Norwegian School of Economics
Bergen, Fall 2022

Do Smart Beta ETFs Outperform the World Market?

An empirical analysis on the returns of smart beta ETFs in the European and US markets

Frida Føreland and Pia Solheim Kreutz

Supervisor: Jørgen Haug

Master thesis, Economics and Business Administration

Major: Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgement

This thesis was written as the final part of our Master’s degree in Economics and Business Administration at The Norwegian School of Economics (NHH), with a specialization in Financial Economics.

We wish to extend our thanks and gratitude to our supervisor Jørgen Haug for valuable guidance, and for challenging our approaches and mindsets to work independently. He has always been available for guidance when needed, providing valuable suggestions and dialogue. We would also like to thank the Norwegian School of Economics for providing access to databases and literature that has enabled us to complete our study. Finally, we would like to extend our gratitude to our families for their support.

Norwegian School of Economics

Bergen, December 2022

Frida Føreland

Pia Solheim Kreutz

Abstract

This thesis investigates if smart beta ETFs in the US and/or Europe deliver excess return relative to the world market and how performance compares between the two markets. We focus on nine smart beta categories in our two-part analysis over a time period from January 2007 to June 2022. The constructed smart beta ETF portfolios are evaluated using risk-adjusted performance measures and a multi-factor benchmark model. The multi-factor benchmark model uses the MSCI World Index as the market factor and additional well-documented risk factors, thus used as our proxy for the world market. From this multi-factor model, we estimate alphas for the different categories in order to evaluate performance. We find that all the US smart beta ETFs categories in our sample, except low volatility, earn excess returns above the world market. The European portfolios do not perform as well with only three categories earning abnormal returns, these are momentum, fundamentals weighted, and equal weighted. These results are supported by the analysis of risk-adjusted returns, where the performance measures suggest a higher performance than the MSCI World Index when taking risk into account for most categories.

Contents

List of figures

List of tables

1. Introduction

In the global financial market, there exists a wide variety of investment products. One such product is exchange traded funds (ETFs), which have grown significantly in popularity over the past two decades. In fact, ETFs are the fastest growing product in the investment industry, both in terms of assets under management (AUM) and in terms of product innovation (Trackinsight, u.d.). One reason for ETFs popularity is their strategy of investing as index trackers and the opportunity to trade fund shares on an exchange. As for the breadth in product range, rule-based strategies and risk-based investing are good examples of the trends within the ETF landscape. An example is smart beta ETFs, which are ETFs that employ rule-based strategies along with alternatively constructed indexes to target risk factors (Choy, Dutt, Garcia-Zarate, Gogoi, & Johnson, 2022). These risk factors are commonly expressed in multi-factor asset pricing models, such as growth, value, and momentum. The product is not limited to equity investments, and there exists funds that for instance focus on fixed income. However, in this thesis the focus is on equity smart beta ETFs.

Within the ETF market, smart beta ETFs have experienced the strongest growth over the last 10-15 years (Choy, Dutt, Garcia-Zarate, Gogoi, & Johnson, 2022), which is one of the reasons we choose to focus on this financial product. Smart beta ETFs can be considered a blend of passive and active investing, and although they follow an index, the strategy also considers alternative factors in choosing which stocks to invest in from the index. In terms of the chosen index these ETFs stand out as they typically do not follow more traditional stock indexes, but rather benchmarks that have an active methodology, trying to either improve returns or alter the risk-profile of the index relative to a traditional benchmark. Smart beta ETFs try to reach their investment strategy's objective by systematically selecting, weighting, and rebalancing their fund portfolio based on a concentrated exposure to market and/or company factors (Florent, 2021). However, it is important to distinguish smart beta ETFs from factor portfolios. Although smart beta ETFs are based on factor investing research, they differ from a factor portfolio as they are long-only portfolios with factor tilts, while a factor portfolio are long-short portfolios (Rabener, 2019b).

In this thesis we aim to look closer at smart beta ETFs available in the US and Europe and examine the performance of smart beta categories against the world market through risk-adjusted returns and multi-factor models. We want to examine how a relatively new financial product performs with an international focus, and whether this performance differs between categories, as well as across markets. The categories of smart beta ETFs studied are value, growth, quality, momentum, dividend, low volatility, multi-factor, fundamentals weighted, and equal weighted. In addition to looking at abnormal returns and risk-adjusted performance measures, we consider the active investment styles of the categories through the factor-based regressions.

Following this, our research question is:

> *How do the performance of US and European smart beta ETF categories compare relative to the MSCI World Index when using risk-adjusted performance measures and multi-factor models?*

To answer this question, we conduct a two-part analysis. We construct market cap-weighted portfolios for each category in both markets. The sample time period is from January 2007 until June 2022. In the first part of the analysis, we look at various risk-adjusted performance measures for each portfolio, using the MSCI World Index as benchmark. In the second part we conduct a factor-based regression analysis. For the regression models we use each category's monthly return in excess of the risk-free rate as our dependent variable. We employ a multi-factor model as our benchmark model, assuming an alpha estimation obtained above the benchmark model is the excess returns gained by a portfolio relative to benchmark. Since we focus on an international investment landscape, we use the MSCI World Index as the market factor and the developed world market factors size, value, quality, momentum, and betting against beta as additional risk factors. The multi-factor model is thus employed as a proxy for the world market benchmark. The objective of the analysis is to evaluate the performance of the different categories in the US and Europe relative to the world market and how the categories in one market perform relative to the equivalent category in the other. At the time of this master thesis, the second half of 2022, the current market situation is characterized by a high level of uncertainty. Therefore, we find it relevant to add an additional analysis where we look at abnormal returns in times of varying market regimes. The incentive behind this additional analysis is to examine whether any categories can earn excess returns when controlling for positive or negative market trends. We develop and motivate the economic strategy in more detail in section 4.

Several studies have been conducted to provide insight to the performance of smart beta ETFs. These are primarily focused on funds in either the US or Europe. Two of the studies we have used for inspiration are conducted by Glushkov (2015) and by Bowes and Ausloos (2021). The US study by Glushkov (2015) looks at equity smart beta ETFs in the period 2003-2014. The study analyzes smart beta ETF performance relative to their self-declared benchmark and a blended benchmark, finding no conclusive evidence that smart beta ETFs earn abnormal returns in the period. The study also looks at factor exposure, and further conclude that there is potential for unintended factor tilts in smart beta ETFs that could offset the return advantage from the ETFs intended factor tilts. For inspiration on the European market, we consider the work by Bowes and Ausloos (2021) who extend Glushkov's study and look at the performance of smart beta ETFs over the period 2005-2017 using three asset pricing models. In addition, the study assesses smart beta ETFs' factor exposure. Bowes and Ausloos' (2021) study conclude that the smart beta ETFs, on average, fail to outperform their benchmark in terms of risk-adjusted returns.

The findings in our study contribute to the literature as an up-to-date analysis of both the US and European market when compared to a benchmark representing the world market. From our analysis we find that the US smart beta ETFs deliver excess returns when evaluated against the multi-factor model for all categories, except low volatility. The European portfolios generally perform worse than their US counterparts, and only three of the nine categories earn a positive and significant alpha. Additionally, the results show that the size of the monthly abnormal returns in percentage in the US is higher across all categories with significant alphas compared to their European counterparts. The findings from the analysis of the multi-factor model are supported by the risk-adjusted performance measures. We find that the US portfolios provide higher Sharpe ratios and Treynor ratios across all categories, except momentum, compared to the European portfolios. The information ratios of the US portfolios are all above what is considered a good investment which further support the US smart beta ETFs ability to earn consistent abnormal returns. In the analysis of varying market trends, we find that the excess returns of the smart beta ETF portfolios, relative to benchmark, largely disappear for both markets in down periods. During up periods, the analysis shows no considerable difference from the results of the full period model.

The thesis is further structured in the following way: Part two provides more background information on smart beta ETFs, as well as a review of previous literature on this topic. In part three we explain how we collect our data and the choices made during the data collection process. In part four the methodology used in our analysis is described, along with a discussion on potential weaknesses in the applied models. The results of the two-part analysis are presented in part five and further discussed in part six. Finally, we present our conclusion in part seven.

2. Background & Literature Review

In this section we start by presenting exchange traded funds (ETFs) and further introduce smart beta ETFs, looking closer at how they choose their strategy and benchmark, and what the different strategies entail. Thereafter, we review some existing literature.

2.1 Exchange Traded Funds

Exchange traded funds (ETFs) are securities that track indexes, currencies, bundles of assets, commodities, and/or other assets. ETFs are traded on stock exchanges in the same way as regular stocks, making investing in the entire stock market more accessible for private and institutional investors at a potential lower cost (Glushkov, 2015). Passive ETFs are the more widespread variety and typically track an index. These ETFs are regularly updated to reflect the changes in their tracked benchmark. Many ETF types exist, such as equity, fixed income, credit, as well as mixes. Equity ETFs invest in a variety of company stocks, similar to mutual funds, making the investment product highly diversified (Trackinsight, u.d.).

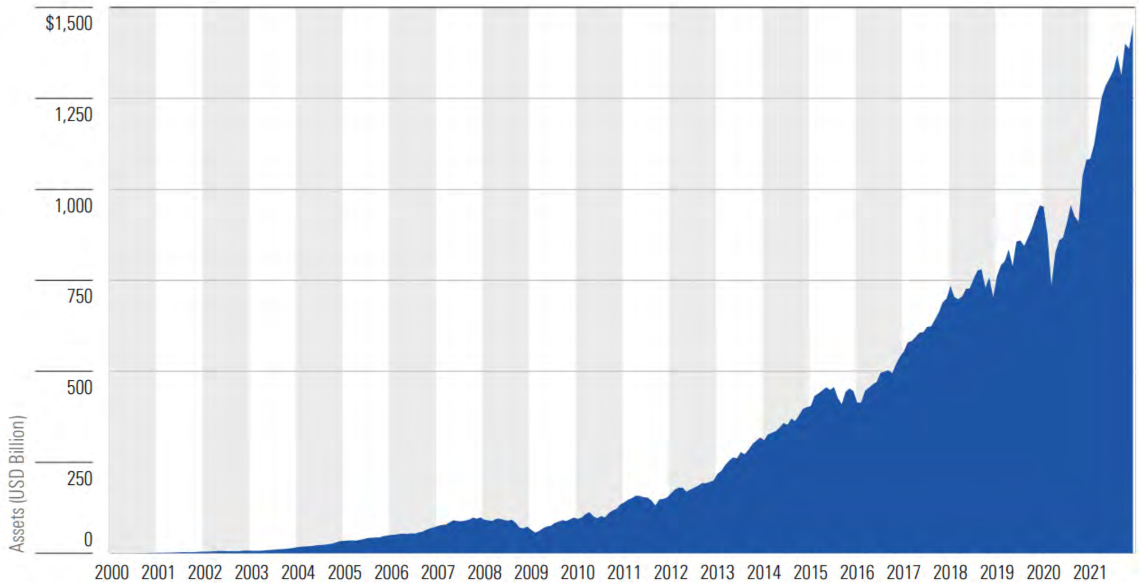
Over the past decade, ETFs have grown significantly globally, with AUM of $7.3 trillion and a total net cash flow of $3.7 trillion from 2012-2021 (Hooper & Sharp, 2022). The first ETFs started out investing in broad-based indexes, offering diversification at a low cost. Since the early 2000s the market has evolved into more specialized ETFs, such as smart beta ETFs and sector ETFs that track niche portfolios while charging higher fees. Smart Beta ETFs allow for exposure to risk factors in a diversified manner and can therefore be ideal for investors looking to maximize their returns while allowing for the potential to minimize risk. Broad-based ETFs can be said to compete on price while the more specialized ETFs compete on quality (Ben-David, Franzoni, Kim, & Moussawi, 2021). Where competition on quality can be defined as product attributes, except price, that are attractive to investors.

2.2 Smart Beta ETFs

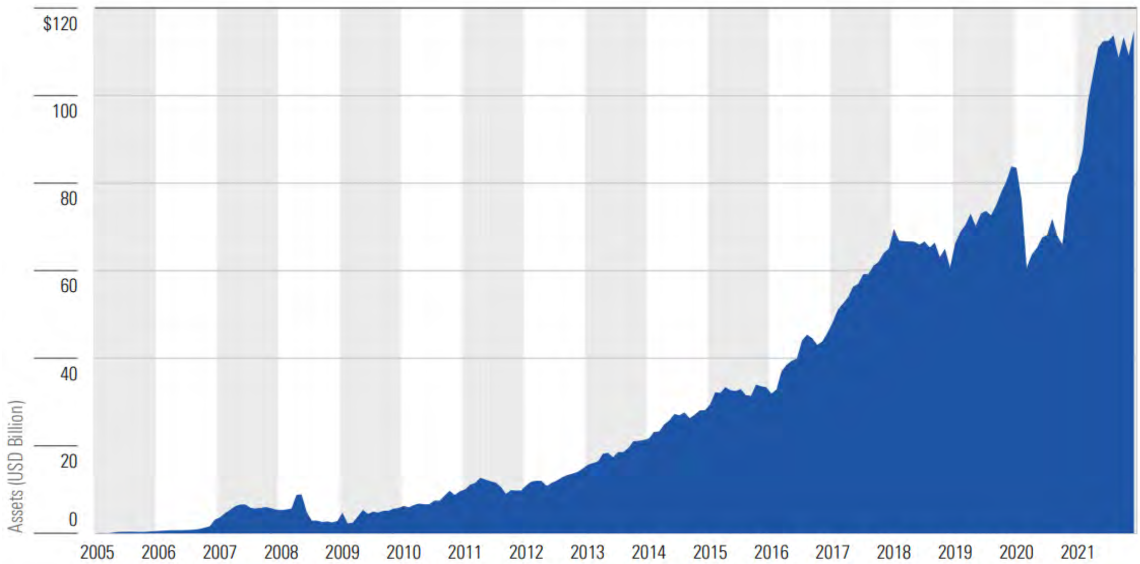
According to a report by Morningstar the market for smart beta ETFs has grown faster than the broader ETF market in the past decade, with collective AUM on a global scale of around $1.65 trillion as of 31st December 2021 (Choy, Dutt, Garcia-Zarate, Gogoi, & Johnson, 2022). This growth in AUM is shown in figure 2.1 for the US and European markets. The US constitutes the largest and most diverse pool of smart beta ETFs, accounting for 46% of the total number of smart beta ETFs, which in turn account for 88% of global smart beta assets. Despite the significant growth in AUM, there has been a decrease in the number of new funds launched in recent years. The report suggests that the downturn in new launches, together with strong competition in ETF fees, could imply the global market has reached maturity.

Figure 2.1: Smart Beta ETF Asset Growth.

Panel A: US asset growth



Panel B: European asset growth



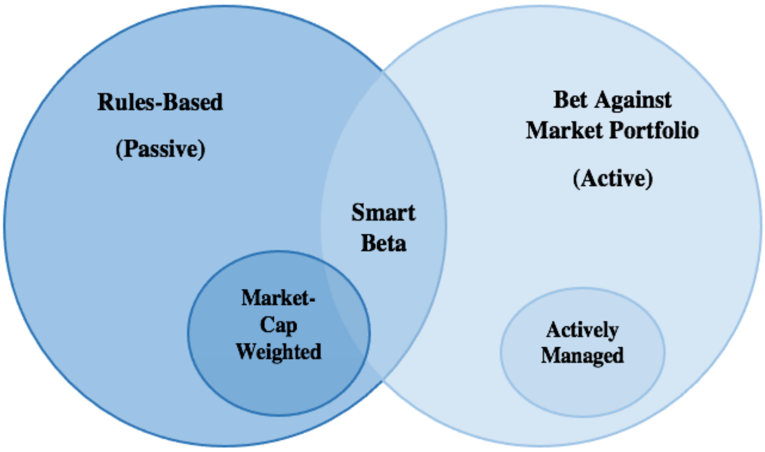
Note: Data as of Dec. 31, 2021. From “A Global Guide to Strategic-Beta Exchange-Traded Products” by Choy et al., 2022, *Morningstar Manager Research*.

Most smart beta ETFs track cap-weighted indexes, also known as market-weighted indexes, and aim to deliver excess returns and/or minimize risk relative to a traditional benchmark by tilting their portfolios towards various factors (Johnson, 2014). The tracked indexes are typically rather specific, with a higher level of complexity than their underlying traditional stock index, such as the S&P 500 or STOXX Europe 600. The more specified indexes result in many of these benchmarks having a rather short track record, as well as an underlying design with the sole purpose of serving as the basis of an investment product. Since smart beta ETFs are index-linked investments they have a goal of achieving a beta of 1 as measured against their benchmark. In a way, smart beta strategies capture risk premia in the same way as active managers, meaning the investment strategy tries to take advantage of the benefits of both active and passive investment through the choice of benchmark.

One argument for investing in smart beta ETFs is their potential to provide diversification and risk reduction during different market cycles (Glushkov, 2015). If a market experiences a negative trend, smart beta ETFs with a defensive strategy may provide an advantage as their portfolios are tilted towards factors whose return premium is negatively correlated with the market. From the correlation table between the MSCI World Index and different factors in appendix A2 we see that the factors quality and momentum have a negative unconditional correlation with the world market return in excess of the risk-free rate, suggesting quality- and momentum-related funds might have an advantage during down periods. During a positive market period some categories of smart beta ETFs might be able to position their portfolios to better capture additional sources of return premium compared to the return of the aggregate market.

Figure 2.2 show the intersection points between smart beta ETFs and active and passive managed funds. Smart beta ETFs can be considered a blend of passive and active investing as they follow an index while also considering alternative factors when deciding which stocks to invest in from the index. In terms of costs, smart beta ETFs have, on average, a higher expense ratio than passive funds but are generally less expensive than active funds (CFI, 2022b).

Figure 2.2: Smart beta ETF position relative to passive and active funds.



Edited copy from Johnson *(2014)*.

Smart beta ETFs are a relatively new investment product, resulting in lower trading volumes affecting the product's liquidity (Madhavan, 2016). Meaning despite smart beta ETFs offering the investors an opportunity to minimize risk, it might not allow them to exit their position easily if a particular fund has poor liquidity, increasing the overall risk. Concerning the product's total cost, the trading cost of smart beta ETFs could increase as a by-product of the securities purchases from an index. Because of these transaction costs, savings between smart beta ETFs and active funds might not be substantial.

2.2.1 Smart Beta ETF Categories

On a broad basis, smart beta ETFs can be divided into three classifications: return-oriented, risk-oriented and other. The return-oriented strategies aim to track a niche index and thus improve returns relative to a standard benchmark. In terms of risk, the return-oriented strategies seek to keep risk at the same level as the standard benchmark. Typical examples of this strategy are smart beta ETFs with a factor tilt, such as value- and growth funds. Alternatively, another way of earning a return is by isolating a specific return source, such as through a dividend strategy. Risk-oriented strategies entail either reducing or increasing risk relative to a standard benchmark as a way of maximizing the risk-reward ratio. Typical examples are low volatility and high-beta categories. The smart beta strategies categorized as others, encompass a variety of strategies. Examples include equal-weighted funds and funds tracking commodity or multi-asset benchmarks. It is however important to keep in mind that the categories can be somewhat overlapping, for example, value, quality, and dividend. The final categorization will depend on what the issuer identifies as their factor strategy criteria.

2.2.1.1 Return Oriented

Value

The strategy behind value smart beta ETFs is to be exposed to stocks that seem to be trading for less than their book or intrinsic value, meaning investing in undervalued stocks as the market tends to act irrational when encountering good or bad news (Hayes A. , 2022a). Investing in funds that favor value stocks is often considered a conservative approach, as they may earn a higher return in volatile markets, but with less potential for growth (Dierking, 2022).

Growth

Growth smart beta ETFs are exposed to stocks displaying growth or heavily weight constituents based on growth characteristics (Choy, Dutt, Garcia-Zarate, Gogoi, & Johnson, 2022). Which growth characteristics the ETF is exposed to will depend on the chosen index and therefore vary across index providers. Examples of growth characteristics include long-term projected earnings growth, historical earnings growth, cash flow growth, and book-to-value growth. Growth stocks are often viewed as expensive investment products, resulting in a negative exposure toward the value factor (HML) in the Fama-French models (Reed, 2022).

Quality

Issuers of quality ETFs will attempt to identify quality characteristics through screening segments in the stock market and subsequently have more extensive exposure to these through weighting methodology (Choy, Dutt, Garcia-Zarate, Gogoi, & Johnson, 2022). Although academics have not identified a singular stock characteristic that serves as a proxy for quality, Hsu, Kalesnik and Kose (2019) find that some measurements of quality are robust predictors of future excess returns and risk-adjusted returns. These are profitability, accounting quality, payout/dilution, and investment factors. Which quality characteristics an ETF is exposed to will therefore vary across issuer.

Momentum

The smart beta category momentum follows a strategy where stocks are selected and weighted based on factors such as adjustments to earnings estimates, earnings surprises, and price momentum (Choy, Dutt, Garcia-Zarate, Gogoi, & Johnson, 2022). The momentum strategy aims to “buy past winners and sell past losers” (De Bondt & Thaler, 1985). Jagadeesh and Titman (1993) find evidence that the momentum strategy generated excess return in the period 1965-1985. The momentum factor has a negative relationship with the value factor (HML), as value-investing exploits fundamentally cheap assets.

Dividend

Dividend-exposed smart beta ETFs aim to create value by investing in dividend-paying stocks. The weight of each stock depends on the criteria the fund manager has decided on, such as dividend growth, dividend stability, dividend yield paid to investors, or a mix of all three (Choy, Dutt, Garcia-Zarate, Gogoi, & Johnson, 2022). The rationale of dividend exposure is that companies that pay dividends reflect financially healthy and well-established companies (Florent, 2021). The Morningstar report on the global smart beta ETF market (2022) reveals that dividend smart beta ETFs continue to remain one of the most popular strategies. This is in large part due to the interest environment and the increased demand for income during the last decade.

Fundamentals Weighted

The fundamentals weighted smart beta ETFs objective is to create value by picking stocks based on fundamental measures of a company’s value. These fundamental measures may include adjusted sales, cash flow, dividends, share buybacks, and others (Choy, Dutt, Garcia-Zarate, Gogoi, & Johnson, 2022). Contrary to categories with a single factor exposure, the fundamentals weighted smart beta ETFs are exposed to several factors.

Multi-Factor

Multi-factor smart beta ETFs aims to gain value by being exposed to multiple factors instead of only one singular (iShares, u.d.). The strategy is to choose their exposure to factors that are recognized as long-term drivers of value, for example, momentum, low size, and value (Bender, Briand, Melas, & Subramanian, 2013).

2.2.1.2 Risk Oriented

Low Volatility

The strategy behind low volatility is to include stocks that exhibit a lower level of volatility than their peers (Choy, Dutt, Garcia-Zarate, Gogoi, & Johnson, 2022). Metrics such as market beta or standard deviation can be used to measure risk. The strategy is based on the belief that contrary to the CAPM’s intuition, riskier stocks do not necessarily generate higher returns due to risk premiums. This is supported by Haugen and Heins (1972) who find that stock portfolios with lower variance in monthly returns experience higher average returns than riskier counterpart portfolios in the long run.

2.2.1.3 Other

Equal Weighted

Equally weighted smart beta ETFs do not take one specific factor into account, rather the strategy is based on being equally weighted in every component of the chosen index. This allows for broader exposure to different factors with predetermined weights, allowing for diversification (Bovaird, 2022). Additionally, DeMiguel, Garlappi and Uppal (2009) find that 1/N portfolios perform better in terms of Sharpe ratio compared to 14 asset-allocation models considered in their research. However, the equal weighted smart beta strategy displays one of the highest transaction costs compared to the other categories (Esakia, Goltz, Sivasubramanian, & Ulahel, 2017).

2.3 Literature Review

This section presents insights into empirical research on smart beta ETFs. Previous literature on smart beta ETFs is relatively scarce, and the studies conducted are mainly on the performance of smart beta ETFs in the US and Europe separately.

Glushkov (2015) was one of the first to publish a comprehensive study on smart beta ETF performance. The study looks at the performance of smart beta ETFs relative to their self-declared benchmark, as well as a blended benchmark, constructed with passive investible ETFs. The study considers a period of 11 years, from 2003-2014. In the sample of US-domiciled equity smart beta ETFs, Glushkov do not find conclusive evidence that smart beta ETFs outperform their risk-adjusted benchmarks in the period. Several research papers have attempted to replicate Glushkov’s study. For example, Johnson (2017) examine the smart beta ETFs performance in the US from 2007-2017 and analyze their returns against a blended benchmark constructed through the use of passive investible ETFs. A distinction between Johnson and Gloshkov’s studies is that Johnson also separates the categories according to cap size. In addition, Rompotis’s (2019) consider to what extent smart beta ETFs produce alpha relative to their respective cap-weighted self-declared benchmarks. Like Gluskov, neither research paper find evidence that smart beta ETFs outperform their chosen benchmarks in the studied period. On the contrary, Mateus et al. (2020) find that their sample of US equity smart beta ETFs outperform traditional ETFs over the period June 2000-May 2017.

Most research limit their studies to smart beta ETFs domiciled in the US. There has, however, been a development in the smart beta field in Europe in recent years. Bowes and Ausloos (2021) extend the work by Glushkov and consider smart beta ETFs in Europe from 2005-2017. The study analyzes a sample of European smart beta ETFs' factor exposure and performance. Bowes and Ausloos (2021) use the smart beta ETFs' directly assigned benchmarks by Morningstar to assess the categories' ability to generate abnormal returns. They find that the European smart beta ETFs on average, fail to outperform their benchmarks in terms of risk-adjusted returns.

To summarize, there are several studies on the performance of smart beta ETFs. However, most of the research find no evidence of the funds outperforming their benchmarks. Further, the studies vary in terms of the benchmark, where some focus on the product's return relative to their self-declared benchmarks, directly assigned benchmarks from a financial data platform, or a blended benchmark of passive ETFs.

3. Data

In this section we will start by describing how we select the smart beta ETFs and how the portfolios of smart beta ETFs are constructed. We also present our choice of index data and factors for our analysis. All data is extracted in USD.

3.1 Smart Beta ETF

For data on smart beta ETFs in the US and Europe we use the Morningstar Direct database. We download data for each fund on: Morningstar's categorization for strategic beta group, ticker, index selection, index weighting, primary prospectus benchmark, investment area, firm name, branding name, inception date, prospectus net expense ratio, monthly return from January 2007 to June 2022, and monthly fund size from January 2007 to June 2022. Morningstar places each smart beta ETF in one category based on the strategy in their prospectus, and we select the following categories to be included in our sample: value, growth, quality, momentum, dividend, low volatility, multi-factor, fundamentals weighted, and equal weighted. We only include funds with an inception date before July 2021 to make sure each fund in the sample has at least 12 months of data. Secondly, the funds are screened based on whether they had primary shares. This screening helps remove duplicates since some funds have the same ticker, but with different share classes. Funds without a ticker are also removed from the sample. One limitation to the data sample from Morningstar is that only funds that are still operational are included. The omission of closed funds creates a problem of survivorship bias where our data could suffer from an overestimation of historical performance. However, Morningstar's data on "dead" smart beta ETFs is inconsistent and could thus not be included in our data sample.

Our final sample consists of 486 US smart beta ETFs and 276 European smart beta ETFs. The accumulated number of smart beta ETF funds per category per year for each market is shown in table 3.1. In Europe we note that several of the categories, in addition to the low volatility category in the US, do not have funds that exist in the beginning of our time period in 2007. This means that for several of our categories we have data on return and fund size for a shorter period of time.

Table 3.1: Accumulated number of smart beta ETF funds per category per year.

Panel A: US market

Category	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Dividend	30	32	33	36	40	48	62	70	87	110	119	125	130	131	133
Fundamentals weighted	8	12	12	14	14	14	20	20	20	20	21	24	27	27	27
Growth	22	22	24	29	29	29	29	29	30	32	32	34	38	38	38
Momentum	14	14	14	14	14	19	20	22	25	27	29	29	29	30	30
Multi-factor	31	31	33	33	48	56	59	65	90	108	128	137	144	149	154
Equal weighted	16	16	16	19	19	21	21	22	23	23	26	27	27	27	27
Quality	5	5	5	5	5	6	7	7	9	10	12	13	15	15	15
Low volatility					5	7	11	11	13	15	18	18	18	18	18
Value	22	22	24	29	29	30	31	32	34	37	38	40	42	43	44
Total	**148**	**154**	**161**	**179**	**203**	**230**	**260**	**278**	**331**	**382**	**423**	**447**	**470**	**478**	**486**

Panel B: European market

Category	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Dividend	13	15	18	18	22	26	30	40	53	73	92	99	104	107	113
Fundamentals weighted	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Growth	1	2	2	2	3	3	3	3	3	3	4	5	5	6	7
Momentum								1	2	4	6	8	8	8	9
Multi-factor		1	1	1	1	1	4	7	13	14	31	38	42	43	43
Equal weighted					1	1	2	6	7	8	8	10	10	11	13
Quality								2	10	13	15	24	24	25	25
Low volatility						5	5	6	9	13	21	25	26	34	36
Value		1	2	3	3	5	5	6	13	16	18	23	23	24	25
Total	**19**	**24**	**28**	**29**	**35**	**46**	**54**	**76**	**115**	**149**	**200**	**237**	**247**	**263**	**276**

Morningstar calculates monthly total return by taking the change in monthly net asset value (NAV), reinvesting all income and capital-gains distributions during that month, and dividing this change by the starting NAV. Returns are not adjusted for sales charges, unless otherwise stated, but the total return does account for management, administrative, 12b-1 fees and other costs taken out of a fund's assets.

From the sample of smart beta ETFs, we construct a value weighted portfolio for each smart beta ETF category in both markets. This is done by weighting each fund's return by the size of the fund for each month. For each smart beta ETF category, we are left with a portfolio consisting of several funds which is used for further analysis.

3.2 Market Indexes

Data on the different indexes is downloaded from Bloomberg. For the US, European and world market the following indexes are the MSCI US Broad Market Index (hereafter MSCI US), the STOXX Europe Total Market Index (TMI), and the MSCI World Index respectively. We choose the MSCI US as the market index for the US as it represents about 99% of US equities, and includes companies across large, mid, small, and micro capitalizations (MSCI, 2022a). For the European market the STOXX Europe TMI represents the Western European region as a whole and covers about 95% of the free float market capitalization across 17 European countries, comprised of large, mid, and small capitalization indices (Qontigo, 2022). Lastly, the MSCI World Index is used as it is a good proxy for the world equity market and captures large and mid-capitalization companies across 23 developed market countries (MSCI, 2022b).

3.3 Factors and Risk-Free Rate

For our factor-based regressions we extract monthly data on the returns of the size (SMB), value (HML) and momentum (WML) factors from the Kenneth R. French data library (2022)[1]. We download the data for the Developed Market Factor and Returns[2] and for the US and European markets. We also retrieve data on the monthly risk-free rate of return from the Kenneth R. French data library, where the 1-month Treasury rate is a proxy for the risk-free rate. The data on returns of the quality (QMJ) and betting against beta (BAB) factors is retrieved from the AQR Data Sets (2022)[3]. The Pastor-Stambaugh aggregated liquidity factor is extracted from Wharton Research Data Services (2022)[4].

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International

[2] The Kenneth R. French data library considers the following as developed markets: Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, Norway, New Zealand, Portugal, Sweden, Singapore and United States.

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

[4] https://wrds-www.wharton.upenn.edu/login/?next=/pages/get-data/pastor-stambaugh-and-other-liquidity-factors/liquidity-factors/pastor-stambaugh/

4. Methodology

In this section we will describe the methodology used to evaluate the performance of smart beta ETFs in the US and Europe compared to the world market. We employ a two-part analysis, where we start by computing different measures of risk-adjusted return. Further, we run multi-factor models on the different smart beta ETF categories for the two markets. The regression analysis is built upon a multi-factor model as proxy for systematic risk, where several well-documented factors are included. We use different market indexes in excess of the risk-free rate as the market risk premium factor and employ the factors size, value, quality, momentum, and betting against beta. We explain our choice of market index, as well as how we look at the returns for periods of different market trends. At the end of the section, we describe the various tests performed to ensure robustness in our results and mention some weaknesses regarding our regression model.

4.1 Performance Measures

When evaluating fund performance, risk-adjusted returns are typically used. There exist several measures of fund return, with varying degrees of complexity. In academic literature there is no consensus on a particular method of measuring and reporting portfolio performance, but there are certain measures more often used (Bauer, Christiansen, & Døskeland, 2022). A limitation of evaluating fund performance when looking at risk-adjusted performance is that the metrics do not give any indication of future performance but can only be used as a way of evaluating historical data.

Annualized Returns

In this paper, we use annualized total return for fund performance measures. This is a geometric mean which takes into account the effect of compounding. The annualized returns in this paper are calculated by scaling our monthly observations using the following formula:

$$R_i^A = \left(\sum_{i=1}^{n} \left(1 + R_{i,t}\right)\right)^{\frac{scale}{n}} - 1 \qquad \textbf{(4.1)}$$

Where R_i^A is the annualized return on portfolio i, $R_{i,t}$ is the return on portfolio i at time t, scale is the number of periods within the year, here monthly (=12), and n equals total number of periods under analysis.

Standard Deviation

The annualized standard deviation is calculated using the following formula:

$$\sigma_i^A = \sqrt{scale} * \sigma_i \tag{4.2}$$

Where σ^A is the annualized standard deviation of portfolio i, scale is the number of periods within the year, here monthly (=12), and σ_i is standard deviation of portfolio i.

Jensen's Alpha

Jensen's alpha is a continuation of the CAPM and represents the average return on a portfolio or an investment in excess of the return predicted by the CAPM (Jensen, 1969). Jensen's alpha can be used as a risk-adjusted performance measure that take the risk-free rate of return for the time period and provides the abnormal return of an investment. Assuming the CAPM is correct, Jensen's alpha is calculated as:

$$\alpha_i = R_{i,t} - \left(Rf_t + \beta_{Mkt} * \left(R_{Mkt,t} - Rf_t\right)\right) \tag{4.3}$$

Where α_i is Jensen's alpha of portfolio i, i.e., the abnormal return, $R_{i,t}$ is the return on portfolio i at time t, Rf_t is the risk-free rate of return at time t, β_{Mkt} is market beta, and $R_{Mkt,t}$ is the return on the market portfolio at time t.

Sharpe Ratio

The Sharpe ratio is a widely used measure and is targeted at the total return and risk level of a portfolio (Bauer, Christiansen, & Døskeland, 2022). The Sharpe ratio measures the excess return per unit of risk and is considered the most straightforward measure of the trade-off between portfolio return and total volatility. The higher the Sharpe ratio, the better risk-adjusted performance of the portfolio.

The Sharpe ratio is calculated as:

$$SR = \frac{R_i - Rf}{\sigma_i} \tag{4.4}$$

Where SR is the Sharpe ratio, R_i is the return on portfolio i, Rf is the risk-free rate of return, and σ_i is the standard deviation of portfolio i.

Limitations to the use of the Sharpe ratio is that it uses the standard deviation of a portfolio, used as the proxy for portfolio risk, in its denominator. This assumes that returns on investments are normally distributed, which is not always the case (Fernando, 2022). In financial markets, returns can go to extremes more often than a normal distribution would suggest, and as a result the calculation of the standard deviation for the denominator may understate tail risk. Another aspect to consider is that market returns can be subject to serial correlation, where returns in adjacent time periods may be correlated due to the influence of the same market trend. Serial correlation tends to result in lower volatility, when there is positive autocorrelation, which provides an accurate reflection of risk, as investments are less risky over longer time horizons. However, lower volatility due to serial correlation can result in investment strategies dependent on serial correlation factors exhibiting misleadingly high Sharpe ratios.

Information Ratio

The information ratio (IR) is another widely used measure. This measure seeks to summarize the mean-variance properties of an active portfolio and gives a measure of the average excess return over benchmark per unit of volatility of the excess return (Goodwin, 1998):

$$IR = \frac{R_{i,t} - R_{B,t}}{\sigma_{ER}} \tag{4.5}$$

Where IR is the information ratio, $R_{i,t}$ is return on portfolio i at time t, $R_{B,t}$ is return on benchmark at time t, and σ_{ER} is tracking error of portfolio i, which is calculated as $\sigma_{ER} = \sqrt{\frac{1}{T-1} * \sum_{t=1}^{T} (ER_t - \overline{ER})^2}$, where $ER_t = R_{i,t} - R_{B,t}$ and $\overline{ER}$ equals the arithmetic average of excess returns over the historical period form t=1 through T.

The IR is often used as a measure for the skill and ability of a fund manager to generate excess returns relative to a benchmark, in addition to trying to identify the consistency of performance by incorporating the standard deviation of the portfolio. The higher the IR, the better. A ratio above 0.40 is generally considered quite good, and a ratio below 0.4 indicates the fund failed to earn abnormal returns for a sufficiently long time, while a negative ratio means the active manager failed on the objective of outperforming the benchmark (Informa, 2016). An IR above 1 for long periods of time is rare.

Limitations to the use of the IR is that it cannot be used to make decisions about how much to allocate to a particular asset class as it does not contain any information on correlations between asset classes. Another limitation is tied to incentive problems for fund managers. Since smart beta ETFs track a benchmark, the fund manager could wish to maximize their information ratios if this is tied to compensation. When a manager is benchmarked, they typically maximize relative returns while minimizing the variability in relative returns, and view the benchmark as a risk-free asset, thus do not take into account risks that are present within the benchmark (Norges Bank Investment Management, 2020). This could result in the manager adding risk on top of those already within the benchmark, leading to a risk-shifting issue from the manager to the investor, as the manager wish to maximize their information ratio, while the investor would like to maximize the Sharpe ratio of the portfolio.

Treynor Ratio

The Treynor ratio, also known as the reward-to-volatility ratio, is a performance metric used to determine a portfolio's excess return adjusted for systematic risk (Kenton, 2020). The Treynor ratio is similar to the Sharpe ratio, but instead of using a portfolio's standard deviation as measurement of risk, the Treynor ratio uses a portfolio's systematic risk as measured by beta. The beta of a portfolio measures the tendency of the portfolio to change in response to changes in return for the overall market. The ratio indicates how much return an investment earned for the amount of risk taken, and the higher the Treynor ratio the more suitable an investment is.

The Treynor ratio can be calculated as:

$$TR = \frac{R_i - Rf}{\beta_i} \tag{4.6}$$

Where TR is the Treynor ratio, R_i is return on portfolio i, Rf is the risk-free rate of return, and β_i is the beta of portfolio i.

A limitation of the Treynor ratio is that the ratio's accuracy is reliant on the use of an appropriate benchmark to measure beta, as this will highly affect the systematic risk.

4.2 Regression Model

The final benchmark model used in our regressions, a multi-factor model constructed with the market factor and the risk factors size, value, momentum, quality, and betting against beta, is shown in equation 4.7:

$$R_{i,t} - Rf_t = \alpha_i + \beta_{Mkt}(R_{Mkt,t} - Rf_t) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{WML}WML_t + \beta_{QMJ}QMJ_t + \beta_{BAB}BAB_t + \epsilon_t \quad \textbf{(4.7)}$$

Where $R_{i,t} - Rf_t$ is the return on portfolio i in excess of the risk-free rate at time t, α_i is alpha of portfolio i, i.e the intercept/abnormal return, $R_{Mkt,t} - Rf_t$ is expected return of the market in excess of the risk-free rate at time t, β_{Mkt} is market beta, SMB_t is size premium at time t (small minus big), HML_t is value premium (high minus low), WML_t is momentum premium at time t (winners minus losers), QMJ_t is quality premium at time t (quality minus junk), BAB_t is betting against beta premium at time t, $\beta_{SMB}, \beta_{HML}, \beta_{WML}, \beta_{QMJ}, \beta_{BAB}$ is the exposure to the factors, and ϵ_t is the error term at time t.

In our model we subtract the risk-free rate of return from the portfolio returns and from the market portfolio, which is represented by the market indexes. This is done because the total rate of return represents compensation for both investment risk and the time value of money, the risk-free rate (Bodie, Kane, & Marcus, 2008). Thus, the excess return above the risk-free return represents a premium, or reward, for bearing risk.

Multi-factor models were developed to address the problem that arose from the empirical evidence that a single market risk factor cannot fully explain expected returns. One such model is the Fama-French three-factor model where the two factors size (small minus big (SMB)) and value (high minus low (HML)) were introduced as additional risk factors along with the market risk premium (Fama & French, 1993). The model is an expansion of the CAPM, and when controlling for the two factors is better able to isolate the outperformance of a portfolio or an investment compared to the market. This three-factor model was further expanded by Mark Carhart (1997) through the inclusion of a momentum factor. Carhart included the additional factor after observing that poorly performing stocks kept doing so, and that well-performing stocks kept performing well. The momentum factor (winners minus losers (WML)) in the expanded factor model captures these effects on the return of portfolios that have performed well in the past in excess of portfolios that have performed poorly in the past. We further include the factors quality and betting against beta in our model. In the study “Quality minus junk” Asness, Frazzini and Pedersen (2019) show that investors pay more for firms with higher quality characteristics. A quality minus junk (QMJ) portfolio produce high risk-adjusted returns by investing long in high quality stocks and short in junk stocks. The betting against beta (BAB) factor represents a factor associated with low volatility investing. Frazzini and Pedersen (2014) find evidence that long leveraged low-beta assets and short high-beta assets produce significant positive risk-adjusted returns, as the high beta assets is associated with a lower alpha.

We employ the multi-factor model to evaluate the performance of the different smart beta ETF categories, using the model as market proxy. This is mainly done by considering the portfolios’ abilities to earn alpha against the multi-factor model on the whole sample period. Where alpha represent the unexplained excess returns and can be interpreted as evidence of skill or some kind of additional risk not captured by the factor model. Factor models are useful as they help assess whether a fund is offering something unique, alpha, rather than just repackaging known factor exposures that could have been obtained with low-cost index funds.

In addition to estimating alphas, the regressions can be used to analyze the different categories’ active investment style (Bodie, Kane, & Marcus, 2008). This is done through looking at the estimated slope coefficients to the systematic factors, as these can be interpreted as the active exposure to each factor. The risk-free return is not subtracted from the factor portfolios as these portfolios represent net zero investment positions, and as a result require no compensation for time value, only for risk. The total “return” on the factor portfolios may therefore be interpreted as a risk premium. Since the factor portfolios used to construct the factors represent portfolios with zero net investments, they are not investment portfolios by themselves. The regression coefficients of the factors rather correspond to the additional returns an investor achieves when adding a position in these portfolios to the rest of their portfolios. Thus, the coefficients help identify active investment style through the average rewards earned for exposures to the different sources of risk for which they proxy.

For the independent variables in the regressions, we can interpret the beta coefficient in different ways. If the beta coefficient of the market factor is equal to 1.0 it means that the portfolio would rise by 1% for each gain of 1% on the market portfolio. If the coefficient is greater than 1.0 it would imply that the portfolio is riskier than the market portfolio, and less risky if lower than 1.0. For the size factor a positive coefficient indicates a portfolio that favors small-cap stocks, and vice versa if negative. A positive coefficient of the value factor means that a portfolio has a positive relationship with the value premium, or that the portfolio behaves like one with exposure to value stocks. If the beta is negative, the portfolio behaves more like a growth stock portfolio. The coefficient of the quality factor indicates that the fund favors stocks with robust (high) operating profitability if positive, and vice versa if negative. If the beta coefficient of the momentum factor is positive, it implies that the portfolio is exposed to market leading (or winning) stocks, and if negative it implies a tilt towards laggards (or losers). Lastly, a positive coefficient of the betting against beta factor, indicates a portfolio that favors exposure to low-volatility stocks and if negative, it indicates exposure to high-volatility stocks.

In terms of factor exposure and analyzing the active investment style of the smart beta ETF categories, it is mainly relevant for the categories with a single factor focus. These categories are value, growth, quality, momentum, and low volatility. As for dividend, multi-factor, fundamentals weighted, and equal weighted, their strategies do not fit one single factor. It is however important to note that a significant coefficient for a category's intended factor do not necessarily mean the funds in the portfolio follow their stated investment strategy.

4.2.1 Choice of Market Index, Factor Exposure and Risk-Free Rate

Although most smart beta ETFs do not use traditional stock market indexes as their chosen benchmark, we decide to use the MSCI World Index as the market factor in the regression model. This is done to give the analysis a global investment perspective. We find it reasonable to conduct our analysis with an international focus as the smart beta ETFs are not restricted to investments in their domicile. We choose to use a multi-factor model with a world index and developed world factors as market proxy since if an investor invests in a smart beta ETF, either in Europe or in the US, they are likely to face exposure to global investments. This is also reasonable from a CAPM perspective, as the model implies that the optimal risky portfolio is the market portfolio, and in an international setting an index such as the MSCI World is a reasonable proxy for the global market. One should however note that the global CAPM perspective relies on an assumption of completely integrated capital markets and thus no transaction costs (Stulz, 1995). Given our international investment focus, the factors in our multi-factor model are downloaded to reflect returns on the developed world. As for the risk-free rate we use the US 1-month T-bill. This is done because we use US dollars as currency for our data, and there is no one risk-free rate for the European market as a whole. Additionally, as a rule of thumb one should choose the risk-free rate of the most stable government body offering T-bills in the given currency (CFI, 2022a), which in our case is the US government 1-month T-bill.

To give a more robust view we also include an analysis of each market separately. We therefore regress the US and European smart beta ETF portfolios using the MSCI US and STOXX Europe TMI as the market index and US and European factors respectively. We choose to use broad market indexes instead of more narrow indexes such as the S&P 500 and the STOXX Europe 600, since a total stock market index encompass a broader range of stocks and represent a larger portion of a market's equity market capitalization (Zoll, 2012). An index such as the S&P 500 tracks the 500 largest US stocks as measured by the value of their shares, and therefore have a larger weighting of higher-value companies than lower-value companies. Broader market stock indexes on the other hand, include both large-, mid-, and small-cap stocks and aim to measure the performance of all publicly traded stocks in their respective market. Therefore, the use of the MSCI US and STOXX Europe TMI serves as better market proxies of the general market which is beneficial in the analysis of the smart beta ETF categories in the two markets separately.

It is worth noting that the country weight for the US is 70.19% of the MSCI World Index (MSCI, 2022b), meaning the index is significantly more influenced by the American stock market than the rest of the world. This is reflected in the high correlation between the MSCI World and the MSCI US indexes which is at 0.975[5]. Regardless of the lower percentage in the MSCI World the correlation between STOXX Europe TMI and MSCI World is still high at 0.953. As for MSCI US and STOXX Europe TMI the correlation is lower at 0.877.

[5] Correlation matrix for the three indexes can be found in appendix A3.

4.3 Test for Up and Down Periods

In addition to our regression model for the full time period, we include regressions on the smart beta ETF categories during times of varying market sentiment. This is done to analyze whether any categories can generate returns in excess of the world market when controlling for positive or negative market trends. It is common to consider the stock market as having up and down periods, and there are several equity market indicators that can be used to define such periods. One such indicator is the 200-day moving average of a given benchmark, where trends are indicated by whether the 200-day moving average is above or below benchmark (Cao, Rapach, & Zhou, 2015). If the 200-day moving average is above the benchmark then it indicates a down market, and if the moving average is below, then an up market prevail. This method of defining different market trends is utilized along with the MSCI World Index in order to further our analysis.

In periods with varying market sentiment, it is interesting to take liquidity into account. Seeing as smart beta ETFs are regarded as less liquid than, for example passive ETFs, liquidity is a factor that can impact performance. There are several types of liquidity when considering smart beta ETFs. The three main types to consider are market liquidity, the liquidity of the smart beta ETF market, and lastly the liquidity of the assets in the fund's underlying portfolio.

In this paper we choose to focus on market liquidity as it has been proven to affect asset prices and expected returns, and periods recognized as "down" are typically characterized by low market liquidity (Hameed, Kang, & Viswanathan, 2010). Further, empirical evidence suggest that investors are compensated for holding illiquid assets. Given theory and empirical studies on liquidity's effect on expected returns we conduct a separate analysis where a liquidity factor is included in the main regression model for the two different market regimes. We conduct the separate analysis on these periods as we expect the market liquidity to be high in up periods and low in down periods. Pastor and Stambaugh (2003) find that market-wide liquidity is a state variable that is important for asset pricing, as expected stock returns are related to the sensitivity of returns to fluctuations in aggregated liquidity. In order to measure how liquidity affect stock returns, Pastor and Stambaugh propose a long-short tradable portfolio. This portfolio is recognized as the liquidity factor in the Pastor-Stambaugh Model. The model argues that more illiquid stocks tend to earn higher returns, thus one should expect the coefficient to be more negative in periods with low liquidity. This liquidity measure is widely used in previous literature as seen in research by Cao, Chen, Liang and Lo (2013) and Chernenko and Sunderam (2016), among others. Other popular measures of liquidity are for example the bid-ask spread of assets, the Amihud illiquidity measure, and turnover ratios. However, we choose to include the Pastor-Stambaugh liquidity factor since we want to consider market-wide liquidity, as well as due to restrictions in our underlying data.

4.4 Model Testing

From the Gauss Markov theorem, it follows that the ordinary least squares estimator of the coefficients of a linear regression model is the best linear unbiased estimator when the following assumptions are satisfied: i) linear parameters, ii) no perfect collinearity, iii) zero conditional mean, iv) homoscedasticity and v) no serial-/autocorrelation (Wooldridge, 2018). The assumptions of the underlying regression model for the full period are briefly discussed, but for further comments and results of the tests, see appendix A1.

The first assumption regarding linear parameters can be tested but taking the large existing literature on linear factor models into account one can consider this assumption to be satisfied (Fama & French, 2015; Frazzini & Pedersen, 2014; Asness, Frazzini & Pedersen, 2019). The multicollinearity assumption is tested for by applying the variation inflation factor (VIF). This test indicates that we do not have a problem with multicollinearity.

In order to ensure the regressions efficiency and correct standard errors we conduct tests for the assumptions iii) – v). From the results of the tests we conclude that the Gauss-Markov assumptions are satisfied, except for the assumption regarding homoscedasticity for selected regressions. Because selected regressions violate the homoscedasticity assumption, we ran the regressions with robust standard errors. However, this result only in minor changes in coefficient sizes and not in their significance level. We therefore continue with our original OLS regression without restrictions.

In addition to testing the model for the five Gauss Markov theorem assumptions, we conduct a test for stationarity as we have time series data. Stationarity indicates the same probability distribution of the data over time (Wooldridge, 2018). The results of the test display no problem of non-stationarity at a 10% significant level.

4.5 Model Weaknesses

Like many other financial models, the Fama-French model has been criticized throughout the years. One of the major criticisms of the three-factor model has been regarding the value premium (HML). The factor has been criticized for being sample-specific and, as indicated by Black (1993) "mere artifact of data mining", meaning the premium is unlikely to recur in future returns. Another remark on the model by Penman et al. (2007), argues that listed market ratios are based on accounting principles and therefore reflect "book value" rather than the risk exposure of the firm. Since the development of the three-factor model, Fama and French (1993) have recognized that it has its limitations in capturing short-term continuation of returns. The momentum factor proposed by Mark Carhart is advocated to be the missing factor in capturing such returns (Carhart, 1997).

As for "quality minus junk" (QMJ) and "betting against beta" (BAB), there are certain risks in adding more explanatory variables to a model (Blitz, Vliet, & Hanauer, 2018). Their arguments are based on the risk of correlation between the included factors. The BAB factor introduced by Frazzini and Pedersen (2014) has received critique in the newly published study "Betting against Betting Against Beta" by Novy-Marx and Velikov (2022). The article argues that Frazzini and Pedersen's constructed methodology results in an ultimately equal-weighting strategy, deviating from the conventional market-cap weighting strategy, leading to prominent positions in very small-cap stocks with high transaction costs. Lastly, research on the quality factor (QMJ) has found evidence of the factor obtaining abnormal returns. However, there is some dispute about how to capture the risk-premia from the quality factor. Asness, Frazzini, and Pedersen (2019) broadly define quality as "characteristics that investors should be willing to pay a higher price for, everything else equal." This is a broad definition, and while some academics will define quality as a one-metric measure, others argue that one should use a multi-metric measure to capture the factor.

5. Results

In this section we present the results of our analysis. The analysis is conducted with the objective of answering our following research question:

How do the performance of US and European smart beta ETF categories compare relative to the MSCI World Index when using risk-adjusted performance measures and multi-factor models?

We start the analysis by looking closer at the smart beta ETF categories across the US and European markets through different performance measures. Thereafter, we present the regression results for the main model. We also take a closer look at regression models for the US and European markets separately.

5.1 Portfolio Overview

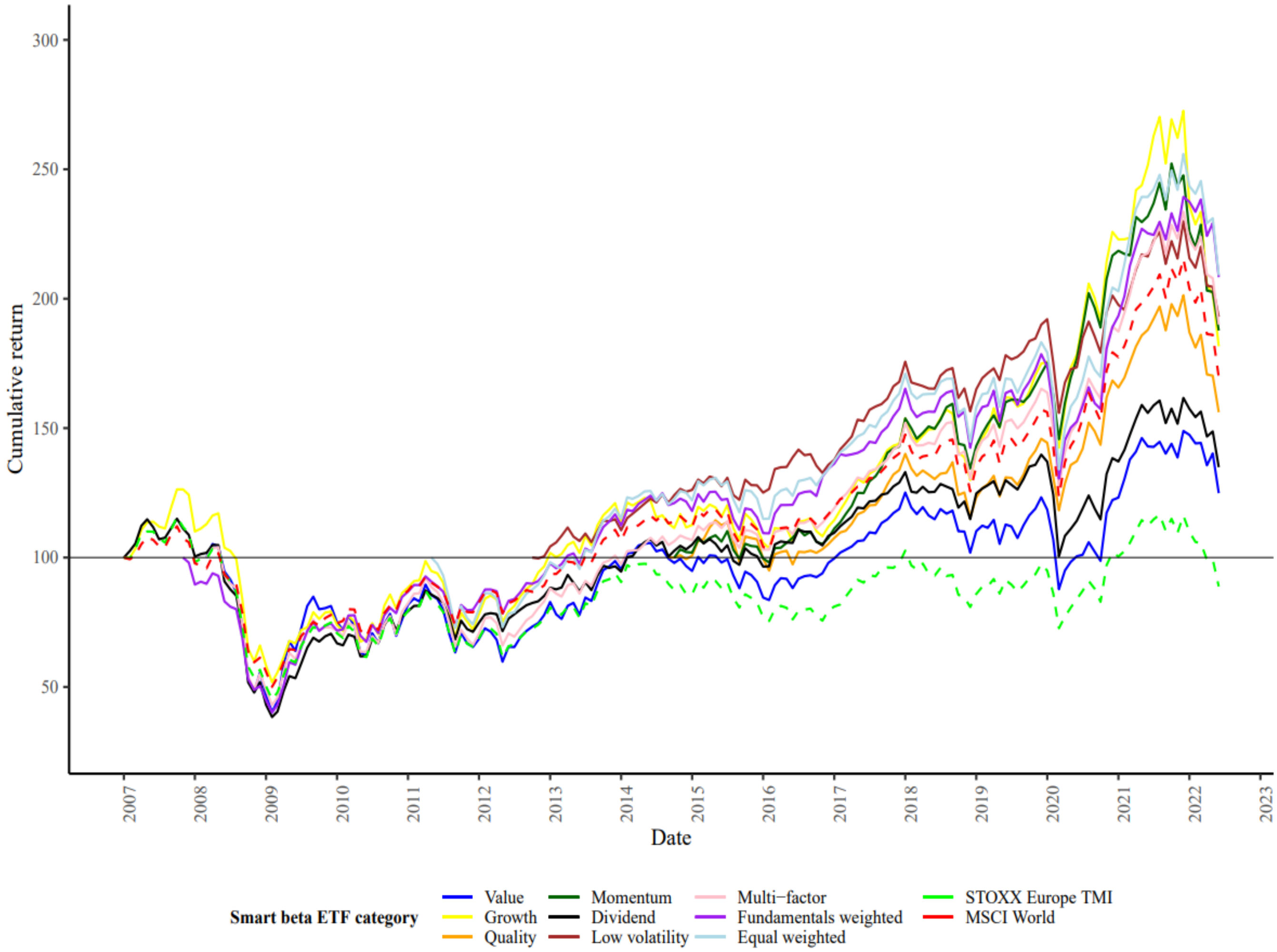
5.1.1 Cumulative Returns

Figure 5.1 shows the cumulative returns of the different smart beta ETF categories in Europe, while figure 5.2 shows the cumulative returns of the categories in the US. The first noteworthy finding is that the American smart beta ETF categories have a substantially higher cumulative return compared to their European counterparts. The figures do however indicate a similar overall market trend. For example, we see that both markets were affected by the global financial crisis in 2009, and that there was a marked increase in return after the crash following the COVID-19 shock in March/April 2020, as well as a notable fall in returns throughout 2022. This is interesting to note for the upcoming analysis of return split by periods of up and down markets.

For Europe we see that the categories value and dividend stand out compared to the others as their cumulative returns in the last 4-5 years have been the lowest. We see a similar trend in the US, where the dividend and value categories have the lowest cumulative return, alongside fundamentals weighted, but there is not as large a difference as we observe in the European market. In the US market the growth category has a much higher return, especially after the market crash following the COVID-19 crisis, compared to the other categories, with equal weighted performing second best. In addition, the growth portfolios appear more volatile than the other categories and the market. This observed volatility illustrates the importance of further analysis of the categories' performance and more specifically risk-adjusted returns, rather than only considering one simple measure of return.

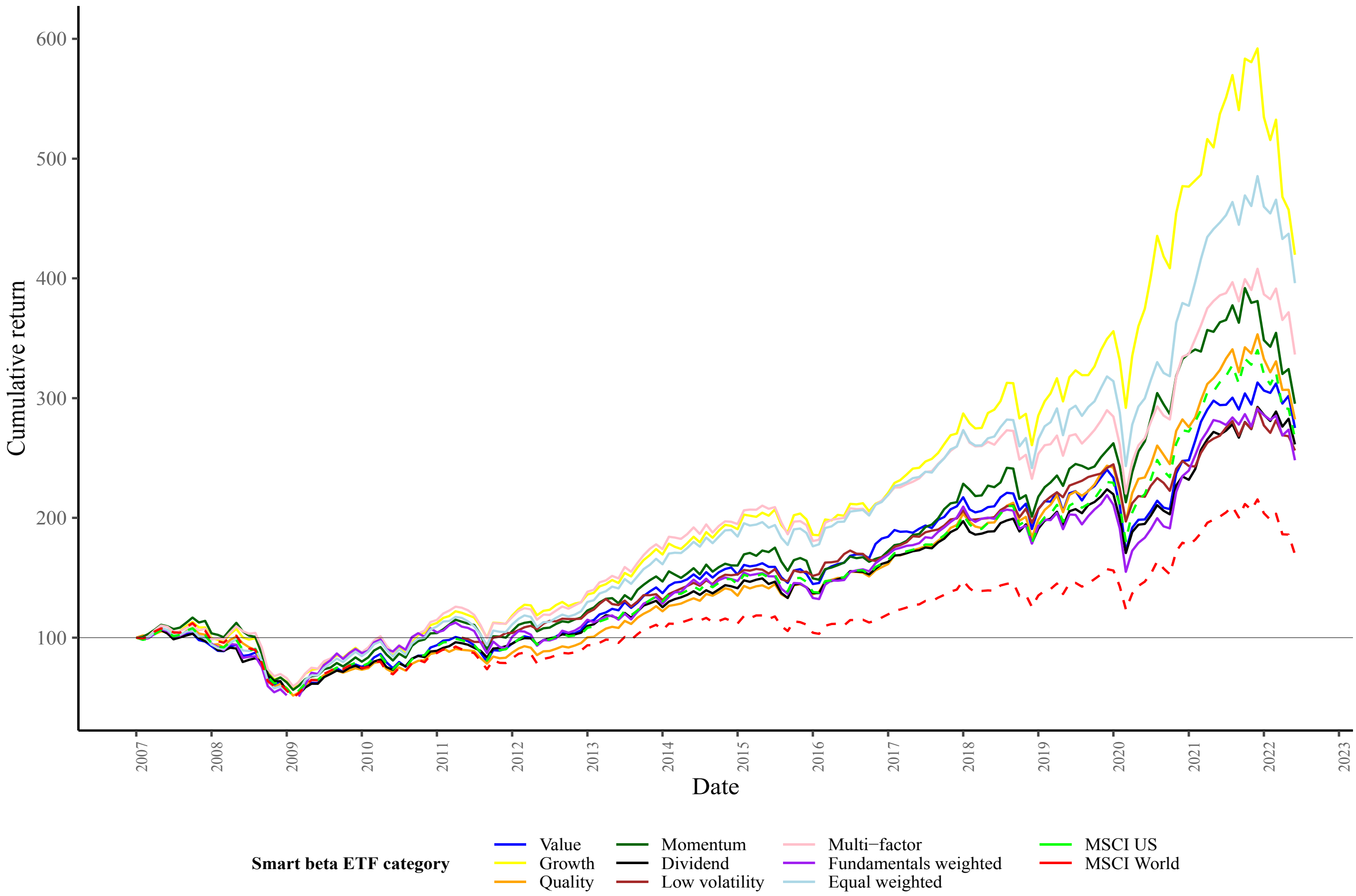
Compared to the stock indexes it is worth mentioning that the European smart beta ETF categories in large part have a level of cumulative return similar to the MSCI World Index, with the STOXX Europe TMI performing at a comparably lower level. For the American smart beta ETF categories however, they have a cumulative return more similar to the MSCI US, with the MSCI World Index at a lower level of cumulative return.

Figure 5.1: Cumulative total return for each smart beta ETF category portfolio in Europe.



Data from January 2007-June 2022, indexed to start at $100.

Figure 5.2: Cumulative total return for each smart beta ETF category portfolio in the US.



Data from January 2007-June 2022, indexed to start at $100.

5.1.2 Portfolio Returns

Table 5.1 shows descriptive statistics on a monthly basis for each smart beta ETF category within the two markets, as well as the market indexes. From the table we see that returns in the US market exceeds the returns in the European market across all categories, except for momentum. The momentum category has a 0.117 percentage-points higher monthly return in Europe than in the US. Further, the US's top three smart beta categories are growth, equal-weighted and low volatility, with returns of 0.787-, 0.754-, and 0.710-percent, respectively. These are also the top three performing categories across the two markets. For the European market's top three categories, we have momentum, low volatility, and equal-weighted with returns of 0.687-, 0.568-, and 0.556-percent, respectively. From this, we note that the highest-performing category in Europe will rank as number four across both markets.

As for the standard deviation we note that the value portfolio in Europe has the highest monthly standard deviation in the sample, which is in line with the fact that this category has the lowest minimum return and highest maximum return. The low volatility portfolios display the lowest standard deviation, which is expected following the category's strategy. From the 95% confidence intervals on the monthly returns, we note that for most portfolios the range goes above and below zero. Only the growth US, low volatility US, and equal weighted US portfolios have confidence intervals with an all-positive range.

Table 5.1: Descriptive statistics of the smart beta ETF categories and market indexes on a monthly basis.

Category	Market	N	Monthly return (%)	Std. Dev (%)	Confidence interval 95% (%)	Min (%)	Max (%)
Value	US	186	0.554	4.92	[-0.158, 1.266]	-18.50	14.40
	Europe	171	0.130	6.92	[-0.915, 1.175]	-28.10	31.10
Growth	US	186	0.787	4.92	[0.076, 1.499]	-18.80	14.80
	Europe	186	0.325	5.91	[-0.530, 1.180]	-22.90	15.60
Quality	US	186	0.570	4.45	[-0.076, 1.214]	-19.30	12.00
	Europe	93	0.480	4.35	[-0.416, 1.376]	-9.80	12.70
Momentum	US	186	0.596	4.87	[-0.108, 1.301]	-19.20	12.40
	Europe	92	0.687	4.22	[-0.187, 1.561]	-11.10	9.90
Dividend	US	186	0.522	4.28	[-0.097, 1.141]	-14.70	11.90
	Europe	186	0.166	5.64	[-0.650, 0.982]	-28.50	19.30
Low volatility	US	133	0.710	3.03	[0.190, 1.230]	-12.20	8.20
	Europe	116	0.568	3.35	[-0.048, 1.185]	-11.00	8.70
Multi-factor	US	186	0.664	4.78	[-0.027, 1.356]	-19.90	12.90
	Europe	171	0.376	5.98	[-0.527, 1.279]	-26.80	22.00
Fundamentals weighted	US	186	0.501	5.40	[-0.280, 1.282]	-21.20	19.30
	Europe	175	0.420	5.51	[-0.402, 1.242]	-23.10	18.20
Equal weighted	US	186	0.754	5.10	[0.016, 1.492]	-20.80	17.30
	Europe	133	0.556	4.87	[-0.280, 1.391]	-17.70	15.00
Indexes	MSCI World	186	0.291	4.68	[-0.386, 0.968]	-19.00	12.70
	MSCI US	186	0.537	4.65	[-0.135, 1.210]	-17.80	13.20
	STOXX Europe TMI	186	-0.060	5.56	[-0.864, 0.744]	-21.70	17.00

Note: Calculations uses geometric mean. The confidence interval assumes t-distribution with n-1 degrees of freedom.

In table 5.2 the differences in annual returns throughout the period between the two markets in each smart beta ETF category is displayed. The table provides a direct comparison of the total returns across the US and European categories for each year in our sample. For simplicity, we have marked the years where US returns exceed European returns green. From the table we note that 2014 was the first year all smart beta ETF categories were present in both markets. It can be observed that over the period, the US has generally earned a higher return than Europe across all categories, except in the years 2007, 2012, and 2017. There are a couple of observations that stand out when looking at the table. Since 2017, only the European portfolios within the multi-factor and fundamentals weighted categories were able to earn a higher total return than their US counterparts for the last four out of six years. As for the fundamentals weighted category it was in fact the only category in the US to obtain a higher annual return than the European portfolio in 2007, 2012 and 2017.

Table 5.1 and 5.2 show that, on average, the smart beta ETFs in the US have a higher return, both for the entire period and annually. Overall, the tables give a good starting point for comparing returns across the two markets. However, we cannot conclude anything from these numbers alone, as we must control for various risk factors before concluding on potential differences in risk-adjusted returns.

Table 5.2: Relative return between US and Europe on an annual basis.

Category	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Value		1.90 %	-2.14 %	1.60 %	0.96 %	-0.29 %	0.28 %	1.06 %	0.23 %	0.80 %	-0.47 %	0.68 %	0.33 %	0.27 %	0.31 %	0.72 %
Growth	-1.03 %	0.92 %	0.97 %	0.66 %	1.35 %	-1.28 %	0.54 %	1.50 %	0.22 %	0.53 %	-0.17 %	0.66 %	-0.04 %	0.47 %	0.20 %	0.92 %
Quality								1.43 %	-0.56 %	1.01 %	-0.35 %	0.80 %	0.42 %	0.04 %	0.40 %	0.47 %
Momentum								-0.59 %	0.02 %	-0.09 %	-0.37 %	0.08 %	0.03 %	0.25 %	0.01 %	0.35 %
Dividend	-1.00 %	2.00 %	-1.33 %	0.30 %	0.94 %	-0.58 %	0.82 %	0.17 %	0.16 %	0.42 %	-0.08 %	0.45 %	0.22 %	0.33 %	0.55 %	1.09 %
Low volatility						-0.11 %	0.25 %	0.18 %	-0.01 %	0.12 %	-0.30 %	0.58 %	0.12 %	-0.29 %	0.25 %	0.69 %
Multi-factor		2.23 %	-0.53 %	0.92 %	1.27 %	-0.78 %	1.00 %	0.31 %	-0.23 %	0.31 %	-0.17 %	-0.06 %	-0.13 %	0.07 %	-0.11 %	0.24 %
Fundamentals weighted	0.81 %	0.74 %	0.60 %	0.34 %	-0.92 %	0.20 %	-0.13 %	0.53 %	0.01 %	0.06 %	0.24 %	-0.11 %	-0.18 %	0.16 %	-0.19 %	-0.34 %
Equal weighted					2.60 %	-0.76 %	0.46 %	0.70 %	0.03 %	0.34 %	-0.01 %	0.40 %	0.35 %	0.52 %	0.17 %	-0.01 %

Positive numbers mean US outperformed European smart beta ETFs (US return-Europe return). The table only includes returns for years where both US and European smart beta ETFs exist within each category.

5.1.3 Risk-Adjusted Performance Measures

In table 5.3 the results of the categories risk-adjusted performance are displayed. Metrics for annualized return and standard deviation, Sharpe ratio, Treynor ratio, information ratio (IR), and Jensen’s alpha are included. Considering Jensen’s alpha, a metric for excess return over the MSCI World Index, the results indicate positive alphas for both markets across all categories, except the European smart beta categories value and dividend. Thus, with a single-factor model the results imply overall managerial skills.

As for the Sharpe ratio of each category, we see that the smart beta ETFs in the US market have a substantially higher ratio than the European categories. Further, the Sharpe ratios of the categories in the US are closer to the MSCI US Index, whereas the European categories' average Sharpe ratio is closer to the MSCI World Index. From the Sharpe ratio results in table 5.3, we see that the category in both markets with the highest Sharpe ratio is low volatility with ratios of 0.7648 and 0.5359 in the US and European markets, respectively. One of the reasons for the high Sharpe ratios could be the category's low exposure to risk, as seen in the low annualized standard deviation. However, we need to be careful to use the Sharpe ratio as the only measure to determine which category outperforms the others. The Treynor Ratios illustrate a similar picture as the Sharpe ratios, the differences being that the risk is measured by the category's systematic risk, beta, and not their standard deviations.

While the Sharpe ratio and Treynor ratio measures the performance in excess of the risk-free rate, the information ratio (IR) measures the category's performance relative to the MSCI World Index. The IR is often used as a measure of a portfolio manager's skill, trying to identify the consistency of performance. The two categories, multi-factor and equal-weighted in the US market, have an IR above 1, indicating a high rate of return in the portfolios compared to the world market and low tracking errors, translating to the manager's capabilities to earn abnormal returns over time. Regarding the IR for the European categories, their ratios are substantially lower than in the US, and even negative in some instances, as the case is for value, dividend, and low volatility. The negative information ratios signify underperformance, as the active premiums are negative. The categories in the European market with the highest IR are momentum and fundamentals weighted; nevertheless, as seen with the returns, these have a lower IR than the equivalent categories in the US.

Based on the three tables presented so far, we see a trend where the smart beta ETFs across most categories in the US obtains higher returns and have superior risk-adjusted performance measures compared to Europe.

Table 5.3: Performance measures of smart beta ETF categories in Europe and the US over the sample period.

Category	Market	Annualized return	Annualized std. dev	Sharpe Ratio	Treynor Ratio	IR	Jensen´s Alpha
Value	US	6.86%	17.03%	0.3547	0.0611	0.5764	3.40%
	Europe	1.57%	23.98%	0.0331	0.0060	-0.2774	-2.44%
Growth	US	9.87%	17.05%	0.5300	0.0903	1.2049	6.26%
	Europe	3.98%	20.48%	0.1554	0.0267	0.0578	0.44%
Quality	US	7.06%	15.40%	0.4055	0.0678	0.8861	3.60%
	Europe	5.92%	15.07%	0.3392	0.0520	0.1272	0.68%
Momentum	US	7.40%	16.87%	0.3899	0.0672	0.6679	3.94%
	Europe	8.56%	14.63%	0.5285	0.0839	0.5826	3.49%
Dividend	US	6.45%	14.82%	0.3803	0.0662	0.4906	3.20%
	Europe	2.01%	19.54%	0.0629	0.0109	-0.2165	-1.37%
Low volatility	US	8.86%	10.50%	0.7648	0.1251	0.4140	4.57%
	Europe	7.04%	11.61%	0.5359	0.0801	-0.0273	1.19%
Multi-factor	US	8.27%	16.57%	0.4491	0.0758	1.0168	4.72%
	Europe	4.61%	20.72%	0.1839	0.0321	0.0724	0.42%
Fundamentals weighted	US	6.18%	18.72%	0.2867	0.0493	0.4102	2.62%
	Europe	5.16%	19.07%	0.2285	0.0392	0.3693	1.95%
Equal weighted	US	9.43%	17.68%	0.4865	0.0818	1.2409	5.73%
	Europe	6.88%	16.88%	0.3592	0.0529	0.2159	0.51%
Indexes	MSCI World	3.55%	16.21%	0.1699			
	MSCI US	6.64%	16.12%	0.3616			
	STOXX Europe TMI	-0.72%	19.28%	-0.0767			
Risk-free rate		0.77%					

Note: Jensen´s alpha calcultated as single factor model (CAPM) alpha.
Performance measures uses MSCI World as benchmark and US 1-month T-bill as risk-free rate.
For some categories there are varying data availibility, making the index returns used for the performance measure calculations different than stated in the table.

5.2 Regression Analysis

We evaluate the performance of the smart beta ETF categories in the two markets against a multi-factor model with a selection of well-documented factors. This is first performed for the whole sample period, then on the periods for "up" and "down" markets. The regressions are used to look at whether any categories deliver excess returns above the multi-factor benchmark model, which we use as proxy for the world market. The unexplained excess returns, or alphas, can be interpreted as evidence of skill or some kind of additional risk not captured by the factor model. In addition, we consider the active investment styles of the categories through factor exposures. To further explore the existence of alphas in the two markets we run regressions on each market separately, using each market's respective factors and broad stock market indexes as benchmarks. For all the regressions we have taken the monthly returns of the portfolio within each category and subtracted the risk-free rate, giving us the relevant dependent variable.

5.2.1 The Full Time Period Regression Model

The results of our regression model for the full time period are shown in table 5.4. Here we see the factor exposures of each smart beta ETF category, as well as whether they earned a positive and significant alpha. The market premium is also included for each category and is statistically significant and near one across all regressions. This is consistent with what we expect of smart beta ETFs. Even though smart beta ETFs track more niche indexes, these ultimately have similar trends as the general market. For several of the categories – value, growth, quality, dividend, and multi-factor – only the US smart beta ETFs earn a significant positive alpha. While the momentum, fundamentals weighted, and equal weighted smart beta ETFs provide excess return compared to the world market in both the US and Europe. The last category, low volatility, does not provide excess return in the US, and has a significant negative alpha in Europe. These results indicate that the smart beta ETFs in the US are better able to deliver excess returns above the world market, whereas the European do not perform as well.

In terms of factor exposure, it is interesting to note which categories have factor tilts towards their intended strategy. Firstly, we see that the value category in both markets have a significant positive tilt for the value factor. The value factor for the growth smart beta ETFs is negative and significant in both markets. This is to be expected since the value factor takes value stocks minus growth stocks, so a negative exposure means a tilt towards growth stocks. We see the same for the quality category, where the quality factor has a positive and significant tilt in the US market, but not in Europe. Momentum on the other hand has a significant and positive exposure to the momentum factor in both markets, as does the low volatility category to the betting against beta factor. For the remaining categories, dividend, multi-factor, fundamentals weighted, and equal weighted, there is no one targeted factor in their strategy, but we can still note statistically significant positive and negative exposures to the various factors.

Table 5.4: Regression results for smart beta ETF portfolios monthly returns in excess of the monthly risk-free rate for full time period, for both the US and European market.

Full period

Dependent variable:

	Value		Growth		Quality		Momentum		Dividend		Low volatility		Multi-factor		Fund. weighted		Equal weighted	
	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US
Constant (α)	0.221	0.379***	0.093	0.577***	0.242	0.230**	0.195*	0.459***	-0.097	0.223*	-0.244*	-0.068	0.188	0.468***	0.267**	0.433***	0.269*	0.596***
	(0.182)	(0.105)	(0.147)	(0.093)	(0.146)	(0.085)	(0.096)	(0.101)	(0.146)	(0.108)	(0.119)	(0.123)	(0.146)	(0.099)	(0.089)	(0.113)	(0.105)	(0.102)
Mkt-Rf	1.089***	1.040***	1.200***	1.042***	0.989***	0.986***	0.950***	0.993***	1.073***	0.943***	0.854***	0.788***	1.063***	1.020***	1.025***	1.008***	1.078***	1.060***
	(0.052)	(0.030)	(0.042)	(0.027)	(0.041)	(0.024)	(0.027)	(0.029)	(0.042)	(0.031)	(0.034)	(0.035)	(0.042)	(0.029)	(0.025)	(0.032)	(0.030)	(0.029)
SMB	-0.172	0.320***	-0.105	0.187**	0.099	0.164**	-0.128	0.251***	0.004	0.035	-0.068	-0.0002	0.031	0.430***	0.072	0.353***	0.128	0.259***
	(0.129)	(0.075)	(0.104)	(0.066)	(0.104)	(0.060)	(0.068)	(0.071)	(0.104)	(0.077)	(0.084)	(0.088)	(0.104)	(0.070)	(0.063)	(0.080)	(0.075)	(0.072)
HML	0.372***	0.358***	-0.350***	-0.393***	-0.018	-0.086*	-0.192***	-0.246***	0.198**	0.252***	-0.025	0.027	-0.033	0.067	0.248***	0.156***	0.117**	-0.006
	(0.072)	(0.043)	(0.061)	(0.038)	(0.058)	(0.035)	(0.039)	(0.041)	(0.060)	(0.045)	(0.049)	(0.050)	(0.058)	(0.041)	(0.036)	(0.046)	(0.043)	(0.042)
QMJ	-0.357**	0.247***	-0.048	0.043	-0.019	0.232***	-0.192**	-0.180*	0.013	0.373***	0.263**	0.436***	-0.183	0.071	-0.077	0.003	-0.150*	0.133
	(0.123)	(0.074)	(0.103)	(0.065)	(0.092)	(0.059)	(0.062)	(0.070)	(0.102)	(0.075)	(0.078)	(0.079)	(0.099)	(0.069)	(0.061)	(0.078)	(0.067)	(0.071)
WML	-0.317***	-0.021	0.035	0.062	0.082	-0.037	0.306***	0.266***	-0.181***	-0.071	0.052	0.051	-0.213***	0.113***	-0.161***	-0.238***	-0.096*	-0.103**
	(0.061)	(0.036)	(0.050)	(0.031)	(0.075)	(0.029)	(0.050)	(0.034)	(0.050)	(0.037)	(0.059)	(0.056)	(0.049)	(0.034)	(0.030)	(0.038)	(0.048)	(0.034)
BAB	0.013	-0.186***	-0.042	-0.152***	-0.196*	-0.006	0.084	-0.134**	0.227***	-0.115*	0.228***	0.199**	0.124	-0.118**	0.123**	-0.006	0.007	-0.141**
	(0.082)	(0.048)	(0.067)	(0.042)	(0.079)	(0.039)	(0.052)	(0.046)	(0.067)	(0.049)	(0.067)	(0.070)	(0.066)	(0.045)	(0.040)	(0.051)	(0.060)	(0.046)
Observations	171	186	186	186	93	186	92	186	186	186	116	133	171	186	175	186	133	186
R^2	0.910	0.934	0.911	0.950	0.924	0.948	0.965	0.939	0.904	0.909	0.896	0.846	0.921	0.939	0.965	0.938	0.957	0.944
Adjusted R^2	0.906	0.932	0.908	0.948	0.918	0.947	0.962	0.937	0.901	0.906	0.890	0.838	0.918	0.937	0.964	0.936	0.954	0.942

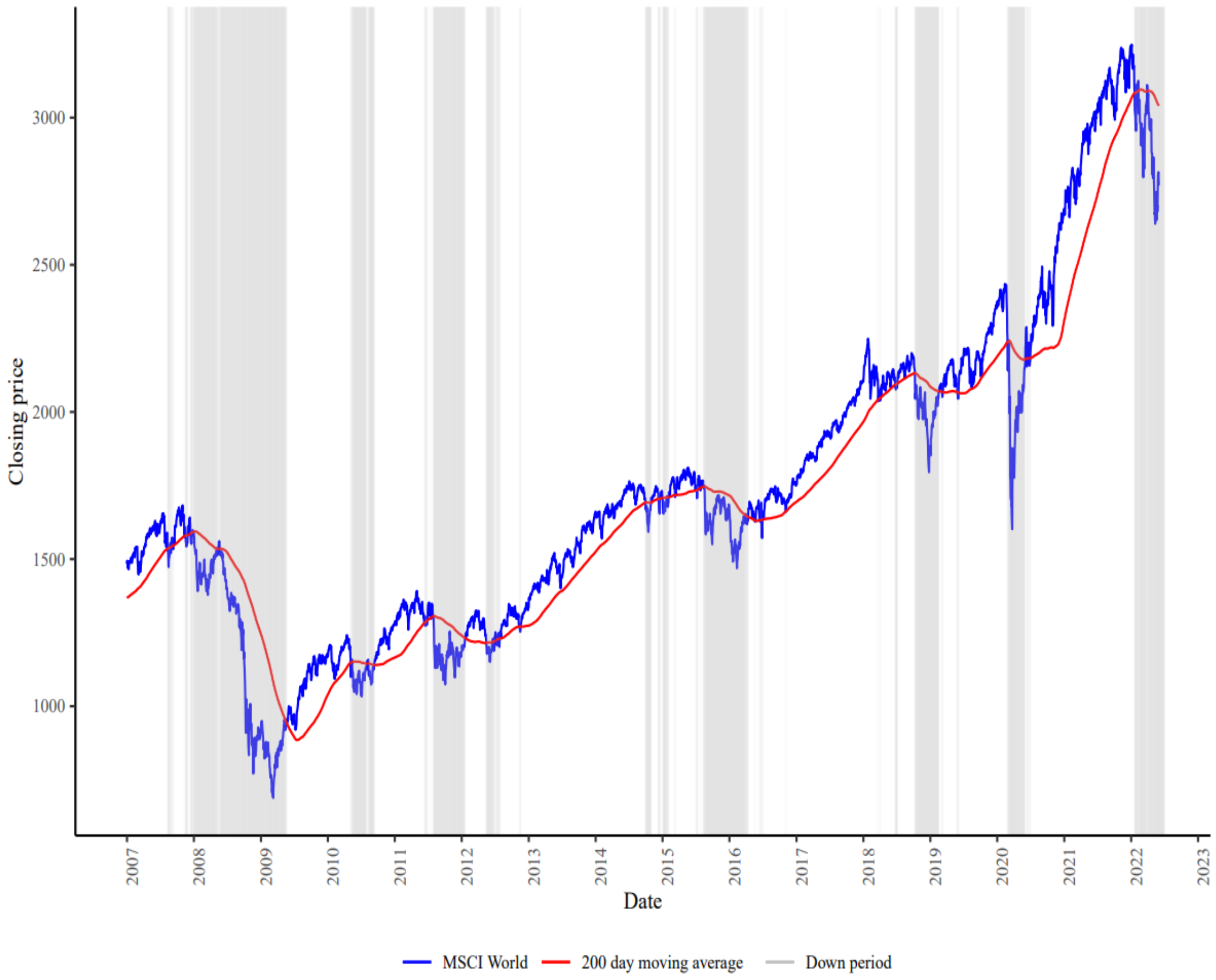
Note: *P<0.05; **P<0.01; ***P<0.001 are indicative of whether results are significant at a 5-pct., 1-pct. and 0.1-pct. level, respectively (standard errors in parenthesis).

The table provides the results for the full period in both markets using the developed world factors and MSCI World as market benchmark. All models are estimated based on monthly data from January 2007 to June 2022, as far as data availability allows for each category. The dependent variables are return of portfolio in excess of the monthly risk-free return. The constant represents the monthly alpha, i.e. the monthly abnormal returns in percentages. The coefficients on the explanatory variables captures the difference in exposure between the smart beta ETF portfolios and the market. The explanatory variable Mkt-Rf is the value-weighted market return minus the risk-free rate. The remaining explanatory variables are small minus big (SMB), high minus low (HML), quality minus junk (QMJ), winners minus losers/momentum (WML), and betting against beta (BAB).

5.2.2 Up and Down Periods

In addition to the full period model, we look closer at the returns of the smart beta ETF categories in times of different market regimes. Firstly, we consider up periods, then down periods. Since January 2007 we can from figure 5.3 see the development of the MSCI World Index and its 200-day moving average. The shading in gray indicates periods defined as down market, where the MSCI World is below its 200-day average. As expected, we note down periods at the time of the global financial crisis, the 2015-2016 stock market selloff and the COVID-19 crisis, among others.

Figure 5.3: Development of the MSCI World Index and it's 200-day moving average from January 2007 until June 2022.



Shading indicates "down" periods, defined as where the MSCI World is below its 200-day moving average.

5.2.2.1 Up periods

In the sample there is a total of 137 up periods out of the 186 months in total. The regression on these up periods is depicted in table 5.5. Of the smart beta ETF categories in the US all are able to earn positive and statistically significant abnormal returns during up periods compared to the world market, except dividend and low volatility. For the European categories only momentum, fundamentals weighted and equal weighted earn a significant positive alpha, with low volatility’s alpha being negative and significant.

Table 5.5: Regression results for smart beta ETF portfolios monthly returns in excess of the monthly risk-free rate during up periods, for both the US and European market.

Up periods

	Dependent variable:																	
	Value		Growth		Quality		Momentum		Dividend		Low volatility		Multi-factor		Fund. weighted		Equal weighted	
	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US
Constant (α)	-0.069	0.303*	0.110	0.674***	0.199	0.415***	0.272**	0.537***	-0.232	0.095	-0.416**	-0.164	0.100	0.477***	0.258*	0.272*	0.244*	0.504***
	(0.194)	(0.126)	(0.179)	(0.109)	(0.143)	(0.101)	(0.102)	(0.119)	(0.157)	(0.096)	(0.138)	(0.136)	(0.167)	(0.117)	(0.099)	(0.135)	(0.114)	(0.116)
Mkt-Rf	1.108***	1.021***	1.202***	1.018***	1.034***	0.947***	0.981***	0.967***	1.002***	0.948***	0.874***	0.768***	1.051***	1.002***	1.006***	1.050***	1.077***	1.054***
	(0.052)	(0.035)	(0.049)	(0.030)	(0.041)	(0.028)	(0.029)	(0.033)	(0.043)	(0.027)	(0.039)	(0.039)	(0.045)	(0.032)	(0.027)	(0.037)	(0.033)	(0.032)
SMB	-0.311*	0.397***	-0.202	0.198**	0.292**	0.117	-0.097	0.270***	-0.078	0.172**	-0.084	-0.063	-0.132	0.432***	0.074	0.426***	0.070	0.267***
	(0.120)	(0.079)	(0.112)	(0.068)	(0.098)	(0.063)	(0.070)	(0.074)	(0.098)	(0.060)	(0.093)	(0.092)	(0.103)	(0.073)	(0.062)	(0.084)	(0.077)	(0.073)
HML	0.429***	0.361***	-0.404***	-0.378***	-0.010	-0.062	-0.185***	-0.220***	0.211**	0.235***	-0.012	0.040	0.0005	0.114*	0.310***	0.305***	0.113*	0.069
	(0.080)	(0.054)	(0.076)	(0.046)	(0.059)	(0.043)	(0.042)	(0.050)	(0.066)	(0.041)	(0.059)	(0.058)	(0.069)	(0.050)	(0.041)	(0.057)	(0.048)	(0.049)
QMJ	-0.384**	0.275***	-0.030	0.045	0.122	0.243***	-0.222***	-0.120	-0.047	0.385***	0.224*	0.315***	-0.232*	0.141	-0.084	0.111	-0.119	0.176*
	(0.118)	(0.079)	(0.113)	(0.069)	(0.087)	(0.063)	(0.062)	(0.075)	(0.099)	(0.061)	(0.088)	(0.085)	(0.102)	(0.074)	(0.061)	(0.085)	(0.071)	(0.073)
WML	-0.204*	0.029	-0.018	0.123**	0.024	-0.0001	0.375***	0.358***	-0.096	0.005	0.053	0.110	-0.145*	0.170***	-0.059	0.017	-0.096	0.020
	(0.080)	(0.052)	(0.074)	(0.045)	(0.073)	(0.042)	(0.052)	(0.049)	(0.065)	(0.040)	(0.067)	(0.064)	(0.069)	(0.048)	(0.041)	(0.056)	(0.054)	(0.048)
BAB	0.092	-0.129	0.011	-0.182**	-0.124	-0.147**	0.011	-0.197**	0.278**	-0.032	0.281***	0.163*	0.155	-0.195**	0.004	-0.145*	-0.010	-0.131*
	(0.103)	(0.067)	(0.094)	(0.057)	(0.081)	(0.053)	(0.058)	(0.063)	(0.083)	(0.051)	(0.081)	(0.081)	(0.088)	(0.062)	(0.052)	(0.071)	(0.068)	(0.061)
Observations	126	137	137	137	73	137	73	137	137	137	96	106	126	137	127	137	106	137
R^2	0.885	0.902	0.873	0.928	0.928	0.921	0.962	0.911	0.864	0.924	0.871	0.823	0.882	0.908	0.950	0.902	0.944	0.919
Adjusted R^2	0.879	0.897	0.867	0.925	0.922	0.917	0.959	0.907	0.857	0.921	0.862	0.812	0.876	0.904	0.947	0.897	0.941	0.915

Note: *P<0.05; **P<0.01; ***P<0.001 are indicative of whether results are significant at a 5-pct., 1-pct. and 0.1-pct. level, respectively (standard errors in parenthesis).

The table provides the results for "up periods" in both markets using the developed world factors and MSCI World as market benchmark. All models are estimated based on monthly data from January 2007 to June 2022, as far as data availability allows for each category. The dependent variables are return of portfolio in excess of the monthly risk-free return. The constant represents the monthly alpha, i.e. the monthly abnormal returns in percentages. The coefficients on the explanatory variables captures the difference in exposure between the smart beta ETF portfolios and the market. The explanatory variable Mkt-Rf is the value-weighted market return minus the risk-free rate. The remaining explanatory variables are small minus big (SMB), high minus low (HML), quality minus junk (QMJ), winners minus losers/momentum (WML), and betting against beta (BAB).

5.2.2.2 Down periods

In the sample there is a total of 49 down periods out of the 186 months in total. The regression on these down periods is displayed in table 5.6. In contrast to the up periods there is few smart beta ETF categories that provide a positive and significant alpha during the down periods. Only multi-factor smart beta ETFs in the US and fundamentals weighted in both the US and Europe do so. The results indicate that few of the smart beta ETFs are able to generate excess returns relative to the world market during down periods. A potential drawback to the results of the down periods regression is that the track record of some smart beta ETF categories might be insufficient to draw reliable inferences. For example, we note that the momentum and quality categories in Europe only have 19 and 20 observations, respectively.

Table 5.6: Regression results for smart beta ETF portfolios monthly returns in excess of the monthly risk-free rate during down periods, for both the US and European market.

	Down periods																	
	Dependent variable:																	
	Value		Growth		Quality		Momentum		Dividend		Low volatility		Multi-factor		Fund. weighted		Equal weighted	
	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US	Europe	US
Constant (α)	0.667	0.341	0.081	0.179	0.766	0.125	0.232	0.269	0.147	0.137	0.686	0.369	0.221	0.686*	0.504*	0.731**	0.548	0.513
	(0.579)	(0.280)	(0.400)	(0.259)	(0.532)	(0.219)	(0.369)	(0.276)	(0.445)	(0.352)	(0.353)	(0.346)	(0.434)	(0.278)	(0.244)	(0.249)	(0.361)	(0.289)
Mkt-Rf	1.065***	1.072***	1.145***	1.086***	0.770***	1.031***	0.852***	0.999***	1.219***	0.951***	0.738***	0.885***	1.105***	1.010***	1.079***	0.919***	1.022***	1.069***
	(0.148)	(0.070)	(0.100)	(0.065)	(0.134)	(0.055)	(0.096)	(0.069)	(0.111)	(0.088)	(0.089)	(0.095)	(0.111)	(0.069)	(0.061)	(0.062)	(0.099)	(0.072)
SMB	0.217	0.166	0.216	0.231	-0.749	0.307*	-0.320	0.285	0.240	-0.301	-0.367	-0.057	0.543	0.443*	-0.013	0.154	0.306	0.311
	(0.382)	(0.178)	(0.254)	(0.164)	(0.351)	(0.139)	(0.244)	(0.175)	(0.283)	(0.223)	(0.233)	(0.261)	(0.286)	(0.176)	(0.160)	(0.158)	(0.272)	(0.183)
HML	0.462*	0.434***	-0.275*	-0.403***	-0.045	-0.144*	-0.228*	-0.218*	0.316*	0.395**	-0.032	0.044	-0.016	0.052	0.222**	0.146	0.134	-0.015
	(0.183)	(0.091)	(0.130)	(0.084)	(0.130)	(0.071)	(0.092)	(0.089)	(0.144)	(0.114)	(0.087)	(0.102)	(0.137)	(0.090)	(0.079)	(0.081)	(0.107)	(0.094)
QMJ	-0.402	0.295	-0.178	0.201	-0.786*	0.311*	-0.253	-0.168	0.284	0.431	-0.014	0.634*	-0.055	-0.041	0.012	-0.188	-0.307	0.168
	(0.377)	(0.183)	(0.262)	(0.169)	(0.342)	(0.143)	(0.256)	(0.180)	(0.291)	(0.230)	(0.227)	(0.236)	(0.282)	(0.182)	(0.159)	(0.163)	(0.246)	(0.189)
WML	-0.320*	-0.067	0.092	-0.010	0.099	-0.046	0.068	0.209**	-0.208*	-0.163*	-0.112	-0.020	-0.213*	0.123	-0.202***	-0.358***	-0.078	-0.175**
	(0.127)	(0.062)	(0.089)	(0.057)	(0.211)	(0.049)	(0.146)	(0.061)	(0.099)	(0.078)	(0.140)	(0.117)	(0.095)	(0.062)	(0.054)	(0.055)	(0.122)	(0.064)
BAB	-0.097	-0.238*	-0.164	-0.202*	0.053	0.052	0.238	-0.160	0.137	-0.152	0.350*	0.354	-0.008	-0.070	0.245**	0.123	0.016	-0.204*
	(0.179)	(0.089)	(0.127)	(0.082)	(0.231)	(0.070)	(0.159)	(0.087)	(0.141)	(0.112)	(0.153)	(0.190)	(0.134)	(0.088)	(0.077)	(0.079)	(0.199)	(0.092)
Observations	45	49	49	49	20	49	19	49	49	49	20	27	45	49	48	49	27	49
R^2	0.930	0.961	0.941	0.966	0.958	0.971	0.979	0.960	0.933	0.920	0.970	0.926	0.948	0.960	0.977	0.976	0.973	0.963
Adjusted R^2	0.919	0.955	0.933	0.961	0.938	0.967	0.968	0.955	0.923	0.908	0.955	0.903	0.940	0.954	0.974	0.972	0.965	0.958

Note: *P<0.05; **P<0.01; ***P<0.001 are indicative of whether results are significant at a 5-pct., 1-pct. and 0.1-pct. level, respectively (standard errors in parenthesis).

The table provides the results for "down periods" in both markets using the developed world factors and MSCI World as market benchmark. All models are estimated based on monthly data from January 2007 to June 2022, as far as data availability allows for each category. The dependent variables are return of portfolio in excess of the monthly risk-free return. The constant represents the monthly alpha, i.e. the monthly abnormal returns in percentages. The coefficients on the explanatory variables captures the difference in exposure between the smart beta ETF portfolios and the market. The explanatory variable Mkt-Rf is the value-weighted market return minus the risk-free rate. The remaining explanatory variables are small minus big (SMB), high minus low (HML), quality minus junk (QMJ), winners minus losers/momentum (WML), and betting against beta (BAB).

5.2.2.3 Up and down periods with liquidity factor

In addition to running regressions on the up and down periods using the main model, we also run a regression where a liquidity factor is included as a robustness check. This is done to control for the effects of changes in market liquidity, which is especially interesting in down periods as they typically coincide with reduced liquidity. Generally, ETFs domiciled in a European country tend to be less liquid compared to ones in the US. This could mean that the European portfolios are more sensitive to the liquidity factor. However, from the results of the multi-factor model with the liquidity factor we find few changes from the main model presented above, thus a table showing the regression outputs is not included in this paper. In up periods there is no significant beta coefficient for the liquidity factor for any of the smart beta ETF categories. One interesting change is a considerable decline in the size of the alpha for the European momentum portfolio when the liquidity factor is included. As for down periods, we again see no significant coefficients for the liquidity factor. Despite this, when liquidity is introduced the significant positive alphas for the two fundamentals weighted portfolios disappear, and only the multi-factor category in the US retain their significantly positive alpha. In sum, we find no indication that market liquidity impacts our main findings for either market. A limitation to these findings is that the downloaded liquidity factor only includes data up to and including December 2021, and thus these regressions include six months less data than the main model. As a result, the changes between the multi-factor models with and without liquidity could be due to the different time periods under analysis.

5.2.3 US and European Models

In addition to our main model using the MSCI World Index and developed world factors, we have also conducted a regression analysis of the two markets separately for the full time period. For each market we have employed a multi-factor model with regional market index and factor exposures.

From table 5.7 we see the results of the regression on the European market. For all categories the market premium is positive and statistically significant. All categories, except dividend and low volatility, provide positive significant alphas. It is interesting to note that for many of the categories there are few significant slope coefficients to the different factors compared to the main model.

Table 5.7: Regression results for smart beta ETF portfolios monthly returns in excess of the monthly risk-free rate, for the European market.

	European model								
	Dependent variable:								
	Value	Growth	Quality	Momentum	Dividend	Low volatility	Multi-factor	Fund. weighted	Equal weighted
Constant (α)	0.620***	0.537***	0.772***	0.734***	0.247	0.175	0.678***	0.723***	0.742***
	(0.146)	(0.130)	(0.197)	(0.212)	(0.144)	(0.168)	(0.152)	(0.158)	(0.152)
Eur-Rf	0.966***	1.061***	0.810***	0.816***	0.958***	0.782***	0.911***	0.836***	0.897***
	(0.037)	(0.033)	(0.050)	(0.054)	(0.036)	(0.042)	(0.038)	(0.040)	(0.039)
SMB	-0.180*	-0.138	-0.086	-0.065	0.037	0.026	0.069	0.075	0.192*
	(0.086)	(0.075)	(0.127)	(0.136)	(0.084)	(0.102)	(0.090)	(0.094)	(0.091)
HML	0.125	-0.612***	-0.366***	-0.486***	0.023	-0.089	-0.260**	-0.048	-0.098
	(0.079)	(0.072)	(0.105)	(0.113)	(0.079)	(0.091)	(0.083)	(0.086)	(0.081)
QMJ	-0.214	-0.317*	-0.451*	-0.495*	0.218	0.422**	-0.298*	-0.074	-0.183
	(0.135)	(0.122)	(0.185)	(0.197)	(0.135)	(0.154)	(0.141)	(0.147)	(0.135)
WML	-0.255***	0.106*	0.067	0.297**	-0.209***	0.023	-0.125*	-0.160**	-0.030
	(0.050)	(0.045)	(0.093)	(0.099)	(0.050)	(0.069)	(0.053)	(0.055)	(0.060)
BAB	0.070	-0.035	-0.093	-0.024	0.099	0.018	0.072	-0.004	-0.095
	(0.054)	(0.048)	(0.084)	(0.090)	(0.054)	(0.072)	(0.057)	(0.059)	(0.067)
Observations	171	186	93	92	186	116	171	175	133
R^2	0.942	0.933	0.869	0.843	0.910	0.808	0.916	0.891	0.910
Adjusted R^2	0.940	0.931	0.860	0.832	0.907	0.798	0.912	0.887	0.905

Note: *P<0.05; **P<0.01; ***P<0.001 are indicative of whether results are significant at a 5-pct., 1-pct. and 0.1-pct. level, respectively (standard errors in parenthesis).

The table provides the results for the full period in the European market using European factors and STOXX Europe TMI as market benchmark. All models are estimated based on monthly data from January 2007 to June 2022, as far as data availability allows for each category. The dependent variables are return of portfolio in excess of the monthly risk-free return. The constant represents the monthly alpha, i.e. the monthly abnormal returns in percentages. The coefficients on the explanatory variables captures the difference in exposure between the smart beta ETF portfolios and the market. The explanatory variable Mkt-Rf is the value-weighted market return minus the risk-free rate. The remaining explanatory variables are small minus big (SMB), high minus low (HML), quality minus junk (QMJ), winners minus losers/momentum (WML), and betting against beta (BAB).

The model for the US market is displayed in table 5.8. For all categories the market premium is positive and statistically significant. In the US market the categories with a positive and statistically significant alpha are: value, growth, momentum, multi-factor and equal weighted. In contrast to the European market there is a higher level of significant factor exposure for the American smart beta ETF categories.

Table 5.8: Regression results for smart beta ETF portfolios monthly returns in excess of the monthly risk-free rate, for the US market.

US model

Dependent variable:

	Value	Growth	Quality	Momentum	Dividend	Low volatility	Multi-factor	Fund. weighted	Equal weighted
Constant (α)	0.173^{***}	0.269^{***}	0.090	0.202^{*}	0.131	-0.001	0.253^{**}	0.223	0.305^{***}
	(0.045)	(0.042)	(0.089)	(0.082)	(0.085)	(0.124)	(0.080)	(0.123)	(0.053)
US-Rf	0.950^{***}	1.050^{***}	0.928^{***}	0.986^{***}	0.864^{***}	0.682^{***}	0.944^{***}	0.903^{***}	1.013^{***}
	(0.012)	(0.011)	(0.023)	(0.021)	(0.022)	(0.032)	(0.021)	(0.032)	(0.014)
SMB	0.107^{***}	0.107^{***}	-0.104^{**}	0.108^{**}	-0.103^{**}	-0.182^{***}	0.175^{***}	0.033	0.095^{***}
	(0.020)	(0.018)	(0.039)	(0.036)	(0.037)	(0.054)	(0.035)	(0.054)	(0.023)
HML	0.306^{***}	-0.253^{***}	-0.073^{**}	-0.161^{***}	0.208^{***}	-0.034	0.050^{*}	0.159^{***}	0.035^{*}
	(0.014)	(0.013)	(0.028)	(0.026)	(0.027)	(0.039)	(0.025)	(0.039)	(0.017)
QMJ	0.016	-0.034	0.017	-0.227^{***}	0.084^{*}	0.084	-0.095^{*}	-0.196^{***}	-0.010
	(0.022)	(0.020)	(0.042)	(0.039)	(0.040)	(0.057)	(0.038)	(0.059)	(0.025)
WML	-0.036^{**}	0.033^{**}	-0.063^{**}	0.170^{***}	-0.056^{**}	-0.030	0.046^{*}	-0.200^{***}	-0.105^{***}
	(0.011)	(0.011)	(0.022)	(0.021)	(0.021)	(0.042)	(0.020)	(0.031)	(0.013)
BAB	-0.012	-0.014	0.073^{*}	-0.003	-0.035	0.209^{***}	0.045	0.092^{*}	0.019
	(0.015)	(0.014)	(0.030)	(0.028)	(0.029)	(0.050)	(0.027)	(0.042)	(0.018)
Observations	186	186	186	186	186	133	186	186	186
R^2	0.987	0.988	0.937	0.956	0.938	0.826	0.956	0.918	0.983
Adjusted R^2	0.986	0.988	0.935	0.954	0.936	0.818	0.954	0.915	0.982

Note: *P<0.05; **P<0.01; ***P<0.001 are indicative of whether results are significant at a 5-pct., 1-pct. and 0.1-pct. level, respectively (standard errors in parenthesis).

The table provides the results for the full period in the US market using US factors and MSCI US as market benchmark. All models are estimated based on monthly data from January 2007 to June 2022, as far as data availability allows for each category. The dependent variables are return of portfolio in excess of the monthly risk-free return. The constant represents the monthly alpha, i.e. the monthly abnormal returns in percentages. The coefficients on the explanatory variables captures the difference in exposure between the smart beta ETF portfolios and the market. The explanatory variable Mkt-Rf is the value-weighted market return minus the risk-free rate. The remaining explanatory variables are small minus big (SMB), high minus low (HML), quality minus junk (QMJ), winners minus losers/momentum (WML), and betting against beta (BAB).

6. Discussion

In the following section we include further discussion of the findings from our analysis. As these findings are discussed, it should be kept in mind that an alpha different from zero may represent a pricing error and could therefore suggest that an inadequate asset pricing model has been used. For example, there might be factors that are not controlled for in the regressions that could explain the abnormal returns. Even so, we base the discussion on the interpretation that alpha represents abnormal returns for our sample.

Table 6.1: Summary of the alphas found in the regression analysis.

		Alpha (α)				
		Main model			Regional models	
Category	Market	Full period	Up periods	Down periods	US model	European model
Value	US	0.379***	0.303*	0.667	0.173***	
	Europe	0.221	-0.069	0.341		0.620***
Growth	US	0.577***	0.674***	0.179	0.269***	
	Europe	0.093	0.110	0.081		0.537***
Quality	US	0.230**	0.415***	0.125	0.090	
	Europe	0.242	0.199	0.766		0.772***
Momentum	US	0.459***	0.537***	0.269	0.202*	
	Europe	0.195*	0.727**	0.232		0.734***
Dividend	US	0.223*	0.095	0.137	0.131	
	Europe	-0.097	-0.232	0.147		0.247
Low volatility	US	-0.068	-0.164	0.369	-0.001	
	Europe	-0.244*	-0.416**	0.686		0.175
Multi-factor	US	0.468***	0.477***	0.686*	0.253**	
	Europe	0.188	0.100	0.221		0.678***
Fundamentals weighted	US	0.433***	0.272*	0.731**	0.223	
	Europe	0.267**	0.258*	0.504*		0.723***
Equal weighted	US	0.596***	0.504***	0.513	0.305***	
	Europe	0.269*	0.244*	0.548		0.742***

Note: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

The alphas represent the monthly abnormal returns in percentage. The dependent variable in each regression model is the monthly returns of the smart beta ETF category portfolio in excess of the risk-free monthly returns.

The main model use the MSCI World and developed world factors as independent variables. The US model use MSCI US and US factors as independent variables. The European model use STOXX Europe TMI and European factors as independent variables.

6.1 Discussion of Each Category

Value

From the performance measures and factor regressions of the value category across the two markets, one can note that there appears to be a large difference in return between the US and European market. When considering annualized return, table 5.3 show that the US value portfolio has an annualized return of 6.86% while in Europe the annualized return is only 1.57%. Another aspect from table 5.3 that suggests the US value smart beta ETFs outperform the European portfolio is the fact that the information ratio and Jensen's alpha is negative in Europe, but positive in the US. Additionally, the annualized standard deviation of the European portfolio is the highest among all categories at 23.98%, while the US portfolio has a standard deviation of 17.03%. The high standard deviation of the European portfolio deviates from what one might expect from this category as value investing is often considered a conservative strategy.

From the regression analysis, summarized in table 6.1, we see that the US portfolio earns a significant positive alpha in all models except during down periods. The European portfolio does not indicate excess return above the world market in the main model, which is reasonable given the portfolios low returns. However, when using the European model, the portfolio earns a significantly positive alpha relative to the European market. This find aligns with what we can infer from the Sharpe ratios in table 5.3. The risk-adjusted returns in table 5.3 shows that the value portfolio in the US has a higher Sharpe ratio than the MSCI World Index, but not the MSCI US, although the difference is not large. While the European portfolio has a lower Sharpe ratio compared to the world market, it is higher than the STOXX Europe TMI. As for the category's factor tilt, we can note from table 5.4 that the value category in both the US and Europe have a positive and significant slope coefficient for the value factor (HML) in the main model. This aligns with the strategy of exposing the portfolio investments to value stocks. In addition, we know from section 2.2.1 that the value factor and momentum have an opposing strategy, resulting in the two being negatively correlated. From the main model in table 5.4, we find evidence of this statement, as value has a negative exposure to the momentum (WML) factor.

In total, when looking at the value category's performance measure and regression models it is reasonable to conclude that the US portfolio of funds are able to deliver excess returns and provide a comparably higher return than the European portfolio.

Growth

The analysis of the growth category illustrates a rather different picture of performance across the two markets. From table 5.3 we see that the US portfolio has the highest annualized return of 9.87% and an IR above 1, indicating outperformance of the MSCI World Index. In contrast, the performance of the growth smart beta portfolio in Europe has one of the lowest annualized returns of 3.98% and has a notably lower Sharpe ratio than the MSCI World Index as well as a particularly low IR. Further, from table 5.3 it should be noted that the category in both markets has higher standard deviations than the world market. The annualized standard deviation is rather similar to that of the value portfolio. The similarity is interesting as one might expect the standard deviation of the growth portfolio to be higher due to the notion that growth stocks are commonly recognized as more risky investments compared to value (Chandler, 2022).

Moving on to the regression analysis, we see from table 6.1 that the US portfolio earn significant excess return above the world market, while the European portfolio fail to do so. Table 6.1 show that the growth smart beta ETFs in the US generate the second highest abnormal returns across all categories in both markets. The alpha in the main model for the full period is statistically significant at a 0.1% level. On the contrary, Europe's growth smart beta ETFs do not have a statistically significant alpha in either model and therefore do not generate abnormal returns. Looking closer at the alphas presented in table 6.1, we note that even though the category in the US generates statistically significant alphas in the up periods, there is no evidence that it does so in the down periods.

The growth category can be said to have a single factor focus, and its exposure to the value factor (HML) can illustrate whether or not the portfolios have the factor tilt the strategy would suggest. From table 5.4 we see that the category, in both markets, have significant negative beta coefficients for the value factor. This aligns with the category's strategy of a portfolio investing in growth stocks.

After analyzing the growth category's performance measures and regression models there is an indication that the performance of the US portfolio exceeds that of the world market and the European portfolio.

Quality

The smart beta category quality generates an annualized return of 7.06% in the US and 5.92% in Europe during the sample period, as seen in table 5.3. Compared to the MSCI World Index the portfolio in both the US and Europe earn a higher Sharpe ratio, while also showcasing a lower annualized standard deviation compared to the world index. However, from table 6.1 we see that the category only displays a significantly positive alpha for the US portfolio in the full period and up models. For the US market it is interesting to take note of the size of the alpha for the full time period and for the up periods model. For the entire time period the alpha is equal to 0.230% monthly return compared to 0.415% during up periods. The difference suggests the category is able to take advantage of positive market trends. When looking closer at the category's factor exposure we see that the quality category only has a significantly positive beta coefficient in the US for the quality factor (QMJ).

Momentum

In the analysis of momentum in section 5.1.2 we point out the category as the only one with a higher annualized return in Europe compared to the US. Table 5.3 shows that the momentum portfolio in Europe has a higher Sharpe ratio and Treynor ratio than the US portfolio. However, we note underperformance of the European portfolio relative to the US when directing the focus to the active return performance measures IR and Jensen's alpha. From the alphas presented in table 6.1, we find for the full period model that Europe's alpha is only statistically significant at a 5% level, while the US has an alpha that is substantially higher and statistically significant at 0.1%. Nevertheless, we see that the momentum smart beta ETF portfolio in Europe achieves a higher alpha in "up periods" than the US. But as for most categories, the momentum portfolio has no significant alphas in either market during down periods.

Regarding factor tilts, we see a positive slope coefficient for the momentum factor (WML) in both the US and Europe in the regressions in table 5.4. The positive factor tilts indicate that the smart beta category follows its alleged momentum strategy. Opposite to what we noted for the value category, the category's exposure to the value factor (HML) is negative and significant, in line with what is expected.

Dividend

From table 6.1 we see that the dividend category can be said to be the category with the least evidence of achieving returns above the world market of our included categories for the analyzed time period. This is interesting as the dividend category is one the most popular smart beta ETF categories, and a category with one of the largest number of funds. The only significantly positive alpha we find is for the US portfolio in the model for the full time period, with a significance level of 5%. This is supported by the findings in table 5.3, where the Sharpe ratio for the US portfolio is higher than the Sharpe ratio of the MSCI World Index. As for the European portfolio we can note that the Sharpe ratio is below the MSCI World Index, and the portfolio has a negative information ratio, which suggest underperformance.

Low Volatility

From the risk-adjusted performance measures of the low volatility category across the two markets, one can note that the category stands out from the others across both markets. Table 5.3 show that the low volatility smart beta ETFs in the US and Europe have a substantially higher Sharpe ratio than the MSCI World Index, as well as the other categories. However, when considering the IR for the portfolio in Europe, we note a value of -0.0273, signifying underperformance. For the US portfolio the IR is 0.4140, which is generally considered a good investment, and it also has the highest Treynor ratio of all the portfolios. The two portfolios have the lowest annualized standard deviation of all the categories, which is in line with the intended strategy.

Directing the focus toward the regression analysis, we discover less supporting evidence for the category generating abnormal returns in the US. We observe from table 6.1 that the category's alpha across all models is not statistically significant in the US, separating it from the other smart beta ETF categories. Further, in the European market we see evidence that support the portfolio's underperformance as it generates statistically significant negative alphas across the full time period and in the up periods. Additionally, the negative alpha becomes more negative and even more statistically significant in up periods. This is an interesting find as it supports Haugen and Heins' (1972) paper on low volatility where they find that there is a positive relationship between standard deviation and returns in periods categorized as "up".

In terms of intended factor tilts for the category we see from table 5.4 that it has a factor exposure that supports their strategy as the coefficients for betting against beta (BAB) is significantly positive for both markets, indicating an exposure to low volatility stocks. The regression models adjusted R-squared are 89.6- and 84.6-percent for Europe and US, respectively. Meaning that the goodness of fit of the models are the lowest compared to the regression models on the other categories. Nevertheless, the adjusted R-squared values for the models run on low volatility is still high. Further, we notice that the category's exposure to the market portfolio in the regression models are somewhat lower compared to the others in both markets. These findings are supported by an analysis done by Quantilia (u.d.) that found that as a factor (not smart beta category), low volatility in the US has a lower correlation with the market compared to other factors.

To summarize, the analysis indicates that low volatility smart beta ETFs perform better in the US market than in the European market. The US category exceeds the European's performance with its higher annualized return, Sharpe ratio, IR, Treynor ratio, and Jensen's alpha. On the other hand, the factor regressions are harder to use as a basis for comparison. The significant negative alpha in the European market indicates poor performance relative to the world market. Overall, there is little evidence that supports that either the US or European portfolios are able to deliver excess returns relative to the world market.

Multi-Factor

The multi-factor category's alphas presented in table 6.1 shows that the US portfolio is the only one that earns a significant and positive alpha across all regression models. The multi-factor US portfolio is in fact one of only three portfolios that are able to earn a positive and significant alpha during market downturns. The category appears to perform best during down periods as we can note the size of the alpha, at 0.686% monthly return, is highest for this model. In addition, from table 5.3, we note that the portfolio has an information ratio above 1, indicating outperformance relative to the MSCI World Index, and a Sharpe ratio above both the world and US indexes. As for the European market we only see a positive significant alpha in the European model, indicating the portfolio only provide excess returns above the European market, but not the world. Despite this, the Sharpe ratio is higher than the MSCI World Index, as well as the STOXX Europe TMI.

In terms of looking at the active investment style it is hard to conclude anything from the factor exposures in the regression models in table 5.4. Since multi-factor smart beta ETFs are exposed to several factors, but across different funds these chosen factors might vary, it is difficult to infer a meaning for a portfolio consisting of several funds.

Fundamentals Weighted

In the analysis on fundamentals weighted smart beta ETFs in the two markets, we note that both markets have slightly higher annualized and risk-adjusted returns than the MSCI World Index. When comparing the US and European portfolios in table 5.3 one can note a similar level of return and risk, with the US having a slightly higher annualized return and lower risk resulting in higher risk-adjusted returns.

Moving on to the portfolios' ability to generate abnormal returns, we find that in both markets there is positive statistically significant alphas. From table 6.1, the US has a monthly alpha of 0.433%, while the alpha in Europe is 0.267% in the full period model. Looking into the models of different market regimes, we find that the alphas are statistically significant in both markets in the up and down periods. This find is unique as no other category has generated statistically significant abnormal returns in both markets in the down periods. In fact, we can note that the size of the monthly abnormal returns increases in the down periods compared to the full time period for both markets, suggesting the category is able to tilt their strategies towards factors whose return premium is negatively correlated with the market.

The regression analysis illustrates an impressive picture of the fundamentals weighted category's ability to deliver excess returns above the world market for both the US and European portfolios across the different time periods in the main model. As for the risk-adjusted performance measures however, the category does not perform noticeably better than the other categories.

Equal Weighted

The analysis of the equal weighted smart beta ETFs in the two markets indicates a higher annualized return and a slightly higher standard deviation than the MSCI World Index as seen from table 5.3. Moreover, we see that the category achieves higher risk-adjusted returns than the MSCI World Index in Europe and the US. The information ratio stands out in the US market, as it is the highest across all portfolios. This category displays the largest spread in Jensen's alpha, with the US portfolio having a 5.22 percentage point higher annual metric than the European portfolio. Nevertheless, both markets have statistically significant alphas when considering the results in table 6.1. Throughout the full period, the category in the US has a monthly alpha of 0.596% and Europe's alpha is 0.269%. The alphas are statistically significant at a 0.1% and 5% level for the US and Europe, respectively. Further, we note that the alphas in the model up periods maintain the same level of monthly abnormal return, with only a small reduction, at the same statistical significance as for the full period across both markets.

6.2 Why Use the Main Model?

In our analysis and discussion, we have placed the most weight on the results from the model using the MSCI World Index and developed world factors as market proxy. This is because this model is more directly tied to answer our main research question, as the regressions allow us to assess whether US and European smart beta ETF categories produce excess returns relative to a world market-based multi-factor model. Despite this, it is still interesting to consider how the results change when the model for each respective market is analyzed, as the regional models give a more nuanced analysis of the different smart beta ETF categories.

If mainly focusing on the question of excess returns relative to either the world, US, or European market the alphas from the different regression models provide a good starting point for discussion. When analyzing the US smart beta ETFs, they provide a more positive image of abnormal returns when comparing to the world market than the US market, as three categories lose their significant alphas. On the other hand, we see the opposite for the European smart beta ETFs, as in the European model only two categories fail to earn significant abnormal returns, and the size of the alphas all increase relative to the main model.

The differences across the models gives a better understanding of the importance of which market one compares returns to. As seen in table 5.3 the annualized return of the MSCI US is 6.64% while the annualized return on the MSCI World Index is 3.55% and -0.72% for the STOXX Europe TMI. This indicates quite a large difference in returns over the entire time period, and consequently a substantial effect on the results of the regressions in terms of the impact of the market risk premium. It is important to keep this in mind, but as we have chosen to conduct our study with a global investment perspective, we focus mainly on the results of the main regression model. If an investor invests in a smart beta ETF, they will likely face exposure to global investments, unless the chosen fund has a particular regional focus. This is further supported by looking at where the European smart beta ETFs invest. Of the European smart beta ETFs only 37% invests with a focus in Europe, while 28% focus on investments in the US, 26% invests globally and 9% in APAC[6]. Unfortunately, Morningstar does not provide disclosure of the geographical investment area for all the US smart beta ETFs, but we can note that for the funds with listed investment areas there appears to be a mix of US and global exposures. This lack of data is a limitation as we cannot compare the two markets. Nevertheless, it seems reasonable to assume from the limited data that the US smart beta ETFs will have a somewhat similar global focus and invest both inside and outside the US market. In addition to the investment focus of the funds, the main model is more suitable for comparing performance between the US and European market as the model uses the same market return and factor exposures resulting in a similar basis for comparison.

[6] A pie chart of investment area for European smart beta ETFs can be found in section A3 in the appendix.

7. Conclusion

The purpose of this thesis has been to evaluate the performance of smart beta ETFs in the US and European market. This has been done by comparing returns to the world market in a two-part analysis. As there is limited research where both the US and European market for smart beta ETFs is included, we have sought to contribute to the literature by comparing both regions to the world market and look at an updated time span. Through our two-part analysis we have examined the different categories' risk-adjusted returns and their ability to earn abnormal returns against a multi-factor model in the period from January 2007 to June 2022. We further split the sample period into up and down periods to assess potential changes in the categories' abnormal returns during times of varying market trends.

The results of our regression analysis suggest that all the US smart beta ETF categories, except low volatility, are able to generate a significant positive alpha, thus delivering excess returns above the multi-factor model for the full time period. As for the European smart beta ETF portfolios we see less evidence of abnormal returns, as only three of the nine categories earned a positive and significant alpha against the multi-factor benchmark model, with low volatility indicating underperformance. Additionally, we see that the size of the monthly abnormal returns in percentage in the US is higher across all categories with significant alphas compared to their European counterparts. These results are supported by the risk-adjusted performance measures. The US categories provide higher Sharpe ratios and Treynor ratios across all categories, except momentum, compared to the European portfolios. The Sharpe ratios for the US portfolios are also all higher than the Sharpe ratio of the MSCI World Index, indicative of higher returns relative to their additional risk. The information ratios of the US portfolios are all above what is considered a good investment which further support the US smart beta ETFs ability to earn consistent abnormal returns.

By including an analysis of up and down periods, it is interesting to see that the abnormal returns disappear across almost all categories for both the US and European smart beta ETFs during down periods. Although three of the portfolios generate a significant positive alpha, the argument for investing in smart beta ETFs on the basis of their potential to utilize defensive strategies to take advantage of market downturns does not appear to hold. As for up periods, there is not a substantial difference from the results of the full period model, with the size of the alphas either increasing or decreasing, but not to a large extent. These positive significant returns of certain categories in up periods, and in down periods for the US multi-factor and both markets' fundamentals weighted portfolios, could be attributable to greater market risk. However, as we only estimate risk-adjusted performance measures for the full time period, it is not possible to be conclusive.

Our findings are interesting as they contribute to previous literature. Glushkov (2015), Bowes and Ausloos (2021), and Rompotis's (2019) do not find any indication of smart beta ETFs outperforming their respective benchmarks, while Mateus et al. (2020) do find some evidence to support smart beta outperforming traditional ETFs. Since we have conducted our analysis with a global investment focus, hence comparing returns with the world market, our study provides a new and broader perspective to the smart beta ETF investment landscape.

Regardless of the abnormal returns of several smart beta ETF categories this paper does not provide insight into individual smart beta ETF funds' performance, meaning alpha in this context is not necessarily a measure of an individual fund manager's ability to create abnormal returns. The results can thus not be used as basis for what funds to invest in. However, the findings are meaningful for investors looking to invest in the smart beta ETF landscape, as it provides insight into what strategies are able to deliver excess returns relative to a world multi-factor model. Another aspect to consider for a potential investor is the fact that European citizens are largely blocked from trading many US-domiciled ETFs since the introduction of the EU MiFiD regulation in 2018 (Bannon & MacManus, u.d.). The restriction is due to the requirements for documentation in the US not being fully compliant with EU regulations. Therefore, despite our results indicating that US smart beta ETFs are a better option, only professional investors in the EU are allowed to invest in US-domiciled ETFs.

In conclusion, we find that the returns of all US smart beta ETF categories, except low volatility, are in excess of the world market when performance is evaluated against risk-adjusted performance measures and multi-factor models. As for the European market, fewer categories deliver excess returns.

7.1 Limitations

There are certain limitations to the analysis conducted in this paper. These limitations might impact our results and our interpretations throughout the paper.

A potential limitation to our analysis is the variation in the number of funds and the market size within each category, as can be seen from section 3.1 and appendix A3. The inconsistent time intervals for each smart beta ETF category relative to another makes it more difficult to provide an accurate comparison of the performance between categories. Further, we have not included transaction costs. The data used in the analysis is gathered from Morningstar, and transaction costs are not subtracted from the returns. Because transaction costs can vary across categories and issuers of individual funds, the monthly return of each category might be affected in a way that the significant abnormal returns are reduced or even eliminated from the regression results.

The performance of the smart beta ETFs is based on historical data and does not necessarily indicate the different portfolios' future performance. However, there are limited alternatives to better perform fund analysis, and historical data must be considered adequate for this purpose. As previously mentioned, survival bias is another limitation since the data used in the analysis are returns from surviving smart beta ETFs in the sample period. The results can therefore display positive skewness as we do not include funds whose bad performance led to closure.

7.2 Further Research

This paper presents a broader overview of smart beta ETF as an investment product across two markets. It could therefore be interesting to analyze the individual funds within the categories, especially fundamentals weighted and multi-factor, as these are the portfolios with the most persistent performance. With a narrower focus it could be interesting to differentiate between managerial skill and luck in generating excess returns by employing a bootstrapping method, for instance as done by Fama and French (2010). In terms of managerial skill, it would be interesting to study potential differences across fund managers. US managers could profit from more experience since the US smart beta ETF market is more mature than the European, which might provide further explanation as to why the US portfolios perform better. Finally, one could identify what factors the most successful individual funds are exposed to.

References

AQR. (2022). *Datasets*. Retrieved from AQR: https://www.aqr.com/Insights/Datasets

Asness, C. S., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, 1-25.

Asness, C. S., Frazzini, A., & Pedersen, L. H. (2019). Quality Minus Junk. *Review of Accounting Studies*, 34-112.

Bacon, C. R. (2008). *Practical portfolio performance measurement and attribution* (Vol. 546). John Wiley & Sons.

Bannon, D., & MacManus, C. (n.d.). *ETF market in Europe*. Retrieved from Deloitte: https://www2.deloitte.com/ie/en/pages/financial-services/articles/etf-market-in-europe.html

Bauer, R., Christiansen, C., & Døskeland, T. (2022). *A Review of the Active Management of Norway's Government Pension Fund Global.* Review for Ministry of Finance and Norges Bank Investment Management.

Ben-David, I., Franzoni, F., Kim, B., & Moussawi, R. (2021). Competition for Attention in the ETF Space. *National Bureau of Economic Research*.

Bender, J., Briand, R., Melas, D., & Subramanian, R. A. (2013). *Foundations of Factor Investing.* MSCI.

Black, F. (1993). Beta and return. *Streetwise: the best of the Journal of portfolio management* , 8-18.

Blitz, D., Vliet, P. V., & Hanauer, M. (2018). *Fama-French 5-factor model: why more is not always better*. Retrieved from Robeco: https://www.robeco.com/es/vision-del-mercado/2022/03/fama-french-5-factor-model-why-more-is-not-always-better.html

Bodie, Z., Kane, A., & Marcus, A. J. (2008). Essentials of Investments. New York: McGraw-Hill/Irwin.

Bovaird, C. (2022, August 24). *Smart beta ETFs can provide higher returns and lower volatility than passively managed funds*. Retrieved from Business Insider: https://www.businessinsider.com/personal-finance/smart-beta-etf?r=US&IR=T

Bowes, J., & Ausloos, M. (2021). Financial Risk and Better Returns through Smart Beta Exchange-Traded Funds? *Risk and Financial Management*, 283.

Cao, C., Chen, Y., Liang, B., & Lo, A. W. (2013). Can Hedge Funds Time Market Liquidity? *Journal of Financial Economics*.

Cao, C., Rapach, D., & Zhou, G. (2015, February 20). *Which Hedge Fund Styles Hedge Against Bad Times?* Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2311464

Carhart, M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*(1), 57-82.

CFI. (2022a, January 21). *Risk-Free Rate*. Retrieved from Corporate Finance Institute (CFI): https://corporatefinanceinstitute.com/resources/knowledge/finance/risk-free-rate/

CFI. (2022b, October 24). *Smart Beta ETF*. Retrieved from Corporate Finance Institute: https://corporatefinanceinstitute.com/resources/wealth-management/smart-beta-etf/

Chandler, S. (2022, September 16). *A growth stock is a company expected to rise faster than the overall market, offering bigger gains for investors who don't mind risk*. Retrieved from Insider: A growth stock is a company expected to rise faster than the overall market, offering bigger gains for investors who don't mind risk

Chernenko, S., & Sunderam, A. (2016). Liquidity transformation in asset management: Evidence from the cash holdings of mutual funds. *National Bureau of Economic Research*.

Choy, J., Dutt, M., Garcia-Zarate, J., Gogoi, K., & Johnson, B. (2022). *A Global Guide to Strategic-Beta Exchange-Traded Products.* Morningstar Manager Research.

Cochrane, J. (2011). "Presidential Address: Discount Rates. *The Journal of Finance 66*(4), 1047-1108.

De Bondt, W. F., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance*, 793-805.

de Saint Florent, B. (2021). Will smart beta ETFs revolutionize the asset management industry? *Deloitte Performance Magazine - Issue 36*.

DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal Versus Naive Diversification: How Inefficient is the 1/N Portfolio Strategy? *The Review of Financial Studies*.

Dierking, D. (2022, October 30). *Value vs. Growth ETFs: How Do You Choose?* Retrieved from Investopedia: https://www.investopedia.com/articles/investing/011316/value-vs-growth-etfs-how-do-you-choose.asp

Esakia, M., Goltz, F., Sivasubramanian, S., & Ulahel, J. (2017). Smart Beta Replication Costs. *The Hedge Fund Journal*.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3-56.

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

Fama, E. F., & French, K. R. (2010). Luck versus Skill in the Cross-Section of Mutual Fund Returns. *The Journal of Finance* .

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics* .

Fernando, J. (2022, June 06). *Sharpe Ratio Formula and Definition With Examples*. Retrieved from Investopedia: https://www.investopedia.com/terms/s/sharperatio.asp#toc-sharpe-ratio-pitfalls

Florent, B. d. (2021). Will smart beta ETFs revolutionize the asset management industry? Understanding smart beta ETFs and their impact on active and passive fund managers. *Performance Magazine* (36).

Frazzini, A., Pedersen, L. H., & Asness, C. S. (2019). Quality minus junk. *Review of Accounting Studies*, 34-112.

French, K. R. (2022). *Kenneth R. French' Data Library*. Retrieved from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International

Frost, J. (2019). *Guidelines for Removing and Handling Outliers in Data*. Retrieved from Statistics By Jim: https://statisticsbyjim.com/basics/remove-outliers/

Glow, D. (2022, April 12). *A history of ETFs in Europe* . Retrieved from ETF Stream: https://www.etfstream.com/features/a-history-of-etfs-in-europe/

Glushkov, D. (2015). How Smart are 'Smart Beta'ETFs? Analysis of Relative Performance and Factor Exposure. *Wharton Research Data Services*.

Goodwin, T. H. (1998). The Information Ratio. *Financial Analyst Journal*.

Graham, B., & Dodd, D. L. (1934). *Security analysis; Principles and Technique* (Vol. 1). McGraw-Hill.

Grau-Carles, P., Doncel, L. M., & Sainz, J. (2019). Stability in mutual fund performance rankings: A new proposal. *International Review of Economics & Finance*.

Hair, J. F., Anderson, R., Tatham, R., & Black, W. C. (1995). *Multivariate Data Analysis.* New York: Macmillan: Prentice Hall.

Hameed, A., Kang, W., & Viswanathan, S. (2010). Stock Market Declines and Liquidity. *The Journal of Finance*.

Haugen, R. A., & Heins, J. A. (1972, December 1). *On the Evidence Supporting the Existence of Risk Premiums in the Capital Market.* Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1783797

Hayes, A. (2022a, January 29). *Value Investing*. Retrieved from Investopedia: https://www.investopedia.com/terms/v/valueinvesting.asp

Hayes, A. (2022b, May 31). *Fama and French Three Factor Model Definition: Formula and Interpretation*. Retrieved from Investopedia: https://www.investopedia.com/terms/f/famaandfrenchthreefactormodel.asp

Hooper, P., & Sharp, D. (2022, April 21). *As ETFs rise, it's time to hone your ETF trading strategies*. Retrieved from Vanguard:

https://advisors.vanguard.com/insights/article/asetfsriseitstimetohoneyouretftradingstrategies

Hsu, J., Kalesnik, V., & Kose, E. (2019). *What is Quality?* Financial Analysts Journal.

Informa. (2016). *Information Ratio.* Retrieved from Informa Investment Solutions.

iShares. (n.d.). *A new way to invest: iShares smart beta ETFs*. Retrieved from iShares by Blackrock: https://www.ishares.com/ch/institutional/en/themes/smart-beta?switchLocale=y&siteEntryPassthrough=true

iShares. (n.d.). *ETF Pricing and Valuations*. Retrieved 2022, from iShares.byBlackRock: https://www.ishares.com/ch/individual/en/education/etf-pricing-and-valuations?switchLocale=y&siteEntryPassthrough=true

Jain, R., & Chetty, P. (2020, February 12). *What is a stationarity test and how to do it?* Retrieved from Project Guru: https://www.projectguru.in/what-is-a-stationarity-test-how-to-do-it/

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*(48), 65-91.

Jensen, M. C. (1969). Risk, The Pricing of Capital Assets, and The Evaluation of Investment Portfolios. *The Journal of Business*, 167-247.

Johnson, B. (2014, June 13). *The Strategic Factor of Smart Beta*. Retrieved from Morningstar: https://www.morningstar.co.uk/uk/news/125534/the-strategic-factor-of-smart-beta.aspx

Johnson, B. (2017, July 13). *Have Strategic-Beta ETFs Delivered For Investors? (Part 1).* Retrieved from Morningstar: https://sg.morningstar.com/sg/news/159946/have-strategic-beta-etfs-delivered-for-investors-(part-1).aspx

Kenton, W. (2020, October 14). *Treynor Ratio*. Retrieved from Investopedia: https://www.investopedia.com/terms/t/treynorratio.asp

Kenton, W. (2022a, July 25). *Historical Return*. Retrieved from Investopedia: https://www.investopedia.com/terms/h/historical-returns.asp

Kenton, W. (2022b, August 4). *Capital Asset Pricing Model (CAPM) and Assumptions Explained*. Retrieved from Investopedia: https://www.investopedia.com/terms/c/capm.asp

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 13-37.

Madhavan, A. N. (2016). *Exchange-traded funds and the new dynamics of investing.* Oxford University Press.

Mateus, C., Mateus, I. B., & Soggiu, M. (2020). Do smart beta ETFs deliver persistent performance? *Journal of Asset Management*, 413-427.

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*, 768-783.

MSCI. (2022a). *MSCI US Broad Market Index (USD).* Retrieved from MSCI: https://www.msci.com/documents/10199/6a62b31c-55b4-446e-84eb-e7d785885a4d

MSCI. (2022b, September 30). *MSCI World Index (USD).* Retrieved from MSCI: https://www.msci.com/documents/10199/178e6643-6ae6-47b9-82be-e1fc565ededb

MSCI. (n.d.). *Factor Focus: VALUE.* Retrieved from MSCI.com: https://www.msci.com/documents/1296102/1339060/Factor+Factsheets+Value.pdf

Norges Bank Investment Management. (2020). *Portfolio Delegation and the Effects of Benchmarks: Discussion Note.* Norges Bank Investment Management.

Novy-Marx, R., & Velikov, M. (2022, January). Betting against betting against beta. *Journal of Financial Economics, 143*(1), pp. 80-106.

Pastor, L., & Stambaugh, R. F. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political economy*.

Penman, S. H., Richardsom, S. A., & Tuna, I. (2007). The Book-to-Price Effect in Stock Returns: Accounting for Leverge. *Journal of Accounting Research, 45*(2), 427-467.

Qontigo. (2022). *STOXX Europe Total Market* . Retrieved from STOXX: https://www.stoxx.com/index-details?symbol=BKXP

Quantilia. (n.d.). *The low volatility factor explained*. Retrieved from Quantilia: https://www.quantilia.com/the-low-volatility-factor-explained/

Rabener, N. (2019a, July). *Growth: Factor Investing Sinning?* Retrieved from Finominal: https://insights.finominal.com/research-growth-factor-investing-sinning/

Rabener, N. (2019b, September 23). *Smart Beta vs. Alpha + Beta*. Retrieved from CFA Institute: https://blogs.cfainstitute.org/investor/2019/09/23/smart-beta-vs-alpha-beta/

Ratner, B. (2009). The correlation coefficient: Its values range between +1/−1, or do they? *Journal of Targeting Measurement and Analysis for Marketing*.

Reed, E. (2022, August 30). *How Does the Fama French 3 Factor Model Work?* Retrieved from Smart Asset: https://smartasset.com/investing/fama-french-3-factor-model

Rompotis, G. G. (2019). A performance evaluation of smart beta exchange traded funds. *International Journal of Financial Markets and Derivatives*, 124-162.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 425-442.

Simons, K. (1998). Risk-Adjusted Performance of Mutual Funds. *New England Economic Review*.

Statista Research Department. (2022, May 23). *Biggest smart beta ETFs traded in the U.S. by assets 2022* . Retrieved from Statista: https://www.statista.com/statistics/1199383/largest-smart-beta-etfs-traded-usa/

Stulz, M. R. (1995). The cost of capital in internationally integrated markets: The case of Nestlé. *European Financial Management*.

Summer, L. H. (1986). Does the Stock Market Rationally Reflect Fundamental Values? *The Journal of Finance 41*(3), 591-601.

Trackinsight. (n.d.). *A brief history of ETFs*. Retrieved from Trackinsight: https://www.trackinsight.com/en/education/history-of-etfs

Trackinsight. (n.d.). *What are Equity ETFs?* Retrieved from Trackinsight: https://www.trackinsight.com/en/education/what-are-equity-etfs

Treynor, J. L. (1961). *Market Value, Time, and Risk*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2600356

Wall, E. (2016, October 3). *Passive Investing: What is Smart Beta?* Retrieved from Morningstar: https://www.morningstar.co.uk/uk/news/124762/passive-investing-what-is-smart-beta.aspx

Wharton Research Data Services. (2022). *Wharton Research Data Services*. Retrieved from https://wrds-www.wharton.upenn.edu/login/?next=/pages/get-data/pastor-stambaugh-and-other-liquidity-factors/liquidity-factors/pastor-stambaugh/

Wooldridge, J. M. (2018). *Introductory Econometrics - A modern approach.* Cengage Learning, Inc.

Zoll, A. (2012, September 4). *S&P 500 vs. Total Stock Market: Which Is Right for You?* Retrieved from Morningstar: https://www.morningstar.com/articles/566429/sp-500-vs-total-stock-market-which-is-right-for-you

Appendix

A1 Model Testing

To ensure that we do not have problems related to our regressions, we conduct multiple tests to assess the Gauss-Markov assumptions and potential stationarity. The tests are conducted on the main model for the full period, as the paper's main analysis is based on these regressions.

A1.1 Portfolio Distributions

The sample size in our analysis is between 92 and 186 observations, which is sufficient in terms of what is required to rely on the central limit theorem (Wooldridge, 2018). For each category, we construct histograms with a density line to look at the regressions' distribution of the residuals. In addition, we also include QQ-plots for each category. From the figures A.1-A.9 we see that for the majority of our regressions the error term is normally distributed. However, for some of the categories we note some skewness, especially for the category fundamentals weighted in Europe, which displays negative skewness. From the QQ-plots we note that the residuals in the regressions form a fairly straight line, but with some potential outliers.

Figure A.1: Histograms and QQ-plots for model residuals, Value portfolio in Europe and US.

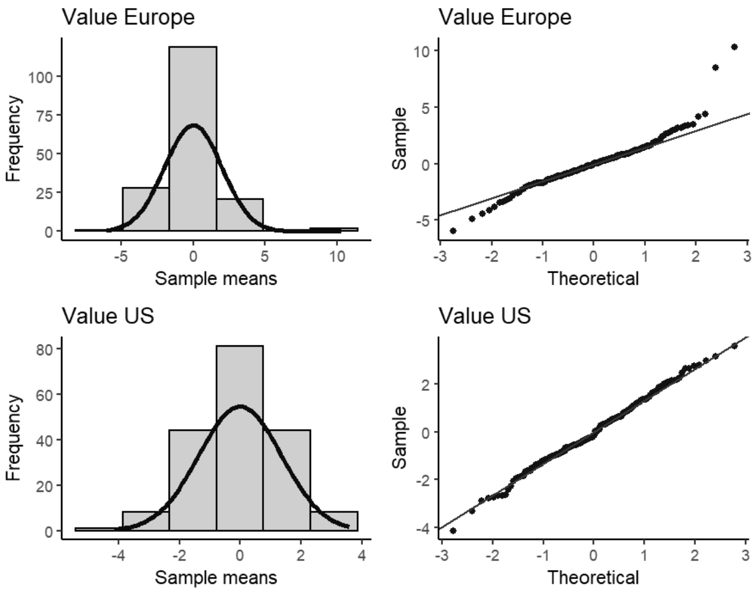


Figure A.2: Histograms and QQ-plots for model residuals, Growth portfolio in Europe and US.

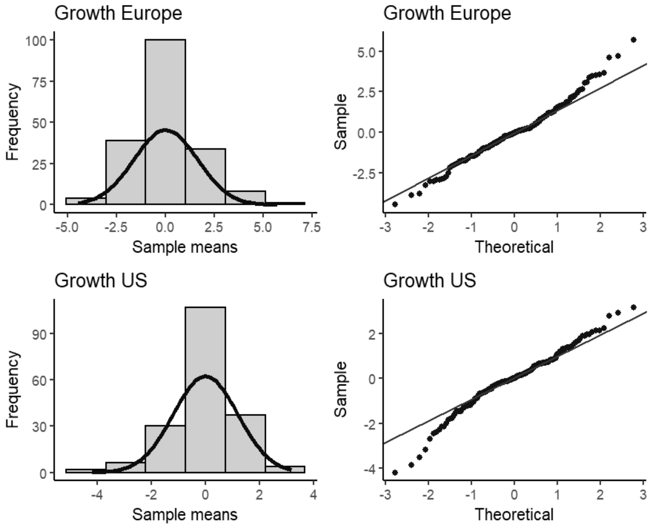


Figure A.3: Histograms and QQ-plots for model residuals, Momentum portfolio in Europe and US.

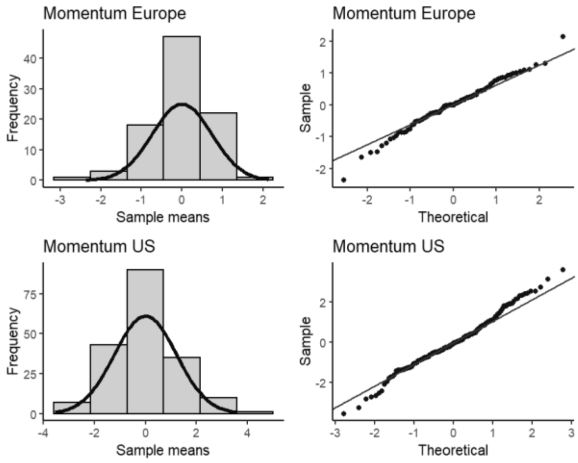


Figure A.4: Histograms and QQ-plots for model residuals, Quality portfolio in Europe and US.

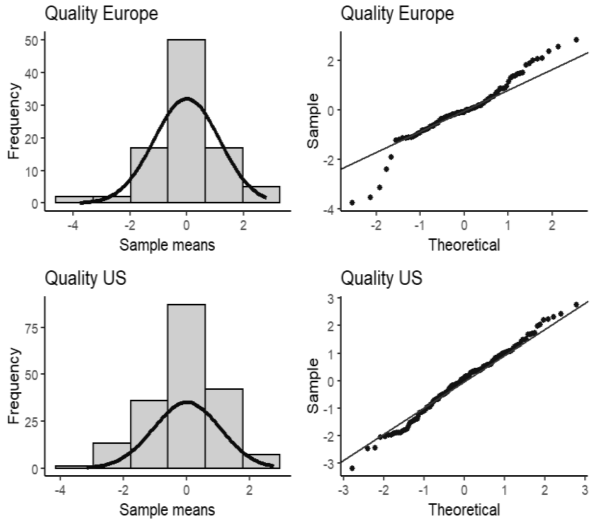


Figure A.5: Histograms and QQ-plots for model residuals, Low volatility portfolio in Europe and US.

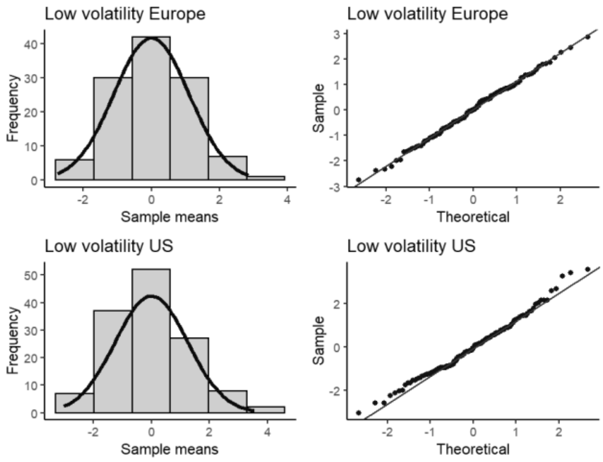


Figure A.6: Histograms and QQ-plots for model residuals, Dividend portfolio in Europe and US.

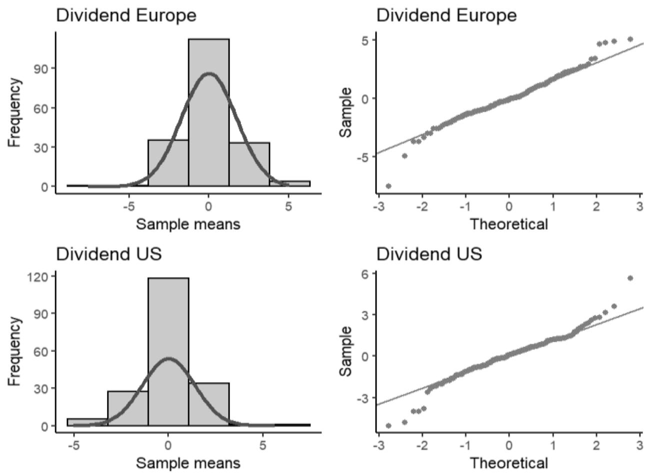


Figure A.7: Histograms and QQ-plots for model residuals, Multi-factor portfolio in Europe and US.

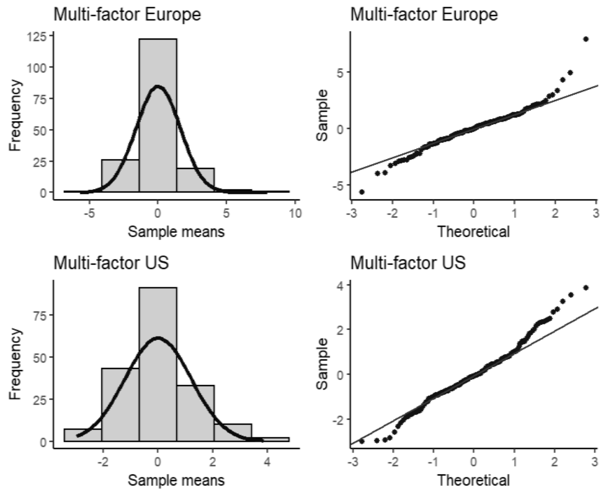


Figure A.8: Histograms and QQ-plots for model residuals, Fundamentals weighted portfolio in Europe and US.

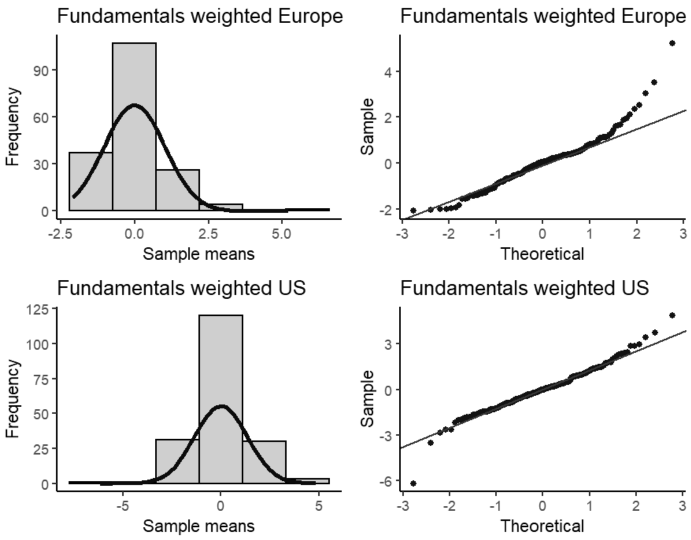
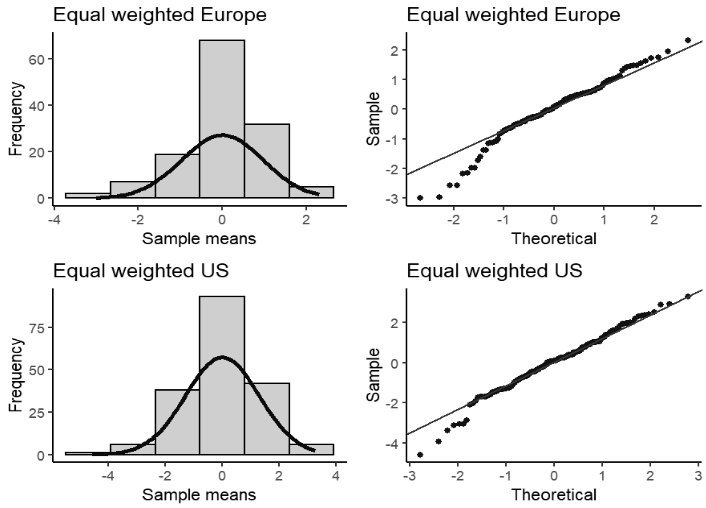


Figure A.9: Histograms and QQ-plots for model residuals, Equal weighted portfolio in Europe and US.



A1.2 Breusch-Pagan Test for Homoscedasticity

Table A.1 displays the results of the Breusch-Pagan test for homoscedasticity. The null hypothesis of the test is that the variation of the residuals is constant, meaning that in the case where the null hypothesis is not rejected the regression does not have a problem with heteroscedasticity. A low p-value indicates a problem with heteroscedasticity. From the table, we see that we might have a problem with heteroscedasticity for certain categories if we look at a 5% significance level. The categories in question are Value US and Europe, Momentum Europe, Dividend US and Europe, Fundamentals weighted US and Europe, and Equal weighted Europe. Because of this we run the regressions with robust standard errors. However, this result only in minor changes in coefficient sizes and not in their significant level. We therefore continue with the regressions without correcting for robust standard errors. Another aspect that supports this decision is that because the dependent variables are monthly historical returns all observations are a natural part of the studied population (Frost, 2019).

Table A.1: Breusch-Pagan Test for homoskedasticity.

	BP	P-value
Value		
US	3.471	0.062
Europe	14.109	0.000
Growth		
US	0.862	0.353
Europe	0.006	0.940
Quality		
US	0.586	0.444
Europe	0.455	0.500
Momentum		
US	0.072	0.788
Europe	4.552	0.033
Dividend		
US	44.440	0.000
Europe	8.170	0.004
Low volatility		
US	1.621	0.203
Europe	0.271	0.602
Multi-factor		
US	0.849	0.357
Europe	1.974	0.160
Fundamentals weighted		
US	3.960	0.047
Europe	19.066	0.000
Equal weighted		
US	1.373	0.241
Europe	4.169	0.041

A1.3 Breusch-Godfrey Test for Autocorrelation

Table A.2 show the results from the Breusch-Godfrey test for autocorrelation in the regressions in the main model. Autocorrelation will not directly have an effect on the coefficient estimates in regression (Wooldridge, 2018). However, if one does have a problem with autocorrelation one should adjust for this. The null hypothesis of the test is that there is no autocorrelation, meaning low p-level indicates possible autocorrelation. From the results of the Breusch-Godfrey test we note that we overall do not have a problem with autocorrelation, except from one regression. The regression on the momentum portfolio in the US has a p-value under 5%, indicating possible autocorrelation in this regression. However, this find is not surprising as we know that historical returns can have a predicting power on future returns (Kenton, 2022a), and from section 2.2.1 we know that the momentum strategy is recognized as a strategy that uses previous performance to pick stocks.

Table A.2: Breusch-Godfrey test for autocorrelation.

	LM	P-value
Value		
US	0.000	0.996
Europe	0.001	0.972
Growth		
US	0.659	0.417
Europe	0.488	0.485
Quality		
US	2.413	0.120
Europe	0.398	0.528
Momentum		
US	3.915	0.048
Europe	0.518	0.472
Dividend		
US	1.125	0.289
Europe	0.475	0.491
Low volatility		
US	0.001	0.973
Europe	0.730	0.393
Multi-factor		
US	0.434	0.510
Europe	1.874	0.171
Fundamentals weighted		
US	1.703	0.192
Europe	0.032	0.859
Equal weighted		
US	0.103	0.748
Europe	2.251	0.134

A1.4 Augmented Dickey-Fuller Test for Unit Root

To test for stationarity in our regressions we use the Augmented Dickey-Fuller test for unit root, as seen in table A.3. The test is conducted on all the dependent and independent variables used in our regressions. The null hypothesis is that the data is non-stationary, meaning a unit root is present. Hence, a high p-value indicates that we have a problem as our data is non-stationary. From table A.3, we can note that at a 10% significance level, all dependent and independent variables are stationary. However, the dependent variables Quality Europe and Momentum Europe are not stationary at a 5% significance level. This finding is not surprising as these regressions have the least number of observations (Jain & Chetty, 2020).

Table A.3: Augmented Dickey-Fuller test.

	ADF	P-value
Value		
US	-5.916	0.010
Europe	-5.7141	0.01
Growth		
US	-5.513	0.010
Europe	-4.839	0.010
Quality		
US	-5.739	0.010
Europe	-3.342	0.069
Momentum		
US	-5.395	0.010
Europe	-3.186	0.095
Dividend		
US	-5.649	0.010
Europe	-5.282	0.010
Low volatility		
US	-5.661	0.010
Europe	-5.096	0.010
Multi-factor		
US	-5.949	0.010
Europe	-5.581	0.010
Fundamentals weighted		
US	-5.618	0.010
Europe	-5.412	0.010
Equal weighted		
US	-5.919	0.010
Europe	-5.018	0.010
Factors		
Mkt-Rf	-5.222	0.010
SMB	-4.877	0.010
HML	-5.365	0.010
QMJ	-5.465	0.010
WML	-5.304	0.010
BAB	-4.709	0.010

A2 Multicollinearity

A2.1 Correlation Matrix of Independent Variables

Table A.4 shows the Pearson correlation between the independent variables included in the regression model. From the table we see that most variables are correlated, but not to the extent where we suspect multicollinearity to be a problem. The highest correlation is between the momentum factor (WML) and the quality factor (QMJ) at 0.49. According to Ratner (2009) this does not qualify as strong correlation; hence we do not suspect multicollinearity between the momentum and quality factor.

Table A.4: Correlation matrix between the independent variables.

	Mkt-RF	SMB	HML	QMJ	WML	BAB
Mkt-RF	1					
SMB	0.13	1				
HML	0.09	0.09	1			
QMJ	-0.73	-0.38	-0.23	1		
WML	-0.37	-0.12	-0.45	0.49	1	
BAB	0.01	0.21	-0.17	0.08	0.35	1

A2.2 The Variance Inflation factor

To further test for multicollinearity in our data we use the variation inflation factor (VIF) to measure the amount of multicollinearity. There are different opinions on what the maximum value of the variation inflation factor should be. Hair et al. (1995) suggested a level of 10 as acceptable. From table A.5 we see that none of the independent factors have a level of the VIF above 2.97, which further strengthen the assumption that we do not have a problem with multicollinearity.

Table A.5: The Variance Inflation Factor.

	VIF
Mkt-RF	2.36
SMB	1.34
HML	1.28
QMJ	2.97
WML	1.77
BAB	1.27

A3 Miscellaneous

A3.1 Correlation Matrix of Market Indexes

Table A.6 displays the correlation between the indexes used in the different regression models. In this paper, we use the MSCI World Index as benchmark for the risk-adjusted performance measures, and for the market risk premium in the main regression model. The table shows that the correlation between the regional indexes, Europe TMI and MSCI US, and the world index is near 1.

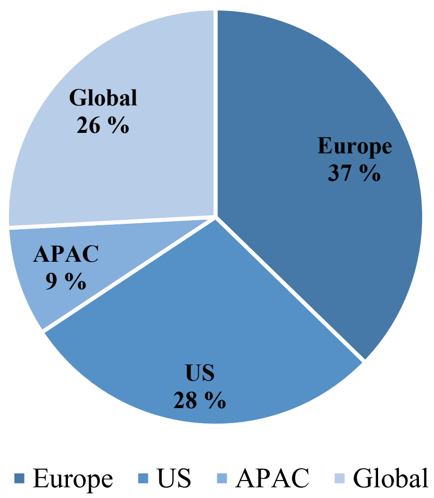
Table A.6: Correlation matrix between the different stock indexes.

Index	MSCI World	STOXX Europe TMI	MSCI US
MSCI World	1.000		
STOXX Europe TMI	0.953	1.000	
MSCI US	0.975	0.877	1.000

A3.2 Investment Area for European Smart Beta ETFs

Figure A.10 shows each investment area's share for European smart beta ETFs. From the figure, we see that 63% of the European smart beta ETFs invest in other parts of the world than Europe.

Figure A.10: Investment area for European smart beta ETFs.



A3.3 Top 10 Smart Beta ETFs in Terms of Net Assets

Table A.7: Top 10 smart beta ETFs in terms of net assets in the US and Europe.

US smart beta ETFs

Name	Ticker	Category	Primary Prospectus Benchmark	Issuer	ER (%)	Net Assets ($)	Inception Date
Vanguard Value ETF	VTV	Value	CRSP US Large Cap Value TR USD	Vanguard	0.04	139 173 896 824	26/01/2004
Vanguard Growth ETF	VUG	Growth	CRSP US Large Cap Growth TR USD	Vanguard	0.04	133 731 719 930	26/01/2004
Vanguard Dividend Appreciation ETF	VIG	Dividend	S&P US Dividend Growers TR USD	Vanguard	0.06	71 272 726 516	21/04/2006
iShares Russell 1000 Growth ETF	IWF	Growth	Russell 1000 Growth TR USD	iShares	0.18	57 203 960 475	22/05/2000
Vanguard High Dividend Yield ETF	VYM	Dividend	FTSE High Dividend Yield TR USD	Vanguard	0.06	55 636 885 499	10/11/2006
iShares Russell 1000 Value ETF	IWD	Value	Russell 1000 Value TR USD	iShares	0.18	51 002 256 296	22/05/2000
Vanguard Small-Cap Value ETF	VBR	Value	CRSP US Small Cap Value TR USD	Vanguard	0.07	42 449 279 091	26/01/2004
Schwab US Dividend Equity ETF™	SCHD	Dividend	DJ US Dividend 100 TR USD	Charles Schwab	0.06	34 391 385 354	20/10/2011
Invesco S&P 500® Equal Weight ETF	RSP	Equal weighted	S&P 500 Equal Weighted TR USD	Invesco	0.20	28 968 551 571	24/04/2003
iShares S&P 500 Growth ETF	IVW	Growth	S&P 500 Growth TR USD	iShares	0.18	27 965 963 854	22/05/2000

European smart beta ETFs

Name	Ticker	Category	Primary Prospectus Benchmark	Issuer	ER (%)	Net Assets ($)	Inception Date
iShares Edge MSCI World Value Factor ETF	IWVL	Value	MSCI World Enhanced Value NR USD	BlackRock	0.30	5 080 105 141	03/10/2014
SPDR® S&P US Dividend Aristocrats ETF	UDVD	Dividend	S&P High Yield Dividend Aristcrts NR USD	State Street	0.35	4 333 635 120	14/10/2011
iShares Edge MSCI Wld Min Vol ETF	MVOL	Low volatility	MSCI World Minimum Vol (USD) NR USD	BlackRock	0.30	3 886 674 970	30/11/2012
Xtrackers S&P 500 Equal Weight ETF	XDEW	Other	S&P 500 Equal Weighted NR USD	Xtrackers	0.25	3 742 843 351	10/06/2014
iShares Edge MSCI USA Value Factor ETF	IUVL	Value	MSCI USA Enhanced Value NR USD	BlackRock	0.20	3 259 183 707	13/10/2016
Vanguard FTSE All World High Dividend Yield ETF	VHYD	Dividend	FTSE AW High Dividend Yield TR USD	Vanguard	0.29	3 097 770 205	21/05/2013
iShares Edge MSCI Europe Value Factor ETF	IEVL	Value	MSCI Europe Enhanced Value NR EUR	BlackRock	0.25	3 034 689 013	16/01/2015
iShares Edge MSCI World Quality Fctr ETF	IWQU	Quality	MSCI World Sector Neutral Quality NR USD	BlackRock	0.30	2 296 568 413	03/10/2014
iShares Edge MSCI USA Quality Fac ETF	IUQA	Quality	MSCI USA Sector Neutral Quality NR USD	BlackRock	0.20	2 279 512 820	13/10/2016
iShares STOXX Global Select Dividend 100 (DE)	ISPA	Dividend	STOXX Global Select Dividend 100 NR EUR	iShares	0.46	1 949 187 358	25/09/2009