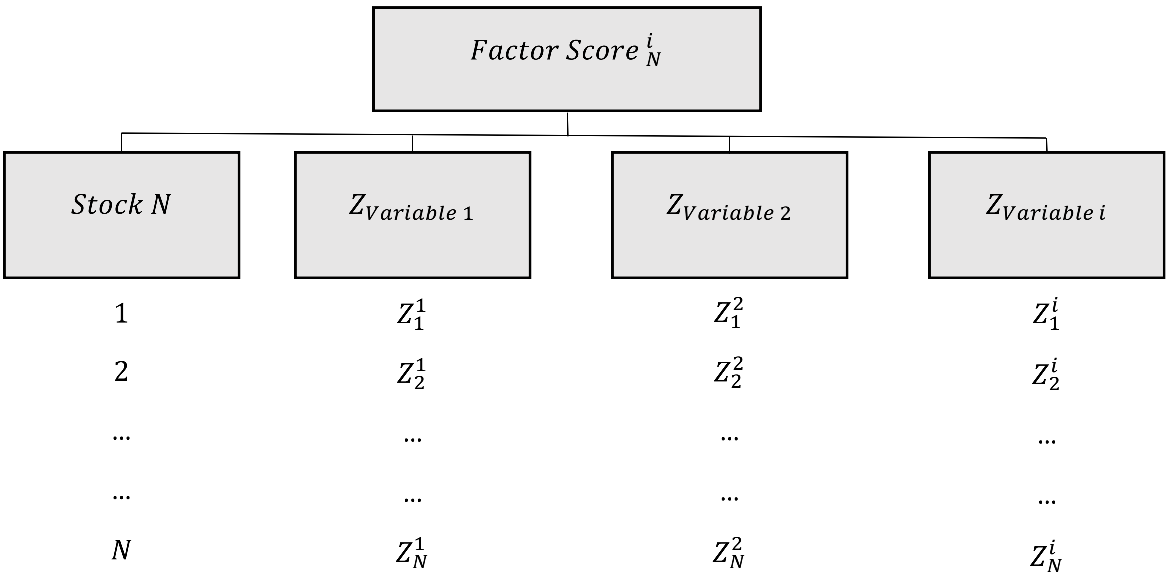

Figure 10: Step 2 – Illustration of factor scoring process where the standardized variables (Z_N^i) boils down to a factor score for each stock (See Appendix C for details)

The third and last step in this process is to apply a weighting scheme to the selected stocks. Using the same Fundamental Indexation Smart Beta approach established by Arnott et al. (2005), the weight of each stock is based on their contribution to the sum of all factor scores. The equation below illustrates this method:

$$W_i = \frac{Factor\ Score_i}{\sum_{i=1}^{40} Factor\ Score_i} \tag{8}$$

Where W_i is the weight for each stock and $\sum_{i=1}^{40} W_i = 1$ (see Appendix D for specific examples on the weighting procedure).

4.2.2 Value

A multitude of variables that define the value factor are presented in academia. For example, Fama & French (1993) used different price-to-fundamental ratios such as price-to-earnings, price-to-book, sales-to-earnings, price-to-cash flows, and book-to-market equity. In this thesis, the Value Portfolio will include the variables P/E, P/B, and P/CF (for definitions, see Appendix A). Thus, the factor score equation for the Value factor becomes:

$$Value\ Score_i = \frac{(-Z_{P/E_i} - Z_{P/B_i} - Z_{P/CF_i})}{n}, \qquad n = 3 \tag{9}$$

Where Z_{P/E_i} is the standardized score for the variable P/E for stock i, Z_{P/B_i} is the standardized score for the variable P/B for stock i, and Z_{P/CF_i} is the standardized score for the variable P/CF for stock i. The minus sign before these ratios is due to the fact that low price-to-fundamental ratios are desired, and thus, lower ratios will produce higher scores.

4.2.3 Low Volatility

This factor is simply based on a single variable, the volatility of returns in 260 days. Using the same logic as the price-to-fundamental ratios in the value factor, low volatility is desired. Hence, stocks exhibiting low volatility will produce higher scores, and the factor score equation becomes:

$$Low\ Volatility\ Score_i = \frac{-Z_{Volatility_i}}{n}, \qquad n = 1 \tag{10}$$

Where $Z_{Volatility_i}$ is the standardized score for the variable Volatility for stock i.

4.2.4 Quality

There are differing opinions on what best defines the quality factor. Simple definitions were presented by Novy-Marx (2013), who used gross profit-to-asset metrics. Piotroski (2000) gives a more nuanced perspective covering profitability, financial leverage, and operational efficiency. However, Hsu et al. (2019) established an even more comprehensive definition, identifying seven characteristics that build upon previous literature to find variables that offer reliable sources of return premia. Therefore, drawing inspiration from previous literature – especially Piotriski (2000) and Hsu et al. (2019), the chosen variables are CFO, ROA, ROE, and Debt/Equity, which captures the desired characteristics. Thus, the factor score equation for the Quality factor becomes:

$$Quality\ Score_i = \frac{(Z_{CFO_i} + Z_{ROA_i} + Z_{ROE_i} - Z_{D/E_i})}{n}, \qquad n = 4 \qquad (11)$$

Where Z_{CFO_i} is the standardized score for the variable CFO for stock i, Z_{ROA_i} is the standardized score for the variable ROA for stock i, Z_{ROE_i} is the standardized score for the variable ROE for stock i, and Z_{D/E_i} is the standardized score for the variable D/E for stock i. Stocks with high CFO, ROA, ROE, and low D/E will produce the highest scores.

4.2.5 Momentum

Carhart (1997) defined the momentum factor as the proclivity for stocks that have performed well or poorly in the recent past (three to twelve months) to continue doing so in the near future. Jegadeesh & Titman (1993), who thoroughly tested the six-month trading strategy, found significant outperformance with a return of 12.01% per year on average. This paper will adopt the same definition of the momentum factor as previous literature but alter it slightly by incorporating risk. The product of this integration is 6- and 12-month Sharpe-Momentum variables. Using both the six- and twelve-month formation periods yields the combination of a high probability of outperformance based on previous research, serves as an appropriate option when using a yearly rebalancing scheme, and offers a more straightforward implementation that suits Smart Beta strategies' passiveness. Stocks exhibiting high Sharpe-Momentum will produce higher scores, and the factor equation becomes:

$$Momentum\ Score_i = \frac{(Z_{6m\ SM_i} + Z_{12m\ SM_i})}{n}, \qquad n = 2 \qquad (12)$$

Where $Z_{6m\,SM_i}$ is the standardized score for the 6-month Sharpe-Momentum variable for stock i, and $Z_{12m\,SM_i}$ is the standardized score for the 12-month Sharpe-Momentum variable for stock i.

4.3 Performance analysis - Jensen's Alpha test

To measure performance in the Smart Beta portfolios, the Jensen's Alpha test is applied. The test is based on the CAPM framework and is used to measure the risk-adjusted performance against the market. It shows the difference between the actual return and the return predicted by CAPM. The regression model is as follows:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p\,(r_{Mt} - r_{ft}) + \varepsilon_t \tag{13}$$

Where $r_{pt} - r_{ft}$ is the excess portfolio return at time t, α_p is the intercept of the regression which represents the portfolio performance compared to the theoretical performance index, and $\beta_p\,(r_{Mt} - r_{ft})$ signifies the sensitivity of the portfolio to the market. The aim is to find positive and significant alpha, which indicates that cross-sectional returns have been found (Bodie et al., 2014).

5. Results and Analysis

This section will summarize the Smart Beta portfolio results, outline the robustness tests' procedure, analyze the performance of the individual portfolio results, and end with portfolio correlation.

5.1 Summary portfolio performance

$$H_0: \alpha = 0$$

$$H_1: \alpha \neq 0$$

	Value Portfolio	Low Volatility Portfolio	Quality Portfolio	Momentum Portfolio
Alpha (α) daily	0.01%	0.03%	0.07%	0.06%
Alpha (α) yearly	2.30%	6.86%	18.06%	15.98%
P-Value	0.325	0.000*	0.000*	0.000*
R^2	0.7715	0.7857	0.8461	0.6311
Beta	0.80	0.60	0.81	0.73
H_0 Rejected	No	Yes	Yes	Yes

Table 1: Summary Jensen's Alpha test results with HAC Newey-West regression
*Note: * Denotes statistically significant results at any level*

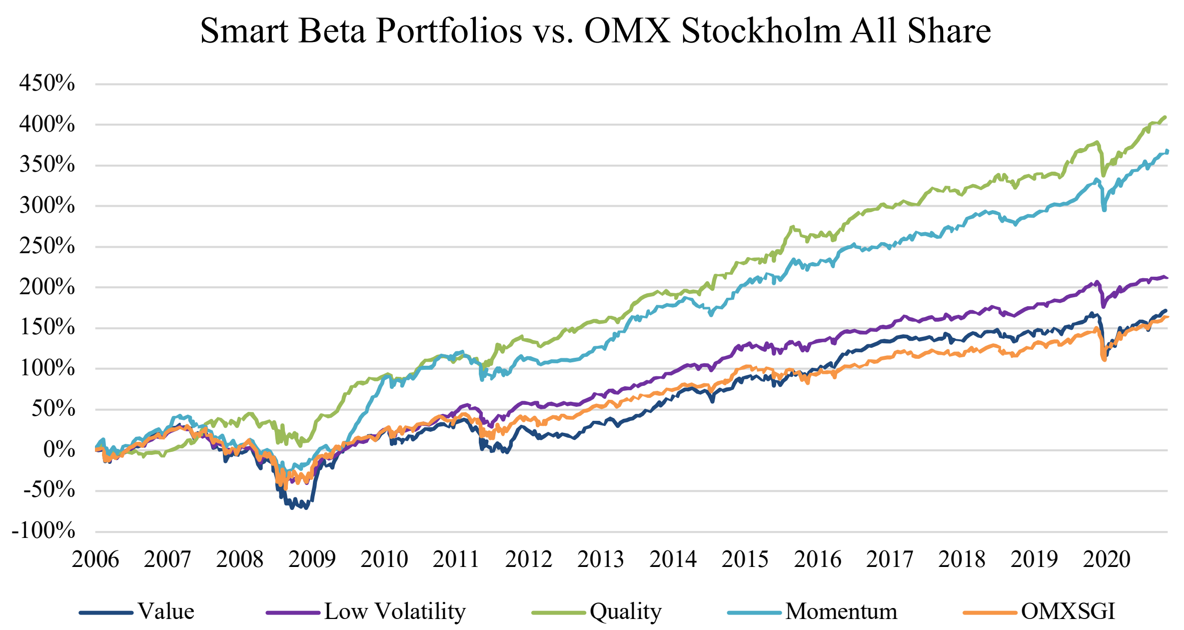

Figure 11: Smart Beta Portfolios vs. OMXSGI

In Table 1, one can observe significant outperformance in the Quality, Momentum, and Low Volatility portfolios versus the theoretical performance index (OMXSGI), on a risk-adjusted basis. This leaves the Value portfolio with no statistical evidence of outperformance, i.e., alpha not different from zero. Among the portfolios, Quality delivered the highest return of 18.06%, with Momentum close behind with a return of 15.98%, while Low Volatility and Value lagged behind with 6.86% and 2.30%, respectively, measured on a yearly basis.

The R^2 values lie in the range 0.6 - 0.8, indicating different levels of reliability in the betas and that the market explains 60% - 80% of the returns. Hence, a higher R^2 would indicate greater reliability in the level of risk each portfolio holds relative to the market. From what the results show, a positive correlation between risk and return is observed in each of the portfolios except in the insignificant Value portfolio.

Before ending up at the results observed in Table 1, all regressions have undergone robustness checks to ensure reliable results as signs of serial correlation were observed in the initial OLS output (see Appendix E for details).

5.2 Robustness tests

As this thesis handles time-series data, it is crucial to test for stationarity to prove that the results of the regressions are not fabricated. The chosen method is the Augmented Dickey-Fuller test since it considers cases where serial correlation is an issue. There are some critiques to the Augmented Dickey-fuller test as it could have a fairly high Type I error rate, but besides these, it is widely used in research and is considered one of the most important tests when handling time-series data (Mushtaq, 2011).

$$H_0: Unit\ Root$$
$$H_1: No\ unit\ Root$$

Augmented Dickey-Fuller Test

Portfolio	Value	Low Volatility	Quality	Momentum
T-Test	-19.890	-18.925	-19.329	-21.183
P-Value	0.000*	0.000*	0.000*	0.000*
H_0 Rejected	Yes	Yes	Yes	Yes

Table 2: Summary Unit Root test
*Note: * Denotes statistically significant results at any level*

Table 2 summarizes the Augmented Dickey-Fuller Test, where the null hypotheses for all Smart Beta portfolios are rejected. Hence, one can conclude that the time series data is stationary.

Addressing the observed signal of serial correlation, the Breusch-Godfrey Test is used due to its ability to test for higher-order serial correlation, which the Durbin-Watson Test cannot. In the case of serial correlation and/or heteroscedasticity with large sample data, one can run the regressions using HAC (heteroscedasticity- and autocorrelation-consistent) standard errors or simply Newey-West estimator to correct the OLS standard errors in situations of both autocorrelation and/or heteroscedasticity (Gujarati & Porter, 2009).

$$H_0: No\ serial\ correlation$$

$$H_1: Serial\ correlation$$

Breusch-Godfrey LM Test

Portfolio	Value	Low Volatility	Quality	Momentum
Chi-squared χ^2	64.059	7.435	63.527	5.059
Prob > χ^2	0.000*	0.006*	0.000*	0.025*
H_0 Rejected	Yes	Yes	Yes	Yes

Table 3: Summary of LM test
*Note: * Denotes statistically significant results at the 0.05 level*

The Breusch-Godfrey LM test confirms serial correlation and hence, to correct for this, the HAC Newey-West regression has been used (see Table 1).

5.3 Individual portfolio results

This section will go through all individual portfolios and compare them to the benchmark index.

5.3.2 Value Portfolio

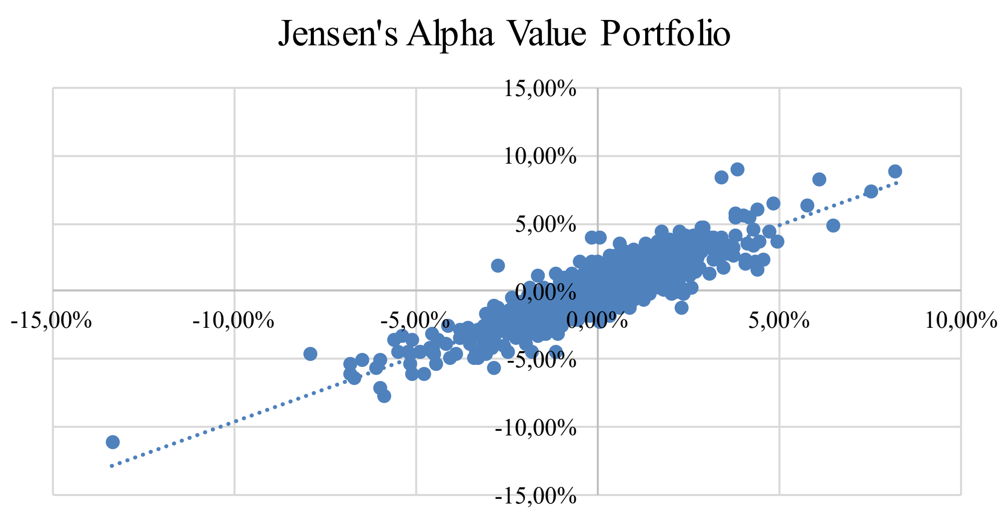

Figure 12: Value Portfolio daily risk adjusted returns on Y-axis and OMXSGI daily risk adjusted returns on X-axis

The scatterplot illustrated in Figure 12 shows the relationship between the Value- and the market portfolio – observed in daily returns, where the x-axis represents the market portfolio and the y-axis the Value portfolio. The bottom left- and top right corners show the days where the portfolios are positively correlated and exhibit negative- and positive returns, respectively. Conversely, the top left- and bottom right corners show the days where the portfolios are negatively correlated. Hence, the top left corner shows the days where the Value portfolio is positive, and the market portfolio is negative, and vice-versa for the bottom right corner.

As seen in Table 1, the Value portfolio shows a positive but statistically insignificant alpha of 2.30%. Hence, one cannot conclude that the value factor explains any excess returns. This differs from older studies such as Basu (1997) and Rosenberg et al. (1985), who found outperformance using value-oriented portfolios. However, as evidenced by Fama & French (2014) in their five-factor model, they found that when omitting the value factor from their model, no loss in the description of average returns was observed. Meaning that the value factor might have lost some of its prudence.

Furthermore, a possible explanation for the insignificant alpha could be due to the susceptibility to the phenomenon called "value trap." This susceptibility is widespread for rules-based strategies such as Smart Beta investing due to the nature of its passiveness. The principle of a value trap is the notion that investors perceive a stock to be cheap due to its low valuation multiples, such as low P/E, P/B, and P/CF, but neglects to investigate possible reasons for these low multiples (Penman & Reggiani, 2018). Thus, to be successful using a value investing strategy, one must be meticulous in assessing each company's situation – which is in direct conflict with the passive foundation Smart Beta strategies lies upon.

Therefore, the value trap phenomenon might be a possible explanation for the poor performance observed in the Value portfolio during the 2008 financial crisis. In crises, struggling companies tend to be the ones most adversely affected, often resulting in bankruptcies. Hence, implementing a Fundamental Indexation Smart Beta strategy on the Value factor might not be worthwhile as it requires more emphasis on active investing, which is in conflict with the passive framework the methodology is built upon.

Lastly, another explanation for the insignificant alpha could be that this factor has been over-exploited, making this strategy overcrowded and, hence, leaving no room for excess returns.

Figure 13 below illustrates the performance of the Value portfolio with a return of 172% compared to the market with a return of 164%.

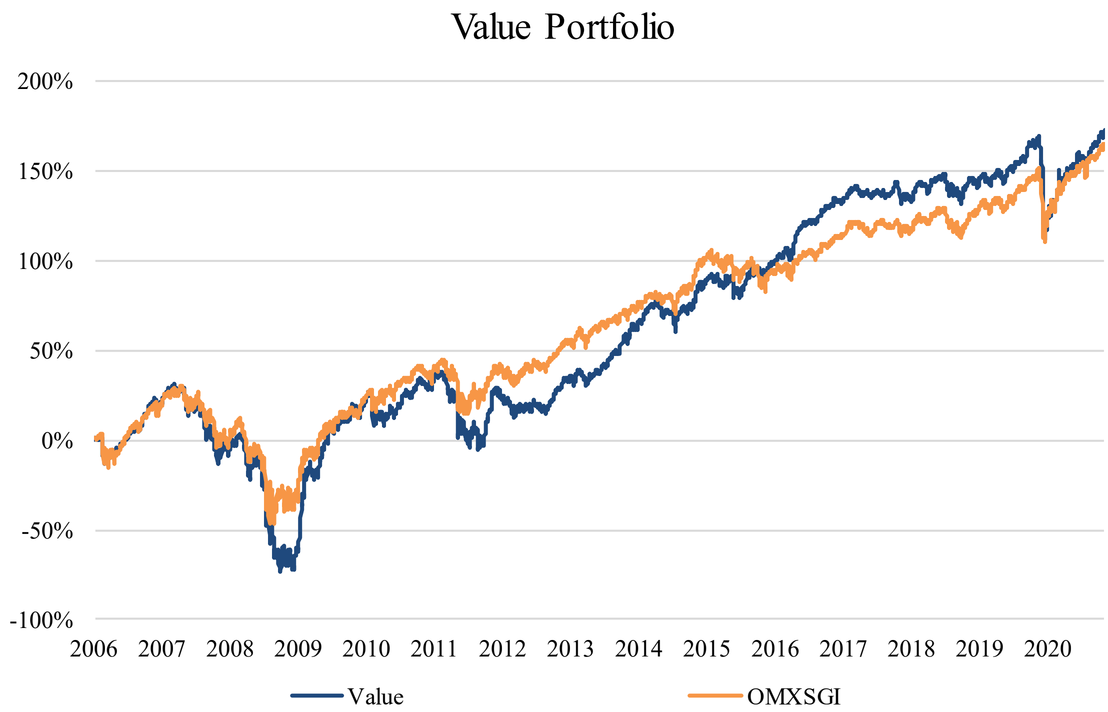

Figure 13: Value Portfolio Performance versus OMXSGI.

5.3.4 Low Volatility

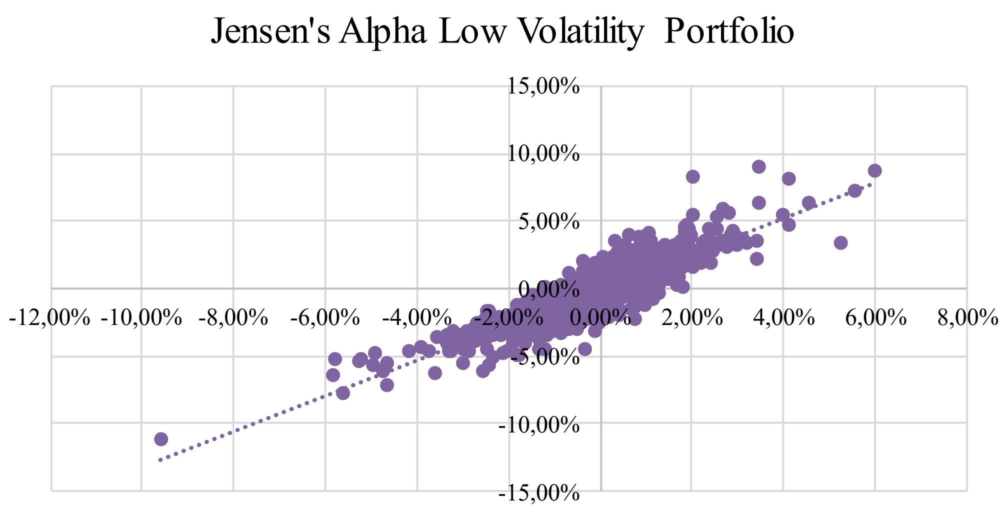

Figure 14: Low Volatility Portfolio daily risk adjusted returns on Y-axis and OMXSGI daily risk adjusted returns on X-axis

As seen in Table 1, the Low Volatility portfolio shows a significant and positive yearly alpha of 6.86%. Hence, one can conclude that the Low Volatility portfolio contains characteristics that provide additional value to investors. This relatively high outperformance, considering its significantly lower risk (Beta of 0.6), versus the benchmark index might seem puzzling as the general principle in finance is that of "higher risk higher return." However, the low volatility anomaly has been continuously proven in previous literature, such as Baker & Haugen (2012), who found outperformance of low volatility stocks in all markets globally, including Sweden.

These findings may seem highly controversial – which they are, but the results speak for themselves, and one might start questioning the CAPM framework itself. The highly simplified assumptions which CAPM rests upon do perhaps not reflect the real world.

Figure 15 below illustrates the performance of the Low Volatility portfolio with a return of 215% compared to the market with a return of 164%.

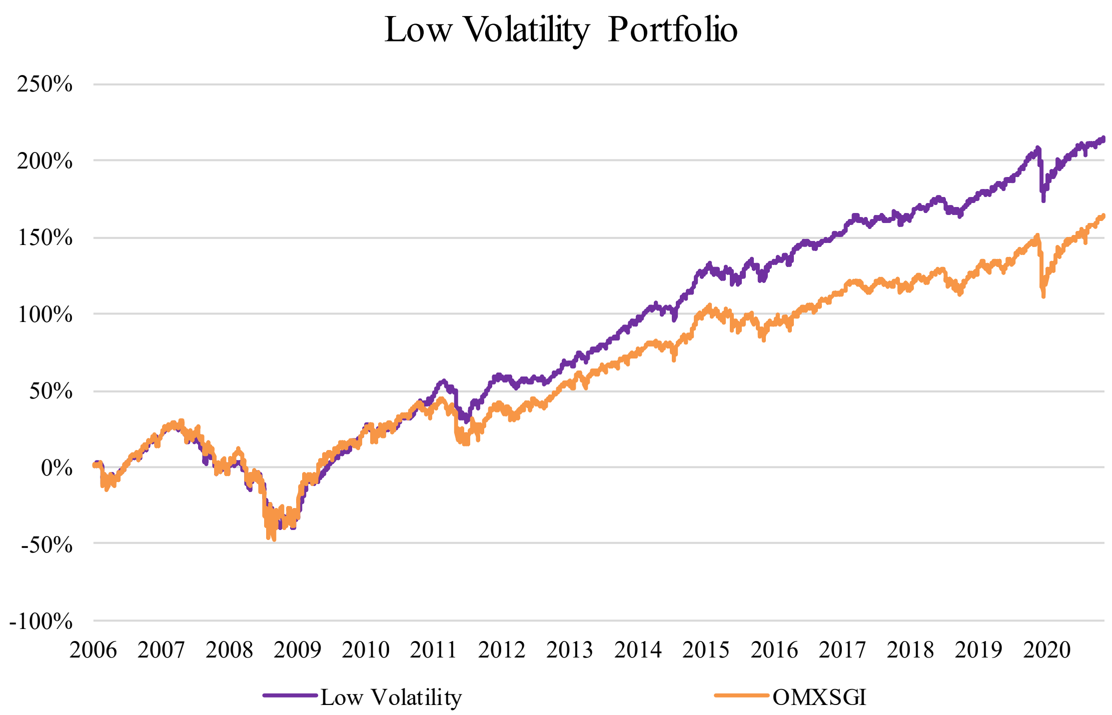

Figure 15: Low Volatility Portfolio Performance versus OMXSGI.

5.3.1 Quality Portfolio

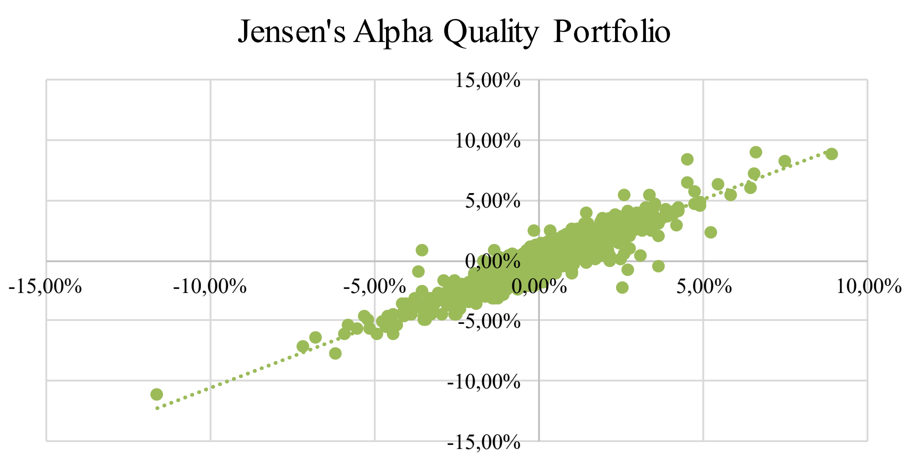

Figure 16: Quality Portfolio daily risk adjusted returns on Y-axis and OMXSGI daily risk adjusted returns on X-axis

As seen in Table 1, the Quality portfolio shows a significant and positive yearly alpha of 18.06%. Hence, one can conclude that the Quality portfolio contains characteristics that provide additional value to investors. This is in line with previous studies such as Asness et al. (2019), who came to the same conclusion where they found persistent outperformance of high-quality stocks compared to the market. These results are perhaps the least surprising since the ability to generate earnings is the key driving force for a company's success on the stock market.

Another interesting aspect, clearly visible in Figure 17 below, is the relatively low negative impact during the 2008 financial crisis. This has been theorized by Campbell et al. (2009) to be due to the fact that characteristics of companies' cashflows influence security prices more than macroeconomic factors, meaning that well-run companies have an inherent competitive edge which is especially apparent in crises. This phenomenon is called "flight-to-quality" and has been observed in more recent research as well, such as in Brooke et al. (2018), who studied Australian firms.

Figure 17 below illustrates the performance of the Quality portfolio with a return of 410% compared to the market with a return of 164%.

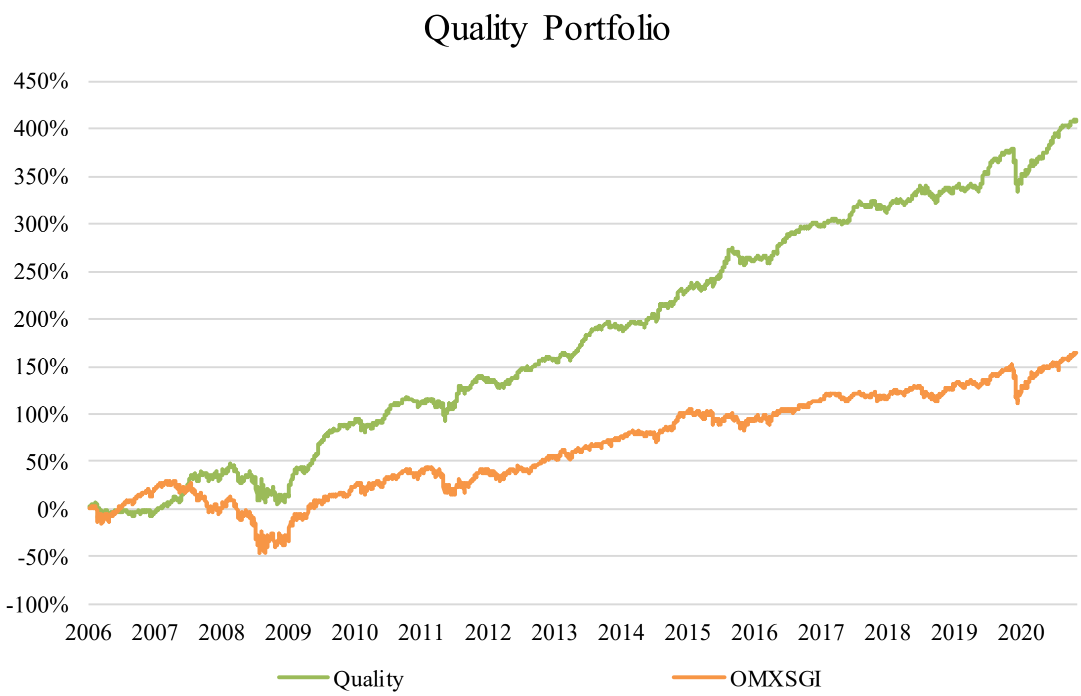

Figure 17: Quality Portfolio Performance versus OMXSGI.

5.3.3 Momentum Portfolio

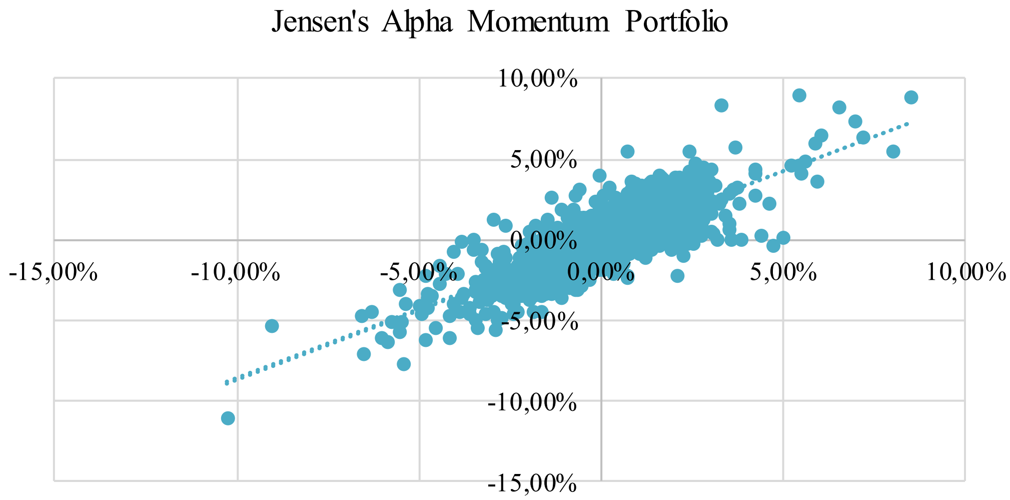

Figure 18: Momentum Portfolio daily risk adjusted returns on Y-axis and OMXSGI daily risk adjusted returns on X-axis

In Table 1, one can see that the Momentum portfolio shows a significant and positive yearly alpha of 15.98%. Hence, one can conclude that the Momentum portfolio contains characteristics that provide additional value to investors. This result is in line with previous research from Jegadeesh & Titman (1993) and Fama & French (2012). Academia has not been able to find an explanation for these cross-sectional returns however, and it remains an anomaly. As mentioned in the previous research section, the search for an explanation for this anomaly has led to the creation of a new discipline within economics, namely Behavioral Finance. Barberis et al. (1998) traced the Momentum effect to investors' overreaction of stock prices to a series of good or bad news and underreaction of stock prices to news such as earnings announcements. They proposed that investors pay disproportionate attention to the strength of evidence they are presented with and neglect this information's statistical weight. One cannot disregard the possibility of this applying to the results found in this thesis.

Another explanation could be the fear of missing out (FOMO) aspect, where investors "move with the herd" in either direction – up or down. Fearing missed opportunities, pushing stock prices higher, and overreacting to negative events, pushing stock prices lower.

Figure 19 on the next page illustrates the performance of the Momentum portfolio with a return of 369% compared to the market with a return of 164%.

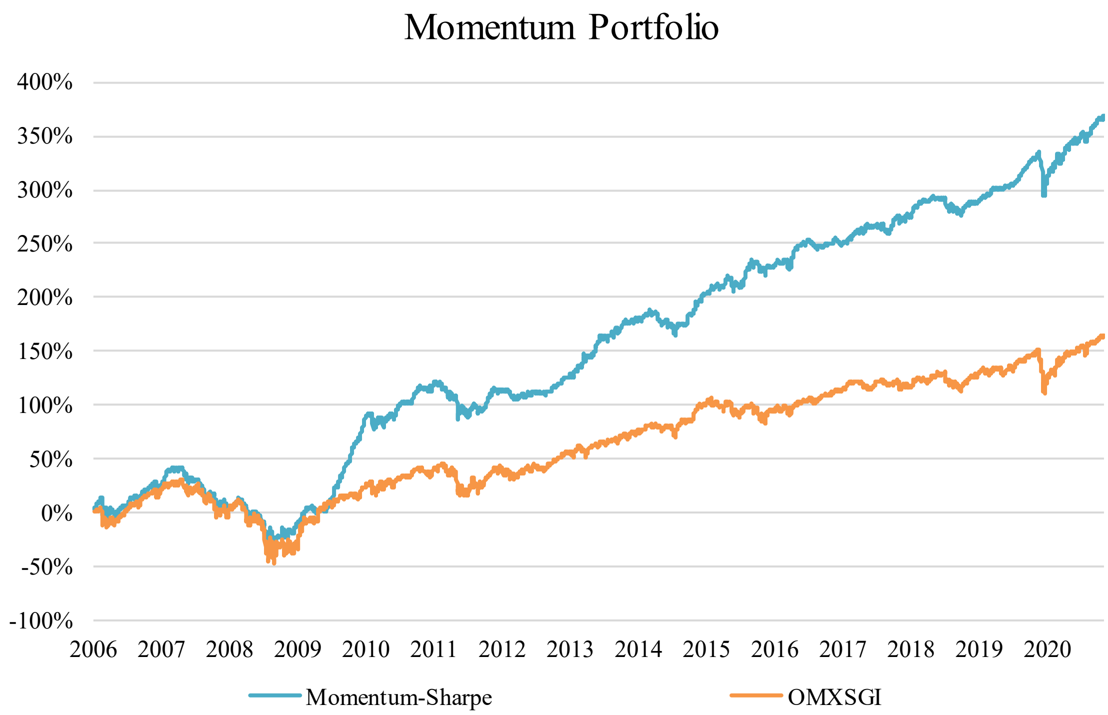

Figure 19: Momentum Portfolio Performance versus OMXSGI.

5.4 Portfolio correlation

Correlation Matrix

	OMXSGI	*Value*	*Low Volatility*	*Quality*	*Momentum*
OMXSGI	1				
Value	0.8783	1			
Low Volatility	0.8864	0.8783	1		
Quality	0.9198	0.8656	0.8735	1	
Momentum	0.7944	0.7888	0.8207	0.8127	1

Table 4: Correlation matrix for Smart Beta portfolios and OMXSGI.

As shown in Table 4, all Smart Beta portfolios have a high degree of correlation against the market. This outcome is expected since the passive nature of Smart Beta strategies makes them inherently similar to the benchmark they are compared with.

The Quality portfolio possesses the highest correlation with the OMX Stockholm All-Share Index. This can be explained by observing the underlying variables that make up the portfolio, where quality companies with revenue-generating characteristics often are the largest securities – resulting in more overlap with the benchmark index. For example, the top 5 securities in the

Quality portfolio for the last rebalancing year 2020 (see Figure 7) consisted of Volvo, H&M, Evolution Gaming, Atlas Copco, and Investor – all included in the large-cap index, OMXS30.

The portfolio exhibiting the lowest correlation with the market is Momentum. One may argue that this could be due to the prevalence of small-cap stocks, which are inherently associated with the Momentum factor due to their high growth nature.

Lastly, the relatively high- and similar correlations of the Value- and Quality portfolios versus the market, considering their substantial differences in yearly alpha (18.06- and 2.30%), seems to indicate the inclusion of worse-performing stocks in the Value portfolio and better-performing stocks in the Quality portfolio out of the same universe of securities.

6. Conclusion

Three out of four Smart Beta portfolios produced significant- and positive alphas, where the single non-significant portfolio was Value. These results prove that the Fundamental Indexation Smart Beta strategy succeeds, especially those with exposure to the variables used in the Quality and Momentum portfolios, in finding cross-sectional returns. Therefore, evidence of violations of the EMH hypothesis – that markets are efficient, is found in this study. Also, the basic tenant of finance, "higher risk higher return," is proven false as significant outperformance of the Low Volatility portfolio was found. Albeit controversial, this anomaly has been proven in previous research as well, such as in Haugen & Heins (1972), Ang et al. (2006), Baker & Haugen (2012), and Blitz et al. (2013).

A potential explanation for the significant outperformance of the Smart Beta portfolios could be due to the negligence of management- and transaction costs. The observed alphas will undoubtedly be lower if one accounts for the costs associated with actively building and rebalancing the portfolios according to Smart Beta methodologies. However, as evidenced by Amenc et al. (2014), who found outperformance using Smart Beta strategies even when assuming unrealistically high transaction costs, the severity of costs like these on the results of this study might therefore not be too grave.

The inclusion of the recent coronavirus crash of 2020 provides an interesting data point for the Fundamental Indexation Smart Beta strategy on OMXSGI. During the 2008 financial crisis, trends such as flight-to-quality were observed for the Quality portfolio. However, during the coronavirus crash, this did not occur. Instead, the downturn was major and sudden, and the normal correlation patterns in the economy were dispersed – every asset class experienced similar drawdowns. As a result, the Smart Beta portfolios experienced remarkably similar downfalls, as shown in Figure 11. Moreover, this historic event was met with quick action from central banks and governments, who provided unprecedented levels of stimulus. This helped put the crisis to a halt and instead propelled the equity markets to new heights. As a result, in the recovery phase, the Quality- and Momentum portfolios surged above their all-time high levels, while the Low Volatility- and Value portfolios barely reached their pre-crash levels. In other words, the trends observed before the crash were exacerbated in the recovery phase, resulting in significant increases in stock prices for companies exhibiting Quality- and Momentum characteristics and less significant upturns for companies related to Low Volatility- and Value characteristics.

One aspect worth considering when assessing the Value portfolio results is that the variables P/E and P/B are not applicable to real estate- and investment companies. These companies are often valued using different price-to-NAV (Net Asset Value) ratios instead, e.g., in 2019, 15 out of the 40 companies in the Value portfolio were real estate companies. Therefore, the true characteristics of a value company might not have been found – potentially damaging for the performance of the portfolio as a whole.

Ultimately, the Smart Beta strategy presented in this thesis has proven capable of finding cross-sectional returns versus the benchmark index OMXSGI. Hence, the results from this study move in line with previous research in the majority of the portfolios. The single non-significant Value portfolio offers a deviation from past literature. However, as evidenced in the Fama & French (2014) five-factor model, the Value factor might have lost some of its prudence as they found that when omitting this variable from their model, no loss in the description of average returns was found.

6.1 Further Research

Combining Smart Beta portfolios could be a way to increase diversification and decrease risk in the portfolios. It would be interesting to conduct a detailed investigation into how these combinations would affect risk-adjusted returns and if these could be specialized to accommodate investors' different risk preferences. Therefore, the nutrient/factor analogy presented in the introduction would be expanded upon by combining factors to reach a "complete meal" instead of only providing a single nutrient.

Altering the current equal weighting scheme of the variables contained in the Smart Beta portfolios as well as testing different variables could be aspects worth considering. For example, one could change the weights in the Quality portfolio to CFO 25%, ROA 30%, ROE 30%, and D/E 15%. The optimal weighting- and variable selection process is highly subjective, producing opportunities for further research to tinker with various procedures to find "the optimized solution."

A longer time period and different markets are two more avenues to consider. Since most years observed in this thesis were during booming economies with large central bank stimulus, longer time periods could offer more diverse economic climates. In addition, implementing the Smart Beta strategy in other regions and markets could help determine the efficacy of each portfolio by expanding the breadth of securities available.

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Appendix A

P/E

The Price-to-Earnings (P/E) ratio measures the relationship between the price of a stock and its earnings per share (EPS).

$$P/E = \frac{Share\ Price}{EPS} \tag{14}$$

P/B

The Price-to-Book (P/B) ratio measures the relationship between the price of a stock and its book value per share (BVPS).

$$P/B = \frac{Share\ Price}{BVPS} \tag{15}$$

P/CF

The Price-to-Cash Flow (P/CF) ratio measures the relationship between the price of a stock and its operating cash flow per share.

$$P/CF = \frac{Share\ Price}{Opearting\ cash\ flow\ per\ share} \tag{16}$$

Volatility

Volatility is the standard deviation of returns and measures the degree of variation of the stock prices. This paper measures the degree of variation in 260 days.

$$Volatility = Standard\ Deviation\ * \sqrt{260} \tag{17}$$

CFO

Cash flow from operations (CFO) displays the true cash-generating operations and the amount of money a company brings in from its regular business activities. CFO does not contain investment- and financing activities.

$$CFO = Net\ income + Non\ Cash\ Adjustments + \Delta Working\ Capital \tag{18}$$

ROA

Return on Assets (ROA) measures the relationship between a company's earnings and its total assets.

$$ROA = \frac{Net\ Income}{Total\ Assets} \tag{19}$$

ROE

Return on Equity (ROE) measures the relationship between a company's earnings and its shareholders' equity.

$$ROE = \frac{Net\ Income}{Shareholders'\ Equity} \tag{20}$$

D/E

The Debt-to-Equity (D/E) ratio measures financial leverage and shows the relationship between a company's debt- and equity financing.

$$D/E = \frac{Total\ Liabilities}{Total\ Shareholders'\ Equity} \tag{21}$$

Sharpe-Momentum

A performance measure that adjusts for the risk in a stock by capturing its volatility.

$$Sharpe - Momentum = \frac{Mean\ Return\ -\ Risk\ Free\ Rate}{Standard\ Deviation} \tag{22}$$

Appendix B

The standardization process conducted in the methodology section is a procedure that supposes normal distribution with a mean of zero and standard deviation of one. This process neutralizes all variables and makes it possible to compare variables with different units. In other words, one can transform any X-value (factor variable V_N^i) into a Z-score (factor score Z_N^i) by subtracting the mean of the factor variable and dividing by the standard deviation, as observed in the formula below (Frey, 2018):

$$Z = \frac{X - \mu}{\sigma} \sim (0,1) \tag{23}$$

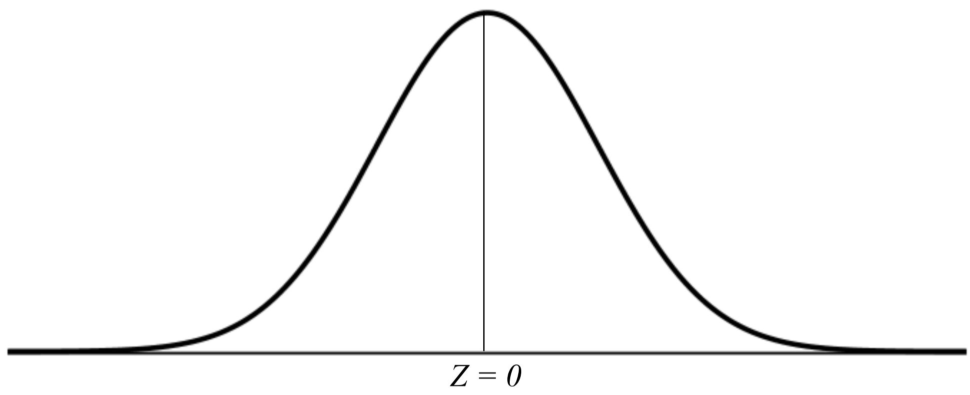

Figure 20: Standard Normal Distribution curve

All variables have been standardized according to this process, where the stocks exhibiting the 40 highest factor scores are included in the Smart Beta portfolios.

Appendix C

Value Portfolio

	Name	P/E	P/B	P/CF	Score P/E	Score P/B	Score P/CF	Factor Score	Weight
1	INTERNATIONAL PETROLEUM CORP	1,86	0,24	1,20	-0,27	-0,47	-0,70	0,48	3,28%
2	MEKONOMEN AB	4,98	0,48	1,55	-0,24	-0,43	-0,68	0,45	3,08%
3	SCANDIC HOTELS GROUP AB	4,31	0,47	1,79	-0,25	-0,43	-0,66	0,45	3,06%
4	BONAVA AB	6,94	0,59	2,19	-0,23	-0,41	-0,64	0,43	2,92%
5	NEW WAVE GROUP AB -B SHS	4,54	0,46	3,32	-0,25	-0,43	-0,58	0,42	2,88%
6	TRATON SE	4,00	0,44	3,82	-0,25	-0,44	-0,55	0,41	2,84%
7	LUCARA DIAMOND CORP	9,65	0,51	2,74	-0,20	-0,42	-0,61	0,41	2,83%
8	RATOS AB-B SHS	9,35	0,68	2,50	-0,21	-0,40	-0,63	0,41	2,80%
9	GRANGES AB	6,10	0,85	3,30	-0,23	-0,37	-0,58	0,39	2,70%
10	BULTEN AB	15,11	0,53	3,39	-0,15	-0,42	-0,58	0,38	2,63%
11	FERRONORDIC AB	4,67	1,32	2,64	-0,25	-0,29	-0,62	0,38	2,63%
12	SEMAFO INC	11,93	0,87	2,88	-0,18	-0,36	-0,60	0,38	2,63%
13	BYGGMAX GROUP AB	9,85	0,95	2,99	-0,20	-0,35	-0,60	0,38	2,62%
14	ACADEMEDIA AB	12,33	1,12	2,59	-0,18	-0,32	-0,62	0,37	2,56%
15	HUMANA AB	11,07	0,92	3,43	-0,19	-0,36	-0,57	0,37	2,56%
16	AMBEA AB	18,37	0,72	3,00	-0,13	-0,39	-0,60	0,37	2,54%
17	BERGS TIMBER AB-B SHARES	13,85	0,56	4,31	-0,17	-0,42	-0,53	0,37	2,53%
18	INWIDO AB	7,25	0,83	4,69	-0,22	-0,37	-0,51	0,37	2,51%
19	LUNDIN MINING CORP	17,67	0,71	3,58	-0,13	-0,39	-0,57	0,36	2,49%
20	NOBIA AB	7,05	1,34	3,46	-0,23	-0,28	-0,57	0,36	2,47%
21	BETSSON AB	6,57	1,06	4,53	-0,23	-0,33	-0,52	0,36	2,46%
22	DOMETIC GROUP AB	8,93	0,68	5,51	-0,21	-0,40	-0,46	0,36	2,44%
23	SSAB AB - B SHARES	21,12	0,37	4,76	-0,10	-0,45	-0,50	0,35	2,40%
24	BILIA AB-A SHS	7,11	1,74	2,93	-0,22	-0,22	-0,60	0,35	2,38%
25	BOLIDEN AB	8,41	1,17	4,70	-0,21	-0,31	-0,51	0,34	2,36%
26	MILLICOM INTL CELLULAR-SDR	27,40	1,16	1,67	-0,05	-0,32	-0,67	0,34	2,35%
27	BONAVA AB-B SHARES	6,94	0,59	6,83	-0,23	-0,41	-0,39	0,34	2,35%
28	SAS AB	14,69	0,76	5,13	-0,16	-0,38	-0,48	0,34	2,34%
29	LINDAB INTERNATIONAL AB	8,38	1,13	5,16	-0,21	-0,32	-0,48	0,34	2,32%
30	ROTTNEROS AB	7,23	1,01	5,81	-0,22	-0,34	-0,45	0,34	2,30%
31	LOOMIS AB	8,74	1,50	4,15	-0,21	-0,26	-0,54	0,33	2,29%
32	SEMCON AB	7,65	1,27	5,17	-0,22	-0,30	-0,48	0,33	2,27%
33	SWEDBANK AB - A SHARES	6,18	0,88	6,90	-0,23	-0,36	-0,39	0,33	2,24%
34	SAAB AB-B	12,51	1,23	4,83	-0,18	-0,30	-0,50	0,33	2,24%
35	STORA ENSO OYJ-R SHS	8,04	0,96	6,55	-0,22	-0,35	-0,41	0,32	2,22%
36	FAGERHULT AB	11,54	1,17	5,91	-0,19	-0,31	-0,44	0,31	2,15%
37	NYFOSA AB	5,87	0,83	8,12	-0,24	-0,37	-0,32	0,31	2,12%
38	AUTOLIV INC-SWED DEP RECEIPT	7,49	1,79	4,85	-0,22	-0,21	-0,50	0,31	2,12%
39	ELECTROLUX AB-SER B	14,70	1,51	5,07	-0,16	-0,26	-0,49	0,30	2,06%
40	RECIPHARM AB-B SHS	20,30	1,22	5,17	-0,11	-0,30	-0,48	0,30	2,04%
...	...	...	...	...	...	...	...	...	...
367	XVIVO PERFUSION AB	505,26	4,42	78,37	4,13	0,24	3,46	-2,61	N/A
368	KARO PHARMA AB	561,70	1,82	100,39	4,63	-0,20	4,65	-3,02	N/A
369	KARNOV GROUP AB	1600,00	3,07	16,80	13,72	0,01	0,14	-4,62	N/A
	Mean	*32,79*	*3,02*	*14,11*				∑ Top 40 scores	∑ Weight
	Standard Deviation	*114,26*	*5,91*	*18,57*				14,61	1

Table 5: Complete Smart Beta Value Portfolio 2020-04-01, consisting of raw data, standardized scores, factor scores, and weights

Low Volatility Portfolio

	Name	Volatility:D-260	Score Low Vol.	Factor Score	Weight
1	KARO PHARMA AB	23,86	-1,38	1,38	3,57%
2	ASTRAZENECA PLC	27,80	-1,18	1,18	3,04%
3	SVENSKA HANDELSBANKEN-B	27,96	-1,17	1,17	3,01%
4	TELIA CO AB	28,54	-1,14	1,14	2,94%
5	AXFOOD AB	28,69	-1,13	1,13	2,92%
6	ESSITY AKTIEBOLAG-B	29,21	-1,10	1,10	2,84%
7	INVESTOR AB-B SHS	29,24	-1,10	1,10	2,84%
8	TELE2 AB-B SHS	30,38	-1,04	1,04	2,68%
9	SWEDISH MATCH AB	30,44	-1,04	1,04	2,68%
10	TIETOEVRY OYJ	30,55	-1,03	1,03	2,66%
11	LUNDBERGS AB-B SHS	30,83	-1,02	1,02	2,62%
12	ASSA ABLOY AB-B	31,15	-1,00	1,00	2,58%
13	HEBA FASTIGHETS AB-B	31,25	-0,99	0,99	2,56%
14	KABE GROUP AB-B	31,33	-0,99	0,99	2,55%
15	SKANSKA AB-B SHS	31,42	-0,98	0,98	2,54%
16	BERGS TIMBER AB-B SHARES	31,50	-0,98	0,98	2,53%
17	ELTEL AB	31,91	-0,96	0,96	2,47%
18	INVESTMENT AB ORESUND	31,94	-0,96	0,96	2,47%
19	ICA GRUPPEN AB	31,96	-0,96	0,96	2,47%
20	SAGAX AB-D	31,98	-0,95	0,95	2,47%
21	INVESTMENT AB LATOUR-B SHS	32,02	-0,95	0,95	2,46%
22	EASTNINE AB	32,03	-0,95	0,95	2,46%
23	AB TRACTION -B SHS	32,08	-0,95	0,95	2,45%
24	WALLENSTAM AB-B SHS	32,18	-0,94	0,94	2,44%
25	SECURITAS AB-B SHS	32,71	-0,92	0,92	2,37%
26	ABB LTD-REG	32,80	-0,91	0,91	2,35%
27	IES I SVERIGE HOLDING II AB	32,91	-0,91	0,91	2,34%
28	AAK AB	32,91	-0,91	0,91	2,34%
29	SEB-C	32,99	-0,90	0,90	2,33%
30	INDUSTRIVARDEN AB-C	33,08	-0,90	0,90	2,32%
31	BEIJER ALMA AB	33,25	-0,89	0,89	2,29%
32	DUSTIN GROUP AB	33,31	-0,88	0,88	2,28%
33	HIQ INTERNATIONAL AB	33,47	-0,88	0,88	2,26%
34	JOHN MATTSON FASTIGHETSFORET	33,62	-0,87	0,87	2,24%
35	BE GROUP AB	34,20	-0,84	0,84	2,16%
36	HUMANA AB	34,38	-0,83	0,83	2,14%
37	GHP SPECIALITY CARE AB	34,44	-0,82	0,82	2,13%
38	HOLMEN AB-B SHARES	34,55	-0,82	0,82	2,11%
39	NORDEA BANK ABP	35,05	-0,79	0,79	2,05%
40	ERICSSON LM-A SHS	35,16	-0,79	0,79	2,03%
...	...	...	...	...	...
367	MOBERG PHARMA AB	116,07	3,50	-3,50	N/A
368	OASMIA PHARMACEUTICAL AB	120,03	3,71	-3,71	N/A
369	ELECTROLUX PROFESSIONAL AB-B	159,56	5,80	-5,80	N/A
	Mean	*50,02*		∑ Top 40 scores	∑ Weight
	Standard Deviation	*18,89*		38,73	1

Table 6: Complete Smart Beta Low Volatility Portfolio 2020-04-01, consisting of raw data, standardized scores, factor scores, and weights

Quality Portfolio

	Name	Debt/Equity	CFO (SEK)	ROA (%)	ROE (%)	Score D/E	Score CFO	Score ROA	Score ROE	Factor Score	Weight
1	VOLVO AB-B SHS	111,35	4093707678	7,18	27,38	0,06	4,09	0,23	0,46	1,18	5,03%
2	HENNES & MAURITZ AB-B	31,01	3042100912	11,24	23,25	-0,44	2,99	0,43	0,37	1,06	4,51%
3	EVOLUTION GAMING GROUP	8,91	206129803	44,38	67,57	-0,58	0,02	2,09	1,34	1,01	4,31%
4	ATLAS COPCO AB-B SHS	44,39	1820450028	15,86	34,54	-0,36	1,71	0,66	0,61	0,84	3,57%
5	INVESTOR AB-B SHS	17,89	1535499132	21,69	27,06	-0,53	1,41	0,95	0,45	0,84	3,57%
6	SINTERCAST AB	2,51	3986709	40,12	45,23	-0,62	-0,19	1,88	0,85	0,79	3,37%
7	ASTRAZENECA PLC	124,88	3093000000	2,19	10,43	0,15	3,04	-0,02	0,08	0,74	3,15%
8	BURE EQUITY AB	0,50	75812509	36,12	36,73	-0,64	-0,11	1,68	0,66	0,71	3,05%
9	TELIA CO AB	118,90	2917746433	2,77	7,53	0,11	2,86	0,01	0,02	0,69	2,96%
10	INDUSTRIVARDEN AB-C	3,72	410271206	28,38	30,19	-0,62	0,24	1,29	0,52	0,66	2,84%
11	KAROLINSKA DEVELOPMENT	13,65	-832597	30,90	46,48	-0,55	-0,19	1,41	0,88	0,66	2,83%
12	SANDVIK AB	33,37	1853012980	7,16	14,24	-0,43	1,74	0,23	0,17	0,64	2,74%
13	ABB LTD-REG	72,11	2325000064	3,18	10,47	-0,18	2,24	0,03	0,08	0,63	2,70%
14	KINNEVIK AB - B	6,55	275642179	28,32	30,00	-0,60	0,09	1,29	0,51	0,62	2,66%
15	ESSITY AKTIEBOLAG-B	81,84	2042010829	5,82	18,20	-0,12	1,94	0,16	0,25	0,62	2,64%
16	BIOGAIA AB-B SHS	0,00	15368791	28,53	37,05	-0,64	-0,18	1,30	0,67	0,61	2,59%
17	CTT SYSTEMS AB	13,54	11441804	27,16	42,24	-0,55	-0,18	1,23	0,78	0,60	2,54%
18	STORA ENSO OYJ-R SHS	55,85	1838920507	6,32	12,46	-0,29	1,73	0,18	0,13	0,58	2,48%
19	EPIROC AB-B	36,95	758425185	15,22	28,27	-0,41	0,60	0,63	0,48	0,53	2,25%
20	MIPS AB	0,06	6663909	25,63	29,58	-0,64	-0,19	1,15	0,50	0,53	2,25%
21	ASSA ABLOY AB-B	51,22	1329438374	8,90	18,00	-0,32	1,20	0,31	0,25	0,52	2,21%
22	SVENSKA CELLULOSA AB SCA	14,04	348298146	19,45	28,86	-0,55	0,17	0,84	0,49	0,51	2,19%
23	INVISIO AB	7,08	16617362	24,32	30,88	-0,59	-0,18	1,08	0,53	0,51	2,17%
24	BILLERUDKORSNAS AB	41,50	265526419	19,03	39,74	-0,38	0,08	0,82	0,73	0,50	2,15%
25	HOLMEN AB-B SHARES	11,60	303636948	18,14	27,47	-0,57	0,12	0,78	0,46	0,48	2,05%
26	BOLIDEN AB	13,93	994418504	9,25	14,39	-0,55	0,85	0,33	0,17	0,47	2,03%
27	COREM PROPERTY GROUP-B	92,56	49569579	18,96	56,60	-0,05	-0,14	0,82	1,10	0,46	1,95%
28	HEXAGON AB-B SHS	40,92	1233727914	6,93	12,36	-0,38	1,10	0,21	0,13	0,45	1,94%
29	MYCRONIC AB	10,68	57398776	19,01	31,95	-0,57	-0,13	0,82	0,56	0,45	1,94%
30	ERICSSON LM-B SHS	58,11	1793090686	0,82	2,62	-0,27	1,68	-0,09	-0,09	0,44	1,89%
31	SECTRA AB-B SHS	11,75	41768810	17,47	33,92	-0,56	-0,15	0,74	0,60	0,44	1,88%
32	VNV GLOBAL LTD	8,95	279422992	17,93	19,80	-0,58	0,10	0,76	0,29	0,43	1,85%
33	EQT AB	9,15	267558028	16,37	22,65	-0,58	0,09	0,69	0,35	0,43	1,82%
34	VITROLIFE AB	4,22	42287887	19,96	23,29	-0,61	-0,15	0,87	0,37	0,42	1,81%
35	NCAB GROUP AB	31,34	16084347	16,07	39,80	-0,44	-0,18	0,67	0,73	0,42	1,78%
36	OEM INTERNATIONAL AB-B	16,30	30664247	17,52	28,91	-0,54	-0,16	0,74	0,49	0,40	1,72%
37	SKF AB-B SHARES	48,12	992246664	6,13	16,10	-0,34	0,84	0,17	0,21	0,39	1,67%
38	CONCENTRIC AB	7,57	40934621	14,75	29,69	-0,59	-0,15	0,61	0,51	0,39	1,66%
39	MULTIQ INTERNATIONAL AB	5,09	2918454	16,57	26,30	-0,61	-0,19	0,70	0,43	0,39	1,65%
40	OREXO AB	48,74	30852258	15,73	37,09	-0,33	-0,16	0,65	0,67	0,37	1,60%
...	...	...	...	...	...	...	...	...	...	...	...
367	EPISURF MEDICAL AB-B	14,25	-6343009	-123,91	-161,72	-0,55	-0,20	-6,34	-3,71	-2,43	N/A
368	SEB-C	643,26	-9581187477	0,74	13,25	3,42	-10,22	-0,10	0,14	-3,40	N/A
369	STARBREEZE AB	1209,05	5864295	-47,93	-233,73	7,00	-0,19	-2,53	-5,30	-3,75	N/A
	Mean	*101,20*	*185369792*	*2,66*	*6,68*					∑ Top 40 scores	∑ Weight
	Standard Deviation	*158,33*	*955901217*	*19,97*	*45,37*					23,42	1

Table 7: Complete Smart Beta Quality Portfolio 2020-04-01, consisting of raw data, standardized scores, factor scores, and weights

Momentum Portfolio

	Name	Sharpe:M-6	Sharpe:Y-1	Score Sharpe 6m	Score Sharpe 12m	Factor Score	Weight
1	BACTIGUARD HOLDING AB	10,16	4,60	10,31	6,57	8,44	11,40%
2	SINCH AB	8,12	3,88	8,34	5,58	6,96	9,40%
3	EVOLUTION GAMING GROUP	3,61	2,49	3,96	3,70	3,83	5,17%
4	ROLLING OPTICS HOLDING AB	3,83	1,38	4,17	2,20	3,19	4,30%
5	GETINGE AB-B SHS	1,53	1,61	1,94	2,51	2,23	3,01%
6	CALLIDITAS THERAPEUTICS-B	1,86	1,27	2,26	2,05	2,16	2,92%
7	EQT AB	0,97	1,87	1,40	2,86	2,13	2,88%
8	ARJO AB - B SHARES	1,77	1,23	2,17	1,99	2,08	2,82%
9	MIPS AB	1,42	1,39	1,83	2,21	2,02	2,73%
10	SWEDISH MATCH AB	2,37	0,65	2,75	1,21	1,98	2,68%
11	BHG GROUP AB	1,33	1,39	1,75	2,21	1,98	2,67%
12	K2A KNAUST & ANDERSSON-B	0,67	1,84	1,11	2,82	1,96	2,65%
13	STOCKWIK FORVALTNING AB	1,14	1,46	1,56	2,30	1,93	2,61%
14	VITEC SOFTWARE GROUP AB-B	0,62	1,64	1,06	2,54	1,80	2,44%
15	KARO PHARMA AB	1,71	0,81	2,11	1,42	1,77	2,39%
16	INVISIO AB	1,24	1,13	1,66	1,86	1,76	2,37%
17	EOLUS VIND AB-B SHS	0,02	1,91	0,48	2,91	1,69	2,29%
18	ARCTIC PAPER SA	1,28	1,00	1,69	1,68	1,69	2,28%
19	JOHN MATTSON FASTIGHETSFORET	0,47	1,38	0,91	2,20	1,55	2,10%
20	LIME TECHNOLOGIES AB	1,09	0,79	1,52	1,40	1,46	1,97%
21	LUNDBERGS AB-B SHS	0,53	1,17	0,97	1,90	1,44	1,94%
22	CONCEJO AB	1,58	0,37	1,99	0,82	1,41	1,90%
23	HOLMEN AB-B SHARES	0,75	0,95	1,19	1,62	1,40	1,89%
24	SECTRA AB-B SHS	0,70	0,91	1,13	1,56	1,35	1,82%
25	MEDCAP AB	0,01	1,27	0,47	2,05	1,26	1,70%
26	NCAB GROUP AB	0,91	0,42	1,34	0,89	1,12	1,51%
27	PRICER AB-B SHS	0,62	0,62	1,05	1,17	1,11	1,50%
28	ARISE AB	0,13	0,91	0,58	1,56	1,07	1,44%
29	BALCO GROUP AB	-0,11	1,06	0,35	1,76	1,06	1,43%
30	LUNDIN GOLD INC	-0,13	1,04	0,33	1,74	1,04	1,40%
31	OPUS GROUP AB	0,79	0,37	1,22	0,83	1,02	1,38%
32	ADDLIFE AB-B	0,61	0,43	1,05	0,91	0,98	1,32%
33	ASTRAZENECA PLC	0,25	0,66	0,70	1,22	0,96	1,30%
34	NIBE INDUSTRIER AB-B SHS	0,55	0,40	0,99	0,87	0,93	1,26%
35	CAVOTEC SA	0,54	0,41	0,98	0,88	0,93	1,25%
36	INSTALCO AB	0,13	0,65	0,58	1,21	0,90	1,21%
37	AXFOOD AB	0,02	0,72	0,48	1,31	0,89	1,20%
38	SVENSKA CELLULOSA AB SCA-B	0,42	0,43	0,87	0,90	0,89	1,20%
39	STARBREEZE AB	0,31	0,44	0,76	0,93	0,84	1,14%
40	HEBA FASTIGHETS AB-B	0,07	0,60	0,53	1,14	0,83	1,12%
...	...	...	...	...	...	...	...
367	DUSTIN GROUP AB	-1,57	-1,30	-1,07	-1,44	-1,26	N/A
368	TRATON SE	-1,60	-1,43	-1,09	-1,61	-1,35	N/A
369	LUCARA DIAMOND CORP	-1,88	-1,69	-1,36	-1,96	-1,66	N/A
	Mean	*-0,47*	*-0,24*			∑ Top 40 scores	∑ Weight
	Standard Deviation	*1,03*	*0,74*			74,01	1

Table 8: Complete Smart Beta Momentum Portfolio 2020-04-01, consisting of raw data, standardized scores, factor scores, and weights

Appendix D

Specific Scoring and Weighting examples

Detailed scoring and weighting procedure for *International Petroleum Corp* in the **Value Portfolio** (Numbers taken from Table 5 in Appendix C):

1. Standardized Scores

$$Standardized\ Score\ P/E = \frac{1.86 - 32.79}{114.26} = -0.27$$

$$Standardized\ Score\ P/B = \frac{0.24 - 3.02}{5.91} = -0.47$$

$$Standardized\ Score\ P/CF = \frac{1.20 - 14.11}{18.57} = -0.70$$

2. Factor Score

$$Factor\ Score = \frac{-(-0.27)\ -\ (-0.47)\ -\ (-0.70)}{3} = 0.48$$

3. Weight

$$Weight\ = \frac{0.48}{14.61} = 3.28\%$$

Detailed scoring and weighting procedure for *Karo Pharma AB* in the **Low Volatility Portfolio** (Numbers taken from Table 6 in Appendix C):

1. Standardized Scores

$$Standardized\ Score\ Low\ Volatility = \frac{23.86 - 50.02}{18.89} = -1.38$$

2. Factor Score

$$Factor\ Score = -(-1.38) = 1.38$$

1. Weight

$$Weight\ = \frac{1.38}{38.73} = 3.57\%$$

Detailed scoring and weighting procedure for *Volvo AB* in the **Quality Portfolio** (Numbers taken from Table 7 in Appendix C):

1. Standardized Scores

$$Standarized\ Score\ D/E = \frac{111.35 - 101.20}{158.33} = 0.06$$

$$Standardized\ Score\ CFO = \frac{4093707677 - 185369792}{955901216} = 4.09$$

$$Standardized\ Score\ ROA = \frac{7.18 - 2.66}{19.97} = 0.23$$

$$Standardized\ Score\ ROE = \frac{27.38 - 6.68}{45.37} = 0.46$$

2. Factor Score

$$Factor\ Score = \frac{-0.06 + 4.09 + 0.23 + 0.46}{4} = 1.18$$

3. Weight

$$Weight\ = \frac{1.18}{23.42} = 5.03\%$$

Detailed scoring and weighting procedure for *Bactiguard Holding AB* in the **Momentum Portfolio** (Numbers taken from Table 8 in Appendix C):

1. Standardized Scores

$$Standardized\ Score\ Sharpe - Momentum\ 6m = \frac{10.16\ -\ (-0.47)}{1.03} = 10.31$$

$$Standardized\ Score\ Sharpe - Momentum\ 12m = \frac{4.60\ -\ (-0.24)}{0.74} = 6.57$$

2. Factor Score

$$Factor\ Score = \frac{10.31 + 6.57}{2} = 8.44$$

3. Weight

$$Weight\ = \frac{8.44}{74.01} = 11.40\%$$

Appendix E

The Durbin Watson test statistic detects serial correlation in the error terms from a statistical regression. The output range spans from 0 to 4, where 0 signals severe positive serial correlation, 4 signals severe negative serial correlation, and 2 signals no serial correlation (Gujarati & Porter, 2009).

	Value Portfolio	**Low Volatility Portfolio**	**Quality Portfolio**	**Momentum Portfolio**
Durbin Watson	1.282	1.455	1.316	1.467

Table 9: Durbin Watson statistic from the initial OLS output

The Durbin Watson results from the initial OLS regression indicated that all portfolios show signs of positive autocorrelation, and therefore, to ensure reliable results, all regressions have undergone robustness checks.