Vaasan yliopisto
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Investing in Smart Beta ETFs

Relative Performance and Factor Exposure

School of Accounting and Finance
Master's thesis in Finance
Master's Programme in Finance

Vaasa 2023

University of Vaasa
School of Accounting and Finance

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Title of Thesis:	Investing in Smart Beta ETFs: Relative Performance and Factor Exposure
Degree:	Master of Science in Economics & Business Administration
Programme:	Master's Programme in Finance
Supervisor:	Timo Rothovius
Year:	2023 **Pages:** 79

ABSTRACT :

During the past decade, the so-called "Smart Beta" has gained much attention and popularity amongst investors. The growth has been driven by fresh fund inflows, the launch of new funds, and the entrance of new players. However, there is a wide dispute on the viability of smart beta products and whether or not they deliver the desired positive alpha and factor exposure expected by investors. This paper uses historical data divided into eight well-known factor strategy categories to examine the relative performance and factor exposure of 399 US-domiciled smart beta exchange-traded funds—the sample data range from 2000 to January 2023. The relative performance is measured with three regressions using the most well-known asset pricing models, such as the Capital Asset Pricing Model (CAPM) and Fama and French three and five-factor models. As ETFs are generally known as active funds and obtain higher costs than passive benchmark funds, the thesis also accounts for regression results after controlling for fees. Similarly, to other previous studies this thesis finds no conclusive empirical evidence to support the hypothesis that smart beta ETFs provide consistent abnormal return over broad market passive benchmarks.

The regression results using the of CAPM and Fama and French three and five-factor models show that with this measured sample size and selected ETF funds the factor strategies as collective do not provide statistically significant and consistent excess return compared to the broad market benchmark portfolio. However, during the sample period of June 2000 to January 2023 the growth factor managed to provide positive and better than benchmark portfolio alpha although not significant. This is contrary to Fama and French (1998) findings where value stocks outperformed growth stocks during the period of 1975 through 1995. Momentum and multi factor strategies also offer better alpha values compared to the broad market benchmark used although the alpha values are negative and not statistically significant. These regression result findings are consistent when measured with all three asset pricing models.

Compared to other previous studies this thesis provides evidence in its own time period and the period may differ depending on specific factor ETFs first available data point. Therefore, the thesis combines three time periods for variability (full sample period, half sample period, past three years). Further studies within this sample would be to add risk-adjusted results as well as to compare the returns against the specific underlying benchmark index provided by the ETF issuer. Additional risk-adjusted performance measures could be added such as Sharpe and Sortino ratios and Jensen's alpha. Wider results could be added by using similar measures as Glushkov (2015).

KEYWORDS: Smart Beta, Strategic Beta, ETFs, Enhanced Indexes, Factor Exposure, Factor Investing, Factor Allocation, Risk-Premium

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Tekijä: Olli Saarijärvi
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Oppiaine: Master's Programme in Finance
Työn ohjaaja: Timo Rothovius
Valmistumisvuosi: 2023 **Sivumäärä:**79

TIIVISTELMÄ :
Viimeisen vuosikymmenen aikana niin kutsuttu "Smart Beta" on saanut paljon huomiota ja suosiota sijoittajien keskuudessa. Kasvua ovat johtaneet nettomerkinnät rahastoihin, uusien rahastojen lanseeraus ja uusien toimijoiden alalle tulo. Smart beta-tuotteiden kannattavuudesta ja siitä, tuottavatko ne sijoittajien toivomaa positiivista alfaa sekä ja faktori altistusta ei varsinaisesti ole olemassa yhtenäisyyttä. Tässä tutkimuksessa käytetään historiallista hintadataa 399 Yhdysvalloissa noteeratusta smart beta ETF rahastosta, jotka on jaettu kahdeksaan tunnettuun faktori strategialuokkaan, ja pyritään arvioimaan näiden performanssia suhteessa kokonaismarkkinaa jäljittelevään portfolioon. Otostiedot vaihtelevat vuoden 2000 kesäkuusta tammikuuhun 2023. Suhteellista suorituskykyä mitataan kolmea tunnettua hinnoittelumallia käyttämällä, joita ovat Capital Asset Pricing Model (CAPM) sekä Faman ja Frenchin kehittämät kolmen ja viiden faktorin hinnoittelumallit. Koska ETF:t ovat yleisesti ottaen aktiivisia rahastoja ja niiden kustannukset ovat korkeammat kuin passiivisten vertailurahastojen, opinnäytetyössä huomioidaan myös regressiotulokset rahaston palkkiot huomioiden. Samoin kuin muissa aiemmissa tutkimuksissa, tämä opinnäytetyö ei löydä vakuuttavaa empiiristä näyttöä olettamuksille, että smart beta ETF:t tarjoaisivat johdonmukaista ylituottoa suhteessa koko markkinaa seuraaviin passiivisiin vertailurahastoihin.

CAPM:n sekä Faman ja Frenchin kolmen ja viiden faktorin hinnoittelumalleilla, tällä otoskoolla sekä valituilla ETF-rahastoilla mitattaessa faktori strategiat eivät kollektiivina tarjoa tilastollisesti merkitsevää ja johdonmukaista ylituottoa verrattuna laajaan markkinoiden vertailusalkkuun. Kesäkuun 2000 ja tammikuun 2023 välisen näytejakson aikana kasvu osake strategia kuitenkin onnistui tarjoamaan positiivisen ja vertailusalkun alfaa paremman, vaikkakaan eivät tilastollisesti merkittäviä. Tämä on vastoin Faman ja Frenchin (1998) havaintoja, joissa arvo-osakkeet menestyivät paremmin kuin kasvuosakkeet vuosina 1975–1995. Momentum- ja moni faktori strategiat tarjoavat myös parempia alfa-arvoja verrattuna käytettyyn laajaan markkinoiden vertailuarvoon, vaikka alfa-arvot ovat negatiivisia eivätkä tilastollisesti merkittävä. Nämä regressiotulostulokset ovat johdonmukaisia, kun ne mitataan kaikilla kolmella omaisuuserien hinnoittelumallilla.

Verrattuna muihin aikaisempiin tutkimuksiin tämä opinnäytetyö tarjoaa todisteita omalla aikajaksollaan ja ajanjakso voi vaihdella riippuen tietyn ETF:n ensimmäisestä saatavilla olevasta datapisteestä. Tästä syystä opinnäytetyössä yhdistetään kolmea vaihteluväliä (koko otosjakso, puolet otosjaksosta, viimeiset kolme vuotta). Lisätutkimukseen oikeuttavia lisäyksiä tässä otoksessa olisi oivallista lisätä riskipainotettuja tuloksia sekä vertailla tuottoja ETF:n liikkeeseenlaskijan tarjoamaan tiettyyn taustalla olevaan vertailuindeksiin. Muita riskipainotettuja suorituskykymittareita voitaisiin lisätä, kuten Sharpen ja Sortinon suhdeluvut ja Jensenin alfa.

AVAINSANAT: Smart Beta, Strategic Beta, ETFs, Enhanced Indexes, Factor Exposure, Factor Investing, Factor Allocation, Risk-Premium

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1 Introduction

1.1 Background motivation

The shared objective of Smart beta ETFs, as stated by Morningstar (2021), is to "enhance returns or minimize risk relative to a traditional market-capitalization-weighted benchmark" through the application of different weighting methodologies to gain exposure to a variety of factors, including size, value, volatility, and others. Based on institutional-level investor questionnaires, most investors are examining Smart Beta funds to purchase exposure for a recognized variable instead of using it simply as a tool to achieve "alpha." Nevertheless, at the very same time, identical research studies show that investors who use factor investing methods need more than just a suitable course of exposure. They are more interested in "factor exposure that can deliver a successful risk-adjusted profit with ease of application." (Amenc et al., 2015).

The existence and popularity of the so-called "Smart Beta" (SB.) ETFs date from the growing popularity of ETFs. According to the 2022 ICI Investment Company Fact Book, ETFs have issued $3.7 trillion in net shares in the past ten years. More than 2,570 funds were available in the US ETF market at the end of 2021, which continued to be the biggest market globally and accounted for approximately 71 percent of the $10.1 trillion in global ETF assets. As an asset class, ETFs continue to capture a growing percentage of all trades in financial markets and the exponential rise in market value overall. At year-end 2021, total net assets in ETFs in the United States comprised 21% of the assets managed by investment firms.

Smart Beta (SB) ETFs were one of the fastest-growing ETF market sectors that have gained much attention in the past 20 years. However, we take a slight step back to times when the SB ETFs were a highly dominant investment vehicle in the industry. According to Bloomberg Intelligence, approximately 400 US-based Smart Beta funds managed $400 billion, or roughly 20% of all domestic ETF assets, by the end of 2014. In May 2000, there were virtually no such funds. In 2014, FTSE Russell began conducting annual smart beta surveys among its institutional clientele, which in 2019 possessed 178 asset owners and had an estimated AUM of more than $5 trillion in total. FTSE Russell smart beta investor survey show that 78% of survey participants as of 2019 have adopted, are exploring, or intend to evaluate smart beta techniques. The poll has shown that throughout those six years, global institutional asset owners have become increasingly interested in allocations to investable products and strategies based on smart beta indexes.

The FTSE survey has yet to be done since 2019. However, the results of the most recent EDHEC European ETF, smart beta, and factor investing study, released in 2021, indicated a slowdown in adopting smart beta and factor investing methods and an increase in interest in the addition of an SRI/ESG component. According to the survey, using smart beta and factor investing methods is most commonly done for risk control and performance enhancement. Only 37% of respondents stated they intended to use smart beta and factor investing products more frequently, and 73% said they would devote less than 20% of their total investments to these strategies.

According to the latest Morningstar's Global Guide to Strategic-Beta Exchange-Traded Products (2022), the strategic-beta market expanded more quickly than the overall ETP industry for most of the last decade. The emergence of new companies, fresh fund flows, and new product releases have contributed to the rise of strategic-beta ETPs. The market-share growth of these products has, however, stalled lately. This market sector has matured. The rate of net fresh inflows has leveled out. For the first time in 2020, the number of strategic-beta ETPs decreased year over year as closures outweighed new launches. Just 12 net new products were added to the worldwide strategic-beta ETP menu in 2021, indicating a 0.9% growth over the end of 2020. In the meantime, many ETPs' fees have increased. The asset-management sector has advanced to create momentum behind new product lines as the strategic-beta ETP landscape has settled. Actively managed exchange-traded funds, thematic funds, and investing in environmental, social, and governance issues currently take center stage.

The report shows that smart beta and factor investing techniques have lost some appeal when considering asset allocations. However, considering the high demand and rising popularity of these investment vehicles in the 2019 FTSE poll, the shift in favor has been rapid. Participants in the survey are keeping within the smart beta and factor methods but are focusing on more particular goods within the category. For example, SRI/ESG and fixed income are crucial objectives for developing smart beta and factor investing solutions in the future. Additionally, respondents to the survey wanted to see more specialized smart beta and factor investing solutions created.

There are conflicting theoretical underpinnings for smart beta, and no consensus definition exists in academic literature. However, it is widely acknowledged that smart beta strategies are long-only strategies that favor factors like size, value, momentum, or low volatility to beat the capitalization-weighted market. (Jacobs & Levy, 2014; Malkiel, 2014). Assness, Ilmanen, Israel, and Moskowitz (2015), on the other hand, define smart beta as a tilt toward long-only, cap-weighted portfolios with high market exposure. Smart beta tries to improve the return on asset class monitoring by deviating from the usual market cap-weighted method, in which investors purchase shares or bonds in proportion to their market value.

A deeper assessment from Jacobs & Levy (2014) shows that as smart beta employs rules-based selection and weighting, rebalances at predefined intervals and does not attempt to make explicit projections of returns and risks for specific assets, smart beta is frequently referred to as passive investing. However, the choice not to hold the capitalization-weighted market portfolio is conscious in and of itself. Therefore, more operational decisions must be made to target the specific factor(s) and specify the factor(s), the selection universe, the weighting mechanism, and the rebalancing criteria.

All this spam comes from style premium, which researchers have extensively investigated for decades. Among the most influential researchers in the field are Kenneth French and Eugene Fama. They also used size and value within their initial 1990s study to explain the cross-section of stock market returns. (1992, 1993). When using the three-factor model, the authors conclude that the book-to-market ratio and anticipated returns have a positive link, whereas company size and expected returns have a negative correlation. This suggests that investors may get more significant returns by purchasing small-cap value companies than the conventional capital asset pricing model would imply.

1.2 Hypothesis

The growing popularity of Smart Beta ETFs amongst investors has been visible during the past ten years, and their interest is holding steady despite some speculation of maturing. On the other hand, exponentially growing fund inflows and products available are showing continuous growth. While studies contemplate Smart Beta investing to individual stocks and portfolio building, this thesis's sole aim is to focus on ETFs providing the assigned factor exposure specifically. In addition, the objective is to provide evidence of whether or not the specific smart beta categories generate meaningful alpha to investors compared to the cheapest available passive cap-weighted alternatives.

The thesis aims to expand the previous literature by widening the assigned smart beta ETF scope and attaining the categorization data from different sources. So, there might be some variability in the categorizations. The periods studied started from the first available return of the smart beta portfolio ETFs and also narrowed down to starting from Jan/2010 as well as the most recent three-year period. The reasoning is to capture the post-financial crisis period and the recent pandemic period, as these market conditions differ significantly from a macroeconomic perspective. This change of time frame analyzed gives the variability for the results but also helps to gain more evidence on the questions this thesis tries to look for answers to.

In a fundamental level this thesis aims to provide evidence and examine the profitability of factor strategies in smart beta ETFs by providing positive and statistically significant alpha. Therefore, the null hypothesis and alternative hypothesis is constructed as follows:

> H_0: Factor strategies in smart beta ETFs are not capable of generating consistent statistically significant and positive alpha compared to passive benchmark portfolio.
>
> H_1: Some factor strategies in smart beta ETFs are able to provide consistently positive alpha compared to passive benchmark portfolio.

The hypothesis is intended to follow Glushkov (2015) and remain as short, simple, and precise as possible in attaining the main results. Also, to see if the analyzed data and used methods capture the same hypothesis, there is no empirical evidence to support the hypothesis that factor strategies in Smart Beta ETFs outperform their assigned benchmarks on a 5% significance level. This is to conclude as an overall sample rather than concentrating on a specific strategy but also spot differences and possible excess returns. Contrary to Glushkov this thesis uses a passive broad-market benchmark portfolio and tries to reject the null hypothesis on a 5% statistical significance level.

1.3 Thesis structure

The thesis is accompanied by eight main chapters discussing investing in smart beta EFTs, while the first introductory chapter provides some reasoning and history behind smart ETF investing and why it has been a relevant topic of discussion during the more or less past decade. The subchapter also points out the relevant hypothesis and research questions that this thesis intends to provide answers to.

To extensively understand the fundamentals of ETFs and smart beta strategy, the second chapter aims to comprehensively provide information on the mechanics and structure of Exchange-Traded-Funds without forgetting the risks and costs incurred when investing

in active screening component funds. This will be accompanied by an introduction to the smart beta strategy, which has been by other sources also labeled as "Strategic beta" and has gained much attention during the 21st century due to its growing popularity amongst investors while academics are trying to provide reasoning as to whether these strategies provide any significant outperformance, which this thesis also tries to shed up light. Also, shortly introducing the smart beta categories used in this study.
The third and fourth chapter introduces some basic principles of market efficiency and its problems and the most notable anomalies behind the asset pricing models used in this thesis. Therefore, the fifth chapter combines and discusses the widely known asset pricing models, including Capital Asset Pricing Model (CAPM) and Fama and French three- and five-factor models.

The sixth chapter shortly introduces the data attained for this study and the description of the broad benchmark portfolio used to compare the smart beta portfolio results. Chapter seven discusses the regression results provided by the different asset pricing models, and chapter eight finalizes the thesis into conclusions and discusses the aspects to improve.

2 Exchange-traded funds – ETFs

This part of the thesis explains theoretical underpinnings of a relatively new investment product, the exchange-traded funds (ETFs). Understanding mechanics, strategy in process creation, and drivers behind ETFs' market share increase are crucial to this argument. Critical for investors is also to understand the risks and expenses of investing in ETFs.

As per Lettau and Madhavan (2018), a financial product called an exchange-traded fund (ETF) tries to track the performance of a particular index. ETFs are made up of various equities and bonds, and they also want to match the performance of their underlying benchmark index. ETFs are a modern take on conventional mutual funds but have several dissenting characteristics. In contrast to traditional mutual funds, for instance, ETF shares, like stocks, are capable of being traded throughout the day.

Standard & Poor's Depository Receipt, the first ETF, was released in 1993 to track the performance of the S&P 500 index. Other forms of ETFs were launched in later years in addition to the traditional ETFs that tracked broad market indices. Since the late 1990s, industry-sector, commodity, bond, and overseas ETF growth has been remarkably rapid. ETFs built to adhere to specific investment strategies utilized by active mutual and hedge funds have started appearing in recent years. One ETF created to capture momentum is the iShares MSCI USA Momentum Factor (MTUM) ETF. (Bodie et al. 2013; Lettau & Madhavan, 2018).

ETFs are a practical, cost-effective tool for investors looking to increase or decrease exposure to broad markets, particular industries or geographical areas, or specialized investment approaches. Demand for ETFs has significantly increased over the last ten years as institutional and retail investors increasingly choose them as investment vehicles. Net share issuance of ETFs has reached $3.7 trillion during the last ten years. Sponsors have added additional ETFs with a broader range of investment objectives in response to rising investor demand. The US ETF business remained the largest in the world, with $7.2 trillion in total net assets at the end of 2021. (Investment Company Fact Book, 2022)

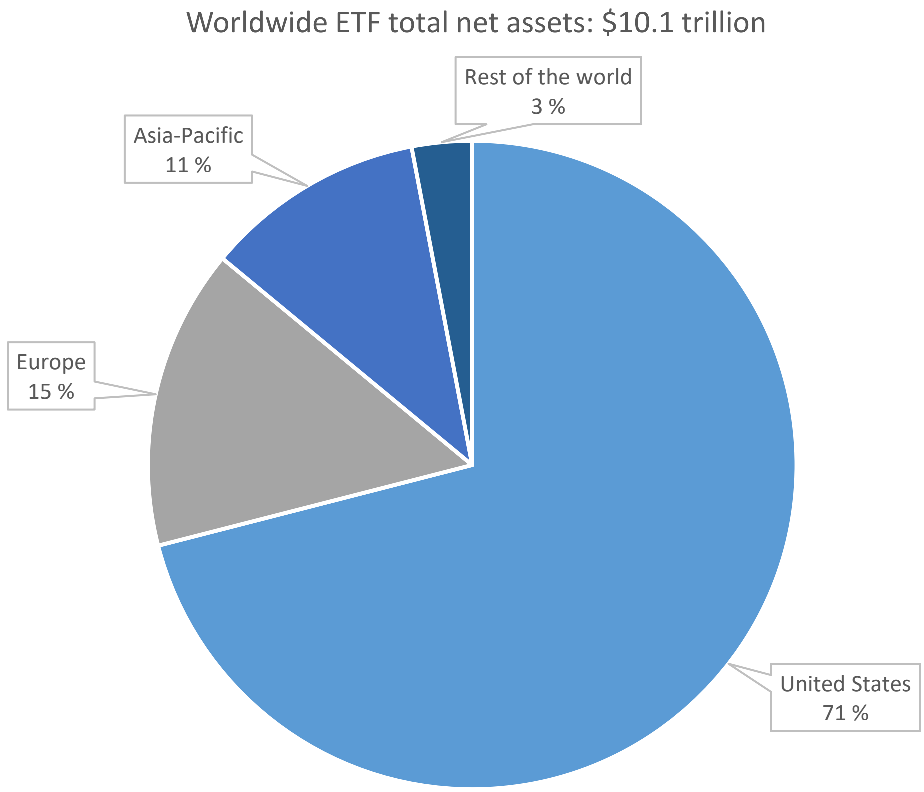

Figure 1. The United States has the largest ETF market. Percentage of total net assets, year-end 2021. (Investment Company Institute and ETFGI, 2022)

Along with overall ETF market growth, Morningstar, in their recent Global Guide to Strategic-Beta Exchange-Traded Products (2022), points out that within the broader Exchange-Traded Products (ETP) market, the strategic/smart beta space has grown more rapidly during the past decade or so. Net cash flows, new launches, and new players' entries have contributed to the growth in strategic-beta ETPs. The market-share growth of these products has, however, stopped more recently. However, this market sector has matured. As a result, the rate of net new inflows has stalled. For the first time in 2020, the number of strategic-beta ETPs decreased year over year as closures outweighed new launches. Just 12 new items were added to the worldwide strategic-beta ETP menu in 2021, indicating a 0.9% growth over the end of 2020. In the meantime, many ETPs' fees have increased. The asset-management sector has continued to create momentum behind new product lines as the strategic-beta ETP landscape has settled. Actively managed exchange-traded funds, thematic funds, and investing in environmental, social, and governance issues currently take center stage.

On the other hand, consulting powerhouse PwC argued in their last year's survey (2022) regarding ETFs' future that the Global ETF AUM is set to top $20 trillion by 2026. The majority of the executive respondents of the survey predict that worldwide ETF AUM will reach at least $18 trillion by 2026, indicating a 14.6% CAGR between June 2021 and June 2026. PwC projects more than $20 trillion in global ETF AUM by 2026, or a 17% CAGR over the following five years. Given the worldwide ETF CAGR of 22% over the previous five years ending in December 2020, as well as record inflows, new entrants, innovative products, and distribution opportunities, this appears to be a realistic goal. The United States continues to lead the way regarding ETF market size and growth. Other markets, meanwhile, are rapidly expanding. Survey respondents in Europe are among the most optimistic about future growth. In addition, Asia-Pacific survey participants' considerable interest in crypto and other thematic ETFs demonstrates the demand for innovation in rapidly emerging and maturing regional markets.

These predictions for the continuously growing ETF market are supported by the most recent Investment Company 2022 yearbook Over the last decade, institutional investors have recognized ETFs to be a useful vehicle for investing in, or hedging against, wide stock market fluctuations. The rising understanding of these investment vehicles among regular people and their financial advisers has influenced demand for ETFs. Figures 1 and 2 provide clear evidence of the exponential demand, especially in the past few years as total net assets have grown significantly to top 7 billion USD. Domestic broad-based U.S equity ETFs have the lion’s share of the market share.

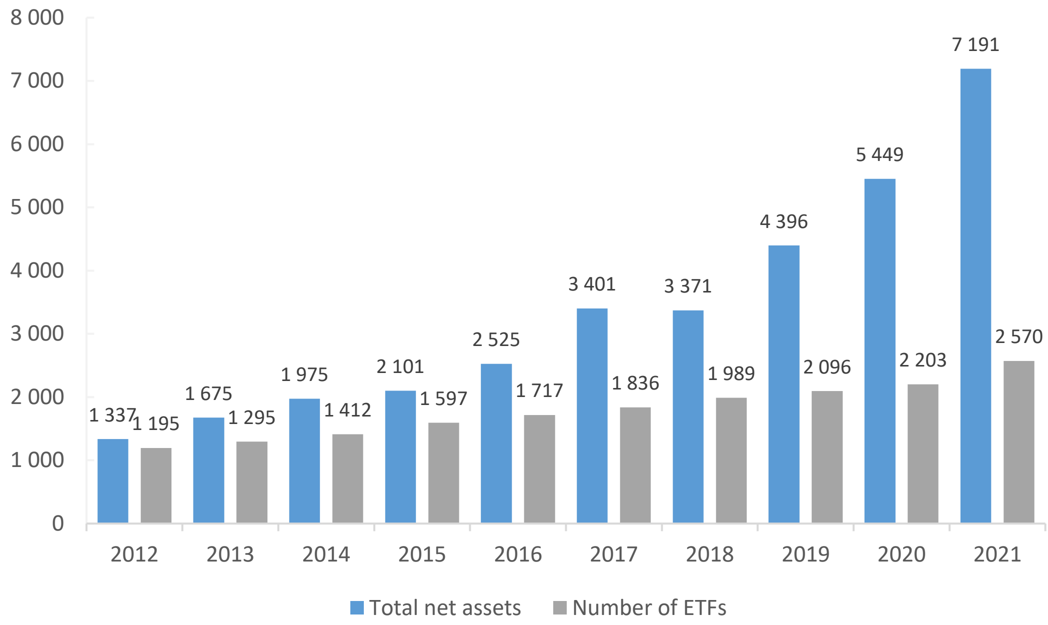

Figure 2. Total net assets and number of ETFs. Billions of dollars, year-end. (IC Yearbook 2022)

In Table 1 there is a more detailed visualization behind the total net assets. As we can see, the Broad-based domestic equity ETFs are by far the most popular within the net assets. This is most likely as these types of funds are most easy to understand and widely used amongst both retail and institutional investors. The issuance of new funds has been in a steady rise within the past decade presenting a solid 8% CAGR over the period of 2012-2021 while the total net assets number has been in a parabolic rise coming with an 18% CAGR. With these growth rates in mind the total net asset target of $20 trillion by 2026 from PwC survey (2022) is well reachable. However, considering recent market turbulences these figures will most likely decrease in the coming years.

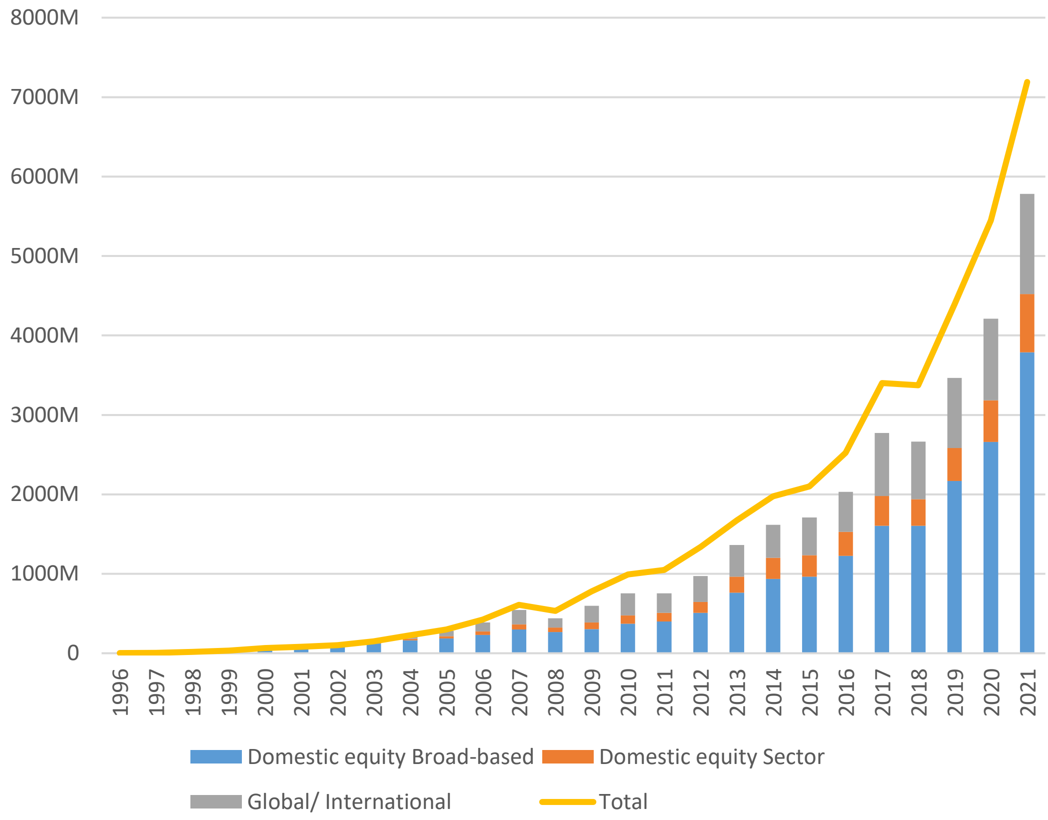

Table 1. Total Net Assets by Type of Fund, year-end (IC Yearbook, 2022)

Similarly, to table 1 exponential and steady growth of total net assets, in table 2 we can see that the demand for ETFs has increased over the past ten years as large investors discovered ETFs to be a handy instrument for investing in, or similarly hedge against, broad equity market swings. Demand for ETFs has been impacted by a greater understanding of these types of investments among ordinary investors and financial advisors. 2021 was a record year for ETF net issuance as the total number shoot up to $935 billion compared to previous year's $501 billion. This is a significant doubling of net issuance which shows that the momentum behind the popularity of these investment vehicles seems to be holding very well.

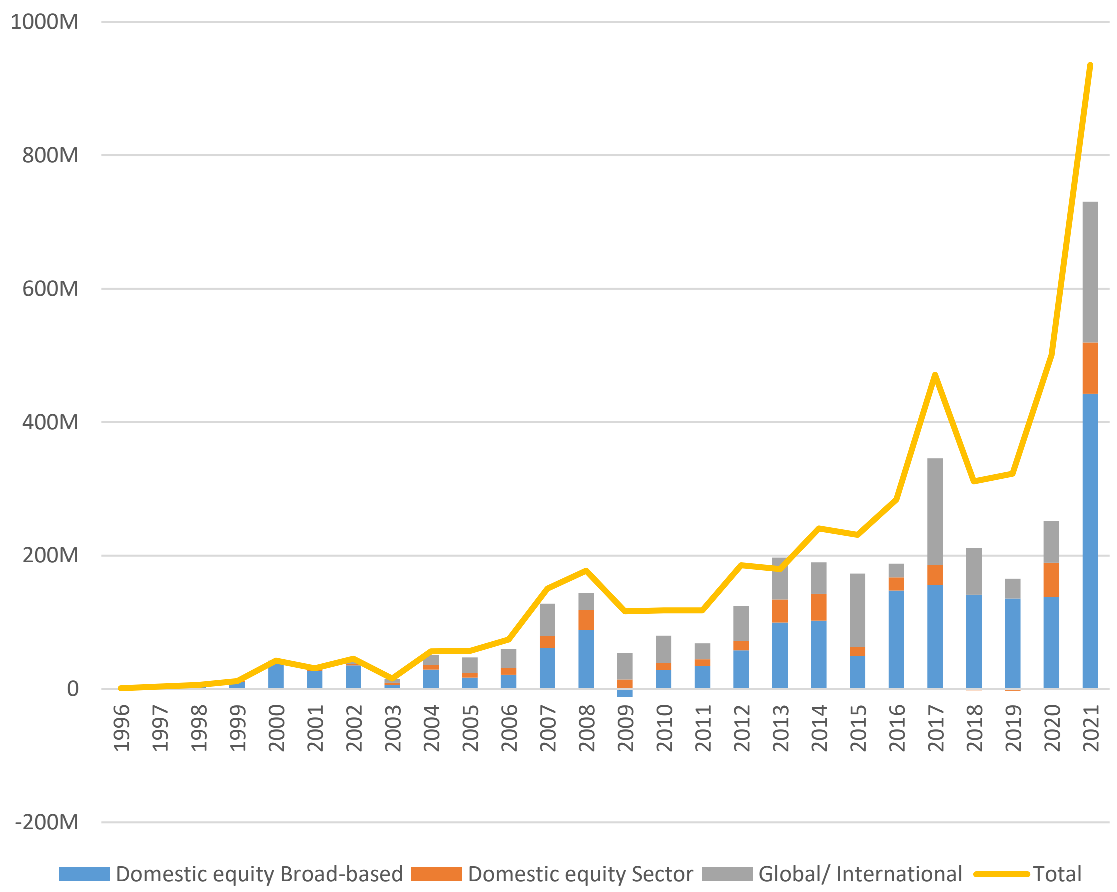

Table 2. Net Issuance by Type of Fund, annual (IC Yearbook, 2022)

2.1 Mechanics and characteristics

The market expansion and rising popularity of ETFs have numerous causes. Like a mutual fund, the majority of ETFs aim to track a certain index. Indexing, a tracking method, represents the replication mechanism through which the ETF tracks the assets of the target benchmarks in all market conditions. The majority of ETFs still adhere to a specified benchmark, although there are actively managed ETFs on the market that attempt to surpass their benchmark index. The ETFs are for long-term passive asset management due to their index-imitation tactics. The ETFs often have minimal fees, are transparent, liquid, and tax-efficient, and make it simple to diversify investor portfolios. Due to their resemblance to regular shares, ETFs are quite straightforward and simple to utilize. They can also be traded on regular exchanges daily with real-time price fluctuations. (Lettau and Madhavan, 2018).

According to Dellva (2001), flexible trading regulations and intraday trading of ETFs foster a climate in which investors pursue short-term financial gains while pursuing a hot industry or fund. Despite the fact that these products are designed for long-term investors and aim to replicate an index's performance, investors employ the trading aspects of ETFs. Barber and Odean's (2000) research, however, shows that investors who trade more frequently tend to experience poorer returns than those of investors who trade less frequently.

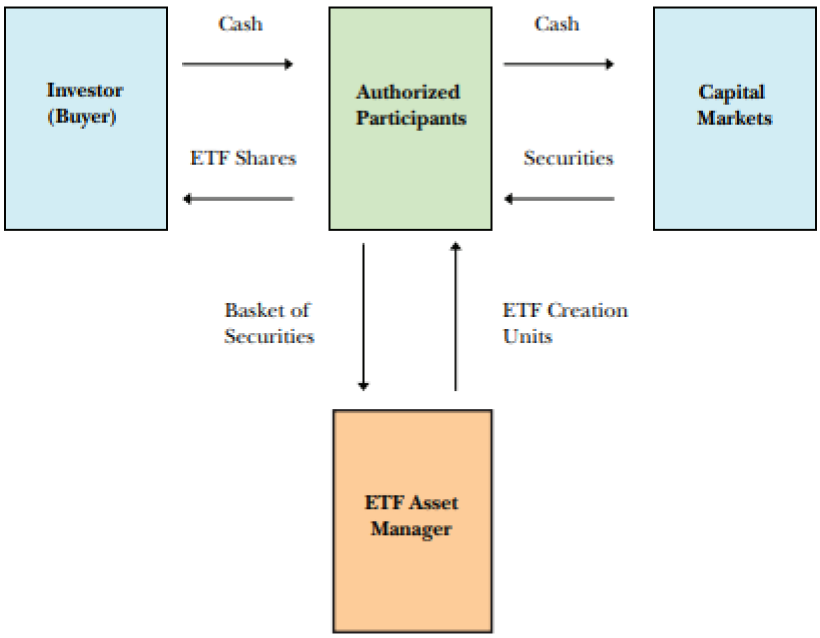

Figure 3. ETF architecture (Lettau & Madhavan, 2018)

Despite ETFs being similar to regular mutual funds holding various stocks it does not directly connect with financial markets. Usually, the ETF manager works within a legal contract together with one or multiple parties called Authorized Participants or APs. These parties are usually bigger financial institutions or market makers who in turn are connected to financial markets. The ETF manager can either issue or redeem shares with these Aps in larger block trades as usually done with financial institutions and they will then receive cash or other securities. This is usually known as the creation mechanism (Figure 3) as the shares of an ETF are adjusted by supply and demand. (Lettau and Madhavan, 2018).

2.2 Risks and costs

The asset allocation and the fee structure it entails, as Markowitz's (1952) contemporary portfolio theory has previously shown, are two of the most important components of a successful investment strategy. These two characteristics have an impact on return performance both directly and indirectly. Reducing fees is a certain strategy to boost returns over an extended period of time, and asset allocation influences how risky an investment is on the whole. Understanding the full costs and hazards of one's investment is crucial to making effective investment decisions.

Compared to conventional mutual funds, ETFs provide cheaper transaction fees and favorable tax treatment for investors. Even though ETF shares must be purchased through brokers at a cost to investors, the fund will spend less on distribution, recordkeeping, and marketing to small participants as a consequence, which might lower total management costs. Continuing, ETFs offer lower transaction costs since the underlying securities are unaffected by secondary market activity because they are not traded directly with the fund. As a result, investors' transaction expenses decrease when redeeming shares. (Lettau & Madhavan 2018.)

An important contrast between an ETF and a mutual fund structure is that transaction expenses connected with an ETF are externalized. Without going deeper into the functionality of externalization, in simple terms, the mutual fund's remaining investors are responsible for paying the transaction fees paid by those who redeemed or subscribed. Contrarily, with ETFs, the investors selling the fund will deal directly with the fund's buyers at a price set by the market. The ETF management does not need to interface with the capital markets in order to engage in net selling. (Lettau & Madhavan 2018.)

ETFs' capacity to offer tax advantages over conventional mutual funds and substantially cut or even eliminate transaction expenses is predicated on how they are created and redeemed. Mutual fund share redemptions may result in capital gains taxes owed by the remaining owners, as the mutual fund is required to sell the underlying securities to cover the redemption. The ETF managers have the option to satisfy substantial share redemptions by sending the underlying securities to the redeeming party rather than cash. ETF managers have the opportunity to save ETF investors from future capital gains taxes by deferring the sale of the underlying securities. (Poterba & Shoven 2002.)

Development in terms of fee structure for smart beta ETFs has been moving in favorable direction from an investor standpoint. As expense ratios will keep falling as the market becomes increasingly saturated and competitive, it will deliberately increase the attractiveness of smart beta ETFs compared to its actively managed peers. As per Morningstar (2021) the fees charged by smart beta ETFs will remain under pressure as providers strive to differentiate themselves in a highly competitive environment wherein investors frequently have difficulty distinguishing between apparently identical strategies.

According to Investment Company Institute’s research on fee development (2021) during the preceding 24 years, the expense ratios of long-term mutual funds have generally decreased significantly. Equity mutual fund expense ratios on average decreased to 0.50 percent in 2020 from 0.51 percent in 2019. Exchange-traded fund (ETF) fee rates are under pressure from economies of scale and competition. Funds with relatively low costs continued to get the majority of inflows.

Like in any other investment vehicle, whether it be mutual fund, hedge fund or any other underlying asset, investors can lose money. ETFs make no difference. The key question amongst investors is whether certain types of risk are included which make ETFs riskier than generally thought. Lettau and Madhavan (2018) contend that although certain worries do exist about ETFs, these concerns, like in other financial sectors, are usually based on misconceptions. The concerns associated are divided between individuals and generally index investing’s effects on markets and macroeconomy.

2.2.1 Fund closures, shorting and counterparty risk

The possibility of losing their entire investment is a common concern for individual investors. Like mutual fund closures, ETF closures are a typical occurrence. Every year, between 50 and 80 ETFs liquidate. (Madhavan, 2016) Even as the liquidation of ETF might attract some media coverage there should be no investment risk whatsoever like in company bankruptcy scenarios since the underlying assets should not have direct impact. As the EFT closes its price ought to equal its net asset value. These risks might be larger for other exchange-traded products. (Lettau and Madhavan, 2018.)

Another problematic defined risk, which can turn into significant investor losses and even significant problems in the financial system, is selling short ETFs. Without going into detail on what the specific terms account for, in short, selling short ETFs means that There may be more outstanding ETF shares than there are total long and synthetic long holdings. (Bradley and Litan, 2010.) Critics claim that when investors were to sell all their ETF shares at once, the fund would conceivably become "bankrupt" since the number of shares sold would be greater than the amount of assets that could be sold. (Lettau and Madhavan, 2018.)

There can also be counterparty risk as specific types of ETPs enter into swap positions with investment banks by security lending. This brief swap of a security from its original owner to a different entity, such as a hedge fund, usually with reasons such as a short sale, is known as securities lending. Since the lender continues to be the legitimate owner of the security, they are vulnerable to any changes in the security's price during the loan's term. However, securities lending can improve market liquidity and price efficiency by decreasing the costs of expressing adverse thoughts through short selling by preventing the emergence of asset bubbles. While the practice is common and has a major economic impact, scholarly research on the lending of securities is still in its infancy. (Lettau and Madhavan, 2018.)

2.2.2 Flash events and systemic risk

"Flash events," characterized by abrupt price changes and following reversals in condensed time spans, are a different issue that worries both investors and regulators interested in financial markets. One example being the flash crash of May 6th, 2010, when Dow Jones declined 1000 points in a matter of 20 minutes and many well-known and fundamentally sound stocks traded in unjustified prices. The effect on ETFs was extravagantly misinformed to be much worse what it actually was. The significant market movements on May 6 were accompanied by prices for these instruments that were markedly different from their underlying NAVs, leading some analysts to link these price and trade changes to the day's market movements. (Wurgler, 2011.)

Additionally, Madhavan (2012) discusses several market structure problems that may play a role in flash events, such as rising market fragmentation and the proliferation of new venues. Furthermore, he discovers proof suggesting the market disruption was caused by forceful "order-sweeping" transactions instead of structural issues with ETFs. Order-sweeping trades are defined as massive transactions carried out simultaneously at the current price range instead of spreading out over a period of time in an effort to get the best price.

2.2.3 Liquidity mismatch

It's common to define liquidity simply as the capacity to trade without significantly changing the price of the underlying asset. Liquidity issues with ETFs can occur on multiple fronts. Liquidity in the main market refers to the ability of Authorized Participants (APs) to purchase actual assets and transfer them to the ETF issuer in exchange for shares in the fund, or vice versa. APs play a crucial part in modifying the number of ETF shares outstanding to take supply and demand into account, which frequently raises concerns about systemic risk if they were to stow away during a crisis.

However, other APs are very likely to give support if one AP stopped participating in a specific ETF. (Lettau and Madhavan, 2018.)

The secondary markets, or the places whereby units of ETFs are actually exchanged, are the subject of an additional set of worries. As was previously said, the amount of liquidity in the secondary market might be several times more than in the main market. In this regard, the secondary market liquidity of ETFs is typically higher than or equivalent to the liquidity of the underlying assets. The trading of ETF shares on secondary market exchanges has no direct impact on the trading of underlying stocks; rather, it reflects changes in the ETF's ownership. In simple terms, the existence of ETFs can somewhat boost financial market liquidity. This cushion is cumulative in terms of financial stability. (Lettau and Madhavan, 2018.)

2.2.4 Underlying market impacts

The impact of investing in indexes as a possible distorting factor on the value of underlying assets has been questioned by certain writers. The effects of the introduction of a benchmark or ETF are unclear from an academic standpoint. By employing index funds, individual investors can cut their own transaction costs when dealing with knowledgeable counterparties since these assets have lower informational asymmetry costs. (Kyle, 1985.)

Liquidity in the underlying equities may drop as traders relocate to the index fund market. Nevertheless, the development of a low-cost diversified index fund may provide new liquidity investors with a means of entering the marketplace that had been unable to do so because of expenses or other restraints. Concerns and discussions have shifted to the impact of indexing on stock market pricing, with some commentators predicting that the development of indexing will cause prices to diverge from value. Because index trackers are frequently based on market-cap weighting, it is possible that pricing defects in underlying shares may multiply. For example, the mechanical operation of index funds, which are price-taking mechanisms, perpetuates a bubble in technology businesses. (Lettau and Madhavan, 2018.)

2.3 Smart beta ETFs

Smart Beta ETFs use weighting methods which differentiate them from conventional market cap-based indexes, and their main motivation is to attempt to beat an overall portfolio by concentrating upon a few variables which are frequently associated with equity gains. The difference between conventional active and passive investment techniques is muddled by smart beta ETFs. These ETFs provide accessibility to risk characteristics that active mutual funds and hedge funds have historically exploited together with the fact that there is no active stock picking from portfolio managers because smart beta ETFs follow certain benchmarks in a straightforward and rule-driven manner. As a result, factor ETFs often have lower cost ratios than equivalent actively managed mutual funds and hedge funds. (Lettau & Madhavan 2018.)

The biggest and broadest market of strategic-beta Exchange-Traded-Products is located in the US. A grand total of 46% of all strategic-beta ETPs, or 88% of all worldwide assets, are traded on the U.S. market. Regarding the scale and level of development of the financial services and asset management sectors in the United States, that ought to not be surprising. In May 2000, the initial first group of strategic-beta ETPs entered the American market. The very first and one of the largest strategic-beta ETPs are the iShares Russell 1000 Growth ETF IWF and iShares Russell 1000 Value ETF. The funds in question constituted the original grouping of strategic beta, adding systematic style tilts to the investment products. (Morningstar, 2022.) As per this publication Morningstar prefers to refer smart beta as “strategic beta” and Exchange-Traded-Products include also other asset classes exploiting factor strategies such as fixed income and commodity ETFs.

Smart beta is theoretically based on a mix of concepts. It is unclear if the additional gains are the result of absorbing systematic factor risk or inefficiencies in the market.

Furthermore, there are additional issues concerning the origins of additional gains: whether they are attributable to the factors targeted, biases induced by a deviation from capitalization weighting, or rebalancing? According to several research, the additional profits of a variety of smart beta strategies are entirely explained by size and value characteristics. There also exists debate about how the balancing process, irrespective of component weightings, adds to excess returns. (Jacobs and Levy 2014.)

Smart beta is sometimes referred by the term passive investing since it employs clear selection by rules, with rebalancing at predefined periods, and fails to try to arrive at detailed projections of risk and return for individual stocks. However, deciding not to keep the basic broad market index fund is a proactive choice in and of itself. Smart beta methods need extra active judgments to determine the exact factor or factors to focus on, as well as to specify the factor or factors, the choice of target stock universe, the weighting mechanism, and the rebalancing criteria. (Jacobs and Levy 2014.)

This thesis provides information on some of the most well-known and most favored factors that smart beta products are trying to capture such as value, growth, momentum and multi factor strategies to name a few. To conclude some of the factors used in this analysis, the intention is to provide short explanations and some previous literature on them excluding multi factor and equal weight strategies since they are more or less went through in other ways.

For an extended period of time, professional investors, and academics have debated the idea that value strategies outperform the broad market. (Graham & Dodd 1934; Dreman 1977). Value stocks are defined by investment managers as firms with high book-to-market equity (B/M), earnings-to-price (E/P), or cash flow-to-price (C/P) ratios (Fama and French, 1998). Generally, investors looking to find value stocks aim to buy companies that are priced lower than their intrinsic value. According to Fama and French (1992), equities with greater earnings-to-price ratios provide better returns. Rosenberg, Reid, and Lanstein (1984) demonstrate that equities with high book compared to market equity values outperform the broader market.

In contrast to value stocks, growth stocks tend to have high stock price-to-fundamentals ratios, such as earnings, revenue, and book value (Lettau & Madhavan 2018). The wide understanding in academics and previous research has been that the value stocks outperform growth stocks. Contradictory to these scholars, Mohanram (2005), who adds different firm-specific variables including, such as earnings stability, growth stability, intensity of research and development, capital investments and advertising commitments, to measure growth stocks performance with combining traditional fundamentals like cash flows and earnings finds differing results. Despite the fact that the majority of the rewards come from the short side, a long-short strategy that buys high-growth stocks and sells low-growth stocks can provide significant excess returns.

The main principle behind momentum aims to profit off equities which are on a favorable trend. This pattern of behavior relies on previous development of stock prices, and the method is generally known as buying winners and selling losers. Historical prices should not be used to predict the movements of future stock prices based on the efficient market hypothesis weak form of efficiency. (Bodie et al. 2013). This momentum strategy of buying past winners and selling losers was heavily studied by Jegadeesh and Titman (1993) as they discovered substantial positive return for 3 to 12 months holding periods in the U.S. stock market during 1965 to 1989. They discover that the financial performance of these methods is not attributable to systematic risk or delayed stock price responses to prevalent factors. However, some of the anomalous gains obtained in the initial year after portfolio building faded away during the next two years. A comparable sequence of returns is observed following the earnings releases of previous winners and losers. Momentum factor was later added to Fama and French (2018) five-factor model as the most common asset pricing models, including FF5, failed to capture momentums positive effects on investment returns.

High-beta and high-volatility equities have historically lagged low-beta and low-volatility equities, contradictory to the usual concepts in finance. This paradox could be justified partially via the reality that the average professional investment manager's goal to outperform a predetermined benchmark inhibits arbitrage activities in both high-alpha and low-beta equities. They demonstrate that low risk consistently outperforms high risk, irrespective of whether the risk is characterized by beta or volatility. (Baker, Bradley and Wurgler 2011). Similarly, continuing with low-risk strategies, Walkshäusl (2014) studies the investing behavior, and co-movement of minimum-volatility, low-volatility, and low-beta strategies in foreign markets. The author provides evidence that these low-risk strategies usually have major over-weighting in non-cyclical companies in a specific industry, such as consumer staples and utilities sectors, which is the primary return driver of low-risk strategies. They conclude that these low-risk strategies are equally effective in global markets.

Asness, Frazzini & Pedersen (2019) define quality as attributes for which investors are prepared to pay premium. They propose valuation attributes which imply that the price of stocks should rise in terms of their qualitative characteristics such as profitability, growth, and safety. Evidence from empirical studies suggests that the average prices of high-quality equities are slightly higher. Overall, they conclude based on these attributes that high-quality equities produce excellent risk-adjusted returns which is why the portfolio should be built by buying the high-quality companies containing the previously mentioned characteristics and selling the lower quality junk stocks. This way the investor should obtain higher risk-adjusted returns.

The distribution of dividends is regarded as being amongst the most important financial decisions of companies, and dividend payments may impact the interest of shareholders as well as a company's future growth. Ever since the early 90s the growing popularity of ETFs has also gained traction to funds classified as dividend ETFs as related to high yields and stability in portfolios. (Chen, Dang and Kien, 2019.) The debate over whether empirical research has demonstrated a favorable association involving equity returns and dividend yields continues. Litzenberger and Ramaswamy (1982) explained there being a positive, non-linear link between dividend policy and equity returns. Naturally, substantial dividends are advantageous for shareholders since they provide a swift return, although modest dividend ratios can also be beneficial. According to Bodie et al. (2021), a company's rapid expansion may be indicated by low dividend payments because capital turnover associated with potential investments in high-potential projects yields high overall returns.

3 Efficient Markets

In 2013 the public saw the release of the research "Two Pillars of Asset Pricing" by economist Kenneth French and Eugene Fama. The authors give an empirical examination of asset pricing models and draw the following conclusion: Market risk and size are the two key variables that might account for the difference in average stock returns.

A market that accurately signals resource allocation through pricing is considered to be optimal. In other words, it should be a market where businesses can decide where to invest their money in terms of production and where investors can choose from a variety of securities that represent ownership in business operations, presuming that security prices always completely represent the information that is already available. A market is said to be efficient when its prices properly reflect all available information. (Fama, 1970)

Generally speaking, of market efficiency, it is widely accepted to assume that as new information on the market arises all market participants become aware of the news and therefore the information delivers to asset prices without delays. Continuing, neither technical nor fundamental analysis would be applicable to provide investors with abnormal returns compared to holding a randomly selected portfolio of stocks and holding them through time. (Malkiel, 2003.)

Around 120 years ago, Bachelier's hypothesis of asset values following the random walk process began the protracted and contentious study of effective capital markets. He introduced Brownian motion into the option pricing model, consequently incorporating mathematics into finance. Malkiel (1973) popularized the phrase "random walk hypothesis" in his book "A Random Walk Down Wall Street," and numerous scholars, including Fama, went on to enhance it. (1965, 1970). The most widely accepted theory on effective capital markets is based on Fama's research. For the theory to produce a viable potential for efficiency, it must make the following assumptions about how markets behave:

i. Zero transaction fees. This is required to ensure that no traders have an unfair advantage over others and that all traders have the same cost level.
ii. All market participants have unrestricted access to all the information.
iii. Market participants widely agree upon the impact of that knowledge on an asset's market price. This indicates that every valuation model considers the same data and delivers the same result.

When the above-mentioned requirements are met, the asset's current price accurately represents all the information. This must reflect reality correctly, and the markets have much more friction. This is hardly proof that markets could be more effective. Although not essential for market efficiency, the criteria i.–iii. are sufficient. Various investors place varying importance on different pieces of information. As a result, they do not all agree on how the new knowledge will affect the price of an asset. The main requirement is that no single investor should be able to estimate the value of an asset, outperform other investors in value approximations, and reap excess returns on others' accounts consistently and accurately. (Fama, 1970)

3.1 Three levels of efficiency

The efficiencies of the theory are divided into three information subsets by Fama (1970): First, tests with weak forms are provided, in which historical prices serve as the information set. The next stage is to look at semi-strong form testing to see if prices can really react to new information that is made public. (Such as releases of yearly earnings, stock splits, etc.). Widely known strong form tests are used to establish if investors or organizations have exclusive access to information that is critical when it comes to price development.

The weak form of market efficiency is conducted when the market reflects all available information. In low-efficiency markets, technical analysis is thus a waste of time. The goal of weak efficiency tests is to find serial correlation in asset returns. The theory of efficient market hypothesis is more or less connected to the theory of random walk, where consecutive price changes are random deviations from past prices. Therefore, as the information flow is unhampered it immediately affects the assets price. (Fama 1970).

When all accessible information about the assets, such as yearly reports, interim reports, and disclosures of new security problems, to name a few, is reflected in market pricing, in addition to knowledge about past returns of the assets, a semi-strong form of efficiency is attained. The conventional method for testing the semi-strong version of market efficiency is through event studies. Studies frequently focus on occurrences like stock splits and yearly earnings reports. Fama, Fisher, Jensen, and Roll in 1969 were the first academics to research the semi-strong form of market efficiency. They investigate whether stock split information is effectively integrated into stock prices and discover data that supports efficient market hypothesis.

Finally, there is a powerful version of market efficiency in which no investor has monopolistic access to any knowledge that might impact the price of an item. Insider trading does not provide enormous gains in a world of great efficiency. The personal profits made by specialized groups of individuals with monopolistic information access, such as management teams of publicly traded companies, have been submitted to market efficiency tests. The efficient market hypothesis fails at this level, according to the tests since investors with monopolistic access to knowledge have made excess profits. (Niederhofer & Osbourne, 1966; Fama, 1970.)

3.2 Efficient market hypothesis critique

This generally known theory is one of the most fundamental but divisive ideas in finance, as we have previously explained. A ton of research discovers serial correlations and non-randomness in stock prices, which relates to the concept that a stock's past performance predicts its future performance. According to Lo, Mamaysky, and Wang's (2000) research, traders' classic charting methods, like double-bottoms and head-and-shoulders, offer additional information and may be helpful across asset markets.

There are also a lot of controversial findings regarding technical trading strategies. Allen and Karjalainen (1999) train Using daily prices from 1928 to 1995, a genetic algorithm was used to learn technical trading rules for the S&P 500 index. During the out-of-sample test periods, the rules do not typically outperform a basic buy-and-hold strategy after transaction expenses. When the volatility is minimal and the daily returns are positive, the rules can determine when to include a period in the index and when to exclude it. Low-order serial correlation in stock index returns substantially explains these latter outcomes.

Similar findings have Ready (2002) who compares the technical trading guidelines created by Allen and Karjalainen (1999) with the moving average guidelines investigated by Brock, Lakonishok, and LeBaron (1992) to analyze the consistency of daily returns for Dow Jones Industrial Average. He contends that this comparison provides evidence in favor of the theory that data snooping caused the Brock et al. (1992) moving average rules' apparent effectiveness (after transaction costs). Investors and businesses alike would prefer to employ technical analysis if it were trustworthy to increase portfolio returns and better timing of security offers. His findings serve as a reminder that previous data trends, even though they seem quite consistent, might not hold going forward.

Jegadeesh (1993) and Chan et al. (1996), that show autocorrelation being good in medium time intervals are contrary to research by De Bondt and Thaler (1985) indicates that autocorrelation is unfavorable in extended durations. According to De Bondt et al., behavioral factors—the tendency for most individuals to respond to unexpected and major news—are to blame for the long-term price reversal. When Kahneman and Tversky released their well-known study on prospect theory in 1979, they first put out the argument suggesting investors aren't logical value maximizers, leading to over and underestimated reactions. Overreaction and underreaction on recent developments are widespread, according to Fama (1998).

There are several seasonal and day-of-the-week patterns in stock returns in addition to medium- and long-term autocorrelation. Thalers (1987) January effect is most likely the widely known phenomena behind this. The effect that asserts that the month of January has higher average monthly returns compared to other months of the year. The small stock universe was found to have robust evidence of this phenomenon. Malkiel (2003) contends that the January impact could be more consistent and reliable over time. Malkiel adds that because nonrandom and seasonal occurrences have a minimal economic impact, investors cannot make excess profits after trading expenses.

Efficient market theory is generally questioned and endorsed simultaneously, which has sparked an academic discussion and resulted in many studies with diverse findings. Schwert carried out an intriguing investigation in 2002. Once academic publications on several anomalies were published, he discovered that some had diminished or even disappeared. According to Schwert, the size and value effects in stock returns, momentum, and post-earnings announcement drift, among others, compared to what was stated in the original scholarly articles, are weaker. This implies that individuals that bring scholarly research-based investment ideas into action could benefit by the market oddity or render the market more efficient. As a result, markets are efficient to the point where obtaining persistent and scalable surplus profits is exceedingly difficult. There are brief abnormalities and random mispricing, but chronic and extensive anomalies are uncommon.

4 Earlier Literature

This chapter is devoted to presenting some earlier research on the well-known anomalies in the market, which later will be also presented in the asset pricing models used in this thesis to provide the results through regressions.

4.1 Low beta

Low beta or low risk, often known as defensive strategy, has a long history and has seen a comeback in recent years. The first impetus for defensive strategies came from Fischer Black, who noticed in 1972 that the security market line in US equities (the line connecting market beta to average returns) was too flat in comparison to what theory predicted. In other words, returns from high-risk investments were not as high as those from low-risk assets.

Frazzini and Pedersen's later studies (2011, 2014) have demonstrated that this pattern extends beyond stocks to a wide range of markets and asset classes. Stocks can be sorted according to their predicted betas, and positive risk-adjusted returns can be obtained by buying the stocks with the lowest betas and selling the ones with the highest betas. A portfolio maintains its market neutrality while capturing the fact that the lower-beta stocks deliver a greater risk-adjusted return than the higher-beta stocks by de-levering the higher-beta stocks to balance the short portfolio's beta with the long portfolio's beta.

Similar findings come from Walkshäus (2014) as he investigates the effectiveness, investing behavior, and co-movement of low-beta, low-volatility, and minimum-volatility strategies in global markets. First, the authors note that one of the primary, sector-specific return drivers of all low-risk strategies is the notable overweighting of non-cyclical equities from the consumer staples and utilities sectors relative to the market. Second, during the whole sample period, both before and after the recent financial crisis, minimum-volatility, low-volatility, and low-beta strategies generate similarly large and statistically significant CAPM and three-factor model alphas in the segments of established markets and emerging markets. Although low-risk methods could keep risk down, there was no notable outperformance throughout the crisis. Except for the European market, where they resemble growth strategies, all low-risk strategies have broad similarities with small-cap and value strategies. Third, low-volatility, low-beta, and minimum-volatility strategies typically display sizable and significant co-movements between and within markets. The authors do not discover strong evidence that one tactic consistently outperforms another. They conclude that low-beta, low-volatility, and minimum-volatility strategies are all helpful for taking part in low-risk investment globally.

Like value and momentum premiums, there are opposing arguments for why low beta equities outperform high beta equities in terms of returns. The most convincing explanation for the outperformance of low-risk equities, according to Asness et al. (2015), is that many investors are reluctant to use leverage or are restricted from doing so. Leverage restrictions force return-oriented investors to buy high beta equities to meet their targets, even though they might use leverage to buy low risk stocks and achieve comparable or superior risk-adjusted returns. As a result, investors who are ready to take the opposite tack and hold low beta stocks may benefit over the long term while market players with leverage restrictions reduce the potential returns of high beta equities.

4.2 Size

“It is found that smaller firms have had higher risk adjusted returns, on average, than larger firms” as Banz (1981) puts it and continues that this "size factor," which has been there for at least 40 years at the time of his writing, is proof that the capital asset pricing model is incorrectly defined. Although there is little variation in return between average-sized and large enterprises, the size effect is not linear in the market value; the main effect occurs for extremely small firms. It is unknown if size in and of itself causes the effect or if size is merely a proxy for one or more real, unknowable factors that are related to size. In their analyses, small stocks outperformed large stocks in terms of average returns, even after accounting for risk using CAPM. The joint assumption that the CAPM is accurate and that the market is efficient can therefore be viewed as being rejected because of their findings. Fama and French (1993) continued with the same direction and showed that factors related to size (market capitalization) together with market factor and book-to-market equity explain rather well average stock returns.

There have been conducted several studies to find reasoning on why the small cap stocks tend to outperform large cap stocks. Chan, Chen, and Hsieh (1985) conduct that small and large stocks respond differently to risk factors that are crucial for asset pricing. This perspective highlights that the differences in time series reactions between small and large stocks to changes in the underlying risk factor account for the risk differences between them. They determine that production risk and variations in the risk premium are more of a concern for smaller firms. Huberman, Kandel, and Karolyi (1987) discovered that returns of businesses within a given size range tended to react to risk variables similarly and moved collectively.

These studies have demonstrated that there are risk disparities between small and large companies, but they provide no recommendations as to why. Smallness does not automatically imply more risk, nor can disparities in market capitalization account for the divergent reactions of large and small enterprises to economic news.

Chan and Chen (1991) suggest that the smaller companies analyzed in the empirical literature are frequently what are known as marginal companies. They are inefficient manufacturers, have lost market value because of subpar performance, and are probably struggling with cash flow issues and significant financial leverage. They are marginal in that they are less likely to withstand challenging economic conditions and that their pricing tends to be more susceptible to changes in the economy. They create two size-matched return indices that are meant to replicate the return behavior of marginal companies, and they discover that these return indices are crucial for understanding the time-series return difference between large and small companies. Bhandari (1998) had same findings that common stock returns are positively correlated to the financial leverage when measured by debt/equity ratio. According to their evidence the "premium" associated with the debt/equity ratio is not likely to be just some kind of "risk premium".

Fama & French (1993, 1995) similarly make the connection between size and profitability, explaining why small cap stocks typically have lower earnings per share. They add a requirement that if markets are rational, factors must work as proxies for risk, but they do not insist that this is the case.

4.3 Value

There have been for years widely accepted arguments amongst scholars and investment professionals that value strategies generally outperform the broad market. Research from Lakonishok, Shleifer and Vishny (1994) shows evidence that value strategies yield higher returns mainly because the strategies take advantage of the typical investors' suboptimal behavior. Not because the value strategies are fundamentally riskier than other strategies. While there is consensus that value strategies deliver higher returns, there is still significant disagreement about how to interpret this phenomenon. The value investing strategies advise purchasing shares of companies whose prices are low as compared to their earnings, dividends, book value, or other indicators of fundamental value.

While some individuals might erroneously believe that value investing is a method for finding bargains it is actually a thorough investment philosophy that emphasizes the need to do in-depth fundamental analysis, target long-term investment results, control risk, and avoid following the herd. (Graham and Todd, 1934) Even though value investing has been studied by academics' decades, it has also more recently gained academics attention. Some argue that stocks with high E/P ratios earn higher returns while extreme losers outperform the market over the subsequent several years. Others show that that stocks with high book relative to market values of equity outperform the market. (See e.g., Basu (1977), Jaffe, Keim, and Westerfield (1989), Chan, Hamao, and Lakonishok (1991), and Fama and French (1992), De Bondt and Thaler (1985, 1987), Rosenberg, Reid, and Lanstein (1984)).

Even though most of the early research conducted on value investing has been based on experimenting the U.S equity market, Fama and French (1998) find the value premium to be found also in international markets and Chan, Hamao and Lakanishok (1991) find the same value premium performing in Japanese stock market. Asness, Moskowitz and Pedersen (2013) have similar findings as per their results that there is a persistent value premia across diverse markets and asset classes.

The performance of value premium has also been widely documented in Nordic stock markets. Firstly, in 2014 Cakici and Tan investigate value premium together with momentum in 23 developed international stock markets and find over performance for value strategies in all Nordic countries except Sweden. Grobys and Huhta-Halkola (2019) also found value premium when using average ranking approach for the value and momentum strategy in the Nordic equity market. In their sample period spanning from 1993 to 207 the value anomaly showed excess returns when small stocks were part of the portfolio. Leivo and Pätäri in their 2009 paper examine the performance of various value strategies in the Finnish stock market during the 1993-2008 period with different value ratios (i.e., E/P, EBITDA/EV, CF/P, D/P, B/P, and S/P). Their results are consistent with the previous research and show that the value premium in the Finnish stock market is well supported by all of the performance tests used and cannot be explained by risk or size effect. Most of the value portfolios under examination perform much better than both the market portfolio and comparable glamour portfolios. The outcomes further demonstrate that by basing portfolio selection criteria on composite value measures, the risk-adjusted performance of value portfolios can be improved. Using long-short strategies that capitalize on value premium, the performance could be further enhanced.

4.4 Profitability

Profitability, defined using gross profits-to-assets, predicts the distribution of average returns with nearly identical accuracy as book-to-market, supplying economically significant insight beyond what is provided in values. Although possessing smaller book-to-market ratios and greater market capitalizations, profitable companies earn substantially greater average returns than unprofitable enterprises. (Novy-Marx, 2010.) Contradictory to these findings is Fama and French (1993; 2006) who say that profitability contributes very little to the forecast of returns offered by size and book-to-market. The distinction with Novy-Marx (2010) is that profitability within this context refers to gross profits rather than earnings. The term meaning of gross profitability is being referred to as being the other side of value. Although being growth strategies which offer great protection against value, approaches centered around gross profitability offer similar average excess return like value does. Since both of these impacts are so closely intertwined, it can be helpful to consider profitability in terms of value.

Considering these findings, according to Berk (1995) the profitability of value strategies is implied to be purely mechanical. Generally, companies that are required to generate higher rates of return due to investors' demand of cost of capital are priced lower. These companies can be seen as riskier companies. According to a comparable premise, companies possessing productive resources ought to earn greater average returns versus companies with unproductive resources. Efficient businesses for which investors insist excellent returns on investment ought to be valued comparably to less efficient businesses with lower returns on investment. Variance in productivity therefore aids in identifying variance between the investors' required returns. Profitable businesses create greater earnings than unprofitable businesses since efficiency allows for this variance, with better profitability suggesting higher necessary rates. (Novy-Marx, 2010.)

There is some variety in which accounting measures are applicable and shows the true economic profitability of a firm. Novy-Marx (2010) disputes gross profitability's goodness as the most adequate measure and states that the farther on income statement one goes the more contaminated, they become and therefore are less adequate to measure economic profitability. He adds the question ultimately being empirical while also considering profitability measures by earnings and free cashflows as earnings are popularly consumed by financial media as financial economists are more concerned on free cashflows. The author concludes these three measures by valuing gross profits-to-assets highest as essentially this profitability metric also anticipates earnings and cash flow long term.

While Novy-Marx preferred the gross profitability measure there have been advocates for other measures such as ROE, operating profitability and cash profitability which have also showed robust results. Fama and French in their 2018 paper use cash profitability versus operating profitability as the variable to six-factor models profitability factors. In this paper the six-factor model using cash profitability produces higher average returns than the comparable model which uses operating profitability.

Hanauer and Huber (2018) add to the existing literature by investigating if the most commonly used international asset pricing models could be improved by adding the profitability factor to the ones that do not already contain it. Or if the model containing the profitability factor could be improved by changing the underlying measure of profitability. Their results show that there is considerable proof suggesting the impact of profitability factor is present in all global markets, since the included definitions of profitability other than ROE are effectively priced outside of the United States. Same as Fama and French (2018) the authors find cash-based gross profitability being the leading profitability factor in developed and emerging markets as well as Japan and APAC region (excluding Japan). Europe is the only region where cash-based operating profitability shows better performance compared to gross profitability. Furthermore, across the majority of developed and emerging market countries, the cash-based profitability factor demonstrates positive average returns and alphas. Since accrued expenses unfavorably anticipate future earnings, Hanauer and Huber concluded that the impact of profitability factor presents a broad and international occurrence and therefore cash-based gross profitability should replace the operating profitability measure used in the Fama-French five-factor model definition.

4.5 Investment

It is clearly shown in the literature that low-investment companies beat high-investment companies across time and long term. As a result of this discovery, the investment component (CMA, or cautious minus aggressive) was integrated into the dominant asset pricing models. Hou, Xue and Zhang (2014) show that companies with lower discount rates (lower capital expenses and consequently lower expected returns) spend more. Companies that have higher discount rates, meaning higher cost of capital and higher expected returns, face difficulties with future investments and therefore invest less. By this explanation, authors imply that the investment factor anticipates future returns since higher capital costs entail lower NPV of fresh capital and low investment and vice versa. Therefore, all else being equal, companies that spend more should earn lower expected returns than firms that invest less.

Fama and French have same implications in their 2015 paper that companies with high profitability factor usually have lower rates of investments and vice versa. They see that this link reflects the different investment opportunities between companies. To follow, higher profitability companies tend to attract investment opportunities with higher profit potential and therefore do not require sizeable investments for future growth. Also, the profitability factor has a positive correlation with expected average returns even after adjusting for other popular factors such as size, value, and momentum. This will eventually drive towards the implication that investors are rewarded for investing in a profitable company that has also other competitive advantages such as credible management, ability to innovate or otherwise good positioning in the market compared to competitors. The authors also used recent asset growth as reliable proxy for future investment even though it is harder to forecast.

Continuing the valuation theory that expected investment ought to be negatively related to expected earnings, Rizova and Saito (2020) show that recent growth in company’s assets is a systematic proxy for firms investments in the future. They find a negative investment effect throughout developed and emerging markets and across sectors. The effect is substantially larger in small caps than in large caps, and it is mostly driven by the underperformance of firms that have high investments.

Most recently, contradictory findings show Cakici and Zaremba (2021) who review the Fama-French (2015) five-factor models factors' performance in international markets. The findings offer strong proof that the value, profitability, and investment variables are considerably less trustworthy than previously believed. Their effectiveness is highly influenced by the area and time frame under study. In addition, the smallest companies are responsible for the majority of factor returns. The large companies that make up the majority of global market capitalization have almost little value or investment benefits. These results raise questions about the five-factor model's relevance in global markets because the smallest companies are often not invested in by big financial institutions because of the funds size restrictions.

5 Traditional Asset Pricing Models

Shortly presenting the most well-known and widely accepted asset pricing models dating all the way from Sharpe (1964) and Lintners (1965) CAPM to Fama and French three (1992) and five-factor models (FF, 2014).

5.1 Capital asset pricing model (CAPM)

Academics and practitioners have long used the Sharpe (1964) and Lintner (1965) asset pricing models to guide their thinking on average returns and risk. The foundation of CAPM is a theory of market equilibrium for asset pricing under difficult circumstances. The key outcome of the model entails that the market portfolio of invested money is mean-variance efficient to the degree of Markowitz's portfolio theory from 1952. A single-component model called CAPM calculates an asset's necessary rate of return. The CAPM formula is frequently represented below:

$$E(R_i) = R_f + \beta_i \left[E(R_m) - R_f \right] \tag{1}$$

where $E(R_i)$ represents the anticipated return on asset i, R_f is the risk-free rate of return, β_i is the beta of asset i, and $E(R_m)$ is the market portfolio's projected return. In short, the CAPM suggests that the sensitivity of an asset to shifts in economic activity, which is frequently referred to as systemic risk, may be utilized to compute its expected return. The sloping variable of an asset's return regressed on market returns is used to determine an asset's systematic risk. This suggests that more significant returns are anticipated for assets with a higher correlation to economic activity, such as high-beta stocks. Consequently, it is anticipated that assets unaffected by economic activity, such as low-beta equities, will have lower returns. (Sharpe, 1964; Lintner, 1965)

5.2 Three-factor model

Eugene Fama and Kenneth French believed that the asset pricing ought to be multidimensional depending on a number of proven factors. Whereas the CAPM model covers market risk or systematic risk, the Fama-French three-factor model adds company attributes as proxy to the CAPM. The CAPM, on the other hand, is a single component model. Fama and French (1992) merged the three distinct factors into a single model, the Fama-French Three Factor Model. They noticed that integrating size and value factors boosted the market component model's explanatory power as compared to any previous factor model, like the Capital Asset Pricing Model (CAPM), that prevailed the asset pricing theory but created substantial anomalies. (Fama and French, 1993)

Despite Sharpe and Lintner laying the foundations of asset pricing, Fama and French (1992) find numerous empirical inconsistencies of the model. The size effect of Banz (1981) is the most noticeable. He demonstrates that the equity value, (the price of a stock multiplied by the number of shares outstanding), contributes to the interpretation of the cross-section of average returns, which are provided by market β. According to their β estimations, average returns on small (low equity value) stocks are too high, while average returns on large stocks are too low.

The SLB model's positive relationship between leverage and average return, as Bhandari (1988) has demonstrated, is another inconsistency. It is conceivable that risk and expected return are correlated with leverage, but in the SLB model, leverage risk should be captured by market β. However, Bhandari discovers that in tests that in addition to β involve size (ME), leverage assists in the explanation of the cross-section of average stock returns.

The ratio of a firm’s book value of common equity, BE, to its market value, ME, is found to be positively connected to average returns on U.S. stocks by Stattman (1980) and Rosenberg, Reid, and Lanstein (1985). According to Chan, Hamao, and Lakonishok (1991), book-to-market equity, commonly known as BE/ME, plays a significant part in explaining the distribution of average returns on Japanese stocks. In tests that also take size and market β into account, Basu (1983) demonstrates that earnings-price ratios (E/P) contribute to the explanation of the cross-section of average returns on U.S. stocks.

Fama and French (1992) argued that when assets are valued in a rational manner stock risks are multidimensional, which may explain CAPM's inability to explain stock anticipated returns. This conclusion was based on the previously discussed empirical differences. According to Fama and French (1993), size and B/M must be used as proxies for the sensitivity of returns to common and unvarying risk variables. As a result of this approach, they created their renowned three factor model in 1993. The model includes two extra risk factors to the market derived from the CAPM: size and B/M (value) components. Returns or excess returns of zero cost portfolios were built by holding a long position in small stocks and short position in large stocks, as well as long companies with high B/M and short companies with low B/M. As a result, the variables are frequently referred to as small minus big (SMB) and high minus low (HML). The projected excess return of portfolio i, as predicted by the three-factor model, is:

$$E(R_i) - R_f = \beta_i\left[E(R_m) - R_f\right] + s_i E(SMB) + h_i E(HML) \tag{2}$$

where, $E(R_m) - R_f$, $E(SMB)$, and $E(HML)$ are expected premiums. The factor sensitivities β_i, s_i, and h_i, are the slopes in the time-series regression. According to the model, the expected portfolio return that is higher than the risk-free rate $E(R_i) - R_f$ is accounted for by the return's sensitivity to three variables:

i. The excess return on a broad market portfolio $(R_m - R_f)$
ii. The difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (SMB, small minus big)
iii. The difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks (HML, high minus low).

According to Fama and French (1995), book-to-market equity and slopes on HML serve as a proxy for relative distress. Strong firms with consistently high earnings have low BE/ME and negative slopes on HML, while weak firms with consistently poor earnings typically have high BE/ME and positive slopes on HML.

5.3 Five-factor model

In relation to earlier studies, Novy-Marx in 2013 argues that even though earnings have explanatory power, when predicting the cross section of average returns, profitability, as determined by the ratio of a company's gross earnings to its assets, has nearly the same predictive capacity as book-to-market (B/M). Even among the biggest, most liquid stocks, gross profits-to-assets complements book-to-market by adding economically meaningful information above that provided by valuations. These findings diverge from those of past research.

As the evidence now available implies the three-factor model of Fama and French fails to adequately account for most of the variation in average returns associated with profitability and investment, which prompted them to look at a model that adds profitability and investment factors to the market, size, and B/M elements of the three-factor model (FF, 1993).

The three-factor model of Fama and French is outperformed by the five-factor model that aims to capture the size, value, profitability, and investment patterns in average stock returns (FF, 1993). The primary flaw in the five-factor model is its inability to account for the low average returns on small stocks, whose returns behave like those of companies with high investment levels but low profitability. The model's performance does not depend on how the factors are defined. The value element of the three-factor model is no longer necessary for describing average returns after profitability and investment variables are included (FF, 2014).

Motivated by the findings of other research Fama and French (2015) add profitability and investment factors to the three-factor model:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \quad (3)$$

According to the model, the sensitivity of a portfolio's returns to five factors—market, size, value, profitability, and investment—explains the predicted excess returns on that portfolio. The difference between the returns of a portfolio of stocks with high profitability and those with low profitability (RMW, robust minus weak) is used to measure the profitability factor. The difference between the returns of a portfolio of stocks with low investment versus those with high investment (CMA, conservative versus aggressive), on the other hand, is used to measure investment factor.

6 Data and Methodology

In the following chapter discussion turns to the data gathered for the characteristics and performance of particular ETFs. The research hypothesis that was first presented in chapter one is examined using the findings. In this chapter, the broad description of data and its attributes is expanded upon. This section explains the reasoning behind the selection of a certain sample of ETFs.

Although previous chapters introduce the methodology for gathering data on ETF performances, new methods are also discussed later in this chapter. The price development of the ETFs has been gathered from Bloomberg, and the explanatory variables for the regression analysis from the Kenneth R. French database. Depending on when ETFs were first introduced to the market, different sample periods for computations were used in this thesis. Since some ETFs are still relatively new to the market, sample times may differ from one another.

Factor	*Explanation*
Value	Stocks discounted relative to their fundamentals
Minimum volatility	Stable, lower risk stocks
Quality	Financially healthy companies
Style	Smaller, high-growth companies
Momentum	Income incentive to hold riskier securities
Multi Factor	Combining variety of single factors
Growth	Stocks expected to grow above the market average
Dividend	Stocks offering regular cash income to shareholders

Table 3. Factor groups and definitions (Blackrock 2022).

6.1 Data description

The performances of the Smart Beta ETFs and factor regressions are the primary subjects of this research. Data sample is formed from ETFs that invest in broadly defined factors studied in the academic literature. The ETFs discussed have been gathered from VettaFi ETF database. The returns and NAV calculations are limited to contain data until 31/1/2023 as per the same time region is available on Kenneth R. French database for regressions explanatory variables. The selection has been narrowed to contain only U.S listed equity ETFs and the categorization to each Smart Beta category has been conducted based on Bloomberg data as well as the return data. All factor categories examined in the paper can also be found from Glushkov (2015) research which has been used as base research in this example.

Table 4 below showcases the top 20 largest domestic equity smart beta exchange-traded funds (as of Jan 31, 2023) measured by total assets under management. Along with the 5-year return and fun flow as well as inception date, expense ratio and number of holdings. As we can see the top largest funds hold extensively more assets compared to the latter part of the list. They also have reasonably low expense ratios. As previously noted, the investor has a deep diversification inside the fund when examining the number of holdings.

ETF Name	Total Assets	5 Year Return	5 Year FF	Inception	ER	# of Holdings
Vanguard Value ETF	$98 231 400 000	42,43%	$47 965 121 941	2004-01-26	0,04%	345
Vanguard Growth ETF	$74 389 000 000	62,72%	$20 060 769 637	2004-01-26	0,04%	254
Vanguard Dividend Appreciation ETF	$62 213 800 000	56,78%	$17 842 157 778	2006-04-21	0,06%	291
iShares Russell 1000 Growth ETF	$59 158 200 000	67,71%	$ -8 247 502 547	2000-05-22	0,18%	513
iShares Russell 1000 Value ETF	$49 506 400 000	32,27%	$ 4 244 638 127	2000-05-22	0,18%	853
Vanguard High Dividend Yield Index ETF	$47 228 300 000	40,19%	$21 291 627 226	2006-11-10	0,06%	442
Schwab US Dividend Equity ETF	$44 680 800 000	65,59%	$31 893 494 618	2011-10-20	0,06%	101
Invesco S&P 500® Equal Weight ETF	$33 895 500 000	47,87%	$15 188 043 830	2003-04-24	0,20%	503
iShares S&P 500 Growth ETF	$28 210 600 000	55,74%	$ -3 989 966 274	2000-05-22	0,18%	229
iShares MSCI USA Min Vol Factor ETF	$27 572 500 000	44,02%	$ 6 122 334 741	2011-10-18	0,15%	166
iShares S&P 500 Value ETF	$24 358 100 000	44,33%	$ 4 776 807 701	2000-05-22	0,18%	406
Vanguard Small Cap Value ETF	$23 781 900 000	27,54%	$ 7 544 062 608	2004-01-26	0,07%	860
iShares Core Dividend Growth ETF	$22 744 700 000	54,12%	$15 956 414 712	2014-06-10	0,08%	448
SPDR S&P Dividend ETF	$22 307 300 000	48,10%	$ 2 510 025 797	2005-11-08	0,35%	123
iShares Select Dividend ETF	$21 508 000 000	40,18%	$ -941 663 786	2003-11-03	0,38%	98
iShares ESG Aware MSCI USA ETF	$19 000 300 000	53,96%	$17 670 141 078	2016-12-01	0,15%	319
iShares MSCI USA Quality Factor ETF	$18 165 400 000	49,13%	$ 8 140 554 041	2013-07-18	0,15%	126
iShares MSCI EAFE Value ETF	$15 865 800 000	1,31%	$10 242 329 440	2005-08-01	0,35%	484
Vanguard Mid-Cap Value ETF	$15 453 200 000	28,97%	$ 5 213 254 669	2006-08-17	0,07%	197

Table 4. Top 20 largest ETFs

6.2 Benchmark

The core objective of the thesis seeks to assess the returns of Smart Beta ETFs to the lowest available passive capitalization-weighted options, including broad-based market and classic style-based value/growth benchmarks. The broad market benchmark portfolio consists of the following four ETFs: S&P500 ETFs, consisting of SPDR S&P500 ETF TRUST, iShares Core S&P 500 ETF, SPDR Portfolio S&P 500 ETF and Vanguard S&P 500 Index ETF

When evaluating the performance of Smart-Beta ETFs used in this research we need to compare the results in a predetermined portfolio of relevant benchmark ETFs. According to Cremers, Petajistö, and Zitzewitz (2012), an inadequate selection of the benchmark might result in skewed results. Certain research studies employ Fama and French three-factor model or Carhart four-factor model as benchmark, however these may end up in substantial negative alphas for passive indexes. To assess the success of mutual funds and ETFs, practitioners frequently employ a simple benchmark index. To evaluate the performance of Smart-Beta ETFs, an appropriate benchmark should be a passively managed portfolio of ETFs with comparable risk exposures. (Cremers et al., 2012).

As a result, this research examines the performance of selected Smart-Beta ETF portfolios with four different S&P500 equity ETFs that represent the benchmark market index. The thesis focus group being U.S domiciled equity ETFs, the corresponding benchmark portfolio of ETFs is comparable to the ETFs being studied based on the attributions mentioned. They are not synthetic, and all were issued in the United States. However, the time period might differ between factor tilt portfolio groups.

6.3 Descriptive statistics

This thesis uses a sample of 399 US-domiciled Smart Beta ETFs which target both domestic US markets as well as foreign markets. The main objective of the study being the relative performance of the assigned smart beta category portfolios compared to the portfolio of four broad-market benchmark ETFs.

The descriptive data for the monthly returns of each smart beta portfolio in the empirical section from their respective start date sample period ending January 2023 are shown in Table 5. The SPDR S&P500 ETF TRUST, iShares Core S&P 500 ETF, SPDR Portfolio S&P 500 ETF, and Vanguard S&P 500 Index ETF comprise the S&P500 ETF portfolio. Finally, the remaining portfolios will be used to evaluate the performance of various smart beta factor methods. Every month, all portfolios are similarly weighed, and returns are balanced. The smart beta portfolio is an ETF market cap-weighted portfolio comprising all ETFs classified as smart beta.

Portfolio	# of ETFs	Min	Max	Mean	Median	St.Dev	Kurtosis	Skewness
S&P 500 ETF Portfolio	**4**	-0,1606	0,1242	0,0042	0,0090	0,0437	0,7800	-0,4934
Value	**52**	-0,2115	0,1804	0,0055	0,0115	0,0491	2,7961	-0,6129
Quality	**22**	-0,1828	0,1137	0,0046	0,0110	0,0478	1,2705	-0,6634
Multi factor	**127**	-0,2055	0,1405	0,0066	0,0117	0,0475	2,7294	-0,7029
Momentum	**17**	-0,2128	0,1433	0,0075	0,0147	0,0530	2,0663	-0,8063
Low/Min Vol/Variance	**23**	-0,1540	0,1023	0,0057	0,0089	0,0352	2,8649	-0,7937
Growth	**47**	-0,1974	0,1445	0,0063	0,0112	0,0526	1,0358	-0,5914
Equal Weight	**38**	-0,2039	0,1528	0,0060	0,0108	0,0491	2,8038	-0,6828
Dividend	**73**	-0,1919	0,1405	0,0028	0,0072	0,0447	3,2843	-0,7906

Table 5. Descriptive statistics

From table 5 we can see that seven out of the eight smart beta categories have higher mean return while six out of eight have a better median return on the sample period compared to the S&P 500 benchmark portfolio. Momentum had the best mean and median returns over the full sample period. However, this return does not come without the cost of risk shown here with the highest standard deviation. The dividend category had the worst risk-return trade-off, which we can also see from the regression results. This is slightly concerning considering the category is amongst the most popular within investors according to fund flows.

7 Results

Based on backtested track record, several smart beta providers assert that their techniques consistently outperform the market. One thing this thesis tries to prove is that are these strategies really that "smart"? There is a lot of evidence in the literature to suggest that elements other than the beta component of the Capital Asset Pricing Model are important. However, there is little evidence to back up the claims that excess returns can be consistently and simply collected using a straightforward factor-based method or that they are actually "excess" given the potential risk they carry. (Jacobs & Levy 2014).

The results of the empirical models and data mentioned in the previous chapter will be presented in this chapter. To begin, the chapter compares the performance of different strategy Smart-beta ETFs to the benchmark ETF group across various empirical models and time periods. Finally, the chapter shows results from various screening methods and Smart-beta factors in ETF investment decision making to determine which attributes are driving the results. The inception date refers to the specific smart beta category's first available ETF return. From the inception date onwards the monthly return attributes grow rather quickly and the number of ETFs in the category is the number of ETFs in the last monthly return measured as of Jan 31st, 2023. The Low/Min Vol/Variance smart beta category has same results on half period as the full period since the first portfolio ETF returns are dated from June 2011.

The thesis presents the results from the different asset pricing methods previously described in the following order: CAPM, Fama and French three-factor model, Fama and French five-factor model. After that we also go through results after controlling for the fund fees. The five-factor model is considered as the foundational asset pricing method in this thesis. For presentational considerations, all alphas are annualized and given as a percentage as in previous comparable research. The significance level is indicated by stars next to the numbers as follows: *** at the 1% level, ** at the 5% level, and * at the

10% level. All the result tables in this study's analysis show the significance levels in a consistent manner. Under the alphas, in the brackets, are the t-ratios.

7.1 Results from the CAPM

Portfolio	Full Period Since Inception	Half Period 01/01/2010	Last 3 Years 1/2020 - 1/2023	Inception date
Benchmark	-1,25** -[2,09]	-0,34 -[0,49]	-0,39 -[0,27]	29/02/2000
Value	0,04 [0,03]	-1,93 -[1,07]	-2,43 -[0,46]	30/06/2000
Quality	-3,25** -[2,04]	-1,93 -[1,18]	-3,36 -[1,15]	31/01/2006
Multi Factor	-1,07 -[0,90]	-1,17 -[0,85]	-2,11 -[0,69]	28/02/2005
Momentum	-0,62 -[0,37]	-0,80 -[0,43]	-0,60 -[0,18]	30/11/2006
Low/Min Vol/Variance	-1,63 -[1,03]	-1,63 -[1,03]	-3,28 -[0,91]	30/06/2011
Growth	0,28 [0,23]	0,96 [0,67]	-1,61 -[0,81]	30/06/2000
Equal Weight	-2,85* -[1,90]	-1,68 -[0,95]	-2,04 -[0,50]	30/05/2003
Dividend	-5,00*** -[3,11]	-3,14 -[1,63]	-5,41 -[1,07]	30/09/2003

Table 6. Regression results from CAPM

From table 6 we can see that only growth and value factors show positive alphas in the full sample period while all the other smart beta strategies generate negative alphas, including the broad market S&P 500 benchmark portfolio. Despite being positive the alphas generated by growth and value are low numbers as 0.28% and 0.04% respectively. However, the t-statistics from those two categories do not show significance on any level.

The broad market S&P 500 benchmark portfolio shows a negative 1.25% alpha. Also, the multi factor and momentum strategies outperform the assigned benchmark portfolio generating less negative alpha of -1.07% and -0.62% respectively. No statistical significance on these two categories. The worst performer strategy was the dividend group with a negative 5% return over the full sample period with a statistical significance level of 1%. Glushkov (2015) also find dividend-oriented ETFs to be the worst performer although being the most popular the most popular SB category both in terms of managed AUM and investor flows.

Accordingly, the CAPM suggests that value, growth, multi-factor, and momentum smart beta strategies outperform the used S&P 500 broad market benchmark portfolio, with only the first two categories having a positive alpha on the full sample period and the latter two having less negative alphas. Moreover, the results from value and growth strategies are even more relevant as per the inception date; the sample has the same number of observations as the benchmark portfolio.

Narrowing down the sample period to more or less post-financial crisis period starting from January 2010, we find the benchmark portfolio outperforming all the smart beta categories except growth which is a major outperformer from this group with a positive alpha of 0.96%. Overall, the post-crisis decade has been considered a favorable operating environment for growth stocks with nimble technology-driven business models, extraordinarily good liquidity conditions, and low rates—no statistical significance in these results.

Considering the last three years as a post covid era, we can see now all the categories performing worse than the benchmark portfolio and all having negative alphas with no statistical significance. As liquidity tightens and rates rise, growth is not performing so well anymore. Throughout the results, momentum remained relatively stable, while the dividend was the worst performer.

These regression results from CAPM imply that null hypothesis holds and cannot be rejected as there is no consistency on the strategies to provide statistically significant and positive alpha compared to the benchmark portfolio. However, as per the alternative hypothesis, growth strategy is able to provide positive alpha on full and half sample period although not being statistically significant.

Portfolio	# of ETFs	Alpha	Beta	R2	Std. Error
Benchmark	4	-1,25**	0,92***	0,982	0,008
		-[2,09]	*[86,37]*		
Value	52	0,04	0,97***	0,913	0,020
		[0,03]	*[36,86]*		
Quality	22	-3,25**	0,95***	0,920	0,019
		-[2,04]	*[33,45]*		
Multi Factor	127	-1,07	0,99***	0,953	0,014
		-[0,90]	*[45,84]*		
Momentum	17	-0,62	1,04***	0,932	0,019
		-[0,37]	*[35,86]*		
Low/Min Vol/Variance	23	-1,63	0,72***	0,903	0,015
		-[1,03]	*[24,65]*		
Growth	47	0,28	1,08***	0,951	0,016
		[0,23]	*[50,67]*		
Equal Weight	38	-2,85*	1,03***	0,923	0,019
		-[1,90]	*[36,77]*		
Dividend	73	-5,00***	0,90***	0,893	0,020
		-[3,11]	*[30,22]*		

Table 7. CAPM factor loadings for the full sample period.

The complete CAPM regression findings for the whole sample period are shown in table 7. Since the factor loadings are consistent across all models, only the chapter on the five-factor model discusses them.

7.2 Results from the three-factor model

Portfolio	Full Period Since Inception	Half Period 01/01/2010	Last 3 Years 1/2020 - 1/2023	Inception date
Benchmark	**-1,09****	**-0,65**	**-0,26**	29/02/2000
	-[1,97]	*-[1,08]*	*-[0,26]*	
Value	**-1,33**	**-0,98**	**-4,37****	30/06/2000
	-[1,38]	*-[0,75]*	*-[2,24]*	
Quality	**-1,93**	**-1,93**	**-3,79**	31/01/2006
	-[1,18]	*-[1,18]*	*-[1,50]*	
Multi Factor	**-0,75**	**-0,67**	**-3,12***	28/02/2005
	-[0,67]	*-[0,52]*	*-[1,74]*	
Momentum	**-0,55**	**-0,27**	**-1,34**	30/11/2006
	-[0,35]	*-[0,16]*	*-[0,50]*	
Low/Min Vol/Variance	**-1,78**	**-1,78**	**-4,20***	30/06/2011
	-[1,21]	*-[1,21]*	*-[1,76]*	
Growth	**0,38**	**1,05**	**-1,39**	30/06/2000
	[0,38]	*[0,82]*	*-[0,96]*	
Equal Weight	**-2,73***	**-1,01**	**-3,50***	30/05/2003
	-[1,86]	*-[0,63]*	*-[1,90]*	
Dividend	**-4,85*****	**-2,92**	**-6,93****	30/09/2003
	-[3,33]	*-[1,65]*	*-[2,46]*	

Table 8. Regression results from the three-factor model

As we now discuss the findings from the Fama and French three-factor model we can already see similarities with the previous findings from CAPM. From table 8 we can see that on full sample period growth is now the only smart beta category providing positive alpha of 0.38% with no statistical significance. On the CAPM, value also had positive alpha (0.04%) but this time with three-factor model alpha is negative (-1.33%). While growth has the only positive alpha value, multi factor and momentum strategies outperform the benchmark portfolio by having less negative alpha values of -0.75% and -0.55% respectively as the S&P 500 benchmark portfolio generated a negative -1.09% alpha value. No statistical significance in these smart beta portfolio values except the benchmark portfolio having statistical significance on 5% level. Similarly, to CAPM the worst performer was again the dividend category with a negative -4.85% alpha on a 1% statistical significance level. Glushkov (2015) also finds dividend-oriented ETFs to be the worst performer although being the most popular SB category both in terms of managed AUM and investor flows. Overall, the categories perform slightly poorer compared to CAPM model as we add more explanatory variables to arrive at the three-factor model.

Accordingly, the three-factor model suggests that growth, multi-factor, and momentum smart beta strategies outperform the used S&P 500 broad market benchmark portfolio, while only the growth portfolio having a positive alpha on the full sample period and the latter two having less negative alphas compared to benchmark portfolio. Moreover, the results from value and growth strategies are even more relevant as per the inception date; the sample has the same number of observations as the benchmark portfolio.

With the half sample period starting from January 2010, we find the growth portfolio performing exceptionally well compared to other groups with the only positive value in this table generating 1.05% alpha. Momentum was the second strategy outperforming the benchmark portfolio with a less negative alpha of -0.27% while the benchmark portfolio had a negative alpha of -0.65%. Overall, the post-crisis decade has been considered a favorable operating environment for growth stocks with nimble technology-driven business models, extraordinarily good liquidity conditions, and low rates—no statistical significance in these results. Adding explanatory variables to the asset pricing models seems to be generating better results on the best performing smart beta strategy.

With the post covid time period the benchmark portfolio is now outperforming the smart beta portfolios with a less negative alpha of -0.26%. Growth has now suddenly performed way worse than in the previous sample periods, having a negative alpha value of -1.39%. Since the macroeconomic environment has rapidly changed and as a result of tightening liquidity conditions and interest rate rises, growth is not performing so well anymore, and the broad market benchmark portfolio seems to be weathering the storm.

These regression results from the three-factor model imply that null hypothesis hold and cannot be rejected as there is no consistency on the strategies to provide statistically significant and positive alpha compared to the benchmark portfolio. However, as per the alternative hypothesis, growth strategy is able to provide positive alpha on full and half sample period although not being statistically significant. Momentum is another strategy that can provide less negative alpha compared to passive benchmark portfolio on full and half sample period although not statistically significant.

Portfolio	# of ETFs	Alpha	Beta	SMB	HML	R2	Std. Error
Benchmark	4	-1,09**	0,95***	-0,13***	0,01	0,985	0,007
		-[1,97]	*[91,32]*	*-[7,14]*	*[0,53]*		
Value	52	-1,33	0,94***	0,17***	0,44***	0,964	0,013
		-[1,38]	*[51,79]*	*[5,40]*	*[18,58]*		
Quality	22	-1,93	0,91***	-0,04	0,04	0,926	0,017
		-[1,18]	*[28,61]*	*-[0,71]*	*[1,08]*		
Multi Factor	127	-0,75	0,95***	0,22***	0,06***	0,960	0,013
		-[0,67]	*[43,42]*	*[5,52]*	*[2,18]*		
Momentum	17	-0,55	1,00***	0,27***	-0,06	0,941	0,018
		-[0,35]	*[34,02]*	*[4,83]*	*-[1,57]*		
Low/Min Vol/Variance	23	-1,78	0,73***	-0,10*	0,16***	0,918	0,014
		-[1,21]	*[25,44]*	*-[1,90]*	*[4,46]*		
Growth	47	0,38	1,03***	0,24***	-0,17***	0,966	0,014
		[0,38]	*[54,36]*	*[7,45]*	*-[6,91]*		
Equal Weight	38	-2,73*	0,98***	0,17***	0,08*	0,927	0,018
		-[1,86]	*[33,32]*	*[3,16]*	*[1,94]*		
Dividend	73	-4,85***	0,89***	-0,13***	0,27***	0,914	0,018
		-[3,33]	*[30,64]*	*-[2,37]*	*[6,84]*		

Table 9. Three-factor model factor loadings for the full sample period

The complete three-factor model regression findings for the whole sample period are shown in Table 9. Since the factor loadings are consistent across all models, only the chapter on the five-factor model discusses them.

7.3 Results from the five-factor model

As the Fama and French five-factor model being the foundational asset pricing model in this thesis we include the discussion on sensitivity factors in its own subchapter after analyzing the regression results from the model.

Portfolio	Full Period Since Inception	Half Period 01/01/2010	Last 3 Years 1/2020 - 1/2023	Inception date
Benchmark	**-1,52***** *-[2,65]*	**-0,68** *-[1,10]*	**-0,89** *-[0,93]*	29/02/2000
Value	**-2,54***** *-[2,61]*	**-1,26** *-[0,96]*	**-5,17***** *-[2,68]*	30/06/2000
Quality	**-3,92**** *-[2,37]*	**-2,65** *-[1,60]*	**-6,53***** *-[2,66]*	31/01/2006
Multi Factor	**-0,99** *-[0,87]*	**-0,90** *-[0,69]*	**-3,69**** *-[1,97]*	28/02/2005
Momentum	**-0,27** *-[0,16]*	**-0,21** *-[0,12]*	**-1,03** *-[0,38]*	30/11/2006
Low/Min Vol/Variance	**-2,69*** *-[1,89]*	**-2,69*** *-[1,89]*	**-6,26**** *-[2,58]*	30/06/2011
Growth	**0,30** *[0,29]*	**1,12** *[0,87]*	**-0,99** *-[0,62]*	30/06/2000
Equal Weight	**-3,10**** *-[2,07]*	**-1,27** *-[0,77]*	**-3,95**** *-[2,09]*	30/05/2003
Dividend	**-5,43***** *-[3,60]*	**-3,74**** *-[2,09]*	**-9,03***** *-[3,11]*	30/09/2003

Table 10. Regression results from the five-factor model.

Similarities arise with our foundational asset pricing model of the thesis being the Fama and French five-factor model. From table 10 we can see that on full sample period growth is again similar to three-factor model results the only smart beta category providing positive alpha of 0.30% with no statistical significance. While the alpha is positive it’s slightly lower than in the three-factor model (0.38%). While value had a positive alpha value (0.04%) with the CAPM it has now with five-factor model performed way poorer having a negative -2.54% return. Clearly when adding more explanatory variables in the asset pricing model it seems to be clearly weighing value strategy’s performance. While growth has the only positive alpha value, multi factor and momentum strategies still outperform the benchmark portfolio by having less negative alpha values of -0.99% and -0.27% respectively as the S&P 500 benchmark portfolio generated a negative -1.52% alpha value. No statistical significance in these smart beta portfolio values while the benchmark portfolio has statistical significance on 1% level. Similarly, to other previously analyzed results on other asset pricing models, the worst performer was again the dividend category with a negative -3.74% alpha on a 5% statistical significance level. Similarly, to Glushkov (2015), dividend-oriented ETFs being the worst performer although being the most popular SB category both in terms of managed AUM and investor flows. Overall, the categories perform slightly poorer compared to CAPM and three-factor model as we add two more explanatory variables to the model to arrive to Fama and French five-factor model.

Accordingly, the five-factor model suggests that growth, multi-factor, and momentum smart beta strategies outperform the used S&P 500 broad market benchmark portfolio, while only the growth portfolio having a positive alpha on the full sample period and the latter two having less negative alphas compared to benchmark portfolio. Moreover, the results from value and growth strategies are even more relevant as per the inception date; the sample has the same number of observations as the benchmark portfolio.

With the half sample period starting from January 2010, we find the growth portfolio performing exceptionally well compared to other groups with the only positive value in this table generating 1.12% alpha. Momentum was the second strategy outperforming the benchmark portfolio with a less negative alpha of -0.21% while the benchmark portfolio had a negative alpha of -0.68%. Overall, the post-crisis decade has been considered a favorable operating environment for growth stocks with nimble technology-driven business models, extraordinarily good liquidity conditions, and low rates—no statistical significance in these results. Adding explanatory variables to the asset pricing models seems to be generating better results on the best performing smart beta strategy.

With the post covid time period the benchmark portfolio is now outperforming the smart beta portfolios with a less negative alpha of -0.89%. Growth has now suddenly performed way worse than in the previous sample periods, having a negative alpha value of -0.99%. Since the macroeconomic environment has rapidly changed and as a result of tightening liquidity conditions and interest rate rises, growth is not performing so well anymore, and the broad market benchmark portfolio seems to be weathering the storm.

These regression results from the five-factor model imply that null hypothesis hold and cannot be rejected as there is no consistency on the strategies to provide statistically significant and positive alpha compared to the benchmark portfolio. However, as per the alternative hypothesis, growth strategy is able to provide positive alpha on full and half sample period although not being statistically significant. Momentum is another strategy that can provide less negative alpha compared to passive benchmark portfolio on full and half sample period although not statistically significant.

7.4 Factor loadings on the five-factor model

Table 11 below shows the five-factor model regression results from the full sample period. Similarly, to presented on the previous asset pricing models previously show we now summarize the factor loadings and R2 values. For presentational considerations, all alphas are annualized and given as a percentage as in previous comparable research. The significance level is indicated by stars next to the numbers as follows: *** at the 1% level, ** at the 5% level, and * at the 10% level. All the result tables in this study's analysis show the significance levels in a consistent manner. Under the alphas, in the brackets, are the t-ratios. R2 is a measure of statistical significance in the regression model that estimates the portion of variance determined by the independent variable for the dependent variable and, in general, illustrates how successful the model is. The standard error evaluates the degree to which the sample distribution resembles a population and hence indicates the correctness of the alpha by using standard deviation.

Portfolio	# of ETFs	Alpha	Beta	SMB	HML	CMA	RMW	R2	Std. Error
Benchmark	4	-1,52***	0,96***	-0,11***	0,01	0,05**	0,03	0,986	0,007
		-[2,65]	[85,74]	-[6,03]	[0,30]	[2,38]	[1,23]		
Value	52	-2,54***	0,96***	0,23***	0,33***	0,12***	0,08*	0,967	0,013
		-[2,61]	[50,69]	[7,21]	[10,58]	[3,36]	[1,77]		
Quality	22	-3,92**	0,94***	0,08	-0,01	0,14*	0,02	0,922	0,019
		-[2,37]	[29,61]	[1,31]	-[0,26]	[1,86]	[0,27]		
Multi Factor	127	-0,99	0,94***	0,25***	0,02	0,05	0,01	0,961	0,013
		-[0,87]	[41,80]	[5,97]	[0,45]	[0,96]	[0,10]		
Momentum	17	-0,27	1,00***	0,26***	-0,12**	-0,10	0,05	0,942	0,018
		-[0,16]	[32,59]	[4,39]	-[2,31]	-[1,34]	[0,55]		
Low/Min Vol/Variance	23	-2,69*	0,72***	0,04	0,08*	0,26***	0,13*	0,928	0,013
		-[1,89]	[25,18]	[0,76]	[1,66]	[3,98]	[1,71]		
Growth	47	0,30	1,03***	0,25***	-0,21***	0,02	-0,04	0,966	0,014
		[0,29]	[49,95]	[7,36]	-[6,07]	[0,49]	-[0,75]		
Equal Weight	38	-3,10**	0,98***	0,21***	0,02	0,05	0,07	0,929	0,018
		-[2,07]	[32,32]	[3,67]	[0,31]	[0,75]	[0,82]		
Dividend	73	-5,43***	0,90***	-0,06	0,25***	0,11	0,06	0,914	0,018
		-[3,60]	[29,59]	-[1,14]	[5,01]	[1,54]	[0,68]		

Table 11. Full sample period factor loadings on the five-factor model.

Similarly to Glushkov (2015), this thesis also aims to capture if Smart beta ETFs gave investors the expected factor exposure they intend to look for. Reasoning behind this amongst academics is that the primary justification professional asset managers give for using alternative equity beta is to have exposure to rewarded risk factors in order to achieve an effective risk-adjusted return with a simple application while also being concerned about being exposed to a risk of unintended consequences of undesirable risks.

In table 11 overall high R2 values imply that the empirical model is working rather good together with relatively low standard errors. According to the high R2 values the five-factor model has strong explanatory weight in it. In this sample all the smart beta portfolios except the dividend portfolio load positively and significantly to the size factor (SMB) which implies that the smart beta ETFs lean to move along with smaller stocks. Dividend and value portfolios as presumed load positively on (HML) while growth has negative loadings. These are characteristic findings. The low/min vol/variance strategy loads positively and significantly on both the investment and profitability factors.

As per Fama and French (1993) when comparing the different asset pricing models previously presented, we can see that adding more factors to the model increases the models' explanatory power. Firstly, in the three-factor model integrating size and value factors boosted the market component model's explanatory power as compared to any previous factor model, such as the CAPM theory, by having higher R2 values.

7.5 Results after controlling for fees

Previous results have been taking into consideration the expense ratios of the ETFs both in Smart-Beta ETFs as well as in the S&P 500 benchmark portfolio. In this chapter, the alphas are shown and discussed after controlling the fees to see if any significant performance attribute is added. The relevant S&P 500 benchmark portfolio includes four ETFs: SPDR S&P 500 ETF TRUST, iShares Core S&P 500 ETF, SPDR Portfolio S&P 500 ETF, and Vanguard S&P 500 Index ETF. As the returns are monthly observations, the expense ratio has also been taken into consideration on a monthly level. Each smart beta category has been calculated with the median expense ratio of the ETFs included, and this median expense ratio has been considered when conducting the regression results on each smart beta category.

As discussed in the fourth chapter, the funds accrue costs, and these costs have a significant impact on investment returns. Furthermore, Smart-Beta ETFs have higher costs because of their screening methods and strict investment decision-making principles. Each Smart-Beta category's median expense ratio has been calculated and used in the regressions. The smart beta categories had a median expense ratio of 0.34%. Notably, the worst performing category, the dividend category, also had the second highest expense ratio of 0.42%, which, together with the poor performance results, does not comfort investors. The benchmark group had a median expense ratio of 0.09%. As a result, Smart-Beta screening incurs considerably higher costs than the passive counterpart that does not screen, and fee characteristics are critical to control.

Portfolio	Full Period Since Inception	Half Period 01/01/2010	Last 3 Years 1/2020 - 1/2023	Inception date
Benchmark	**-1,43****	**-0,59**	**-0,80**	29/02/2000
	-[2,49]	*-[0,95]*	*-[0,84]*	
Value	**-2,31****	**-1,03**	**-4,94*****	30/06/2000
	-[2,37]	*-[0,79]*	*-[2,56]*	
Quality	**-3,59****	**-2,31**	**-6,20****	31/01/2006
	-[2,17]	*-[1,39]*	*-[2,52]*	
Multi Factor	**-0,62**	**-0,53**	**-3,32***	28/02/2005
	-[0,54]	*-[0,41]*	*-[1,77]*	
Momentum	**0,08**	**0,14**	**-0,68**	30/11/2006
	[0,05]	*[0,08]*	*-[0,25]*	
Low/Min Vol/Variance	**-2,44***	**-2,44***	**-6,58*****	30/06/2011
	-[1,72]	*-[1,72]*	*-[2,71]*	
Growth	**0,53**	**1,35**	**-0,76**	30/06/2000
	[0,51]	*[1,05]*	*-[0,47]*	
Equal Weight	**-2,60***	**-0,77**	**-3,45***	30/05/2003
	-[1,73]	*-[0,47]*	*-[1,83]*	
Dividend	**-5,01*****	**-3,32***	**-8,61*****	30/09/2003
	-[3,33]	*-[1,86]*	*-[2,96]*	

Table 12. Regression results from the five-factor model after controlling fees.

Table 12 shows that after controlling fees, growth is still the best-performing smart beta category, generating the highest alpha value of 0.53%. In comparison, the alpha before controlling fees was 0.30%. Momentum is another category performing with a positive alpha value of 0.08% compared to an alpha value of negative -0.27% before controlling for fees. Compared to the benchmark portfolio, which had a negative -1.43% alpha, these two smart beta categories perform very well. Benchmark portfolio results are statistically significant on a 5% level, while growth and momentum offer no statistical significance. Of the seven smart beta category portfolios, only growth, momentum, and multi-factor strategies outperform the benchmark portfolio.

Switching on to the post-financial crisis period starting from January 2010, the growth portfolio is again performing very well, generating an alpha of 1.35% compared to an alpha value of 1.12% before fee controlling. The post-crisis decade has been considered a favorable operating environment for growth stocks with nimble technology-driven business models, extraordinarily good liquidity conditions, and low rates. With the previously well-performing momentum category, there is little change. As mentioned earlier, the category performed very stably through different time periods. The benchmark portfolio is narrowing down the difference printing a negative -0.59% alpha while still growth, momentum, and multi-factor strategies are performing better—no statistical significance on these mentioned portfolios.

During the past three years period, none of the portfolios generated positive alphas, while now only momentum and growth strategies provide less negative alphas of -0.76% and 0.68%, respectively, compared to the benchmark portfolio of 0.80%. Conversely, the multi-factor strategy is now performing poorly with a negative -3.32% alpha while previously beating the benchmark portfolio. The same macroeconomic principles apply here, as previously mentioned, that the performances are less attractive compared to previous time periods as the markets have faced considerable turbulence after the breakout of the pandemic.

To conclude, even as the smart beta portfolio ETFs incur higher costs than broad market benchmark ETFs due to high conviction screening attributes, paying higher fees in hopes of better performance attributes is still reasonable, especially with the growth category. However, this better performance is required through higher risk and volatility in terms of high standard deviation, as mentioned previously when examining the descriptive statistics of the portfolios.

8 Discussion and conclusions

The thesis takes a look into smart beta ETFs and their performance compared to broad-market benchmark portfolio measured by most commonly known asset pricing models. Exchange-Traded-Funds have been in huge popularity for decades and most recently the factor strategy smart beta ETFs has gained fund inflows in a growing space. This last chapter of the thesis concludes the main results provided earlier and discusses the reasoning and effects, also shedding light on what could be improved or studied more on the subject.

The empirical part of the thesis investigates the performance of smart beta exchange-traded-funds and their relative performance against broad market index portfolio. The main point is to see if the smart beta ETFs consistently provide more alpha than the passive counterpart, which consists of the portfolio of S&P500 ETFs. The thesis uses data from 399 U.S listed factor ETFs categorized to each smart beta category based on categorization available on Bloomberg. The sample period contains data from 2000 until January 2023 which is the last monthly data available on Fama and French data website. The regression is computed using three main asset pricing models containing CAPM and Fama and French three and five-factor models. By these parametric the thesis tries to answer the hypothesis on whether the smart beta factor ETFs are able to consistently outperform the broad-market benchmark portfolio as a whole.

The academic literature referring to findings that value stocks have higher returns than growth stocks Fama and French (1998) show value stocks outperforming growth stocks in twelve of thirteen major markets for the period 1975 through 1995. Contrary to wide variety of academics explaining that value stocks outperform growth stocks, results in this research show otherwise. Possible reasoning in this is that the market fundamentals and sector allocations have shifted significantly merely in the time span studied in this thesis which is post the tech bubble of early 21st century. The rapid growth of technology and digitalization in general have gained more traction during the past decade. Another discretion to previous scholars provides Mohanram (2005), who adds different firm-specific variables including, such as earnings stability, growth stability, intensity of research and development, capital investments and advertising commitments, to measure growth stocks performance such as combining traditional fundamentals like cash flows and earnings. A long-short strategy that buys equities with high growth potential and sells equities with low growth potential can produce considerable excess returns. These firm-specific variables presented by Monahan are heavily present when we look at today's growth companies popular amongst investors.

The results from all asset pricing models show that in this thesis the null hypothesis holds and cannot be rejected. Factor strategies as a collective are not able to provide consistently positive and statistically significant alpha. However, considering this thesis time period starting from 2000, the growth factor has been outperforming value as the market sentiment has changed and the monumental change in information technology has driven growths performance. Growth factor is the only factor strategy that consistently provides positive but not statistically significant alpha. Similar to Glushkov (2015) who finds that while 60% of smart beta fund categories beat their raw passive benchmark, he neither finds conclusive empirical evidence for consistent outperformance. Similarly, this thesis results do not show consistent results for outperformance. However, investors can find positive and consistent alpha in growth strategy in the full and half sample period while the outperformance compared to benchmark portfolio diminishes when measured on the past three years period. From this finding we can accept the alternative hypothesis.

Further studies would be to contain the same sample size and underlying ETFs but broaden the research for each factor category to contain the self-declared benchmark by the ETF provider rather than a portfolio of broad market S&P500 benchmark which were used in this study. Then the structure would lean more on Glushkov (2015) who also uses two other types of benchmarks; risk-adjusted version of the self-declared benchmark and a blended benchmark constructed by using the combination of passive funds and factor exposures. One could also add a section where risk-adjusted performance would be accompanied to analysis by using Sharpe and Sortino ratios or Jensen’s alpha to name a few.

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