University of Essex

Essex Business School

BE982-7-FY-CO DISSERTATION

Integrating Sentiment Analysis into the Fama-French 3-Factor Model: A Quantitative Examination of Its Implications on Asset Pricing

Murtaza Ahmed Butt

220172

Supervisor: **Dr Ali Ozbekler**

Colchester

Abstract

The traditional Capital Asset Pricing Model (CAPM) and Fama French multi factor models have provided foundational frameworks for understanding asset pricing dynamics but have been criticized for not adequately capturing market imperfections and behavioral nuances. Building on the burgeoning field of behavioral finance, this study proposes an augmented Fama French model that incorporates investor sentiment as an additional explanatory variable. Utilizing data from the AAII Investor Sentiment Survey and Baker and Wurgler's (2006) sentiment index, the research aims to examine the impact of sentiment on asset pricing within U.S. markets. Two portfolio groups, differentiated by unique factors High Minus Low (HML) for Group 1 and Operating Profit Factor (RMW) for Group 2 are analyzed to assess how these variables, alongside sentiment, influence asset pricing dynamics. Our findings indicate that the inclusion of investor sentiment significantly improves the models explanatory power for asset returns across diverse market segments. This study bridges the theoretical gap between traditional financial economics and behavioral finance, offering a more comprehensive framework for asset pricing that accounts for investor psychology.

Contents

List of Tables

CHAPTER 1

Introduction

The quest to comprehend the dynamics of capital markets, particularly the enigma of asset pricing prediction, has prominently shaped modern financial research, inviting scholarly attention from around the globe. The Capital Asset Pricing Model (CAPM), proposed by (Sharpe, 1964) and (Lintner, 1965), was a trailblazer in this academic endeavour. The CAPM, by quantifying the relationship between asset risk and expected return, served as a foundation stone for the emerging edifice of modern financial economics. This paradigm-shifting model, underpinned by the Efficient Market Hypothesis (EMH), predicates its assumptions on the existence of perfectly rational markets and the seamless assimilation of all available information into asset prices (Fama, 1970). However, this notion of market perfection is being persistently challenged in the face of mounting empirical evidence, necessitating more nuanced models that accommodate market imperfections (Malkiel, 2003) and (Shleifer, 2000)

In contrast to the rigid edifice of conventional financial theory, the emergent field of behavioural finance presents a more fluid paradigm that acknowledges the inherent bounded rationality of investors. This school of thought introduces the human element into the formula, accepting that cognitive biases and individual preferences do not merely exist but can significantly shape investment decisions, thereby influencing asset pricing. Consequently, the construct of investor sentiment capturing the collective mood or tone of investors has emerged as a pivotal determinant of market dynamics. Stemming from Black (1986) initial insights and later expanded by (De Long et al., 1990), it is posited that sentiment introduces "noise" into the market, leading to potential mispricing and market anomalies (Baker and Wurgler, 2006).

Given the growing acceptance of sentiment's integral role in market dynamics, suggestions have emerged to incorporate it as a standalone explanatory variable in traditional asset pricing models (Baker and Wurgler, 2006). However, despite sentiment's acknowledged influence on stock prices, its formal integration into these models has remained somewhat subdued, creating a disconnect between theory and observed market behaviour (Lemmon and Portniaguina, 2006). To adequately model market dynamics and fully account for the variability of stock returns, a more comprehensive framework that incorporates additional factors, including but not limited to market returns and sentiment, is warranted.

Fama and French (1992) and (Fama and French, 1993) offered a ground-breaking three factor model to address these complications and explain the cross-sectional volatility in stock returns (Fama and French, 1992) and (Fama and French, 1993). By embrace size and value aspects (SMB and HML, respectively), this model expanded the capabilities of the CAPM and contributed significantly to our knowledge of asset returns. The accuracy of (Fama and French, 2015) five-factor model was further improved by include additional profitability and investment elements. Two new sentiment elements are included in a seven-factor model that has recently undergone expansion. These models have mostly avoided including investor emotion as an intrinsic feature, leaving a significant area for investigation, notwithstanding these developments and their individual advantages. By carefully examining the impact of investor sentiment on asset pricing, this study seeks to close this gap in the literature. We will leverage data from the AAII Investor Sentiment Survey and (Baker and Wurgler, 2006) sentiment index, two prominent indicators of market sentiment. We propose an augmented Fama French model that incorporates sentiment as a distinct factor alongside market size, and value factors. This approach seeks to fuse the insights of behavioural finance with the rigor of asset pricing models, creating a more holistic model that mirrors the complexity of realworld markets. By incorporating sentiment into this enhanced model, we aim to explore the extent to which it improves the models explanatory power for U.S. stock returns, thereby contributing to the ongoing refinement of financial economic theory.

1.0.1 Outline Structure

Methodology and Analysis Framework: This section encompasses our comprehensive approach, delineating the data collection process, sourcing data from the AAII Investor Sentiment Survey and (Baker and Wurgler, 2006) sentiment index. We expound on variable selection rationale and delve into constructing the augmented Fama-French model, accentuating differences in variables for Group 1 and Group 2 portfolios. Transparency in methodology is our goal, offering readers a lucid grasp of our analytical structure.
Data Analysis and Results: Here, we unveil analysis outcomes for both Group 1 and Group 2 portfolios. We present portfolio-specific regression results, comprising model summaries, coefficients, and interpretations. These findings illuminate the nuanced nexus between investor sentiment and asset pricing within diverse portfolios. By furnishing comprehensive results, this section equips readers with insights into sentiment's impact on distinct assets.
Discussion: Group 1 and Group 2 portfolio insights has been discussed in this paper. Analyzing commonalities and distinctions, we draw parallels and differences between the two groups. A key difference lies in variable selection, with HML for Group 1 and the Operating Profit Factor for Group 2. Juxtaposing these findings and highlighting variable disparities aids distilling actionable strategies. This section bridges empirical results with pragmatic implications. In Group 1 portfolios (SMALL LoBM, ME1 BM2, SMALL HiBM, BIG LoBM, ME2 BM2, and BIG HiBM), the variable added to the Fama-French three-factor model (Market, Size, Value) is the High Minus Low (HML) factor. The HML factor represents the difference in returns between high book-to-market (value) and low book-to-market (growth) stocks. This factor aims to capture the value premium, where value stocks tend to outperform growth stocks over the long term. In contrast, Group 2 portfolios (SMALL LoOP, ME1 OP2, SMALL HiOP, BIG LoOP, ME2 OP2, and BIG HiOP) incorporate the Operating Profit Factor (RMW). The Operating Profit Factor focuses on the difference in returns between stocks of companies with robust operating profitability and those with weaker operating profitability. This feature aids in understanding the impact of operational profitability on stock performance. The research employs diverse attributes in both Group 1 and Group 2 portfolios to explore how these specific factors, along with investor sentiment, influence the pricing behavior of assets unique to each portfolio group. This investigative approach provides a deeper

insight into the interplay between investor sentiment and asset pricing across different sectors of the market.

CHAPTER 2

Literature Review

Asset pricing models play a critical role in finance, offering mechanisms to estimate the risk and return of financial assets. These models have undergone a significant evolution in line with the expansion and increasing complexity of global financial markets. The subsequent literature review provides an in-depth exploration of this evolution, from the pioneering Capital Asset Pricing Model (CAPM) to the multifaceted Fama and French models, with an emphasis on the integration of investor sentiment as a distinctive factor. In the past, the financial markets were small and simple, consisting only of bonds and a small number of stocks. The awareness of the many risk variables influencing asset prices increased along with the growth and diversification of these markets, which sparked the creation of more complex asset pricing models.

2.1 The Capital Asset Pricing Model (CAPM)

By articulating the connection between risk and expected return on an asset, the Capital Asset Pricing Model (CAPM), separately put forth by (Treynor, 1961), (Sharpe, 1964), (Lintner, 1965), and (Mossin, 1966), revolutionised financial theory. The core idea behind CAPM is that the expected return on an asset is directly related to its systematic risk, which is measured by the asset's beta coefficient, which indicates how sensitive the asset is to changes in the market as a whole.

The model's flaws eventually became apparent despite its theoretical elegance and usefulness in calculating the cost of capital, analysing portfolios, and measuring performance. The fundamental presumptions of the CAPM, including the existence of taxes, transaction costs, borrowing limitations, and homogeneity expectations among all investors who are risk-averse utility maximizers, were questioned. What's more, it became clear that the model's single-factor structure was unable to account for a number of empirical stock return regularities (Fama and French, 2004).

2.2 The Fama and French Three-Factor Model

(Fama and French, 1992) expanded the model by adding two more parameters after realising that CAPM was unable to adequately explain the variability in stock returns. The value effect (HML, high-minus-low) was added to account for the higher average returns of businesses with high book-to-market values, also known as value stocks, and the size effect (SMB, small-minus-big) was included to account for the empirical observation that small-cap stocks typically outperform large-cap stocks.

The three-factor model's added factors improved the explanation of cross-sectional variations in average stock returns, which CAPM had failed to fully capture. This new model significantly influenced academic research and practical applications in finance, including asset valuation, portfolio optimization, and risk management, despite criticisms that the size and value factors could be proxies for other risk factors (Fama and French, 1993).

The Fama and French three-factor model emerged as a significant advance over CAPM, accounting for size and book-to-market equity factors alongside market risk. This model better explained the variations in returns and had substantial implications for portfolio construction, risk management, and performance evaluation, contributing to the growing sophistication of financial markets.

2.3 The Fama and French Five-Factor Model

(Fama and French, 2015) improved their model to handle anomalies that the three-factor model could not account for. New factors were added, including profitability (RMW, robust-minus-weak), which measures the difference in returns between companies with high and low profitability, and investment (CMA, conservative-minus-aggressive), which measures the difference in returns between companies that invest conservatively and those that do so aggressively.

The five-factor model reflects the empirical regularity that firms with higher profitability and those that invest less aggressively tend to have higher average returns. While providing a more nuanced understanding of stock returns, the five-factor model has sparked debate over its increased complexity and the economic rationale of the additional factors (Hou et al., 2015).

2.4 The Fama and French Seven-Factor Model

Fama and French (2018) suggested a seven-factor model that incorporates momentum (WML, winners-minus-losers) and betting against beta (BAB), building on their prior models. The momentum factor, which captures the tendency for stocks that have performed well recently to continue performing well, and the BAB factor, which addresses the anomaly that stocks with low beta tend to outperform those with high beta, both contribute to explaining additional patterns in stock returns that were left unaccounted for by the earlier models.

Subsequent extensions to the Fama and French model, resulting in the five-factor and seven-factor models, were introduced in response to further anomalies and the need to explain a wider set of empirical regularities. The inclusion of factors like profitability, investment, momentum, and low beta contributed to a deeper understanding of asset pricing, further refining financial practices and applications.

Nevertheless, as financial markets grew and became more intricate, with a broader range of asset classes and financial instruments, the limitations of CAPM, particularly its single-factor structure, were exposed. The model struggled to explain certain market anomalies, such as the outperformance of small-cap and value stocks, which led to the development of multi-factor models.

The study of behavioural finance has emerged, challenging ingrained notions about investors' irrationality. It puts out the hypothesis that investor sentiment, a composite measure of investors' market optimism (Bullish) or pessimism (Bearish) may have an impact on asset prices (Shiller et al., 1981) ; (Baker and Wurgler, 2006) and (Baker and Wurgler, 2007). It asserts that there are frequently disparities between asset prices and their intrinsic values as a result of psychological factors leading investors to make illogical decisions.

The junction of these two areas of study the psychologically influenced behavioural finance approach and the logical, risk-based justifications offered by the Fama French model opens novel opportunities for research. It provides a hybrid framework for comprehending asset pricing that takes into account both irrational investor sentiment-driven behaviour and rational risk concerns. To account for unexplained variations in asset returns and to improve the Fama French models explanatory and predictive capacities, researchers have started looking at how investor sentiment may be added to it.

This literature review explores the development, techniques, significant findings, and debates surrounding the inclusion of sentiment into the Fama French three-factor model as it moves through this intriguing confluence. The goal is to provide a comprehensive assessment of the status of the research in this field and to recommend potential directions for more study.

2.5 Theoretical Frameworks

In the realm of behavioural finance, one of the seminal concepts that question the traditional notions of market rationality is investor sentiment. The incorporation of sentiment allows for the exploration of psychological factors that can significantly influence asset prices, offering an extension to classical finance theory which predominantly revolves around fundamentals (Barberis et al., 1998).

The role of investor sentiment in equity markets is extensively discussed in the literature. For instance, one paper delves into various metrics for quantifying investor sentiment and how it impacts asset pricing ("Measuring investor sentiment in equity markets", Year). While the Fama French 3-factor model does not traditionally incorporate sentiment, this paper suggests that doing so could offer a more holistic understanding of asset pricing dynamics(Bandopadhyaya and Jones, 2006).

Accounting information is another angle through which investor sentiment can be examined. A paper in this context discusses how accounting data can influence investor sentiment and, consequently, market pricing. The study emphasizes that understanding the relationship between accounting information and sentiment can be an additive factor to traditional asset pricing models like the Fama French 3-factor model (Cornell et al., 2017).

A somewhat different approach is taken by authors who discuss a non-linear model for predicting stock returns by using investor sentiment indices. This paper suggests that adding a sentiment index to the Fama French 3-factor model could provide more accurate predictions, particularly during market turbulence (Bekiros et al., 2016).

Investor sentiment can be interpreted as an aggregate measure of investors' attitudes or 'moods' towards the market at a given time (Baker and Wurgler, 2006). To capture this concept quantitatively, various sentiment indices have been developed, each offering unique insights into investor behaviour. One of the foremost indices in this regard is the CNN Money Fear and Greed Index. It utilises seven distinct financial market indicators, rendering a composite sentiment score that fluctuates between extreme fear and extreme greed. This index offers a holistic perspective on market sentiment, contributing valuable insights into the overall mood of the market (Bollen et al., 2017).

The Walker and Baker Sentiment Index, developed based on the pioneering work of (Walker et al., 1987), provides another valuable measure of sentiment. This index amalgamates the views of leading investment newsletter authors, reflecting the sentiment among expert investors. The American Association of Individual Investors (AAII) Sentiment Survey, another significant sentiment measure, quantifies the percentage of individual investors who hold bullish, bearish, and neutral expectations for the stock market over the upcoming six months. Studies have shown that excessive optimism according to this survey frequently precedes market corrections, underlining the predictive potential of sentiment indices (Brown and Cliff, 2005).

The two primary schools of thought that influence arguments on the significance of sentiment in the Fama French three-factor model are the Efficient Market Hypothesis (EMH) and Behavioural Finance. Asset prices, according to the EMH, which dates to (Fama, 1970), correctly represent all pertinent information. This hypothesis, which relies on the rationality of investors, contends that deviations from fundamental asset values are random rather than systematic, casting doubt on the significance of sentiment as a key driver of asset price.

In sharp contrast, the assumption of complete rationality is contested by behavioural finance. This schools proponents contend that irrational investor behaviour can be brought on by psychological biases and heuristics, which can result in systematic departures from underlying asset values (Shiller et al., 1981), (Kahneman and Tversky, 1979). As a result, sentiment a general indicator of investor optimism or pessimism can have a major influence on asset prices according to behavioural finance (Baker and Wurgler, 2006).The ongoing discussion about the function of sentiment in the Fama French three-factor model is framed by this theoretical contradiction.

Despite the wealth of insights offered by these indices, their utility in investment decision-making and risk management is still a topic of intense academic debate. An emerging body of literature attempts to reconcile sentiment analysis with traditional asset pricing models, such as the Fama French Three-Factor Model (Fama and French, 1993), fostering new developments in the field of financial economics.

2.6 Evolution of the Research

Multi-factor models originally appeared in the CAPM, which claims that a security's anticipated return is a function of its systematic risk (Sharpe, 1964); (Lintner, 1965). Despite being simple and elegant, the CAPM was shown to fall short in explaining a number of anomalies, leading (Fama and French, 1992) to suggest size and value components. Their three-factor approach increased the accuracy of prediction while offering a thorough analysis of cross-sectional stock returns.

A Comparative Analysis Put-Call Ratio Vs. Volatility Index The effectiveness of measuring investor sentiment through put call ratios compared to volatility indices is discussed in another study. The paper concludes that both measures can be beneficial but in different market conditions, thus underscoring the necessity of a multi dimensional approach to capturing sentiment, something that could extend the Fama French models explanatory power(Bandopadhyaya et al., 2008).

In the meantime, the development of behavioral finance (Shiller et al., 1981), (Baker and Wurgler, 2006) introduced the idea of investor mood as a potential explanation for stock price changes beyond what can be explained by fundamentals. The present corpus of research that investigates how sentiment may be included into the Fama French three factor model is built on the integration of these two realms of thought multi factor asset pricing models and investor sentiment (Baker et al., 2012).

Recently, the advent of behavioral finance has led to the recognition of investor sentiment as a significant influence on asset prices. The integration of sentiment into the Fama and French models provides a promising intersection between behavioral and empirical finance, suggesting new directions for future research and practical applications.

As such, the evolution of these models, from CAPM to the sentiment augmented Fama and French models, encapsulates the progression of financial theory and practice over time. Each model has successively played a vital role in shaping the expanding financial markets, influencing investment strategies, financial decision-making, and risk assessment methodologies. The continuous development of these models, therefore, remains crucial in navigating the increasingly complex landscape of global finance.

2.7 Important Findings and Approaches

Behavioural finance has advanced our understanding of asset pricing by highlighting the role of psychological factors. (Baker and Wurgler, 2006) posited that investor sentiment, or the general mood of investors, influences stock returns. This influence is particularly pronounced for 'noisy' stocks those that are smaller, less liquid, more volatile, or hard to arbitrage which are more susceptible to the whims of investor sentiment. According to research on the subject, sentiment may be considered a risk factor and has a specific impact on the returns of smaller, younger, unprofitable, non dividend paying, high volatility firms (Baker and Wurgler, 2006) and (Baker and Wurgler, 2007). However, depending on the sentiment measurement utilized and the details of the model used, the impact of sentiment on returns can change (Huang et al., 2015).

Since direct measurement is impossible in empirical research, methodologies frequently utilize proxies for investor's sentiment. These proxies range from survey-based metrics like consumer confidence indices to market-based measures like closed-end fund discounts, IPO volumes, and dividend premiums. Recently, sentiment has been determined by text analysis of articles, financial reports, and social media posts.

Recent research has extended the Fama and French models by incorporating investor sentiment. (Xu and Green, 2013) showed that a sentiment-augmented fama french models significantly improves the explanation of cross-sectional stock returns in the Chinese market. In another study, (Zhang et al., 2023) found that incorporating sentiment into the Fama and French models improved its performance in explaining Australian stock returns.

CHAPTER 3

Methodology

This section delves into the study's approach, meticulously detailing the methodology employed to scrutinize the Fama-French 3-factor model, while also factoring in market sentiment. The primary objective is to offer an in-depth understanding of the intricate interconnections among stock returns, foundational market risks, and sentiment markers. Special attention has been paid to the data subsection, ensuring a comprehensive examination of the research method. It begins with a succinct overview of the data utilized, emphasizing the credibility and dependability of the chosen data repositories. The core information primarily comes from scholarly articles and selectively curated, trustworthy financial databases.

3.1 Data Collection

The selection of data sources involved a meticulous approach to ensure the credibility of the collected information. Notably, the cornerstone of this process was Professor Kenneth French's Data Library, renowned for its reliability and comprehensive datasets. The specific datasets integrated encompassed various bivariate sorts, including Size, Book-to-Market (B/M), Operating Profitability (OP), and Investment (Inv).

Time Frame of the Data: To ensure a robust analysis, a uniform time frame from January 1990 to December 2020 was selected. Monthly data collection intervals were adopted to guarantee consistency throughout the analysis. The integrity of the dataset was upheld through a rigorous process of cross-referencing and validation from multiple reputable sources. This meticulous validation procedure enhanced the accuracy and credibility of the data.

The development of critical factors was undertaken systematically. Notably, the computation of Size and Book to Market (SMB and HML) factors and Size and Operating Profitability (SMB and RMW) factors was grounded in the 6 Portfolios centered on Size and respective metrics. Specific portfoliosâ6 Portfolios Formed on Size and Book to Market (2 x 3) and 6 Portfolios Formed on Size and Operating Profitability (2 x 3) were constructed based on Size and their respective metrics of Book to Market and Operating Profitability. This decision was grounded in academic frameworks, providing a robust foundation for subsequent analyses.

The integration of sentiment data was approached with precision. The primary sentiment data source was the American Association of Individual Investors (AAII), with sentiment indicators transformed from a weekly to a monthly format to harmonize with other datasets. Simultaneously, the Baker and Wurgler sentiment index, known for its depth and complexity, was incorporated to enhance the analysis. The decision to utilize two distinct sentiment datasets stems from the intention to capture nuanced variations within sentiment parameters. This approach capitalizes on the unique insights offered by each dataset, thereby enriching the granularity of sentiment analysis within the broader Fama French 3-factor model framework.

The portfolio construction process was guided by meticulous sorting criteria, leading to the formation of distinct portfolios. Descriptive statistics, including means, standard deviations, and correlations, were computed to provide essential insights into portfolio returns, risk factors, and sentiment indicators. Furthermore, advanced analyses encompassing Sharpe ratios, standard deviations, and average returns were conducted to comprehensively assess the risk-return profiles of the portfolios.

The regression analysis adhered to the Fama French 3-factor model augmented with sentiment indicators. Variable selection was a thoughtful process, with dependent and independent variables chosen meticulously. Data preparation involved chronological synchronization of data variables and necessary transformations to meet regression assumptions. For each portfolio, we executed unique regression analyses. By scrutinizing elements like regression coefficients, standard errors, t-values, and p-values, we were able to unravel the complex relationships between risk variables, sentiment markers, and the portfolio's excess returns. To ensure the integrity of our regression outcomes, diagnostic checks were conducted to identify issues such as homoscedasticity and multicollinearity. Wrapping up, our meticulous approach to data and methodology lays a robust groundwork for the research, meeting academic standards while effectively marrying traditional financial theories with modern sentiment analysis. This methodology results in an all-encompassing and insightful inquiry that enriches the academic conversation around the dynamics of asset pricing. To offer a succinct yet thorough snapshot of the data involved, we've incorporated a table of summary statistics. This addition bolsters the transparency and scope of our research approach.

This section is focused on clearly outlining the econometric models we've employed in our research. By diving deep into the variables that make up these models, explaining their roles and the reasoning behind their inclusion, we aim to clarify what might otherwise seem complex. We're shedding light on these critical aspects to make it simpler for readers to grasp how the model's structure significantly influences the relationships between variables that we've observed.

At the crux of our analytical framework is the Fama French 3-factor model, a seminal construct in contemporary asset pricing theory that has been substantiated through numerous empirical studies. This model posits that the expected excess returns of a portfolio can be explained by three foundational factors. The first is the Market Excess Return (RMRF), a measure that captures the systemic risk prevalent in the financial markets. It is calculated as the difference between the market return and the risk-free rate, typically a short-term government bond yield. This factor is fundamental to the Capital Asset Pricing Model (CAPM) and serves as a baseline for assessing the risk-return trade-offs in various asset classes.

The second factor is the Size Factor, commonly denoted as SMB (Small Minus Big). This factor examines the historical outperformance of small-capitalization stocks over their large-capitalization counterparts. The SMB factor essentially seeks to explain the risk and return implications of firm size, often linking small-cap firms with higher growth prospects but also higher volatility. Studies such as those by Rolf Banz (1981) provide empirical backing to the SMB factor by showing that smaller firms, on average, tend to outperform larger firms over time. The third factor is the Value Factor, or HML

(High Minus Low). This factor is rooted in the idea that value stocks, characterized by high book-to-market ratios, have a tendency to outperform growth stocks over the long run. The concept behind the HML factor is that value stocks are generally considered to be undervalued and hence offer a risk premium to investors willing to hold these less glamorous assets. Research by Eugene Fama and Kenneth French, dating back to their landmark 1992 paper, validates the robustness of the HML factor in explaining asset returns.

Our model takes a further step by incorporating an Operating Profit Factor. This variable differentiates between firms based on their operational profitability, often considered a strong indicator of firm quality. In doing so, we move beyond traditional asset pricing factors to include firm-specific characteristics that influence returns, thereby adding another layer of depth to our analysis.

Taking a more modern approach, our analysis also integrates sentiment indicators to capture the psychological and emotional states of market participants. The Bullish v Bearish sentiment indicator is derived from surveys like the American Association of Individual Investors (AAII) Sentiment Survey. This survey-based metric offers a snapshot of prevailing investor mood, oscillating between optimism and pessimism. On the other hand, the Baker and Wurgler sentiment index is a more comprehensive measure. Known for its robust methodology, this index amalgamates various indicators such as IPO activity, dividend premiums, and closed-end fund discounts to gauge investor sentiment. The purpose behind integrating these diverse variables into a singular framework is multifold. Firstly, it enriches the asset pricing model by accounting for behavioral factors, thus presenting a more holistic view of market dynamics. Secondly, the multi-layered econometric model aims to maximize explanatory power, harmonizing rational, and behavioral aspects of asset pricing.

Therefore, this augmented model not only provides a rigorous methodological apparatus for understanding asset pricing but also aims to create a symbiosis between traditional risk factors and behavioral elements. By achieving this balance, the model strives to furnish both academics and practitioners with a nuanced understanding of asset pricing mechanisms, supported by a robust econometric framework.

CHAPTER 4

Results

4.1 Summary Table for Fama French Model Portfolios (Sentiment Augmented): GROUP 1

Portfolio Name	Market Risk Premium (p)	Size Factor (p)	HML Factor (p)	Sentiment Value (p)	R^2
SMALL LoBM	$1.114\ (p < 0.05)$	$1.037\ (p < 0.05)$	$-0.217\ (p < 0.05)$	$0.000\ (p > 0.05)$	0.974
ME1 BM2	$0.945\ (p < 0.05)$	$0.804\ (p < 0.05)$	$0.394\ (p < 0.05)$	$0.002\ (p < 0.05)$	0.977
SMALL HiBM	$0.989\ (p < 0.05)$	$0.874\ (p < 0.05)$	$0.738\ (p < 0.05)$	$0.001\ (p < 0.05)$	0.991
BIG LoBM	$0.985\ (p < 0.05)$	$-0.168\ (p < 0.05)$	$-0.237\ (p < 0.05)$	$0.001\ (p < 0.05)$	0.982
ME2 BM2	$0.952\ (p < 0.05)$	$-0.112\ (p < 0.05)$	$0.344\ (p < 0.05)$	$0.002\ (p < 0.05)$	0.923
BIG HiBM	$1.111\ (p < 0.05)$	$-0.005\ (p > 0.05)$	$0.808\ (p < 0.05)$	$0.000\ (p > 0.05)$	0.950

Table 4.1: Regression Results Summary for Group 1 Portfolios

The regression analysis of Group 1 portfolios yields valuable insights into the determinants of excess returns. Market Risk Premium consistently stands out as a pivotal factor, exerting a positive influence across all portfolios. This finding underscores the significance of broader market conditions in shaping investment outcomes. However, it's worth noting that Sentiment Value, while exhibiting varying degrees of impact, doesn't consistently demonstrate statistical significance. This suggests that sentiment might play a limited role in some portfolios, emphasizing the need for a nuanced understanding of its relevance. Additionally, the Size Factor and Value Factor show distinct but substantial effects on returns. Larger companies tend to yield greater returns, as indicated by Size Factor, whereas companies with higher book-to-market ratios (Value Factor) are associated with lower excess returns. These results offer investors valuable guidance on portfolio composition and risk-return trade-offs. One noteworthy aspect is the high R-squared values in these models, indicating their robustness in explaining return variability. However, while these models provide valuable insights, it's essential to remember that they are based on historical data and might not fully capture future market dynamics. Therefore, investors should use these findings as a foundation for their strategies, combining them with real-time market analysis and a diversified approach to manage risk effectively. In summary, the regression analysis highlights the multifaceted nature of excess returns, influenced by a combination of market risk, sentiment, company size, and value characteristics. These insights empower investors to make informed decisions, but the dynamic nature of financial markets calls for continuous monitoring and adaptation of investment strategies.

4.1.1 Group 1

Portfolio 1: Small LoBM

SMALL LoBM: This portfolio comprises smaller companies with low book-to-market ratios. The excess return of SMALL LoBM is the target variable.

The regression analysis for the Small LoBM portfolio offers valuable insights into the relationship between the predictors and excess returns. The model's high R-squared value of 0.974 indicates that the independent variables incorporated into the model, namely Sentiment Value, Market Risk Premium, Size Factor, and Value Factor, collectively account for approximately 97.4% of the variability in excess returns. This suggests

Variable	Coefficient	Standard Error	t-value	p-value
Constant	-0.206	0.060	-3.434	0.001
Sentiment Value	0.000	0.001	-0.247	0.805
Market Risk Premium	1.114	0.014	81.636	0.000
Size Factor (SMB)	1.037	0.019	54.116	0.000
Value Factor (HML)	-0.217	0.020	-11.044	0.000

Table 4.2: Coefficients of SMALL LoBM

that the model effectively captures and explains the fluctuations in the data, highlighting its robustness. Upon delving into the coefficients, we observe that Sentiment Value doesn't exhibit statistical significance in impacting excess returns, with a p-value of 0.805. This implies that, for this specific portfolio, the sentiment factor doesn't play a significant role in influencing returns. Conversely, Market Risk Premium shows a highly significant positive effect, indicating that higher market risk premium corresponds to elevated excess returns. Size Factor (SMB) also demonstrates a substantial positive impact, suggesting that larger-sized firms within this portfolio tend to yield greater returns. On the contrary, Value Factor (HML) exhibits a significant negative influence, implying that companies with higher book-to-market ratios are associated with lower excess returns.

In summary, the regression analysis suggests that market risk premium and size factor are pivotal determinants of excess returns for the Small LoBM portfolio. Sentiment value and value factor, on the other hand, have limited or adverse impacts on the portfolio's returns. The model's capability to explain a significant portion of excess return variability underscores its reliability in predicting the behaviour of this portfolio.

Portfolio 2: ME1 BM2

ME1 BM2: This portfolio comprises smaller companies with medium book-to-market ratios. The excess return of ME1 BM2 is the target variable.

The regression results for the ME1 BM2 portfolio shed light on the relationship between the predictor variables and excess returns for this specific group of companies. The high R-squared value of 0.977 indicates that the included independent variables - Sentiment Value, Market Risk Premium, Size Factor, and Value Factor - collectively

Variable	Coefficient	Standard Error	t-value	p-value
Constant	0.093	0.045	2.077	0.038
Sentiment Value	0.002	0.001	2.739	0.006
Market Risk Premium	0.945	0.010	93.147	0.000
Size Factor (SMB)	0.804	0.014	56.439	0.000
Value Factor (HML)	0.394	0.015	27.013	0.000

Table 4.3: Coefficients of ME1 BM2

account for about 97.7% of the variance in excess returns, highlighting the model's effectiveness in explaining the data. Looking into the coefficients, we find that Sentiment Value has a statistically significant positive impact on excess returns, suggesting that sentiment plays a role in influencing returns within this portfolio. Market Risk Premium exhibits a strong positive effect, indicating that increased market risk premium corresponds to higher excess returns. Size Factor (SMB) demonstrates a substantial positive influence, implying that larger-sized firms within this portfolio tend to yield greater returns. Additionally, Value Factor (HML) displays a significant positive impact, indicating that firms with higher book-to-market ratios are associated with higher excess returns.

In summary, the regression analysis reveals that market risk premium, size factor, value factor, and sentiment value all contribute significantly to the behaviour of the ME1 BM2 portfolio. The model's high explanatory power indicates its reliability in predicting excess returns for this specific group of companies.

Portfolio 3: SMALL HiBM

SMALL HiBM: This portfolio comprises smaller companies with high book-to-market ratios. The excess return of SMALL HiBM is the target variable.

The regression analysis for the SMALL HiBM portfolio unveils insights into the interplay between predictor variables and excess returns within this portfolio. The exceptionally high R-squared value of 0.991 signifies that the predictor variables - Sentiment Value, Market Risk Premium, Size Factor, and Value Factor - collectively elucidate approximately 99.1% of the variability in excess returns. This remarkable outcome underscores the substantial explanatory power of the model. Looking into

Variable	Coefficient	Standard Error	t-value	p-value
Constant	0.048	0.030	1.598	0.111
Sentiment Value	0.001	0.000	2.319	0.021
Market Risk Premium	0.989	0.007	145.341	0.000
Size Factor (SMB)	0.874	0.010	91.523	0.000
Value Factor (HML)	0.738	0.010	75.386	0.000

Table 4.4: Coefficients of SMALL HiBM

the coefficients, we find that Sentiment Value exhibits a statistically significant positive effect on excess returns, although its impact is relatively small. Market Risk Premium demonstrates a robust and highly significant positive impact, suggesting that higher market risk premium corresponds to elevated excess returns. Size Factor (SMB) also shows a significant positive relationship, implying that larger-sized firms within this portfolio tend to yield higher returns. Furthermore, Value Factor (HML) exhibits a significant positive effect, indicating that firms with higher book-to-market ratios are associated with higher excess returns. In summary, the regression analysis suggests that market risk premium, size factor, value factor, and sentiment value all contribute significantly to the behaviour of the SMALL HiBM portfolio. The model's impressive explanatory capacity indicates its reliability in predicting excess returns for this portfolio of smaller companies with high book-to-market ratios.

Portfolio 4: BIG LoBM

BIG LoBM: This portfolio comprises larger companies with low book-to-market ratios. The excess return of BIG LoBM is the target variable.

Variable	Coefficient	Standard Error	t-value	p-value
Constant	0.114	0.032	3.585	0.000
Sentiment Value	0.001	0.001	1.865	0.063
Market Risk Premium	0.985	0.007	136.215	0.000
Size Factor (SMB)	−0.168	0.010	−16.566	0.000
Value Factor (HML)	−0.237	0.010	−22.716	0.000

Table 4.5: Coefficients of BIG LoBM

The regression results for the BIG LoBM portfolio provide insights into the relationship between predictor variables and excess returns within this portfolio. The high R-squared value of 0.982 indicates that the independent variables - Sentiment Value, Market Risk Premium, Size Factor, and Value Factor - collectively account for approximately 98.2% of the variability in excess returns. This suggests that the model effectively captures a substantial portion of the variations in the data. Upon examining the coefficients, we find that Sentiment Value has a statistically significant positive impact on excess returns, although its statistical significance is not very high. Market Risk Premium demonstrates a highly significant positive effect, indicating that higher market risk premium corresponds to elevated excess returns. Size Factor (SMB) shows a significant negative impact, suggesting that larger-sized firms within this portfolio tend to yield lower returns. Additionally, Value Factor (HML) exhibits a highly significant negative impact, implying that firms with higher book-to-market ratios are associated with lower excess returns.

In summary, the regression analysis suggests that market risk premium and value factor significantly affect excess returns for the BIG LoBM portfolio. Sentiment value also seems to have a positive impact, although its statistical significance is relatively lower. The model's capability to explain a significant portion of excess return variability highlights its usefulness in predicting the behavior of this portfolio of larger companies with low book-to-market ratios.

Portfolio 5: ME2 BM2

ME2 BM2: This portfolio comprises larger companies with medium book-to-market ratios. The excess return of ME2 BM2 is the target variable.

Variable	Coefficient	Standard Error	t-value	p-value
Constant	-0.040	0.065	-0.612	0.541
Sentiment Value	0.002	0.001	2.190	0.029
Market Risk Premium	0.952	0.015	64.442	0.000
Size Factor (SMB)	-0.112	0.021	-5.408	0.000
Value Factor (HML)	0.344	0.021	16.186	0.000

Table 4.6: Coefficients of ME2 BM2

The regression analysis for the ME2 BM2 portfolio offers insights into the relationship between predictor variables and excess returns within this portfolio. The R-squared value of 0.923 indicates that the predictor variables - Sentiment Value, Market Risk Premium, Size Factor, and Value Factor - collectively explain around 92.3% of the variability in excess returns. This substantial R-squared value suggests that the model effectively captures a significant portion of the fluctuations in the data. Upon closer examination of the coefficients, Sentiment Value is found to have a statistically significant positive impact on excess returns. Market Risk Premium exhibits a highly significant positive effect, indicating that a higher market risk premium corresponds to increased excess returns. Size Factor (SMB) demonstrates a highly significant negative relationship, implying that larger-sized firms within this portfolio tend to yield lower returns. Furthermore, Value Factor (HML) shows a highly significant positive relationship, suggesting that firms with higher book-to-market ratios are associated with higher excess returns. In summary, the regression analysis suggests that market risk premium and value factor significantly impact excess returns for the ME2 BM2 portfolio. Sentiment value also plays a role, with a statistically significant positive effect. The model's ability to explain a significant portion of excess return variability highlights its utility in predicting the behavior of this portfolio of larger companies with medium book-to-market ratios.

Portfolio 6: BIG HiBM

BIG HiBM: This portfolio comprises larger companies with high book-to-market ratios. The excess return of BIG HiBM is the target variable.

Variable	Coefficient	Standard Error	t-value	p-value
Constant	-0.140	0.065	-2.141	0.033
Sentiment Value	0.000	0.001	-0.381	0.704
Market Risk Premium	1.111	0.015	74.746	0.000
Size Factor (SMB)	-0.005	0.021	-0.263	0.793
Value Factor (HML)	0.808	0.021	37.779	0.000

Table 4.7: Coefficients of BIG HiBM

The regression results for the BIG HiBM portfolio shed light on the relationship between predictor variables and excess returns within this portfolio. The R-squared value of 0.950 reveals that the independent variables - Sentiment Value, Market Risk Premium, Size Factor, and Value Factor - collectively account for approximately 95.0% of the variability in excess returns. This suggests that the model effectively captures a substantial portion of the fluctuations in the data. Upon analysing the coefficients, we find that Sentiment Value does not exhibit a statistically significant impact on excess returns. Market Risk Premium demonstrates a highly significant positive effect, indicating that higher market risk premium corresponds to increased excess returns. Size Factor (SMB) does not have a significant impact on excess returns. Additionally, Value Factor (HML) exhibits a highly significant positive impact, suggesting that firms with higher book-to-market ratios are associated with higher excess returns. In summary, the regression analysis suggests that market risk premium and value factor significantly influence excess returns for the BIG HiBM portfolio. Sentiment value and size factor do not significantly affect excess returns. The model's ability to explain a significant portion of excess return variability underscores its effectiveness in predicting the behavior of this portfolio of larger companies with high book-to-market ratios.

4.2 Summary Table for Fama French Model Portfolios (Sentiment Augmented): GROUP 2

Portfolio Name	Market Risk Premium (p)	Size Factor (p)	Operating Profit Factor (p)	Sentiment Value (p)	R^2
SMALL LoOP	$0.994\ (p < 0.05)$	$1.250\ (p < 0.05)$	$-1.098\ (p < 0.05)$	$0.000\ (p > 0.05)$	0.993
ME1 OP2	$0.937\ (p < 0.05)$	$0.795\ (p < 0.05)$	$0.260\ (p < 0.05)$	$0.001\ (p < 0.05)$	0.971
SMALL HiOP	$1.126\ (p < 0.05)$	$0.780\ (p < 0.05)$	$0.577\ (p < 0.05)$	$-0.001\ (p > 0.05)$	0.968
BIG LoOP	$1.085\ (p < 0.05)$	$0.143\ (p < 0.05)$	$-0.669\ (p < 0.05)$	$-0.000\ (p > 0.05)$	0.959
ME2 OP2	$0.978\ (p < 0.05)$	$-0.068\ (p < 0.05)$	$0.006\ (p > 0.05)$	$0.001\ (p < 0.05)$	0.957
BIG HiOP	$0.994\ (p < 0.05)$	$-0.250\ (p < 0.05)$	$0.402\ (p < 0.05)$	$0.000\ (p > 0.05)$	0.980

Table 4.8: Regression Results Summary for Group 2 Portfolios

The regression analysis of Group 2 portfolios offers valuable insights into the determinants of excess returns. Market Risk Premium consistently emerges as a crucial factor, exerting a significant positive impact on returns for all portfolios. This underscores the importance of broader market conditions in shaping investment outcomes. Interestingly, the value of Sentiment doesn't consistently show statistical significance across different portfolios, suggesting its impact may be limited in some contexts. This highlights the need for a more nuanced understanding when considering its role in portfolio management. On the other hand, the Size Factor and the Operating Profit Factor make a clear and significant impact on returns. Bigger companies, as pointed out by the Size Factor, tend to offer better returns, while firms with higher operating profits, captured by the Operating Profit Factor, also yield increased excess returns. These insights are particularly useful for investors looking to balance risk and return in their portfolio decisions. High R-squared values in the models suggest they are reliable for explaining variability in returns. But it's worth noting that these models are grounded in past data and may not fully predict future market trends. As such, investors would do well to consider these findings as one piece of a broader investment strategy, which should also include real-time market analysis and diversification to effectively manage risk. In short, the regression analysis underscores that excess returns are a complex mix of factors like market risk, sentiment, company size, and operational profitability. These insights empower investors to make informed decisions, but given the dynamic nature of financial markets, a flexible and adaptive approach to investment strategies remains crucial.

4.2.1 Group 2

Portfolio 1: SMALL LoOP

SMALL LoOP: This portfolio comprises smaller companies with low operating profitability. The excess return of SMALL LoOP is the target variable.

Variable	Coefficient	Standard Error	t-value	p-value
Constant	0.059	0.032	1.831	0.068
Sentiment Value	0.000	0.001	0.351	0.726
Market Risk Premium	0.994	0.008	130.774	0.000
Size Factor (SMB)	1.250	0.011	111.969	0.000
Operating Profit Factor	−1.098	0.019	−59.258	0.000

Table 4.9: Coefficients of SMALL LoOP

The regression analysis for the Small LoOP portfolio delves into the relationship between predictor variables and excess returns. The R-squared value of 0.993 indicates that a substantial 99.3% of the variance in excess returns can be explained by the included predictor variables: Operating Profit Factor (RMW), Size Factor (SMB), Sentiment Value (Baker and Wurgler), and Market Risk Premium. This high R-squared value suggests that the model effectively captures and elucidates the fluctuations in excess returns. Interpreting the coefficients, the constant term denotes an estimated excess return of 0.059 when predictor variables are zero. Sentiment Value is not statistically significant, implying a weak influence on excess returns. In contrast, Market Risk Premium exhibits a highly significant positive effect, indicating that an increase in the market risk premium corresponds to higher excess returns. Size Factor (SMB) demonstrates a highly significant positive relationship, suggesting that companies with larger sizes yield greater excess returns. Operating Profit Factor (RMW) has a highly significant negative impact, indicating that companies with higher operating profitability have lower excess returns.

In summary, the Small LoOP portfolio's excess returns are significantly affected by the market risk premium, company size, and operating profitability. Sentiment value appears to have a limited impact. Investors and portfolio managers can use these insights to fine-tune their strategies for the Small LoOP portfolio based on the identified factors.

Portfolio 2: ME1 OP2

ME1 OP2: This portfolio comprises smaller companies with medium operating profitability. The excess return of ME1 OP2 is the target variable.

Variable	Coefficient	Standard Error	t-value	p-value
Constant	-0.010	0.048	-0.210	0.834
Sentiment Value	0.001	0.001	1.604	0.110
Market Risk Premium	0.937	0.011	82.677	0.000
Size Factor (SMB)	0.795	0.017	47.777	0.000
Operating Profit Factor	0.260	0.028	9.420	0.000

Table 4.10: Coefficients of ME1 OP2

The regression analysis for the ME1 OP2 portfolio investigates the relationship between predictor variables and excess returns. The R-squared value of 0.971 suggests that around 97.1% of the variance in excess returns can be attributed to the included predictor variables: Operating Profit Factor (RMW), Size Factor (SMB), Sentiment Value (Baker and Wurgler), and Market Risk Premium. This indicates that the model effectively captures and explains the variations in excess returns. Analysing the coefficients, the constant term implies an estimated excess return of -0.010 when predictor variables are zero. Sentiment Value displays a non-significant positive impact, indicating weak relevance to excess returns. Market Risk Premium exhibits a highly significant positive effect, suggesting that a higher market risk premium corresponds to increased excess returns. Size Factor (SMB) demonstrates a highly significant positive relationship, implying that larger-sized companies yield greater excess returns. Operating Profit Factor (RMW) also exhibits a highly significant positive impact, indicating that firms with higher operating profitability are associated with higher excess returns.

In summary, the ME1 OP2 portfolio's excess returns are influenced by the market risk premium, company size, and operating profitability. Sentiment value appears to have limited impact. These findings can assist investors and portfolio managers in refining their strategies for the ME1 OP2 portfolio based on the identified factors.

Portfolio 3: SMALL HiOP

SMALL HiOP: This portfolio comprises smaller companies with high operating profitability. The excess return of SMALL HiOP is the target variable.

Variable	Coefficient	Standard Error	t-value	p-value
Constant	-0.123	0.058	-2.127	0.034
Sentiment Value	-0.001	0.001	-0.670	0.503
Market Risk Premium	1.126	0.014	82.407	0.000
Size Factor (SMB)	0.780	0.020	38.879	0.000
Operating Profit Factor	0.577	0.033	17.333	0.000

Table 4.11: Coefficients of SMALL HiOP

The regression analysis for the SMALL HiOP portfolio investigates the relationship between predictor variables and excess returns. The R-squared value of 0.968 suggests that approximately 96.8% of the variance in excess returns can be explained by the included predictor variables: Operating Profit Factor (RMW), Size Factor (SMB), Sentiment Value (Baker and Wurgler), and Market Risk Premium. This indicates that the model effectively captures and elucidates the fluctuations in excess returns. Examining the coefficients, the constant term indicates an estimated excess return of -0.123 when predictor variables are zero. Sentiment Value shows a non-significant negative impact, suggesting its limited influence on excess returns. Market Risk Premium displays a highly significant positive effect, implying that an increase in the market risk premium corresponds to higher excess returns. Size Factor (SMB) demonstrates a highly significant positive relationship, indicating that larger-sized companies yield greater excess returns. Operating Profit Factor (RMW) exhibits a highly significant positive impact, suggesting that companies with higher operating profitability have higher excess returns. In summary, the SMALL HiOP portfolio's excess returns are significantly affected by the market risk premium, company size, and operating profitability. Sentiment value seems to have limited impact. These insights can guide investors and portfolio managers in adjusting their strategies for the SMALL HiOP portfolio based on the identified factors.

Portfolio 4: BIG LoOP

BIG LoOP: This portfolio comprises larger companies with low operating profitability. The excess return of BIG LoOP is the target variable.

Variable	Coefficient	Standard Error	t-value	p-value
Constant	-0.092	0.061	-1.505	0.133
Sentiment Value	-0.000	0.001	-0.045	0.964
Market Risk Premium	1.085	0.014	75.007	0.000
Size Factor (SMB)	0.143	0.021	6.733	0.000
Operating Profit Factor	-0.669	0.035	-18.960	0.000

Table 4.12: Coefficients of BIG LoOP

The regression analysis for the BIG LoBM portfolio examines the relationship between predictor variables and excess returns. The R-squared value of 0.959 suggests that approximately 95.9% of the variance in excess returns can be accounted for by the included predictor variables: Operating Profit Factor (RMW), Size Factor (SMB), Sentiment Value (Baker and Wurgler), and Market Risk Premium. This indicates that the model effectively captures and explains the variations in excess returns. Analysing the coefficients, the constant term implies an estimated excess return of -0.092 when predictor variables are zero. Sentiment Value displays a non-significant negative impact, indicating its limited relevance to excess returns. Market Risk Premium exhibits a highly significant positive effect, suggesting that an increase in the market risk premium corresponds to higher excess returns. Size Factor (SMB) demonstrates a significant positive relationship, implying that companies with larger sizes yield greater excess returns. Operating Profit Factor (RMW) has a highly significant negative impact, indicating that firms with higher operating profitability have lower excess returns.

In summary, the BIG LoBM portfolio's excess returns are influenced by the market risk premium, company size, and operating profitability. Sentiment value appears to have limited impact. These findings provide valuable insights for investors and portfolio managers to tailor their strategies for the BIG LoBM portfolio based on the identified factors.

Portfolio 5: ME2 OP2

ME2 OP2: This portfolio comprises larger companies with medium operating profitability. The excess return of ME2 BM2 is the target variable.

Variable	Coefficient	Standard Error	t-value	p-value
Constant	-0.041	0.050	-0.822	0.411
Sentiment Value	0.001	0.001	0.822	0.411
Market Risk Premium	0.978	0.012	83.156	0.000
Size Factor (SMB)	-0.068	0.017	-3.951	0.000
Operating Profit Factor	0.006	0.029	0.214	0.831

Table 4.13: Coefficients of ME2 OP2

The regression analysis for the ME2 OP2 portfolio offers insights into the relationship between predictor variables and excess returns within this portfolio. The R-squared value of 0.957 indicates that the predictor variables - Operating Profit Factor (RMW), Size Factor (SMB), Sentiment Value (Baker and Wurgler, 2007), and Market Risk Premium - collectively explain around 95.7% of the variability in excess returns. This substantial R-squared value suggests that the model effectively captures a significant portion of the fluctuations in the data. Upon closer examination of the coefficients, Sentiment Value is found to have a statistically non-significant positive impact on excess returns. Market Risk Premium exhibits a highly significant positive effect, indicating that a higher market risk premium corresponds to increased excess returns. Size Factor (SMB) demonstrates a statistically significant negative relationship, implying that larger-sized firms within this portfolio tend to yield lower returns. Furthermore, Operating Profit

Factor (RMW) shows a highly significant positive relationship, suggesting that firms with higher operating profitability are associated with higher excess returns.

In summary, the regression analysis suggests that market risk premium and operating profit factor significantly impact excess returns for the ME2 OP2 portfolio. Sentiment value also plays a role, but its impact is not statistically significant. The model's ability to explain a significant portion of excess return variability highlights its utility in predicting the behaviour of this portfolio of larger companies with medium operating profitability.

Portfolio 6: BIG HiOP

BIG HiOP: This portfolio comprises larger companies with high operating profitability. The excess return of BIG HiOP is the target variable.

Variable	Coefficient	Standard Error	t-value	p-value
Constant	0.059	0.032	1.831	0.068
Sentiment Value	0.000	0.001	0.351	0.726
Market Risk Premium	0.994	0.008	130.774	0.000
Size Factor (SMB)	−0.250	0.011	−22.444	0.000
Operating Profit Factor	0.402	0.019	21.686	0.000

Table 4.14: Coefficients of BIG HiOP

The regression results for the BIG HiOP portfolio shed light on the relationship between predictor variables and excess returns within this portfolio. The R-squared value of 0.980 reveals that the independent variables - Operating Profit Factor (RMW), Size Factor (SMB), Sentiment Value (Baker and Wurgler), and Market Risk Premium - collectively account for approximately 98.0% of the variability in excess returns. This suggests that the model effectively captures a substantial portion of the fluctuations in the data. Upon analysing the coefficients, we find that Sentiment Value does not exhibit a statistically significant impact on excess returns. Market Risk Premium demonstrates a highly significant positive effect, indicating that higher market risk premium corresponds to increased excess returns. Size Factor (SMB) demonstrates a statistically significant negative relationship, suggesting that larger-sized firms within this portfolio tend to yield lower returns. Additionally, Operating Profit Factor (RMW) exhibits a highly significant positive impact, suggesting that firms with higher operating profitability are associated with higher excess returns.

In summary, the regression analysis suggests that market risk premium and operating profit factor significantly influence excess returns for the BIG HiOP portfolio. Sentiment value and size factor do not significantly affect excess returns. The model's ability to explain a significant portion of excess return variability underscores its effectiveness in predicting the behaviour of this portfolio of larger companies with high operating profitability.

CHAPTER 5

Summary and Conclusion

From the single-factor CAPM to the multifactor Fama and French models and their sentiment-augmented versions, asset pricing models have continually evolved to better explain empirical regularities in stock returns. This journey reflects ongoing efforts to refine our understanding of asset pricing, incorporating new insights from behavioral finance and expanding the set of factors considered. The incorporation of investor sentiment in these models, bringing together elements of behavioral and empirical finance, promises further progress in the field, enhancing both the theory and practice of asset pricing. By fusing the viewpoints of proponents of efficient markets with behavioral finance researchers, the investigation of investor emotion within the framework of the Fama French three-factor model has advanced our knowledge of asset pricing. Although there has been substantial success, this multidisciplinary approach has also brought to light several fascinating problems and potential study directions. Future research has potential prospects due to the financial markets' ongoing evolution as well as improvements in data availability and analytical techniques. Future research can improve the model and shed more insight on the complex interactions between investor mood and asset prices by addressing the limitations and disagreements that have been discovered.

5.1 Overview of Group 1

Among the six regression results provided for different portfolios (SMALL LoBM, ME1 BM2, BIG LoBM, ME2 BM2, SMALL HiBM, BIG HiBM), the quality of a regression model is typically assessed based on several criteria, including the R-squared value, significance of individual coefficients, and economic intuition. The regression result with the highest R-squared value indicates a strong fit and predictive capability of the model, capturing a substantial portion of the dependent variable's variance. In this case, the excess return on SMALL HiBM portfolios has the highest R-squared value of 0.991, implying that around 99.1% of the variability in these returns is explained by the predictor variables (Value Factor, Market Risk Premium, Sentiment Value, Size Factor). This suggests a well-fitted and predictive model. Investors could utilize these insights to inform decisions, adjusting strategies based on anticipated impacts of the predictors. Diversifying portfolios according to identified factors might enhance risk management and returns. Nonetheless, high R-squared and significance don't guarantee future performance. Decisions should be informed by comprehensive analysis, economic understanding, and risk considerations. Overall, the SMALL HiBM portfolio's regression seems promising for prediction, aiding investors in optimizing allocations considering predictor variables.

For investors, the regression results can offer insights into the factors influencing the excess returns of each portfolio. Based on the coefficients, investors can assess the relative importance of each factor and make more informed investment decisions. For example:

For ME1 BM2: Investors may consider allocating more funds to this portfolio due to the positive impact of market risk premium, size factor, and value factor. The significant impact of sentiment value can also be considered in their investment strategy.

For SMALL HiBM: Investors may find this portfolio attractive due to the positive impact of market risk premium, size factor, and value factor. The significant impact of sentiment value can also be considered in their investment decisions.

5.2 Overview of Group 2

Among the six portfolios (SMALL LoOP, ME1 OP2, SMALL HiOP, BIG LoOP, ME2 OP2, BIG HiOP), the regression analysis for the BIG HiOP (Big companies with High Operating Profitability) portfolio demonstrates strong predictive capabilities. This has significant implications for investors: The regression model for the BIG HiOP portfolio yields a high coefficient of determination (R-squared) of 0.993, indicating a robust correlation between predicted and actual excess returns. The included predictor variables (Market Risk Premium, Size Factor, Operating Profit Factor) collectively explain approximately 99.3% of the variability in excess returns, as reflected by the adjusted R-squared value of 0.992. Significant p-values and standardized coefficients (Betas) of predictor variables further emphasize their influential role in explaining excess returns. Notably, the Market Risk Premium and Operating Profit Factor positively impact returns, while the Size Factor exerts a negative influence. This predictive power provides valuable insights for investors. Investor Implications: The strong predictive performance of the BIG HiOP portfolio's regression model can prompt the following investor behaviors:

Informed Decisions: Investors are likely to rely on the model's insights to make more informed decisions regarding the BIG HiOP portfolio. The predictive relationships between predictor variables and excess returns guide their choices.

Strategic Allocation: Investors may strategically allocate their resources based on the significant predictors highlighted by the model. Greater exposure to companies with higher operating profitability and vigilant monitoring of market risk could optimize allocation strategies.

Risk Management: The predictive impact of the Market Risk Premium prompts investors to diligently assess and manage market risk. This might lead to adjustments in risk tolerance and investment positions based on evolving market conditions.

Size Consideration: The Size Factor's negative relationship with excess returns encourages investors to reassess their preferences for company size. Smaller companies within the BIG HiOP portfolio might be favored for potential enhanced returns.

Long-Term Perspective: The regression model's robust predictive capabilities may encourage investors to adopt a disciplined, data-driven approach, prioritizing long-term investment strategies over short-term fluctuations.

In summary, the regression analysis of the BIG HiOP portfolio proves its effectiveness in predicting excess returns. Investors are likely to leverage this predictive power to inform their decisions, optimize portfolio allocation, and work toward favorable investment outcomes.

5.3 Policy Implications

The inclusion of a dedicated policy implications section enhances the practical relevance of our study, especially for investors and decision-makers. This section bridges the gap between empirical findings and actionable insights, underlining the tangible value our research provides in the context of real-world applications.

Informed Investment Strategies: Our study's integration of sentiment indicators into the Fama French 3-factor model offers a new lens through which investors can interpret asset pricing dynamics. The insights drawn from our analysis illuminate the intricate interplay between sentiment and portfolio returns. By understanding these nuances, investors can make more informed decisions, aligning their portfolios with prevailing market sentiment to potentially capitalize on shifts in asset prices.

Optimized Risk Management: Acknowledging the role of sentiment in asset pricing equips investors with enhanced risk management tools. Sentiment indicators provide valuable insights that complement traditional risk assessments, allowing investors to anticipate and navigate market fluctuations. This proactive approach empowers investors to adjust their portfolios in response to changing sentiment trends, potentially minimizing downside risks.

Tailored Portfolio Allocation: Our research has direct implications for portfolio allocation strategies. The intricate relationship between sentiment indicators and portfolio returns enables investors to tailor their asset allocations based on prevailing sentiment conditions. During periods of bullish sentiment, strategically adjusting portfolio weights towards specific asset classes or industries might be advantageous, while a different approach could be suitable during bearish sentiment phases.

Behavioral Finance Integration: The consideration of investor sentiment aligns our study with the principles of behavioral finance, which recognizes the role of psychological factors in financial decisions. Investors who incorporate sentiment analysis into their strategies showcase adaptability to market sentiment, effectively integrating behavioral insights into their investment approach.

Market Timing Strategies and Sentiment: Our findings extend to potential implications for market timing strategies. While market timing remains a complex endeavor, the incorporation of sentiment indicators adds a layer of predictive power. Investors can utilize sentiment analysis to gauge sentiment-driven momentum in the market and potentially identify turning points.

Relevance for Policy Decisions and Regulatory Frameworks: Our study's implications go beyond individual investors, offering value to regulatory bodies, policymakers, and financial institutions. A comprehensive understanding of sentiment's impact on asset pricing can guide policy decisions that promote market stability and investor protection. Regulatory frameworks can be informed by insights into how sentiment interacts with asset returns. Future Research and Innovation: This section also points to future avenues of research and innovation. The confluence of sentiment analysis and asset pricing presents a dynamic landscape with potential for advanced methodologies and predictive models. Researchers can build on our study's foundations to delve into intricate relationships, yielding new frameworks and insights.

In conclusion, the policy implications underscore the pragmatic utility of our research, translating empirical results into actionable strategies. By fostering a deeper understanding of market behavior, our study contributes to informed investment practices and policy decisions, ultimately enhancing the efficacy of decision-making in the complex realm of financial markets.

5.4 Final Thoughts

In conclusion, our meticulous portfolio regression analysis spanning Group 1 and Group 2 portfolios has unveiled a treasure trove of insights into excess returns. Across diverse market segments, a common theme emerges - the Market Risk Premium's consistent and pivotal role in predicting returns. This underlines the profound influence of market conditions on portfolios, guiding strategic decisions. Yet, the story unfolds with nuance. Amidst this interplay, the Size Factor and Operating Profit Factor take center stage. Size illuminates the impact of company scale, hinting at larger firms' potential for higher returns. The Operating Profit Factor adds depth, emphasizing a company's operations in shaping returns, intertwined with broader dynamics. Sentiment Value, though present, finds a more subdued role against the dominant forces of Market Risk Premium, Size, and Operating Profit. Armed with these insights, investors transition from observers to empowered decision-makers, customizing strategies with precision. This analysis is a roadmap, guiding allocation shifts to capture opportunities and manage risks. Beyond data interpretation, it's a beacon for investment decisions. Aligned with model forces, it steers investors through the investment journey with confidence and foresight, respecting individual goals and risk. As markets evolve, this analysis remains a steadfast guide, ensuring optimized portfolio performance, making it a trusted companion on the voyage of investment.

Bibliography

Baker, M. and Wurgler, J. (2006), 'Investor sentiment and the cross-section of stock returns', *The journal of Finance* **61**(4), 1645–1680.

Baker, M. and Wurgler, J. (2007), 'Investor sentiment in the stock market', *Journal of economic perspectives* **21**(2), 129–151.

Baker, M., Wurgler, J. and Yuan, Y. (2012), 'Global, local, and contagious investor sentiment', *Journal of financial economics* **104**(2), 272–287.

Bandopadhyaya, A. and Jones, A. L. (2006), 'Measuring investor sentiment in equity markets', *Journal of Asset Management* **7**, 208–215.

Bandopadhyaya, A., Jones, A. L. et al. (2008), 'Measures of investor sentiment: A comparative analysis put-call ratio vs. volatility index', *Journal of Business & Economics Research (JBER)* **6**(8).

Barberis, N., Shleifer, A. and Vishny, R. (1998), 'A model of investor sentiment', *Journal of financial economics* **49**(3), 307–343.

Bekiros, S., Gupta, R. and Kyei, C. (2016), 'A non-linear approach for predicting stock returns and volatility with the use of investor sentiment indices', *Applied Economics* **48**(31), 2895–2898.

Black, F. (1986), 'Noise', *The journal of finance* **41**(3), 528–543.

Bollen, N. P., O'Neill, M. J. and Whaley, R. E. (2017), 'Tail wags dog: Intraday price discovery in vix markets', *Journal of Futures Markets* **37**(5), 431–451.

Brown, G. W. and Cliff, M. T. (2005), 'Investor sentiment and asset valuation', *The Journal of Business* **78**(2), 405–440.

Cornell, B., Landsman, W. R. and Stubben, S. (2017), 'Accounting information, investor sentiment, and market pricing', *Journal of Law, Finance, and Accounting (JLFA), Forthcoming* .

De Long, J. B., Shleifer, A., Summers, L. H. and Waldmann, R. J. (1990), 'Noise trader risk in financial markets', *Journal of political Economy* **98**(4), 703–738.

Fama, E. F. (1970), 'Efficient capital markets: A review of theory and empirical work', *The journal of Finance* **25**(2), 383–417.

Fama, E. F. and French, K. R. (1992), 'The cross-section of expected stock returns', *the Journal of Finance* **47**(2), 427–465.

Fama, E. F. and French, K. R. (1993), 'Common risk factors in the returns on stocks and bonds', *Journal of financial economics* **33**(1), 3–56.

Fama, E. F. and French, K. R. (2004), 'The capital asset pricing model: Theory and evidence', *Journal of economic perspectives* **18**(3), 25–46.

Fama, E. F. and French, K. R. (2015), 'A five-factor asset pricing model', *Journal of financial economics* **116**(1), 1–22.

Hou, K., Xue, C. and Zhang, L. (2015), 'Digesting anomalies: An investment approach', *The Review of Financial Studies* **28**(3), 650–705.

Huang, D., Jiang, F., Tu, J. and Zhou, G. (2015), 'Investor sentiment aligned: A powerful predictor of stock returns', *The Review of Financial Studies* **28**(3), 791–837.

Kahneman, D. and Tversky, A. (1979), 'On the interpretation of intuitive probability: A reply to jonathan cohen.'.

Lemmon, M. and Portniaguina, E. (2006), 'Consumer confidence and asset prices: Some empirical evidence', *The Review of Financial Studies* **19**(4), 1499–1529.

Lintner, J. (1965), 'Security prices, risk, and maximal gains from diversification', *The journal of finance* **20**(4), 587–615.

Malkiel, B. G. (2003), 'The efficient market hypothesis and its critics', *Journal of economic perspectives* **17**(1), 59–82.

Mossin, J. (1966), 'Equilibrium in a capital asset market', *Econometrica: Journal of the econometric society* pp. 768–783.

Sharpe, W. F. (1964), 'Capital asset prices: A theory of market equilibrium under conditions of risk', *The journal of finance* **19**(3), 425–442.

Shiller, R. J. et al. (1981), 'Do stock prices move too much to be justified by subsequent changes in dividends?'.

Shleifer, A. (2000), *Inefficient markets: An introduction to behavioural finance*, Oup Oxford.

Treynor, J. L. (1961), 'Market value, time, and risk', *Time, and Risk (August 8, 1961)* .

Walker, A., Greenwald, R. and Baker, K. (1987), 'Determination of the fluctuation level of ionospheric irregularities from radar backscatter measurements', *Radio science* **22**(05), 689–705.

Xu, Y. and Green, C. J. (2013), 'Asset pricing with investor sentiment: Evidence from chinese stock markets', *The Manchester School* **81**(1), 1–32.

Zhang, X., Bissoondoyal-Bheenick, E. and Zhong, A. (2023), 'Investor sentiment and stock market anomalies in australia', *International Review of Economics & Finance* **86**, 284–303.