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ANALYSIS OF QUANTITATIVE INVESTMENT STRATEGIES

Exploring a Behavior Factor Model to Explain Cross-Section of Average Realized Returns in the United States and Europe

Ana Beatriz Pereira Fernandes – 58853

Work project carried out under the supervision of:

Professor Nicholas Hirschey

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Abstract

A behavioral finance model was constructed exploring the cross-section of average realized returns in the United States and Europe. The European model was able to outperform the US model, having a Sharpe ratio of 0.681. Both models are suggested to explain market distressed events.

Two individual strategies, behavioral model and carry trade model, were afterwards combined with a bond portfolio to create a group portfolio, resulting in a Sharpe ratio of 0.46. The group portfolio had a lower Sharpe ratio, suggesting that investing in other portfolios could lead to better risk adjusted returns.

Keywords:

Financial Markets, Behavioral Finance, Stocks, United States, Europe

1. Introduction

Investors frequently fall by behavioral bias when managing their portfolios which can potentially lead to losses. Behavioral finance combines traditional finance, psychology, and neuroeconomics, to analyze how individuals behave and make decisions countering cognitive and emotional behavioral bias (CFA Institute, 2022).

This paper aims to study the characteristics of behavioral finance by constructing a behavior factor model to explain the cross-section of average realized returns by taking long and short positions in the stock market, exploring the differences between the US and Europe. Specifically, “Applying a behavioral model for the US and Europe, are the returns of the two groups significantly different, and what are the main factors impacting this difference?”

The model used is based on the article of Daniel, Hirshleifer, and Sun (2020) that combines a market factor with two theory-based behavior factors, PEAD, the short-term factor, exploring investors’ conservatism in their underreaction to earnings announcements, and FIN, the long term factor, exploring the overconfidence in issuing or repurchasing equity. This model allows investors to gain from return predictability by exploring investors’ behavioral finance bias. The paper will delve into the model performance during market distress events and analyze how the investors’ biases comprised in the model behave in times of uncertainty.

Section 2 describes the article on which the model is based and the literature previously done in the behavioral finance field. Section 3 describes the data extracted and the methodology used. Section 4 analyses the performance analysis of the model constructed, and Section 5 presents the discussion of the results in the context of the previous research done in the field. Section 6 and Section 7 present the limitations and the conclusion of this analysis, respectively.

2. Literature Review

2.1. Model Description

The model adopted for the construction of the investment strategy will be based on Daniel, Hirshleifer, and Sun's (2020) factor model which combines a market factor with two theory-based behavioral factors to explain the cross-section of average realized returns. The two theory-based behavioral factors capture long- and short-horizon mispricing, respectively. In the study, the model was solely applied in the US, precisely for NYSE, AMEX, and NASDAQ stocks.

This model outperformed other proposed models in explaining return anomalies proposed by Hou, Xue, and Zhang (2015), by analyzing a total of 34 anomalies. Comprising twenty-two long-horizon anomalies, defined as anomalies that persist and earn statistically significant positive excess returns for 1 to 3 years after portfolio construction, which were anomalies identified in the category of long-term profitability, value, investment and financing, and intangibles. And, twelve short-horizon anomalies, generally defined as anomalies that become statistically insignificant after 1 year of portfolio construction, were anomalies identified in the category of earnings momentum, return momentum, and short-term profitability (*Table 1 – Appendix*). Additionally, Lu, Stambaugh, and Yuan (2017) studied these previously identified anomalies for France, Germany, and U.K., suggesting that the anomalies are also significant in these countries.

2.1.1. FIN Factor

The long-horizon behavioral factor, FIN factor, explores investors' overconfidence bias. The market is unwilling to fully comprehend the information contained in a firm's decision to issue or repurchase equity, resulting in return predictability (Daniel, Hirshleifer, and Subrahmanyam 1998).

Stein (1996) defends that when the market valuation of the firm is perceived as over- or underpriced, the optimal decision for the firm is to issue or repurchase its own stock. As such, on average, positive abnormal returns follow repurchase activity and negative abnormal returns follow issuance activity. Daniel, Hirshleifer, and Sun's (2020) construction of the financing factor FIN was based on the return spread between issuers and repurchasers. As such, the FIN factor is a 50/50 combination of the 1-year net-share-issuance (NSI), based on Pontiff and Woodgate (2008), and 5-year composite-share-issuance (CSI), based on Daniel and Titman (2006), computed by going long the two value weighted low-issuance portfolios and short the two high-issuance portfolios.

CSI is computed by the firm's 5-year growth in market equity minus the 5-year equity return, in logs. NSI is computed by the firm's 1-year growth in market equity minus the 1-year equity return, in logs, excluding cash dividends.

After CSI and NSI computations, two size groups (small "S" and big "B") and three financial groups (low "L", middle "M", or high "H") are created to which, each stock will be assigned and re-assigned every June. Size group is based on whether the firm's market equity is below or above the NYSE median size breakpoint. Financial groups are independently assessed into three CSI groups (low, middle, or high) using 20% and 80% breakpoints for NYSE firms, and three NSI groups (low, middle, or high). Since NSI groups represent repurchasing and issuing firms, each June, repurchasing firms (with negative NSI) are sorted into two groups using the NYSE median breakpoint, and issuing firms (with positive NSI) are sorted into three groups using NYSE 30% and 70% breakpoints. Then, repurchasing firms with the most negative NSI are placed in the low NSI group, issuing firms with the highest NSI are assigned to the high NSI group, and the remaining firms are classified into the middle group.

Assigned three independent groups for NSI and CSI groups, the financial group is constructed assigning a firm to a high financing group ("H") if both NSI and CSI rankings belong to the high group. If both NSI and CSI rankings are in the low group, the firm is assigned to the low financing group ("L"). The remaining firms are assigned to the middle financing group ("M"). Combining the size group with the financing group led to the creation of six portfolios (SL, SM, SH, BL, BM, and BH), for which we calculate the value-weighted portfolio returns of each month, rebalancing each portfolio in June. Lastly, the monthly FIN factor return is calculated as the average return of the low financing portfolios (SL and BL) minus the average return of the high financing portfolios (SH and BH) (1).

$$FIN = \frac{(rSL+rBL)}{2} - \frac{(rSH+rBH)}{2} \qquad (1)$$

2.1.2. PEAD Factor - Post-earnings announcement drift

The short-horizon behavioral factor, PEAD (Post-earnings announcement drift), explores investors' conservatism bias by predicting abnormal returns due to investors' underreaction to new available public information, not adjusting immediately to earnings announcements (Bernard and Thomas, 1990).

Firms with positive earnings surprises experience positive drift after the announcement, conversely, firms with negative earnings surprises experience negative drift after the announcement (Hirshleifer et al., 2004).

PEAD is based on a two-by-three sort on size and earning-announcement returns, with value-weighted portfolios, by using earnings surprises of quarterly earnings announcements and is implemented by going long firms with positive earnings surprises and short firms with negative surprises.

Daniel, Hirshleifer, and Sun (2020) start to compute CAR as the 4-day cumulative abnormal returns around each quarterly announcement earnings date. After CAR computations, firms are assigned to two size groups (small "S" or big "B") and three earnings surprise groups (low "L", middle "M", or high "H"). Size group is assigned based on the NYSE median size breakpoint in relation to firm's market equity. Earnings surprise groups are based on CAR using 20% and 80% breakpoints for NYSE firms. Combining the size group with the earnings surprise group led to the creation of six portfolios (SL, SM, SH, BL, BM, and BH), for which we calculate the value-weighted portfolio returns. Lastly, the monthly PEAD factor return is calculated as the average return of the high earnings surprise portfolios (SH and BH) minus the average return of the low earnings surprise portfolios (SL and BL) (2)

$$PEAD = \frac{(rSH+rBH)}{2} - \frac{(rSL+rBL)}{2} \qquad (2)$$

2.1.3. European and U.S. behavioral factors

Both US and European institutions are similar in terms of scope, goals, and doctrine (Gutiérrez & Philippon, 2018). European markets are characterized as having a small number of securities, with lower market capitalization and lower liquidity compared with the U.S. markets (Shachmurove, 2002). Loughran and Ritter (1996) suggest that European market characterization leads professionals to respond to long- rather than short-run market fluctuations.

Comparing European firms with U.S.-based peers, European managers tend to adopt more conservative strategies in the firm's decision to issue or repurchase equity, even though indications of mispricing by peer comparison were available (Graham et al. 2013). This can be partially explained by the fact that European stock prices are less informative than those in the U.S. (Dang et al. 2015). Other referred difference highlights the institutional infrastructure since 44.29% of European firms are family controlled, a higher amount in relation to US firms, and only 36.93% are widely held (Faccio and Lang, 2002), affecting firm-specific information and stock prices (Mama, 2017).

Gutiérrez & Philippon (2018) concluded that European markets have lower concentration, lower excess profits, and lower regulatory barriers to entry. Analysing over time, the authors concluded that concentration and profits have increased in the US and remained stable in Europe. Additionally, European institutions have more political independence than US Institutions (Gutiérrez & Philippon, 2018). Shachmurove (2002) explores the effect of globalization, concluding that half of the shares analysed from 13 European stock markets had foreign issuers.

3. **Data & Methodology**

Data was extracted from the WRDS Wharton Research Data Services platform, more precisely from the Global Stock Returns and Characteristics (Jensen, Kelly, and Petersen, 2022) to the interval between 01/01/2007 and 31/12/2023. Monthly stock data was extracted for the United States and Europe.

Previous literature on stock market analysis in Europe extracted only a sample of countries located in this region. By Bauer, Cosemans, and Schotman (2010) that follow the composition of the MSCI Index, the European group is constituted by the stocks available on the exchanges of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, The Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK .

Daniel, Hirshleifer, and Sun (2020), implemented some filters that were also imposed in the construction of this model, by only extracting common stock, a positive book-to-equity ratio stocks, and excluding financial companies, precisely 45-49 Fama and French industry codes were excluded (Fama and French, 1997). The data sample covers all the industries not previously excluded (*Table 3 - Appendix*).

The methodology described above for the calculation of both factors was followed as described by Daniel, Hirshleifer, and Sun (2020). However, some adjustments to the Global Stock Returns and Characteristics data were made. Using the data extracted, some filters were implemented to ensure monthly data for all the years and Standardized unexpected earnings

(CAR) values to all stocks. Therefore, some stocks were excluded from the original file, resulting in 3990 USA stocks and 3098 European stocks analyzed (*Table 2* – Appendix).

By filtering the data, the amount of NYSE stocks resulted in 2 stocks, which could lead to statistical inference when trying to calculate the size group. Therefore, instead of the NYSE Median which is widely adopted in literature due to the Fama and French model, the overall stocks of the country median were used to compute the US size median. European size group was calculated using London Stock Exchange (LSE) median since this exchange provides a bridge between UK and European equities, being one of the largest exchanges in terms of number of stocks and market capitalization, having a high level of liquidity and being inserted in a capital market-oriented economy, the UK.

Daniel, Hirshleifer, and Sun (2020) start to compute CAR as the 4-day cumulative abnormal returns around each quarterly announcement earnings date. In this report, the variable Standardized unexpected earnings (niq su) available in WRDS was used, which is computed by the difference between actual earnings value minus the expected earnings value. The model was computed having a stop loss implemented if the drawdown was more than 20%, the position will be closed by a minimum of 3 months in order to protect investors.

4. Strategy Performance Analysis

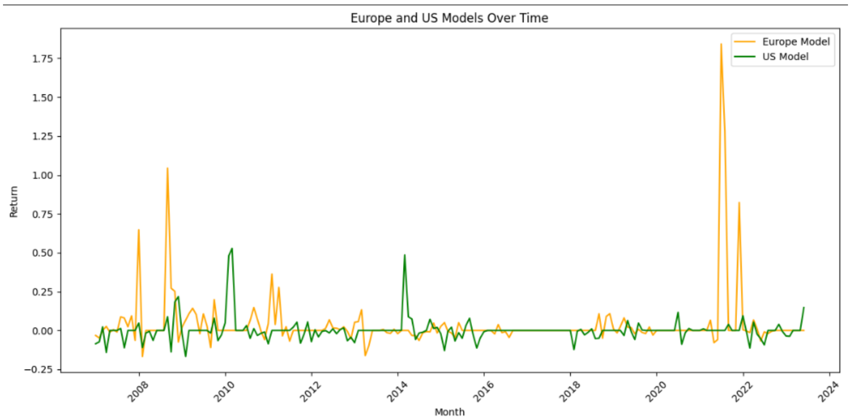
Having computed the models, it's essential to analyze its performance in the past to evaluate feasibility in the future. The USA model and the European model will both be analyzed in terms of performance analysis, with a comprehensive analysis of severe market distress occurring in the period analyzed, Statistical Analysis, and Regression Analysis. Additionally, the models computed will be compared with the same models if a stop loss wasn't implemented.

4.1. Performance Analysis and Statistical Analysis Models

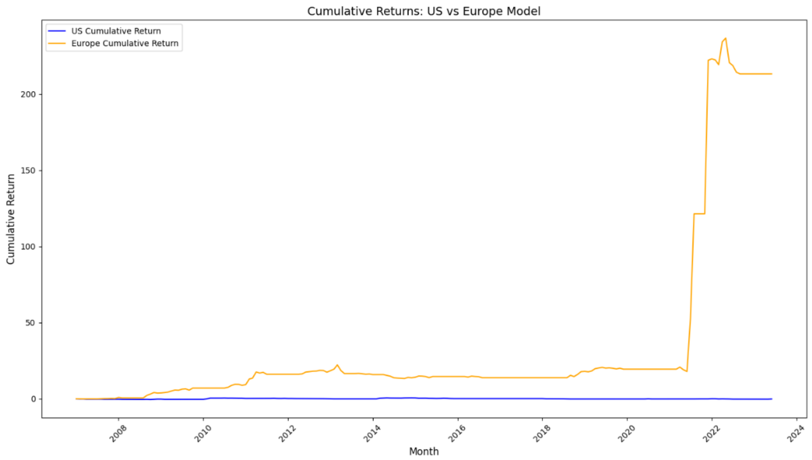
Observing the performance of the European model and the U.S. Model (*Graph 1 and Graph 2*), the European Model generates cumulative returns of 213x at the end of 2023. Following the indications and constructing the model to only work when all the portfolios were available in each specific month, it is perceivable that with the exceptions of some months, the European model only has monthly returns starting on January 2007.

The model presents high volatility during the period observed, especially during severe market distressed events, such as the case of the credit and financial crisis of 2009 and the COVID-19 pandemic crisis in 2020. The models had an additional implementation of a stop loss limit, the drawdown of the period was lower than 20%, otherwise, the position in the market would be closed for one quarter. Since the model comprises high volatility, establishing a stop loss can benefit from the risk exposure to the portfolio.

Graph 1 - US vs Europe Normal Returns



Graph 2 - US vs Europe Cumulative Returns



Analyzing the factors comprising the model, FIN and PEAD, we can observe that in both models, the FIN factors, 68.49%, and 276.24%, have higher volatility than the PEAD factor, 8.67% and 14.46%, in US and Europe models respectively (*Table 4* – Appendix) (*Table 1*). The European model presents the highest Sharpe ratio, 0.681, in comparison with the US model, 0.077. The Sharpe ratio calculates the risk-adjusted returns of each model, for an annualized return of 46.60%, the European model presents a 68.40% volatility. For the European model, PEAD Factor presents a higher Sharpe ratio of 0.4362. On the contrary, in the US model, although both values are negative, the FIN factor presents the highest Sharpe ratio.

Table 1 – Summary Analysis by model and factors

Annualized	Cumulative Return	Mean Return	Volatility	Sharpe Ratio	Skewness	Kurtosis	Maximum Drawdown
USA Model	-0.1535	2.08%	26.99%	0.077	3.936	23.549	-54.00%
FIN USA	-	-42.24%	68.49%	-0.6167	-2.1900	15.5068	-115.38%
PEAD USA	-	-7.49%	8.67%	-0.8674	-1.0334	5.0140	-73.59%
Europe Model	213.20	46.60%	68.40%	0.681	6.330	45.927	-30.39%

FIN Europe	-	-2.36%	276.24%	-0.0085	-0.3021	41.9248	-11.20%
PEAD Europe	-	6.31%	14.46%	0.4362	1.6254	17.1371	-26.44%

Severe market distress events are associated with volatility increase, stock prices decrease and high uncertainty, increasing investors risk aversion (Black,1976). In terms of a firm's payout policies, Bliss et al. (2015) observed that following a crisis, share repurchases and dividends decline, since firms increase cash reserves to protect themselves from market uncertainties. Observing the performance of the models during severe market distress events, specifically, the Financial and Credit Crisis of 2009 and the pandemic crisis of 2020, it's possible to better understand the models' characteristics. During distressed situations, the model tends to increase its volatility, the European model had a volatility of 114.96% in 2008 and the US model had a volatility of 36.65% in 2008 (*Table 2*), compared with an average volatility of 68.40% and 26.99% (*Table 1*), respectively, for the entire period under analysis.

Literature suggests a decrease of 30%-40% in the stock market over the period (Bartram and Bodnar, 2009). Shefrin (2015) suggests that the previous favorable stock market years led investors to be overconfident and less expectant of bad events. Almeida et al. (2016) refer to the 2009 financial crisis affected share repurchases, due to a tightening of credit access and an increase of cash reserves. The FIN Factor model is the return spread between issuers and repurchasers, since the market was under a bubble, the market perception to optimally issue or repurchase as suggested by Stein (1996) could be misleading.

In 2008, both models were positively affected by the crisis, obtaining annualized returns of 20.16% in the US model and 144.59% in the European model, a Sharpe ratio of 0.550 and 1.257, respectively (*Table 2*). During the crisis of 2009, the US model was negatively impacted, generating negative returns of -21.75%. In 2020, the European model incurred a stop loss during a long period of drawdown, therefore, the return was 0.00%.

In 2010 and 2021, however, both models were able to have a positive performance, resulting in a Shape ratio of 1.436 and 1.263 for the US and 1.266 and 1.848 for Europe.

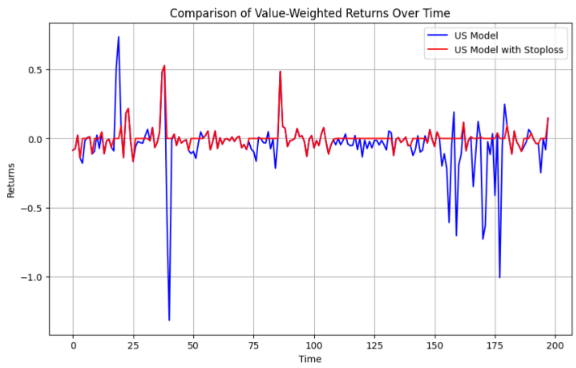
Table 2 – Annual Statistics

Annualized		2007	2008	2009	2010	2020	2021	2022
Returns	US Model	-37.59%	20.16%	-21.75%	98.99%	2.76%	4.99%	-11.31%
	Europe Model	66.57%	144.59%	66.57%	24.18%	0.00%	422.53%	-4.37%
Sharpe Ratio	US Model	-1.946	0.550	-1.098	1.436	0.179	1.263	-0.560
	Europe Model	2.094	1.257	2.094	1.266	0.000	1.848	-0.402
Standard Deviation	US Model	19.32%	36.65%	19.81%	68.93%	15.41%	3.95%	20.20%
	Europe Model	31.79%	114.96%	31.79%	19.09%	0.00%	228.65%	10.87%

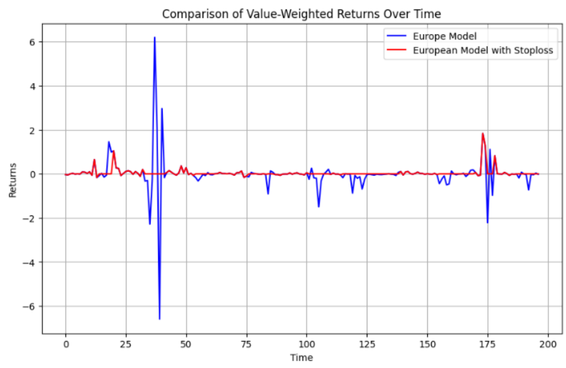
The 2020 pandemic crisis had a worldwide impact, the market overreacted achieving a drawdown of 60%, and the government stimulus contributed to the market correction (Gormsen and Koijen, 2020). Higher uncertainty led markets to be less efficient, resulting in investors overweight recent information and underweight previous information (Vasileiou, 2021).

4.1.1. Performance Analysis Stop Loss Models

Comparing the behavioral models performance with the behavioral models with stop loss implemented if the drawdown was more than 20%, with a closing position for a minimum of 3 months, its perceivable the higher volatility of the models without stop losses. In distressed market events the models without stop losses performed worst (*Graph 3 and Graph 4*)



Graph 3 - US Model vs US Model with Stop Losses



Graph 4 - Europe Model vs European Model with Stop Losses

Portfolios with stop losses were able to perform with an average annualized return of 2.08% and 46.60%, in the US and Europe, respectively. This value is lower when compared with the annualized returns of the models without stop loss. Models without stop losses incurred in much higher drawdowns, -114.36% and -1134.17%, to the US and Europe, respectively (*Table 3*). Sharpe Ratios were also better accounting for stop losses, 0.077 and 0.681, respectively, giving preference to the models with stop losses, better balanced in terms of risk adjustment returns.

Table 3 - Summary of Portfolio Stop Losse comparison

Annualized	Return	Volatility	Sharpe Ratio	Skewness	Kurtosis	Maximum Drawdown
US Model	-49.73%	67.55%	-0.736	-2.073	14.666	-114.36%
US Model with Stop Losses	2.08%	26.99%	0.077	3.936	23.549	-54.00%
Europe Model	3.95%	276.82%	0.014	-0.294	41.732	-1134.17%
Europe Model with Stop Losses	46.60%	68.40%	0.681	6.330	45.927	-30.39%

4.1.2. Regression Analysis

4.1.2.1. CAPM – US Model

The Capital Asset Pricing Model was computed in the time frame, accounting for 198 observations, the SPDR S&P500 ETF Trust (SPY) was used as a proxy to the market return, and risk-free rate was assumed to be 1.25% annualized. The regression results in an alpha of 1.64% with a market risk premium of 34.57%. The R square is 0.035%, therefore, the market risk premium explains little of the returns of the portfolio. Alpha and beta present a p-value of 0.788 and 0.794, respectively, values much higher than the 5% standard, therefore, the model is not statistically significant.

4.1.2.2. CAPM – European Model

The Capital Asset Pricing Model for the European model is computed using as a proxy the MSCI Europe Index and an annualized risk-free rate of 1.25%. The regression resulted in an alpha of -1.4% with a market risk premium of 274.4%. The R square is 6.30%, therefore, the market risk premium explains a small amount of the returns of the portfolio. Alpha and beta present a p-value of 0.677 and 0.001, respectively. Although beta is statistically significant, the model can only explain 6.30% of the regression.

4.1.2.3. Regression Comparison

Daniel, Hirshleifer, and Sun's (2020) CAPM computation between 1991 and 2014, generated an annualized alpha of 2.48% considering the 34 anomalies identified. The model generated a higher alpha for the short-term anomalies in comparison to the long-term anomalies. The results obtained were statistically significant for a p-value of 1%.

5. Discussion

European markets have a lower number of securities, with lower market capitalization and lower liquidity (Shachmurove, 2002), investors respond to long-term rather than short-term fluctuations (Loughran and Ritter, 1996) and managers adopt more conservative strategies (Graham et al., 2013), being 44.29% family-controlled businesses in 2002. These characteristics make the European market more susceptible to conservatism bias and therefore, higher potential returns in the PEAD factor of the model constructed. The Europe PEAD factor had an annualized return of 6.31% and an annualized Sharpe Ratio of 0.4362, compared with the US PEAD factor with an annualized return of -7.49% and an annualized Sharpe Ratio of -0.8674.

The model constructed outperformed other proposed models in explaining return anomalies proposed by Hou, Xue, and Zhang (2015) (Daniel, Hirshleifer, Sun, 2020), however, analyzing the performance of the model over time is important. The European model presents the highest Sharpe ratio, 0.681, in comparison with the US model, 0.077.

Both behavioral models result in positive risk-adjusted returns, however, this portfolios should also be compared with other strategies to better assess risk-adjusted returns. By implementing stock losses mechanisms, the strategy was able to adjust the level of risk.

There are some indications that the model can help explain the periods of severe market distress, in the year before and after the crisis, the model was able to benefit from the overconfidence and uncertainty of the market, both for the US and European Models. In 2008, the model was able to benefit from the market bubble, especially the FIN Factor that analyses overconfidence bias in stock issuance and repurchases. As stated by Shefrin (2015), the previous performance of the market led investors to be overconfident, being in accordance with the results observed.

During the beginning of the 2009 financial crisis the US model was negatively impacted, and, in 2020, both models performed weakly. As markets collapsed and as explained by Almeida et al. (2016) fewer share repurchases were made in this period, leading to lower predicted returns in the FIN Factor, which in addition to the market collapse led to incremental losses. The same resulted in COVID-19, with more uncertainty, an increase in interest rates, and more cash retention.

However, the following period highlights differences between the European and the US Models. In 2009 and 2021, the European model was able to generate positive performance with a Sharpe ratio of 1.257 and 1.848, respectively, while the US model had a negative performance with a Sharpe ratio of -1.098 in 2010 and a 4.99% of annualized returns to a Sharpe Ratio of 1.263, respectively. The US 2009 credit and financial crisis had a systemic impact in Europe and this can partly explain the negative US results, although financial crisis of lower proportions also irrupted in Europe during this period. The higher conservatism of European investors and managers, in relation to US investors and managers, and the European market characteristics, can help explain this results in periods of high uncertainty, by taking more time to adjust the market prices to new information, the model returns obtained, following an initial period of market distress events, can increase in relation to the overall period performance.

6. Limitations

The analysis was conducted by studying the past performance of the model.

Using the Global Stock Returns and Characteristics data set provided by WRDS and adding the proper filters, only 14 stocks of the main USA exchanges (NYSE, NASDAQ, and AMEX) were available for the analysis, which can result in multiple problems for the construction and evaluation of the model, since the size group was defined by the median of all the USA stocks instead of the median of the NYSE has originally done by Daniel, Hirshleifer, and Sun’s (2020). Getting the proper dataset for the USA and applying the size group as defined by the authors can result in different results.

The model is constituted by several stocks ranging from 1 to 44 Fama and French industry codes, further computations to discover the impact of the industry in the model could be done. Analyzing if there are some industries in which managers and investors tend to be more overconfident and conservatism, respectively.

The prices used to derive the results were converted into US dollars. However, the model did not incorporate potential fluctuations in exchange rates or the associated costs stemming from this limitation.

Transaction costs were not accounted for by the model. Especially when constituting a portfolio comprising different stocks, the implied cost of transaction will be quite substantial. Accounting the number of stocks included in the model, a real implementation of the strategy can lead to high transaction values.

7. Conclusion

The behavioral factor model based on Daniel, Hirshleifer and Sun (2020) was computed for European and US stocks of the main exchanges. The model is constituted by a market factor to two theory-based behavior factors, the FIN factor exploring the overconfidence in issuing or repurchasing equity, and the PEAD factor exploring investors' conservatism in their underreaction to earnings announcements. The purpose of the model is to explain the cross-section of average realized returns in the stock market. The European Model presents the highest Sharpe ratio, 0.681, in comparison with the US model, 0.077, being the optimal model between the US and Europe models in terms of risk-adjusted returns. By analyzing the annualized data during market distressed events, it's observable that the model generates positive returns especially before and after a distressed event. Although the model presents high volatility, especially during distressed events, if a stop loss is implemented when the drawdown is more than 20%, and the position is closed by a minimum of 3 months, the model can be implemented to benefit from overconfidence, uncertainty, and conservatism, while considering the risk incurred in the model.

Therefore, the ultimate suggestion would be not to integrate the model by itself but to insert the model in a portfolio, since the model presents high volatility and mainly performs positively before and after a distressed event.

In periods following the crisis, the characteristics of the European market and investors are suggested to explain the good performance of the model, better than the US model, since investors and managers tend to be more conservative and respond to long-term fluctuations rather than short-term fluctuations. These characteristics aligned with the uncertainty of market distress events can lead to positive returns. The European model had an annualized return of 144.59% in 2008 and 422.53% in 2021.

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9. Appendix

Table 1 – List of anomalies (Imported from Daniel, Hirshleifer, and Sun, 2020)

A. Short-horizon anomalies (12)		
Category	Symbol	List of anomalies
Earnings momentum	SUE-1	Standardized unexpected earnings (1-month holding period), Foster, Olsen, and Shevlin (1984)
	SUE-6	Standardized unexpected earnings (6-month holding period), Foster, Olsen, and Shevlin (1984)
	ABR-1	Cumulative abnormal returns around earnings announcements (1-month holding period), Chan, Jegadeesh, and Lakonishok (1996)
	ABR-6	Cumulative abnormal returns around earnings announcements (6-month holding period), Chan, Jegadeesh, and Lakonishok (1996)
	RE-1	Revisions in analysts' earnings forecasts (1-month holding period), Chan, Jegadeesh, and Lakonishok (1996)
Return momentum	R6-6	Return momentum (6-month prior returns, 6-month holding period), Jegadeesh and Titman (1993)
	R11-1	Return momentum (11-month prior returns, 1-month holding period), Fama and French (1996)
	I-MOM	Industry momentum (6-month prior returns, 6-month holding period), Moskowitz and Grinblatt (1999)
Profitability	ROEQ	Quarterly ROE (1-month holding period), Haugen and Baker (1996)
	ROAQ	Quarterly ROA (1-month holding period), Balakrishnan, Bartov, and Faurel (2010)
	NEI	Number of consecutive quarters with earnings increases (1-month holding period), Barth, Elliott, and Finn (1999)
	FP	Failure probability (quarterly updated, 6-month holding period), Campbell, Hilscher, and Szilagyi (2008)
B. Long-horizon anomalies (22)		
Profitability	GP/A	Gross profits-to-assets ratio, Novy-Marx (2013)
	CbOP	Cash-based operating profitability, Ball et al. (2016)
Value	B/M	Book-to-market equity, Rosenberg, Reid, and Lanstein (1985)
	E/P	Earnings-to-price, Basu (1983)
	CF/P	Cash flow-to-price, Lakonishok, Shleifer, and Vishny (1994)
	NPY	Net payout yield, Boudoukh et al. (2007)
	DUR	Equity duration, Dechow, Sloan, and Soliman (2004)
Investment and financing	AG	Asset growth, Cooper, Gulen, and Schill (2008)
	NOA	Net operating assets, Hirshleifer et al. (2004)
	IVA	Investment-to-assets, Lyandres, Sun, and Zhang (2008)
	IG	Investment growth, Xing (2008)
	IvG	Inventory growth, Belo and Lin (2012)
	IvC	Inventory changes, Thomas and Zhang (2002)
	OA	Operating accruals, Sloan (1996) and Hribar and Collins (2002)
	POA	Percent operating accruals, Hafzalla, Lundholm, and Van Winkle (2011)
	PTA	Percent total accruals, Hafzalla, Lundholm, and Van Winkle (2011)

	NSI	Net share issuance, Pontiff and Woodgate (2008)
	CSI	Composite share issuance, Daniel and Titman (2006)
Intangibles	OC/A	Organizational capital-to-assets, Eisfeldt and Papanikolaou (2013)
	AD/M	Advertisement expense-to-market, Chan, Lakonishok, and Sougiannis (2001)
	RD/M	R&D-to-market, Chan, Lakonishok, and Sougiannis (2001)
	OL	Operating leverage, Novy-Marx (2011)

Table 2 – Number of stocks per country

USA	Europe															
USA	AUT	BEL	CHE	DEU	DNK	ESP	FIN	FRA	GBR	GRC	IRL	ITA	NLD	NOR	PRT	SWE
3990	45	79	150	451	94	87	105	450	855	89	25	156	102	118	31	261

Table 3 – Number of Stocks per Fama and French 49 Industry Portfolio Classification

FF49	Europe	USA
1	14	19
2	90	88
3	7	14
4	39	21
5	4	4
6	17	32
7	62	68
8	39	45
9	61	71
10	33	66
11	20	85
12	56	163
13	125	273
14	69	102
15	36	55
16	25	21
17	99	115
18	92	66
19	57	66
20	12	26
21	152	199
22	43	99
23	47	87
24	16	36
25	10	14
26	3	12
27	21	40
28	40	31
29	3	6
30	76	203
31	60	194
32	69	126
33	19	49
34	212	276
35	28	118
36	333	324
37	127	311
38	39	139
39	45	72
40	12	18

41	118	137
42	113	199
43	108	235
44	36	85

Table 4 - Model performance (01-2007 to 12-2023) by factor composition

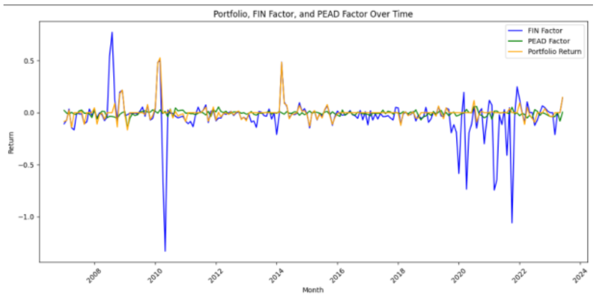


Table 5 - USA by factor - Normal Returns

Table 6 - Europe by factors – normal returns

A Work Project presented as part of the requirements for the Award of a Master's degree in Finance from the Nova School of Business and Economics.

ANALYSIS OF QUANTITATIVE INVESTMENT STRATEGIES

Ana Beatriz Pereira Fernandes – 58853

Nicole Hardock - 58052

Work project carried out under the supervision of:

Professor Nicholas Hirschey

17-12-2024

1. Introduction

Investors should construct diversified, and risk adjusted portfolios. In previous individual papers, two different portfolio strategies were constructed and analyzed, a behavioral finance model exploring the cross-section of average realized returns in Europe and a Carry Trade using currency data.

The purpose of this paper is to combine these models with other assets available to investors, in this case with a bond portfolio, and create a group portfolio, better adjusted in terms of risks to returns, benefiting from diversification in terms of assets and geographic regions used. Additionally, the created group portfolio will be compared with other known portfolios: the 60/40 portfolio and the buy-and-hold stock portfolio.

In Section 2, the individual strategies will be described and analyzed, Section 3 explores the combined portfolio by assessing different portfolios, Section 4 compares the group portfolio created with other portfolios. Section 5 computes the regression analysis using the CAPM model. Section 6 and 7, presents limitations and conclusion, respectively.

2. Individual Strategies

Two models were computed and analyzed to integrate the group portfolio, a behavioral stock model in Europe and a Carry Trade using currency data. Each portfolio will be analyzed in terms of economic motivation, strategy and performance overview.

2.1 Behavioral Strategy

Investors frequently fall by behavioral bias when managing their portfolio, resulting in losses for their portfolio. Accounting for behavioral bias, in this case, the overconfidence bias and the conservatism bias, results in predictability in return.

The behavioral factor model based on Daniel, Hirshleifer, Sun (2020) was computed to the stocks of the European main exchanges. The model is constituted by a market factor to two theory-based behavior factors, FIN factor exploring the overconfidence in issuing or repurchasing equity, and PEAD factor exploring investors conservatism in their underreaction to earnings announcements. The purpose of the model is to explain cross-section of average realized returns by taking long and short positions in the stock market.

The strategy had a negative cumulative value of -93.83% and a Sharpe ratio of 0.1099 during the period observed. However, when applying the model to market distress events, the model is able to generate a positive returns, in 2008, 2009 and 2021, the model had annualized returns of 144.59%, 66.57% and 422.53%, and Sharpe ratio of 1.257, 2.094 and 1.848, respectively.

2.2 Currency Strategy

This study evaluates a dynamic carry trade strategy in FX markets from 2013 to 2023, incorporating momentum filters and stop-loss mechanisms to enhance performance and manage risk. The Momentum 6M strategy delivered the highest annual returns, effectively capturing trends and reducing downside risk compared to the pure carry strategy. Over the period from 2013 to 2023, it achieved an average annual return of 29.32%, outperforming the carry strategy on an average annual return basis. However, as previously noted, this figure is likely influenced by the forward-fill technique applied in June 2013, and should therefore be interpreted with caution. Despite this limitation, the strategy was selected for the group analysis due to its strong performance potential. At the same time, the Momentum 6M strategy also experienced the highest drawdowns, with an annual average of 17.89%, reflecting its vulnerability during trend reversals and market stress. Moreover, its average Sharpe ratio is 0.61, which is the highest value of the compared strategies.

3. Combined Strategy

The two aforementioned strategies have been combined with a bond’s portfolio to better construct a portfolio that maximizes return while minimizing the risk of individual investors. Bonds provide a high risk adjusted return especially in times of uncertainty as financial crisis (Chan et al., 2011). To do so, we will summarize each asset to be used in the group portfolio, followed by the correlation analysis between these assets, construction the group portfolio optimization and analyze it.

3.1 Strategies Summary

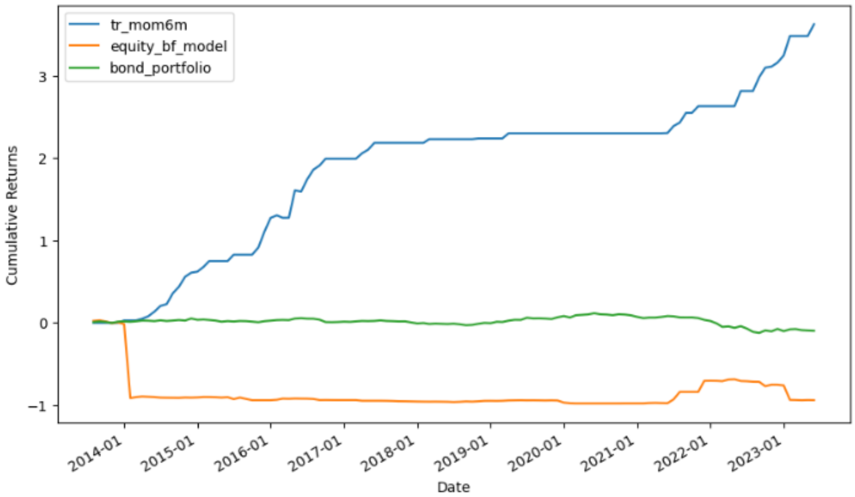
Analyzing the individual strategies, we observe that the currency model provided the best cumulative returns, 362.3%, and the best Sharpe ratio, 1.512, under the time in analysis (*Table 1*).

Table 1: Strategies Summary

	Behavioral Model	Bond Model	Currency Model
Expected Returns	12.32%	-0.92%	15.91%
Standard Deviation	89.22%	4.55%	8.86%
Sharpe Ratio	0.1099	-0.754	1.512
Cumulative Returns	-93.82%	-9.66%	362.3%

The chart displays the cumulative returns of three portfolios from 2014 to mid 2023: Behavioral Model (orange), Bond Model (green), and Currency model (blue) *(Graph 1*). The Currency model strategy shows a remarkable and consistent upward performance, particularly accelerating from 2016 onward, significantly outperforming the other two portfolios. In contrast, the Bonds portfolio remains relatively stable with minor fluctuations and maintains slightly negative cumulative returns. The Equity Model, starting on a downward trend early in the observation period, is able to recover in the period after covid. Overall, the chart highlights that the momentum-hedged carry strategy achieves significantly higher cumulative returns, while the other two strategies underperform in comparison.

Graph 1: Cumulative Return Performance



3.2 Correlation matrix

Examining the correlation matrix reveals the correlation between the different assets available in the portfolio. As observed, the behavioral model and the bond model have a negative correlation of -0.130. Additionally, the currency model and the bond model have a negative correlation of -0.188 (*Table 2*). The correlations between the assets are weak, suggesting that integrating the assets in the same portfolio can lead to risk and volatility reduction benefiting from diversity.

Table 2: Correlation Matrix

	Currency Model	**Behavioral Model**	**Bond Model**
Currency Model	1.000	-0.025	-0.188
Behavioral Model	-0.025	1.000	-0.130
Bond Model	0.188	-0.130	1.000

3.3 Portfolio Optimization

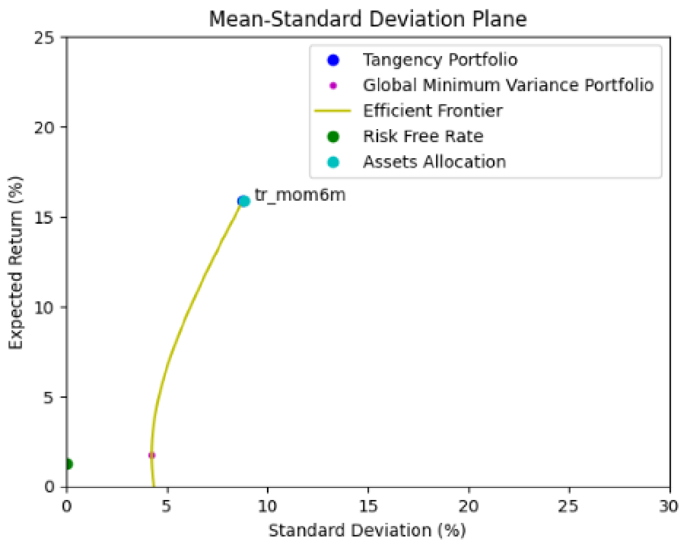
Using the strategies described above, three portfolios were computed: the minimum variance portfolio, tangency portfolio and equal-weights portfolio. Since the behavioral model and the currency model are complex models that already include hedging positions, short positions are not possible and, therefore, were not allowed for the computations of any of the portfolios. The tangency portfolio maximizes the Sharpe ratio, achieving the optimal risk adjusted returns portfolio. The Sharpe ratio, calculated as the portfolio's excess return divided by its standard deviation, measures the risk-adjusted return of an investment. Observing the optimal weights achieved in each portfolio, the bond model is not accounted in the tangency portfolio and the behavioral model only accounts 0.98% (*Table 3*).

Table 3:

Weights (%)	Behavioral Model	Bond Model	Currency Model
Minimum Variance Portfolio	0.82%	83.86%	15.32%
Tangency Portfolio	0.98%	0.00%	99.02%
Equal-weights Portfolio	33.33%	33.33%	33.33%

Markowitz (1952) developed the efficient frontier, accessing the set of optimal portfolio returns for each level of risk (*Graph 2*).

Graph 2: Efficient Frontier



3.4 Optimized Portfolio Statistics

The tangency portfolio is the optimal portfolio choice, having a better risk adjusted return, maximizing the sharpe ratio, 0.4600, resulting in an annualized return of 36.31%. The minimum variance portfolio presents the minimum standard deviation of 4.53%, a difference of 31.78 percentage points in comparison with the tangency portfolio (*Table 4*). The minimum variance portfolio presents a negative Sharpe ratio, partially a result of a higher portfolio weight allocation on the behavioral model strategy.

Table 4: Summary Statistics

Annualized	Tangency Portfolio	Equal-weights Portfolio	Min. Variance Portfolio
Return	36.31%	8.38%	0.27%
Standard Deviation	75.12%	29.43%	4.53%
Sharpe Ratio	0.4600	0.2255	-0.3263
Sortino Ratio	6.2205	0.5108	-0.2392
Cumulative Returns	20.578	1.222	0.027

4. Performance analysis

4.1 Methodology

In order to better assess the performance of the Group Portfolio, additional portfolios as the 60/40 portfolio and a buy and hold S&P500 Index portfolio will be computed to better determined how the portfolio is positioned in terms of Return, Standard Deviation and Sharpe Ratio. The performance of each portfolio was evaluated from August 2013 until June 2023.

The 60/40 Portfolio was computed using a weight of 60% equities, using as proxy the SPDR S&P500 ETF Trust (SPY) and a 40% weight bonds using as proxy the Vanguard's Total Bond Market ETF (BND). The SPY portfolio was created using the buy and hold strategy for the SPDR S&P500 ETF Trust (SPY).

The risk-free rate was derived by averaging the annualized rates over the given period from 2013 to 2023. The rates were provided as annual values specific to each year, reflecting changes in macroeconomic conditions, monetary policy, and interest rate environments. These risk-free rates represent the theoretical return an investor can achieve with zero risk over a given year, typically approximated by government bonds or treasury yields. In order to analyze the sensitivity of the results to changes in the risk-free rate, a shock analysis was conducted. Specifically, the original risk-free rates have been adjusted by adding a range of shocks. For each shock, the adjusted rates were recalculated, and the average risk-free rate across all years were determined (*Table 5*).

Table 5: Sensitivity Analysis on risk free rates

Shock	Average Adjusted Risk-Free Rate
-0.5%	0.75%
0%	1.25%
0.5%	1.75%
1%	2.25%

4.2 Analysis

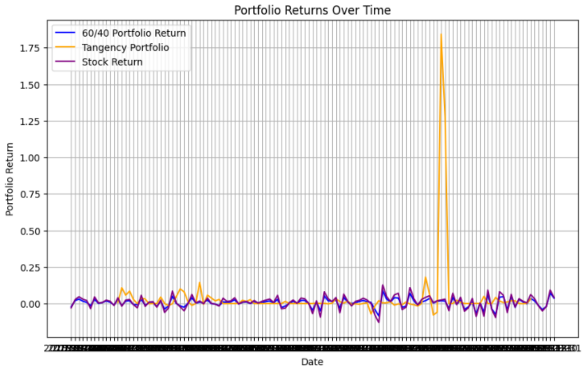
The SPY presents the highest Sharpe ratio, 0.6525, of the three computed portfolios. The group portfolio has the highest annualized return, 36.31%. However, it presents the highest volatility, 75.12% (*Table 6*).

Table 6: Summary Statistics

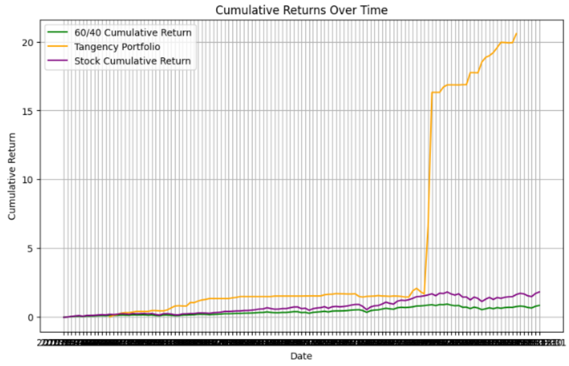
Annualized	Group Portfolio	60/40	SPY
Return	36.31%	6.35%	11.12%
Standard Deviation	75.12%	9.99%	15.12%
Sharpe Ratio	0.4600	0.5098	0.6525
Cumulative Return	20.578	0.837	1.817

In *Graph 3*, it is perceivable to observe the volatility variations over time and how the group portfolio was able to achieve the higher level of volatility compared to other portfolios. The group portfolio achieved the highest cumulative return of 20.578 over the period observed (*Graph 4*).

Graph 3: Portfolio Returns over time



Graph 4: Cumulative Returns over time



5. Regression Analysis

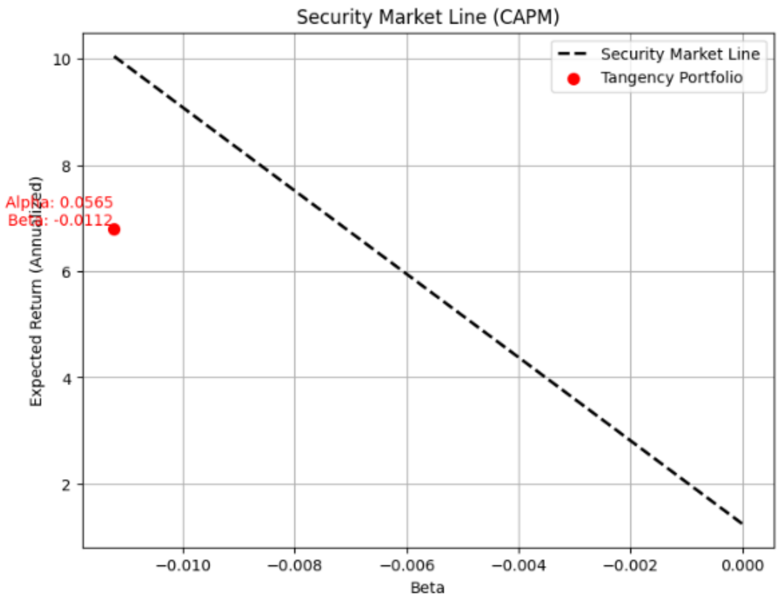
5.1 CAPM

The CAPM was applied to evaluate the performance of the Tangency Portfolio, using the MSCI All World Index as the market benchmark. The assumed risk-free rate for this analysis was 1.25% annually. The purpose of the analysis was to measure the Tangency Portfolio's systematic risk and its performance above or below the market's expected return, represented by alpha.

The Tangency Portfolio's excess returns were calculated by subtracting the risk-free rate from the monthly portfolio returns. Similarly, the market portfolio's excess returns were derived by adjusting the MSCI All World Index returns for the risk-free rate. A linear regression was performed, where the Tangency Portfolio's excess returns served as the dependent variable, and the market's excess returns acted as the independent variable. This regression allows for the estimation of Alpha and Beta.

The regression results indicated an annualized Alpha of 0.0565 and a Beta of -0.0112. The fact that the tangency portfolio is below the security market line shows that the Tangency Portfolio underperformed on a risk-adjusted basis, delivering returns below the expected market return when accounting for the risk-free rate. Additionally, the negative Beta implies that the portfolio's returns were slightly inversely related to the market's movements, although the magnitude is minimal. This indicates that the Tangency Portfolio exhibits little to no systematic risk exposure.

Graph 5: Security Market Line and Tangency Portfolio



The results are visualized in the Security Market Line (*graph 5*). The SML represents the theoretical relationship between Beta and the expected return under the CAPM framework. The Tangency Portfolio's expected return is plotted as a red point on the graph. The deviation below the SML reinforces the negative Alpha, while the positioning near the vertical axis highlights the near-zero Beta. These results collectively indicate that the Tangency Portfolio's performance does not align with market trends and suggests a lack of exposure to systematic risk.

In conclusion, the analysis reveals that while the Tangency Portfolio carries minimal market risk, it fails to outperform the benchmark on a risk-adjusted basis, as reflected by its negative Alpha.

Limitations

First, the portfolio optimization was based on historical data from August 2013 to December 2023. Using a different time span could significantly change the optimal asset allocation. For example, including data from before 2013, when market dynamics may have differed, could potentially alter the weighting for the behavioral model in the tangency portfolio.

Second, the data was obtained from Refinitiv Eikon. While a reputable provider, Refinitiv Eikon's data may not perfectly match that of other sources like Bloomberg or Refinitiv, potentially leading to variations in the results.

Third, the analysis did not include trading costs, which can significantly impact real-world investment returns. This omission may overstate the actual performance of the strategies.

Fourth, a forward-fill method was used to handle missing data points. This can introduce a look-ahead bias, potentially leading to overly optimistic performance estimates.

Fifth, the MSCI All World Index used as a benchmark has its own limitations. It tends to be overweight in US stocks and may not fully represent the global market. Additionally, it has a high concentration of technology stocks, a sector known for its momentum behavior, which could influence the results.

6. Conclusion

The behavioral factor strategy and the carry trade strategy were combined with a bond portfolio to create a group portfolio. The correlations between the strategies are weak, suggest benefits from diversification when integrated in the same portfolio. The purpose was to create a risk adjusted return portfolio, therefore, maximizing the Sharpe ratio, obtaining a result of 0.46, with an annualized return of 36.31%. Compared with the 60/40 portfolio and a stock portfolio, the group portfolio have a lower Sharpe ratio, the best cumulative return and a high value of volatility, suggesting that investing in other portfolios could lead to better risk adjusted returns.

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