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Do Sector ETFs Follow Fama-French Factors?

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Abstract: This thesis explores the impact of Fama-French factors on the performance of sector-specific Exchange-Traded Funds (ETFs) in the U.S. market from September 2010 to September 2019. Various asset pricing models are applied, including the CAPM, Fama-French three-factor, Carhart four-factor, and Fama-French five- and six-factor models, to identify the most effective explanatory model. FF5M (Fama-French five-factor model with momentum) is found to provide the best fit. Based on regression coefficients from the model it is determined that certain factors significantly influence performance of specific sectors.

We construct sector-specific ETF portfolios categorized by the significance of their factor exposures. These portfolios are evaluated using performance metrics such as the Sharpe ratio, Sortino ratio, Treynor ratio, Information ratio, and Omega ratio. The results offer insights into the strategic construction of sector-specific ETF portfolios for improved risk-adjusted returns.

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1 Introduction

Investing in sector ETFs offers a strategic way to gain targeted exposure to specific sectors of the economy, providing diversification, flexibility, cost efficiency, and ease of access. Whether used for thematic investing, risk management, tactical asset allocation, or hedging, sector ETFs can be valuable tools in an investor's portfolio.

Two primary approaches to portfolio construction, as well as two methods to analyse performance or portfolio deconstruction, are by sectors and by style (or factors). While extensive research exists on each of these dimensions individually, studies on their interaction are limited. Additionally, most traditional ETFs that track broad market indices (like the S&P 500 or MSCI World Index) are not designed with factor neutrality as an objective. However, their performance is driven by the market capitalization weights of the underlying securities, which inherently exposes them to various factors like size and value. Thus, sector and factor investing are often intertwined.

This study aims to provide insights into the Fama-French factors' influence on sector ETFs and whether a strategic method can be developed for investing in ETFs within different sectors.

We first evaluate different factor models based on the Fama-French factors. We compare multiple asset pricing models, such as the Capital Asset Pricing Model (CAPM), the Fama-French 3-Factor Model, the Carhart 4-Factor Model, and the Fama-French 5-Factor and 6-Factor Models, using adjusted R-squared as the primary measure of fit. The model with the highest adjusted R-squared is deemed the best fit for explaining sector ETF returns, helping us understand the underlying factors driving sector performance.

Based on the selected model, we compute significant factor coefficients to determine if the sector ETFs are factor neutral. Subsequently, we construct separate portfolios within each sector, dividing them based on the significance of factor exposures.

Finally, we evaluate the performance of the constructed ETF portfolios using various metrics that provide insights into different performance aspects, such as returns, risk, and risk-adjusted returns. Our objective is to determine whether a portfolio can be systematically constructed using factor significance to:

- Deliver higher risk-adjusted returns
- Exhibit lower volatility and downside risk
- Outperform relative to a benchmark
- Demonstrate evidence of manager skill (alpha)

The motivation behind this study is the rapid growth and increasing complexity of financial markets, which have driven investors to seek more effective and simpler strategies for portfolio management. Exchange-Traded Funds (ETFs) have emerged as a popular investment vehicle towards that end. However, the challenge remains to optimize ETF selection to maximize returns and manage risks effectively. As mentioned, this can be achieved by sector or style criteria.

Sector-specific ETFs offer targeted exposure to industries, but their performance can be significantly influenced by various risk factors identified in asset pricing models, such as the Fama-French factors. Understanding the impact of these factors on sector ETF performance is crucial for constructing robust investment portfolios.

Research has shown that sector rotation, which involves shifting investments among different economic sectors based on the business cycle, can enhance returns by aligning investments with prevailing economic conditions (Chong and Phillips, 2015). Additionally, style investing, which focuses on specific securities' characteristics such as growth, value, and momentum, has been demonstrated to lead to predictable patterns in asset prices (Barberis & Shleifer, 2003). Combining these two approaches can be particularly beneficial, as it allows investors to capitalize on both macroeconomic trends and specific securities' attributes, potentially leading to superior risk-adjusted returns and a more robust investment strategy.

This research aims to provide an analysis of how different Fama-French factors can affect the performance of sector ETFs. The study seeks to offer valuable insights for investors looking to enhance their portfolio strategies through factor-based ETF selection. The aim is to bridge the gap between theoretical asset pricing models and practical investment strategies, ultimately contributing to more informed and effective decision-making.

In summary, by combining style investing strategies within sector investing, this thesis seeks to offer a framework for understanding and implementing advanced investment techniques in the modern financial landscape.

2 Background

As one of the most developed nations, the U.S. boasts the largest and most diverse array of sectors and industries. Its highly efficient financial market reflects a wide range of economic activities and global market sentiments. This exceptional efficiency stems from the United States' robust regulatory framework, advanced technological infrastructure, and highly skilled workforce. The transparency and liquidity of the U.S. financial markets further enhance their attractiveness to both domestic and international investors.

Additionally, the extensive availability of data and research, facilitates informed investment decisions and fosters innovation in financial products.

Consequently, fluctuations in the U.S. financial market serve as a bellwether for the global economy, influencing investor sentiment, capital flows, and economic policies worldwide. These fluctuations are not only indicators of domestic economic health but also have ripple effects on global financial systems, underscoring the interconnectedness of modern economies.

Given these factors, this study is focused on U.S.-based ETFs. The breadth and depth of the U.S. market provide a comprehensive environment for analysing sector-specific trends and investment strategies. By examining ETFs in this context, the study can yield insights that are relevant not only to U.S. investors but also to global market participants seeking to understand and navigate the complexities of the international financial landscape.

2.1 ETFs

Exchange traded funds or ETFs are said to be one of the more successful financial innovations in recent decades and that their success is driven by cheapness and convenience (The Economist, 2013). ETFs are beneficial for investors as they can be traded instantaneously and as there is a large variety of funds.

ETFs were introduced on U.S. and Canadian exchanges in the early 90s. In the first several years, they represented a small fraction of the assets under management in index funds. However, the 132% average annual growth rate of ETF assets from 1995 through 2001 (Gastineau, 2002) already illustrated the increasing importance of these instruments back then. The launching of Cubes in 1999 was accompanied by a spectacular growth in ETF trading volume, making the major ETFs the most actively traded equity securities on the U.S. stock exchanges (Deville, 2008). Since then, ETF markets have continued to grow, not only in the number and variety of products, but also in terms of assets and market value.

Fund managers construct ETFs by initially devising an investment strategy rooted in market research, then often opt for an appropriate index in line with this strategy. ETFs can be targeted to many different criteria, for example sector, factor, market index, etc. Once regulatory approval is obtained, they proceed with portfolio construction by acquiring securities in adherence to the selected index's criteria. This entails meticulous selection and weighting of securities according to the index methodology, whether it be market-cap-weighted, equal-weighted, or another method. This enables ETFs to offer targeted exposure or fulfil specific investment objectives. Working with authorized participants, they form creation units, large blocks of ETF shares, by transferring underlying securities to the ETF. Following listing on a stock exchange, managers ensure accurate index tracking by regularly rebalancing the portfolio, adjusting holdings to maintain designated weightings, and closely monitoring ETF performance.

There are various benefits associated with ETFs,

Diversification: ETFs provide instant diversification by holding a basket of stocks. This diversification reduces the unsystematic risk and volatility associated with individual stocks (Madhavan, 2016), where investing in a single stock can expose investors to company-specific risks, such as poor management or unexpected negative news.

Cost effectiveness: Purchasing an ETF incurs a single transaction cost, whereas building a diversified portfolio with individual stocks would require multiple transactions, each incurring costs. This makes ETFs a more cost-effective option for investing (Madhavan, 2016). While ETFs have management fees, they are generally lower than the costs associated with actively managed mutual funds and can be lower than cumulative costs of maintaining an active portfolio of individual stocks.

Ease of access, liquidity and transparency: ETFs are traded on major exchanges in the same manner as individual stocks, offering significant liquidity and flexibility. This ease of trading makes ETFs particularly accessible for retail investors who seek a sophisticated global strategic exposure across different styles, sizes, and sectors without the necessity of researching and selecting individual stocks. Additionally, unlike mutual funds, ETFs provide complete transparency regarding their holdings, allowing investors to know exactly what is in their portfolios, and their straightforward naming conventions further enhance clarity (Hill et al., 2015).

Tax efficiency: Because ETFs can manage the flow of securities in and out of the fund through in-kind transactions, they are less likely to realize capital gains that would need to be distributed to shareholders. This defers the tax liability to the point when the investor decides to sell the ETF shares. As noted in Hill et al. (2015), “About 50% of all equity mutual funds paid out capital gains in 2013, whereas fewer than 5% of ETFs did, and rarely did ETFs pay gains that were significant.”

These characteristics have made ETFs appealing to investors and academics alike.

2.2 Current American ETF Market

Over the past five years, assets in U.S.-listed ETFs have seen remarkable growth. U. S. ETF assets nearly doubled from 2019 to the end of Q1 2024, underscoring the increasing importance of ETFs in the investment landscape. This growth has been paralleled by an increase in trading volumes.

In the first quarter of 2024, trading volumes for the U.S. equity market were $37.9 trillion which includes single stocks, ETFs, and depository receipts. U.S. ETFs alone contributed $10.6 trillion, representing 28.1% of the total U.S. composite volume in the secondary market over the 1st quarter of 2024.

Individual investors in the U.S. have also maintained their active participation in the ETF market. By the end of Q1 2024, individual investor ETF assets reached nearly $1.4 trillion, making up 19% of all U.S.-listed ETF assets—the highest percentage on record till date.

Despite this substantial growth, as of Q1 2024, ETFs represent only 13% of equity and 2.8% of fixed income assets in the U.S. (compared to 10.3% of equities and 2% of fixed income in 2019). ETFs, therefore, still comprise just a fraction of the financial market, indicating that there is still ample space for further growth.

Source: Global ETF Market Facts: three things to know from Q1 2024, iShares – BlackRock, April 2024

2.3 Factor Investing

Factor investing involves selecting investments based on specific characteristics that can explain an asset's returns. This strategy is grounded in the idea that underlying factors, such as firm attributes or style factors, significantly influence asset returns. Assets are viewed as combinations of these factors, with their returns influenced by these attributes, which represent various risks and rewards. Like any investment strategy, the primary goal of factor investing is to achieve superior returns compared to the market by constructing portfolios of securities expected to perform well based on these identified factors.

The inspiration for factor investing comes from arbitrage pricing theory (APT) equation, which expresses the expected return of a security as,

$$R_i = R_f + \sum_{j=1}^{j} b_{ij}\, \lambda_j \tag{1}$$

where λ_j compensates the investor for bearing the risk of asset *i*'s exposure to systematic risk factor *j*. Investors seeking returns above the riskless R_f can scale up expected return by choosing a set of b_{ij} for the portfolio, such that b_{ij} on high λ factors are high (Elton et al., 2017). Over time development led to a more generalized Jensen's model for a portfolio,

$$R_{pt} - R_f = \alpha_p + \sum_{j=1}^{j} \beta_{ij} \lambda_j + e_{pt} \quad (2)$$

where the addition of the alpha factor signifies the expected excess return (over R_f) of a portfolio if all other factors were zero, and e_{pt} is the idiosyncratic error term.

This approach to investment management has gained significant traction due to its focus on capturing risk premiums from systematic risk factors. In a market equilibrium, there is an expectation of a positive return over the risk-free rate associated with identifiable factors. Consequently, every asset exposed to these factor risks earns a premium. Investors can increase their exposure to these factors to achieve higher expected returns, thereby improving the portfolio's beta and potentially enhancing alpha.

Researchers have identified several key factor characteristics that determine expected returns, including market capitalization (size), book-to-market (value), profitability, asset growth (investment), and past return (momentum). Investment portfolios providing exposures to these factors can be constructed by sorting securities based on specific characteristics and buying those that score favourably.

There are several advantages for factor investing,

Enhanced Returns: By targeting specific factors that have historically outperformed the market, investors can potentially achieve higher returns.

Risk Management: Factor investing allows for better risk management by diversifying across multiple factors as needed.

Transparency: Factor-based strategies are typically rules-based and transparent, making it easier for investors to understand the sources of their returns.

Cost Efficiency: Many factor investing strategies can be implemented in a cost-effective manner, often through ETFs, which have lower fees compared to actively managed funds.

However, it does come with potential downsides,

Factor Timing Risk: The performance of individual factors can be cyclical, and poor timing in factor exposure can lead to suboptimal returns.

Complexity: Understanding and implementing factor-based strategies require a sophisticated understanding of financial markets and quantitative methods.

Crowding: As more investors adopt factor investing, the advantages may diminish due to increased competition and market saturation.

Short-term Underperformance: Factors can underperform the market for extended periods, requiring investors to have a long-term perspective and patience.

Factor investing has its roots in the Capital Asset Pricing Model (CAPM) introduced by Sharpe (1964), which highlighted the relationship between systematic risk and expected return. This was further developed by the Fama-French three-factor model (1992), which added size and value factors to better explain asset returns. Subsequent research expanded this to include additional factors such as momentum (Carhart, 1997) and profitability and investment (Fama and French, 2015). The development of these models provided the theoretical foundation for modern factor investing strategies.

In practical terms, factor investing gained popularity with the advent of quantitative investment techniques and the proliferation of data. The launch of factor-based ETFs in the early 2000s made it accessible to a broader range of investors, allowing for the efficient implementation of these strategies. Today, factor investing is a cornerstone of many institutional and individual investment portfolios, offering a robust framework for achieving diversified and risk-adjusted returns.

2.4 Sector Investing, Sector ETFs and Rotation Strategies

Sector investing is a strategy where an investor focuses on specific sectors of the economy, rather than spreading investments across a broad market. This approach allows investors to capitalize on the performance of specific industries or areas expected to outperform the general market.

The initial instances of sector investing began with the launch of the first actively managed sector fund by Fidelity in 1981. It was among the early initiatives to target specific sectors of the economy. This move was significant as it laid the groundwork for sector-specific investment strategies that are now commonly used by investors to gain targeted exposure to different parts of the economy. The evolution of sector investing continued with the introduction of the first sector ETFs in 1998 by State Street Global Advisors, known as the Select Sector SPDRs, which divided the S&P 500 into sector-specific funds and provided investors with the ability to trade sector-specific portfolios throughout the trading day. This launch marked a significant milestone in the history of sector investing, providing investors with powerful tools for tactical asset allocation and sector rotation strategies. There are several benefits to sector-specific investing,

Targeted exposure: Sector-specific investing allows investors to gain targeted exposure to industries they believe will outperform the broader market. Kacperczyk, Sialm, and Zheng (2005) investigated the performance of industry-concentrated mutual funds from January 1984 to December 1999. They argue that fund managers may have outperformed the passive market portfolio by concentrating on specific industries. Their findings showed that funds with a higher industry concentration tended to perform better. This sector specific advantage might even have grown over time. Baca et al. (2000) and Cavaglia et al. (2000) argue that the world's major equity markets have become more integrated, leading to a decline in the influence of country-based components and growth of sector-based components, presenting opportunity with targeted sector exposures.

Capitalize on economic cycles: Different sectors can perform differently at various stages of economic cycles, e.g., technology during expansion, utilities during recession etc. If an investor can accurately predict which sectors will outperform based on market cycle, sector-specific investing can provide higher returns compared to a broad-market approach.

Hedging strategies: Sector investing allows for precise hedging strategies, such as protecting against declines in particular sectors. For instance, if inflation is identified as a significant factor, investor could invest in Consumer staples, where an ETF like the Consumer Staples Select Sector SPDR Fund (XLP) could be used. This ETF includes major companies in the consumer staples sector, such as Procter & Gamble, Coca-Cola, and PepsiCo, which historically have shown resilience during inflationary periods. Thus, by investing in Consumer Staples Sector ETFs, the investor can mitigate the impact of inflation on their portfolio.

However, sector investing also comes with risks,

Concentration risk: Investing heavily in a specific sector could lead to a lack of diversification, increasing exposure to industry-specific risks, such as regulatory changes, technological disruptions, or economic shifts impacting that sector. Furthermore, certain sectors, such as technology or biotechnology, are inherently more volatile than others, leading to greater potential for rapid loss in value.

Need for timing the market correctly: Due to the cyclical nature of sectors, they can experience significant downturns. For example, the energy sector can be highly volatile in periods of fluctuating oil prices. Successfully investing in specific sectors often requires accurate market timing, which is challenging and can lead to significant losses if the timing is incorrect.

Some of the risks of sector investing can be mitigated by investing in sector ETFs and employing sector rotation.

Sector ETFs: Sector ETFs focus on a specific industry, but still offer diversification within that sector by holding a basket of stocks. This reduces the risk associated with investing in a single sector-specific company, as the performance of the sector ETF is spread across multiple firms.

Sector rotation: Sector rotation is an investment strategy that involves shifting investments from one industry sector to another to capitalize on the different performance patterns of sectors during various phases of the economic cycle. The idea is to invest in sectors that are expected to outperform during specific economic conditions and to move out of those expected to underperform. The strategy is based on observable signals of market cycles and macroeconomic conditions has been shown to outperform the S&P500 in various studies conducted by Conover et al. (2005), Dou et al. (2014) and Alexiou and Tyagi (2020).

Chong and Phillips (2015), study rotation strategies and specifically employ sector ETFs to show that these economic-based portfolios, when assessed against the S&P 500 Index and the equal-weighted ETF portfolio, performed relatively well in absolute and relative terms, for the whole period as well as subperiods. Sarwar, Mateus and Todorovic (2018), provide evidence that long-only sector rotation strategies based on signals from FF5 rolling alphas of Fama-French US sector ETF portfolios outperform the S&P500 index. They also observe that the long-short strategy largely remains unsuccessful.

In summary, there is substantial evidence supporting the effectiveness of sector investing, particularly when taken in context of ETFs and rotation strategies.

3 Problem Statement

As financial analysts delve into the complexities of sector investing, an intriguing question arises: Can certain Fama-French factors be more significant in some sectors than in others? This question stems from the observation that factors such as size, value, and momentum, which are well-known for providing returns in general markets, might exhibit varying levels of influence across different sectors. This leads to a deeper inquiry: Is it possible that factors behave differently even within the different ETFs of the same sector, yielding more significant beta values for a subsection of ETFs within sector, thereby leading to a recognizable pattern of higher returns?

An investor keen on maximizing their portfolio's performance can examine whether these factor significance differences be captured, and whether portfolios constructed based on these achieve a higher performance when measured with a metric like Sharpe Ratio etc.

To unravel this, the investor considers the various models available to explain and potentially exploit these behaviours. The CAPM, which incorporates market risk, is a good starting point. But what about the Fama-French three-factor model, which adds size and value to the model. Or the Carhart four-factor model, which adds momentum to the mix? Or the Fama-French five-factor and six-factor models, which introduce profitability and investment factors, along with momentum?

The investor is faced with a critical decision: Which model should they use for their study? They ponder whether to use all the models or to focus on the one that provides the highest fit for explaining the sector ETFs' performance. Previous research offers some guidance, suggesting that different models may explain sector ETFs better than others, depending on the sector in question. By diving into the literature, the investor finds that some studies highlight the superior explanatory power of the Fama-French five-factor model for certain sectors, while others advocate for the six-factor model due to its incorporation of momentum. They must decide whether to adopt a comprehensive approach, using multiple models to cover all bases, or to streamline their analysis by selecting the model that consistently yields the best fit.

After carefully selecting the optimal model, the investor is left with the most crucial question: How to leverage this further to achieve superior returns? This introduces an additional query: Can they filter out underperforming ETFs within a sector based on the factor information derived from the selected model?

4 Methodology

This study aims to analyse the impact of Fama-French factors on sector-specific ETFs to enhance investor value through performance metrics. Our methodology involves several key steps, including data collection, model selection, regression analysis, portfolio construction and performance evaluation.

Data Collection: The dataset spans from September 2010 to September 2019, avoiding the impact of the 2008 financial crisis and the 2019 COVID-19 pandemic crisis. ETF-related data, including sector classifications and monthly Total Return (NAV), was sourced from FactSet. The six Fama-French factors and the monthly risk-free rate were obtained from Kenneth French's website.

Data Screening and Filtering: We included sector ETFs with an inception date on or before September 2010 and complete data for the entire study period. Inverse and leveraged ETFs were excluded. This resulted in a selection of 174 ETFs across various sectors including consumer staples, consumer discretionary, energy, financials, healthcare, industrials, materials, real estate, technology and utilities.

Model Selection: We employed multiple asset pricing models to determine which best explains sector ETF returns:

- Capital Asset Pricing Model (CAPM)
- Fama-French Three-Factor Model
- Carhart Four-Factor Model
- Fama-French Five-Factor Model
- Fama-French Six-Factor Model (including momentum)

These models were evaluated based on their adjusted R^2 values to identify model with the best fit.

Regression Analysis: Using the selected model, we conducted regression tests on the sector ETFs to calculate in-sample (September 2010 to September 2017) regression coefficients (beta). These coefficients help identify which Fama-French factors exert the most influence on each sector, assessing how significantly these factors contribute to returns and their directional impact.

Portfolio Construction: Based on the significance of beta values for each factor, we constructed four distinct categories of equal-weighted portfolios within each sector:

i. A portfolio comprising all ETFs within the sector
ii. A portfolio of ETFs with insignificant beta values
iii. A portfolio of ETFs with significant positive beta values
iv. A portfolio of ETFs with significant negative beta values

Performance Evaluation: Finally, we apply various performance metrics to evaluate these on the out-of-sample data (October 2017-September 2019). The metrics used include:

- Sharpe Ratio
- Sortino Ratio
- Treynor Ratio
- Information Ratio
- Omega Ratio

5 Scope

This section sets the boundaries for the research, helping readers understand the focus and limits of the study, and ensuring that the research remains targeted and manageable.

This thesis aims to investigate the impact of Fama-French factors on sector ETFs in-sample and construct strategic portfolios based on the result of this investigation, and then finally to analyze performance of the constructed portfolios out-of-sample. To that end the study is confined to:

- The U.S. stock market, analysing sector-specific ETFs listed on major U.S. exchanges from September 2010 to September 2019.
- ETFs from sectors including consumer staples, consumer discretionary, energy, financials, healthcare, industrials, materials, real-estate, technology and utilities. Inverse and leverages ETFs are taken out. Factor specific ETFs within sectors are kept in.
- Fama-French's and Carhart's 6 factors, namely, market, size, value, profitability, investment and momentum.
- Metrics of Sharpe ratio, Sortino ratio, Treynor ratio, Information ratio and Omega ratio for performance analysis.

The study also does not address the impact of global economic events on sector performance nor include an analysis of mutual funds or individual stocks.

6 Theoretical Framework

6.1 Factor Models

6.1.1 CAPM

The inquiry into the determinants of stock returns has long been central to the field of modern finance. One of the oldest and most renowned models for explaining stock returns is the Capital Asset Pricing Model (CAPM), which emerged as a cornerstone of financial theory in the 1960s (Lintner, 1965; Mossin, 1966; Sharpe, 1964; Treynor, 1961). In the CAPM framework, stock returns are primarily driven by two factors: systematic risk and idiosyncratic risk. Systematic risk, as defined in the CAPM, arises from exposure to the overall market and is quantified by beta, representing the sensitivity of a security's returns to market movements. Since systematic risk cannot be diversified away, investors demand compensation for bearing this risk, leading to an expected return for each stock that can be modelled as a function of its beta to the market. Bender, J., Briand, R., Melas, D., & Subramanian, R. A. (2013).

The Capital Asset Pricing Model (CAPM) rests on several key assumptions. Firstly, it assumes that all investors share the same expectations and hold mean-variance efficient portfolios. Additionally, it assumes a frictionless market where the mean-variance efficient portfolio for the average investor aligns with the market portfolio, which comprises a value-weighted combination of all available assets. However, the actual market portfolio is not directly observable, leading to ongoing debates about the model's empirical validity. Hence, when applying the CAPM, researchers often use a proxy for the market portfolio.

Sharpe and Lintner's formulation of the CAPM assumes that investors can borrow and lend at risk-free rates. CAPM is a single factor model that explains the relationship between systematic risk and expected return.

$$E[Ri] = Rf + \beta i \, (E[Rm] - Rf) \tag{3}$$

In this framework,

(Ri) - the expected return of an asset

(Rf) - the risk-free rate

(βi) - the asset's beta, representing the sensitivity of the asset's expected excess returns to the expected excess market returns.

$(E[Rm]- Rf)$ - the market risk premium,

Beta, a measure of risk, captures an asset's systematic risk based on its correlation with the market. It indicates how an asset's returns move concerning market returns during different market conditions. Beta measures only systematic risk, for which investors demand compensation in the form of a risk premium. These premium aims to incentivize holding riskier assets, particularly those that perform well during market downturns.

The beta is calculated as:

$$\beta i = \frac{[Cov\,(Ri, Rm)]}{Var\,(Rm)} = \rho_{i,m} \, \frac{\sigma_i}{\sigma_m} \tag{4}$$

where,

$\rho_{i,m}$ is the correlation coefficient between the asset ***i*** and the market.

σ_i is the standard deviation for the asset ***i***.

σ_m is the standard deviation for the market.

Key insights from the CAPM theory include the diversification of idiosyncratic risk by the market, each investor's unique optimal exposure to the market portfolio, and the pricing of the market factor in equilibrium. Additionally, the CAPM beta serves as a risk measure for assets, and assets that perform well during market downturns are deemed attractive, with lower associated risk premiums.

The expected return on an ETF at time *t* is derived from the equation (3) and can be written as:

$$R_t^{ETF} = R_{f,t} + \beta_{MKT}^{ETF} \left[R_{MKT,t} - R_{f,t}\right] \tag{5}$$

The market factor beta from equation (4) can also be estimated by running the following time-series regression:

$$R_t^{ETF} - R_{f,t} = \hat{\alpha}_{CAPM}^{ETF} + \beta_{MKT}^{ETF} \left[R_{MKT,t} - R_{f,t}\right] + \varepsilon_t^{ETF} \tag{6}$$

The ETFs' CAPM single factor regression-based benchmark is the:

$$\hat{R}_{CAPM\ Benchmar\ \ ,t}^{ETF} = R_{f,t} + \hat{\beta}_{MKT}^{ETF} \left[R_{MKT,t} - R_{f,t}\right] \tag{7}$$

The ETFs' CAPM alpha is then:

$$\hat{\alpha}_{CAPM}^{ETF} = \bar{R}^{ETF} - \bar{R}_{CAPM\ Benchmark}^{ETF} \tag{8}$$

Or equivalently,

$$\hat{\alpha}_{CAPM}^{ETF} = \bar{R}^{ETF} - [\bar{R}_f + \hat{\beta}_{MKT}^{ETF} \left[\bar{R}_{MKT} - \bar{R}_f\right]] \tag{9}$$

6.1.2 Fama-French 3-Factor model

Fama and French (1992, 1993) introduced a seminal model explaining US equity market returns using three factors: the market, size (large vs. small capitalization stocks), and value (low vs. high book-to-market ratio). Bender, J., Briand, R., Melas, D., & Subramanian, R. A. (2013).

They introduced a three-factor model to capture return attributes beyond the market risk factor in CAPM (Fama & French, 1993). This model includes firm size and value (measured by book-to-market equity) as additional risk factors, which were identified through empirical research (Banz, 1981; Rosenberg et al., 2021). Their findings indicated that stocks with low book-to-market equity and small capitalization tended to yield higher returns, while those with high book-to-market equity and large capitalization had lower returns. Furthermore, Fama and French demonstrated that their three-factor model consistently outperformed CAPM in explaining stock returns across different market conditions (Fama & French, 1998).

In addition to the market portfolio, this model incorporates two additional hedged factor portfolios: the size factor portfolio (SMB), which is long small firms and short, large firms, and the value factor portfolio (HML), which is long high book-to-market equity firms and short low book-to-market equity firms.

The expected return on an ETF is derived from the following equation:

$$R_t^{ETF} = R_{f,t} + \beta_{MKT}^{ETF}\left[R_{MKT,t} - R_{f,t}\right] + \beta_{SMB}^{ETF} R_{SMB,t} + \beta_{HML}^{ETF} R_{HML,t} \tag{10}$$

The factor betas are estimated by running the following time series regression:

$$R_t^{ETF} - R_{f,t} = \hat{\alpha}_{FF3}^{ETF} + \hat{\beta}_{MKT}^{ETF}\left[R_{MKT,t} - R_{f,t}\right] + \hat{\beta}_{SMB}^{ETF} R_{SMB,t} + \hat{\beta}_{HML}^{ETF} R_{HML,t} + \varepsilon_t^{ETF} \tag{11}$$

The ETFs' FF 3 factor regression-based benchmark is then:

$$\hat{R}_{FF\,3\,Benchmark,t}^{ETF} = R_{f,t} + \hat{\beta}_{MKT}^{ETF}\left[R_{MKT,t} - R_{f,t}\right] + \hat{\beta}_{SMB}^{ETF} R_{SMB,t} + \hat{\beta}_{HML}^{ETF} R_{HML,t} \tag{12}$$

The ETFs' generalized FF 3 factor alpha is then:

$$\hat{\alpha}_{FF\,3}^{ETF} = \bar{R}^{ETF} - \bar{R}_{FF\,3\,Benchmark}^{ETF} \tag{13}$$

Or equivalently,

$$\hat{\alpha}_{FF\,3}^{ETF} = \bar{R}^{ETF} - [\bar{R}_f + \hat{\beta}_{MKT}^{ETF}\left[\bar{R}_{MKT} - \bar{R}_f\right] + \hat{\beta}_{SMB}^{ETF} \bar{R}_{SMB} + \hat{\beta}_{HML}^{ETF} \bar{R}_{HML}] \tag{14}$$

6.1.3 Carhart 4-Factor model

Carhart (1997) later added a momentum factor to the model, resulting in the "Fama-French-Carhart" model, which has become a cornerstone of financial literature. Carhart introduced momentum as a persistent risk factor to complement the FF 3 factor model, inspired by his research on the persistence of mutual fund performance (Carhart, 1997). Leveraging the observed persistence in stock performance, particularly documented as a successful strategy to achieve notable abnormal returns (Jegadeesh & Titman, 1993).

In addition to the FF3 portfolios, this model integrates an extra hedged momentum factor portfolio. The momentum factor portfolio involves taking long positions in winners and short positions in losers from the past six months, identified as (WML).

The expected return on an ETF is derived from the following equation:

$$R_t^{ETF} = R_{f,t} + \beta_{MKT}^{ETF}\left[R_{MKT,t} - R_{f,t}\right] + \beta_{SMB}^{ETF} R_{SMB,t} + \beta_{HML}^{ETF} R_{HML,t} + \beta_{MOM}^{ETF} R_{MOM,t} \tag{15}$$

The factor betas are estimated by running the following time series regression:

$$R_t^{ETF} - R_{f,t} = \hat{\alpha}_{FFC4}^{ETF} + \hat{\beta}_{MKT}^{ETF}\left[R_{MKT,t} - R_{f,t}\right] + \hat{\beta}_{SMB}^{ETF} R_{SMB,t} + \hat{\beta}_{HML}^{ETF} R_{HML,t} + \hat{\beta}_{MOM}^{ETF} R_{MOM,t} + \varepsilon_t^{ETF} \quad (16)$$

The ETFs' FFC 4 factor regression-based benchmark is then:

$$\hat{R}_{FFC\ 4\ Benchmar\ \ ,t}^{ETF} = R_{f,t} + \hat{\beta}_{MKT}^{ETF}\left[R_{MKT,t} - R_{f,t}\right] + \hat{\beta}_{SMB}^{ETF} R_{SMB,t} + \hat{\beta}_{HML}^{ETF} R_{HML,t} + \hat{\beta}_{MOM}^{ETF} R_{MOM,t} \quad (17)$$

The ETFs' generalized FFC 4 factor alpha is then:

$$\hat{\alpha}_{FFC\ 4}^{ETF} = \bar{R}^{ETF} - \bar{R}_{FFC\ 4\ Benchmark}^{ETF} \quad (18)$$

Or equivalently,

$$\hat{\alpha}_{FFC\ 4}^{ETF} = \bar{R}^{ETF} - [\bar{R}_f + \hat{\beta}_{MKT}^{ETF}\left[\bar{R}_{MKT} - \bar{R}_f\right] + \hat{\beta}_{SMB}^{ETF} \bar{R}_{SMB} + \hat{\beta}_{HML}^{ETF} \bar{R}_{HML} + \hat{\beta}_{MOM}^{ETF} \bar{R}_{MOM}]$$
(19)

6.1.4 Fama-French 5-Factor model

Fama and French proposed an adjustment to their three-factor model to incorporate systematic connections between returns, firms' profitability, and investment behaviour (Fama & French, 2015). Their study revealed that this modified model offers a better explanation for the cross-section of stock returns compared to the original three-factor model.

In addition to the FF 3 portfolios, this model introduces two extra hedged factor portfolios: profitability and investment. The profitability factor portfolio entails taking long positions in firms with strong profitability and short positions in those with weak profitability, denoted as (RMW). Similarly, the investment factor portfolio involves taking long positions in firms with conservative investment strategies and short positions in those with aggressive investment strategies, denoted as (CMA).

The expected return on an ETF is derived from the following:

$$R_t^{ETF} = R_{f,t} + \beta_{MKT}^{ETF}\left[R_{MKT,t} - R_{f,t}\right] + \beta_{SMB}^{ETF} R_{SMB,t} + \beta_{HML}^{ETF} R_{HML,t} + \beta_{RMW}^{ETF} R_{RMW,t} + \beta_{CMA}^{ETF} R_{CMA,t} \quad (20)$$

The factor betas are estimated by running the following time series regression:

$$R_t^{ETF} - R_{f,t} = \hat{\alpha}_{FF5}^{ETF} + \hat{\beta}_{MKT}^{ETF}\left[R_{MKT,t} - R_{f,t}\right] + \hat{\beta}_{SMB}^{ETF} R_{SMB,t} + \hat{\beta}_{HML}^{ETF} R_{HML,t} + \hat{\beta}_{RMW}^{ETF} R_{RMW,t} + \hat{\beta}_{CMA}^{ETF} R_{CMA,t} + \varepsilon_t^{ETF} \quad (21)$$

The ETFs' FF 5 factor regression-based benchmark is then:

$$\hat{R}^{ETF}_{FF5\,Benchmark,t} = R_{f,t} + \hat{\beta}^{ETF}_{MKT}\left[R_{MKT,t} - R_{f,t}\right] + \hat{\beta}^{ETF}_{SMB}\, R_{SMB,t} + \hat{\beta}^{ETF}_{HML}\, R_{HML,t} + \hat{\beta}^{ETF}_{RMW}\, R_{RMW,t} + \hat{\beta}^{ETF}_{CMA}\, R_{CMA,t} \quad (22)$$

The ETFs' generalized FF 5 factor alpha is then:

$$\hat{\alpha}^{ETF}_{FF\,5} = \bar{R}^{ETF} - [\bar{R}_f + \hat{\beta}^{ETF}_{MKT}\left[\bar{R}_{MKT} - \bar{R}_f\right] + \hat{\beta}^{ETF}_{SMB}\, \bar{R}_{SMB} + \hat{\beta}^{ETF}_{HML}\, \bar{R}_{HML} + \hat{\beta}^{ETF}_{RMW}\, \bar{R}_{RMW} + \hat{\beta}^{ETF}_{CMA}\, \bar{R}_{CMA}] \quad (23)$$

6.1.5 Fama-French 5-Factor model with MOM (6-Factor model)

The Fama-French 6-factor model encompasses all the factors from the Fama-French 5-factor model, along with the momentum factor introduced by Carhart in his 4-factor model. Consequently, the Fama-French 6-factor model comprises the following factors: Market, SMB, HML, RMW, CMA, and MOM.

The expected return on an ETF is derived from the following:

$$R^{ETF}_t = R_{f,t} + \beta^{ETF}_{MKT}\left[R_{MKT,t} - R_{f,t}\right] + \beta^{ETF}_{SMB}\, R_{SMB,t} + \beta^{ETF}_{HML}\, R_{HML,t} + \beta^{ETF}_{RMW}\, R_{RMW,t} + \beta^{ETF}_{CMA}\, R_{CMA,t} + \beta^{ETF}_{MOM}\, R_{MOM,t} \quad (24)$$

The factor betas are estimated by running the following time series regression:

$$R^{ETF}_t - R_{f,t} = \hat{\alpha}^{ETF}_{FF5} + \hat{\beta}^{ETF}_{MKT}\left[R_{MKT,t} - R_{f,t}\right] + \hat{\beta}^{ETF}_{SMB}\, R_{SMB,t} + \hat{\beta}^{ETF}_{HML}\, R_{HML,t} + \hat{\beta}^{ETF}_{RMW}\, R_{RMW,t} + \hat{\beta}^{ETF}_{CMA}\, R_{CMA,t} + \hat{\beta}^{ETF}_{MOM}\, R_{MOM,t} + \varepsilon^{ETF}_t \quad (25)$$

The ETFs' FF 6 factor regression-based benchmark is then:

$$\hat{R}^{ETF}_{FF6\,Benchmar\;\;,t} = R_{f,t} + \hat{\beta}^{ETF}_{MKT}\left[R_{MKT,t} - R_{f,t}\right] + \hat{\beta}^{ETF}_{SMB}\, R_{SMB,t} + \hat{\beta}^{ETF}_{HML}\, R_{HML,t} + \hat{\beta}^{ETF}_{RMW}\, R_{RMW,t} + \hat{\beta}^{ETF}_{CMA}\, R_{CMA,t} + \hat{\beta}^{ETF}_{MOM}\, R_{MOM,t} \quad (26)$$

The ETFs' generalized FF 6 factor alpha is then:

$$\hat{\alpha}^{ETF}_{FF\,6} = \bar{R}^{ETF} - [\bar{R}_f + \hat{\beta}^{ETF}_{MKT}\left[\bar{R}_{MKT} - \bar{R}_f\right] + \hat{\beta}^{ETF}_{SMB}\, \bar{R}_{SMB} + \hat{\beta}^{ETF}_{HML}\, \bar{R}_{HML} + \hat{\beta}^{ETF}_{RMW}\, \bar{R}_{RMW} + \hat{\beta}^{ETF}_{CMA}\, \bar{R}_{CMA} + \hat{\beta}^{ETF}_{MOM}\, \bar{R}_{MOM}] \quad (27)$$

6.2 Performance measures

For conducting a comprehensive study on different investor preferences, it is important to use a variety of performance and risk metrics that cater to the diverse needs and risk appetites of investors.

6.2.1 Sharpe Ratio

Developed by William Sharpe in 1966, Sharpe Ratio is a widely used measure to assess the risk-adjusted return, indicating how much excess return is received for the extra volatility endured. This can be useful for measuring the performance of a single sector ETF or a portfolio of ETFs.

$$\textit{Sharpe Ratio} = \frac{R_p - R_f}{\sigma_p} \tag{28}$$

where R_p is the portfolio return, R_f is the risk-free rate, and σ_p is the standard deviation of the portfolio's excess return.

6.2.2 Sortino Ratio

Sortino ratio is similar to Sharpe ratio, but it only focuses on the downside risk, and is thus preferred by investors more concerned with downturns.

$$\textit{Sortino Ratio} = \frac{R_p - R_f}{\sigma_d} \tag{29}$$

and σ_d is the downside deviation.

6.2.3 Treynor Ratio

For investors with well diversified portfolios systematic risk is the main concern. For this purpose, Treynor ratio can help as it measures the excess return per unit of market risk (beta).

$$\textit{Treynor Ratio} = \frac{R_p - R_f}{\beta_p} \tag{30}$$

where β_p is the portfolio's beta.

6.2.4 Information Ratio

For investor looking to assess the performance of active managers relative to a market benchmark, information ratio can be a useful measure. It measures the excess return of a portfolio compared to a benchmark, adjusted for the tracking error.

$$Information\ Ratio = \frac{R_p - R_b}{\sigma_{p-b}} \quad (31)$$

where R_b is the benchmark return and $\sigma_{p\text{-}b}$ is the tracking error.

6.2.5 Omega Ratio

Omega ratio is an alternative to Sharpe ratio and can be useful for investor looking for a more comprehensive assessment of risk vs reward than the traditional measures. It was introduced by Keating and Shadwick in 2002 and is defined as the ratio of the probability-weighted gains to losses for a given return threshold, typically the risk-free rate. The key aspect of the Omega ratio is that it integrates both sides of the return distribution — capturing both the upside potential and the downside risk beyond a specified minimum acceptable return (MAR).

$$\Omega(r) = \frac{\int_r^{\infty}[1-F(x)]dx}{\int_{-\infty}^{r} F(x)dx} \quad (32)$$

where $F(x)$ is the cumulative distribution function of returns and r is the minimum acceptable return. In practical terms, the numerator captures the area under the probability curve above the MAR, representing the potential for returns higher than the MAR. The denominator captures the area under the curve below the MAR, representing the risk of falling short of the MAR. Higher Omega ratios would thus indicate that the returns distribution is skewed towards more favourable outcomes relative to the MAR and would be preferred as it signifies more gains per unit of risk.

6.2.6 Alpha

Alpha is a key performance metric that measures the excess return on an asset beyond what is predicted by an equilibrium asset pricing model. A positive alpha indicates that a sector ETF has outperformed its expected return, providing significant value to the average investor. Alpha was introduced by Michael Jensen in 1968 to evaluate mutual fund managers. Jensen originally used the Capital Asset Pricing Model (CAPM) to calculate alpha (Jensen's Alpha), but CAPM adjusts for only one systematic risk factor (market risk). Consequently, relying solely on CAPM may result in overestimating the alphas of sector ETFs. This limitation arises because CAPM does not account for other systematic risks that could impact returns, such as size, value, and momentum factors, which are considered in multifactor models like the Fama-French three-factor model or the Carhart four-factor model. Therefore, multiple different alpha values can be evaluated for different models. We select the appropriate alpha later based on the results on our study.

7 Data

This section outlines the data utilized in this thesis. It details the process of data collection and the selection criteria for both the ETFs and the factors involved. The timeframe selected for the data spans from September 2010 to September 2019. This period was specifically chosen to try and exclude the crisis periods for the 2008 financial crisis and the 2019 COVID-19 pandemic crisis, to ensure that these major economic disruptions do not skew the analysis.

7.1 Data Sources

The etf.db database was used as the primary source for ETF-related data, including the names of various sectors and all corresponding US-based ETFs within those sectors.

The monthly Total Return (NAV) data for each ETF, categorized by sector, was then sourced from FactSet. Furthermore, the monthly data for the six Fama-French factors, along with the monthly risk-free rate, were obtained from the Kenneth French website.

7.2 Data Screening and Filtering

7.2.1 Sector ETFs

Sector ETFs that established on or before September 2010 were selected, aligning with the commencement of the data sample period in September 2010. Additionally, it was required for the ETFs to have complete data for the entire study duration from September 2010 to September 2019. The monthly NAV data of ETFs was gathered and were treated as the monthly adjusted closing price, which is already adjusted for dividends and stock splits.

Table 1 details the different sectors along with the number of ETFs selected from within each. Inverse and leveraged ETFs were excluded.

Table 1 Different sectors and the corresponding numbers of ETFs contained for the US market

Sector	*Number of ETFs*
Consumer Staples	11
Consumer Discretionary	13
Energy	26
Financials	19
Healthcare	16
Industrials	16
Materials	26
Real Estate	14

Technology	22
Utilities	11

7.2.2 Fama-French Factors

The Fama/French 5 factors (2x3) were constructed using the 6 value-weight portfolios formed on size and book-to-market, the 6 value-weight portfolios formed on size and operating profitability, and the 6 value-weight portfolios formed on size and investment (See the description of the 6 size/book-to-market, size/operating profitability, size/investment portfolios)

MKT (Market Return Minus Risk-free Rate) measures the excess return of the market over the risk-free rate. Rm – Rf also called market factor, is one of the 6 Fama French factors. Rm-Rf, the excess return on the market, value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price data at the beginning of t, and good return data for t minus the one-month Treasury bill rate (from Ibbotson Associates).

SMB (Small Minus Big) is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios.

HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios

RMW (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios

CMA (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios.

They use six value-weight portfolios formed on size and prior (2-12) returns to construct MOM. The portfolios, which are formed daily, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (2-12) return. The daily size breakpoint is the median NYSE market equity. The daily prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles.

MOM/ WML (Winners minus Losers) is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.

7.2.3 Risk-Free Rate

The monthly data for the risk-free rate (Rf) was obtained from Kenneth French's website, which employs the one-month Treasury bill rate, sourced from Ibbotson Associates, as the risk-free rate.

8 Empirical Analysis and Results

8.1 In-sample

8.1.1 Model performance

Different models can be considered for evaluation of factor significance on sector ETFs. The fit of the model can be tested with Adjusted R^2 values. Additionally, a lower number of significant alphas in a model can also indicate a better fit, as significant alphas suggest that the model is not fully capturing the risk-return characteristics of the ETFs, indicating potential mispricing or omitted variables. **Table *2*** describes the median adjusted R^2 values and **Table *3*** gives the number of ETFs with significant alphas for the in-sample period, per sector for each model considered.

Table 2: Median Adjusted R^2 values for sector ETFs

Sector	*Number of ETFs*	*CAPM*	*FF3*	*FFC4*	*FF5*	*FF5 + MOM*
Consumer Staples	11	0.43	0.56	0.61	0.60	**0.69**
Consumer Discretionary	13	0.77	0.78	0.78	0.82	**0.82**
Energy	26	0.47	0.56	0.58	0.58	**0.59**
Financials	19	0.77	0.83	0.83	0.84	**0.85**
Healthcare	16	0.50	0.63	0.63	**0.68**	0.68
Industrials	16	0.77	0.85	0.85	0.85	**0.86**
Materials	26	0.62	0.63	**0.67**	0.62	0.67
Real Estate	14	0.34	0.36	**0.38**	0.35	0.37
Technology	22	0.71	0.79	0.80	0.83	**0.84**
Utilities	11	0.20	0.21	0.23	0.26	**0.31**

Table 3: Number of ETFs with significant alphas (90% Confidence)

Sector	*Number of ETFs*	*CAPM*	*FF3*	*FFC4*	*FF5*	*FF5 + MOM*
Consumer Staples	11	5	4	**2**	**2**	**2**
Consumer Discretionary	13	**1**	**1**	**1**	**1**	**1**
Energy	26	24	25	21	23	**20**
Financials	19	4	4	4	**3**	**3**
Healthcare	16	3	4	**1**	9	8
Industrials	16	**4**	5	5	5	**4**

Materials	26	19	17	10	15	**12**
Real Estate	14	**0**	2	**0**	2	**0**
Technology	22	1	**0**	1	**0**	1
Utilities	11	5	4	**1**	**1**	**1**

We can observe that,

- CAPM model gives the worst explanatory power for all sectors. Even though the market factor remains a crucial factor in explaining returns, it is clearly not comprehensive. CAPM and FF3 also often show a greater number of significant alphas as well, this indicates that they might be missing important factors that are captured by the more comprehensive models.
- The FF5+MOM model consistently provides the highest adjusted R^2 values across most sectors. This indicates that it captures the variance in ETF returns better than simpler models. It also shows fewer significant alphas in many sectors, suggesting that it effectively captures the risk-return dynamics and leaves less unexplained variation (alpha). This indicates a better model fit and lower chances of omitted variables or mispricing.
- MOM provides a clear advantage in fit and explanation, with FFC4 generally having a better fit and lower number of significant alphas than FF3, and FF5M generally having a better fit and lower number of significant alphas than FF5.
- Different sectors respond variably to the factor models, with some sectors (e.g., Consumer Discretionary, Financials) showing consistently high explanatory power, while others (e.g., Utilities, Real Estate) exhibit lower explanatory power. Same goes for alphas, Energy and Materials have considerably higher percentage of significant alphas than other sectors.

Results between sectors can vary in fit performance.

Consumer Discretionary, Financials, Industrials, and Technology: These sectors show relatively high adjusted R^2 values across all models, indicating that the models are effective in these sectors. The number of significant alpha generator ETFs within these sectors is also generally low.

Consumer Staples: This sector shows moderate adjusted R^2 values, still with a low number of significant alpha ETFs.

Utilities and Real Estate: These sectors show relatively low adjusted R^2 values across all models. This highlights the potential need for additional factors or alternative models to better capture the returns in these sectors. Even so, the number of significant alphas for these sectors is very low.

Materials: The FF5 model shows a dip in explanatory power compared to FF3 and FFC4, which could indicate sector-specific dynamics affecting returns.

Healthcare: This sector is somewhat of an outlier. While the FF5 model demonstrates the highest explanatory power, it also shows the highest number of significant alphas. This could also suggest that simpler models fail to capture truly significant alphas, although further research would be needed to confirm this.

Energy: This sector exhibits the highest number of significant residual alphas and low-to-moderate model fit performance. Similar to Utilities and Real Estate, Energy may require additional factors beyond the scope of this study to fully explain its performance.

Based on the above observations, we conclude that investors should consider using the FF5+MOM model for sector analysis and portfolio construction, as it balances explanatory power and fit effectively. However, for sectors with low explanatory power or high number of significant alphas, additional research into alternative factors or models may be beneficial or even necessary.

8.1.2 Factor statistics

Table *4* provides the descriptive statistics for the regression factors of the FF5+MOM model. Results indicate that the average market premium is strongly positive in the in-sample period, whereas other factors have lower overall influence, with MOM having the highest mean after MKT. Overall, all factors indicate high volatility compared to the mean, with SD values ranging from 1-3%. The high volatility, especially in MKT, SMB, HML and MOM factors indicates that even though gains are to be made with factor specific investing, it could come with substantial risks. Overall, the factor median values are generally positive except for HML and CMA indicating that investors have been compensated for most of the factor risk taken positively.

Table 4: Descriptive statistics of regression factors (%)

	MKT	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
Mean	1.169	0.026	-0.015	0.087	0.022	0.223
SD	3.282	2.297	2.183	1.637	1.383	2.950
Min	-7.590	-4.550	-4.130	-3.880	-2.480	-7.910
Median	1.135	0.280	-0.340	0.140	-0.015	0.330
Max	11.350	7.070	8.210	3.480	3.700	9.980

If Fama-French factor values are highly correlated, it can lead to multicollinearity in regression analysis, which complicates the interpretation of the regression coefficients. Multicollinearity occurs when two or more independent variables in a regression model are highly correlated, making it difficult to determine the individual effect of each variable on the dependent variable. ***Table 5*** reports the correlations across the 6 Fama-French factors. The strongest correlation being between HML and CMA factors, which indicates that these factors could be intrinsically tracking similar properties within securities, or to put it simply, value stocks might be having more conservative investment policies and growth stocks might be behaving more aggressively.

Table 5: Correlation matrix of the Fama-French factors

	MKT	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
MKT	1.000					
SMB	0.360	1.000				
HML	0.137	0.266	1.000			
RMW	-0.431	-0.475	-0.244	1.000		
CMA	-0.028	0.127	0.635	0.033	1.000	
MOM	-0.293	-0.147	-0.436	0.158	-0.167	1.000

It can also be observed that the MKT factor is positively correlated with SMB and HML, however negatively with RMW and MOM, and has a low negative correlation with CMA. Allocating investments in a way that balances positively, negatively and low correlated factors can optimize the risk-adjusted returns. For example, combining market factor exposure with factors like profitability and momentum can help mitigate risk.

To further test the multicollinearity when using the FF5+MOM model, the Variance Inflation Factor (VIF) can be used. VIF quantifies how much the variance of an estimated regression coefficient is increased because of collinearity with the other predictors (factors) in the model. VIF for a factor X_i is calculated as:

$$VIF_i = \frac{1}{1 - R_i^2}$$

where R_i^2 is the R-squared value obtained from regressing Xi on all the other factors. High values of R_i^2 would indicate that Xi is highly collinear with other factors, and lead to a high VIF. VIF values above 10 typically indicate high multicollinearity, which can be problematic in regression analysis as it may inflate the variance of coefficient estimates and make the model unstable. The lowest VIF value on the other hand is 1 for when R_i^2 is zero.

Table 6 indicates that most VIF values for the factors are close to 1 for the in-sample period, indicating that multicollinearity is not a significant issue. The highest VIF value is 2.293 for HML, which is still within acceptable limits.

Table 6: VIF of the factors for the chosen model

Variables	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
VIF	1.373	1.392	2.293	1.541	1.835	1.356

8.1.3 Sector statistics

The analysis of sector returns during the in-sample period in ***Table 7*** reveals distinct performance characteristics and risk profiles for each sector. Sectors with higher returns generally have higher volatility, suggesting a risk-return trade-off. However, energy and materials have the lowest mean returns and highest volatility. The skewness in the median and mean values for certain sectors (e.g., Healthcare and Technology) suggests asymmetric return distributions for specific sectors.

Table 7: Sector statistics for equal-weighted portfolios for the in-sample period

	Mean	*SD*	*Min*	*Median*	*Max*
Consumer Staples	0.984	2.832	-6.231	1.005	7.141
Consumer Discretionary	1.066	3.853	-10.304	1.267	13.752
Energy	0.097	5.919	-18.859	0.065	16.536
Financials	1.112	4.559	-11.146	1.555	14.366
Healthcare	1.465	4.412	-14.388	2.151	8.857
Industrials	1.125	3.801	-9.993	1.290	13.021
Materials	0.361	5.545	-18.558	-0.044	16.236
Real Estate	0.814	3.857	-11.217	0.792	12.244
Technology	1.353	4.240	-9.281	2.021	14.310
Utilities	0.803	2.907	-5.079	0.975	8.503

8.1.4 Significance level of factors within sectors

When using the FF5+MOM model to explain returns for the in-sample period, certain factors may be more significant than others from sector to sector. To test this, we examine the number of ETFs in each sector which have significant factors (90% confidence). **Table *8*** below illustrates the results. In the table, negative and positive significant beta values have been segregated, so as to not misinterpret the true impact of the market factors on the ETFs.

Table 8: Number of ETFs with significant factors (90%) in sectors (Red: Negatively Significant Beta, Green: Positively Significant Beta)

Sector	Number of ETFs	ALPHA	MKT	SMB	HML	RMW	CMA	MOM
Consumer Staples	11	2	11	1 6	6	6	6 1	9
Consumer Discretionary	13	1	13	7	4	9 1	2 2	31
Energy	26	20	26	12	15 1	5	2 4	11
Financials	19	3	19	8 2	18	1 13	15	9 2
Healthcare	16	8	16	8 1	15	12	3	0
Industrials	16	2 2	16	12	1 3	2	5	1 6
Materials	26	12	23	10	1 3	1 3	3	22
Real Estate	14	0	14	3	1	0	1	8 2
Technology	22	1	22	4 7	10	12	16	19
Utilities	11	1	11	8	0	1	5	6 2
Overall Significance	174	30%	98%	51%	45%	38%	37%	56%

We observe for the various factors,

MKT: All sectors have significant positive market exposure, indicating strong alignment with overall market movements. This suggests that sector ETFs generally move in tandem with the broader market.

SMB: Significant size exposure varies across sectors, with Consumer Discretionary, Energy, Financials, Healthcare, Industrials and Materials showing predominantly positive size exposure, indicating a tilt towards smaller firms. In contrast, Consumer Staples, Technology and Utilities show predominantly negative size exposure, indicating a tilt towards larger firms.

HML: Sectors like Energy and Financials have strong positive value exposure, while Healthcare and Technology show predominantly negative value exposure, indicating a prevalence of growth stocks.

RMW: Consumer Staples and consumer discretionary provide robust stable earnings, while Energy, Financials, Healthcare and Technology are tilted towards low profitability. For Financials, this can be due to the long period of low interest rates. For Energy, it might be due to the transition into renewables straining profitability. Meanwhile, weak profitability in Healthcare and Technology might be driven by the need to innovate and competition.

CMA: Most sectors are neutral to positive towards conservative investment policies. Exception being Technology and Financials. Technology can be obvious, due to competition and the need for growth, which would require aggressive reinvestment. For Financials, the in-sample period might be special due to the post 2008 financial crisis recovery where new regulatory requirements required significant investments in risk management systems, compliance infrastructure, and capital buffers.

MOM: Consumer Staples, Financials, Real Estate and Utilities are positive for momentum, reflecting stability and demand. Volatility in oil prices might be driving Energy sectors negative momentum: Similarly for materials, volatility in commodity prices could cause the negative momentum. Meanwhile, varying investor sentiment and sector rotation to perceived undervalued sectors could have caused the negative momentum in Technology.

Overall, we can see that factors such as market, size, value, profitability, investment, and momentum significantly influence sector returns. These factors interact with sector-specific characteristics, shaping the performance and risk profiles of different sectors. Each sector responds differently to various factors, indicating that factor sensitivities are crucial in understanding sector dynamics and guiding investment strategies.

ALPHA: Alpha is negative or insignificant for most sectors except for Healthcare, underscoring the challenges in active management and potential inefficiencies with sector-specific investment. Even in Healthcare, where half of the ETFs exhibit significant positive alphas, this may be due to the sector's overall strong performance rather than the result of active management - though further study is needed to confirm this. Nevertheless, not all ETFs within the sectors are negative, suggesting that fund managers can still influence the performance of specific ETFs.

8.2 Out-of-sample

8.2.1 Factor statistics

When comparing the performance of ETFs, it is crucial to consider the influence of factors during the specific out-of-sample period, as these influences may differ from the in-sample analysis. This helps determine whether factors impact sectors as expected or in a sector-specific manner during the out-of-sample period.

Table 9: Descriptive statistics of regression factors (%)

	MKT	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
Mean	0.798	-0.365	-0.530	0.233	-0.078	0.452
SD	4.303	2.524	2.578	1.238	1.765	3.897
Min	-9.570	-4.460	-4.780	-2.420	-3.250	-8.680
Median	1.430	-0.770	-0.460	0.520	0.010	0.040
Max	8.400	4.780	6.750	3.160	3.590	7.560

As can be seen, the out-of-sample period reveals notable shifts in the behaviour of factors compared to the in-sample period. The average market premium decreased with higher volatility, while size and value factors showed significant performance changes. The profitability factor remained stable with stronger performance, and the momentum factor demonstrated somewhat increased volatility. These shifts underscore the importance of continuously monitoring factor influences and adjusting investment strategies accordingly to navigate different market environments effectively. Investors looking to capitalize may also want to study these factors values in a rolling window. As can be seen in ***Figure 1***, the rolling factor means are tending to be cyclical in the study period, however the cycles are not necessarily aligned.

Figure 1 FF5M Factor 24-month rolling means

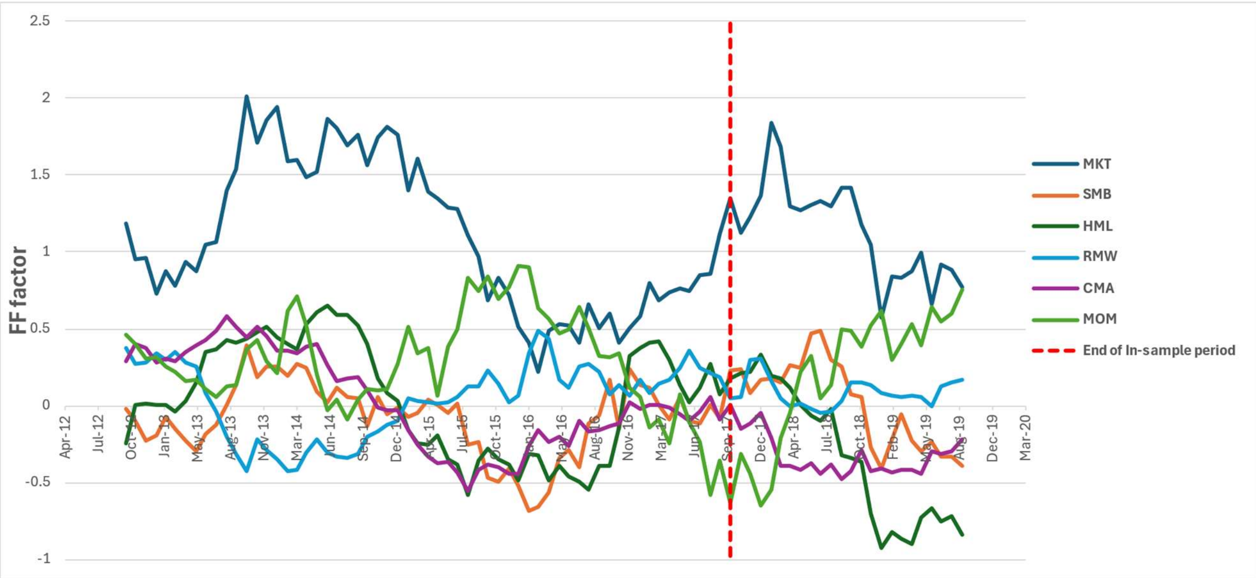


Table 10 describes the correlation matrix for the factors in the out-of-sample period.

Table 10: Correlation matrix of the Fama-French factors (out-of-sample)

	MKT	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
MKT	1.000					
SMB	0.376	1.000				
HML	0.043	0.083	1.000			
RMW	0.010	-0.463	0.214	1.000		
CMA	-0.403	-0.149	0.543	0.041	1.000	
MOM	-0.375	-0.292	-0.636	-0.234	-0.328	1.000

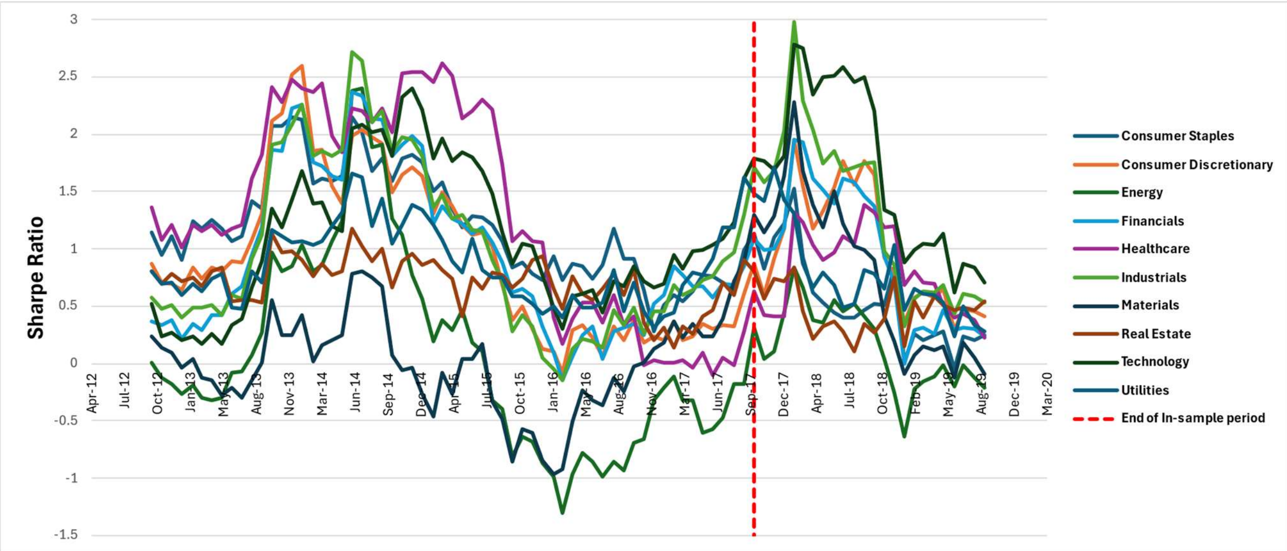
It can be seen that the relationships between some factors have shifted, becoming stronger or weaker. For example, the relationship between HML and MOM has become more strongly negative. However, the negative relationship between other factors such as

SMB and RMW has remained consistent, indicating stable interaction between size and profitability.

8.2.2 Sector-specific cyclical statistics

Understanding the cyclical influence of the market on sectors is crucial for effective sector investment. While the primary aim of this study is to devise a sector allocation strategy rather than a sector selection or rotation strategy, analysing the cross-sector performance within the study period provides valuable context for our observations. ***Figure 2*** displays the 24-month rolling Sharpe Ratios for equal-weighted sector portfolios. The influence of the market on sectors is clearly visible. Sectors such as consumer discretionary, technology, industrials and financials are tending to outperform during periods of expansion. Consumer Staples and Utilities tend to have more stable Sharpe Ratios during economic contractions, implying their defensive nature. These sectors typically provide essential goods and services, maintaining relatively steady performance even during downturns. The Healthcare sector shows relatively high and stable Sharpe Ratios throughout the period, indicating consistent performance. This may be due to ongoing innovation and the non-cyclical demand for healthcare services.

Figure 2 Sector-wise 24-month rolling Sharpe ratios (annualized) for equal-weighted sector portfolios



8.2.3 Performance based on factor betas

Based on the in-sample factor beta significance, we can categorize the ETFs within each sector and for each factor as:

i. Insignificant beta factor ETFs

ii. Significant +ve beta factor ETFs

iii. Significant –ve beta factor ETFs

For example, in the consumer staples sector, 4 ETFs exhibit insignificant SMB factor betas, 1 ETF has a significant positive SMB factor beta, and 6 ETFs have significant negative SMB factor betas. Three separate equal-weighted portfolios can be constructed with the ETFs based on these beta categories. Additionally, a fourth equal-weighted portfolio can be constructed with all ETFs within the sector. Finally, various performance measures for these four separate portfolios per sector can be compared out-of-sample to determine the performance advantage, if any, of the factor-based sector portfolios.

It is important to note that a portfolio constructed based on, for example, SMB beta significance is not isolated from the influence of other factors. On the contrary, its performance may still be significantly affected by factors such as HML, MOM, CMA and RMW, which can either enhance or counteract the influence of SMB on the overall portfolio returns. The rationale behind this approach to portfolio construction is that if certain factors have a dominant influence on specific sectors, then selecting ETFs within those sectors based on the significance of these factors can potentially enhance performance and perhaps that pattern is predictable.

8.2.3.1 Sharpe Ratio

While Sharpe Ratio is typically annual, here we calculate the monthly Sharpe Ratio and annualize it by multiplying the result with the square root of 12. This is to have more granularity on the low amount of data owing to the relatively short history of sector ETFs. Caveat on this method could be that this assumes that monthly returns are independently and identically distributed which might not be true in general due to patterns such as seasonality. Also, volatility clustering can mean that the annual volatility is different from the “annualized” volatility. Still, this method provides a way to compare the different portfolios constructed for our study.

Portfolios based on SMB

Generally, sectors do not benefit significantly from positive SMB exposure (except Materials), with most sectors showing lower Sharpe ratios for portfolios with significant positive SMB beta values. Sectors like Consumer Staples, Technology, and Utilities perform better with significant negative SMB exposure, indicating a preference for larger firms. Other sectors, such as Consumer Discretionary, Energy, Financials, Healthcare, Industrials, and Real Estate, perform well with insignificant SMB beta values over significant positive beta values, again suggesting that avoiding size factor exposure or tending towards ETFs with larger firms can enhance returns in these sectors as well. The only outlier is Materials where significant positive beta portfolio performs better than insignificant, however even then the Sharpe ratio is 0.

Table 11: Sharpe Ratio of portfolios created based on SMB beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.270 (11)	0.060 (4)	0.150 (1)	**0.416 (6)**
Consumer Discretionary	0.338 (13)	**0.374 (6)**	0.303 (7)	
Energy	-0.353 (26)	**-0.002 (14)**	-0.544 (12)	
Financials	0.191 (19)	**0.373 (9)**	0.127 (8)	-0.272 (2)
Healthcare	0.126 (16)	0.143 (7)	0.102 (8)	**0.371 (1)**
Industrials	0.450 (16)	**0.506 (4)**	0.434 (12)	
Materials	-0.121 (26)	-0.199 (16)	**0.000 (10)**	
Real Estate	0.651 (14)	**0.680 (11)**		0.390 (3)
Technology	0.636 (22)	0.573 (11)	0.483 (4)	**0.828 (7)**
Utilities	0.516 (11)	-0.426 (3)		**0.914 (8)**

Portfolios based on HML

Results for HML are more sector specific than for SMB. Specifically, selecting significant negative beta ETFs (growth-oriented) over insignificant within Consumer Staples, Consumer Discretionary, Industrials and Technology sectors would be rewarded. For the Energy sector, picking insignificant beta ETFs over significant positive beta would yield better performance again displaying a tendency towards growth rather than value. Financials, Healthcare, Materials, Real Estate and Utilities show one-sided influences for the HML factor, making factor-based investment allocation within these sectors less effective.

Table 12: Sharpe Ratio of portfolios created based on HML beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.270 (11)	-0.072 (5)		**0.553 (6)**
Consumer Discretionary	0.338 (13)	0.247 (9)		**0.536 (4)**
Energy	-0.353 (26)	**0.304 (10)**	-0.543 (15)	-0.138 (1)
Financials	0.191 (19)	0.104 (1)	**0.195 (18)**	
Healthcare	0.126 (16)	**0.355 (1)**		0.112 (15)
Industrials	0.450 (16)	0.433 (12)	0.281 (1)	**0.609 (3)**
Materials	-0.121 (26)	-0.125 (22)	-0.090 (1)	**0.119 (3)**
Real Estate	0.651 (14)	**0.675 (13)**		0.222 (1)
Technology	0.636 (22)	0.522 (12)		**0.762 (10)**
Utilities	**0.516 (11)**	**0.516 (11)**		

Portfolios based on RMW

Results indicate that the sensitivity of sectors to the RMW factor varies significantly. For Consumer Staples and Consumer Discretionary, portfolios with positive RMW beta values perform the best, consistent with these sectors' defensive nature, where robust earnings are rewarded. Similarly, for Financials and Technology, selecting ETFs with insignificant RMW beta values over those with significant negative RMW beta values is beneficial, again indicating a preference for profitability.

Energy and Healthcare are outliers, where selecting ETFs based on significant negative RMW betas values would have yielded better performance. Industrials, Materials, Real Estate, and Utilities show a more one-sided response to the RMW factor, suggesting that factor-based ETF selection within these sectors would not be as effective.

Table 13: Sharpe Ratio of portfolios created based on RMW beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.270 (11)	0.081 (5)	**0.409 (6)**	
Consumer Discretionary	0.338 (13)	0.058 (3)	**0.432 (9)**	0.344 (1)
Energy	-0.353 (26)	-0.465 (21)		**0.390 (5)**
Financials	0.191 (19)	0.217 (5)	**0.222 (1)**	0.178 (13)
Healthcare	0.126 (16)	-0.021 (4)		**0.166 (12)**
Industrials	0.450 (16)	**0.488 (14)**	0.229 (2)	
Materials	-0.121 (26)	-0.148 (22)	-0.090 (1)	**0.097 (3)**
Real Estate	**0.651 (14)**	**0.651 (14)**		
Technology	0.636 (22)	**0.710 (10)**		0.560 (12)
Utilities	0.516 (11)	**0.577 (10)**	0.067 (1)	

Portfolios based on CMA

Consumer Staples, Consumer Discretionary, Healthcare, Industrials, and Utilities benefit from firms with conservative investment policies, as indicated by higher Sharpe ratios of significant positive beta ETF portfolios. Similarly, for Financials, insignificant CMA beta portfolio performs better than significant negative portfolio, again preferring conservative investment policies. On the contrary, Energy and Technology show better performance with firms having aggressive investment policies. Materials and Real Estate have one-sided ETFs with regards to this factor, making factor-based allocation less effective.

Table 14: Sharpe Ratio of portfolios created based on CMA beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.270 (11)	0.025 (4)	**0.476 (6)**	-0.133 (1)
Consumer Discretionary	0.338 (13)	0.333 (9)	**0.464 (2)**	0.216 (2)
Energy	-0.353 (26)	-0.446 (20)	-0.176 (2)	**0.410 (4)**
Financials	0.191 (19)	**0.353 (4)**		0.156 (15)
Healthcare	0.126 (16)	0.084 (13)	**0.379 (3)**	

Industrials	0.450 (16)	0.430 (11)	**0.492 (5)**	
Materials	-0.121 (26)	**-0.105 (23)**	-0.116 (3)	
Real Estate	0.651 (14)	**0.675 (13)**	0.222 (1)	
Technology	0.636 (22)	0.602 (6)		**0.645 (16)**
Utilities	0.516 (11)	-0.002 (6)	**1.064 (5)**	

Portfolios based on MOM

Momentum produces some strong results. Consumer Staples, Consumer Discretionary, Financials, Real Estate and Utilities benefit from firms with positive momentum, as indicated by higher Sharpe ratios of significant positive factor portfolios. Similarly, for Energy and Materials, insignificant factor portfolio outperforms the significant negative factor portfolio, again preferring winners over losers. Outliers are Industrials and Technology, where the significant negative factor portfolio is slightly better than the insignificant portfolio.

Table 15: Sharpe Ratio of portfolios created based on MOM beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.270 (11)	-0.488 (2)	**0.449 (9)**	
Consumer Discretionary	0.338 (13)	0.358 (9)	**0.421 (3)**	-0.015 (1)
Energy	-0.353 (26)	**-0.181 (15)**		-0.521 (11)
Financials	0.191 (19)	0.223 (8)	**0.269 (9)**	-0.272 (2)
Healthcare	**0.126 (16)**	**0.126 (16)**		
Industrials	0.450 (16)	0.450 (9)	0.335 (1)	**0.463 (6)**
Materials	-0.121 (26)	**0.169 (4)**		-0.172 (22)
Real Estate	0.651 (14)	0.465 (4)	**0.732 (8)**	0.394 (2)
Technology	0.636 (22)	0.602 (7)		**0.649 (15)**
Utilities	0.516 (11)	0.526 (3)	**0.873 (6)**	-0.580 (2)

Summary

To summarize, factor information can be effectively used to select ETFs across most sectors due to the variety of ETFs available within each sector, which respond differently to various factors. This diversity allows investors to leverage factor-based strategies to enhance portfolio performance.

However, for certain factors within specific sectors, the beta behaviour is consistent across most ETFs, making factor-based selection less effective. In these cases, the uniform response to the factor, means that distinguishing between ETFs based on factor information is not possible, limiting the benefits of factor-based investing for those specific sector-factor combinations. ***Table 16*** captures the result with sectors where factor information can be utilized or not.

Table 16: Can factor significance information be utilized to generate better performing sector ETF portfolios?

	SMB	*HML*	*RMW*	*CMA*	*MOM*
Consumer Staples	✓	✓	✓	✓	✓
Consumer Discretionary	✓	✓	✓	✓	✓
Energy	✓	✓	✓	✓	✓
Financials	✓	×	✓	✓	✓
Healthcare	✓	×	✓	✓	✓
Industrials	✓	✓	×	✓	✓
Materials	✓	×	×	×	✓
Real Estate	✓	×	×	×	✓
Technology	✓	✓	✓	✓	✓
Utilities	✓	×	×	✓	✓

8.2.3.2 Sortino Ratio

Considering only downside deviation reduces the overall volatility compared to the Sharpe ratio, resulting in generally higher absolute values for Sortino ratios. While sector-specific deviations may still exist depending on the downside deviations across sectors, our analysis finds that the conclusions derived from Sharpe ratios are consistent with those from Sortino ratios. This indicates that the insights gained from Sharpe ratios regarding factor-based investing are also applicable when evaluated using Sortino ratios.

Portfolios based on SMB

Considering only downside deviation does not change the conclusion on SMB from Sharpe Ratio.

Table 17 : Sortino Ratio of portfolios created based on SMB beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.301 (11)	0.074 (4)	0.197 (1)	**0.503 (6)**
Consumer Discretionary	0.443 (13)	**0.496 (6)**	0.357 (7)	
Energy	-0.475 (26)	**-0.002 (14)**	-0.704 (12)	
Financials	0.289 (19)	**0.556 (9)**	0.182 (8)	-0.534 (2)
Healthcare	0.179 (16)	0.203 (7)	0.146 (8)	**0.526 (1)**
Industrials	0.572 (16)	**0.649 (4)**	0.552 (12)	
Materials	-0.181 (26)	-0.336 (16)	**0.000 (10)**	
Real Estate	0.913 (14)	**0.934 (11)**		0.720 (3)
Technology	0.860 (22)	0.761 (11)	0.730 (4)	**1.121 (7)**

Utilities	0.766 (11)	-0.599 (3)		**1.395 (8)**

Portfolios based on HML

Sortino ratio based on HML beta-based portfolios, are also in-line with conclusions from Sharpe ratio.

Table 18: Sortino Ratio of portfolios created based on HML beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.301 (11)	-0.085 (5)		**0.587 (6)**
Consumer Discretionary	0.443 (13)	0.297 (9)		**0.770 (4)**
Energy	-0.475 (26)	**0.551 (10)**	-0.727 (15)	-0.221 (1)
Financials	0.289 (19)	0.140 (1)	**0.296 (18)**	
Healthcare	0.179 (16)	**0.498 (1)**		0.160 (15)
Industrials	0.572 (16)	0.562 (12)	0.382 (1)	**0.800 (3)**
Materials	-0.181 (26)	-0.180 (22)	-0.118 (1)	**0.220 (3)**
Real Estate	**0.913 (14)**	0.912 (13)		0.390 (1)
Technology	0.860 (22)	0.711 (12)		**1.052 (10)**
Utilities	**0.766 (11)**	**0.766 (11)**		

Portfolios based on RMW

There is no significant change in conclusion for this factor either.

Table 19: Sortino Ratio of portfolios created based on RMW beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.301 (11)	0.104 (5)	**0.405 (6)**	
Consumer Discretionary	0.443 (13)	0.086 (3)	0.516 (9)	**0.614 (1)**
Energy	-0.475 (26)	-0.598 (21)		**0.749 (5)**
Financials	0.289 (19)	**0.335 (5)**	0.324 (1)	0.287 (13)
Healthcare	0.179 (16)	-0.032 (4)		**0.234 (12)**
Industrials	0.572 (16)	**0.626 (14)**	0.281 (2)	
Materials	-0.181 (26)	-0.225 (22)	-0.118 (1)	**0.132 (3)**
Real Estate	**0.913 (14)**	**0.913 (14)**		
Technology	0.860 (22)	**1.029 (10)**		0.740 (12)
Utilities	0.766 (11)	**0.920 (10)**	0.080 (1)	

Portfolios based on CMA

No significant change in conclusion for this factor either compared to the Sharpe ratio conclusions.

Table 20: Sortino Ratio of portfolios created based on CMA beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.301 (11)	0.025 (4)	**0.536 (6)**	-0.226 (1)
Consumer Discretionary	0.443 (13)	0.440 (9)	**0.653 (2)**	0.287 (2)
Energy	-0.475 (26)	-0.568 (20)	-0.282 (2)	**0.808 (4)**
Financials	0.289 (19)	**0.447 (4)**		0.245 (15)
Healthcare	0.179 (16)	0.119 (13)	**0.574 (3)**	
Industrials	0.572 (16)	0.539 (11)	**0.643 (5)**	
Materials	-0.181 (26)	**-0.152 (23)**	-0.240 (3)	
Real Estate	**0.913 (14)**	0.912 (13)	0.390 (1)	
Technology	0.860 (22)	**0.887 (6)**		0.855 (16)
Utilities	0.766 (11)	-0.004 (6)	**1.375 (5)**	

Portfolios based on MOM

Interestingly, for Industrials and Technology, the preference towards significant negative beta portfolios is no longer present when accounted for by Sortino ratio.

Table 21: Sortino Ratio of portfolios created based on MOM beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.301 (11)	-0.845 (2)	**0.458 (9)**	
Consumer Discretionary	0.443 (13)	0.482 (9)	**0.504 (3)**	-0.023 (1)
Energy	-0.475 (26)	**-0.236 (15)**		-0.688 (11)
Financials	0.289 (19)	0.370 (8)	**0.383 (9)**	-0.534 (2)
Healthcare	**0.179 (16)**	**0.179 (16)**		
Industrials	0.572 (16)	**0.588 (9)**	0.474 (1)	0.582 (6)
Materials	-0.181 (26)	**0.223 (4)**		-0.268 (22)
Real Estate	0.913 (14)	0.777 (4)	**0.991 (8)**	0.710 (2)
Technology	0.860 (22)	**0.930 (7)**		0.832 (15)
Utilities	0.766 (11)	0.995 (3)	**1.158 (6)**	-1.150 (2)

8.2.3.3 Treynor Ratio

We will again investigate if Treynor ratio can present some additional or conflicting information compared to the Sharpe ratio.

Portfolios based on SMB

Similar conclusions as for Sharpe ratio.

Table 22: Treynor Ratio of portfolios created based on SMB beta value and significance

Sector	*Equal Weighted*	*Insignificant*	*Significant +ve*	*Significant -ve*

	(Count)	*(Count)*	*(Count)*	*(Count)*
Consumer Staples	0.048 (11)	0.011 (4)	0.030 (1)	**0.080 (6)**
Consumer Discretionary	0.054 (13)	**0.062 (6)**	0.049 (7)	
Energy	-0.060 (26)	**0.000 (14)**	-0.095 (12)	
Financials	0.032 (19)	**0.062 (9)**	0.022 (8)	-0.051 (2)
Healthcare	0.022 (16)	0.025 (7)	0.018 (8)	**0.071 (1)**
Industrials	0.074 (16)	**0.086 (4)**	0.071 (12)	
Materials	-0.021 (26)	-0.038 (16)	**0.000 (10)**	
Real Estate	0.173 (14)	**0.194 (11)**		0.099 (3)
Technology	0.110 (22)	0.099 (11)	0.089 (4)	**0.146 (7)**
Utilities	0.117 (11)	-0.072 (3)		**0.286 (8)**

Portfolios based on HML

Largely similar conclusions as for Sharpe ratio.

Table 23: Treynor Ratio of portfolios created based on HML beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.048 (11)	-0.012 (5)		**0.112 (6)**
Consumer Discretionary	0.054 (13)	0.040 (9)		**0.089 (4)**
Energy	-0.060 (26)	**0.055 (10)**	-0.096 (15)	-0.029 (1)
Financials	0.032 (19)	0.017 (1)	**0.033 (18)**	
Healthcare	0.022 (16)	**0.076 (1)**		0.019 (15)
Industrials	0.074 (16)	0.071 (12)	0.048 (1)	**0.108 (3)**
Materials	-0.021 (26)	-0.021 (22)	**-0.015 (1)**	-1.252 (3)
Real Estate	0.173 (14)	**0.184 (13)**		0.062 (1)
Technology	0.110 (22)	0.090 (12)		**0.137 (10)**
Utilities	0.117 (11)	**0.117 (11)**		

Portfolios based on RMW

Similar conclusions as for Sharpe ratio.

Table 24: Treynor Ratio of portfolios created based on RMW beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.048 (11)	0.014 (5)	**0.078 (6)**	
Consumer Discretionary	0.054 (13)	0.010 (3)	**0.070 (9)**	0.066 (1)
Energy	-0.060 (26)	-0.081 (21)		**0.074 (5)**
Financials	0.032 (19)	0.037 (5)	**0.040 (1)**	0.030 (13)
Healthcare	0.022 (16)	-0.004 (4)		**0.029 (12)**
Industrials	0.074 (16)	**0.081 (14)**	0.038 (2)	
Materials	-0.021 (26)	-0.026 (22)	-0.015 (1)	**0.017 (3)**

Real Estate	**0.173 (14)**	**0.173 (14)**		
Technology	0.110 (22)	**0.126 (10)**		0.097 (12)
Utilities	0.117 (11)	**0.137 (10)**	0.015 (1)	

Portfolios based on CMA

Similar conclusions as for Sharpe ratio.

Table 25: Treynor Ratio of portfolios created based on CMA beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.048 (11)	0.004 (4)	**0.098 (6)**	-0.024 (1)
Consumer Discretionary	0.054 (13)	0.054 (9)	**0.079 (2)**	0.038 (2)
Energy	-0.060 (26)	-0.077 (20)	-0.036 (2)	**0.085 (4)**
Financials	0.032 (19)	**0.058 (4)**		0.026 (15)
Healthcare	0.022 (16)	0.014 (13)	**0.072 (3)**	
Industrials	0.074 (16)	0.070 (11)	**0.082 (5)**	
Materials	-0.021 (26)	**-0.017 (23)**	-0.051 (3)	
Real Estate	0.173 (14)	**0.184 (13)**	0.062 (1)	
Technology	0.110 (22)	0.110 (6)		**0.111 (16)**
Utilities	0.117 (11)	0.000 (6)	**0.448 (5)**	

Portfolios based on MOM

Similar conclusions as for Sharpe ratio.

Table 26: Treynor Ratio of portfolios created based on MOM beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.048 (11)	-0.089 (2)	**0.087 (9)**	
Consumer Discretionary	0.054 (13)	0.059 (9)	**0.068 (3)**	-0.003 (1)
Energy	-0.060 (26)	**-0.031 (15)**		-0.090 (11)
Financials	0.032 (19)	0.037 (8)	**0.045 (9)**	-0.051 (2)
Healthcare	**0.022 (16)**	**0.022 (16)**		
Industrials	0.074 (16)	0.074 (9)	0.058 (1)	**0.077 (6)**
Materials	-0.021 (26)	**0.030 (4)**		-0.031 (22)
Real Estate	0.173 (14)	0.109 (4)	**0.228 (8)**	0.100 (2)
Technology	0.110 (22)	0.110 (7)		**0.111 (15)**
Utilities	0.117 (11)	0.128 (3)	**0.290 (6)**	-0.109 (2)

8.2.3.4 Information Ratio

CRSP benchmark data from Kenneth-French website is taken as market benchmark for calculating these ratios Comparing conclusions with Sharpe ratio again and highlighting if necessary.

Portfolios based on SMB

Largely similar conclusions as for Sharpe ratio.

Table 27: Information Ratio of portfolios created based on SMB beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	-0.710 (11)	-0.993 (4)	-0.533 (1)	**-0.414 (6)**
Consumer Discretionary	-0.674 (13)	**-0.402 (6)**	-0.682 (7)	
Energy	-1.380 (26)	**-1.124 (14)**	-1.259 (12)	
Financials	-0.871 (19)	**-0.513 (9)**	-0.765 (8)	-1.267 (2)
Healthcare	-0.732 (16)	-0.795 (7)	-0.574 (8)	**-0.435 (1)**
Industrials	-0.189 (16)	-0.222 (4)	**-0.155 (12)**	
Materials	-1.295 (26)	-1.163 (16)	**-1.122 (10)**	
Real Estate	-0.073 (14)	**0.009 (11)**		-0.359 (3)
Technology	0.463 (22)	0.328 (11)	0.152 (4)	**0.896 (7)**
Utilities	-0.353 (11)	-1.846 (3)		**-0.009 (8)**

Portfolios based on HML

Similar conclusions as for Sharpe ratio.

Table 28: Information Ratio of portfolios created based on HML beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	-0.710 (11)	-1.464 (5)		**-0.227 (6)**
Consumer Discretionary	-0.674 (13)	-0.957 (9)		**0.106 (4)**
Energy	-1.380 (26)	**-0.446 (10)**	-1.261 (15)	-0.843 (1)
Financials	-0.871 (19)	-1.125 (1)	**-0.818 (18)**	
Healthcare	-0.732 (16)	**-0.176 (1)**		-0.749 (15)
Industrials	-0.189 (16)	-0.169 (12)	-0.280 (1)	**-0.038 (3)**
Materials	-1.295 (26)	-1.480 (22)	-0.724 (1)	**-0.203 (3)**
Real Estate	-0.073 (14)	**-0.041 (13)**		-0.378 (1)
Technology	0.463 (22)	0.202 (12)		**0.700 (10)**
Utilities	**-0.353 (11)**	**-0.353 (11)**		

Portfolios based on RMW

Largely similar conclusions as for Sharpe ratio.

Table 29: Information Ratio of portfolios created based on RMW beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	-0.710 (11)	-1.056 (5)	**-0.413 (6)**	
Consumer Discretionary	-0.674 (13)	-0.795 (3)	-0.292 (9)	**-0.257 (1)**
Energy	-1.380 (26)	-1.370 (21)		**-0.087 (5)**
Financials	-0.871 (19)	-0.707 (5)	**-0.595 (1)**	-0.865 (13)
Healthcare	-0.732 (16)	-1.072 (4)		**-0.564 (12)**
Industrials	-0.189 (16)	**-0.101 (14)**	-0.486 (2)	
Materials	-1.295 (26)	-1.262 (22)	**-0.724 (1)**	-0.760 (3)
Real Estate	**-0.073 (14)**	**-0.073 (14)**		
Technology	0.463 (22)	**0.631 (10)**		0.250 (12)
Utilities	-0.353 (11)	**-0.306 (10)**	-0.669 (1)	

Portfolios based on CMA

Largely similar conclusions as for Sharpe ratio.

Table 30: Information Ratio of portfolios created based on CMA beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	-0.710 (11)	-1.202 (4)	**-0.275 (6)**	-1.231 (1)
Consumer Discretionary	-0.674 (13)	-0.704 (9)	**-0.064 (2)**	-0.522 (2)
Energy	-1.380 (26)	-1.342 (20)	-0.898 (2)	**-0.065 (4)**
Financials	-0.871 (19)	**-0.694 (4)**		-0.832 (15)
Healthcare	-0.732 (16)	-0.757 (13)	**-0.349 (3)**	
Industrials	-0.189 (16)	-0.275 (11)	**-0.016 (5)**	
Materials	-1.295 (26)	-1.432 (23)	**-0.524 (3)**	
Real Estate	-0.073 (14)	**-0.041 (13)**	-0.378 (1)	
Technology	**0.463 (22)**	0.417 (6)		0.462 (16)
Utilities	-0.353 (11)	-0.961 (6)	**0.139 (5)**	

Portfolios based on MOM

Largely similar conclusions as for Sharpe ratio.

Table 31: Information Ratio of portfolios created based on MOM beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	-0.710 (11)	-1.680 (2)	**-0.370 (9)**	
Consumer Discretionary	-0.674 (13)	-0.501 (9)	**-0.392 (3)**	-0.574 (1)
Energy	-1.380 (26)	**-1.239 (15)**		-1.399 (11)
Financials	-0.871 (19)	**-0.659 (8)**	-0.695 (9)	-1.267 (2)
Healthcare	**-0.732 (16)**	**-0.732 (16)**		

Industrials	-0.189 (16)	**-0.142 (9)**	-0.314 (1)	-0.166 (6)
Materials	-1.295 (26)	**-0.544 (4)**		-1.274 (22)
Real Estate	-0.073 (14)	-0.322 (4)	**0.100 (8)**	-0.348 (2)
Technology	0.463 (22)	0.391 (7)		**0.494 (15)**
Utilities	-0.353 (11)	-0.304 (3)	**0.025 (6)**	-1.718 (2)

8.2.3.5 Omega Ratio

Omega ratio can depend on the number of observations, since it is calculating area under the curve of cumulative returns compared to a benchmark. It would disregard absolute ratio values in favour of a probabilistic approach and can thus provide insights which are different from those obtained from the more traditional performance ratios. As threshold for calculating Omega ratio, we use the mean risk-free rate over the out-of-sample period.

Portfolios based on SMB

It can be observed that insignificant portfolios are the worst performers. Investors might be better off ignoring factor significance and investing in an equal-weighted sector portfolio.

Table 32: Omega Ratio of portfolios created based on SMB beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	1.400 (11)	1.400 (4)	1.400 (1)	**1.667 (6)**
Consumer Discretionary	**1.667 (13)**	1.400 (6)	**1.667 (7)**	
Energy	**1.182 (26)**	1.000 (14)	**1.182 (12)**	
Financials	**1.400 (19)**	1.182 (9)	**1.400 (8)**	1.000 (2)
Healthcare	**1.000 (16)**	0.846 (7)	0.846 (8)	**1.000 (1)**
Industrials	**1.667 (16)**	1.182 (4)	**1.667 (12)**	
Materials	**1.000 (26)**	0.846 (16)	**1.000 (10)**	
Real Estate	**1.667 (14)**	**1.667 (11)**		1.182 (3)
Technology	**1.182 (22)**	**1.182 (11)**	**1.182 (4)**	**1.182 (7)**
Utilities	**1.667 (11)**	0.714 (3)		**1.667 (8)**

Portfolios based on HML

The results are mixed with Consumer Staples and Consumer Discretionary still outperforming with the significant negative beta portfolios. However, Energy switches from insignificant to significant positive ETFs. This could be because Omega ratio, by considering the cumulative distribution of returns, might be better at capturing periods of outperformance in healthcare compared to the other ratios.

Table 33: Omega Ratio of portfolios created based on HML beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	1.400 (11)	1.182 (5)		**1.667 (6)**
Consumer Discretionary	1.667 (13)	1.667 (9)		**2.429 (4)**
Energy	1.182 (26)	1.182 (10)	**1.400 (15)**	0.714 (1)
Financials	**1.400 (19)**	1.182 (1)	**1.400 (18)**	
Healthcare	1.000 (16)	**1.400 (1)**		1.000 (15)
Industrials	**1.667 (16)**	**1.667 (12)**	1.400 (1)	1.000 (3)
Materials	**1.000 (26)**	**1.000 (22)**	**1.000 (1)**	0.500 (3)
Real Estate	**1.667 (14)**	**1.667 (13)**		**1.667 (1)**
Technology	1.182 (22)	1.182 (12)		**1.667 (10)**
Utilities	**1.667 (11)**	**1.667 (11)**		

Portfolios based on RMW

Consumer Staples and Consumer Discretionary still outperform with the significant positive beta portfolios. However, for other sectors investors might be better off holding the entire basket of ETFs in an equal-weighted portfolio.

Table 34: Omega Ratio of portfolios created based on RMW beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	1.400 (11)	1.182 (5)	**2.000 (6)**	
Consumer Discretionary	1.667 (13)	1.182 (3)	**2.000 (9)**	1.000 (1)
Energy	**1.182 (26)**	**1.182 (21)**		0.846 (5)
Financials	1.400 (19)	**1.667 (5)**	**1.667 (1)**	1.400 (13)
Healthcare	**1.000 (16)**	**1.000 (4)**		0.846 (12)
Industrials	**1.667 (16)**	**1.667 (14)**	1.400 (2)	
Materials	1.000 (26)	0.846 (22)	1.000 (1)	**1.182 (3)**
Real Estate	**1.667 (14)**	**1.667 (14)**		
Technology	**1.182 (22)**	**1.182 (10)**		1.000 (12)
Utilities	**1.667 (11)**	1.400 (10)	**1.667 (1)**	

Portfolios based on CMA

Factor neutral ETFs perform the best across most sectors for CMA except for Consumer Staples and Utilities, where an investor might be rewarded for holding conservative firms.

Table 35: Omega Ratio of portfolios created based on CMA beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	1.400 (11)	1.400 (4)	**1.667 (6)**	1.000 (1)
Consumer Discretionary	1.667 (13)	**2.000 (9)**	1.667 (2)	1.000 (2)
Energy	1.182 (26)	**1.400 (20)**	0.714 (2)	1.000 (4)
Financials	1.400 (19)	**1.667 (4)**		1.400 (15)
Healthcare	1.000 (16)	0.846 (13)	**1.182 (3)**	
Industrials	**1.667 (16)**	**1.667 (11)**	**1.667 (5)**	
Materials	1.000 (26)	**1.182 (23)**	0.600 (3)	
Real Estate	**1.667 (14)**	**1.667 (13)**	**1.667 (1)**	
Technology	**1.182 (22)**	**1.182 (6)**		**1.182 (16)**
Utilities	1.667 (11)	1.400 (6)	**2.000 (5)**	

Portfolios based on MOM

Largely similar conclusions for momentum for Omega ratio, compared to the Sharpe Ratio.

Table 36: Omega Ratio of portfolios created based on MOM beta value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	1.400 (11)	1.000 (2)	**1.667 (9)**	
Consumer Discretionary	1.667 (13)	1.667 (9)	**2.429 (3)**	0.846 (1)
Energy	**1.182 (26)**	**1.182 (15)**		1.000 (11)
Financials	**1.400 (19)**	**1.400 (8)**	**1.400 (9)**	1.000 (2)
Healthcare	**1.000 (16)**	**1.000 (16)**		
Industrials	**1.667 (16)**	**1.667 (9)**	1.182 (1)	**1.667 (6)**
Materials	1.000 (26)	**1.667 (4)**		0.846 (22)
Real Estate	1.667 (14)	1.400 (4)	**2.000 (8)**	1.182 (2)
Technology	1.182 (22)	1.000 (7)		**1.400 (15)**
Utilities	1.667 (11)	1.667 (3)	**2.000 (6)**	1.000 (2)

Summary

Omega ratio paints an interesting picture. More sectors benefit from factor neutrality and holding equal weighted portfolios. However, importance of considering the momentum factor is again highlighted by this ratio as with other ratios.

8.2.4 Performance based on alphas

Based on the FF5M model fit performance, we select the FF5M alpha to conduct a performance comparison for our study. Alpha is a simpler measure than the ratios investigated before, and it bypasses the systematic beta factors. If more effective portfolios can be constructed based on alpha values alone, this would be preferable for simplicity. Moreover, with alpha values, an investor can safely assume that significant positive alpha ETFs can be expected to outperform the insignificant alpha values and insignificant alpha ETFs are expected to outperform the significant negative ETFs.

Our study confirms this assumption about alpha trends. However, when we compare the alpha results to those obtained from beta factors, we find that portfolios constructed based on beta factor significance most often outperform those based solely on alpha. This underscores the effectiveness of beta strategies in portfolio construction. Also, potentially due to the simple nature of alpha, the performance results from the various performance metrics are largely similar.

Table 37: Sharpe Ratio of portfolios created based on alpha value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.270 (11)	**0.449 (9)**		-0.488 (2)
Consumer Discretionary	0.338 (13)	**0.376 (12)**		-0.015 (1)
Energy	-0.353 (26)	**-0.237 (6)**		-0.384 (20)
Financials	0.191 (19)	0.185 (16)		**0.224 (3)**
Healthcare	0.126 (16)	-0.018 (8)	**0.279 (8)**	
Industrials	0.450 (16)	0.368 (12)	**0.723 (2)**	0.662 (2)
Materials	-0.121 (26)	**0.005 (14)**		-0.243 (12)
Real Estate	**0.651 (14)**	**0.651 (14)**		
Technology	0.636 (22)	0.629 (21)	**0.775 (1)**	
Utilities	0.516 (11)	**0.618 (10)**		-0.547 (1)

Table 38: Sortino Ratio of portfolios created based on alpha value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.301 (11)	**0.458 (9)**		-0.845 (2)
Consumer Discretionary	0.443 (13)	**0.469 (12)**		-0.023 (1)
Energy	-0.475 (26)	**-0.301 (6)**		-0.522 (20)
Financials	0.289 (19)	0.279 (16)		**0.332 (3)**
Healthcare	0.179 (16)	-0.026 (8)	**0.384 (8)**	
Industrials	0.572 (16)	0.468 (12)	**0.967 (2)**	0.841 (2)
Materials	-0.181 (26)	**0.007 (14)**		-0.396 (12)
Real Estate	**0.913 (14)**	**0.913 (14)**		
Technology	0.860 (22)	0.854 (21)	**1.008 (1)**	
Utilities	0.766 (11)	**0.958 (10)**		-1.370 (1)

Table 39: Treynor Ratio of portfolios created based on alpha value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	0.048 (11)	**0.087 (9)**		-0.089 (2)
Consumer Discretionary	0.054 (13)	**0.061 (12)**		-0.003 (1)
Energy	-0.060 (26)	**-0.041 (6)**		-0.065 (20)
Financials	0.032 (19)	0.031 (16)		**0.037 (3)**
Healthcare	0.022 (16)	-0.003 (8)	**0.049 (8)**	
Industrials	0.074 (16)	0.060 (12)	**0.137 (2)**	0.117 (2)
Materials	-0.021 (26)	**0.001 (14)**		-0.042 (12)
Real Estate	**0.173 (14)**	**0.173 (14)**		
Technology	0.110 (22)	0.109 (21)	**0.131 (1)**	
Utilities	0.117 (11)	**0.149 (10)**		-0.157 (1)

Table 40: Information Ratio of portfolios created based on alpha value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	-0.710 (11)	**-0.370 (9)**		-1.680 (2)
Consumer Discretionary	-0.674 (13)	**-0.552 (12)**		-0.574 (1)
Energy	-1.380 (26)	**-1.239 (6)**		-1.406 (20)
Financials	-0.871 (19)	**-0.832 (16)**		-0.969 (3)
Healthcare	-0.732 (16)	-0.979 (8)	**-0.441 (8)**	
Industrials	-0.189 (16)	-0.422 (12)	**0.491 (2)**	0.131 (2)
Materials	-1.295 (26)	**-0.947 (14)**		-1.397 (12)
Real Estate	**-0.073 (14)**	**-0.073 (14)**		
Technology	0.463 (22)	0.447 (21)	**0.897 (1)**	
Utilities	-0.353 (11)	**-0.232 (10)**		-1.123 (1)

Table 41: Omega Ratio of portfolios created based on alpha value and significance

Sector	*Equal Weighted (Count)*	*Insignificant (Count)*	*Significant +ve (Count)*	*Significant -ve (Count)*
Consumer Staples	1.400 (11)	**1.667 (9)**		1.000 (2)
Consumer Discretionary	1.667 (13)	**2.000 (12)**		0.846 (1)
Energy	1.182 (26)	1.182 (6)		**1.400 (20)**
Financials	**1.400 (19)**	**1.400 (16)**		1.182 (3)
Healthcare	**1.000 (16)**	0.846 (8)	**1.000 (8)**	
Industrials	1.667 (16)	1.400 (12)	**2.000 (2)**	1.182 (2)
Materials	1.000 (26)	**1.182 (14)**		1.000 (12)
Real Estate	**1.667 (14)**	**1.667 (14)**		
Technology	1.182 (22)	1.182 (21)	**2.000 (1)**	
Utilities	1.667 (11)	**2.000 (10)**		0.714 (1)

9 Additional Considerations

When interpreting the results of this study, several considerations must be taken into account,

Survivorship Bias: The data may be biased due to the limited set of ETFs included in the analysis. We excluded ETFs for which FactSet had no data for the analysis period. As a result, ETFs that did not survive the period were removed, potentially introducing survivorship bias.

Factor Data for Stocks: The factor values were taken from Kenneth French's website, which are based on stocks, but we used them for the study of ETFs. This discrepancy (as noted by Huij and Verbeek, 2009) could affect the accuracy of our findings.

Inclusion of Factor ETFs: The choice of ETFs for this study includes factor ETFs, which might inherently fit better with factor models compared to the CAPM model. Additionally, the dataset includes ETFs composed of stocks from other regions, such as Europe, which may yield misleading results for a US-based study.

Portfolio Comparison: The comparison of portfolio performance might seem unfair as each portfolio contains a different number of ETFs. This variation can affect the comparability of results.

Market Cycles and Periods: Further studies need to be conducted across different market cycles and periods to ensure the persistence and robustness of the results, as factor behaviour may change with market conditions.

Dynamic ETF Composition: As new ETFs are introduced within sectors, this study should be replicated to include these new additions. The evolving composition of ETFs within sectors necessitates periodic reassessment to maintain the relevance of the findings.

10 Conclusions

This study set out to explore the influence of Fama-French and Carhart’s factors on sector ETFs and consequently determine whether sector ETFs are factor-neutral. Subsequently, the aim of the study was to explore the effectiveness of factor-based investing when constructing a sector ETF portfolio.

By employing multiple asset-pricing models, including CAPM, Fama-French 3-Factor, Carhart 4-Factor, and Fama-French 5- and 6-Factor models, we aimed to identify which model best explains sector ETF returns. The analysis revealed that the Fama-French 5-Factor model with momentum (6-Factor model) provided the best fit across most sectors, highlighting the significant role of multiple systematic risk factors beyond market risk alone.

Our findings indicate that sector ETFs are in fact not factor-neutral, as various factors significantly influence their returns. By examining sector-specific ETF performances, we determined that portfolios constructed using factor significance can indeed outperform equal-weighted sector portfolios.

By further examining the performance of high alpha ETFs, the study confirms the reliability of using alpha values to gauge ETF performance, with significant positive alpha ETFs consistently outperforming those with insignificant or negative alphas. However, the superior performance of beta-based portfolios underscores the added value of a multi-factor approach.

Sector-specific analyses revealed that certain sectors, such as Consumer Staples, Consumer Discretionary, Energy and Technology, benefit more from factor-based investing. In contrast, sectors like Materials and Real Estate showed mixed results, indicating that the effectiveness of factor-based strategies can vary significantly across different sectors.

Furthermore, the research highlights the importance of considering various performance ratios in evaluating performance, as different ratios provide varied insights into the aspects of overall volatility, downside risk and performance against benchmarks. The consistency between the conclusions drawn from these metrics reinforces the robustness of our findings.

In conclusion, this study demonstrates that factor-based investing, particularly when leveraging the FF5+MOM model, can lead to more effective sector ETF portfolio construction. In practical terms, this research aids investors in constructing portfolios that align with specific investment objectives by leveraging sector-specific factor exposures. By understanding how different factors influence sector ETF returns, investors can better manage risks and optimize their portfolios for higher returns.

11 Future Research

Future research could investigate integrating sector rotation strategies, like those examined using alphas in previous studies (Sarwar et al, 2018), with the sector allocation strategies discussed in this study. Research can also include using betas as signals for sector rotation and allocation.

Additionally, the integration of machine learning techniques in future research could enhance the predictive power and robustness of factor models. Machine learning algorithms, such as random forests, support vector machines, and neural networks, can capture complex nonlinear relationships and interactions between factors that traditional linear models might miss. These advanced methods can provide deeper insights and more accurate predictions of sector ETF performance under varying market conditions.

Future research could also explore the impact of global economic events on sector-specific factor exposures and extend the analysis to other geographical markets to enhance the robustness and applicability of these findings. Additionally, investigating the role of emerging factors, such as ESG (Environmental, Social, and Governance) criteria, and their influence on sector ETF performance could offer valuable insights for sustainable investing strategies.

Overall, this study contributes to the existing literature by providing empirical evidence on the factor dynamics of sector ETFs and offers actionable insights for investors aiming to refine their sector allocation strategies based on systematic risk factors. By incorporating advanced analytical techniques and considering broader economic contexts, future research can further enrich our understanding of sector ETF performance and investment strategies.

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